Transitioning Transit : Modeling the Electrification of an Intracity Bus System

by

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Submitted to the Institute of Data, Systems, and Society and the
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Abstract

In the past few years, there has been a significant push towards the electrification of transportation as an important climate change mitigation strategy, especially given that transportation contributes to over 15 % of greenhouse gas emissions. While a lot of the present research is focused around the electrification of the private vehicle fleet, another segment of transportation that merits attention is public transit. In many developing countries, public transit buses while being a popular mode of commute, are also hugely responsible for air pollution. This includes particulate matter pollution that poses very significant health risks. However, there are challenges that limit the adoption of electric buses, including limited driving range, high battery costs and most importantly, developing charging infrastructure best suited to meet travel needs. This thesis seeks to begin addressing these challenges by developing a transit bus electrification model that can calculate the energy needs of a city bus system with minimal operational data and uses the network properties of the system to identify an optimal cost solution for operating an electric bus fleet. It also seeks to understand the factors that drive this transition. The model is applied to the city of Delhi's transportation system, which further highlights the importance of making route-specific decisions when transitioning to electric buses.

The model developed in this thesis may enable policymakers and transit authorities to make informed, data-driven decisions, as they proceed to electrify their public transportation systems.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

The recently released UN Intergovernmental Panel on Climate Change (IPCC) Report [Masson-Delmotte et al., 2021] re-asserted the grave concerns that numerous scientists have raised over the last few decades: Global warming is a phenomenon that can have catastrophic consequences for life on Earth - and it is very much real. With decades of pollution and carbon emissions behind us, we are now at the point where we must actively work towards a decarbonized, sustainable future.

Combating climate change requires us to closely examine all sectors producing greenhouse gas emissions. One such sector facing increasing scrutiny is transportation. In 2016, transportation was responsible for 16.2% of the world's CO_2 emissions.[Ritchie and Roser, 2020]
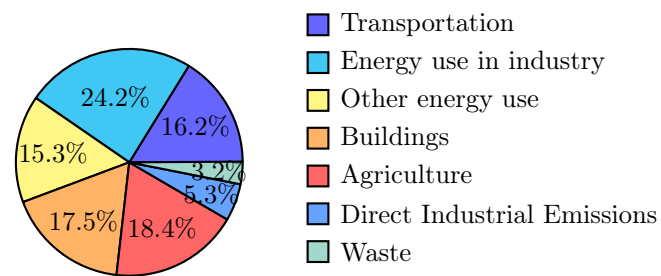
Figure 1-1: Global CO_2 emissions by sector

1.1   Decarbonizing Transportation

Globally, transportation emissions have been steadily increasing at an alarming rate of 1.9% annually, since 2000[1][IEA, 2021c]. As can be seen from Figure 1-2, the biggest

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[1]2020 was an exception, where the rate slowed to 0.5% because of the pandemic

source for these emissions are passenger cars. The auto sector contributes roughly 3 percent of all GDP output; with the share being even higher in Asian markets like China and India. With increasing car sales, there are more vehicles on the roads and with the sheer number of trips growing over the last few decades, today they are responsible for the release of 3.6 GT of carbon dioxide into the atmosphere. It is then no surprise that, thus far, a large amount of the research on strategies to decarbonize transportation, focuses on eliminating emissions from private passenger vehicles.

Different kinds of solutions have been proposed to solve this issue. One popular
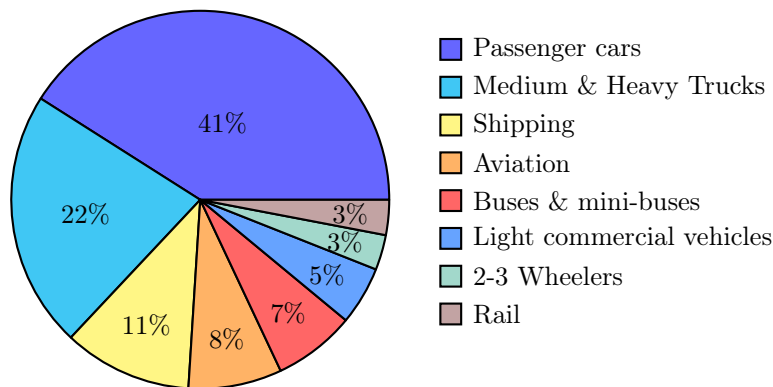
Figure 1-2: Emissions by mode[IEA, 2021c]

framework, to structure policy measures for transport decarbonization, is the "Avoid-Shift-Improve" framework [IEA, 2021c]. The idea behind this framework is simple - we need to "avoid" unnecessary transportation (by improving land-use and reducing trip time), "shift" to environment friendly transport modes (by increasing trip efficiency) and "improve" on existing transportation technology.

A key piece of the puzzle, then, is "shifting" to modes of transport that have a considerably lower carbon footprint than private passenger vehicles. On road, this could happen if we switch from private to public transport, primarily buses . Public transport buses have 33% [EPA, 2018] lesser emissions-per passenger mile, as compared to private passenger cars. The merits of developing and promoting the use of public transit buses are becoming increasingly evident and they have now become a central focus of the transportation strategy for climate action plans of cities and

countries around the world.

In China for e.g., Beijing's Transport Action Plan targets the optimization of its 80 public transit bus routes. In India, Delhi's Climate Action Plan speaks extensively about augmenting the existing public transport network, with a specific goal targeting an increase in the modal share of buses. In the United States, Chicago and Denver are some examples of cities that share similar goals in expanding and promoting the usage of public transport.

However, despite their carbon footprint being smaller, public transport is still nowhere close to being the zero emission alternative we desire. Often powered by fossil fuels like diesel, they themselves contribute to over 7% of transportation emissions today - a number that is only bound to increase if we do promote a switch to public transport as it exists currently. This motivates research on adequately planning to decarbonize this mode of transportation as well.

1.1.1   Decarbonizing Public Transit Buses

There are several ways of thinking about decarbonizing public transport buses. Consider this modified form of the popular Kaya Identity, for transportation -

$$\text{GHG emissions} = \text{Fuel Carbon Intensity} * \text{Energy Intensity} * \text{Activity} \qquad (1.1)$$

In order to reduce our net greenhouse (GHG) emissions, we must thus reduce atleast one of these three factors, namely *Fuel Carbon Intensity*, *Energy Intensity* or *Activity*.

Reducing the amount of the *Activity* of these buses would require taking radical measures in reducing land use and reworking existing routes to be more optimal. Reducing *Energy Intensity* with existing powertrains is also a challenging undertaking - since it might be difficult to increase the efficiency of these buses given technical limitations. This leaves us with the strategy of reducing the *Fuel Carbon Intensity* itself - and this is a promising one.

A significant amount of research and industrial action has led to huge strides in the

development of Electric Vehicles (EV) - i.e., vehicles that use electricity from the grid as fuel. Electric vehicles have several advantages - not only are their powertrains more efficient than internal combustion engine vehicles (ICEV), but reducing the "fuel" carbon intensity of these vehicles is very much more technologically possible - and, in fact, is a concurrent goal that the energy sector is working towards, a shift to renewable electricity. This motivates the idea of using electricity-powered buses as a promising option to reduce the carbon footprint of public transport as it exists today.

1.2 Electrification of Public Transit

A case for the electrification of buses can be made on several grounds.

* First, under the right circumstances (which will further be elaborated on in Section 2.4), electric buses have lesser emissions than equivalent diesel ones.

* Second, some preliminary studies have shown that not only do these buses benefit us environmentally, they are also economically attractive alternatives. [Khandekar et al., 2018] find that the Total Cost of Ownership of Battery Electric Buses can be significantly lower than that of their diesel counterparts, if battery costs continue to drop as they have done so in the recent past.

* Another reason why switching to electric buses (and other vehicles) is being promoted by many countries, is because it dramatically reduces a country's reliance on the import of fuel from other oil-rich countries and eliminates the risk of price inflation that comes with it. India's FAME (Faster Adoption and Manufacturing of (Hybrid &) Electric Vehicles)[Dept of Heavy Industry, 2012] scheme specifically states that achieving fuel security is a key goal of the efforts to speed up vehicle electrification.

* Apart from this, historically, electric buses have shown higher adoption rates, as compared to their passenger vehicle counterparts, and it seems to be a good avenue to accelerate electrification overall. This can be attributed to some

unique features of this mode of transportation. For one, transit fleets have a higher replacement rate - in the US, for e.g., 5000-6000 of the 70000 odd buses in the fleet are replaced every year. This gives us ample opportunity to replace an older technology with a newer technology, such as the electric bus. Moreover, public transport is often controlled by some form of government authority. This allows us to support electrification more easily, and with lesser resistance, using policy measures. Several countries provide subsidies on the purchase and operation of electric buses, as well as funds to build the required infrastructure to support it. The next section further elaborates on the current state of bus electrification.

1.3   Review of Public Bus Fleet Electrification Plans

A recent study by researchers at Bloomberg NEF found that over 70% of buses in cities across the world will be electric by 2040, which is quite substantial [McKerracher et al., 2020]. This kind of accelerated adoption is only possible with government support, in the form of mandates, subsidies and incentives, in place. While by no means exhaustive, this section reviews some key initiatives and policies that have been announced in different parts of the world.

1.3.1   USA

In the United States, it is expected that 33% of the $\sim$ 70000 odd strong public bus fleet will be electric by 2045 [Casale, 2019]. The Federal Transit Authority (FTA) has run the Low or No Emission Program since 2016, which essentially grants funding for purchase of zero-emission buses to states. For the fiscal year 2021, the grants worth over 180 million $ were distributed as a part of the program.[US Department of Transportation, 2021]

At the state level, governments have announced mandates and other forms of incentives to aid this transition. California was one of the first states to do so with the Innovative Clean Transit Rule (ICTR) - which mandates that by 2023, 25% of new buses purchased must be "zero emission vehicles" (ZEV) and that by 2029, 100%

of orders from California transport agencies should be ZEVs.

1.3.2   Asia - India and China

India

India introduced the Faster Adoption and Manufacturing of (Hybrid and) electric vehicles (FAME) scheme in 2015 and then introduced a new version of the policy document, i.e. FAME Phase II in 2019. In the context of electric buses, this regulation offers a maximum demand incentive of 20000 Rs./kWh, under the operational expense (OPEX) model for every electric bus procured by a State Transport Undertaking (STU). The maximum subsidy per bus is capped at 5.5 million rupees (i.e. ₹55 lakh.[Dept of Heavy Industry, 2012]

Apart from bus procurement, the government also subsidizes the development of the required charging infrastructure network.

Similar to the US, states in India too have their own policy briefs, schemes and regulations to further promote the adoption of e-buses. The state of Maharashtra, for eg., joined the Transformative Urban Mobility Initiative (TUMI) E-Bus mission that seeks to design specialized implementation plans to deploy electric buses at the city scale. The implications of these policies will further be discussed in section 3.6

China

We would be remiss if this discussion on electric bus policy didn't specifically talk about China's, where 99% [Report, 2020] of the world's electric buses currently are. China has been able to greatly accelerate e-bus adoption because of strong policy backing and the drive to meet air quality targets. The policy support primarily comes in the form of

- Subsidies - Battery electric buses (BEB) can optain > 640, 000 RMB as operational subsidy [Lumiao and Zhanhui, 2020]htt

- Tax Incentives - Under the *Notice on the Purchasing of NEV for Urban Public*

> *Transport Enterprises Exempted from Vehicle*, electric buses are exempt from vehicle purchasing taxes

Several local governments also provide their own operational subsidies and incentives. Further, cities like Shenzhen and Shanghai have mandated that only ZEVs can be purchased by bus operators.

1.3.3 Europe

67% of all buses sold in Europe are expected to be zero-emission buses ($\approx$ 65000 e-buses), which is eight times the number of electric buses present in the fleet today. This will be the result of a number of EU programs. One such initiative is the EU clean vehicle directive that sets minimum requirements on the purchase of electric +and fuel cell buses in all member states. The EU also funds the ELIPTIC (ELectrIfication of Public Transport In Cities) project that seeks to understand methods "to electrify urban public transport systems by optimizing the use of existing infrastructure in European cities - making public transport the backbone of electric mobility, thus leading to reduced fossil fuel consumption and improved air quality." [ELIPTIC, 2018]

Member states have each announced their own electrification plans and policies as well. In 2016, the Netherlands set an ambitious target to completely decarbonize its 5500 strong public bus fleet by 2030, with 100% zero-emission new buses from 2025 onwards. Belgium intends to decarbonize its entire public bus fleet of 2,300 buses by 2035, with the challenging objective to electrify inner city buses by 2025. Germany, as a part of its Klimaschutzprogramm, plans to electrify 50% of its total public transit bus fleet by 2030. In 2015, France passed the Energy Transition Law for Green Growth, which requires public transport operators to replacetheir bus fleet low-emission buses which are 'ecologically friendly' by 2025. In the UK, the city of London has announced plans to completely decarbonize all its 9,000 buses by 2034, which was earlier targeted for 2037. The Confederation of Passenger Transport has

set a target for all new buses to be ultra-low or zero-emission by 2025. The aim is that all sales of new buses should be zero-emission by 2035. Italy, while lagging behind most of the other Western European nations, has adopted a sustainable bus plan over the period 2019-2033 which offers funding for the electrification of public buses to meet the EU's minimum requirements. [Luman, 2021]

1.4   Barriers to the adoption of electric buses

Despite strong support from governments across the globe, for a number of years now, electric buses haven't yet taken over the world. Why is that?

The transition to electric buses is challenging on different fronts. A report on the *Barriers to Adopting Electric Buses* [WRI - World Resources Institute, 2019] analyzes these challenges and classifies them into three kinds - technological, institutional and financial. It also identifies the stakeholders it most affects. Figure 1-3 from the report summarizes the same.

Looking at these barriers, it is observed that the underlying cause of a number of these challenges is the lack of adequate modeling tools to implement a long-term plan for electrifying the fleet. Examples of challenges from the table that could perhaps be overcome with a better transit electrification planning model include :

- Range and power limitations of e-buses

- Lack of operational data

- Lack of information on how to start

- Limited planning for long-term implications

- High upfront capital costs of buses and charging infrastructure

Table ES-1 | Barriers Matrix

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

Source: Authors.

Figure 1-3: Barriers to the adoption of electric buses [WRI - World Resources Institute, 2019]

1.4.1 Motivation for this research

The key motivation for this research is to develop a *Transit Bus Electrification Model* that can help overcome some of the barriers presented in the previous section.

This thesis seeks to provide a model that transit planners and policymakers can use, as a starting point, to understand cost-optimal strategies to electrify their own transit fleets, even with limited operational data. These strategies will help cut down on unnecessary costs incurred on batteries/charging infrastructure, by attempting to find the minimal cost solution for buying and operating an electric transit fleet. Further, it will take into account the limited range of electric buses while proposing a

17

plan, so that this is no longer a cause for concern. The strategy proposed will consider long term implications by taking into account the lifetime of all investments and uncertainties in all cost factors. The model proposed also seeks to be scalable across cities so that any city is able to plan for the future electrification of its fleet. The proposed model is the based on data which is the largely in the public domain and can hence be a simple and useful tool for city planners in public transit electrification.

With the electrification of buses being an important step towards decarbonizing transport and mitigating climate change, this research hopes to assist transit authorities make the transition towards an electrified bus fleet.

Chapter 2

Transit Bus Electrification Model

How can we better plan for the electrification of a city's public transit bus system, such that we meet operational requirements and minimize the costs of this transition? This primary research question has several elements and is further broken up into the three research questions below -

1. What are these "operational requirements", i.e. energy demand, for a given set of public transit routes? How do we calculate them, given lack of operational data?

2. How do we meet these requirements, i.e. how should we set up the charging infrastructure network and make bus purchasing decisions, such that we meet operational constraints and minimize costs?

3. What are the benefits of this transition (primarily, emissions)? How can different policy measures be used to support this transition?

2.1 Preliminaries

2.1.1 SESAME - A modular approach to systems analysis

Before visiting the research questions stated above, it is important to ascertain that all models developed, meet the key design goals as well. This section discusses the

underlying implementation methodology behind the analytical model proposed in this thesis.

As mentioned in section 1.4.1, one key design goal for this research is to ensure the scalabililty of the electrification planning model, across several datasets, i.e. in this case, several cities. Currently, models built around specific datasets pertain to a single city..

- ..disallow easy comparisons between performances of electrified transit systems

- ..cannot be easily applied to a new city's transit system without information on specific assumptions and data required by the model, that may or may not have been collected by the new city's transit authorities.

- ..could require code for these models to be rewritten or reformulated based on the data available, making them computationally inefficient

This leads to the idea of using a modular, object-oriented framework, that would allow a model to be scalable across regions.

Currently, one such tool, that utilizes such a framework for systems analysis, is the Sustainable Energy Systems Analysis Modeling Environment (SESAME) from the MIT Energy Initiative (the author of this thesis is a key developer of this tool).

Sustainable Energy Systems Analysis Modeling Environment (SESAME)

SESAME is a system-scale energy analysis tool to estimate emissions and costs from today's energy systems.
It provides a consistent platform for Lifecycle Assessment (LCA) and Techno-economic assessment (TEA) of energy pathways and energy systems, across regions [Gençer et al., 2020]. It utilizes Python's powerful object-oriented programming methods, to build classes and functions that can be reused across different datasets (with certain key characteristics.) [Arbabzadeh et al., 2021] further elaborate on the backend design for this tool.

A key strength of the SESAME tool is its ability to take into account the temporal, operational and geospatial charcteristics of energy systems. This feature extends to the passenger car fleet model, that was developed as a part of SESAME's system analysis capabilities. This model seeks to understand the challenges and implications of electrifying the passenger car fleet, in regions such as the United States and Norway, under different sets of assumptions. It finds that temperatures, charging strategies and hourly variation in the power grid of a region can have a significant impact on the emissions from electric vehicles [Miller et al., 2020].

The model for this thesis seeks to implement a similar scalabality across regions and apply the learnings from the passenger car fleet model to another mode of transportation - the public transportation sector. It has thus been developed using SESAME's core methods and will be implemented as an extension of the tool in the future.

The next section further elaborates on the code structure for the model that permits this scalability.

Using Object Oriented Programming to build scalable system models

A term coined by Alan Kay in 1966, "Object-Oriented Programming" refers to a paradigm by which certain properties and methods can be bundled together into an óbject. It is helpful to organize code in situations where we would like the same behaviour and attributes to be implemented across different data inputs of the same form. This makes it ideal for the model in this research.

Four objects are created -

* `CityTransitData` - This class reads in and stores all the relevant data for a city as the class' properties. It implements methods to perform calculations and determine key route characteristics, such as drive profiles, energy consumption etc.

* `CityTransitNetwork` - This class builds a network model for the transit systems

and implements methods to calculate key system characteristics, such as centrality (as a measure of node importance.It accepts an instance of `CityTransitData` as a parameter, during its initialization)

* `CityTransitOptim` - This class builds the optimization model, used to determine charging and battery size requirements of routes. It accepts instances of `CityTransitData` and `CityTransitNetwork` as parameters, during its initialization.

* `CityTransitOvernight` - This class builds the overnight charging scheduling optimization model, used to assign overnight slow chargers to depots at routes. It accepts instances of `CityTransitData` and `CityTransitOptim` as parameters, during its initialization.

The methods implemented in these classes are the key contribution of this thesis and will be described in greater detail in the sections that follow.

2.1.2 Estimating energy consumed using minimal operational data

With an implementation strategy in hand, this section seeks to answer the first research question posed -

What are the "operational requirements", i.e. energy demand, for a given set of public transit routes? How do we calculate them, given that there is often lack of operational data?

The energy needs of a bus can broadly be divided into two categories - tractive (or operational) energy needs and non-tractive (or auxiliary) energy requirements. Each of these components themselves depend on several key operational factors.

Existing studies such as [Asamer et al., 2016, Ma et al., 2021] have determined that a bus' tractive energy needs depend on

(a) .. the drive cycle of a bus. The drive cycle of a bus is essentially a time series of the speed of the vehicle. When calculated (instead of directly measured using dynamometers and other such devices), it is dependent on parameters including speed, acceleration and the halting pattern of the bus. Some standard drive cycles that have been developed previously include the Manhattan bus cycle, the Orange County bus cycle, EPA HD-UDDS cycle etc.

(b) .. mass or load of the bus. The mass of the bus includes the fixed mass of its chassis and battery/engine, along with the mass of its passengers. Often, there are regulations that place restrictions on the maximum load that can be carried aboard a bus at any time. As will be seen, this is an important factor, especially when we consider electric bus whose battery can often make up a large part of the permissible load. Moreover, greater the mass of the bus, greater the energy it needs to move.

(c) .. other parameters including elevation of the route, the road grade, traffic etc.

For an electric bus, another important factor that comes into play is regenerative braking. Regenerative braking technology allows the bus to convert kinetic energy into electrical energy that can either be used immediately or stored for later use within the battery. This greatly improves the efficiency of an electric bus, as compared to a conventional diesel or CNG vehicle, as energy is constantly regenerated as the bus halts several times during its regular operation around the city.

A bus' auxiliary energy needs primarily arise due to energy required to heat/cool the inner environment, ventilation and the operation of lighting and other electronics.. This makes it primarily dependent on

(a) .. the outside temperature - the more extreme the temperature outside, the greater the energy required to heat or cool to a comfortable temperature.

(b) .. the trip duration, because as is obvious, longer the trip, longer the need for auxiliary demands to be met.

(c) .. other factors including the volume of the bus, the passage rate of passengers, number of passengers etc.

The energy consumption of a bus is an important factor to understand before electrifying the fleet as this is the constraint that we *have* to ensure is satisfied - the bus should always have enough energy to meet its operational requirements.

Why is it important to understand the energy requirements of every bus by route? The operation of an electric bus is significantly different from that of a diesel bus on the same route. Given the high energy density of diesel, gasoline and CNG as fuels, a conventional internal combustion engine powered bus can travel over 800 km at a stretch and only has to stop to refuel at most once or twice during a day. The same is *not* true of an electric bus. Not only is the energy density of an electric bus battery considerable lower, it is also bounded by a maximum capacity. For an electric bus to operate without fear of running out of "fuel" in the middle of a trip, we must have knowledge of the trip's energy needs before hand, along with information on the remaining capacity in the bus, so it can be charged accordingly at the few locations where chargers are available.

Now, drive cycles change from route to route, temperatures change from city to city. To more accurately determine the energy needs of a bus during its daily operation, along every unique path it takes, requires an understanding of the local operational conditions. This is a difficult task. Installing devices that measure a bus' energy (or even just drive cycle) on every route is an expensive undertaking, both in terms of effort and money. On the other hand, not determining a route specific energy metric could result in inefficient performance of the bus, as every route is unique.

There currently exist very few methods for transit authorities to determine their buses' energy needs accurately. This motivates the need for a comprehensive literature review of existing methods to calculate energy consumption of a bus and the consequent implementation of a suitable energy model, that requires minimal data to

be collected, in order to be widely used across transit system operators with different budgets and goals.

Literature Review

Energy models can be broadly classified into two types - Fuel Cycle Models and Vehicle Cycle (or Vehicle Activity) Models. As the latter are more apt for route-level, microscale modelling, given they take into account local operational characteristics, this literature review focuses on Vehicle Activity Models.

First we look at existing models used by regulatory agencies across the globe. In Europe, HBEFA is a popular vehicle activity model to determine energy consumption. HBEFA calculates engine power as function of load, speed and acceleration. However, the data used is largely proprietary and mainly applicable in the European context [Keller et al., 2017].

The model developed by Environmental Protection Agency (EPA) in the US to determine energy and emissions from the transportation sector is the MOtor Vehicle Emission Simulator (MOVES) [EPA, 2020]. MOVES allows the use to input custom drive cycles or use standard drive cycles. MOVES uses Vehicle Scaled Power (VSP), also called Scaled Tractive Power (STP) as a surrogate for the engine load. VSP is generally defined as power per unit mass of the vehicle and is a function of vehicle speed, acceleration, and road grade, and is thus dependent on the drive cycle. VSP is then used to determine energy consumed and emissions from the vehicle. MOVES is publically available for download. However, the issue with using MOVES to calculate energy, is the vast amount of data required - not only does it require extensive amounts of data on drive cycle of every bus in the fleet, it also requires inputs such as weather data, fleet composition, road grade etc. Alternatively, the model can use standardized drive cycles to calculate results, but this comes at the cost of understanding the true impact of the operational charcteristics of a route on energy consumption. Moreover, MOVES is a highly computationally expensive

model. All of this makes it difficult to make it scalable across regions. In their work, [Xu et al., 2016] attempt to resolve this problem by building a lookup table based on MOVES data for over 4000 runs, for a variety of different drive cycle, weather and road grade scenarios. The tool associated with their work, the Fuel and Emissions Calculator, attempts to accept minimal inputs such as location, season, number of buses, number of runs/bus/day, drive cycle and route length, to calculate emission and energy requirements. However, while the simplified version does solve the data issue it comes at the cost of granularity of the data - to calculate the energy requirements of a fleet where every route has different inputs would require several different runs. Moreover, it still expects drive cycle information to be known by route which is most often not easily available.

All the above models are not ideal for this study for one of two reasons - either they are unable to develop route wise energy metrics and rely on standardized metrics to find results or they require extensive amounts of data. In order to meet our model design goals, we thus implement another type of energy model from literature - a longitudinal dynamics model. There already exist a few studies that use a longitudinal dynamics model, coupled with a simplified auxiliary energy consumption model, to estimate energy consumption. A study by [Gallet et al., 2018] uses this kind of model to estimate the energy consumption of a bus fleet in Singapore. The inputs required for the model are limited to operational details such as route length, bus schedule and bus assignment information, that are available with all transit operators. Further, the model develops synthetic driving profiles for every route based solely on these operational characteristics. In this manner, the model developed in the paper is able to calculate route-wise energy demand with minimal operational data. This makes it highly suitable for the work in this thesis and has been implemented, with a few key modifications, to understand energy consumption.

The subsequent sections detail the methods involved. One key addition to the model, that is a contribution of this thesis, is to process publically available GTFS

(General Transit Feed Specification) data and directly use this as an input to the model. Since GTFS is a standardized transit data format, this further increases the scalability of the model across regions. The next section elaborates further on how this is implemented.

Data Description

In order to bring transparency to and establish a data standard for public transport systems, the General Transit Feed Specification (GTFS) was developed. Transit authorities across the world publish their data using the format specified by GTFS, for which there now exist a number of processing applications. GTFS data has two components - a static component containing schedule, fare, and geographic transit information and a real-time component containing current arrival and departure predictions, along with the position of the vehicle.

Two reasons that make GTFS the ideal data format for this research is

1 - it is information that every transit authority already collects (i.e. no extra expense on account of data collection is required,) and it meets the "minimal operational data" requirement

2 - the standardized format would allow the model to be scalable across cities, with very little extra effort.

The static component of the GTFS data proves to be sufficient for this analysis – the files used include stoptimes.txt, stops.txt, trips.txt and routes.txt. Ideally, the shapes.txt file, which includes a matching of routes to different shapes on a map, is also included but given that it is not mandatory under the GTFS specification, it is often missing from the static data available. However, for cities that do not contain a shapes file, one can easily be generated using the GTFS Shapes to Features tool in ArcGIS.

Depending on the transit authority, GTFS data may or may not include information on the bus assigned to any given route during a day. If this is not included, this is one extra piece of information that is required. While in some cases this data is not publically available in an accessible format, it is still data that every transit authority already collects and so it should be easy to obtain this data for use in the model.

Processing GTFS Data

The information required from the GTFS Data is as follows.

- The list of distinct routes. Then, for every route:

- The stops along the route

- The driving distance between consecutive stops on the route (henceforth referred to as a "link")

- The time required to traverse every link on the route

- The average speed on every link on the route

- Then, the "path" followed by a bus during the day - this could be a single route or a set of routes that the bus is assigned to during the day.

- Finally, a "link-list" is required to be generated. Link-List is the term used to represent a stop-by-stop dataframe of the entire path traversed by a bus during the day, that includes all of the above information.

While distances between stops can also be found using a linear-referencing tool on ArcGIS, in the interest of making the model as Python-based (and open source) as possible, an algorithm to find the distances using Python is determined as below.

o First, haversian distances between all points in the shapes.txt file, for any given route, are calculated. Haversian distance is an appoximation of the great-circle

distance between any two points, given their geographic coordinates. Additionally, the geographic coordinates are converted to their equivalent cartesian coordinates for all points in the shape file. This is useful for the next step.

o While we have the order of every stop on the route and we have the coordinates of these stops, one cannot directly use these to get the driving distance between the two stops. Instead, since it is known that the bus follows the path given by the shape file, *k-tree regression* is used to determine the closest point on the shape file to every stop and then, the previously calculated haversian distances between points to determine the link driving distance.

o Next, in order to find the time of travel between two stops, the stoptimes.txt GTFS file is used. It should be noted that the schedule is an approximation of actual travel time.

o Finally, using the driving distance and time calculated as above, average speed for a link is calculated.

After this has been carried out for all routes in the GTFS file, link-lists based on bus assignment information are generated. Thus, every "path" has its own link-list.

Once this process has been carried out for all the buses in the system, the set of *unique* paths are identified, along with the number of buses that follow the same path during a day ($nbuses_r$). Since energy requirements of all buses following the same path during a day are identical, it makes sense to reduce the system size to only the number of unique paths. A different dataframe, with information on the different buses following every path, is also maintained.

Longitudinal Dynamics Model to calculate energy consumption

Methods prescribed in [Gallet et al., 2018] have been used to implement this model. This was found to be the most suitable energy model to calculate tractive energy needs, from the comprehensive literature review in section 2.1.2. The section below

29
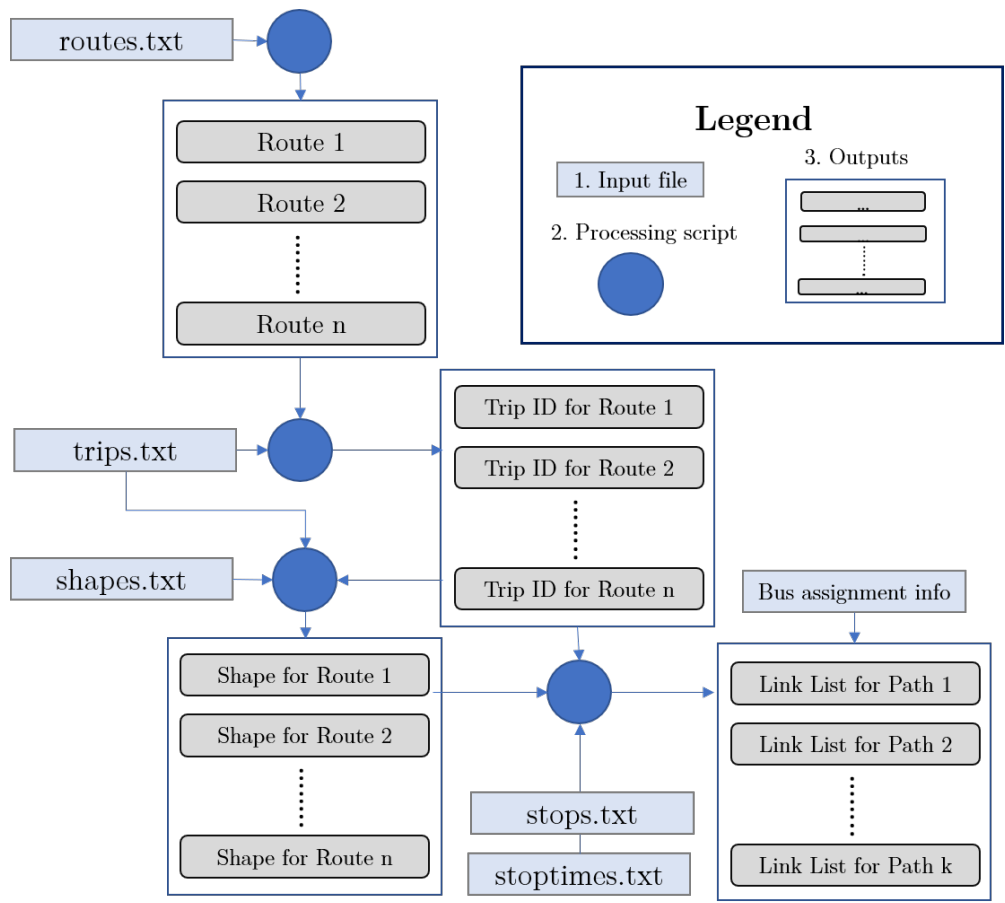
Figure 2-1: GTFS Processing Flowchart

describes the methods in detail.

Building a synthetic drive profile

As discussed earlier, the drive cycle of a bus on a route can significantly affect the energy consumed to meet its tractive needs. Thus, the very first task is to uniquely determine drive cycle by route, based on the average link speeds that have been calculated thus far. The process is as follows:

- Let v_{avg} be the average link speed (i.e. the average speed of the bus between any two stops.) Since the bus is traveling in a city, it would make sense that even during the trip from one bus stop to another it will start and stop several times. Let the number of halts during a trip be n_h. Let the link distance be d and, consequently, the distance between any two halts be $d_h = \frac{d}{n_h+1}$. It is assumed that for the same link, the speed profile between all halts is identical.

- Now, if $v_{avg} > 25$ km/hr, the number of halts (n_h) between two stops is set to 1. For every 5km/hr-step that v_{avg} takes under 25km/hr, an extra halt is added. This makes sense because slower the average speed, more the bus must have been required to brake during its journey.

- During its journey between any two halts the bus will have a phase of acceleration and deceleration, and may include a phase of constant speed (coasting). The split between the 3 phases is calculated as :

$$d_h = d_{accel} + d_{decel} + d_{coasting}; v_{coasting} = 1.5 * v_{avg}$$

$$(d_{accel}, d_{decel}, d_{coasting}) = \begin{cases} \text{if } d_{coasting} >= 0 & \begin{cases} d_{accel} = \frac{v_{coasting}}{2a_+^2} \\[2mm] d_{decel} = \frac{v_{coasting}}{2a_-^2} \\[2mm] d_{coasting} = d - d_{accel} - d_{decel} \end{cases} \\[12mm] \text{if } d_{coasting} < 0 & \begin{cases} d_{accel} = d\frac{a_+}{a_+ + a_-} \\[2mm] d_{decel} = d\frac{a_-}{a_+ + a_-} \\[2mm] d_{coasting} = 0 \end{cases} \end{cases}$$

$$(2.1)$$

- Speed is then determined as a function of time using the equations of motion, i.e. $v(t) = v(t_0) + \frac{1}{2}at^2$, where $a = a_+$ for $t <= \frac{v_{coasting}}{a_+}$, $a = a_+$ for $< t <= \frac{v_{coasting}}{a_-}$ and $a = 0$ for the remaining time in between. For the purpose of this analysis, to keep it simple yet reasonably accurate, we assume a standard acceleration of $a_+ = 1m/s^2$ and a standard deceleration of $a_- = 1.5m/s^2$.

- This gives us the speed between any two halts as the bus travels between two stops. To get the complete profile, first the speed profile is duplicated $n_h + 1$ times to cover the entire link and then the speed profiles so generated for all the links on the route are concatenated together. In this manner we get the complete drive cycle of any bus on its route, that is uniquely based on the average speeds on the route, the different segments on the route and the total length of the route.

- Figure 2-2 plots an example drive profile built for a bus route in Delhi's transit system.

Calculating Operational Energy by route

The energy required to operate an electric bus can be split into 4 components, as below -

- * $E_{inertia}$ or the energy required to overcome inertia of rotating components, only applicable when the vehicle is accelerating or decelerating. Here, δ is the factor
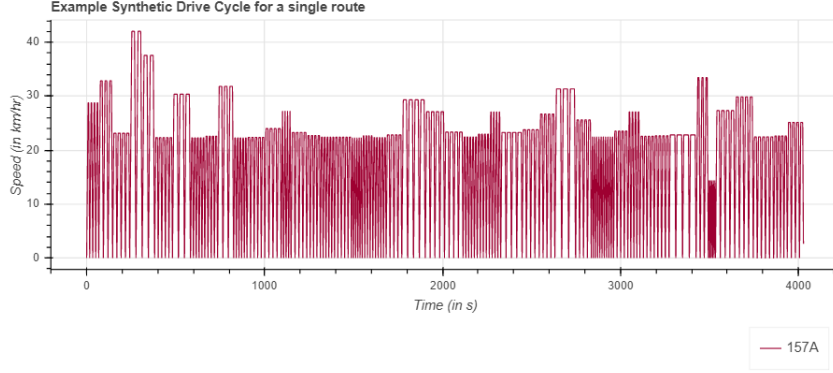
Figure 2-2: Example Synthetic Drive Profile generated for a single route

of inertia.

$$E_{inertia} = \begin{cases} \delta * M * a * \eta * d & \forall a \neq 0 \\ 0 & , a = 0 \end{cases} \tag{2.2}$$

* $E_{rolling}$ or the energy required to overcome rolling friction. f is the coefficient of friction and α is the elevation.

$$E_{rolling} = M * g * f * \cos \alpha * \eta * d \tag{2.3}$$

* $E_{climbing}$ or the energy required to overcome climbing friction

$$E_{climbing} = M * g * f * \sin \alpha * \eta * d \tag{2.4}$$

* E_{drag} or the energy required to overcome aerodynamic drag. Note that this component is not directly dependent on the mass of the bus, but rather on the surface area. Here, $K_d = 0.5_d A$, where C_d is the drag coefficient, A is the surface area and ρ is the density of air.

$$E_{drag} = \begin{cases} K_d * a * d * (\eta * d) & \forall a \neq 0 \\ K_d * v^2 * (\eta * d) & , a = 0 \end{cases} \tag{2.5}$$

Parameter	Value [Gallet et al., 2018]	Unit
C_d	0.7	
ρ	1180000000	kg/km^3
f	0.008	
η_t	0.97	
η_{PE}	0.95	
η_m	0.91	
δ	1.1	
r_{reg}	0.6	
m_{pax}	75	kg
a_+	12960	km/hr^2
a_-	19440	km/hr^2
g	127008	km/hr^2

Table 2.1: Parameters for Energy Model

The η in the above equations takes into account (1) the efficiency of the powertrain (2) the regenerative capacity of the powertrain. So we have

$$\eta_{accel} = \frac{1}{\eta_{PE}\eta_t\eta_m}$$

$$\eta_{decel} = r_{reg}\eta_{PE}\eta_t\eta_m$$

(2.6)

where η_{PE}, η_t and η_m are the inverter, gearbox and motor efficiency respectively. r_{reg} is the regenerative capacity of the drivetrain, and is assumed to be 0.6. Table 2.1 summarizes the parameter values used in the model.

Finally,

$$E_{traction} = \underbrace{E_{inertia} + E_{rolling} + E_{climbing}}_{E_m,\ \text{mass dependent}} + E_{drag}$$

(2.7)

Note that the equation makes a distinction between components of energy that are dependent on the load of the bus and the component that isn't. While for the initial part of our analysis it is assumed that the load of the bus is fixed, to get average energy consumption numbers by routes, the distinction becomes important in the next part of the analysis, where the optimization model takes into account the fact that a bigger battery means a bigger load on the bus, which then affects the energy consumed. This is further elaborated on in Section 2.3

Auxiliary Energy Consumption Model

The second key modification made to the energy model in [Gallet et al., 2018] is to implement a more city-specific auxiliary energy consumption model from literature. In their work, [Bartłomiejczyk and Kołacz, 2020] specifically model the auxiliary energy consumption model of an electric bus. The study is based on measurements carried out using the electric bus network in Gdynia (Poland). Although carried out for trolleybuses, the authors note that similar results can be expected of battery electric buses as well and hence the model is deemed to be applicable to the work in this thesis.

In the paper, the authors study the dependence of ambient air temperature on heating and cooling power demand from an electric bus. They find that the fall in outside temperature in November - March causes a significant increase in energy consumption. Further, they develop a simple linear regression model to understand the quantitaive effect of temperature difference between the inside and the outside of the bus on auxiliary energy demand. This is given by

$$P(\Delta T) = 0.91 * \Delta T + 0.44 \ \ \forall \ \Delta T > 5^o C \tag{2.8}$$

Next, we use route characteristic to determine the routewise auxiliary energy demand of the system. We thus get :

$$E_{aux} = P_{aux} * trip\_duration \text{ (in sec)} \tag{2.9}$$

Admittedly, the auxiliary energy consumption is heavily simplified and only classifies the dependence of two factors - outside temperature in a city and trip duration - in the calculation. However, it is still an improvement in accuracy, at almost no cost given that data required in minimal, and is thus employed in our calculations.

Finally the net energy requirement, for every link in every route, can be calculated

by summing the tractive energy demand and the auxiliary energy demand. In this way we identify a model that can calulate routewise energy metrics for an electric bus system, with minimal operational data.

$$E_{net} = E_{traction} + E_{aux} \tag{2.10}$$

2.2 Identifying network properties of the city transit system

So far, we have developed route-wise metrics, such as route length, energy consumption etc., to characterize a city bus system. This section will look at identifying metrics that can help characterize the system as *a whole.* One important question we face is identifying important bus stops and hubs in the system that could potentially serve as charging stations. The model developed in this section will borrow from the notion of using network centrality to measure node importance, as has been done in literature before, and apply it to solving the problem of identifying locations for charging infrastructure deployment. The goal is to use some of these system-wide characteristics to initialize the optimization model in the next section.

Network Centrality

In social networks, centrality is a metric that is used to identify the relative importance of the different nodes (or actors) in the network. Some commonly used centrality metrics can be interpreted as follows:

Metric	Measures
Degree	Number of edges connected to a node
Betweenness	Number of times a node lies on the shortest path between other nodes
Closeness	Average length of shortest path between the node and all other nodes
PageRank	How connected a node is, also taking into account that edges from more central (or well-connected) nodes contribute more than edges from less central nodes to the ranking

Table 2.2: Common Centrality Metrics

The idea behind using centrality in this application is, akin to finding important actors in social networks, centrality metrics have the ability to find the most important nodes to place our charging stations. After careful consideration of the metrics in the table above, PageRank was considered the most relevant, given its ability to holistically identify high traffic stops. Furthermore, given that we might want to take into consideration the energy demanded by bus trips, the *edge-weighted* form of the metric was calculated.

Traditionally, the PageRank algorithm was used to identify and rank webpages, by search engines. It is calculated according to Eq. 2.11, where $\hat{\phi}$ is the vector of PageRanks of all nodes. The system of equations for all nodes can then be solved using the random walk algorithm. In the equation, α is the damping factor, which prevents the algorithm from getting stuck in isolated parts of the web. Based on conventional literature values, α is chosen to be 0.85.

$$\hat{\phi} = \frac{(1-\alpha)\mathbf{e}}{N} + \alpha A^T \hat{\phi} \quad ; \text{ where } \quad A = (a_{ij}) = \frac{a_{ij}}{d_i^{out}} \tag{2.11}$$

Symbol	Definition
d_i^{out}	Out-degree of node i, i.e.(the number of outgoing edges from a node)
α	Damping factor
a_{ij}	1 iff edge exists between node i and j, 0 otherwise
w_{ij}	Weight of edge between node i and j
N	Number of nodes in the system
$\mathbf{e}$	Unit vector

Table 2.3: Parameters in Network Model

However, since its inception, PageRank has also found many other applications in social networks. In transportation, for eg., researchers have used this method to identify important bus stops. It is this notion of the PageRank we wish to use in this thesis. However, one important change is made to the conventional calculation of PageRank. We should consider edge weights as well, since these are indicative

of the energy requirements of travel, an important consideration in charging station placement. In their report, [Zhang et al., 2021] modify Pagerank calculations such that they are now calculated relative to their edge weights instead of relative to their degrees. This is shown in Eq. 2.12. Here s_i^{out} refers to the strength of a node, calculated as $s_i^{out} = \sum_{j \in V} w_{ij}$.

$$\hat{\phi}_{new} = \frac{(1-\alpha)\mathbf{e}}{N} + \alpha A^T \hat{\phi}_{new} \quad ; \text{ where } \quad A = (a_{ij}) = \frac{a_{ij} w_{ij}}{s_i^{out}} \qquad (2.12)$$

Literature Review

Network analysis has long been used to study and characterize public transit systems, albeit in a different context. [Li et al., 2020] used network centrality measures to understand spatial characteristics of the transit system. [Dong et al., 2019] use complex networks and graph theory to measure the importance of bus stops in Jinan's transit network.[Wang et al., 2020] further use PageRank to rank the importance of charging stations along the routes of electric taxis, in terms of their ability to disrupt travel in case of node failure. There has so far, to the best knowledge of the author of this thesis, not been a study that attempts to use network centrality to identify charging locations for an intracity bus system.

Methods

The city transit system was modeled as a network in the following manner:

* **Nodes**: Each bus stop of the transit system was treated as an independent node.

* **Edges**: There exists a directed edge E_{ij} between the nodes i and j for every bus that travels from stop i to stop j. Multiple edges are permitted.

* **Edge Weight**: The weight w_{ij} of any edge E_{ij} is equal to the energy consumed to travel from stop i to stop j.

Intuitively, the higher the PageRank , the higher the number of trips that end up at this node after having consumed high amounts of energy (since PageRank calculates both the immediate influence of higher weighted edges on a node, as well as places higher importance on nodes connected to higher weighted incoming edges, it should be able to identify nodes upto which the cumulative energy consumed by the trips is relatively higher.) From this it follows that higher the PageRank of a stop, more likely that trips upto this point have consumed a lot of energy and thus it would be a good idea to place a charging station at this point so buses can replenish their energy.

Thus, higher the PageRank more "optimal" the bus stop is probably as a charging station location. The model also calculates a simpler centrality metric - weighted degree centrality, which should also intuitively give us the nodes at which high energy trips end, but will not be able to capture cumulative trends. Weighted degree can be calculated as $\hat{d} = \sum w_{ij}$.

The bus stops with the highest PageRank and/or Weighted Degree are then identified as potential locations for charging stations, and consequently used in the initialization of the optimization model. Section 2.3 further explains this initialization in the *Other Data* section.

2.3 Determining optimal-cost charging strategy using MILP model

One of the most challenging barriers to accelerated adoption of electric buses is range anxiety, or rather, the need to develop appropriate charging infrastructure such that there is no more range anxiety.

As mentioned before, electric bus batteries are less energy dense than conventional carbon based fuels. They can only travel a limited distance without being refueled,

if designed the same way as a diesel bus. Now, there are two ways to tackle this problem.

- One, design bigger buses, equipped with bigger batteries, to travel on the same route or

- Two, develop charging stations across the city that are optimally located for a bus to charge as and when it needs to, without great deviation from its current operational routine.

Naturally, each of these strategies has its pros and cons and the table 2.4 below compares the two options.

	Pros (+)	Cons (-)
Bigger battery bus	Requires less investment for charging infrastructure	Higher upfront cost to purchase buses
	Minimal disruption of operation as it exists currently	More overnight charging infrastructure might be required; places extra strain on grid
Smaller battery bus	Lower upfront purchase costs	Requires significant investment to develop strong charging infrastructure network
	Potentially, less overnight charging infrastructure required	Might require schedule to be modified in order to account for on-route charging time

Table 2.4: Comparing electric bus system design strategies

It is important to jointly evaluate both of these options, given that the tradeoff involved could depend on local operational characteristics. This is the key drive force for the model developed in this section.

Literature Review

In recent years, there have been more studies that seek to understand the best ways to charge an electric bus fleet. A few of these are as follows -

[Kunith et al., 2016] use a mixed-integer linear optimization model to determine cost-effective placements of charging stations in the city of Berlin. In their paper, [Bak et al., 2018] evaluate strategies to deploy public transit charging stations using an economic efficiency analysis, for the city of Daegu in South Korea. [Bi et al., 2018] solve an interesting multi-objective lifecycle optimization problem for University of Michigan's transit system and determine both charging station locations as well as other variables such as number of charging stations, battery size by route etc. While present literature shows promising results, there is scope for further improvement.

Table 2.5 summarizes the key findings from a comprehensive literature review of 10 such studies. It is observed that, currently, most studies are applied to small scale transit systems. Further there seems to be no study that comprehensively evaluates every aspect of electric bus operation - some studies fail to consider the effect of battery cost and only optimize across charging strategies. Other studies do not consider the implications of optimization results on overnight charging methods and only optimize for opportunity charging strategies. Still others fail to consider the impact of key parameters such as time of charging, leading to unrealistic results.

The work in this thesis hopes to develop an optimization model that evaluates all key decision variables, such as battery size, charging cost, and time of charging, to suggest a minimal cost solution operating strategy for a large electric bus system. It seeks to provide a comprehensive solution by also developing an overnight charging scheduling model.

The next sections further elaborate on the methods developed.

Sr. No	Paper	Method	Optimizes for	Opp. Charge	ON Charge	Batt Size	Unique Constraint	Model size	Case Study
1	[?]	Particle Swarm to solve MILP	Rated power and charger quantity minimization	yes	no	no	time, power available	9-12 routes	Belleville, Stratford, Cornwall
2	[Iliopoulou et al., 2019]	Particle Swarm with MIP	Cost and travel time minimization	yes	no	no	route re-design	12 routes	Dummy
3	[?]	Robust optimization of MILP	Cost minimization	yes	no	yes	energy consumption uncertainty, time	34 buses	Utah
4	[Bi et al., 2018]	Genetic algorithm	Cost, emissions and energy	yes	no	yes, capped at 25 kWh		7 routes, 29 Buses	UMich
5	[Chen et al., 2020]	Genetic algorithm - MINLP	Cost minimization	yes - DWPT tech	no	yes	service life	3 routes, 6 buses	Xi'an
6	[He et al., 2019]	MILP	Cost minimization	yes	no	yes	demand charges	34 buses	Salt Lake City
7	[Alwesabi et al., 2021]	MILP	Cost minimization	yes - DWC tech	no	yes		7 buses	Binghampton Uni
8	[Guschinsky et al., 2021]	Randomized Heuristic Algorithm + Particle Swarm Optimization	Maximize passenger demand met	yes	no	yes	time, energy demand	26 routes	Minsk, Belarus
9	[Bagherinezhad et al., 2020]	Relaxed second order cone program	Power distribution operating costs	yes	yes	no	power distribution	11 routes	Park City, UT
10	[Wang et al., 2017]	MILP	Recharging cost minimization	yes	no	no		17 routes, 30 buses	Davis, CA

Table 2.5: Summary of Literature Review on studies examining electric bus charging

Methods

Research Question

This section addresses the second research question posed -

> How should we set up the charging infrastructure network and make bus purchasing decisions, such that we meet operational constraints of the transit system and minimize costs of buying and operating an all-electric bus fleet?

Here, "operational constraints" refers to the energy required to travel on routes, as well as the technological limits of an electric bus. The model seeks to "minimize costs of buying and operating an all-electric bus fleet" - i.e. seeks to find the optimal cost solution by analyzing the tradeoff between investing in more charging infrastrcuture as opposed to investing in bigger battery buses. Lastly, it assumes the complete electrification of all buses in the fleet. A potential mix of hybrid buses and other low carbon fuel alternatives in the fleet are outside the scope of this analysis.

Variables

The model in this analysis has three primary outputs - 1. the battery size of a bus by path. 2. the location of charging stations and the number of chargers at every stop. 3. the operation of a bus in a day (i.e charging events required during a day at different stops, along with the amount it charges every time to keep it on track.)
Apart from these, the model requires a variable to keep track of the energy remaining on a bus as it travels, that depends on how much it consumes and how much it charges up until any point.
Table 2.9 defines the variables in the model.

Primary Model

The problem at hand is formulated as a Mixed Integer Linear Programming (MILP) Model in the following manner:

Variable	Definition	Unit	Domain
$batt\_size_r$	Battery size of a bus on path r	kWh	[60,550]
$z_{i,r}$	Charger required at stop i for buses on path r		Binary
w_i	Total Number of chargers present at stop i		Integers
$amt_{j,r}$	Amount charged at the start of trip j by a bus on path r	kWh	[60,550]
$e_{j,r}$	Energy in battery at the start of trip j for a bus on path r	kWh	[60,550]
$y_{j,r}$	Charging happened at the start of trip j for a bus on path r		Binary

Table 2.6: Variables in optimization model

Objective Function

The goal is to minimize the total costs of buying *and* operating an all-electric bus fleet. There are thus two investment decisions to be made - first, buying buses of appropriate battery sizes and second, developing enough charging infrastructure to support operations. It is important to consider both of these aspects of investment simultaneously, as the decisions made are dependent on each other. Here, some assumptions are made:

- In this analysis, the cost of buying a bus is replaced by the cost of buying the battery of the bus. The battery cost makes up for >40%[Worford, 2021] of the bus' cost and is the factor that is really variable and dependent on the battery size.

- The cost of a charger includes installation, labour and technology costs. For the sake of simplicity, it is assumed that this cost does not change based on the number of chargers that are installed at a stop and the net cost is solely calculated on a per charger basis. This will be updated in the next phase of the model

- A direct comparison of the costs of a battery and a charger would be inaccurate, as the two have different lifetimes. Hence, it is the *equivalent annual cost* that is considered during optimization.

Apart from these explicit costs, another implicit cost is considered by the model - the cost of additional travel time, that might be required to charge a bus when it is

operational.

Different studies treat on-route charging time differently. Some studies ([Kunith et al., 2016, Xylia et al., 2017]) impose a constraint that restricts charging time to the preexisting idle time of a bus at a stop. Others [Gormez et al., 2021, Wang et al., 2017] add a penalty on any extra time spent on charging, but do not impose a strict constraint on what is permitted. The model in this analysis chooses to adopt a combination of both. While, realistically, no bus on-route should spend too much time at a bus stop when it is on active duty with passengers on board, it is also fair to require existing bus systems to adapt appropriately in ways that would better suit an electricity-powered fleet. Hence, the model does not restrict charging time to the idle-time at stops but does place an upper bound on the maximum time a bus can spend charging (chosen to be 10 minutes.) Further, in order to ensure that any extra time that passengers might have to waste because of this activity is penalized accordingly, a penalty cost is added to the objective function. The time required to charge a bus is a sum of the docking/undocking time and the actual time required to charge (which is based on charger size and the amount charged by a bus.) It is assumed that only charging done at stops that are *not* the bus' depot, are penalized. This is a fair assumption as when buses stop at depots during the day, it is usually for a long period of time and hence no "extra" time is required to charge the bus.

Section 2.3 further discusses how the penalty factor and other parameters related to the objective function are determined

Given the above, the objective function becomes :

$$
\max_{w,batt\_size,amt,e,z,y,policy\_subsidy} C_{charger} \sum_{i=1}^{N_s} w_i + C_{battery} \sum_{r=1}^{m} nbuses_r * batt\_size_r +
$$

$$
\alpha \sum_{r=1}^{m} nbuses_r \left(\sum_{j=1}^{n_r} (t_{fixed} * y_{j \notin \text{depot},r} + t_{charging} * amt_{j,r}) \right)
$$

(2.13)

Parameter	Definition	Unit
$C_{charger}$	Annualized Cost of installing 1 fast charger	$/charger
$C_{battery}$	Annualized Cost of purchasing battery per kWh	$/kWh
α	Annual cost penalty due to charging time	$/s
$t_{charging}$	Time required to charge a bus by 1 kWh	s/kWh
t_{fixed}	Time required to dock/undock charger	s
$nbuses_r$	No. of unique buses that are assigned to path r in a day	-
m	No. of unique paths in transit system	-
N_s	No. of unique bus stops in transit system	-
n_r	No. of links (i.e. trips) made by bus on route r during a day	-

Table 2.7: Parameters in objective function of optimization model

Constraints

The model is constrained by the operational requirements of the city transit system. There are several ways to formulate these constraints. [Ding et al., 2015, Chen et al., 2018] formulate the problem as a nonlinear optimization problem. Other studies [Bi et al., 2018, Chen et al., 2020] use bi-objective/multi-objective genetic algorithms to optimize across different factors.

A majority of studies use Linear Programming to model the problem. Some examples include [Kunith et al., 2016, Xylia et al., 2019, Alwesabi et al., 2021]

This study chooses to formulate linear constraints, primarily to meet the design goal of scalablility. For cities with large transit systems, the number of variables grows exponentially, as do the number of constraints. Formulating the problem as a nonlinear optimization problem would make it increasingly difficult for these large transit system optimizations to converge to a solution. Moreover, an MILP model, as formulated below, proves to be sufficient to model the most important constraints.

The constraints themselves are as follows:

* The bus is required to always have atleast 20% of battery capacity remaining at the end of any trip. At the beginning of the day, the battery is assumed to be fully charged. Here, the constraint takes into account that the energy required for a trip itself depends on battery size. The parameters are further explained

in section 2.3

$$e_{j,r} + amt_{j,r} - trip\_energy_{j,r} >= 0.2 * batt\_size_r, \text{ where}$$

$$trip\_energy_{j,r} = (M_{body} + n_{pax}m_{pax} + density * batt\_size_r) * \epsilon_{j,r}^m + E_{j,r}^{nm}$$

$$\forall j \neq 0$$

$$(2.14)$$

* The bus can only access upto 80% of its stored energy (and will only charge upto this point)

$$e_{j,r} + amt_{j,r} <= 0.8 * batt\_size_r \qquad (2.15)$$

* The energy of the bus at the beginning of its next trip is updated based on charging amount and the energy consumed during a trip. Of course, no charging is permitted when the bus begins its operations for the day, when it is assumed to be fully charged, with 80% of its energy available.

$$e_{j+1,r} = 0.8 * batt\_size_r - trip\_energy_{j,r} \ \forall \ j = 0 \ \text{(i.e. first trip of the day)}$$

$$e_{j+1,r} = e_{j,r} + amt_{j,r} - trip\_energy_{j,r} \ \forall \ j \neq 0$$

$$(2.16)$$

* Next, if a bus charges a positive amount, a charging event should occur (i.e. $y_{j,r} = 1$)

$$M * y_{j,r} >= amt_{j,r} \forall \ j, r \qquad (2.17)$$

* Charging on any path r can only happen at a given stop i, if a charger is built for that particular path at that stop.

$$z_{i,r} >= y_{j,r} \forall \ \text{trip } j \text{ that start at stop } i \text{ for a path } r, \forall r \qquad (2.18)$$

* The number of chargers built at any stop i depend on the charger sharing

scheme proposed. In this study, for the sake of operational convenience, it is assumed that every k buses, plying on the same path r require one charger, and no chargers are shared between buses on different paths. k and the choice of charger sharing scheme are further explained in section 2.3

$$w_i >= \sum_{r=\text{route } r \text{ has a trip starting at } i} z_{i,r} * \lceil (\frac{nbuses_r}{k}) \rceil \qquad (2.19)$$

* Finally, as explained in the previous section, a constraint is imposed on the maximum time a bus can charge at any stop, given real world implications.

$$amt_{j,r} * t_{charging} + t_{fixed} <= t_{max} \qquad (2.20)$$

Parameter	Definition	Unit
$\epsilon_{j,r}^m$	Energy per unit mass of bus for trip j on path r	kWh/kg
$E_{j,r}^{nm}$	Drag + Auxiliary energy required for trip j on path r	kWh
M	Large constant	
k	Number of buses on the same path that share a charger	s

Table 2.8: Parameters in constraints of optimization model

Complete Model

In its entirety, the model is as follows:

$$\max_{w,batt\_size,amt,e,z,y} C_{charger} \sum_{i=1}^{N_s} w_i + C_{battery} \sum_{r=1}^{m} nbuses_r * batt\_size_r +$$

$$\alpha \sum_{r=1}^{m} nbuses_r \left(\sum_{j=1}^{n_r} (t_{fixed} * y_{j\notin\text{depot},r} + t_{charging} * amt_{j,r}) \right)$$

s.t.
$$e_{j,r} + amt_{j,r} - trip\_energy_{j,r} >= 0.2 * batt\_size_r, \text{ where}$$

$$trip\_energy_{j,r} = (M_{body} + n_{pax} m_{pax} + density * batt\_size_r) * \epsilon_{j,r}^m + E_{j,r}^{nm}$$

$$e_{j,r} + amt_{j,r} <= 0.8 * batt\_size_r$$

$$e_{j+1,r} == e_{j,r} + amt_{j,r} - trip\_energy_{j,r}$$

$$M * y_{j,r} >= amt_{j,r} \ \forall \ j, r$$

$$z_{i,r} >= y_{j,r} \ \forall \ \text{trip } j \text{ that start at stop } i \text{ for a path } r, \forall r$$

$$w_i >= \sum_{r=\text{route } r \text{ has a trip starting at } i} z_{i,r} * \left\lceil \left(\frac{nbuses_r}{k} \right) \right\rceil$$

$$M * y_{j,r} \geq amt_{j,r}$$

$$amt_{j,r} * t_{charging} + t_{fixed} <= t_{max}$$

$$batt\_size_r \in [60, 550]$$

$$w_i \in \mathbb{Z}^+$$

$$z_{i,r} = 0 \text{ or } 1$$

$$amt_{j,r}; \ e_{j,r} \geq 0$$

$$y_{j,r} = 0 \text{ or } 1$$

$$\forall j = 2 \ldots n_r; \quad \forall r = 1, \ldots, m$$

Data Description

Energy Data

The primary data input for the optimization model is the operational requirements
(i.e. energy needs) of buses by path. This comes from the energy model in Section
2.1.2. Just as in the energy model, we perform an optimization for all *unique paths* in

the system, instead of all buses. This is reasonable because a bus on the same path should follow the same charging strategy, and will likely use the same infrastructure. As the optimization model optimizes for battery size and seeks to take into account the impact of battery size on load and, consequently, trip energy, mass dependent energy components (E^m) and drag and auxiliary energy (E^{nm}), that are independent of the mass of the bus, are calculated and stored as separate parameters. From Eq 2.7

$$E^m = M_{bus} * \epsilon^m = M_{bus} * (e_{rolling} + e_{inertia} + e_{climbing})$$
$$E^{nm} = E_{drag} + E_{aux}$$

(2.21)

e_m and E_{nm} are the outputs of the energy model that are fed into the optimization model. Their units are J/kg and J respectively. Lastly, the load of the bus (M_{bus}) is a function of the battery size of the bus route and is calculated as follows:

$$M_{bus_r} = M_{glider} + M_{pax} * n_{pax} + EnergyDensity * (batt\_size_r)$$

(2.22)

The mass of the glider is chosen to be 12000 kg, the number of passengers (n_{pax}) to be an average of 20, with the average mass of a passenger (M_{pax}) being 75 kg. The energy density of a Li-ion battery is about 14.29 kg/kWh [He et al., 2019].

Cost Data

Since the objective is to minimize the cost of buying and operating an electric bus fleet, cost inputs to the model also play an important role. The two most important cost inputs include (a) battery cost (per kWh) and (b) charger cost. Moreover, as both of these two elements have a different lifetime and will require to be replaced at different frequencies, we consider their equivalent annual costs instead, by calculating the Capital Recovery Factor for each and multiplying it with the base value. The capital recovery factor (CRF) is itself given by :

$$CRF = \frac{i(1+i)^L}{(1+i)^L - 1}$$

(2.23)

where i is the discount rate assumed and L is the lifetime of the infrastructure in question. For the purpose of this analysis, a 10% discount rate is assumed for both batteries and charging infrastructure. A lifetime of 7 years is assumed for the battery and 20 years for fast chargers, based on literature values [Khandekar et al., 2018].

In order to provide a comprehensive assessment that takes into account the variability of battery prices, the model is run for a base cost of 150\$/kWh. Section 3.7.1 further carries out a sensitivity analysis on this factor.

Charging infrastructure costs are also associated with some degree of uncertainty. They can vary based on charging technology and size installed. While a detailed investigation of how choice of technology and size can affect optimization results is beyond the scope of the analysis, a sensitivity to charger costs is carried out in section 3.7.2. A fast charger of size 320kW is chosen as the base case for this analysis, as buses require high capacity chargers given their larger battery size. The cost of this charger was assumed to be $\approx$ 95,000 \$ (or 7,076,160 ₹) based on literature [Khandekar et al., 2018].

Another "cost" input that the model considers is the penalty (α) imposed on buses that charge on-route. According to the US Department of Transportation[USDOT, 2016], one way to calculate the cost of travel time is using average wages. Thus, the penalty cost factor is calculated as:

$$\alpha = \left((\text{Average Wage/s in region}) * n_{pax} + (\text{Average Wage of Bus Driver/s}) \right) * 365 \tag{2.24}$$

The unit for α is \$/s.

The last cost number that is an optional input to the model is the subsidy provided to 1. buy buses 2. develop charging infrastructure. This will vary from region to region, based on the policy schemes that exist. Section 3.6 discusses how the subsidies provided in India under the Faster Adoption and Manufacturing of Electric (and Hybrid) II (FAME II) Scheme affect optimization results.

Other Data

A few other inputs on the operation of the bus fleet might be required. These inputs are treated as optional in the model. The output of the network model discussed in section 2.2 can be used to initialize the optimiztaion model. As discussed, centrality metrics help identify stops that have high traffic and serve as a measure of node importance. In the optimization model, stops can be initialized with a charger at the beginning of the optimization if they have either a high degree centrality or a high pagerank centrality. Further in order to exploit the network properties of a public transit system, another relevant input could be the number of buses that share a charger. In their study [Johnson et al., 2020], NREL researchers find that a single charger can be shared by upto 8 buses. Other studies such as [De Filippo et al., 2014] find that over 22 buses can share a charger, while still others [Bak et al., 2018] assume a 3 buses per charger estimate. Another factor to be considered is *when* the chargers become available. It is significantly harder to coordinate charger sharing between buses of different routes, that could arrive at the same stop at the same time, than it is to coordinate charger sharing between buses of the same route which arrive at the stop sequentially. In order to be conservative about our capability to take advantage of charger sharing, this study assumes that every charger is shared by 3 buses that ply on the same route. (It should be noted that this number, like all the other data fed to the model, is treated as a user input and can be changed based on the policy maker's perception of how charger sharing could work, even allowing the user to permit chargers to be shared by buses across routes, if that is a possibility)

Implementation

The model is implemented on Python using the `Pyomo` package [Pyomo, 2019]. It is solved using the `Gurobi` solver.

Additional Analysis : Overnight Charging System Requirements

The model above assumes that all buses are charged overnight before they begin their operations for the day. One important thing to note, however, is that it does *not* automatically rule out the possibility of having a transit system that is solely supported by overnight charging - in fact, a solution in which $w_i = 0$ $\forall$ i essentially implies that no fast chargers are built in the optimal solution. This formulation thus allows us to objectively determine what the optimal cost charging strategy would be without any preconceived biases.

Fast chargers are a necessity for any charging done on-route because of the limited time available to charge a bus when it is on duty. The question then becomes - should we simply use fast chargers to charge the bus overnight as well? The answer to this is not straightforward. Using fast chargers to charge overnight would reduce the total number of chargers required and allow us to reuse the same infrastructure. However, continuous high power charging has negative consequences on both the electricity grid as well as the bus' battery. [Oualmakran et al., 2020] find that increased congestion and reduced power quality are two serious consequences of high power charging on the grid. [Glücker et al., 2021] find that battery ageing is hastened by fast charging. Moreover, fast charging is no longer a necessity - a bus has over 8 hours of uninterrupted time to charge overnight.

In order to reduce the negative effects of fast charging on buses, this study proposes their use only when it is necessary (i.e. and only for opportunity charging during the day) and proposes developing slow charging infrastructure to charge buses overnight.

With that in mind, an additional overnight charging optimization model is proposed to schedule the charging of buses and reduce the total number of slow chargers required. There are other ways to approach the overnight charging model as well

- [Houbbadi et al., 2019] design a model that minimizes the cost of battery ageing. Other studies such as [Jahic et al., 2019] look at minimizing the peak load, while [Gao et al., 2018] looks at reducing electricity charges. This analysis focuses solely on minimizng net infrastructure cost, by minimizing total chargers required, since this is the largest cost component. Further, having optimized for the operation of a fleet prior to this, this model is able to use the optimal battery sizes determined by the previous optimization model, to inform scheduling decisions.

Overnight Scheduling Optimization Model

The variables in the model are as follows:

Variable	Definition	Domain
$x_{b,r,c,d}$	Charger c in depot d is assigned to the bth bus on path r	Binary
$s_{c,d}$	Charger c in depot d is utilized by some bus	Binary

Table 2.9: Variables in overnight charging model

The objective of the model is simply to minimize the total number of slow chargers required. Thus :

$$\min_{s,x} \sum_{d=1}^{D} \sum_{c=1}^{N_d} s_{c,d} \tag{2.25}$$

Here D is the total number of depots and N_d is the maximum number of chargers that are allowed on depot d. The heuristic to determine N_d is as follows:

- Given the optimal bus battery size from the output of the previous optimization model, the assignment of bus to depot and a fixed slow charger size (say $csize$), we can determine the total time required at any depot d using $time\_req_d = \sum_{r \in \text{buses on path } r \text{ charge at depot } d} \frac{nbuses_r * batt\_size_r * 3600}{csize}$. The charger size is chosen to be 80kW, a commonly available slow charger size in today's market.

- Then, we can determine the minimum number of chargers required using $min\_chargers_d = \lceil \frac{time\_req_d}{8*3600} \rceil$, as we assume we have 8 hours to charge overnight.

- Lastly, for operational convenience, we do want to ensure that one bus is only

54

charged using one charger. In this case, we might required a few more chargers than the minimum number of chargers to meet demand. Thus we obtain $N_d = min\_chargers_d + extra$, where $extra$ is a small number, to reduce the number of variables in the model (here, we arbitrarily choose 5)

Next, constraints for the model are formulated as follows. This is also formulated as an MILP model, for the reasons previously stated.

- The total time available at any charger is 8 hours. Note that here $batt\_size_r$ is no longer a variable, but in fact a parameter obtained from the results of the previous optimization.

$$\sum_{r \in \text{buses on path } r \text{ charge at depot } d} \sum_{b=1}^{nbuses_r} x_{b,r,c,d} \frac{batt\_size_r * 3600}{csize} <= 8 * 3600$$

$$\forall c \in \{1 \ldots N_d\}, \forall d$$

$$(2.26)$$

- Every bus should be assigned to a single charger

$$\sum_{c=1}^{N_d} x_{b,r,c,d} = 1 \ \forall \ b \in \{1 \ldots nbuses_r\}, \forall r \qquad (2.27)$$

- A bus can only be assigned to charger number c at a depot d if it exists.

$$s_{c,d} >= x_{b,r,c,d} \ \forall \ b, \forall r, \forall \{c, d\} \qquad (2.28)$$

If a feasible solution to the model doesn't exist, the number of $extra$ chargers can be

increased accordingly. The complete model becomes:

$$\min_{s,x} \quad \sum_{d=1}^{D} \sum_{c=1}^{N_d} s_{c,d}$$

$$s.t. \quad \sum_{r \in \text{buses on path } r \text{ charge at depot } d} \sum_{b=1}^{nbuses_r} x_{b,r,c,d} \frac{batt\_size_r * 3600}{csize} <= 8 * 3600 \forall c \in \{1 \ldots N_d\}, \forall d$$

$$\sum_{c=1}^{N_d} x_{b,r,c,d} = 1 \ \forall \ b \in \{1 \ldots nbuses_r\}, \forall r$$

$$s_{c,d} >= x_{b,r,c,d} \ \forall \ b, \forall r, \forall \{c,d\}$$

$$s_{c,d} \in \{0,1\} \forall \{c,d\}$$

$$x_{b,r,c,d} \in \{0,1\} \ \forall \ b, \forall r, \forall \{c,d\}$$

In this way, an assignment of buses to chargers can be obtained and they can be "scheduled" at a charger, perhaps in decreasing order of charging time.

2.4 Evaluating emission reductions and impact of policy incentives

The model, thus far, is able to determine (1) the energy requirements of an electric bus system and (2) the infrastructure requirements of this system. While this by itself is sufficient to adequately plan for the electrification of a city transit system, there still remains the question of what motivates a transit operator to switch from their conventional buses to electric ones. This section attempts to answer the third research question posed:

> What are the benefits of transitioning to an electric bus fleet (primarily, environmental benefits)? How can different policy measures be used to support this transition?

Emission reduction potential of an electric bus fleet

Chapter 1 speaks in depth about the need to decarbonize public transport, in order to meet our emission reduction goals. This is the primary motivation behind switching to an alternative "fuel" source like electricity to power the bus fleet.

However, contrary to the popular belief, electric buses are not necessarily "zero" emission vehicles. While they do have zero direct, exhaust emissions, the process to generate the additional electricity, that will be used to fuel the bus, can be a highly carbon emitting process if the electricity grid mix is dominated by coal and/or natural gas power plants. In order to understand the holistic impact of electrification on emissions, it is thus important to factor in upstream emissions (from the production of required fuel) into the analysis as well. Hence, a *lifecycle assessment* is more apt to quantify the emission reduction potential of electric buses.

There is a general consensus amongst researchers that electrification will reduce net carbon emissions - and this has been proven across various studies. The degree of reduction is, however, not as clear. [Lie et al., 2021] find that complete electrification of the bus fleet leads to a 52% reduction of emissions. On the other hand, studies like [Song et al., 2018] find that the reduction is minimal under the existing electricity grid. What causes this high degree of variability between different studies?

One immediate answer is the carbon intensity of the electricity grid. In the study by [Lie et al., 2021], the location considered is Trondheim, a city in Norway. Norway's electricity grid mix primarily consists of renewable energy, with over 94.3%[IEA, 2021a] of its electricity being produced by hydro power. This makes the electricity very clean and net emissions low. [Song et al., 2018]'s study, on the other hand, studies Macau, where 70%[IEA, 2021a] of the electricity is generated using fossil fuels. This causes the upstream emissions from the electricity generated to be very high and the overall emissions from electric buses to be barely less than those of their diesel counterparts.

The key learning is that the grid intensity of the local electricity source must be taken into consideration when calculating emissions from electric buses. For diesel and other carbon fuels, the upstream emissions from fuel extraction and processing

should be taken into account along with exhaust emissions from the vehicle.

Considering this annual emissions from electric buses were calculated as follows:

$$emissions_{y,reg,100\%} = grid\_ci_{y,reg}*(\text{Net daily energy required for routes electrified})*365$$

(2.29)

The net daily energy can be calculated using the optimization results from the model described in section 2.3 - it is the sum of the energy charged overnight (i.e. the battery size) and the sum of all the extra electricity supplied during the day, in the event that the bus charges on-route.

The $grid\_ci_{y,reg}$ is a function of both the year and the region being considered. Most countries are moving towards a cleaner energy grid. In fact, this is one of the reasons why electric buses are more lucrative than other alternative fuel options - because the advancements made by countries towards decarbonizing their electricity grid automatically translate to greater emission reduction from electricity powered vehicles as well! It is thus interesting to look at not only the potential emission reductions, based on today's grid but also how this would change based on the grid intensity of the future.

Lastly, it can be noted that the emissions are also subscripted by a "100%." Here, the 100% refers to the percentage of fleet that is electrified. In an ideal world with a very clean grid and unlimited funds, 100% electrification is highly desirable. However, in the real world this is a much more challenging initiative. For one, some bus routes are significantly harder to electrifiy than others - especially those which have a high daily energy consumption. Moreover, the marginal cost of electrifying these high energy routes could also be high, given that they may require larger batteries or more charging infrastructure. With this in mind, it is also relevant to look at the tradeoff between emission reduction and marginal cost as a function of the percentage of fleet electrified.

To simplify this analysis, it was assumed that for any percentage l of fleet electrification, the $l\%$ of bus paths that had the least total energy consumption per day (taking into account the number of buses plying on that path) are electrified, while the rest are not. The emissions from the buses that are not electrified and are powered by a fossil fuel f are calculated using the simple formula[1]

$$emissions_f = \text{Distance traveled per day} * \text{Lifecycle CI}_f \text{(in g/km)} \qquad (2.30)$$

. The cost of any infratstructure used to support the electrification of that route are subtracted from the net cost.

In this manner, this thesis studies the relationship between carbon emission reduction potential of electric buses and the cost incurred to make the transition.

Limitations of emissions model

It should be noted that this lifecycle analysis excludes emissions from vehicle production (including battery production.) However, as operational emissions are more localized as well as the largest source of transport emissions, it seems reasonable to exclude this for the moment. Other studies like [Xylia et al., 2019] do an excellent job of incorporating this factor into their research as well.

Furthermore, this analysis only considers carbon dioxide emissions. It does not quantify particulate matter (PM), nitrogen oxides and other forms of emissions that are further reduced when we switch to electric buses. The reason that this analysis has not been carried out in this section is because these types of emissions are highly sensitive to actual engine operation, requiring detailed simulations for accurate quantification (which is beyond the scope of the current analysis.) This omission leads to

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[1]Given that this technology has been around for a long time, the emission factors for fossil based fuels, like CNG and Diesel, have been extensively studied in literature. Moreover, these demonstrate lesser dependence on regional conditions. Hence, it is deemed sufficient to use emission factors directly.

the model *understating* the benefits of electric buses in terms of emissions. In reality, electric buses will only have even more significant positive effects on local air quality - the quantification of which is a promising question to explore in future work.

Evaluating policy incentives to support bus electrification

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While the model now has a method to quantify the environmental benefits of bus electrification, another key piece is to understand the policy-based tools that can help accelerate the transition to an electrified fleet.

The high upfront cost of electric vehicles generate positive externalities of consumption, wherein the benefits to the society are greater than benefits to an individual consumer. This is a form of market failure where the socially optimal outcome is not obvious to decision makers (such as transit authorities.) In order to rectify this outcome, different types of policies have been implemented by local, state and federal governments across the world. This thesis will look at how some of these policies affect electrification investment decisions for transit authorities.

As has been discussed earlier in section 1.3, electrification of public transit is the centerpiece of transport decarbonization proposals that have been proposed. While it is one thing to set ambitious targets mandating all ZEVs by a certain year, in order to encourage transit authorities to actually start buying electric buses, the most common tactic has been to offer (a) subsidies based on battery size to purchase buses and (b) subsidies to install charging infrastructure. How do each of these figure into the optimization model?

Firstly, an additional cost component quantifiying the policy subsidy is added to

the objective function in Eq 2.13

$$\max_{w,batt\_size,amt,e,z,y,policy\_subsidy} C_{charger} \sum_{i=1}^{N_s} w_i + C_{battery} \sum_{r=1}^{m} nbuses_r * batt\_size_r +$$

$$\alpha \sum_{r=1}^{m} nbuses_r \left(\sum_{j=1}^{n_r} (t_{fixed} * y_{j\notin \text{depot},r} + t_{charging} * amt_{j,r}) \right)$$

$$- \sum_{r=1}^{m} nbuses_r * batt\_subsidy_r - \sum_{i=1}^{N_s} charger\_subsidy_i$$

$$(2.31)$$

Next, constraints are introduced based on the nature of the policy. In general, one form of this subsidy could be -

$$batt\_subsidy_r <= batt\_size_r * \text{Subsidy per kWh}$$

$$batt\_subsidy_r \in [0, \text{max allowed subsidy per bus}]$$

$$charger\_subsidy_i <= (\% \text{ subsidized}) * C_{charger} * w_i \qquad (2.32)$$

$$charger\_subsidy_r \in [0, \text{max allowed subsidy per station}]$$

It would be interesting to see how the "optimal" decision under the provision of subsidies differs from optimal decisions made without subsidies. Subsidies are generally temporarily provided - significant difference between the two cases could have expensive consequences for transit operators in the long term and should thus be investigated early on.

2.5 Model Summary

Section 2.1.2 discusses methods to calculate energy requirements of an electric bus fleet, even with minimal operational data. Next, section 2.2 provides methods to characterize the transit system as a network, which can be used to determine important characteristics and features of the system in question. Section 2.3 then proceeds to develop a cost optimal strategy to buy and operate an electric transit fleet in a city, under these calculated energy requirements, capitalizing on the network proper-

ties of the system. Finally, 2.4 discusses the factors that motivate the transition to electric buses, in terms of potential environmental benefits and policy support from governments.

All in all, this work provides transit authorities with a comprehensive modeling toolkit to help overcome the barriers associated with the electrification of city transit bus system.

The next section demonstrates one such example of applying the model developed to a city level transit system - that of Delhi's.

Chapter 3

Case Study : Delhi Integrated Multi-Modal Transit System

3.1   Introduction

This section seeks to demonstrate an application of the transit bus electrification model, described in Chapter 2, and derive key results on a cost-optimal strategy to electrify a particular city's bus fleet.

The city of Delhi has been chosen to apply the model. This selection was based on a few reasons -

- Most existing research focuses on small scale transit system with < 100 buses. There currently exist very few works on larger scale transit systems, even though this is where more challenges will crop up.

- India and China have some of the most widely used public transport systems in the world. While China has greatly accelerated bus electrification already, India has begun the transition only recently. Moreover, the country has launched a scheme called the Faster Adoption and Manufacturing of Electric (and Hybrid) Vehicles, to accelerate electrification of transport .

- Electrification is most required in areas where pollution levels are high because of transport.

- Keeping the above three factors in mind, India's capital city, Delhi was chosen. Delhi's transit fleet is not only one of the largest, but also one of the most widely used public transport systems in the world. Further, currently, there is little or no research on the electrification of this city's buses. Moreover, Delhi is notoriously known for high levels of pollution and poor air quality. This makes electrification an urgent need. Furthermore, strong policy backing from the federal and local governments provide favourable conditions for the transition to actually happen.

This thesis seeks to provide a unique contribution by comprehensively analyzing the path to electrifying Delhi's bus fleet, using the model developed.

3.1.1   Review of Delhi's City Bus Network

Figure 3-1: DTC-operated /AC Bus (R) and DTC-operated Non-A/C Bus(L)
(Source: [Wikipedia, 2021])

Delhi's buses are operated by the Delhi Transport Corporation (DTC) and Delhi Integrated Multi-Modal Transit System (DIMTS). It is a $\tilde{6}200$ strong fleet, with 3800 of those buses operated by DIMTS and 2400 of them operated by DTC. DIMTS is a a transportation planning and infrastructure development company that was started

in 2006 as a jointy equity venture between the Government of the National Capital Territory of Delhi and the IDFC foundation, to implement complex transportation projects. DIMTS revamped existing bus operations in Delhi and designated routes to 17 different clusters, that were then each assigned to private operators (managed by DIMTS) or DTC.

All DIMTS operated buses were fitted with a Global Positioning Systems (GPS) device to enable Intelligent Transport Services (ITS). Recently, under the Open Transit Data initiative, DTC, in collaboration with IIIT-D, released GTFS Data for Delhi [DTC, 2021]. However, the data is only comprehensively available for the buses operated by DIMTS, which were fitted with a GPS device. Hence, this study solely focuses on DIMTS-operated routes and buses.

3.2 Energy Consumption Patterns for Delhi's Bus Routes

Data Preprocessing

The following additional steps were taken before processing the GTFS data for Delhi

- The GTFS data provide by Open Transit Delhi provides the routes.txt, trips.txt, stoptimes.txt and stops.txt files for DIMTS buses. However, the latest data published does not have a shapes.txt file. Hence, as proposed in Section 2.1.2, a shapes.txt file is first generated using ArcGIS' GTFS Features to Shapes tool.

- The GTFS data published for Delhi characterizes a route to be a unique unidirectional path taken by a bus i.e. Up and Down are considered to be different routes. Moreover, the same bus does not necessarily follow the exact same route during a day, and each variation is denoted by its own unique route id. (for e.g. 109Up v/s 109STLUp.) Because the data was published with slightly different conventions, additional data to understand a bus's actual operational path during a day was required - and was provided upon request by DIMTS.

- DIMTS-provided data on assignment of "duties" to buses helps determine the set of routes that make up a bus' actual operational path during a day. The columns in the csv provided are - *Depot Name, Duty Name, Route Name, From, To, Sch. Trip Start, Sch. Trip End, Trip Seq., Sch. Km.*

  Using this dataset, the complete "path" for every bus during a day, including before and after it breaks at a depot, were determined. For eg., Duty 109+10 first travels on 109STLUp -> 109Down -> 109Up ->109Adown -> 109AUp. Then at depot Bankner Village the duty changes - here, it is assumed that duty x and xA share the same bus and represent morning and afternoon duty shifts. After a 1.5 hour halt at the depot, the bus then travels on 109Down -> 109Up ->109Adown -> 109AUp->109STLDown -> 109STLUp. This information was used to generate the final linklist for every unique path identified.

After the above steps were carried out, the methods described on Page 27 were used to process the GTFS data and generate link-lists for all unique paths in the system.

Drive Cycles by Route

As a part of the energy model, drive cycles were generated for all routes in the GTFS file, using methods described on page 29. After this, anomalous data points and routes (in this case, routes which showed unreasonably high synthetic speeds at any point in time) were identified and removed from the system.[1]

At the end, unique drive cycles for 691 different routes were determined. Figure 3-5 graphs 5 such drive cyles generated, at random.

The following observations are made based on all drive cycles generated :

1. Each route has speed peaks at different points in time, possibly because of

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[1]The most probable cause for these anomalies was found to be cases wherein *k-tree regression* was unable to correctly do a linear referencing between stops and distances, in the presence of a "looped" route, causing errors in distance and, consequently speed, calculations.
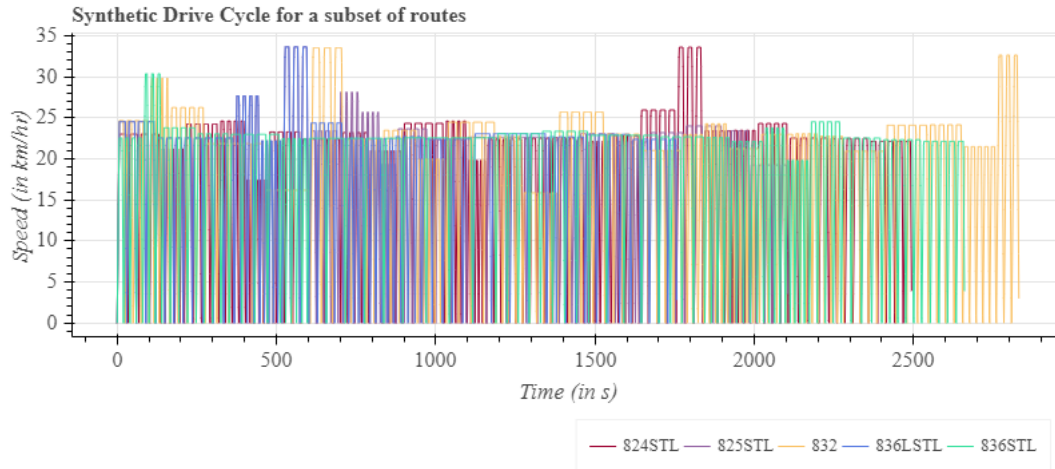
**Figure 3-2:** Synthetic Drive Cycles generated for a subset of routes in Delhi
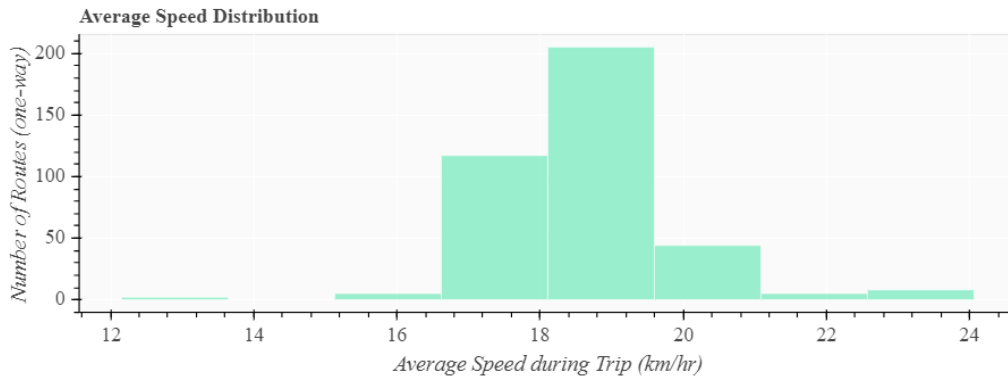
Figure 3-3: Histogram distribution of average speed of routes in Delhi - the average speed is low, as can be expected of a traffic-congested city.

differences in traffic profiles in different segments of their journeys

2. Furthermore, the magnitude of this peak speed (and also, average speed) differs by route.

3. From the above two observations, we can see that different routes indeed have significantly different drive cycles. Using the same standard drive profile for all routes would fail to capture these differences and it is in fact necessary to derive every route's drive cycle independently.

Energy Consumption

After having uniquely determined drive cycles by route, next, the energy requirements of these routes were determined using methods prescribed in section 2.1.2. Then, link lists based on bus assignment information were generated for all unique paths in the system. After removing the anomalous drive cycles mentioned in the previous section, the final system studied comprised of a subset of 66 unique paths that were serviced by over 735 buses during a day.[2] Finally, the daily energy requirement of all of the buses in the system were calculated.

The following observations can be made based on the results thus obtained -
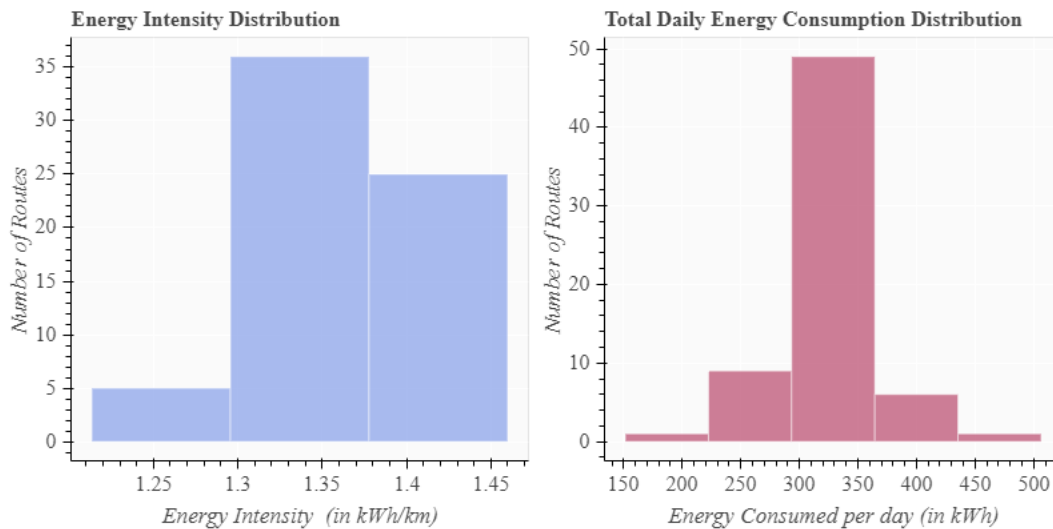
Figure 3-4: (L) Electric Buses have an energy intensity between the range of 1 - 1.5 kWh/km, with the average energy intensity being 1.36 kWh/km
(R) The net daily energy requirement by bus, for the 66 unique paths considered, varies from 150-500 kWh

- The average Energy Intensity was found to be $\tilde{1}.4$ kWh/km for AC buses. The higher value should be expected because of the significant auxiliary energy demand posed by locations with extreme temperatures, such as Delhi.

[2]It should not be noted that this study is thus not a complete representation of Delhi's entire transit system. However, the system size modeled is still one of the largest networks studied in literature (as can be seen from Table 2.5) and one of the first studies done for *any* routes in Delhi, making it valuable despite its scope.
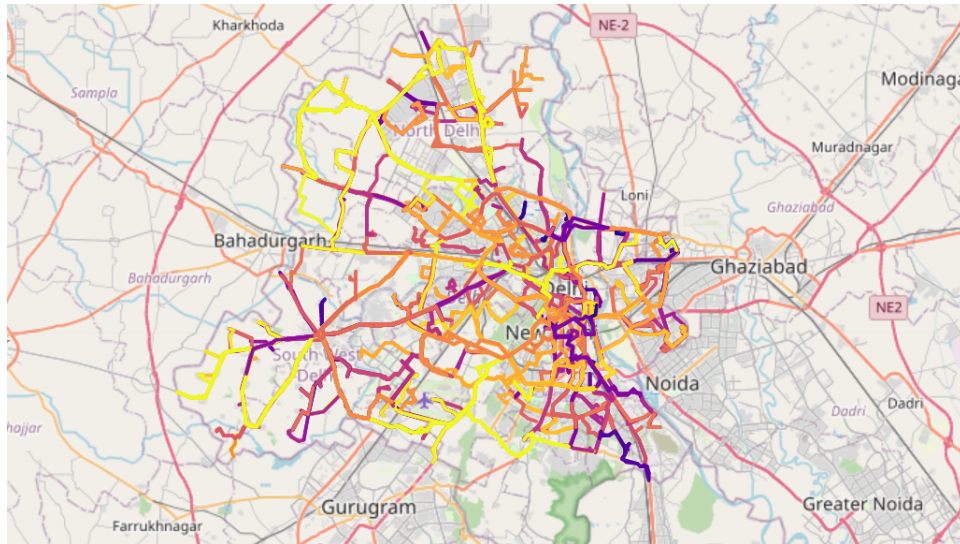
Figure 3-5: Delhi's transit system with route colors weighted by energy required - darker the color, greater the energy requirement

This is in agreement with literature values for other cities [Gallet et al., 2018, He et al., 2019, Bartłomiejczyk and Kołacz, 2020]

- Daily Energy Consumption for certain routes in Delhi can be be as high as 500 kWh. The presence of such high energy routes already indicates that the transit system's demands cannot really be met with overnight charging alone, given that buses manufactured today store at most 450 kWh of energy.

3.3   Measuring Node Importance for the Delhi Transit Network

Using methods described in section 2.2, the Delhi Transit System is modeled as a network. Figure 3-6 represents the networks, using geographic distances to visualize it accurately. Each red node represents a bus stop along the route.

Figure 3-6: Delhi Transit System as a network
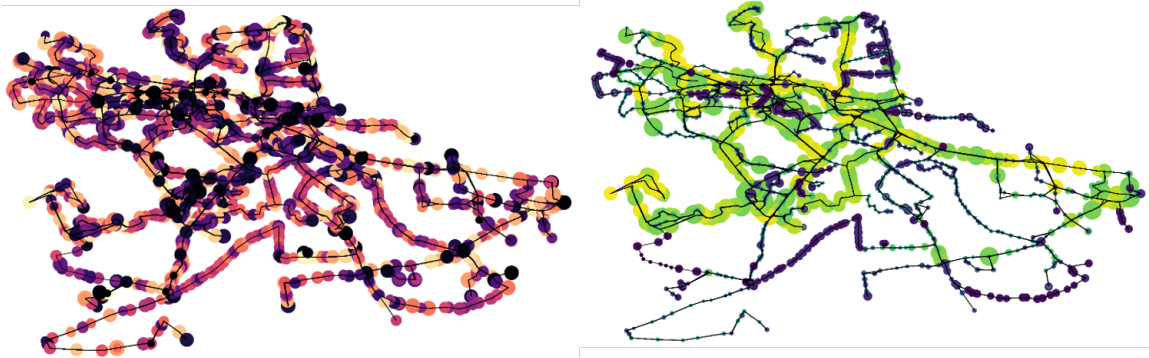
Figure 3-7: Evaluated Centrality for Delhi's Transit System (R) Wt Degree (L) Wt PageRank. Both color and size of nodes indicate centrality value; bigger the node higher the centrality

Next, the weighted PageRank and weighted Degree of each node was calculated. Figure 3-7 visualizes the same and helps identify the nodes with highest traffic, both in terms of energy and trips, during the day. The nodes with the highest PageRank and Degree values were initialized with a charging station, within the optimization model.

3.4 Fleet Operation Cost Optimization

We next apply the charging optimization model described in section 2.3 to find the minimal cost solution for operating an electric bus fleet, on the 66 unique paths that we determined the energy requirements for.

The optimization model is composed of 53227 continuous, 34873 integer (32636 binary) variables and 161571 constraints overall. The base case was run for the India-specific cost inputs specified in Table 3.1

All cost factors were annualized, as explained in section 2.3.

The model successfully runs, with a runtime of 184.2 seconds. The model results can be summarized as follows :

- **Battery Size :**

| Parameter	Value	Unit
Battery	150	$/kWh
320 kW Fast Charger	7,076,160 [Khandekar et al., 2018]	Rs
Penalty Cost (α)	1.6 [ILO, 2018]	$/s
INR-to-USD	0.013	$/INR

Table 3.1: Cost Inputs for Delhi

– Figure 3-8 plots an histogram of battery sizes of the 66 unique paths. It is observed that for a majority of paths, the model chooses to use smaller and average sized batteries of about 100-200 kWh. However, a few routes do require large batteries, sized at over 400 kWh.

– Battery sizes are plotted against the energy intensity of the path - it is observed that more energy intensive routes seem to require larger batteries. This makes intuitive sense as well since if more energy is consumed for the same distance, the bus requires to have more energy onboard.

– Battery sizes are also plotted against the energy requirement of the route. Here, the relationship between the two is murky - while for some cases it appears to be linearly related, in other cases, therr is no relationship. Some high energy routes prefer to use smaller battery buses (possibly with more charging infrastructure) while in other cases, low energy routes prefer bigger batteries [3] This tells us that the network structure and travel patterns of a bus also dictate optimal battery size for the route
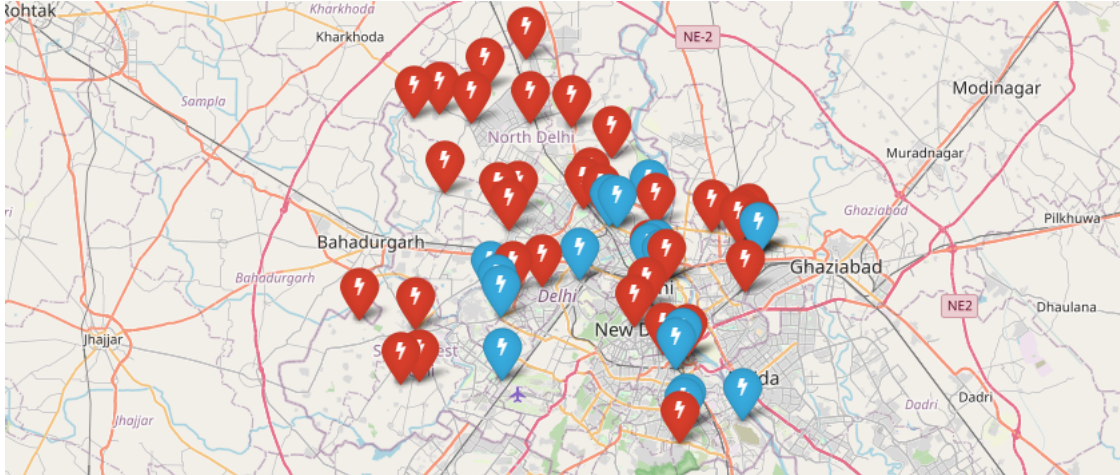
• **Charging Infrastructure**

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[3]There seems to be a point in the Battery Size v/s Daily Trip Energy graph in Fig 3-8 where the battery size is greater than the energy requirement. This can be explained by the fact that given the upper and lower bounds we place on battery capacity that is accessible, only 60% of net capacity is actually available to the bus. In fact it is seen that for this path the energy requirement is 186 kWh and the battery size use is 310 kWh (60% of 310 ≈ 186)
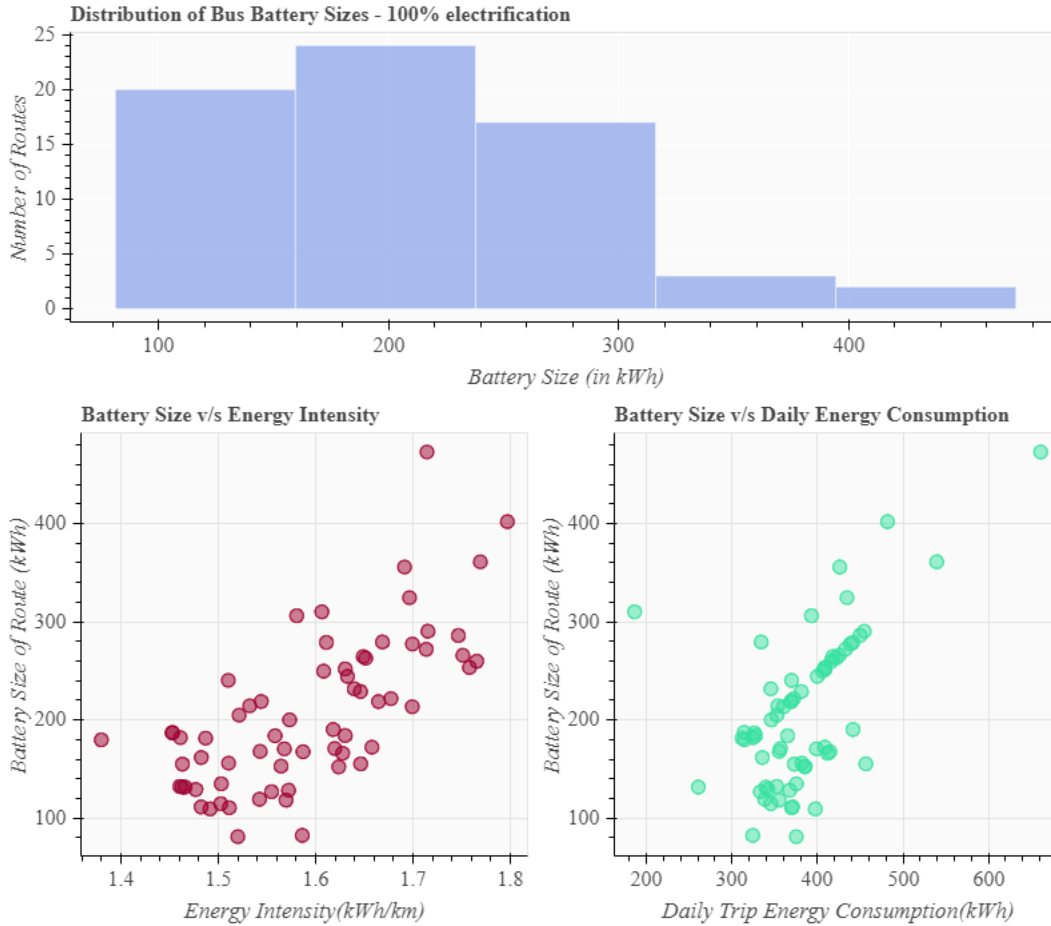
Figure 3-8: The model chooses to invest more in smaller-average sized batteries. It is observed that, as expected, more energy intensive routes require bigger batteries. However, there does not seem to be a clear relationship between total energy required and battery size used

- The model chooses to build an extensive network of chargers to support operations in Delhi, as shown in Figure 3-9.

- The model also provides a tool to visualize the operation of a bus during a day, with indicators for when and where it charges. The visualization tool hopes to provide more clarity on the actual operational strategy for an electric bus. Figure 3-10 captures stills from the tool for route 410 in Delhi

- We now look at the State-of-Charge and Energy of different buses in the fleet, to better understand model results. Here, 4 bus paths which use dif-

Figure 3-9: Charging Infrastructure built by model in Delhi. Red Marker : <5 chargers at stop, Blue Marker : >=5 charger at stop
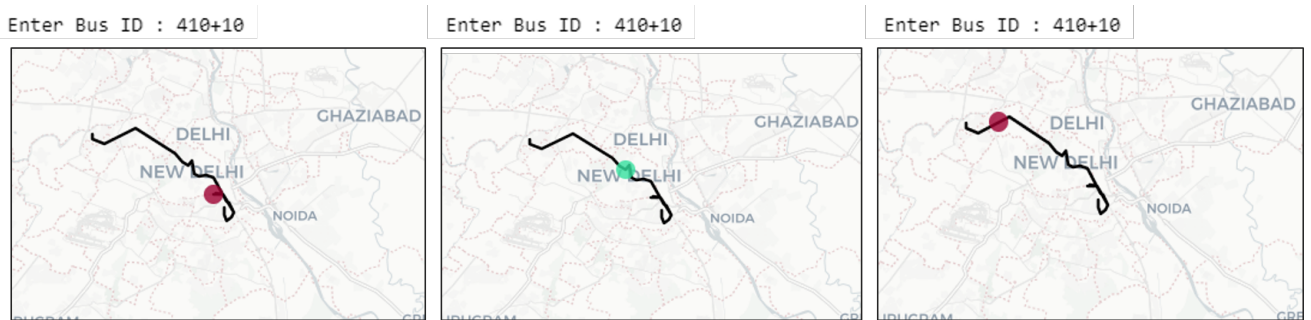

Figure 3-10: Stills from simulation of charging on Route 410 of the Delhi Transit System. Green dot indicates charging (maps have been cropped to fit page)

ferent kinds of charging strategy have been chosen to illustrate the strength of the model in identifying a charging strategy that makes most sense of the numerous options available. From Figure 3-11,

* Consider bus 261+14 - this bus does not require a single charge during the day and relies solely on the overnight charge before it begins its duty. Figure 3-11 support this statement as we can see that the SOC continually decreases during the day. The bus does require a relatively bigger battery, as can be seen from Figure 3-12.

* Bus 107+10, on the other hand requires to be recharged to its full capacity when it reaches this one stop (stop id 1906) - this stop in fact

73
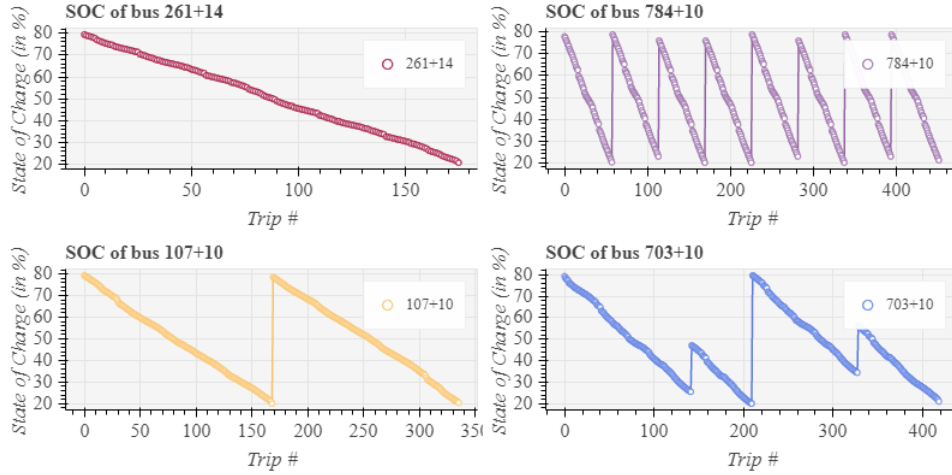
Figure 3-11: (a) State-of-Charge (SOC) for 4 different bus paths
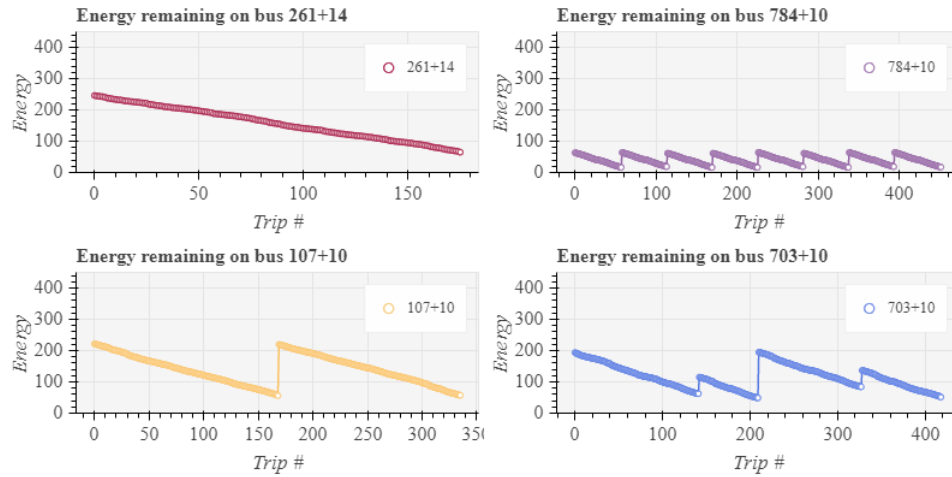
Figure 3-12: (b) Energy on board 4 different bus paths

turn out to be a depot and the bus takes advantage of the fact that charging at a depot comes with no penalty.

∗ Bus 784+10 charges repeatedly at the same stop. However, interestingly, it does not charge at a depot, since this kind of charging can only happen once during the day. This bus takes advantage of the fact that a fast charger on-route can be reused multiple times during the day, as long as it is built. Further to ensure that the total charge time is less than 10 minutes each time, since we want to avoid disruption, the battery size chosen is small.

∗ Bus 703+10 is an interesting case where the bus charges at 2 different kind of stops - it recharges to its full capacity at a depot but also requires a fast charger along the route to ensure that it always has the required battery capacity on board. When it charges on-route, it only requires a sort of "boost" charging, that lasts less than 10 minutes

The above 4 examples only capture a few of the different charging strategies that the model is able to identify as optimal based on path. The diversity in solutions really demonstrates why it is important to develop route specific charging strategies.

All in all, it looks like the model prefers to build more charging stations and use only average size batteries. Some reasons for this could be -

1. Charging stations last longer than batteries that need to be replaced every 7 years. The longer lifetime does seem to have an impact on the cost tradeoff.

2. Utilizing the network properties and the fact that a fast charger can be shared by multiple (here,3) buses means potentially lesser investment is required for routes for chargers, than might be required for larger batteries

3. Depots are only visited once a day. Since only about 80% of bus capacity can be used and atleast 20% has to be maintained, in some cases wherein energy consumption is high, it really becomes inevitable that chargers are built out to support operations.

Overnight Charging

In order to have a complete picture of all infrastructure required, the overnight charging model (as described on page 53) was applied. The optimal battery sizes from the opportunity charging model were used as inputs to the overnight charging scheduling model.

The model composed of 14828 binary variables and 1465 constraints. The results of the model can be summarized as below:

- The model is able to identify a charging schedule that minimizes the total number of chargers required at every depot to succesfully charge all buses to their full capacity overnight. As can be seen from Figure 3-13, a majority of the depots require less than 7 chargers to charge all the buses that park there overnight.
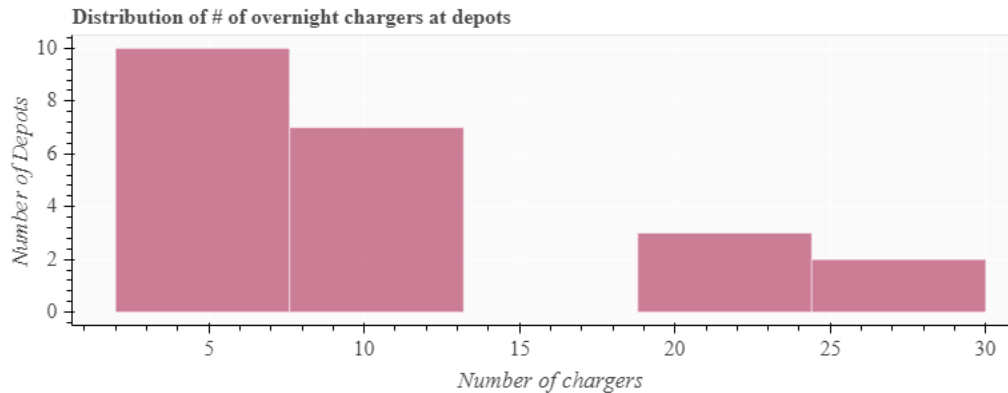
Figure 3-13: Histogram of number of overnight chargers required across depots

- The model is able to successfully provide a charging schedule that dicates the charger at which each bus should be charged and an order to charge all buses assigned to a charger, such that the 8 hours available for overnight charging are optimally utilized. Figure 3-14 provides an example of one such charging schedule generated by the model for all buses scheduled to charged at depot 22 (stop name = Bawana Sec 1 Cluster Depot).
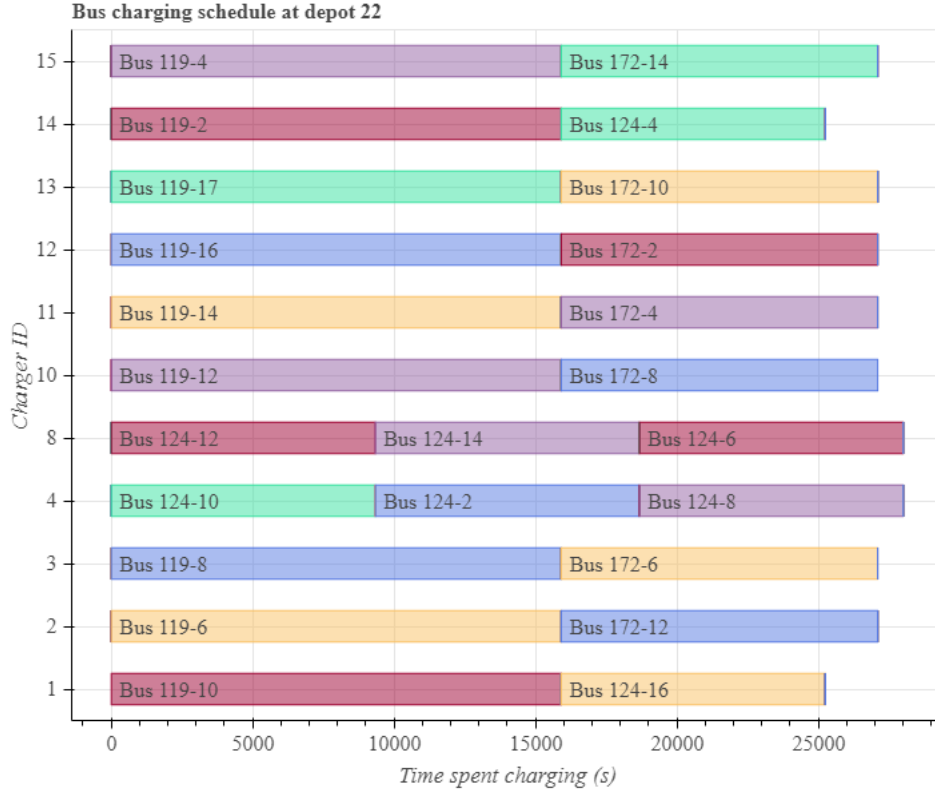
Figure 3-14: Overnight Charging Schedule drafted for depot 22 using optimization model

3.5 Benefits of Electrification - Emission Reduction

Next, we look at the emission reduction potential of transitioning to electric buses.

Given that, here, we only consider a subset of Delhi's bus routes, it seems more fair to consider % reduction in emissions as compared to baseline emissions when buses are electrified, as opposed to looking at absolute values. Baseline emissions themselves are determined based on the fuel that is currently used to power the bus fleet, and calculated using Eq 2.30. In Delhi, most buses are presently powered using CNG (Compressed Natural Gas). In fact, Delhi is the largest operator of CNG across the world! The emissions intensity of CNG (including upstream emissions) was found to be 1746.88 g/km, from a literature review [Lowell, 2013].

Now, as seen in section 2.4, the emissions from electric buses are dependent on the carbon intensity of the electricity grid. Unfortunately, at present, India's elec-
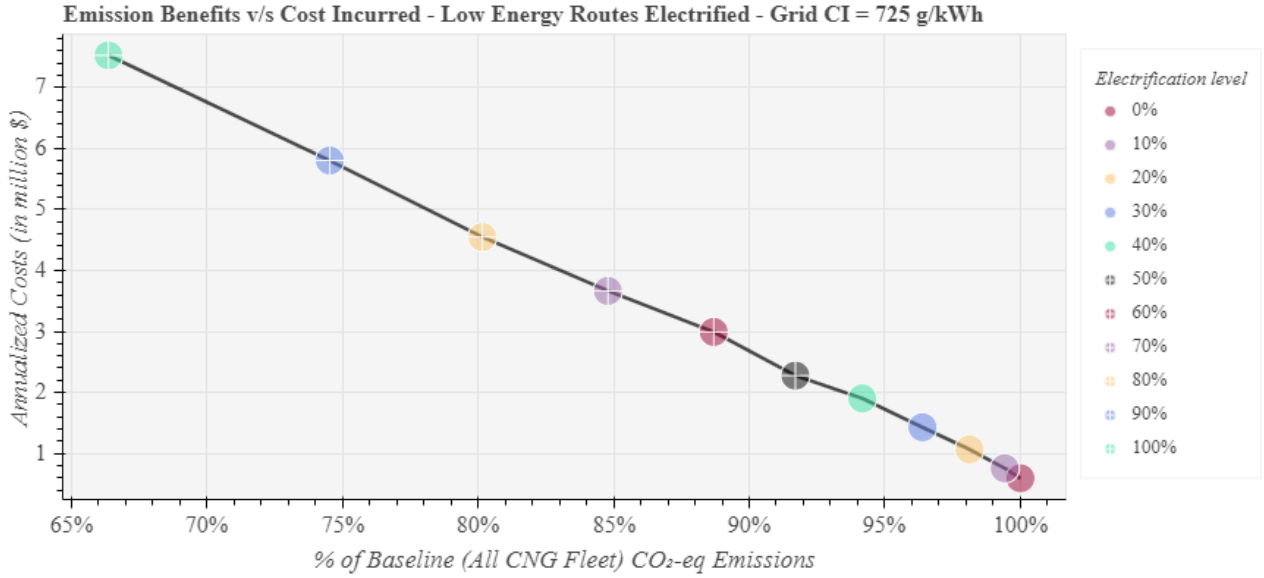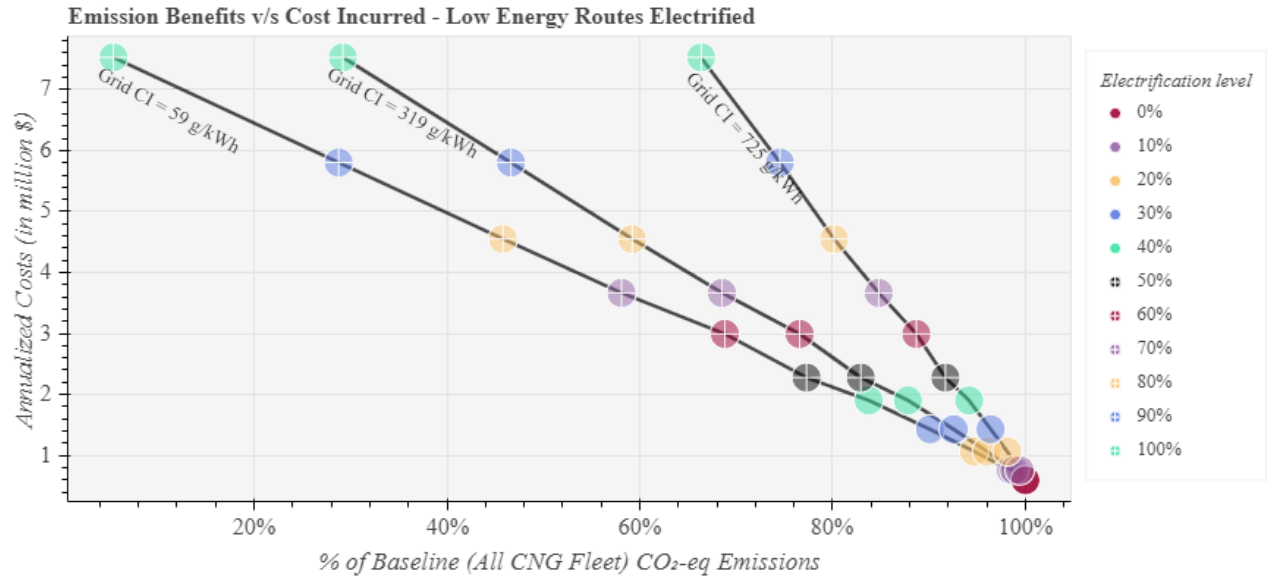
Figure 3-15: Emission Reduction Potential of Electric Buses in Delhi

tricity largely comes from coal-powered plants. As of 2021, 70% of the electricity was generated using coal, while less than 4% of the electricity was generated using solar [IEA, 2021b]. This makes the carbon intensity of the grid relatively high - $\approx$ 725g CO_2-eq/kWh.

Using Eq 2.29 and Eq 2.30, and the optimization results from the model, the emission reduction potential for various levels of fleet electrification were calculated and plotted in Figure 3-15 It is observed that after about 60% of the fleet is electrified, the marginal investment required to electrify the remaining routes reduces. One reason for this can be attributed to the fact that the higher energy routes remaining are routes with greater number of buses operating per route, permitting greater charger sharing. Further, we find that by transitioning to electric buses, despite the high carbon intensity of the grid, the net emissions of the subset of routes can be brought down by 35%, if all routes are electrified (i.e., 100% electrification.)

However, as has been discussed earlier, significant investments are being made to introduce renewables into the grid and reduce the country's dependence on coal and other fossil fuels. In 2019, the leaders of the country announced that 450 GW of

Figure 3-16: Emission Reduction Potential of Electric Buses in Delhi under SDS for the future

renewable capacity would be introduced in the coming years. This effort will greatly bring down the carbon intensity of the electricity grid. How much does electrification of public transport stand to gain from grid decarbonization?

Emissions from electric buses were calculated for the predicted future grid intensity of India in 2030 and 2040. [IEA, 2021b] find that under the Sustainable Development Scenario (SDS), India's grid intenstity will be ≈ 319 g/kWh by 2030 and will be ≈ 59 g/kWh by 2040.

We find that by transitioning to electric buses, the emissions of the routes studied can be brought down by as much as 88% annually, in the presence of a highly decarbonized grid.

3.6   Impact of FAME II on Optimization Results

This section investigates the impact of India's FAME II(Faster Adoption and Manufacturing of Electric (and Hybrid) Vehicles) Scheme on the optimization results.

FAME II supports bus electrification along the following verticals:

(1) *Demand Incentives for the purchase of electric buses*

Policy guidelines [Department of Heavy Industries, 2019] specify that

* A uniform incentive of upto 20000 ₹/kWh will be extended to all buses and are further subject to competitive bidding between Original Equipment Manufacturers.

* Each sanctioned bus will receive incentives upto 40% of the capital cost of the bus, and the maximum incentive available for a standard bus is capped at 55 Lakh ₹

* Incentives offered will be based on Battery Capacity of vehicles and only for vehicles fitted with "Advanced Battery" technologies.

* Incentives will be disbursed using an e-enabled framework and mechanism setup by the Department of Heavy Industries, after they have been certified as eligible.

* Incentives will be offered under the operational expense (OPEX). Under this OPEX model (also known as the Gross Cost Contract model), private operators procure the electric buses and incur the capital expenses while state authorities lease these electric buses on a per-kilometer basis and incur the operational expenses.

The OPEX model allows risks to be distributed between different stakeholders- while the STUs bear revenue risks, the private operators bear financial and technological risks[Agrawal et al., 2019]. This model has its pros - for one, it requires less upfront capital as incentives can be provided on a per kilometer basis (or equivalently, a per kWh basis). Moreover, for a government with minimal past experience and limited funds like India, a model that incentivizes private sector operators is the most appropriate business model as it leverages private sector expertise and lowers the burden of risk on the government[Pranavant et al., 2019].

(2) *Funding for Charging Infrastructure*

The scheme allocates ₹1000 crores for the development of requisite charging infrastructure. Specifically for buses, the scheme states that

"... In addition for the charging of electric buses, it is proposed to provide to the buyer one slow charger per e-bus and one fast charger for every 10 electric buses to be funded under the scheme..."

The guideline states that there is flexibility around this funding and upto 100% of the cost might be funded in interest of promoting e-mobility.

We incorporate the subsidies offered using variables and constraints into our model as follows:

- Purchase Cost :

  We cap the maximum purchase subsidy at 55L ₹. Given that the average cost of a 12m-AC electric bus in India seems to be 130 L₹, across battery sizes [Vijaykumar et al., 2020], it is reasonable to assume that this cap will supercede the 40% cap stated before.[4] We then cap the actual incentive based on battery size. Thus,

$$batt\_subsidy_r <= batt\_size_r * 20000 * \text{usd\_inr}$$
$$batt\_subsidy_r \in [0, \text{max allowed subsidy per bus}]$$

(3.1)

  It should be noted here that it is inherently assumed that transit authorites and private operators availing the subsidy ensure that the bus is operated regularly, since the incentives will only be disbursed on a per km basis. Further, we consider the extreme case wherein the government offers maximum subsidy even under competitive bidding, since Delhi's actual winning bid was not available in literature.

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[4]Since we only consider the battery cost of the bus explicitly, given that it makes up the largest segment of total bus cost, it is implicitly assumed that the bus cost is proportionate the to the battery cost. This is in fact a fairly reasonable assumption. Table 10 in [Hodge et al., 2019] has real world buses of different sizes and we can see that indeed, the fractional cost of the battery is similar for all of them.

- Fast Charger Subsidy :

  Since we build fast chargers in the optimization model, it is assumed that one fast charger per ten electric buses are completely funded under the scheme. Of course, if this number is more than the number of chargers the model chooses to build, the subsidy is capped at the cost of total chargers. Thus

$$charger\_subsidy <= \sum_{i=1}^{N_s} w_i * annualized\_charger\_cost$$

$$charger\_subsidy \in [0, \lfloor \frac{\text{Number of Buses}}{10} \rfloor * annualized\_charger\_cost]$$

$$(3.2)$$

Finally, the objective function becomes:

$$\max_{w,batt\_size,amt,e,z,y,policy\_subsidy} C_{charger} \sum_{i=1}^{N_s} w_i + C_{battery} \sum_{r=1}^{m} nbuses_r * batt\_size_r +$$

$$\alpha \sum_{r=1}^{m} nbuses_r \left(\sum_{j=1}^{n_r} (t_{fixed} * y_{j \notin \text{depot},r} + t_{charging} * amt_{j,r}) \right)$$

$$\underbrace{- \sum_{r=1}^{m} nbuses_r * batt\_subsidy_r - charger\_subsidy}_{\text{FAME II terms}}$$

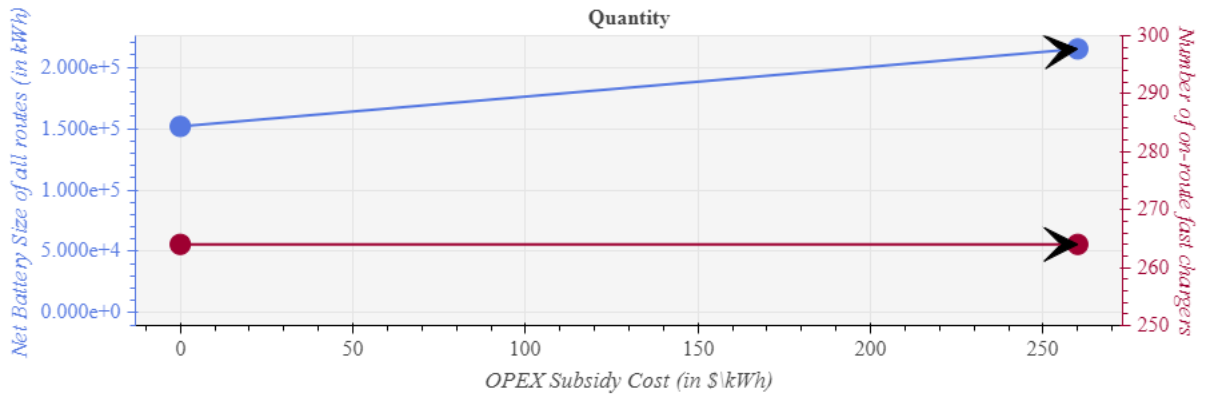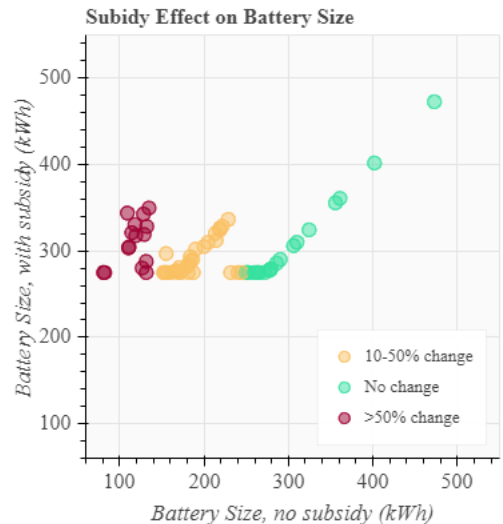$$(3.3)$$

The results of the model are as follows:

Figure 3-17: Effect of subsidy on investment quantity

The model chooses to use larger batteries in the fleet, as shown in Figure 3-17. The number of chargers required remain unaffected.

This results should be understood with a note of caution - without the competitive bidding process, it is obvious that the maximum allowable subsidy will be requested by the service providers. Given that this 55L ₹and the per kWh incentive is 20,000 ₹, this means that model will inevitably use 275 kWh batteries to avail the maximum subsidy.

Figure 3-18: Change in battery size by route

However, it turns out that even despite competitive bidding between vendors, FAME II tenders had high bid prices. Table 3.2 summarizes some key values cited in tenders submitted by a few cities in India. Most cities claim that their buses will run for 200 km on a single charge, and some specify that the expected energy intensity of the routes is 1.4 kWh/km. Given this, it is evident that most operators expect batteries in their buses to be $\approx$ 280 kWh. This leads us to the conclusion that the current

Parameter	Ahmedabad	Navi Mumbai	Bengaluru	Kolkata	DTC (Delhi)
Bid Price (₹/km)	54.9	69.9	N/A	86	N/A
Driving Range in single charge(km)	220	240	225	150	140
Energy consumption upto which STU will pay for	N/A	N/A	≤ 1.4	1.4-1.5	N/A

Table 3.2: Specification for 12m e-buses from FAME-II tenders [Gadepally et al., 2020]

subsidy structure, that is offered on a per kWh basis, encourages transit operators to buy larger sized batteries for their buses, than they should be buying as per the minimal cost solutions. While a per kWh metric might still be the way to implement a capital cost subsidy, an equivalent price signal to promote the development of fast
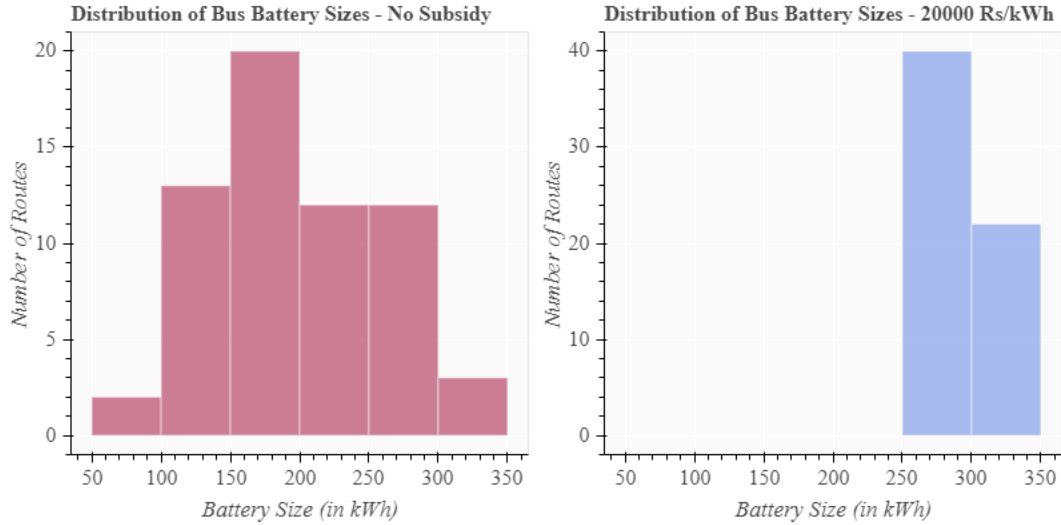
**Figure 3-19:** Battery size distribution under FAME

charging infrastructure should be made to bridge the gap. Presently, the scheme arbitrarily provides funding for 1 fast charger per 10 electric buses. Instead, a more specific funding structure based on the geograohical characteristic of a city should be developed. Further, another reason for the gap between the solutions is an improper evaluation of the value of the system to another stakeholder - the passenger. One way to rectify this could be to have the schemerequire cities to produce operational strategies, that take into account the value of travel time for their passengers. The more comprehensive the bid, the closer we get to the minimal cost solution we desire!

3.7 Sensitivity Analysis

This section examines the influence of different cost factors on optimization results

3.7.1 Battery Cost

Li-ion battery costs have changed greatly in the last decade. As can be seen in Figure 3-20, they have fastly declined from over 600 \$/kWh in 2013 to close to 150 \$/kWh. However, there still remains some uncertainty about the rate of further decline in battery prices. Several factors influence this rate. On the positive side, with growing support for electric vehicles and energy storage systems (ESS), as well as increased investment in the sector, the scientific community has made important strides in advancing battery technology and making
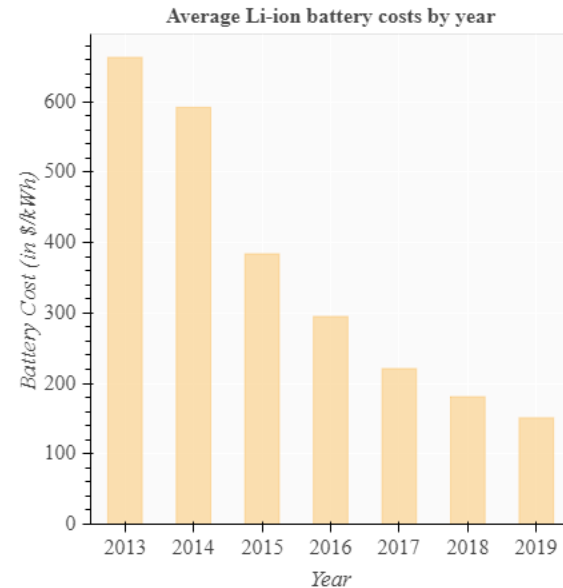

Figure 3-20: Average battery costs [McKerracher et al., 2020]

it cheaper. This is expected to continue. However, one limiting factor that could negatively affect battery prices is the availability of raw materials to meet the growing demand. As studied in [Hsieh et al., 2019], fluctuating rare element prices provide a lower bound on how much battery costs can fall. Lithium, Cobalt, Nickel and Manganese are some of the rare elements that go into making a battery and each of these are in limited supply. Moreover, over 70% of Co mines are currently controlled by China which has the potential to cause geopolitical challenges to the supply chain in the future. Most concerningly, the extraction of these elements from mines has also come into increasing scrutiny for human rights violation and exploitation of labourers [Bhuwalka et al., 2021].

In order to provide a comprehensive assessment that takes into account the variability of battery prices, the model has een run for costs both lower and higher than 150\$/kWh. The results from this analysis are as follows:

- It is observed that as the battery cost decreases, the model does choose to use buses with larger batteries. However, interestingly it still does require an extensive charging network to support operations, and the effect on the number of chargers required is minimal.
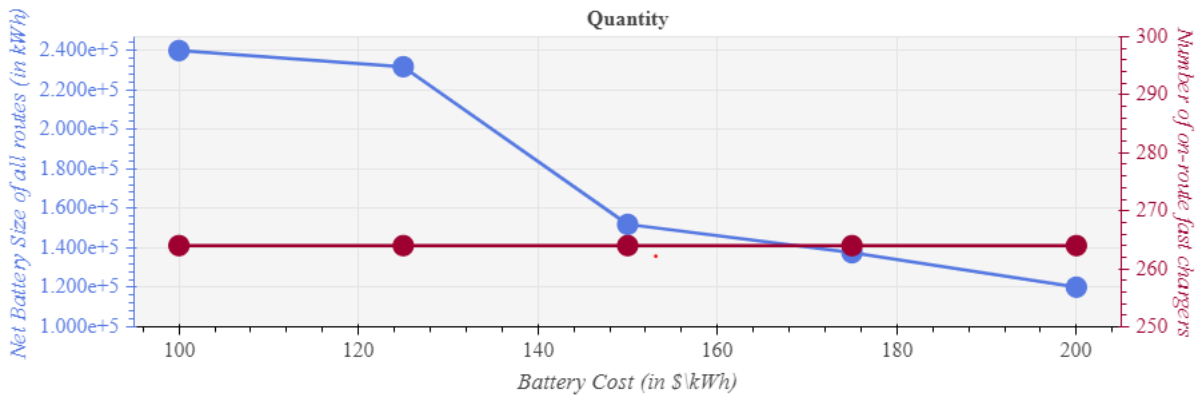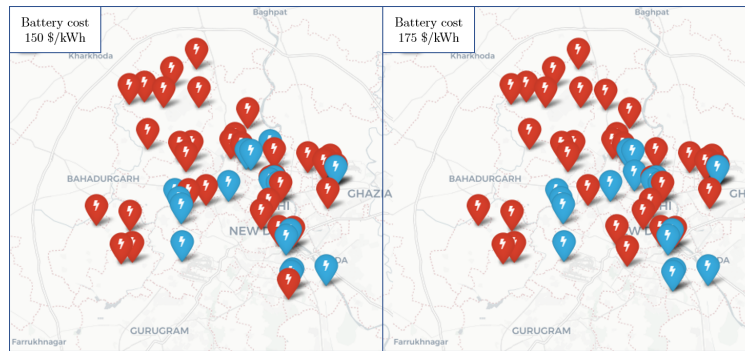

Figure 3-21: Effect of Battery Cost on Quantity of Investment

- Why does the model choose to build bigger batteries then, if it still requires the same number of chargers? This is because, while the *number* of chargers seem to be unchanging despite falling battery costs, the location of the chargers and the time spent on charging does change. Consider Figure 3-22 that graphs the energy remaining onboard two buses, based on the optimization results for various battery costs. We see that the number of times the bus charges decreases. Further, the location changes - bus 108+10, for e.g. chooses to charge just once at a depot, instead of charging multiple times at a stop on the way. Figure 3-26 plots the location of the charging stations for two different battery costs.
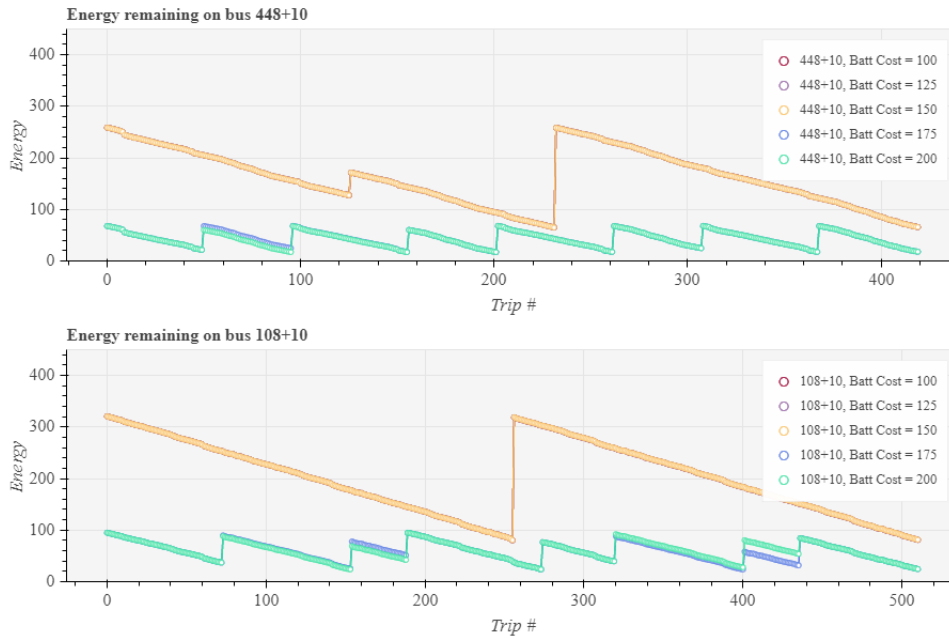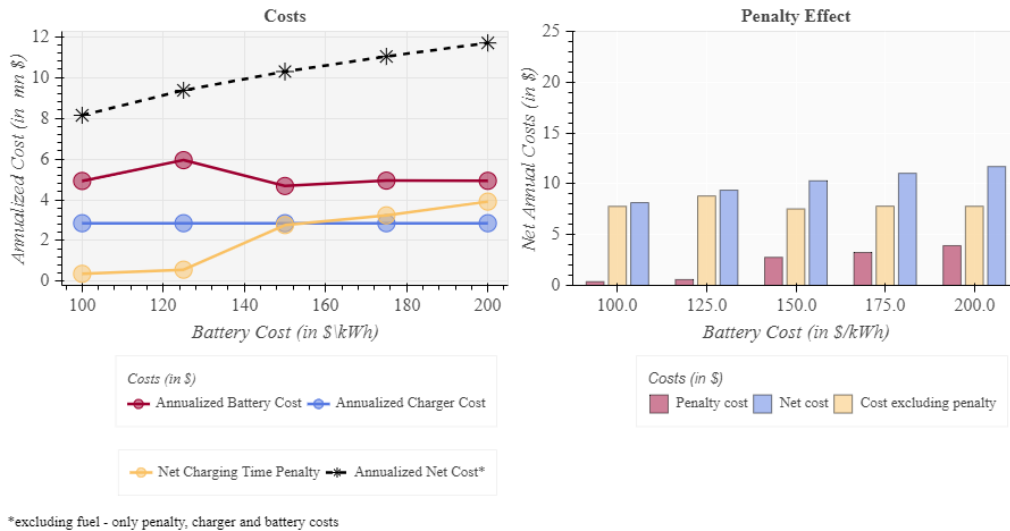
Figure 3-22: Effect of Battery Cost on charging time and location

Figure 3-23: Effect of Battery Cost on location of charging Infrastructure. Red Marker : <5 chargersat stop, Blue Marker : >=5 charger at stop

- Why does the bus choose to change its charging location and time with different battery costs? The answer to this is simple - the penalty cost imposed on shorter duration charging (and charging done at depots) is considerably lesser and having a bigger battery helps bring down this cost number.

Figure 3-24: Effect of Battery Cost on Net Costs

3.7.2 Cost of Charging Infrastructure

We now examine the effect of the cost of charging infrastructure on optimization results. Costs both higher and lower than the base case are chosen to demonstrate the effect of this cost factor on model findings. The observations made were as follows :

- Both the quantity of charging infrastructure and the battery size required seem to be independent of small changes in charger cost. Only a dramatic reduction or increase in costs changes the optimal number of chargers required, and that too very mildly. In a way, this is good news! Given that the optimal solution, in
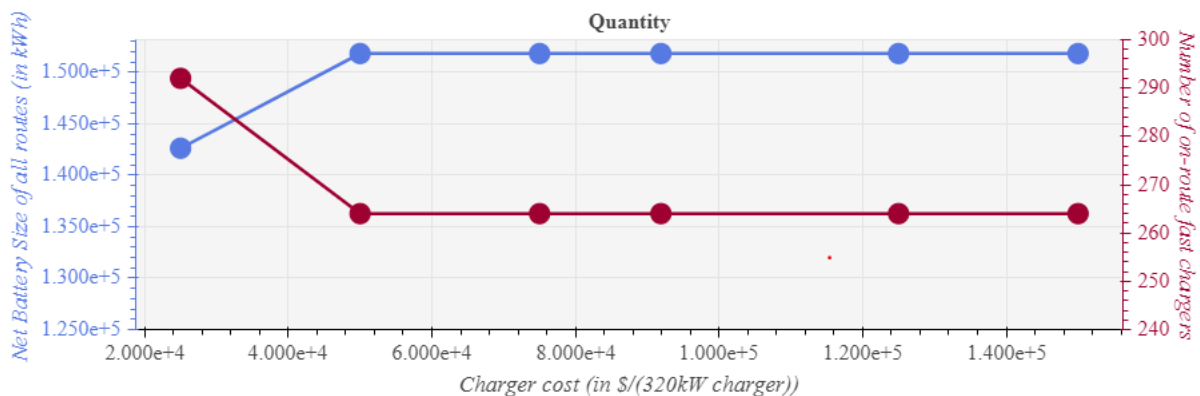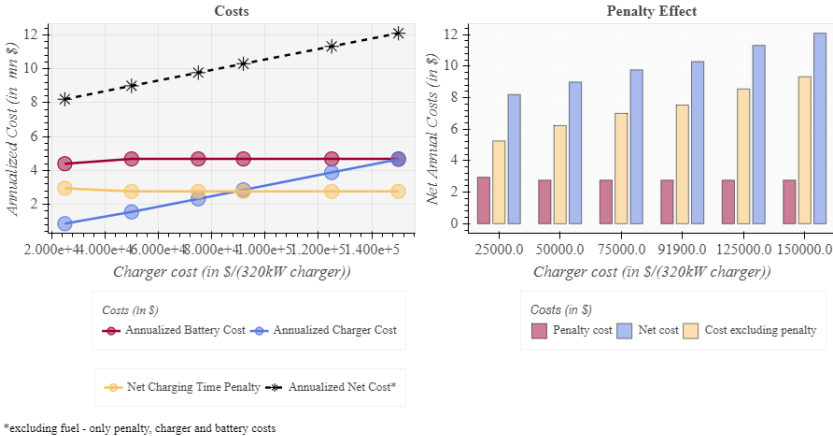

Figure 3-25: Effect of Charger Cost on Quantity of Investment

terms of chargers and batteries, will no longer change with lesser charging costs, long term investments can be made on buses while remaining at the optimal operating schedule.

- However, this also means that net costs become mainly dependent on the per charger cost. Given that the model does choose to build a certain number of chargers on every occasion, our net cost of operation on the charging front can only decrease with a decrease in per charger cost. Further research and investment, on making bus charging technology cheaper, should thus be promoted.

Figure 3-26: Effect of Charger Cost on Net Costs

This concludes the sensitivity analysis section that examines the effect of different cost factors on optimization results.

Chapter 4

Conclusions

4.1   Summary of Findings

Electrification of buses is key to decarbonizing public transport, so that we meet our decarbonization goals. But even as e-buses becomes cheaper with declining battery costs, there exist some barriers to the accelerated adoption of these vehicles. It is observed that some of these barriers such as driving range concerns, high cost of operation, limited availability of knowledge and data etc., can be overcome with a better planning model for the deployment of the electric transit bus fleet.

This serves as the key motivation for this thesis which develops a *Transit Bus Electrification Model* that successfully -

- determines the route-wise energy needs of a transit system with minimal operational data

- leverages the network properties of a public transit system to determine a comprehensive minimal cost operational strategy for an electric bus fleet, using a Mixed Integer Linear Programming (MILP) Model

- determines the emission reduction potential of the transition and the effect of policy incentives to accelerate adoption

The model developed is then applied to a set of 736 buses, following 66 unique paths, in Delhi's Transportation system and is the first study of its kind to comprehensively analyse cost-effective methods to electrify the city's large fleet. This case study reveals several interesting insights. It is observed that, due to route-specific operational characteristics, the drive cycles differ considerably by routes, and these variations are left uncaptured if we use standardized drive cycles to model all routes. Further, we find that buses have vastly varying energy requirements during the day, ranging from 200 kWh to over 500 kWh. The energy intensity of buses, on the other hand, is much more comparable, with the average being 1.36 kWh/km.

The energy model outputs, along with relevant cost inputs are fed to the optimization model which reveals that opportunity charging is key to optimally operating the city's bus fleets. We find that the model prefers to build an extensive fast charging network, with average sized bus batteries instead of a fleet that heavily depends on overnight charging and larger batteries, indicating that opportunity charging is indeed the more cost optimal alternative. Further, we find that for some bus routes in Delhi, opportunity charging is imperative as the energy requirements for these bus routes are very high. Even with on-route charging, there are several different strategies possible and a key strength of the model is that it is able to successfully determine the best one by route. We find that despite depot charging not being penalized, some buses still prefer to do a form of "boost" charging, as the depot can only be visited once a day.

The model then determines the benefits of this transition. We find that even under the highly carbon intensive electricity grid of India, electric buses can lead to a 35% reduction in annual carbon emissions, as opposed to the current CNG fleet. Further, with the expect decarbonization of the electricity grid, we find that electric buses can even lead to 88% lesser emissions in the future. This finding is highly encouraging and suggests that we should accelerate e-bus adoption even further. We then seek to understand how policy incentives affect choices made by decision makers as they

electrify a fleet. We find that FAME II encourages investment in larger battery buses, as opposed to the optimal solution. Possible solutions proposed include the development of more comprehensive bids by transit authorities and service providers that also elaborate on operational strategy. Further it is proposed that more incentives are provided for the development of a good fast charging network, as opposed to the current 1/10-ebus subsidy structure.

Finally, given the uncertainty in cost factors the study performs a sensitivity analysis to the battery costs and charging infrastructure costs. We find that both parameters hardly affect the charging infrastructure investment suggested by the model. However, as battery costs fall the model does move to a solution that encourages a lesser number of charging events and/or charging at the depot.

All in all, the work done in this thesis successfully provides transit authorities with a model that can help overcome the planning barriers associated with the adoption of electric buses.

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