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Multi-stage Planning for Electrifying Transit Bus Systems with Multi-format Charging Facilities

Final Report for
Transit IDEA Project 96

Prepared by:
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Engineering, and Medicine

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EXECUTIVE SUMMARY

In this study, the research team first conducted an extensive literature review regarding the charging formats of electric vehicles and design of electric transit bus systems (ETBS). Key pros and cons of four typical e-bus charging formats—plug-in charging station, high-tension overhead cable, solar charging board, and wireless inductive charging—were summarized:

- A plug-in charging station is fast-charging and low-cost. Significant cons include large parking space requirement and limited number of charging stations.
- High-tension overhead cable, as the most common bus charging format, can ensure a full battery pack at a low cost by allowing the e-buses to charge the battery constantly. Major cons are limited service to electrified lanes, high risk of electrocution, not resilient to hurricane and windstorm.
- A solar charging board can provide electrical energy for e-buses by harvesting heat energy directly from the sun, which can reduce carbon emissions significantly. However, slow charging and cost of equipment limit its applications in bus electrification.
- Wireless inductive charging requires above-ground infrastructure, and the equipment embedded in pavement suffers limited wear and tear.

Based on interviews with local transit authorities and discussion with the Expert Review Panel, this study focused on the combination of plug-in and wireless inductive charging modes, assuming that plug-in charging stations are set up at a transit center/depot; the main decisions that transit authorities need to make are route selection for electrifying and locations of wireless inductive charging. Thus, to create a decision support tool for planning an ETBS with multi-format charging facilities, mathematical models and solution algorithms were proposed for (1) determining locations of dynamic wireless charging facility (DWCF) for an electrified transit network, (2) integrated optimization of route selection for bus electrification and the locations of DWCF, and (3) multi-stage planning for integrated route selection and DWCF locations. The mathematical models optimize two objectives—initial investment cost of DWCF and life-long energy cost for carrying heavy batteries during bus operations. Thus, the models were formulated as bi-objective mixed integer programs. The weighted sum method was used to solve the bi-objective optimization problem for a small-size transit network. However, for a large-size transit network, generic algorithms were proposed to solve the problem.

The multi-stage planning method was applied to a local transit network, HART, in the Tampa Bay area. The transit network used in the case study included 26 routes and 2,328 bus stops. It was assumed that the transit authority needed to choose five routes to electrify now (first stage) and another five in five years (second stage) and to determine where DWCF should be located in the first stage and where additional DWCF need to be located in the second stage. By applying the method and generic algorithm developed, non-dominate solutions of bi-objective optimization problems were identified. By reading the solutions and considering the trade-off between initial investment cost of DWCF and life-long energy cost for carrying heavy batteries during bus operations, the transit authority can make decisions on which routes to be electrified and where the DWCF should be installed in the first and second stages.

Furthermore, the research team developed a Graphic User Interface (GUI) on a Linux system that consolidated data structure design, solution algorithm implementation, economic analysis, and design result visualization. A user manual was produced to help potential users understand and become familiar with the tool. Users can perform scenario analysis with this tool by changing setting parameters such as number of routes to be electrified (or budget constraint), cost of DWCF, price of electricity, etc.

Due to limited time and budget, this study had some limitations. One was that the decision support tool developed in this study did not take capacity constraints of power grid into consideration. It may not be an issue at early stages of transportation electrification. However, with the increase of market penetration of electric vehicles (passenger vehicles and buses), the capacity of a power grid could become a constraint, restricting the locations of charging facilities. In future research, the interdependence between transportation and power grids should be modeled and included. The second limitation is that only one case study was performed during this project. The COVID-19 pandemic imposed many challenges to transit

authorities, and it was difficult for the research team to obtain more case study data during this time period. In addition, the GUI was designed on Linux system, and the beta test had not been performed. One direction of extending this study would be to transfer the Linux-based GUI to web-based GUI with the support of a professional GUI developer and perform a beta test with the support of representatives from transit authorities.

1. IDEA PRODUCT

The product of this IDEA project is a decision support tool that can be used by transit authorities when making electrification-related decisions, including selecting routes for electric bus operations and determining locations for installing dynamic wireless charging facilities (DWCF) to ensure uninterrupted operations of electric buses. Transportation electrification is a continuous effort. By modeling and solving the problem in multiple stages considering the interactions of decisions at different stages, the decision support tool seeks the global optimal solutions in a defined planning horizon.

2. CONCEPT AND INNOVATION

In recent years, countries have worked around the clock with technological advancements to minimize greenhouse gas (GHG) emissions. Transportation is one area of interest, which contributes to 27% of global carbon emissions. Public transportation agencies are turning to electronic means to meet the hefty environmental demands (Kunith, Mendelevitch & Goehlich, 2017). Based on statistical data, the daily concentration of carbon dioxide in the atmosphere now exceeds 400 parts per million (ppm) (Ritchie & Roser, 2020). Reduction of fossil fuel usage is a crucial step towards minimizing GHG emissions. Green energy proves to be resourceful in this effort, which also reduces fuel consumption and noise pollution. The European Renewable Energy Directive has targeted the public transport sector to achieve a 10% transition from fossil fuel to green energy by 2030 (Xylia, etc., 2019).

Bus electrification is an effective way of mitigating carbon emissions in the wake of technological advancements. Electric transit bus systems (ETBS) are receiving increasing attention across the globe. In 2015, the European Union (EU) established legal bindings to support ETBS. Ambitious countries such as Sweden already have aimed at electrifying all their vehicles by the end of 2030. Xylia (2018) highlighted that the size of the global electric fleet has increased exponentially in recent years. By the end of 2016, 345,000 electric bus fleet vehicles were being used on roadways; of this number, China acquired almost 90% of the total electric buses produced in the world (Xylia, 2018), whereas European countries and America accounted for only 1,273 and 200 electric bus fleet vehicles, respectively (IEA, 2017). Despite slow implementation, Europe is a leader in the research and manufacturing of battery-operated buses.

In addition, the electric bus market has shown rapid development in recent years, and many manufacturers are able to provide the market different types of electric buses. For example, Proterra offers the ZX5 electric transit bus, in which an up-to-660 kWh on-board battery is installed; the maximal range on a single charge is claimed to be 329 miles, according to the manufacturer. Canadian manufacturer Nova Bus introduced its new all-electric bus, the LFSe+, with a big battery pack of 594 kWh, which is expected to maintain a range up to 292 miles on a single charge. GreenPower Motor Company has built its electric transit line, EV250/350/550, which is claimed to achieve a range of 200+ miles.

Overall, ETBS have the following advantages compared to the other types of bus systems such gas, diesel, and hybrid buses; electric buses generate zero carbon emission during operation, their energy consumption cost is lower than gas and diesel buses because of the lower rate of electricity and the brake energy recover mechanism, and their quiet operation can provide passengers with a better ride experience.

However, electrification of transit buses faces many issues, such as massive capital investment, limited bus capacity, lack of flexibility, and potentially disrupted operations. Investment cost includes costs for acquiring vehicles, constructing charging infrastructure, and coordinating with utility public works. The huge and heavy on-board batteries reduce the space of electric buses for carrying passengers and increase the weight of the bus. The short range of electric buses may lead to potentially disrupted operations. The flexibility of the transit bus system is restricted by the deployment of charging facilities. These issues regulate the use of electric buses to be fixed in urban areas rather than for long-haul transport.

Hence, it is challenging for a public transit authority to plan the process of electrifying its bus fleet and continue to operate its mixed fleet cost-effectively. To complicate it even more, uncertainties exist during

the electrification process, such as the evolution of battery technologies, changes in ridership, and operational variations.

This study aimed to provide a decision support tool for public transit authorities for facilitating the process of electrifying their transit buses. Specifically, given the periodic budget and transit network and features, the tool would provide outcomes at different stages, including (1) which routes the acquired electric buses should serve, (2) where to deploy charging facilities (both plug-in at stations and dynamic wireless charging facilities embedded in road pavement), and (3) what should be the right size of the onboard battery for a specific route.

The developed methodology was applied to a case study, Hillsborough Area Regional Transit (HART). In addition, the research team developed a Graphic User Interface (GUI) on Linux system that consolidated data structure design, solution algorithm implementation, economic analysis, and design result visualization of the proposed decision support tool.

3. INVESTIGATION

The investigation included a literature review, methodology development, a case study, and GUI design.

3.1 LITERATURE REVIEW

3.1.1 Charging Formats for ETBS

In practice, the major challenge in the application of electric vehicles is the need to recharge them after every few hours of use. Most vehicles do not maintain a large battery pack to allow them to run continually for a day, and most vehicles require charging after every few hours of use. Large electrically-driven vehicles such as buses require larger battery storage capacities, which also make them require longer charging periods. This presents a logistical challenge for fleet owners who require keeping the buses transporting passengers on the road as opposed parked and recharging at parking stations (Luo et al., 2018). To address this logistical challenge, multiple types of e-bus recharging facilities have been developed over the years, with each catering to a different charging need. Based on a literature review, four typical e-bus charging formats are included in this report—plug-in charging station, high-tension overhead cable, solar charging board, and wireless inductive charging. The key pros and cons of each charging format are illustrated as follows.

a. Plug-in or Pantograph Charging Station

The most popular charging mode used for electric vehicles is a plug-in charging system. As shown in Figure 1, this mode requires vehicles to be parked and connected to charging ports over a relatively long period of time dependent on if the charging station is regular or high speed one (Gong et al., 2019). Stationary recharging stations are, therefore, more popular among private electric vehicles, which only transport people from one location to another and remain parked for long periods, thus allowing them to be connected to a charging station.

FIGURE 1 Plug-in charging station for electric bus in Beijing, China

A pantograph charging station is a type of fast-charging station including roof-mounted (up pantograph) and inverted pantograph (down pantograph) (see Figure 2). The difference is that an inverted pantograph consists of an articulated pantograph that descends from the overhead pole to meet two light-weight (approx. 15-20kg) parallel current collector rails on the roof of the bus; for a roof-mounted pantograph, a non-articulated pantograph with a special connection head (approx. 700 kg) is installed on the bus roof and ascends to meet with the receptable on an overhead pole for charging the bus. The weight difference is approximately one passenger. Thus, an inverted pantograph is considered operationally efficient. Also, an inverted pantograph requires less capital investment in infrastructure development by using fewer connectors. There could be other formats of pantograph charging (Leserer, 2021). Different formats, unfortunately, are not compatible with one another. For deploying pantograph charging, relevant standards and compatibility need to be developed further.

FIGURE 2 Roof-mounted and inverted pantograph charging stations (Piercetransit.org)

The key pros of a plug-in or pantograph charging station are fast charging and low charging cost. The fast-charging feature is important because it can allow vehicle users to park their vehicles and wait for 2–3 hours for their batteries to be fully charged. In addition, charging stations have a variety of charge settings, which allow vehicle owners to set the charging speed depending on their available time. In addition, with the prevalence of charging stations and e-vehicles, charging costs are reduced over time. Its significant cons

are large parking space requirements and a limited number of charging stations. Plug-in charging requires e-buses to be stationary for several hours; therefore, a charging station requires a lot of parking space to accommodate a large number of vehicles. A power grid may not be able to serve concentrated plug-in charging stations at one location.

b. High-Tension Overhead Cable

Another common charging form for electric buses is high-tension overhead recharging cables. As shown in Figure 3, this form continues to be in use today in many cities and is an efficient way to recharge an e-bus, but it limits the bus to using a specific track to maintain electrical current flow (Guarnieri, 2020). High-tension overhead cables can ensure a full battery pack at a low cost by allowing the e-buses to continually charge the battery while in operation, which reduces electrical consumption surges (Sutopo et al., 2018). However, significant infrastructure development is needed if more bus routes are electrified, requiring additional high voltage cables to be installed on roads and public places. Also, overhead recharging cables are known to cause obstructions and increase the risk of electrocution due to being installed at low heights.

FIGURE 3 High-tension overhead cable for electric bus in Limoges, France

c. Solar Charging

A solar charging board can provide electrical energy for e-buses by harvesting heat energy directly from the sun, which can reduce carbon emissions significantly (see Figure 4). However, the slow charging and cost of the equipment limit its applications in bus electrification. Solar charging depends on large solar panels that cover a large surface area to generate adequate electrical current to charge batteries. In many situations, the power generated from the bus roof is not sufficient to support continuous operations. Thus, solar charging is used only as an alternative and by vehicles that remain stationary for a long period of time (Koyuncu, 2017) . In addition, solar charging equipment is costly, which makes a solar vehicle very expensive to purchase.

FIGURE 4 Solar-charged electric bus in Shenzhen, China

d. Dynamic Wireless Charging Facility (DWCF)

Wireless inductive charging facilities (DWCF) charge electric buses through power transmitters composed of inverters and inductive cables (Machura & Li, 2019). Inverters are mainly for alternating current and direct current transfer, and inductive cables embedded under the road surface can generate magnetic fields and provide electric vehicles moving across with the energy to charge the battery. The key pros of wireless inductive charging include frequent charging, no need for special infrastructure, and no wear and tear on charging systems of buses. With demand for e-buses on the rise, it is important to develop the required infrastructure to ensure that buses meet consumer needs and expectations while maintaining safety (Liu, Song & He, 2017; Liu & Wang, 2017). DWCF does not hamper other road users, and the locations of DWCF can be well designed to ensure continuous operations of buses (Jang, 2018).

The major cons for wireless inductive charging are slower charging and more power to charge compared to normal means due to the loss of power to the electric field used to connect the coils (Chawla and Tosunoglu, 2012). Moreover, frequent charging and discharging may damage the battery and shorten their lifespan.

In the market, many companies can provide the service for constructing and maintain a DWCF. Momentum Dynamics offers world-leading high-power automated wireless vehicle charging through an inductive charging system. Its technologies can provide robust and modular DC fast-charging solutions ranging from 50–450kw. The technology company Wireless Advanced Vehicle Electrification (WAVE) offers commercially-available inductive charging systems of 50–250kw to power buses on routes throughout the US. Smartroad Gotland installed the world's first wireless electric road for trucks and buses, which can transfer power up to 125kw.

The key pros and cons of different charging format of electric buses are summarized in Table 1.

FIGURE 5. Wireless inductive charging for electric bus in Gumi, South Korea

TABLE 1. Key Pros and Cons of Different Formats of Charging Facilities

Facility Type	Pros	Cons
Charging Station (Plug-in or Pantograph chargers)	• Fast charging speed • Low charging cost	• Limited number of charging stations • Require large parking space • Require bus to stop
High-Tension Cable	• Low charging cost • Continuous charging	• Restricted to electrified lane • Higher capital cost of equipment • Unable to overtake trolley buses • Overhead wires create obstruction • Safety concerns of electrocution • Not resilient to hurricane and windstorm
Solar Charging	• Free energy supply • Reduced carbon footprint • Continuous charging	• Slow charging speed • Expensive charging equipment • Range-dependent (Weather-dependent)
Dynamic Wireless Charging Facility (DWCF)	• Frequent charging • No wear and tear • No special infrastructure • High reliability	• Slow charging speed • Lack of flexibility • Negative impact on battery life • High investment cost

3.1.2 Route Selection for an ETBS

Routes for electric buses can be selected using different research methods. For instance, Zhang et al. (2017) evaluated a sequence scheme and optimal electrification selection model. They used the Monte Carlo simulation strategy in the bid to select the best route to invest money based on various conditions such as weather and traffic flow conditions. Krawiec et al. (2016) used a cost-benefit analysis in an economic sub-model, an ecological sub-model, a technical sub-model, and a transportation model for e-bus route selection. They indicated that these models help companies select bus routes that are worth replacing conventional buses with electric buses. Ushijima-Mwesigwa et al. (2017) studied the optimal placement of wireless charging facilities on road networks by using the particle swarm optimization method. However, these previous research studies did not consider energy consumption of electrified routes, charging facility needs and corresponding economic, and environmental impacts in the electric bus route selection process.

Such measures are endogenous variables that cannot be easily included in the electric bus route selection. Our study filled in this gap by proposing an integrated route selection and charging system design model.

3.1.3 DWCF Location and Battery Size Selection for an ETBS

The key challenge for adopting an ETBS is the battery capacity requirement. Large battery capacity design is determined by the fact that transit buses must operate continuously throughout the day and maintain a specified schedule to ensure quality of service. When battery energy is below the minimum level required to complete a round of service, electric buses must stop for an extended period of time to get charged, which results in schedule delay or requires an additional bus to be dispatched for continuing service. In addition, a large battery greatly increases the initial capital cost of an electric bus, limits available space for carrying passengers, and increases energy consumption during bus operation. Some previous pilot projects explored the possibilities of adopting DWCF for an ETBS, aiming to reduce battery size and keep buses operating normally without the need for off-line charging (Liu, Song & He, 2017; Jeong, Jang & Kum, 2015). Gao et al. (2017) showed that the most typical battery capacity for electric buses designed by original equipment manufacturers (OEMs) are in the range of 200–300 kWh. However, more recently, the battery capacity of e-buses is increasing. For example, Proterra equipped Catalyst E2 35-ft electric buses with no less than 440 kWh of battery capacity (sustainable-bus.com). Lajunen (2018) estimated that energy cost can take up more than 50% of total life cycle cost for diesel buses and up to 20% for electric buses; meanwhile, large battery size related to energy consumption is a significant component. Considering a battery weight-to-energy ratio of 11.36 kg/kWh, a battery pack with 200 kWh can weigh more than 2,000 kg, which counts for more than 16% of the net weight of a transit bus (12,000 kg) (American Public Transportation Association (APTA), 2014).

Many research works have attempted to help with the commercial application of DWCF in an ETBS (Hwang, etc., 2017; Jang, Jeong & Ko, 2015; Jang, Suh & Kim, 2015; Ko, Jang & Lee, 2015; Liu & Song, 2017). For most previous research studies, DWCF location and battery size were selected by minimizing the total investment cost (cost of DWCF and battery). They found that battery cost is a significant portion of the initial capital cost for an ETBS.

For a dynamic charging system, a smaller battery pack with less energy consumption will require more investment in charging facilities. For example, Jang, Jeong & Ko (2015) studied the economic benefits of battery downsizing and the benefits to battery life by introducing a DWCF compared with a stationary charging station. Hwang et al. (2017) studied the deployment of a DWCF in a multi-route environment and analyzed the effect when shared sections of routes were deployed with power tracks. Jang, Suh & Kim (2015) and Liu & Song (2017) studied the deployment of DWCFs in an open environment with the interaction between bus and other private traffic modes by considering stochastic travel time and energy consumption using a robust optimization method. They found that the proposed approach could be used to determine the allocation of wireless charging devices and the appropriate battery size of electric buses for a dynamic wireless power transfer electrical bus system. Krawiec et al. (2016) used the CACTUS software tool to ensure that the process of powering electric buses is supported; a vital part of CACTUS is the battery charging points and concluded that battery drive in electric buses has multiple economic uncertainties. Kunith et al. (2017) investigated the battery sizing problem for different fast-charging ETBS by using a mixed-integer linear optimization model, which can help to determine adequate battery capacity for each bus route. Results were found based on the elaborated trade-off between the charging infrastructure and battery capacity of the bus under diverse operational and infrastructure circumstances. Hwang et al. (2017) discussed system optimization of dynamic wireless charging of electric vehicles that operated in various route environments. They discovered that, compared to single-route optimization applied to every particular path, the multi-route optimization model delivered superior results. Czogalla and Xie (2019) found that battery capacity for a single day of service could be scaled on bus routes with ground grades applied, traffic conditions, and charging potential.

Another factor related to batteries is degradation. Given the degradation of the batteries of electric buses, they should be replaced if their capacity decreases to a certain level. For DWCF design in an ETBS, the DWCF location and battery size should also be determined to minimize battery degradation cost. Many models estimate the degradation of batteries and quantify the cost of the degradation. The degradation cost is determined by the degradation of an exact operation of the battery and the cost of replacing an aged battery. The cyclical degradation model is an effective model to evaluate degradation of batteries. Downing's "Rainflow" counting algorithm, an event-oriented modeling approach (Dufo-López, etc., 2014; Sauer & Wenzl, 2008), is usually applied to calculate cycles and cycle depths of batteries for their degradation estimation. Several research works studied battery degradation using the cyclical degradation model. Shi et al. (2018) studied the optimal control of a battery using the cyclical degradation model to achieve a trade-off between following instruction signals and the impact of degradation from charging and discharging. The cyclical degradation model was also applied to evaluate degradation of a battery in the application of electric vehicles by considering the impacts of charging rate, environment temperature, and depth of discharge (Suri & Onori, 2016; Onori, et al., 2012). In practice, the battery degradation of the electric buses is impacted by many factors such as the climate of locations that operate the electric buses, the road condition of the bus routes, the maintenance for the electric buses, and the charging behaviors of the electric buses.

However, none of these works considered the effect of downsizing a battery on energy consumption reduction. This is a major benefit of integrated DWCF and battery capacity design. A DWCF provides frequent charging for electric buses and makes it possible for downsizing the battery, and a decrease of the weight of the battery can reduce energy consumption for carrying a battery pack. Energy consumption is not only a critical indicator of environment impact but also a primary portion of life cycle cost for a bus system. Therefore, to determine dynamic charging facility locations and on-board battery size, the trade-off between the investment cost of a DWCF and the cost of energy consumption from both environmental and economical perspectives is considered in this study.

3.2 MATHEMATICAL MODELS AND SOLUTION ALGORITHMS

The developed decision support tool will help transit authorities to determine the locations of DWCF and on-board battery sizes for different routes with the objective of minimizing the total investment cost for deploying DWCF and the energy consumption of carrying on-board battery during e-bus operations. Beginning from a base model assuming fully electrification of the entire transit network, binary variables of route selection were added for partial electrification. From a mathematical modeling perspective, the second model is more complicated because the binary variables of route selection make the objective functions and some constraints non-linear. Non-linear mathematical program is difficult to solve and requires non-linearization techniques to transform the non-linear mathematical programming to linear programming. Furthermore, the dynamic planning of electrifying transit network was tackled, i.e., with long-term budget scenarios, how to electrify transit network along various stages. Note that the DWCF locations from current stage will affect the optimal solution of DWCF locations in next stage.

Different models were developed with constraints of the model ensuring that the electric buses operate at a certain level of the state of charge (SOC) of the battery. The models are formulated as bi-objective mixed integer programs. The weighted sum method was applied to solve the problems, and Pareto frontier were obtained to show the tradeoff between two objective functions.

3.2.1 System Setting and Assumptions

A regular transit bus system has the following common elements:

- There are multiple routes for the bus system, and some portions of network links and stops are shared by multiple routes.
- Each route has multiple stops and is assigned several buses to operate.
- Each route has a start and end point of service (base stations) where electric buses stop for an extended time after completing service.

Buses usually are operated in cycles. In each cycle, one bus departs from the base station and finally returns to this station. After the bus completes a cycle, it will continue the next cycle until it completes its assigned block, a vehicle schedule, the daily assignment for an individual bus, which indicates the number of cycles of the bus to be operated on its route in a day. Blocks are important inputs that impact the decisions of DWCF locations. If a bus runs only a few short cycles, the design of the electrification is apt to require installation of a large size battery rather than deploying to the charging facility, because a fully-charged battery can supply sufficient energy for operation of the bus. Otherwise, DWCFs are needed to provide extra energy to the electric buses.

For an electric bus system, a bus-only lane can be set up along the route, or it can have an electric bus operating in an open environment mixed with other traffic modes by incorporating the uncertainties of travel time and energy consumption, as noted in the literature (Jang, Suh & Kim, 2016; Liu & Song, 2017). For this research project, the focus was on an open environment with electric buses mixed with other traffic. In case studies, historical travel times of buses were collected, and the average speeds of different routes were calculated based on the historical travel times.

The following assumptions were made for planning bus electrification in this study:

1. Vehicles are fully charged before starting daily operation.
2. Vehicles serving the same route have the same battery size and follow the same average speed profile.
3. Minimal allowable energy levels of the battery are set in solving the problem for maintaining uninterrupted operation.
4. The electric buses can be equipped with different sizes of batteries based on routes because of differences of the routes such as ridership, road condition, and operation schedule.

Assumption 1 can be relaxed by allocating more DWCFs along each route if enough idling and charging time cannot be ensured at base stations.

In addition, the following are facts regarding battery charging and roadway network:

- The amount of energy charged from a power transmitter is proportional to the travel time on the inductive cable. This is based on the battery charging and discharging characteristics within a certain range of energy level (Ko, Jang & Lee, 2015) .
- The road slope for each route and travel speed for each electric bus are predetermined based on geographic data.

3.2.2 Input Data and Parameters

The input data of the mathematical models for planning the electrification of a transit bus system should include the shapefile of the transit bus network, bus service data, coefficient parameters for estimating the cost and GHG emission, and technical features of the DWCF:

- Shapefile of bus network should illustrate the roadway network served by all bus routes and the slope of each road.
- Bus service data indicate the number and frequency of the buses serving their bus routes and the predetermined bus speed to travel through the route.
- Coefficient parameters are used to calculate the cost of installing inverters and inductive cables for the DWCF and the GHG emission originating from the energy consumption of the electric buses.

- Technical features data indicate the energy supply rate, energy loss of the DWCF, and the technical features of the electric buses for estimating the energy consumption and the battery degradation.

When these data are collected, some preprocessing needs to be conducted on them to transfer them to a form that can be used to formulate the mathematical model. The finalized data used for the model are shown in Table 2.

TABLE 2 Indicators and Parameters for System Setting and Model Development

Indicators and Sets	
Notation	***Description***
i, j, k	Index of node in bus network
r	Index of bus route
f	Index of bus frequency
N	Set of nodes in bus network
N_r	Set of nodes on route r
N^s	Set of nodes with more than one incoming links
A	Set of directed links in bus network
A_r	Set of directed links on route r
R	Set of bus lines
F	Set of bus frequency on route r
Parameters	
Notation	***Description***
l	Length of link in bus network
c^{inv}	Cost of one inverter
c^{con}	Construction cost of inductive cable per unit length
e_{rij}^{fix}	Fixed part of energy consumption for the bus to travel through link (i, j) on route r
e_{rij}^{fix}	Unit energy consumption for the bus to carry per unit battery to travel through link (i, j) on route r
T	Lifespan of electric bus lines studied
α	Interest rate
m	Number of buses in a bus line
c^{ele}	Electricity price
c^{bat}	Battery price
c^{emi}	Emission conversion factor for electricity
p	Energy supply rate of the power transmitter
t_{rij}	Time of the bus traveling through link (i, j) on route r in the network
B^l/B^u	Minimum/maximum battery size
δ_{low}/δ_{up}	Lower and upper bound coefficients for the battery

According to Table 2, the indicators and sets are used to represent the transit bus network. The parameters e_{rij}^{fix} and e_{rij}^{unit} are used to compute the energy consumption of the electric bus traveling through a specific link on the route. These parameters are estimated by the predetermined bus speed, technical features of the electric bus, and slope of the road. The emission conversion factor c^{emi} is the coefficient to calculate the GHG emission for producing the electricity that is consumed by the electric buses.

3.2.3 Mathematical Models

This subsection explains three mathematical models for planning of the electrification of a transit bus system. The representation of the bus network is presented first to facilitate calculation of the cost for investing in a DWCF. Then, two objectives capturing investment cost and energy consumption and the constraints of maintaining the energy level of the electric buses are built for the model. Finally, the three mathematical models are presented for electrifying the entire bus network, selecting bus routes to electrify, and planning electrification of the bus transit system in multiple stages.

a. Network Representation

Let $G(N, A)$ denote the electric bus network where N and A are the sets of nodes and directed links in the network, respectively. Each route in the bus system is divided into short links with equal length l. Each link a is represented as node pair (i, j), i.e., $a = (i, j) \in A$, where $i, j \in N$ and $i \neq j$. Let R denote the set of electric bus lines and A_r and N_r denote all the links and corresponding nodes that form the rth line, respectively. In addition, we denote the set of intersections in $G(N, A)$ with more than one incoming links as N^s, where $N^s \in N$.

b. Objective: Investment Cost of the DWCF

The DWCF applies a power transmitter to charge the battery of the electric buses. One power transmitter contains one inverter and inductive cables deployed on a series of adjacent links. Let binary variable x_{ij} represent if link (i, j) is deployed with an inductive cable, and the total length of the inductive cables can be represented by:

$$l \sum_{(i,j)\in A} x_{ij}$$

Let y_i denote if node i is the start node of a series of adjacent links deployed with inductive cables. Then $\sum_{i\in N} y_i$ can be used to represent the total number of inverters in general cases. However, in cases when inductive cables are deployed with the intersection nodes and those nodes are with multiple incoming links, there may be more than one start node for those inductive cables counted, although only one inverter is equipped for them, as they are adjacent to each other. To account for such situations, let z_i represent if one of the incoming links of intersection $i \in N^s$ is allocated with inductive cables. Then, the number of inverters can be expressed as follows:

$$\sum_{i\in N} y_i - \sum_{i\epsilon N^s} \sum_{(w,i)\in A} x_{wi} + \sum_{i\epsilon N^s} z_i$$

Now the number of inverters and the total length of the inductive cables can be expressed. Hence, the total construction cost for installing the inverters and inductive cables for the electrification of the bus transit system can be calculated as follows:

$$c^{inv}\left\{\sum_{i\in N} y_i - \sum_{i\epsilon N^s} \sum_{(w,i)\in A} x_{wi} + \sum_{i\epsilon N^s} z_i\right\} + c^{con} l \sum_{(i,j)\epsilon A} x_{ij}$$

where c^{inv} denotes the cost of one inverter and c^{con} denotes the cost for constructing the inductive cables per unit length.

c. Objective: Energy Consumption of Battery

In this subsection, the calculation of energy consumption for operating the electrified bus transit system is conducted. With the energy consumption data, the energy consumption cost and the GHG emission can be estimated. The energy consumption is estimated as the product of the price for purchasing electricity from the power grid and the amount of electricity purchased to charge the electric buses for daily operations. The GHG emission is estimated as the product of the amount of electricity consumed by the electric buses and the emission conversion factor.

The process to estimate the energy consumption of the electric bus traveling through an exact route can be explained as follows. Let b_r represent the battery capacity of electric buses on route r, where $r \in R$, and let d_{rij} represent the energy consumption of the electric bus traveling through the link (i, j) on route r. The energy consumption d_{rij} can be expressed as:

$$d_{rij} = e_{rij}^{fix} + e_{rij}^{unit} b_r \; \forall (i,j) \in A_r, \forall r \in R$$

where e_{rij}^{fix} and e_{rij}^{unit} are predetermined parameters estimated based on the electric bus travel speed, road slope, and technical features of electric buses. The term e_{rij}^{fix} represents the fixed part of energy consumption determined after the data preprocessing. The term $e_{rij}^{unit} b_r$ represents the energy consumption for carrying the battery pack and is linearly related to battery size. For the energy consumption calculation and d_{rij} decomposition details, refer to [26].

In this study, the focus was on how battery size change will influence energy consumption, leading to the cost of consuming electricity and the GHG emission for producing the electricity consumed by the electric buses. With the energy consumption of the electric bus traveling through a specific link on the bus route, the total energy consumption of all electric buses can be represented by the following formula:

$$\mathrm{T} \times 280 \times 0.1 \sum_{r \epsilon R} \sum_{f \epsilon F_r} \sum_{(i,j) \epsilon A_r} m_r \, d_{rij}$$

where m_r represent the number of electric buses on route r; 280 is annualization factor for converting daily cost to annual cost considering the difference of weekdays and weekend; and \$0.1 is the price of electricity.

d. Constraints: State of Charge Requirement for Battery

As defined above, there are maximum and minimum allowable SOC for the battery of the electric buses. Let δ_{up} and δ_{low} be the upper and lower limit coefficients for the battery. Then, the upper and lower energy level limits are $\delta_{up} b_r$ and $\delta_{low} b_r$, respectively. Let u_{rfi}, where $i \in N, r \in R, f \in F$ denote the SOC of the battery of the electric bus at node i of its fth round on route r. It should satisfy the following conditions:

$$u_{rfi} \leq \delta_{up} b_r \; \forall i \in N_r, \forall f \in F_r, \forall r \in R$$

$$u_{rfi} \geq \delta_{low} b_r \; \forall i \in N_r, \forall f \in F_r, \forall r \in R$$

To obtain the SOC of electric bus at node j, let s_{rij} represent the amount of energy that is supplied to electric buses when they travel through link (i, j) on route r, p represent the energy supply rate of the power transmitter after considering the energy loss, and t_{rij} represent the travel time of electric buses to travel through link (i, j) on route r. Then s_{rij} can be expressed as

$$s_{rij} = p t_{rij} x_{ij} \; \forall (i,j) \in A_r, \forall r \in R$$

The energy level u_{rfj} at each node j along route r and round f can be obtained based on its energy level at u_{rfi} at its previous node i:

$$u_{rfj} = u_{rfi} - d_{rij} + s_{rij} \; \forall (i,j) \in A_r, \forall f \in F_r, \forall r \in R$$

Let o_r denote the start node and e_r the end node on route r. The energy level of the electric buses that start from base station on route r and round f is u_{rfo_r}, and the energy level of the electric buses that return the base station on route r and round f is u_{rfe_r}. Given the bus cycling on the route, the energy level of the bus at the start of a round should be equal to the energy level of the bus at the end of the last round:

$$u_{rfo_r} = u_{r(f-1)e_r} \; \forall f \in F_r, f > 1, r \in R.$$

e. Decision Variable: Route Selection, Battery Size, DWCF Location

The decision variables for the model are listed in Table 3 and can be classified into two groups, continuous and binary.

TABLE 3 Decision Variables for Model Development

Continuous Variables	
Notation	***Description***
u_{rfi}	Energy level of electric bus at node $i \in N_r$ on route $r \in R$ and round $f \in F_r$
u_{rfo_r}	Energy level of electric bus at start node o_r on route $r \in R$ and round $f \in F_r$
u_{rfe_r}	Energy level of electric bus at end node e_r on route $r \in R$ for round $f \in F_r$
s_{rij}	Energy charged to electric bus when it travels through link $(i,j)\epsilon A_r$ on route $r \in R$
d_{rij}	Energy consumption of electric bus traveling through link $(i,j)\epsilon A_r$ on route $r \in R$
b_r	Battery size of bus on route $r \in R$
Binary Variables	
Notation	***Description***
x_{ij}	Represent if link $(i,j) \in A$ is deployed with charging facilities
y_i	Represent if node $i \in N$ is start node of some links with charging facilities
z_i	Represent if intersection node $i \in N^s$ is connected to link with charging facilities
v_r	Represent if bus line $r \in R$ is selected to electrify

f. Model: DWCF Locations for Fully-Electrified Transit Network

In this subsection, the model to determine the facility locations and battery sizes for electrifying the entire bus network is illustrated. This model can be applied to a transit system that rotates buses on each route. The rotation strategy to operate the electric buses in the transit system allows each bus route to access the service of the electric buses. This strategy is referred to as electrifying the entire bus network. Then, the model is built to minimize the two objectives by installing the DWCF for the entire bus transit system. Based on the above descriptions of parameters and variables, the complete mathematical model to optimize the planning for electrifying the entire transit bus system is as follows:

$$\min c^{inv}\left\{\sum_{i\in N} y_i - \sum_{i\epsilon N^s}\sum_{(w,i)\in A} x_{wi} + \sum_{i\epsilon N^s} z_i\right\} + c^{con} l \sum_{(i,j)\epsilon A} x_{ij}$$

$$\min \mathrm{T} \times 280 \times 0.1 \times \sum_{r\epsilon R}\sum_{f\epsilon F_r}\sum_{(i,j)\epsilon A_r} m_r\, d_{rij}$$

$s.t.$

$$y_i \le \sum_{(i,j)\in A} x_{ij}, \qquad \forall i \in N \qquad (1)$$

$$y_i \le 1 - x_{wi}, \qquad (w,i) \in A \qquad (2)$$

$$y_i \ge x_{ij} - \textstyle\sum_{(w,i)\in A} x_{wi} \qquad \forall (i,j) \in A \qquad (3)$$

$$z_i \leq \sum_{(w,i)\in A} x_{wi} \qquad \forall i \in N^s \qquad (4)$$

$$z_i \geq x_{wi} \qquad \forall i \in N^s, \forall (w,i) \in A \qquad (5)$$

$$d_{rij} = e_{rij}^{fix} + e_{rij}^{unit} b_r \qquad \forall (i,j) \in A_r, \forall r \in R \qquad (6)$$

$$u_{rfi} \leq \delta_{up} b_r \qquad \forall i \in N_r, \forall f \in F_r, \forall r \in R \qquad (7)$$

$$u_{rfi} \geq \delta_{low} b_r \qquad \forall i \in N_r, \forall f \in F_r, \forall r \in R \qquad (8)$$

$$s_{rij} = pt_{rij} x_{ij} \qquad \forall (i,j) \in A_r, \forall r \in R \qquad (9)$$

$$u_{rfj} = u_{rfi} - d_{rfij} + s_{rfij} \qquad \forall (i,j) \in A_r, \forall f \in F_r, \forall r \in R \qquad (10)$$

$$u_{rfo_r} = u_{r(f-1)e_r} \qquad \forall f \in F_r, f > 1, r \in R \qquad (11)$$

$$B^l \leq b_r \leq B^u \qquad \forall r \in R \qquad (12)$$

$$x_{ij} \in \{0,1\} \qquad \forall (i,j) \in A \qquad (13)$$

$$y_i \in \{0,1\} \qquad \forall i \in N \qquad (14)$$

$$z_i \in \{0,1\} \qquad \forall i \in N^s \qquad (15)$$

where constraints (1)–(3) determine if a node is the start node of a series of adjacent links deployed with inductive cables, and constraints (4) and (5) determine if one of the incoming links of an intersection nodes is deployed with inductive cables. Constraints (6)–(11) restrict the battery energy level to be always within the allowable range. The maximum and minimum allowable energy levels are set based on [18], which is beneficial for battery life.

g. Model: Integrated Bus Route Selection and DWCF Locations for Partially-Electrified Transit Network

Electrifying some (not all) electric bus routes in a transit system requires selecting routes from the bus network. As different selections of the bus routes for electrification will lead to different DWCF deployment and corresponding different construction cost and energy consumption, the selection of the electrified routes also needs to be optimized. To facilitate decisions on route selection, a binary variable v_r is introduced to indicate if route r is selected to electrify or not (1 for selected and 0 for not selected). If route r is not selected, the energy consumption of this route should be removed from the objective of total energy consumption, and the constraints that maintain the energy level of the electric buses on this route should also be removed. Some mathematical manipulations are applied to ensure that introducing the binary variable can achieve the above goals and still guarantee the model to be linear. Then, the model for selecting some routes from the transit bus system to electrify can be formulated as follows:

$$\min c^{inv}\left\{\sum_{i\in N} y_i - \sum_{i\epsilon N^s}\sum_{(w,i)\epsilon A} x_{wi} + \sum_{i\epsilon N^s} z_i\right\} + c^{con} l \sum_{(i,j)\epsilon A} x_{ij}$$

$$\min \mathrm{T} \times 280 \times 0.1 \times \sum_{r \epsilon R} \sum_{f \epsilon F_r} \sum_{(i,j) \epsilon A_r} m_r \, d_{rij}$$

$s.t.$ (1) – (5) and

$$\sum_{r \in R} v_r = \bar{v} \tag{16}$$

$$d_{rij} = e_{rij}^{fix} v_r + e_{rij}^{unit} \bar{b}_r \qquad \forall (i,j) \in A_r, \forall r \in R \tag{17}$$

$$\bar{b}_r \leq b_r \qquad \forall r \in R \tag{18}$$

$$\bar{b}_r \leq M v_r \qquad \forall r \in R \tag{19}$$

$$\bar{b}_r \geq b_r - M(1 - v_r) \qquad \forall r \in R \tag{20}$$

$$s_{rfij} = pt_{rfij} x_{ij} \qquad \forall (i,j) \in A_r, \forall r \in R \tag{21}$$

$$u_{rfj} - u_{rfi} + d_{rij} - s_{rij} \leq M(1 - v_r) \qquad \forall (i,j) \in A_r, \forall f \in F_r, \forall r \in R \tag{22}$$

$$u_{rfj} - u_{rfi} + d_{rij} - s_{rij} \geq -M(1 - v_r) \qquad \forall (i,j) \in A_r, \forall f \in F_r, \forall r \in R \tag{23}$$

$$u_{rfi} \leq \delta_{up} b_r \qquad \forall i \in N_r, \forall f \in F_r, \forall r \in R \tag{24}$$

$$u_{rfi} \geq \delta_{low} b_r \qquad \forall i \in N_r, \forall f \in F_r, \forall r \in R \tag{25}$$

$$u_{rfo_r} = u_{r(f-1)e_r} \qquad \forall f \in F_r, f > 1, r \in R \tag{26}$$

$$B^l \leq b_r \leq B^u \qquad \forall r \in R \tag{27}$$

$$x_{ij} \in \{0,1\} \qquad (i,j) \in A \tag{28}$$

$$y_i \in \{0,1\} \qquad \forall i \in N \tag{29}$$

$$z_i \in \{0,1\} \qquad \forall i \in N^s \tag{30}$$

where $\bar{v}$ is predetermined parameter to indicate the number of bus routes to be electrified, M is a big number that should be greater than B^u, and $\bar{b}_r$ are variables to ensure the model of route selection to be linear. Constraints (16)–(20) can ensure that if route r is not selected, the value of d_{rij} is zero and the corresponding energy consumption is also zero. Constraints (21)–(26) can guarantee that the energy level constraint of the battery applies only to the route selected.

h. Model: Multi-stage Dynamic Planning for ETBS

In practice, the electrification of a bus transit system is executed in multiple stages. In each stage, a fixed number of routes are selected to electrify because of the budget limit. Then, a model to sequentially determine the routes selected to electrify in each stage is needed to support the multi-stage planning of the electrification of the bus transit network.

Figure 6 presents the multi-stage dynamic route selection model for the planning of electrifying a bus transit system. In multi-stage dynamic planning for bus network electrification, it is assumed that decision-makers have predetermined the number of stages and the number of routes to be electrified in each stage for the electrification of the entire bus network. Dynamic planning starts with electrifying $\bar{v}_1$ routes in Stage

1 by solving the route selection model. Thereafter, the deployment of the DWCF for the routes selected in Stage 1 should be transferred to next stage. This implies that when solving the route selection model for Stage 2, some links have been electrified, i.e., some variables such as x_{ij}, y_i, and z_i need to be fixed to be equal to 1. Once Stage 2 is solved, the information of the deployment of DWCF in both Stage 1 and Stage 2 need to be transferred to Stage 3. This process continues until all routes on the bus network have been electrified.

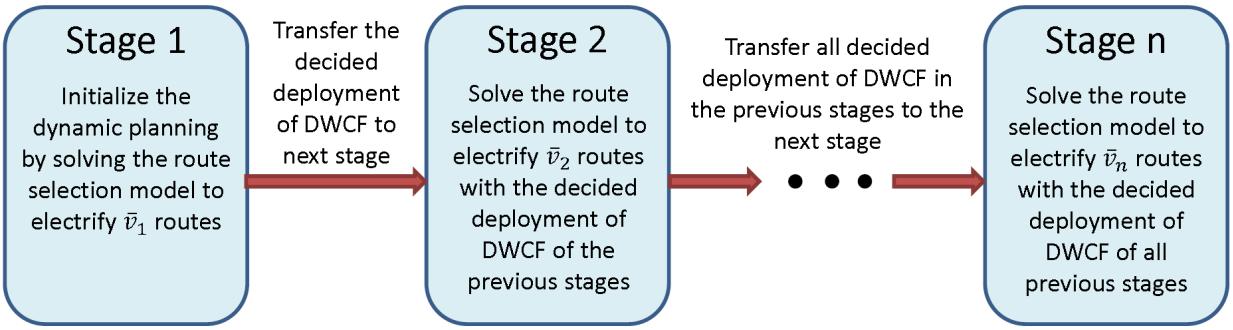

FIGURE 6 Concept of multi-stage dynamic planning model

To solve this multi-stage dynamic model, route selection for each stage is determined first. With the results of route selection, the route selection model is solved for each stage, with some links having been electrified, i.e., the values of some x_{ij}, y_i, and z_i have been fixed to 1, and the selection of routes for each stage having been decided, i.e., the values of variable v_r for $\forall\, r \in R$ have been fixed based on the predetermined route selection. Once all route selection models are solved, the total cost of the predetermined route selection for each stage can be computed. Some heuristics are applied to the process of predetermining the route selection for each stage to help the algorithm obtain the optimal solution that returns the best route selection with minimal total cost quickly.

3.2.4 Solution Algorithm for Bi-objective Optimization Model

a. Preliminaries and Definitions

A multi-objective optimization problem can be stated as follows (33):

$$\underset{x \in \mathcal{X}}{\text{minimize}}\, z(x) := \{z_1(x), \dots, z_p(x)\} \qquad (33)$$

where $\mathcal{X} \subseteq \mathbb{R}^n$ represents the feasible set in the *decision space* and the image $\mathcal{Y}$ of $\mathcal{X}$ under vector-valued function $\mathrm{z} = \{z_1, \dots, z_p\}$ represents the feasible set in the criterion space; i.e., $\mathcal{Y} := \mathrm{z}(\mathcal{X}) := \{y \in \mathbb{R}^p : y = z(x) \text{ for some } x \in \mathcal{X}\}$. For convenience, we also use the notation $\mathbb{R}^p_{\geq} := \{y \in \mathbb{R}^p : y \geq 0\}$ for the nonnegative orthant of $\mathbb{R}^p$, and $\mathbb{R}^p_{>} := \{y \in \mathbb{R}^p : y \geq 0\}$ for the positive orthant of $\mathbb{R}^p$. When $\mathcal{X}$ is defined by a set of affine constraints and $z_1(x), \dots, z_p(x)$ are linear functions, then (32) is a multi-objective linear program (MOLP). When $\mathcal{X} \subseteq \mathbb{Z}^n$, (32) is a multi-objective integer program (MOIP). When $p = 2$, these problems are called a bi-objective linear program (BOLP) and a bi-objective integer program (BOIP), respectively.

- **Definition 1. Non-dominated point** – A feasible solution $x' \in \mathcal{X}$ is called efficient or Pareto optimal, if there is no other $x \in \mathcal{X}$ such that $z_k(x) \leq z_k(x')$ for $k = 1, \dots, p$ and $z(x) \neq z(x')$. If x' is efficient, then $z(x')$ is called a non-dominated point. The set of all efficient solutions $x' \in \mathcal{X}$ is denoted by $\mathcal{X}_E$. The set of all non-dominated points $y' = z(x') \in \mathcal{Y}$ for some $x' \in \mathcal{X}_E$ is denoted by $\mathcal{Y}_N$ and referred to as the non-dominated frontier or the efficient frontier.

- **Definition 2. Supported non-dominated point** – Let $x' \in \mathcal{X}_E$. If there is a $\lambda \in \mathbb{R}^p$ such that x' is an optimal solution to $\min_{x \in \mathcal{X}} \lambda^T \ z(x)$, then x' is called a supported efficient solution and $y' = z(x')$ is called a supported non-dominated point.
- **Definition 3. Extreme supported non-dominated points** – Another important type of non-dominated points is extreme supported non-dominated (ESN) point. ESN points are the extreme points of the convex hull of all non-dominated points.

Let $\mathcal{Y}^e$be the set of extreme points of conv($\mathcal{Y}$). A point $y \in \mathcal{Y}$ is called an extreme supported non-dominated point if $\in \mathcal{Y}^e \cap \mathcal{Y}_N$.

b. Solution Method for MOIP

The set of (feasible) solutions to an MOLP, in the decision space as well as in the criterion space, is convex (assuming that the problem is feasible). Therefore, all efficient solutions to a MOLP are supported, i.e., they can be obtained by optimizing a weighted combination of objective functions. Unfortunately, in general, this is not the case for an MOIP. Therefore, to solve the MOIP is (far) more challenging.

In this work, weighted-sum methods were applied to find all extreme supported non-dominated points for the bi-objective integrated design problem to determine dynamic charging facility location and on-board battery size.

c. Weighted-Sum Method and Algorithm Design

The weighted-sum method [5] finds all extreme supported non-dominated points. It uses the following optimization problem to search a rectangle defined by pints z^1 and z^2.

$$\min_{x \in \mathcal{X}} \{\lambda_1 z_1(x) + \lambda_2 z_2(x)\}$$
$$\text{subject to } z(x) \in R(\, z^1, z^2)$$

with $\lambda_1 = z_2^1 - z_2^2$ and $\lambda_2 = z_1^2 - z_1^1$, which indicate that the objective function is parallel to the line that connects z^1 and z^2 in the criterion space.

This optimization returns either a new and (possibly extreme) supported non-dominated point, one of z^1 and z^2, or a convex combination of z^1 and z^2. If the optimized result in the criteria space (z_1^{new}, z_2^{new})satisfy the following condition $\lambda_1 z_1^{new} + \lambda_2 z_2^{new} < \lambda_1 z_1^1 + \lambda_2 z_2^1$, the optimum point z^{new} is a newly found non-dominated point which will separate the original rectangle to smaller rectangles to be searched. The pseudo-code for the algorithm design of the bi-objective restoration sequence optimization is illustrated as follows.

Step 1. Compute the endpoints z^T and z^B

Step 2. Create a list $List.create(L)$;

Step 3. Add points z^T and z^B to the list L, $List.add(L, z^T)$, $List.add(L, z^B)$.

Step 4. Create a queue *P* with rectangles to be searched, *PQ.create*(*P*). Add rectangle $R(z^T, z^B)$ to the queue, $PQ.add(P, R(z^T, z^B))$.

Step 5. Optimize the weighted sum single objective optimization problem $\min_{x \in \mathcal{X}} \{\lambda_1 z_1(x) + \lambda_2 z_2(x)\}$, if the optimized point in criteria space satisfy the criteria shown below, this point is a newly found ND point which will separate the original rectangle to smaller rectangles to be searched. While the queue is not empty, step 5 will be performed iteratively.

While the queue *P* is not empty, *not PQ.empty(P)* do

PQ.pop (P, $R(z^1, z^2)$)

$x^* \leftarrow \operatorname{argmin}_{x \in \mathcal{X}} (z_2^1 - z_2^2\,) z_1(x) + (z_1^2 - z_1^1) z_2(x)$

z ← z(x^*)

if $(z_2^1 - z_2^2\,) z_1 + (z_1^2 - z_1^1) z_2 < (z_2^1 - z_2^2\,) z_1^1 + (z_1^2 - z_1^1)) z_2^1$ then

$List.add(L, z)$
$PQ.add(P, R(z^1, z))$
$PQ.add(P, R(z, z^2))$
Return L

Following the above pseudo-code, the weighted sum method can be implemented to solve both proposed bi-objective integrated DWCF location and on-board battery size optimization problems. It is used for a small-size regional transit network, as shown in Section 5. However, when the size of transit network increases, the problem becomes computationally intractable if weighted-sum algorithm is used. Thus, the following genetic algorithm is proposed to solve large scale transit networks.

d. Non-dominated Sorting Genetic Algorithm II

Non-dominated Sorting Genetic Algorithm Type two (NSGA II) is a well-known metaheuristic algorithm used to solve numerous multi-objective problems in a variety of fields (Srinivas & Deb, 1994; Deb et al., 2002; Zhou et al., 2011). This algorithm takes advantage of Genetic Algorithm's optimization mechanisms in the context of multi-objective optimization. This compatibility to solve multi-objective problems is given to GA by a fast subroutine that sorts the population of individuals (solutions) into layers of non-dominated points. In other words, this algorithm improves the quality of approximate Pareto-optimal frontier generation by generation, imitating the idea of evolution on the information transmit by individual chromosomes.

Complexity of the problem increases when dynamic decision-making is involved. In the multi-stage planning form of the problem, the model finds the best route and location of wireless charging facilities for them in each given decision stage. In other words, the decision time is provided along with the number of routes to be electrified and the model selects the routes for each decision moment. NSGA II is used to solve Multi-stage Dynamic Planning for the ETBS (Section 4.3.8) and large instances of DWCF location for a fully (Section 4.3.6) or partially (Section 4.3.7) electrified transit network. Next, the modules of the proposed NSGA II algorithm are explained.

Chromosome

A chromosome is basically an encoded version of a solution for a problem that is supposed to be solved by Genetic Algorithm—a complete solution of the problem can be obtained by decoding the chromosome to the value of decision variables. In the proposed algorithm, an array with three parts, schematically shown in Figure 7, is used to represent the individuals/chromosomes compatible with all three forms of the problem. The first part that represents decision variable v_r includes continuous values between 0 and 1. Sorting these values will determine the priority for the routes to be selected for electrification. Clearly, this part of the chromosome must be ignored when solving the full electrification problem. The second part of the chromosome that can obtain only zero and one values associates with the location of charging facilities. The values of this part, related to routes that are not selected by the first part, must be ignored in the decoding process too. Finally, the last part of the chromosome determines the size of the batteries for each route.

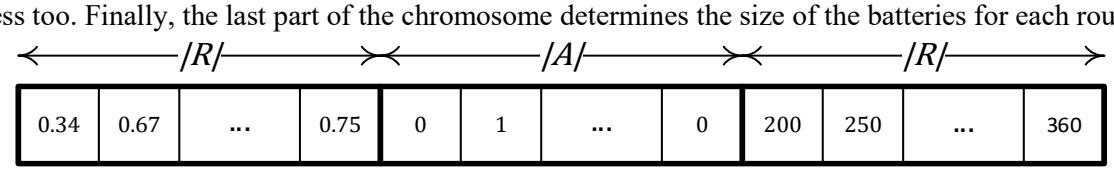

FIGURE 7 Solution representation (chromosome) in proposed algorithm

Solution Evaluation

One of the difficulties of using heuristic algorithms to solve especially multi-objective problems is to determine the goodness of solutions (or chromosomes in our case) and their survival procedure to the next generation. Depending on the problem, different methods are used to evaluate the solutions (Deb, etc., 2000), which are mostly based on the objective functions. In this research, the objective functions are main measure of goodness to evaluate and compare the individuals too. Also, we use a method proposed by (Deb, etc., 2000) to select the survived individuals using non-domination rank and crowding distance. In this method, chromosomes with the highest non-domination rank are chosen to transmit to the next generation, and for individuals with the same non-domination rank, crowding distance becomes the judgement measure.

Crossover

In the proposed algorithm, different recombination methods are used for three parts of the chromosome. For the first and last parts, which represent the route selection and battery sizes and have continuous values, the linear combination of two parents is used. For the middle part, however, a mask combination of two parents is used. In this method, a random set of values is inherited from one parent, and the remaining ones come from the other parent.

Mutation

In the proposed algorithm, one of the three parts of the chromosome was randomly chosen to apply the mutation operators. For a full electrification problem, the first part of the chromosome is removed from the candidates for this selection, as mutation on this part will not change anything in the solution. Different mutations are applied on each part of chromosome. For the first part, a value is randomly selected and flipped. Observations showed that the second part plays a significant role in the objective values, and changing its values to zeros can guide the solutions to local optimums. Therefore, in the second part, a set of values is randomly selected and changed to zeros. Finally, the mutation for the third part of the chromosome is done by resetting the battery size of a randomly-chosen selected route—one of the routes selected by the first part was randomly chosen to be electrified and then its battery size was randomly reset.

The generic algorithm described above was used for the case study of the HART transit network, as shown in Section 6.

3.3. CASE STUDY OF HART TRANSIT NETWORK

3.3.1 Features and Operational Data of HART Transit Network

To conduct a real-field case study for this project, data were requested from HART during the stakeholder interview. HART does not have electric buses, but it has a fleet of 35 compressed natural gas (CNG) buses.

Route distribution for the HART transit network is shown in Figure 8. In total, there are 26 routes and 2,328 stops in the bus network. Note that there are 29 routes in the HART transit network, among which the direction information of three routes were not correct and were removed from this case study. For mathematical modeling purposes, routes were discretized into 50-meter links; as a result, the whole network was divided into 17,795 links. The elevation along each route was obtained from the U.S. Geological Survey

database (Figure 9). With the elevation extracted for the study area, the slopes along each route could be calculated. It was assumed that buses travel at a constant average speed; acceleration and deceleration were modeled only when buses got close to bus stops or left from bus stops. The operating frequency of each bus on the same route was assumed to be the same. The number of buses and operation frequency for each route are summarized in Table 4.

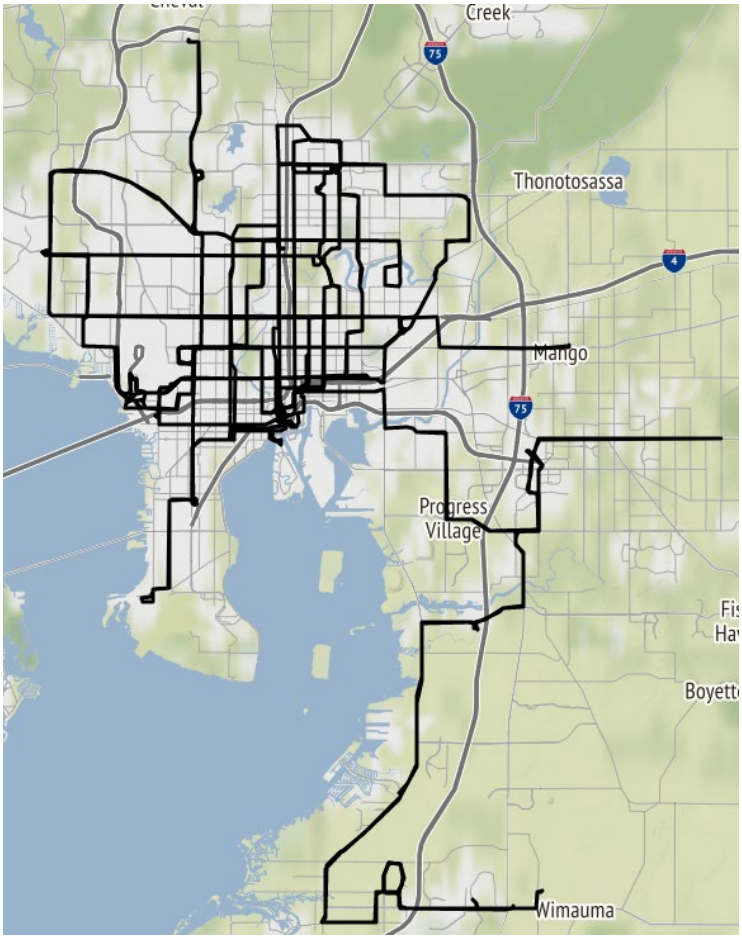

FIGURE 8 HART bus route network

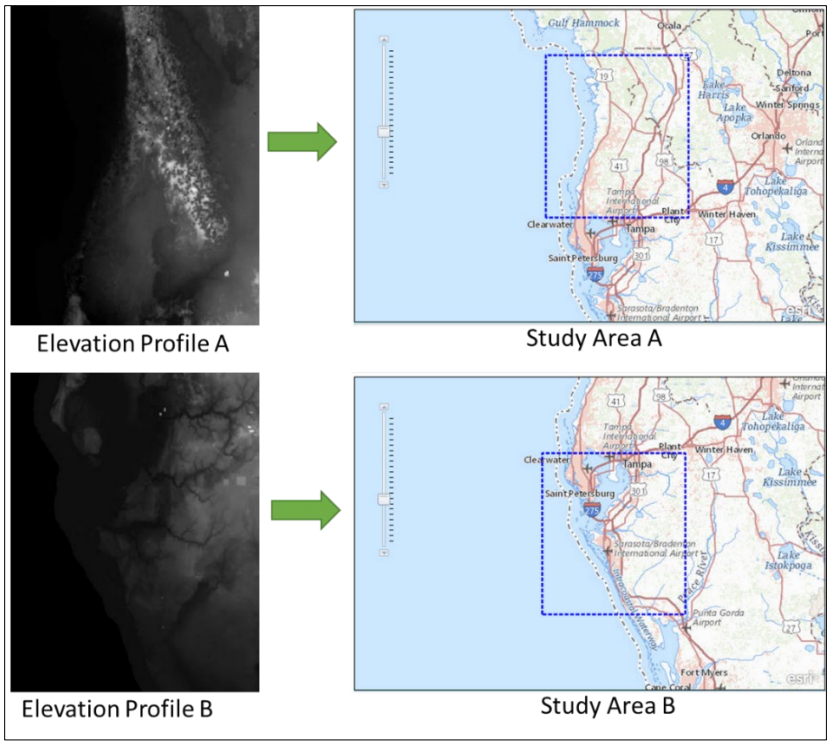

FIGURE 9 Study area elevation profile

TABLE 4 Service Data for HART Bus Lines

Bus Line	Number of Buses per Bus Line	Average Daily Operation Frequency of Each Bus
1	2	9
2	2	9
3	1	18
4	1	18
5	2	10
6	2	10
7	2	10
8	4	12
9	2	9
10	2	9
11	3	19
12	4	9
13	3	6
14	4	10
15	4	9
16	2	10
17	2	9
18	2	9
19	1	19
20	3	9
21	3	12
22	2	10
23	1	18
24	5	7
25	1	18
26	2	10

3.3.2 Technical Features and Cost Data for DWCF and Battery – HART

All technical features and cost data used in this case were similar to that used in Section 5.2, except the discount rate was set to 2%.

While applying the dynamic planning tool, it did not consider the impact to power grid and if the existing power grid can support the operations of DWCF. However, post-analysis can be performed to test if such problem would exist. If so, the routes with power supply issues should be excluded and the tool can be re-run for obtaining optimal solutions.

3.3.3 Model Results for Multi-stage Dynamic Planning of the ETBS

This subsection presents the results of the dynamic planning model for the electrification of the HART transit bus network. It was assumed that there are two stages in the planning problem, with five routes electrified in Stage 1 and the other five electrified in five years.

Note that the dynamic planning tool does not take the impact to power grid into consideration and does not restrict the solution dependent on if the existing power grid can support the operations of DWCF. However, post-analysis can be performed to test if such problem would exist. If so, the selected route with power supply issues should be excluded from the network and the tool can be re-run for obtaining optimal solutions.

Table 5 shows results for different route selections in each stage. Note that the results in Table 5 were obtained by taking both objectives into account. Therefore, instead of only one solution, a frontier of non-dominated solutions was obtained.

TABLE 5 Non-Dominated Points for Multi-stage Dynamic Planning of HART

Route_S1	Route_S2	Cost (10^5)	Energy cons. (10^5)	Total length (km)
3, 6, 8, 9, 10	1, 7, 17, 19, 20	1147.16	664.92	163.95
2, 8, 17, 18, 25	4, 9, 19, 23, 26	437.06	867.66	39.15
3, 6, 8, 9, 20	1, 4, 5, 7, 17	1159.92	664.88	155.65
9, 11, 13, 17, 20	2, 3, 4, 8, 10	586.16	774.23	90.30
3, 6, 8, 9, 10	1, 7, 17, 19, 20	888.56	665.67	121.90

Figure 10 shows the Pareto frontier for this experiment that demonstrates the algorithm found five non-dominated points. Table 11 reports the detail of the solution for all the non-dominated points. In this table, column "Route_S1" and "Route_S2" demonstrate the selected routes in the first and second stage. "Cost (10^5)" and "Energy cons. (10^5)" show the value of the first and second objective function. Finally, column "Total length (km)" reports the total electrified length. By a simple investigation in this table, we observe that the algorithm has found a set of routes as good candidates to be electrified in the first stage.

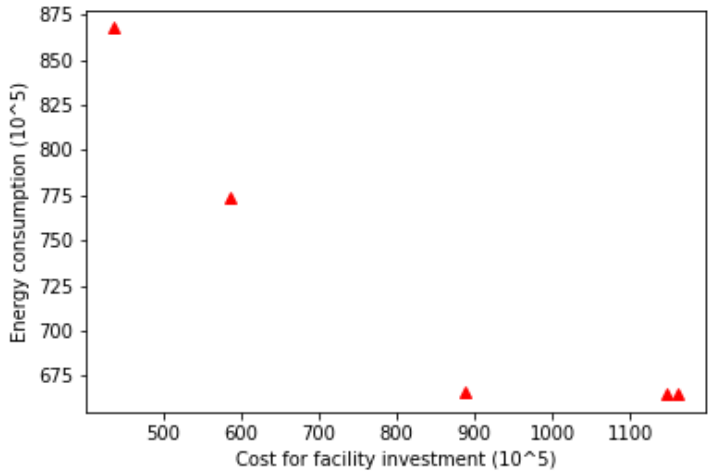

FIGURE 10 Pareto Frontier of non-dominated solutions

Routes 3, 6, 8, 9, 10, and 17 appeared in the first stage of most non-dominated points. The same statement holds for routes 1, 4, 7, and 17 in the second stage. The selected routes in both stages of the first and last non-dominated points are identical, however, the total length of the electrified part is different. This difference, which originates from the difference in selected battery sizes for each route, led to different value of objective functions too. Figure 10 show the two first non-dominated points in Table 5.

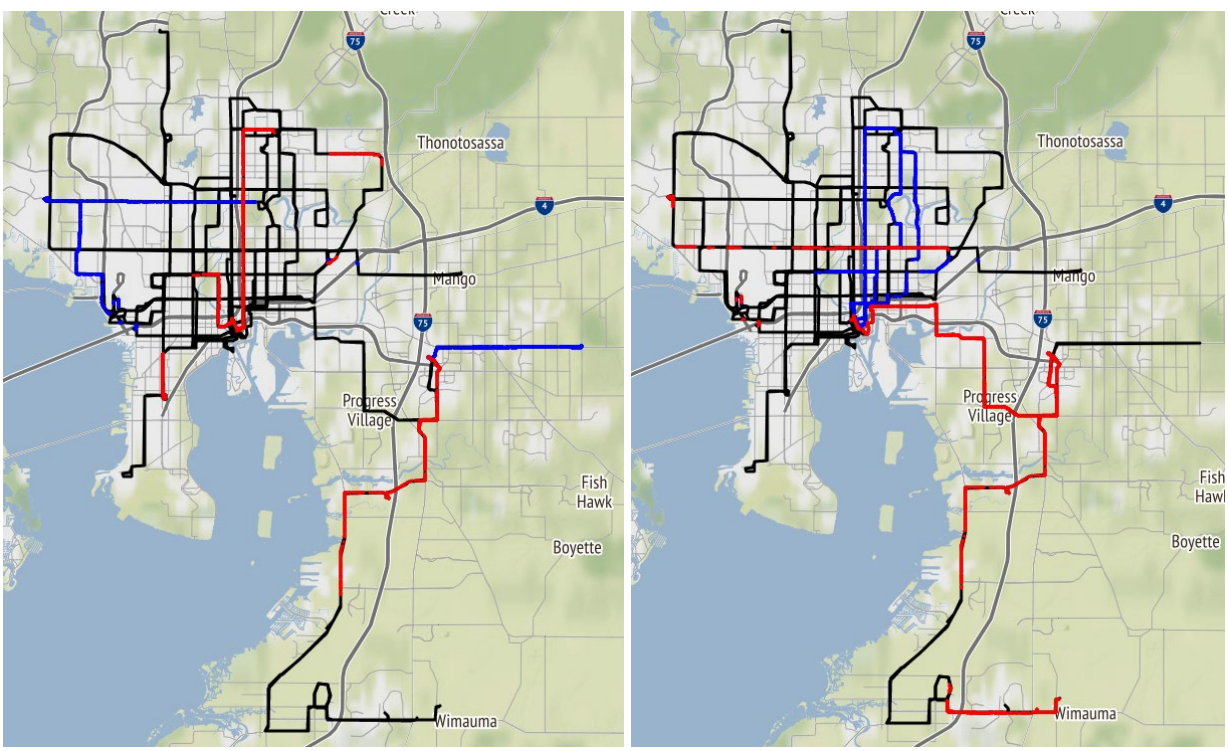

FIGURE 11 Visualization of the first (*left*) and second (*right*) non-dominated points (blue – routes selected at Stage 1, red – routes selected at Stage 2)

3.4. DESIGN OF GRAPHICAL USER INTERFACE (GUI)

The on-hand GUI is designed to solve planning problems of bus lines electrification. This tool features three multi-objective models; fully electrification, partially electrification, and dynamic electrification. The tool can optimally solve the first and second model for reasonably small instances. However, large instances along with the third model are too complex to be solved using optimal methods. For these cases, the tool is featured with a Genetic Algorithm. For more detail on what these three models are and their inputs, outputs, and applications, please refer to Section 3.3.

- Installation and requirements – The GUI requires the following software and packages to be properly installed and functional. Please follow the provided installation instruction from their official reference.
  - Python 3.7.4 or later
  - IBM ILOG CPLEX 12.10
  - Docplex
  - pyproj
  - folium
  - affine
- Getting started – To use the GUI, first the user needs to provide the inputs in the required format. The GUI has been featured to identify some of the irregularity or disorganization in the inputs. However, since any mistake can cause an error or unrecognizable wrong output, the user must make sure about the correctness of the inputs.
- Prepare the inputs – To solve an instance of the problem in the form of all three models, the user needs the following inputs. A folder named 'Input' should be created in the current working directory of python codes to store all the input files.
  - Stop shape file of transit network – The stop shape file contains information of all bus stops in the network. Two key attributes are required, the coordinates of the stops and route names the stops belong to and their corresponding names in the file should be 'geometry' and 'line_name' respectively.
  - Route shape file of transit network – Route shape file includes information of route name, average speed on the route and geometry information of each route. Those attributes should be named as 'line_name', 'avespeed' and 'geometry', respectively.
  - Elevation files – The elevation file provides users elevation of the study area. The elevation database can be accessed from the official website of the United States Geological Survey. Download the lidar data in '.tif' file format of the study area. Our tool is able to obtain the elevation of any routes given its coordinates. Those '.tif' files should be stored in a folder named 'elev'.
  - Operational data of transit network – The operational data contains the number of buses operating on each route and corresponding operational frequency. Each of the information need to be provided in a text file inside '[working directory of the GUI]/Output' folder. It should be mentioned that the GUI creates this folder when it generates the route data from shape files. The name of files for the number of buses and the operational frequency must be named as 'M_r.txt', 'F_r.txt', respectively. The values must be organized under each other in a column wise form, and their order follows the order of route IDs.
  - Scalar parameters – The problem has some scalar parameters that must be provided (refer to technical documentation for more information). Table 6 lists these parameters and a brief description of each parameter.

TABLE 6 Description of Scalar Parameters Required to Solve a Problem in GUI

Parameter	Description
l	Length of the arc in the network (default = 50 meters)
c_{inv}	Fixed cost of inverter ($)
c_{con}	Unit cost of power transmitter ($/meter)

P	Energy supply rate
B_l	Lower bound for the size of batteries
B_u	Upper bound for the size of batteries
$DELTA_l$	Optimum lower level of batteries
$DELTA_u$	Optimum upper level of batteries
T	Planning horizon
V_{bar}	Number of routes that can be electrified (used only in second model)
i	Interest rate
$SizeStep$	Step by which the size of batteries change

- Decision parameters – Dynamic electrification model requires the users to provide the time while making decisions and targeted number of routes to be electrified. For instance, there are a total of ten bus routes in a transit network, and for some reasons, such as budget constraint, the transit authority decides to electrify only three out of then routes in next five years; one route in two years and two routes in five years. The user of the tool needs to create a text file named 'DynamicDecision.txt' that has two rows of numeric values. First row represents the decision time points, and the second row shows the decided number of routes to be electrified. For aforementioned example, the content of 'DynamicDecision.txt' looks as follows:

2	5
1	2

The user needs to place this file inside the folder 'Output' in the directory where the tool is located.

- Generate the data – After providing the shape files, elevation data, and operational data, the user need to generate the readable data using 'Data Preparation' tab of the tool. In data preparation tab the user sets the directory to shape files and the folder of elevation lidar data (Figure 12). The readable data will be generated by clicking on "Prepare Data" button. This step can take from minutes to hours for large instances. Returning the button to active mode means the process is done. If, for any reasons, the data preparing fails, the tool will inform the user by showing an error message. The user can double check whether the data preparation process was successful by inspecting 'Output' folder in tool's directory. A successful data preparation will lead to the generation of text files including the information for all the provided bus routes in shape files. The user must not proceed to the next step without successfully generation the inputs.

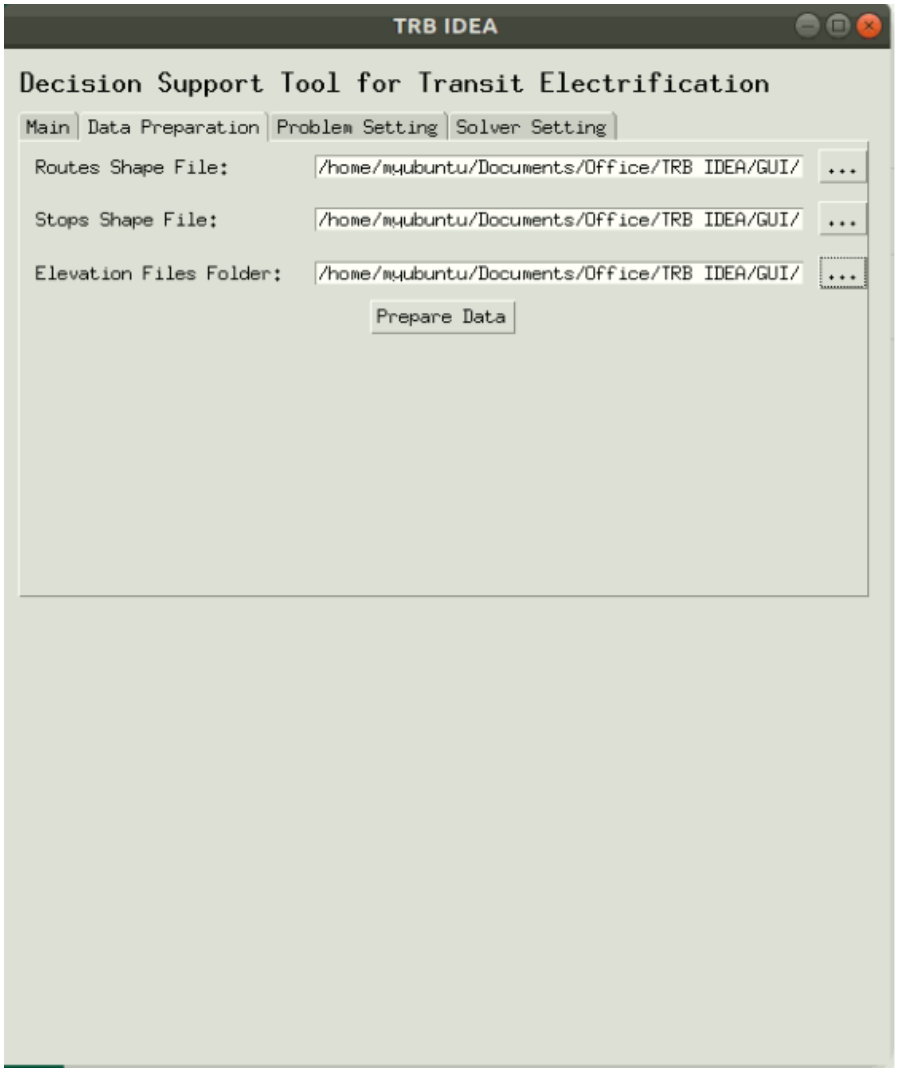

FIGURE 12 Data preparation tab of tool

- Filling the scalar data – Next the user needs to feed the mentioned data in Figure 13 using 'Problem setting' tab of the tool. Fields in this tab (Figure 13) can be identified with names described in Table 6.

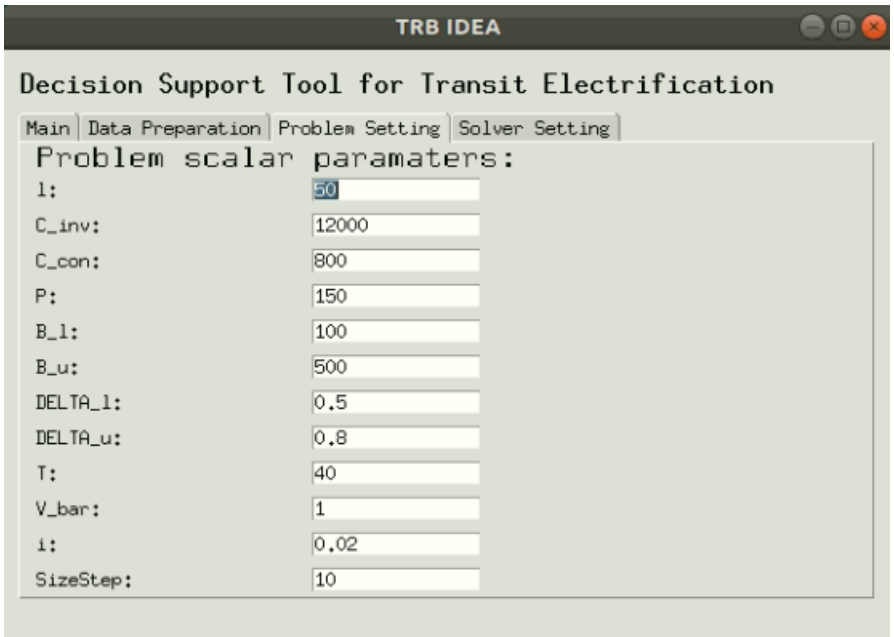

FIGURE 13 Problem setting tab of the tool

- Model selection, solution, and outputs – After providing the parameters and required files and letting the GUI do the data preparation step, everything is ready to solve the model. As it was mentioned above, there are three models featured in this GUI regarding bus route electrification. To solve any of these models, the user only needs to select the desired model ('Fully Elec.', 'Partial Elec.', or 'Dynamic Elec.') and proper solver ('Exact (CPLEX)' or 'Genetic Alg.') in tab "Main" and then click on the button "Solve". Remember that the exact method solver cannot be used for dynamic model. The solution process can be time consuming. Therefore, the user must wait until the button returns to the active status again which must be accompanied by a graph under the "Solve" button if no errors occur. This graph shows the best-found candidate solutions (that are technically called non-dominated points) in terms of two objectives. An output or solution of any instance of the problem is the size of the batteries that must be used in each route ('Battery sizes') and the location of wireless chargers ('Selected Arcs'). In case the 'Dynamic Elec.' model is selected, there will be one more output that shows when each of selected routes are electrified, indicated by 'Timing'. Depending on which output the user has selected to view, the tool will open a new page or a map in the default browser to show the results. 'Battery sizes' and 'Timing' will be printed on the new page. However, the location of 'Selected Arcs' is visualized on the map that opens in any browser. If this map does not open automatically, the user can find the HTML file of the map in the 'Output' folder found in the working directory that can be opened manually. To set the map zoomed on the right location by default, the user must provide the latitude and longitude of where the bus network is located in the main tab (Figure 14).

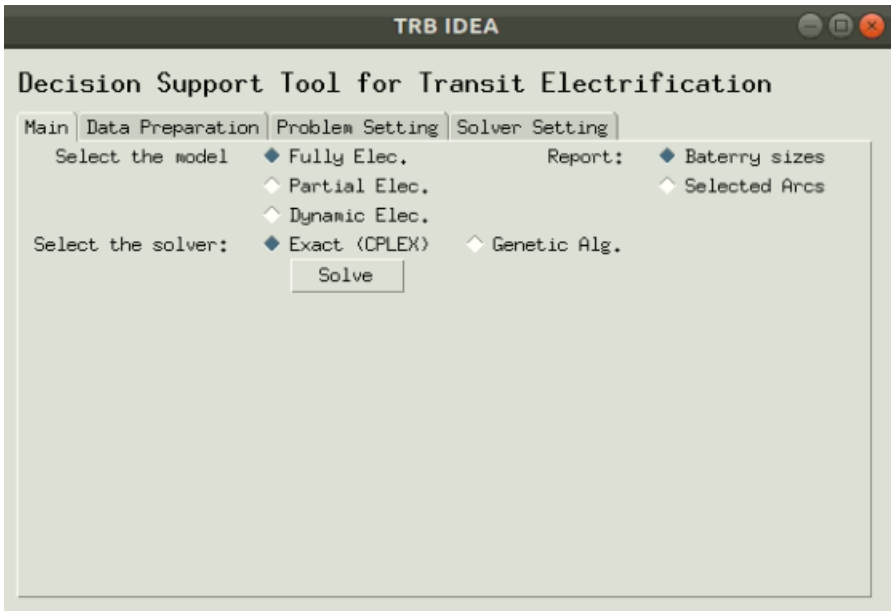

FIGURE 14 Main tab of the tool before solution

- Result visualization – To see the results corresponding to each candidate solution, the user needs to first select the desired output and then click on the point in the generated graph (Figure 15). An example of the result is illustrated in Figure 16.

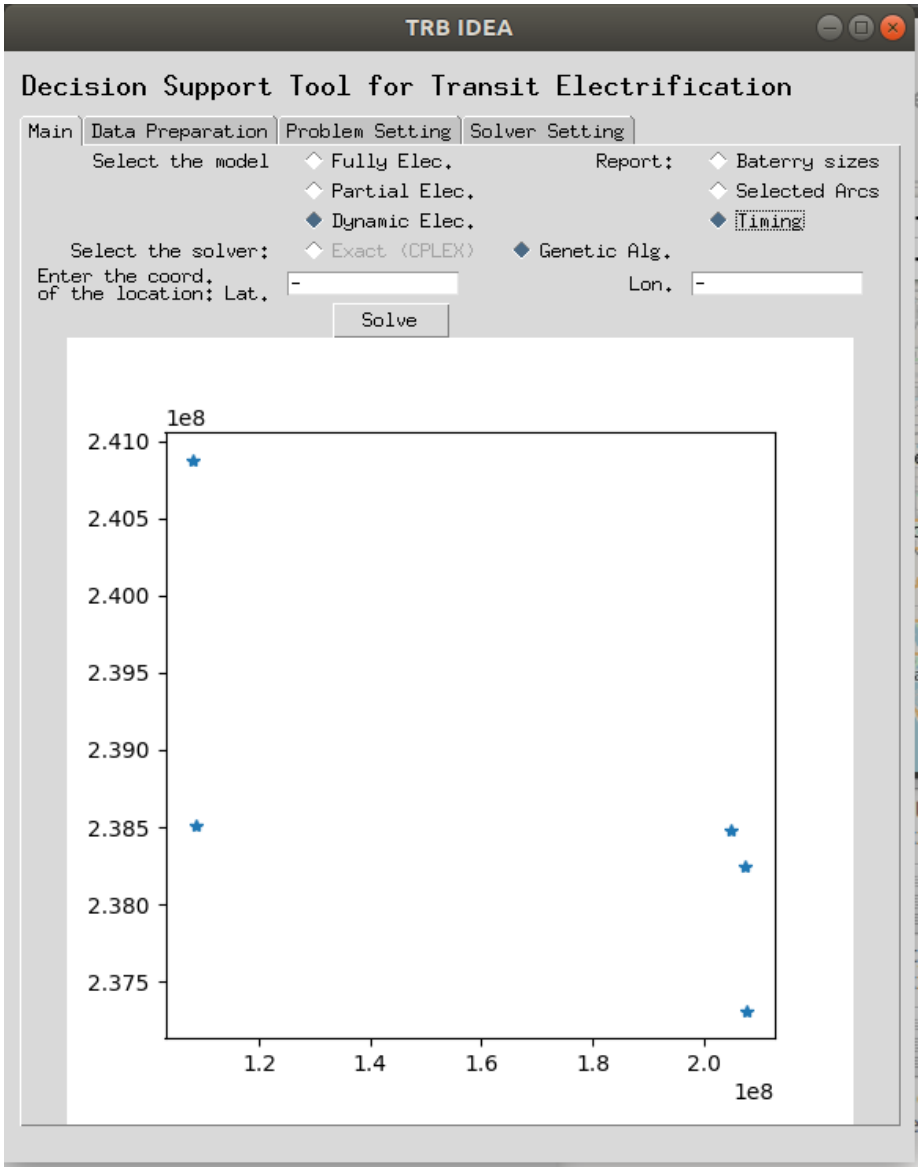

FIGURE 15 Pareto frontier of optional solutions

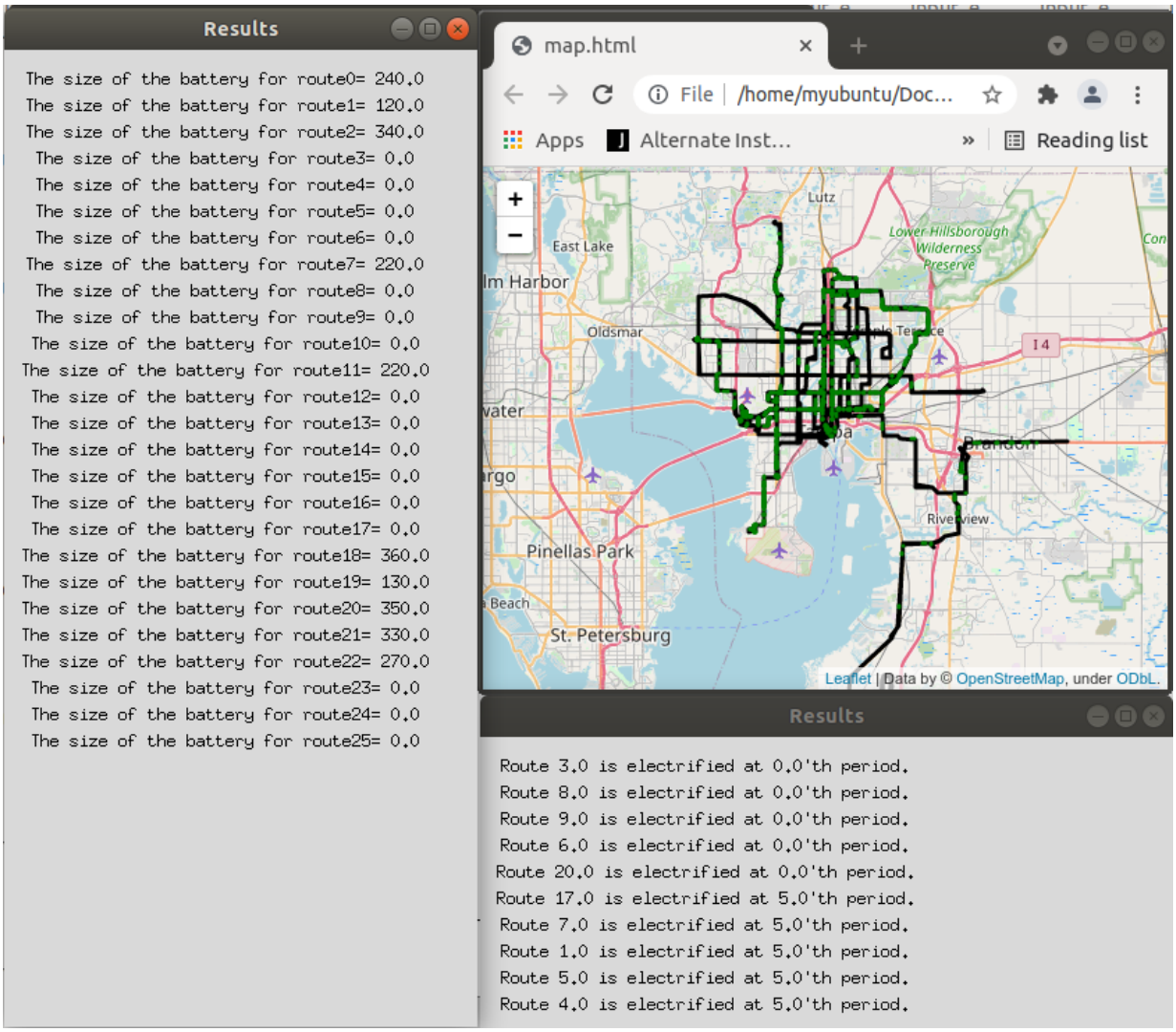

FIGURE 16 Illustration of one solution

- Advance settings – In the last tab of the tool (see Figure 17), some advanced features of the solvers are set that control the speed and accuracy of the solvers. Three of these settings, 'nPareto', 'EPS', and 'TimeLim', relate to the exact solver, and two others, i.e. 'nPopulation' and 'nIteration', relate to the genetic algorithm. 'nPareto' determines the maximum number of non-dominated points, 'EPS' is a parameter to control the accuracy of algorithm in dealing with cuts, and 'TimeLim' is the maximum computation time. Also, 'nPopulations' determines the number of population and 'nIteration' sets the number of generations in the genetic algorithm. For users that may not be familiar with these settings, three options are preset that can be chosen, that is 'Fast', 'Slow', and 'Very Slow'. By click on each option from a drop list, a brief explanation of advantages and consequences is shown. Of course, these options cannot be reliable for any instance of the problem and users should try different values to get an acceptable solution.

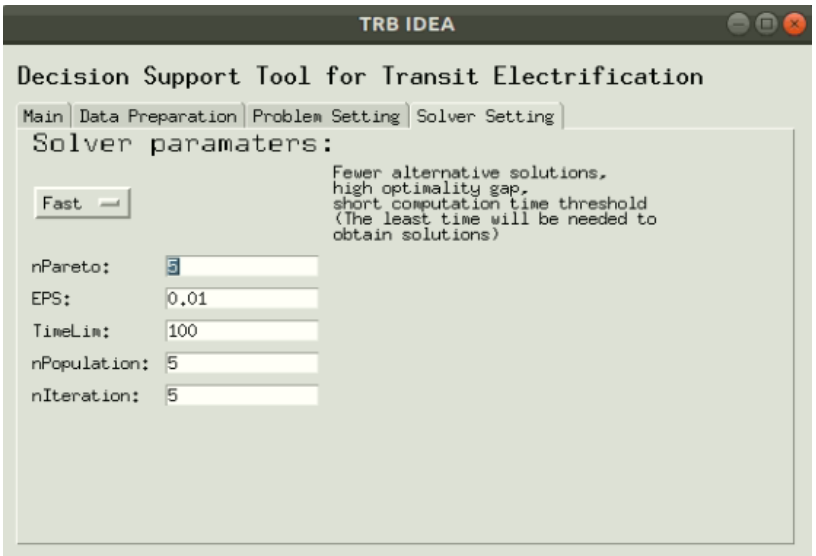

FIGURE 17 Solver setting tab of the tool

4. PLAN FOR IMPLEMENTATION

Due to the COVID-19 pandemic that imposed many challenges for transit authorities and increased the difficulty of obtaining data from transit authorities, only one case study was performed during this project. In addition, due to limited budget, the GUI was designed on a Linux system, and the beta test has not been performed. Thus, before implementing the tool developed from this project, additional efforts need to be made such as applying the tool on other transit network and transferring the Linux-based GUI to web-based GUI with the support of professional GUI developer and organize beta-test with representatives from transit authorities.

5. CONCLUSIONS

This project created a decision support tool for planning an ETBS with multi-format charging facilities. With the help of this tool, a transit authority can make better decisions on fleet electrification, service design, and charging facility location. In this project, mathematical models of DWCF locations for full electrification and partial electrification and models for route selection and DWCF locations were developed. Solutions algorithms were exploited to solve large-scale multi-stage multi-objective optimization problems.

The proposed method was applied to a local transit network, HART, in the Tampa Bay area. For a given scenario, i.e., the transit authority needs to choose five routes to electrify in the first stage and another five in the second stage, the tool identified the best routes to electrify and optimal locations of DWCF in both stages. Following the solutions, the transit authority will bear the minimal total cost of constructing DWCF and energy consumptions in a defined planning horizon.

Furthermore, the research team developed a GUI on a Linux system that consolidated data structure design, solution algorithm implementation, economic analysis, and design result visualization. A user manual was produced to help potential users to understand and become familiar with the tool. Users can perform scenario analysis with this tool by changing setting parameters, such as number of routes to be electrified (or budget constraint), cost of DWCF, price of electricity, etc.

Due to limited time and budget, this study has some limitations. One limitation is that the decision support tool developed in this study did not take capacity constraints of power grid into consideration. It

may not be an issue at early stage of transportation electrification. However, with the increase of market penetration of electric vehicles (both passenger vehicles and buses), the capacity of power grid could become a constraint restricting the locations of charging facilities. In future research, the interdependence between transportation and power grid should be modeled and included. The second limitation is that only one case study was performed during this project. The COVID-19 pandemic imposed many challenges to transit authorities. It was hard for the research team to obtain more case study data during this time period. In addition, the GUI was designed on a Linux system, and the beta test has not been performed. A direction of extending this study is to transfer the Linux-based GUI to web-based GUI with the support of professional GUI developer and organize beta-test with representatives from transit authorities.

6. INVESTIGATOR PROFILES

Dr. Yu Zhang is a Professor in the Department of Civil and Environmental Engineering at the University of South Florida (USF). She leads the Smart Urban Mobility Laboratory at USF and applies mathematical programming and optimization techniques, simulation, econometric and statistical tools to solve the problems for resilient, efficient, and sustainable transportation systems. Her recent efforts are focused on emerging services and technologies in transportation. She has published more than 60 papers in top transportation journals such as *Transportation Research Part B, Transportation Research Part C, Transportation Research Part D, and Transportation Research Part E* (https://orcid.org/0000-0003-1202-626X). She is serving as Associate Editor for *Transportation Research Part D: Transport and Environment and Multimodal Transportation* published by Elsevier, and Section Editor for *Aerospace/Air Traffic and Transportation* published by MDPI. She also serves on the editorial board of *Transportation Research Part C: Emerging Technologies*, *International Journal of Sustainable Transportation*, and *Journal of Air Transport Management* and is a reviewer for many other prestigious journals in transportation research. Dr. Zhang holds a Ph.D. and an M.S. from the University of California–Berkeley in Civil and Environmental Engineering and a B.S. from Southeast University of China in Transportation Engineering.

Dr. Tingting Zhao joined Dr. Yu Zhang's research group in March 2017 as a Postdoctoral Researcher and worked at SUM Lab for two and half years. She worked on transportation electrification and contributed to the proposal writing of this research project. After leaving USF, she worked at the University of Maryland, College Park as an Assistant Research Scientist. She joined Beijing Jiaotong University in China in November 2020 as an Assistant Professor in the College of Transportation. Her area of interests are transportation system resilience, interdependent critical infrastructure resilience, and emerging transportation system design and operation, leveraging data mining, machine learning, mathematical programming, and transportation system modeling and simulation techniques. She obtained a Ph.D. degree in Control Science and Technology at Tsinghua University (China) in 2012 and a B.E. degree in Control Science and Technology at Hefei University of Technology (China) in 2006.

Dr. Vahid Mahmoodian was a Ph.D. candidate of Industrial Engineering at USF while working on this project. His dissertation focused on solving a specific class of non-linear optimization problems called multiplicative programming problems. In addition to developing solution algorithms in this project, he applied simulation-optimization techniques to solve rebalancing problem in shared micromobility. He received an M.S. degree from Iran University of Science and Technology (IUST), Tehran in Industrial Engineering and started a Ph.D. program at IUST, but dropped out after two years and started it over at USF.

Mr. Zhiqiang Wu is a Ph.D. candidate in the Department of Civil and Environmental Engineering at USF. He joined the SUM Lab in August 2016 with research interests focus on multimodal charging facility deployment modeling for electric vehicles in the context of emerging technologies (i.e., dynamic wireless

charging, V2V and V2I connectivity, smart charging, etc.) and network design and demand estimation for urban air mobility (UAM). He obtained holds a B.S. in Civil Engineering from Chang'an University in China.

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Research Results:

Program Steering Committee: J-04 Transit IDEA Program Panel

Month and Year: January 2022

Title: Multi-stage Planning for Electrifying Transit Bus Systems with Multi-format Charging Facilities

Project Number: T-96
Start Date: December, 9, 2019
Completion Date: January, 31, 2022

Product Category:

Principal Investigator: Yu Zhang, PhD, Professor
E-Mail: yuzhang@usf.edu
Phone: 813-974-5846

TITLE: Multi-stage Route Selection and Charging Location for Transit Electrification

SUBHEAD: Developed a decision support tool for transit authorities planning an Electric Transit Bus System with multi-format charging facilities.

WHAT WAS THE NEED?

Overall, ETBS have the following advantages compared to the other types of bus systems such gas, diesel, and hybrid buses; electric buses generate zero carbon emission during operation, their energy consumption cost is lower than gas and diesel buses because of the lower rate of electricity and the brake energy recover mechanism, and their quiet operation can provide passengers with a better ride experience.

However, electrification of transit buses faces many issues, such as massive capital investment, limited bus capacity, lack of flexibility, and potentially disrupted operations. Investment cost includes costs for acquiring vehicles, constructing charging infrastructure, and coordinating with utility public works. The huge and heavy on-board batteries reduce the space of electric buses for carrying passengers and increase the weight of the bus. The short range of electric buses may lead to potentially disrupted operations. The flexibility of the transit bus system is restricted by the deployment of charging facilities. These issues regulate the use of electric buses to be fixed in urban areas rather than for long-haul transport.

Hence, it is challenging for a public transit authority to plan the process of electrifying its bus fleet and continue to operate its mixed fleet cost-effectively. Decision support is needed to assist transit authorities during the electrification process to understand and balance the trade-off between different objectives and make optimal decisions.

WHAT WAS OUR GOAL?

This study aimed to provide a decision support tool for public transit authorities for facilitating the process of electrifying their transit buses. Specifically, given the periodic budget and transit network and features, the tool would provide outcomes at different stages, including (1) which routes the acquired electric buses should serve, (2) where to deploy charging facilities (both plug-in at stations and dynamic wireless charging facilities embedded in road pavement), and (3) what should be the right size of the onboard battery for a specific route.

WHAT DID WE DO?

The investigation included a literature review, methodology development, a case study, and GUI design. Based on interviews with local transit authorities and discussion with the Expert Review Panel, this study focused on the combination of plug-in and wireless inductive charging modes, assuming that plug-in charging stations are set up at a transit center/depot; the main decisions that transit authorities need to make are route selection for electrifying and locations of wireless inductive charging. Bi-objective mixed integer programs and solution algorithms were proposed to optimize two objectives—initial investment cost of DWCF and life-long energy cost for carrying heavy batteries during bus operations. Furthermore, the research team developed a Graphic User Interface on a Linux system that consolidated data structure design, solution algorithm implementation, economic analysis, and design result visualization.

WHAT WAS THE OUTCOME?

This project created a decision support tool for planning an ETBS with multi-format charging facilities. The proposed method was applied to a local transit network, HART, in the Tampa Bay area. For a given electrification scenario, the tool can help the transit authority to determine the routes to be electrified and where to install DWCF at different stages when the decisions nee d to be made.

WHAT IS THE BENEFIT?

With the help of this tool, a transit authority can make better decisions on fleet electrification, service design, and charging facility location. It will lead to lower capital investment and operating expenses of ETBS and ensure the uninterrupted operations of electric buses.

LEARN MORE

Please see final report on the Transit IDEA website for more details.