8-2023

Constrained Route Optimization With Fleet Considerations for Electrified Heavy-Duty Freight Vehicles

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CONSTRAINED ROUTE OPTIMIZATION WITH FLEET CONSIDERATIONS FOR

ELECTRIFIED HEAVY-DUTY FREIGHT VEHICLES

by

Zarin Subah Shamma

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Computer Science

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UTAH STATE UNIVERSITY
Logan, Utah

2023

ABSTRACT

Constrained Route Optimization with Fleet Considerations for Electrified Heavy-Duty

Freight Vehicles

by

Zarin Subah Shamma, Master of Science

Utah State University, 2023

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Department: Computer Science

Heavy-duty freight is a significant contributor to local pollution, air quality, and degradation in the health of regions with significant vehicle density. The health impacts of localized heavy-duty transit cause many at-risk and disadvantaged communities to experience a degraded quality of life. The EVPRE-heavy-duty software framework aims to illustrate the impacts of electrified heavy-duty freight vehicles through analysis of route efficiency (in terms of energy, time, or route distance) with the anticipated health impacts of electrification while honoring freight cost limitations for fleet operators. Our software and algorithms are tested in a simulation environment using many routes commonly employed by freight vehicles in the Salt Lake City area. Algorithmic improvements show an energy reduction of $\sim 6\%$ to $\sim 10\%$ at the cost of $\sim 3\%$ increases in vehicle travel distance.

(70 pages)

PUBLIC ABSTRACT

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Freight Vehicles

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Almost 75% of traffic-related emissions are caused by heavy-duty freight trucks and significantly impact neighborhoods, schools, and communities around shipping and distribution lines. With poor air quality and respiratory health, many children in at-risk and disadvantaged communities experience high rates of asthma, lower attendance in school, and lower concentration. This research creates to improve the impacts of heavy-duty electric freight by improving the route efficiency (in terms of energy, time, or route distance) of EV trucks. Our software and algorithms are tested in a simulation environment using data from several thousand fleet trucks operating in the Salt Lake City area. The software shows an anticipated energy reduction of $\sim 6\%$ to $\sim 10\%$ at the cost of $\sim 3\%$ increases in vehicle travel distance. Further, we anticipate positive health impacts in areas of dense trucking as we reduce the energy needs of electrification for fleet operators.

To my parents, my loving husband, and my little brother...

ACKNOWLEDGMENTS

First, I would like to thank the Almighty for all the blessings He has bestowed upon me.

I am sincerely thankful to be able to work with Dr. Mario Harper. He is not just my major professor but also a genuine source of motivation and direction for me. Under his mentorship, I have enhanced my research skills by learning to delve into the essence and principles of the research subject. I appreciate his invaluable support, enduring patience, and valuable guidance throughout my time here at Utah State University. The NSF Engineering Research Center (ERC) ASPIRE (Advancing Sustainability through Powered Infrastructure for Roadway Electrification) for funding the work and providing data sources invaluable to the calibration and testing of this model. I would also like to thank Dr. Steve Petruzza and Dr. John Edwards for agreeing to be on my thesis committee.

Last but not the least, I express my earnest gratitude to my parents, my husband, my brother, and all those who were beside me when I needed them the most.

Zarin Subah Shamma

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ACRONYMS

EV	electric-vehicle
FASTSim	future automotive systems technology simulator
EVPRE	electric-vehicle path and range estimator
ICE	internal combustion engine
GHG	greenhouse gas
CO_2	carbon dioxide
CO	carbon monoxide
HC	hydrocarbons
NO_x	nitrogen oxides
COPD	chronic obstructive pulmonary disease
PM	particulate matter
MDV	medium-duty vehicle
HDV	heavy-duty vehicle
LDV	light-duty vehicle
MVC	model-view-controller
OSM	open street map
EVSE	electric-vehicle supply equipment

CHAPTER 1

INTRODUCTION

1.1 Impacts of ICE-based Heavy-Duty Freight Vehicles

Mitigating ICE (internal combustion engine) - based heavy duty freight is a core concern for many disadvantaged communities due to their proximity to distribution centers and large roadway arteries. Usually, these communities reside within the close radius of large distribution centers or warehouses responsible for being the route source of more than 100 heavy-duty freight trucks delivering to locations every day. As 98% of the heavy-duty freight vehicles are fueled by diesel, nearby communities get significantly affected by traffic-related particulate matter. Heavy-duty vehicles (HDV) (and, to a lesser extent, medium-duty vehicles (MDV)) need to travel for longer distances and remain in areas longer while idling. They can often be older, inefficient models due to the costs of replacing fleets. The health impacts on disadvantaged communities in the USA are significantly higher than in other communities [1], and health continues to degrade for those living near shipping warehouses, truck terminals, and ports. As shown in Fig. 1.1, the areas around the Utah Inland Port have high to mid-level poverty with higher emissions from heavy-duty ICE-based vehicles. These areas are the most affected ones as most freight vehicles take these highways every now and then for their deliveries.

1.1.1 Degradation of Health and Increasing Air Pollution

ICE or fuel-based engines have been in use since the inception of motor vehicles, while the repercussions of using ICEs (particularly diesel-based engines) have come to light, alternatives have continued to be uneconomical for long-term adoption and investment. Advances in EVs (Electric Vehicles) and EVSE (Electric Vehicle Supply Equipment) are becoming more favorable compared to traditional ICE-based vehicles [2]. While EVs still
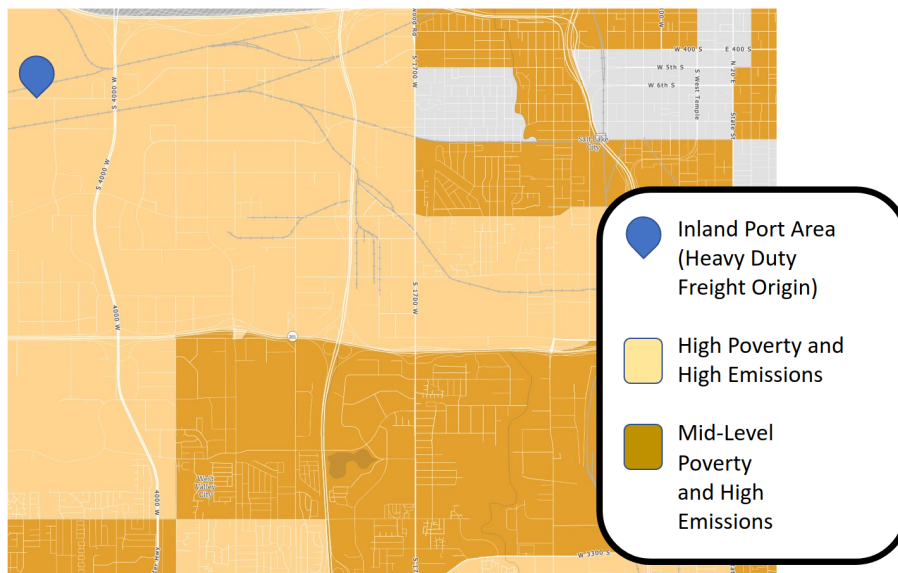
Fig. 1.1: Poverty Status around the Utah Inland Port in Salt Lake City

remain (at the time of writing) more expensive to purchase and operate than ICE alternatives for Heavy-duty trucking, they directly alleviate transportation-based particulate emissions in dense urban areas.

Almost 75% of transport-related emissions are caused by fuel-based HDV used in road transport [3]. Diesel-based vehicles are responsible for emissions of substances such as carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_x), and particulate matter (PM), which are known to affect human health and the environment adversely [4]. In the U.S., transportation sources are responsible for 77% of CO emissions, 45% of NO_x, 36% of volatile organic compounds, and 22% of particulates [5]. Emissions from transportation are the reason for serious health issues, including asthma and more serious respiratory degradation, particularly for children [6,7]. Exposure to diesel exhaust from HDVs has been linked to lung cancer, asthma, bronchitis, and other respiratory diseases. These pollutants also worsen existing conditions, such as chronic obstructive pulmonary disease (COPD) and asthma. Long-term exposure to PM can lead to premature death, especially among vulnerable populations such as children, the elderly, and those with pre-existing health conditions [8], [9]. $\sim$ 29,000 premature deaths in the U.S. were recorded in

2005, which were induced by transportation emissions [10].

According to [11], truck and bus generated CO_2 emissions have increased 2.2% per year. In the studies, it has been found that the most polluting heavy-duty freights cause more than half of the total emissions ranging from 41% to 70% in China [12]. As described in [13], in the U.S., $\sim 30\%$ emissions can be reduced if the long-haul freight emissions could be reduced.

1.1.2   Effects of Age in ICE-based Vehicles

When the age of heavy-duty vehicles increases, their operating efficiency is often reduced, and these vehicles become super-emitters as their percentage of harmful particulate matter emission gets escalated. HDVs operation efficiency is inversely proportional to the increased kilometers traveled, resulting in more wear and tear in vehicle parts and emission control equipment. In Ethiopia, the average age of fleet vehicles is 20 years, contributing almost one-half of the hydrocarbon emissions and more than 27% of the carbon monoxide emissions although the number of those vehicles covers less than 15% of the vehicle population [14]. In a study of Europe, it has been found that approximately 8% higher NO_x emissions with negative implications are recorded because of ~ 10 to 20 years old vehicles [15]. In [16], it has been stated that in Tirana, vehicles aged more than fourteen years had a high percentage of dangerous air pollutants in emissions compared to European standards of emission. The high percentage of air pollutants in the emission can result from the age of vehicles, poor fuel quality, and low maintenance. The average age of US class-8 HDVs has continued to rise, exceeding 12.8 years of operation in 2018 [17]. During pandemic shortages, more trucks were required as shipping increased drastically drawing on repair services to maintain an aging fleet [18].

1.2   Electrification of Heavy-Duty Freight Vehicles

Electrification of freight vehicles offers a high impact on regional health and mitigation of other pollution that influences the wider population of cities and states. The electrification decreases the NO_x emissions by 209 thousand tones (3%) overall. Air quality benefits of

electrification are modest, mostly less than 1 ppb for ozone and $0.5gm^{-3}$ for fine particulate matter ($PM_{2.5}$). According to the research done in [19], continental U.S. NO_x emissions decrease by 3% with the comparable reduction due to off-road and on-road electrification (41–42% of total reduction). With that, CO has decreased 9%, $PM_{2.5}$ has decreased 1% and PM_{10} has decreased 0.5% with the electrification.

Many barriers exist that prevent fleet adoption of heavy-duty electric vehicles, largely due to charging times and costs. Drayage trucks deliver heavy goods from the ports to different warehouses and hubs. They are typically class 8 tractor-trailers with a traveling distance of under 100 miles on average. Delivery trucks like these have short-range and usually fixed routes. This denotes that the electrification of these vehicles can be done reasonably well but it will depend on the particular characteristics of the daily drive cycle. For doing so, the weight and payload capacity of batteries needs to be identified in order to lessen the recharging requirements in the daytime. Electrification of both types of trucks would benefit air quality [20].

Technological challenges like limited range, high costs of big batteries, weight capacity, extended charging time, lack of charging stations, increased demand for electricity generation, etc. are stopping the adoption of electrification of heavy-duty freight vehicles. The first problem arises when bigger batteries need to be installed to avoid range anxiety with limited battery capacity. Small batteries cover a smaller range and big batteries require higher costs. Besides, if small batteries are used for electrification, the lack of charging infrastructure does not allow freight vehicles to deliver goods with long-traveled distances. Along with all of these, the increment in the use of EVs will lead to an increased demand for more generation of electricity which is highly expensive. This study provides energy-efficient routes to mitigate range anxiety and energy usage which will eventually reduce the necessity of frequent recharging.

1.3   Our Contribution

This study builds a simulation framework-based software suitable for heavy-duty freight electric vehicles. In the software, the FASTSim algorithm has been used for the simulation

framework where the information for simulating different models has been gathered using Google Maps API, OpenWeatherMap API, and Geotab API. These APIs provide required elevation data, and weather data like temperature, humidity, wind speed, traffic time information, etc. The software has been designed to provide energy-efficient, time-efficient, and distance-efficient routes. There is another framework within that where some trade-offs are possible with these objectives. Multi-objective optimization has been done using a balanced parameter weight-based optimization technique. The weights for the optimization can be altered by the users according to their choice. It has been shown that significant energy savings can be realized by building route optimizations for heavy-duty freight electric vehicles. Around $\sim 6\%$ to 10% energy consumption can be mitigated following the energy-optimized routes which can lead to a good increment in the adoption of heavy-duty freight electric vehicles. The software is also able to add $\sim 7\%$ to 11% of time efficiency along with the energy efficiency if they want some trade-offs among the multiple objectives.

In Chapter 2, we have discussed the potential barriers that are coming in the way of adopting EVs. The motivation behind this thesis was to build an algorithm so that it can help in mitigating some of the challenges that are becoming great issues for the users of EVs. Chapter 3 presents the available studies on the routing algorithm for electric vehicles. These routing algorithm has been designed for solving electric vehicle routing problems. The studies include different predictive modeling, optimization techniques, and search algorithms like Bellman-Ford, etc. which can be different potential ways of solving the routing problems of EVs. Chapter 4 discusses the internal requirements and calculations for the FATSim framework. FASTSim framework has been used in the software to create a simulation world where all the required information is provided for simulating the selected electric vehicle in a simulating world. This provides some simulated performance that reflects the real-world performance of the EV fulfilling some conditions and requirements. In Chapter 5, our redesigned software has been discussed. All its designing modules have been introduced there. Chapter 6 is all about the simulation procedures and results. All the potential system designs have been discussed in this chapter. The performance of the

designed modules has also been visualized. The statistical analysis of the results has been produced and presented here. Finally, in Chapter 7, the thesis has been concluded with some important remarks and potential future works.

CHAPTER 2

CHALLENGES OF FLEET HEAVY-DUTY FREIGHT

The demand for freight vehicles is increasing every day as medicine, home, food supplies, and deliverable business goods need to be at their destination on time. But these heavy-duty freight delivery vehicles are causing dangerous environmental pollution. Light-duty vehicles (LDVs) are regulated with emissions reduction strategies mostly stating in mind that LDVs account for the biggest portion of vehicles on the road. MDVs and HDVs are about 10% of the vehicles on the road but disproportionately contribute to emissions: about 29% of transportation greenhouse gas (GHG) emissions, 45% of on-road NO_x emissions, and 57% of direct $PM_{2.5}$ (particulate matter ≤ 2.5 microns in diameter) emissions [21]. MDVs and HDVs are critical to goods movement in the US—over 70% of all freight is moved by trucks, the vast majority of which are powered by diesel fuel [22]. Globally, on-road freight is responsible for 6% of total GHG emissions and is increasing [23]. In the urban areas of Europe, 39% of NO_x emissions and 15% of $PM_{2.5}$ emissions make transportation one of the main resources of air pollution [24]. It has been found in [25] that 53,000 deaths have occurred because of $PM_{2.5}$ when additional 5,300 deaths are the results of ozone.

2.1 Barriers in the Adoption of Electric Vehicles

Freight EVs can be the potential component in mitigating GHG emissions but for the successful adoption of electrified freight vehicles, range anxiety, limited cargo capacity, and elevated charging time need to be taken care of.

2.1.1 Range Limitations

The range limitation of EVs refers to the distance an EV can travel on a single battery charge. Although the range of EVs has been increasing with advances in technology, it is still a concern for many drivers, especially those who need to travel long distances regularly. The

range of an EV can vary depending on several factors, including battery capacity, driving style, temperature, and terrain. To address this limitation, automakers, and technology companies are working on improving the range of EVs through various means, such as increasing battery capacity and developing more energy-efficient routing. Additionally, the deployment of fast charging stations is expanding, which can recharge an EV battery to a significant percentage in just a matter of minutes. Despite these efforts, range anxiety remains a significant concern for many potential EV buyers [26].

Although electricity has many advantages as a vehicle fuel, it has two disadvantages: bulky and expensive storage and slow refueling (typically 1–20 kW electric versus $5000 kW^3$ gasoline). This states that EVs will cover less range with one full charge compared to gasoline and the refueling will be more time-consuming [27]. Electric vehicles mostly depend on the state of charge of the batteries installed. Bigger batteries give more ranges but it costs more and can add significant weight to the system, reducing cargo capacity. The EVs have limited range availability compared to ICE-based vehicles. This limited range availability creates anxiety in the drivers of EVs as their habits are different because of the gasoline-enabled driving habits.

EVs provide comfortable and better driving performance for drivers with increasing availability in models and designs. Moreover, their maintenance is inexpensive compared to conventional ones. But these advantages come with some requirements to follow. In order to enjoy the benefits of EVs, drivers must accept the limitations of their driving range and charging times, which can take up to 20 minutes to charge up to 80% battery capacity and several hours to reach full capacity, depending on the charging facilities available [28]. This means that there are limits to the distance that can be traveled with an EV, and commuters who travel more than 75 km to work (15% of commuting trips) may face uncertainty about getting home, particularly in cold weather. To overcome this, they would need to either find charging opportunities during the day, which could require detours, or use alternative transportation options [29].

When it concerns the electrification of heavy-duty freight vehicles, range anxiety becomes more prominent as the freight vehicles require bigger batteries which will need to be charged with more electricity. This leads to a larger charging time (more unused time for driver and asset) as well as the high unavailability of high-power, rapid charging stations.

2.1.2 Higher Costs

In comparison to ICE-based vehicles, EVs have limited functionality at higher expense due to the lack of an economy of scale [30]. Some cost barriers that have hindered the adoption of EVs among consumers:

1. High Upfront Cost: EVs generally have a higher upfront cost compared to conventional vehicles, primarily due to the expensive batteries used to power them. This can be a significant barrier for consumers, especially for those who are price-sensitive [31].

2. Lack of Incentives: In many countries, there is a lack of incentives for EV adoption. This can include subsidies or tax breaks for purchasing an EV or for installing a charging station at home [32]. Without these incentives, the cost of owning an EV can be prohibitive for some consumers.

3. Maintenance Costs: While EVs generally have lower maintenance costs than conventional vehicles, the cost of replacing a battery can be prohibitively expensive. Consumers may be concerned about the long-term costs of owning an EV, especially if they need to replace the battery at some point in the future [33].

4. Resale Value: Finally, the resale value of EVs can be a concern for some consumers. As the technology continues to evolve rapidly, some buyers may be reluctant to purchase an EV that may become obsolete in a few years, leading to lower resale values [34].

2.1.3 Cargo Capacity

The cargo capacity barrier of heavy-duty electric vehicles refers to the limitations on the amount of cargo that can be carried by an electric vehicle. This is an important

consideration for many people when choosing a vehicle, particularly for those who need to transport goods or equipment for work, or for families who need to transport large items such as bicycles, strollers, or luggage. EVs rely on batteries for power, and the weight and space taken up by those batteries can limit the amount of cargo the vehicle can carry [35]. This is because batteries are heavy and require a significant amount of space. In order to maximize range and performance, EV manufacturers must balance the need for larger batteries with the need for cargo space [36].

There are a few reasons why cargo capacity can be a barrier for electric vehicles. First, electric vehicles tend to have smaller overall dimensions than their gas-powered counterparts, which can limit the amount of cargo that can be carried [37]. Additionally, the batteries and other components of electric vehicles can take up space that would otherwise be used for cargo [38]. Another factor to consider is the weight of the cargo. Electric vehicles have a limited payload capacity, meaning that they can only carry a certain amount of weight [39]. This can be particularly problematic for larger electric vehicles, such as electric SUVs or pickup trucks, which may have a higher overall cargo capacity but are still limited by their payload capacity.

However, some electric vehicles are specifically designed with cargo capacity in mind. For example, many electric SUVs and crossovers have a similar cargo capacity to their gas-powered counterparts. Additionally, some electric pickup trucks are being developed with the ability to tow heavy loads, which can increase their overall cargo capacity.

2.1.4 Lack of Public Charging Infrastructure

EVs rely on charging infrastructure to replenish their batteries, but the availability and accessibility of charging stations can vary widely depending on where you live or travel. This can be a major barrier for drivers who are considering switching to an EV, as they need to be confident that they will be able to find charging stations when they need them [40]. There are different types of charging stations with varying charging speeds, ranging from slow Level 1 charging (using a standard wall outlet) to fast Level 3 charging (also called DC fast charging) [41]. However, Level 3 charging stations are currently less common and can be

expensive to install, making it challenging to have a comprehensive charging network [42]. This lack of charging infrastructure can create "range anxiety" among EV drivers, who may be concerned about running out of charge and not being able to find a charging station. This can be a particular issue for those who live in apartment buildings or other locations where they do not have access to a private charging station [43]. There are a few reasons for the current lack of charging infrastructure:

- One is simply that EVs are still a relatively new technology, and the market for them is not yet fully developed. This means that there is less incentive for businesses and governments to invest in charging stations [44].

- Another challenge is the high cost of installing charging infrastructure. Depending on the type of charger and the location, the cost of installation can be quite high. This can be a deterrent for businesses that are considering installing charging stations, as they may not see a clear return on investment [45].

- Finally, there is also a lack of standardization in charging infrastructure. There is a variety of charging standards and connectors in use around the world, which can make it more difficult for EV drivers to find compatible charging stations [46].

2.1.5 Increased Demand for Electricity Generation

The increased demand for electricity generation for EVs is a direct result of the growing popularity of EVs. As more people switch to electric cars, the demand for charging infrastructure and the electricity needed to power these vehicles also increases. Electric vehicles rely entirely on electric power to function, which means that they require a significant amount of electricity to be generated to meet this growing demand. According to a report by the International Energy Agency (IEA) in [47], the number of electric cars on the road surpassed 10 million in 2020, up from just a few hundred thousand a decade ago. This growth is expected to continue, with the IEA projecting that there will be 145 million electric cars on the road by 2030. By using the electric energy stored in their batteries without the need for a recharge, electric vehicles with a range of up to 60 miles (about 97

km) have the potential to reduce CO_2 emissions by 50% and petroleum consumption by over 75% [48].

The widespread deployment of EVs presents both a challenge and an opportunity for power grid operations. While EVs offer benefits, such as reduced emissions and fuel consumption, their unmanaged charging can strain electric grid capacity, especially at the distribution level where capacity limitations are more likely to occur. However, smart charging strategies can harness the flexibility of charging demand to minimize the need for costly grid capacity upgrades and enhance grid system operations. Additionally, the batteries of grid-connected EVs could potentially serve as a large, responsive storage system, further improving grid efficiency [49]. According to the EV scenario projections, wind power generation in Scandinavia and Germany is expected to increase by 7-30% by the year 2030, compared to a scenario without EVs. Additionally, investing in solar power may not be as valuable, with a reduction in value ranging from 22-42% across all EV scenarios when compared to a scenario without EVs [50].

CHAPTER 3

STUDIES ON ROUTING ALGORITHMS FOR ELECTRIC VEHICLES

One of the main barriers in the way of adopting electric vehicles is range anxiety. This anxiety usually occurs in the fear that the batteries of EVs could have been left with no charge in the middle of the road as a result of the unavailability of charging infrastructure nearby. Along with that, the EVs cover less distance with a fully charged battery compared to the ICE-based vehicles with a full amount of fuel. This increases the frequency of recharging the EVs. Also, the time required for a full recharge of the batteries of EVs is quite extended. All of these could have been solved if an energy-efficient routing algorithm could have been designed. The energy-efficient routing algorithm could denote a path in the map that will save the most energy consumption by the EV the most. Energy-efficient routing of electric vehicles involves finding the most optimal route for a vehicle to reach its destination while minimizing energy consumption. This can be achieved by considering various factors such as the vehicle's battery capacity, charging infrastructure along the route, traffic conditions, and road topology.

3.1 Predictive Algorithms

One approach to energy-efficient routing is to use predictive algorithms that take into account the energy consumption of the vehicle under different driving conditions. For example, the algorithm may take into account the vehicle's energy consumption at different speeds, when accelerating or decelerating, and when driving up or down hills. Based on this information, the algorithm can calculate the most energy-efficient route for the vehicle to take. This concept has been applied in [51] to design a model providing energy-efficient routes. In this model, geographical data and weather data are integrated into the vehicle data to predict energy consumption with the help of the Multiple Linear Regression model. A neural network has been inducted into the prediction of unknown driving parameters.

Energy-efficient routing algorithm has been designed in [52] to extend the driving range and battery life of EVs using data mining techniques. Historical driving data has been used here and then they have been clustered to get the class of the goal driver infusing classification approach. The travel time and energy consumption on the basis of the historical speed profiles are tested and the desired ones are achieved.

3.2 Optimization Techniques

The Particle Swarm Optimization (PSO) technique has been used in literature to optimize single to multiple constraints like energy, time, distance, etc. Garcia et al. have used PSO in [53] to develop the energy-efficient route. It has also been stated that PSO is slower than the Bellman-Ford algorithm to get the routes for smaller maps but the situation is the opposite when the map's size gets increased to a certain point. Abousleiman and Rawashdeh have also used PSO in [54] to optimize the energy consumption of EVs up to 9.2%. Rami et al. have used a different optimization technique, Ant Colony Optimization (ACO) in [55] to achieve a better result but ended up reducing $\sim 9\%$ energy consumption which is very good. In [56], PSO and ACO both have been used to get the energy-efficient path. ACO turned out to be more straightforward when PSO caused more modifications even when PSO was faster (400 milliseconds) than ACO (1.8 seconds) to get the solution.

3.3 Bellman-Ford Algorithm

Another approach could have been to use real-time data about traffic conditions and charging infrastructure to adjust the route in real time. For example, if there is a traffic jam on a particular route, the algorithm can redirect the vehicle to a less congested route. Similarly, if the vehicle's battery is running low, the algorithm can direct the driver to the nearest charging station. Numerous routing techniques are currently available for consumers, including tools such as MapQuest and Google Maps which are commonly used on the web. GPS receivers are often integrated into vehicles, which store map information on a flash drive and offer the shortest distance routing.

These routing techniques rely primarily on algorithms based on Dijkstra or Dijkstra-like algorithms. According to the investigation of [56], the Dijkstra algorithm cannot be used for EVs as EVs generate negative path costs by regenerative braking. One of the key requirements for the Dijkstra algorithm is that all the edge costs need to be positive. So, the Bellman-Ford algorithm is a potential one in this kind of scenario as it gives effective results with negative path costs. This theory has been used in the model of [57]. In the model, the energy consumption of EVs has been calculated using different vehicle characteristics like vehicle mass, road grade, velocity, frontal area, drag coefficient, regenerative braking factor, etc. A big road network has been generated where the nodes are the designated places and the routes among them are denoted to the edge. The calculated energy value is given as the edge cost of the graph.

Finally, the Bellman-Ford algorithm has been used to get the most energy-efficient route between two designated points. The same procedure has been followed in [58] but some weather information like temperature, air velocity, etc. are included in the calculation of energy consumption by the EVs. After all these, 8-16% energy efficiency could have been achieved on average for random selections of origin and destination from the map. In [59], the edge weight is represented by a function instead of a constant value like the previous ones and the users can choose the trade-off between energy efficiency and shortest distance with an input parameter as the optimization factor.

3.4   Route Planning for Freight Vehicles

A freight vehicle is a kind of transportation vehicle that must consider preset routes and have hard constraints on delivery times, and utilization (all time spent deployed is expensive in energy consumed while idling, driving, maintenance, etc). Such vehicles can take various forms, such as trucks, trains, or ships, and are typically constructed with bigger cargo areas and more robust engines than those of passenger vehicles. [60] has discussed a planner that provides route choices for urban areas where the time and location information are given for the optimization of the route in delivery. The time and location information is the real-time suggestions. Users' pre-trip information is also used for more accurate future

calculations. Luigi et al. have constructed a tool in [61] for express freight delivery that truck companies can use to optimize the scheduling of pickup and delivery requests. It aims to provide various benefits, such as reducing the need for empty truck journeys and considering the tank status for refueling during operations. The tool includes a data-sharing module for capturing and storing order information. It also utilizes the Google Maps API and TomTom API to gather location and traffic data for the routing algorithm within the fleet module. The planning module then utilizes this information along with real-time data and profit margin to schedule orders and plan routes. As described in [62], an eco-route planner can give an optimal route where the optimization criteria could be fuel consumption or speed, or travel time. [62] and [58] are constructed with the same methodology but the difference is that [62] gives optimal routes for ICE-based heavy-duty freight vehicles and [58] gives optimal routes for electric heavy-duty freight vehicles.

CHAPTER 4

FASTSIM

There are various computer tools available for modeling EVs, with one popular option being Future Automotive Systems Technology Simulator (FASTSim). This tool, supported by the U.S. Department of Energy and provided by the National Renewable Energy Laboratory (NREL), is especially useful for quick analysis of route planning, as it offers a straightforward way to estimate vehicle efficiency, performance, and battery life. While there are other models that offer more detailed information, FASTSim's simplicity and fast processing time make it ideal for real-time planning. Although the tool simplifies vehicle-specific details, it still provides accurate results, as demonstrated by the fact that most vehicles modeled in the simulator consume energy within 5% - 10% of their actual consumption [63]. FASTSim's ease of use, accuracy, and open-source transparency make it a widely referenced tool.

FASTSim is efficient enough to give fast and accurate analytical results using inputs like mass, inertia, fuel converter parameters, air resistance, motor characteristics, battery specifications, tire dimensions, and other relevant vehicle characteristics. It propagates the information including derived data from API keys, roadway information, weather information, etc. within a simulated environment in 0.1 seconds increments. Altogether, it can estimate the vehicle and fuel efficiency. battery life and cost within just 10 seconds when the powertrain comparisons can be graphed in less than 5 seconds [64]. The FAST-Sim model utilizes a small simulation cycle at runtime, by creating emulations of vehicles operating along an edge's length (i.e., road section length) and in a height differential (elevation). This allows it to provide accurate predictions of fuel and energy consumption and performance, even for complex systems with multiple energy sources, such as conventional vehicles, hybrid-electric, plug-in hybrid, all-electric vehicles, etc. The default version of the simulator comes as a package where 20 different vehicle information has been already added

with the facility of integrating new vehicle information.

FASTSim uses a physics-based approach to model the vehicle, which means it simulates the movement of each component in the vehicle and how they interact with each other providing speed-versus-time drive cycles. FASTSim takes some vehicle information as inputs for modeling most high-level vehicle powertrains. These inputs include:

Table 4.1: Input Values for Vehicle Model in FASTSim

Parameter	Value
Drag Coefficient	0.645
Frontal Area	9.5 m^2
Glider Mass	0.645
Center of Gravity	1.07 m
Drive Axle Weight Fraction	0.03
Wheel Base	5.5 m
Cargo Mass	27000 kg

The first four parameters are used to calculate the estimated power consumption meeting one cycle when the last three parameters handle the traction limitations. FASTSim has a high-level representation of the battery. The parameters for the battery implication include:

Table 4.2: Input Values for Battery Model in FASTSim

Parameter	Value
Power	120 kW
Energy	396 kWh
Base Mass	75 kg
Round Trip Efficiency	0.97

The energy management strategy of FASTSim has control of the operation of the battery converter. Its inputs are:

There are some more places for other components' input information which are essential for conventional vehicles relating to the fuel converter. All these input parameters help FASTSim to simulate the environment for an electric vehicle to do a run test within that.

Table 4.3: Input Values for Energy Management Model in FASTSim

Parameter	Value
Battery minimum SOC	0
Battery maximum SOC	1
The speed where the Battery should be Empty	$0\ mph$
The speed where the Battery should be Full	$60\ mph$
Attempted Level of Engine Charging the Battery	0.2

the default one does the simulation for light-duty fuel-based vehicles. But medium-duty and heavy-duty vehicle parameters including the electric ones can be used to get the electric power transfer during the duty cycles. FASTSim is available in two versions:

1. Excel Version of FASTSim: The Excel version has an interactive graphical user interface (GUI) that helps to visualize the duty cycles and their performances in graphs and models. This makes the data handling and customization of the operations simpler. This version also includes battery life comparisons to calculate the energy consumption by EVs.

2. Python Version of FASTSim: The Python version is usually beneficial for integration with large duty-cycle databases. In this thesis work, this version has been extensively used and modified for the fulfillment of the objectives. Python-based FASTSim pairs with the geo-spatial cycles incorporating weather factors like temperature. It also uses roadway characteristics like road grade. This model can be customized for additional energy consumption impacts which is a requirement for evaluating the energy profile of EVs.

4.1 Customized FASTSim for Heavy-Duty Freight Electric Vehicle

In this study, FASTSim is customized to use for a class 8 electric vehicle. For doing so, new vehicle information needed to be integrated into the Python version of FASTSim. Class 8 electric vehicles are heavy-duty trucks that are designed to transport large loads over long distances. These trucks are typically used in commercial applications such as freight and logistics, construction, and mining. Class 8 trucks have a gross vehicle weight

rating (GVWR) of 33,000 pounds or more, and they typically require a lot of power to operate, which makes the development of electric versions of these trucks challenging [65]. One of the biggest challenges in developing Class 8 electric vehicles is ensuring that they have enough range to meet the needs of commercial fleets.

Kenworth is a leading manufacturer of heavy-duty trucks. In recent years, Kenworth has been developing electric truck models as part of its commitment to sustainable transportation. The Kenworth electric truck is designed to offer zero-emission solutions for commercial fleets that need to comply with environmental regulations and reduce their carbon footprint. One of Kenworth's electric truck models is the Kenworth T680E, which is a Class 8 truck designed for drayage and local pickup and delivery applications. The T680E is powered by a 536 horsepower electric motor and a 720-volt battery system that can provide up to 100 miles of range on a single charge. The battery system can be recharged in as little as 3.3 hours using a 180 kW DC fast charger, and in around 6 hours using a 75 kW charger [66]. The Kenworth T680E has a regenerative braking system that helps recharge the battery system while driving, as well as advanced driver assistance systems that improve safety and reduce driver fatigue.

In order to collaborate with Kenworth T680E into FASTSim, different information regarding the vehicle needed to be used as the input. The main goal of doing so is to simulate the performance of the battery and range optimization of T680E using FASTSim.

Table 4.4: Parameter Values for Kenworth T680E Configuration

Parameter	Value
Battery Size	396 kWh
Mass of Vehicle	37194 kg
Air Resistance / Drag Coefficient	0.645
Frontal Area of Vehicle	9.5 m^2

Information stored in Table 4.4 is required for the configuration file. This helps to refer to the specific vehicle information in the FASTSim database. After denoting the selected vehicle type and loading its configuration details, FASTSim requires some more data as

input so that it can use them for the simulation. The data include vehicle parameters, battery parameters, wheel parameters, etc. These data are useful to calculate the vehicle powertrain. The vehicle powertrain links and manages the components in Table 4.5 that are given as the input to the FASTSim. The following equation is used to calculate the power to overcome drag:

$$
\begin{aligned}
power = 0.5 * airDensityKgPerM3 * dragCoef * frontalAreaM2 \\
* (average(prevMpsAch, cycMps)^3)/1000
\end{aligned}
\tag{4.1}
$$

where,

airDensityKgPerM3 - Air Density (kgm^{-3})

dragCoef - Vehicle Drag Coefficient

frontalAreaM2 - Vehicle Frontal Area (m^2)

prevMpsAch - Previous Vehicle Speed (ms^{-1})

cycMps - Current Speed of Input Drive Cycle (ms^{-1})

Table 4.5 has information on seven simulation models like the Vehicle model, Battery model, etc. All these models are emulating the actual vehicle in the simulated world of FASTSim. With this information, the simulated vehicle is acting like the original one. After that, the simulated vehicle is run in the simulated world to see how it performs so that an estimation of its performance in the real world can be visualized.

The data used in the simulation work of the software (stored in Table 4.5), have been collected from the available Kenworth Electric Truck T680E (Fig. 4.1) owned by the USU ASPIRE (Advancing Sustainability through Powered Infrastructure for Roadway Electrification) center.

Table 4.5: Inputs to the Customized FASTSim (Detailed information of Kenworth T680E)

Simulation Model	Parameter	Value
Vehicle	Vehicle Glider Mass	37194.574 kg
	Vehicle Center of Gravity Height	1.07 m
	Drive Axle Weight Function	0.03
	Wheel Base	5.5 m
	Cargo Mass	27000 kg
Motor	Motor Power	150 kW
	Motor Peak Efficiency	0.95
	Motor Time to Full Power	3 s
	Motor Controller Mass	0.833 kg/kW
	Motor Controller Base Mass	21.6 kg
Traction Battery	Battery Power	120 kW
	Battery Energy	396 kWh
	Battery Mass	8 kg/kWh
	Battery Base Mass	75 kg
	Battery Round Trip Efficiency	0.97
	Battery Life Coefficient A (product)	110
	Battery Life Coefficient B (power)	-0.6811
Wheel	Wheel Inertia (one wheel)	0.815 kgm^2
	Number of Wheels	10
	Rolling Resistance Coefficient	0.008
	Tire Radius	0.53 m
	Wheel Coefficient of Friction	0.7
Energy Management	Minimum State of Charge	0
	Maximum State of Charge	1
	Speed where the Battery should be Empty	0 mph
	Speed where the Battery should be Full	60 mph
	Attempted Level of Engine Charging the Battery	0.2
	Speed at which Engine is Commanded On	1 mph
	Power Demand at which Engine is Commanded On	100 kW
Miscellaneous	Charger Efficiency	0.86
	Auxiliary Loads	0.5 kW
	Transmission Mass	114 kg
	Transmission Efficiency	0.98
	Maximum Battery to Fuel Energy Error	0.005
	Maximum Regen	0.98
Validation Data	City AC elect. Consumption w/charging	2.64 $kWh/mile$
	Highway elect. Consumption w/charging	2.877 $kWh/mile$
	Combined elect. Consumption w/charging	2.756 $kWh/mile$
	0-60 MPH Acceleration Time	17 s
	Vehicle Range	150 $miles$

Fig. 4.1: Kenworth Electric Truck T680E utilized for the data usage

Table 4.6: Example of Weather Information from OpenWeatherMap API integrated into Customized FASTSim

Parameter	Value
Temperature	299.06 K
Humidity	34%
Visibility	6.21 $mile$
Wind Speed	2.56 mph
Wind Heading	110 $degrees$

The customized FASTSim has some weather impacts too. The OpenWeatherMap API has been used to get weather information. An example has been given in Table 4.6. This weather information helps FASTSim to calculate the energy consumption with more accuracy as Sina et al. have examined the impact of ambient temperature on the route planning of EVs in [67]. They have found that on average 68% energy consumption can increase in Fleet EVs because of the ambient temperature. This is a key factor to be considered as the heating and cooling of the cabin can significantly affect the battery which can result in the increment of energy discharged from it at the time of the trip.

CHAPTER 5

EVPRE HEAVY-DUTY

5.1 Electric Vehicle Path and Range Estimator (EVPRE)

The Electric Vehicle Path and Range Estimator (EVPRE) software framework creates an energy-efficient route for electric vehicles and estimate the range they can travel from any given starting point. It takes into account details such as the type of vehicle, road conditions, and environmental factors to provide accurate predictions that are relevant to the user's location. Being an open-source tool, users can input their vehicle specifications to obtain range predictions, optimal driving routes, and insights into energy usage for regular driving in their desired areas. This software is intended to facilitate the adoption, experimentation, and utilization of electric vehicles in everyday life.
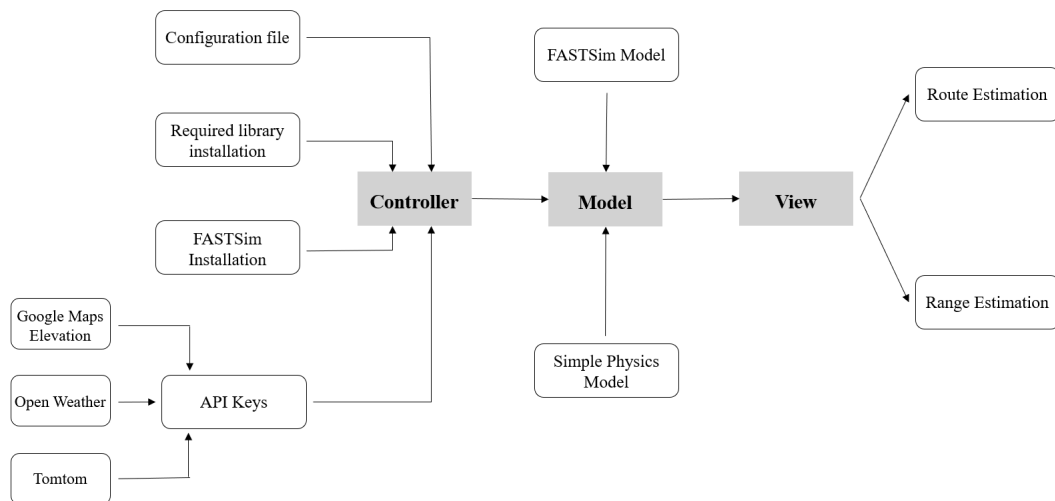
Fig. 5.1: EVPRE System Design that follows Mode-View-Controller design pattern.

The EVPRE software follows the Model-View-Controller (MVC) design pattern and requires multiple API keys to access real-time weather data and elevation information (see

Fig. 5.1). Failure to query data from these keys will result in using historical information instead. Road information is obtained from Open Street Map (OSM) and converted into a graph representation with traffic speed, road grade, latitude, longitude, and length of road segments. The software uses the Bellman-Ford algorithm to calculate routes and energy consumption based on two types of prediction models - a physics-based analytic model and NREL's FASTsim. The physics-based model calculates the power cost at the wheels and translates it up to the motor using the division of P_{motor} and $P_{driveline}$. The software also collects wind speed data from Open Weather Maps and dynamically collects other data during runtime. It includes a modified version of FASTSim that considers additional effects for high-resolution information on power consumption from real-time sources. The FASTSim model uses a small simulation cycle at runtime to create emulations of vehicles operating along an edge's length (i.e., road section length) and elevation differential, using elevation data from Google Maps. Vehicle parameters such as velocity, mass, acceleration, and resistance are stored and ingested similarly to the simple energy model. EVPRE returns the most energy-efficient route between any two points after exploration.

(a) Simple Energy Model   (b) FASTSim Energy Model

Fig. 5.2: Comparison between Simple and FASTSim Energy Model. FASTSim considers factors throughout the drive cycle and street-dependent acceleration profiles. The simplified physics model assumes vehicle constant acceleration profiles.

Jupyter notebooks are used to create visual representations of routes and expected ranges as shown in Fig. 5.2 to illustrate the energy-efficient path and range estimation, and the maps are interactive, allowing users to modify the start and goal pins to generate an optimal route between two points. The size of the map can be adjusted by the user, but caution must be taken not to exceed the API limits of the OpenStreetMaps service. The ma-

jority of internal instructions and user inputs are relayed to models through the controller. A configuration file contains vehicle information, including the model name, configuration details that can be modified by the user, and requirements such as the range coverage and starting coordinates. All necessary packages and the FASTSim model installation required to prepare the controller are provided and installed during the initial setup [68].

5.2 New EVPRE: Heavy-Duty Freight EVs Extension

The EVPRE software has been redesigned and modified so that it can be used for heavy-duty freight electric vehicles. An earlier version of EVPRE software helped to visualize the route estimation and range prediction of light-duty EVs. The new version of the software can now visualize the route estimation with the presence of traffic data for associating with the speed change in roads and it is also suitable for heavy-duty freight electric vehicles. The optimization technique has also been changed. Earlier it was a single-factor optimization technique that has been upgraded to multi-objective optimization so that there could have been some trade-offs among energy consumption, travel time, and distance.

Traffic data are required for increasing the efficiency of the estimation of energy consumption for route optimization. Without the traffic information, the speed change cannot be determined. This was missing in the earlier version of EVPRE which resulted in a constant speed throughout the whole route that does not imitate real-world scenarios. The speeds depend on the ongoing traffic on the road, dependent on the type of vehicle and time of day. The data specific to HDV was obtained through a partnership with Geotab, which maintains HDV fleet operation data for many freight vehicles. If the route optimization is estimated with a constant speed profile, the energy consumption can be calculated as a lower value compared to the real one. This can result in giving extended range coverage which will not be the actual case in practice.

The previous version of EVPRE was optimizing one single factor like energy consumption or travel time or distance traveled. But in reality, some trade-offs will always be needed to choose an efficient route. As it is mentioned earlier, heavy-duty vehicles are highly used for delivering heavy goods on time. If an energy-efficient route is chosen, there is no guar-

antee that the route can get you to the destination on time. Then again, if a time-efficient route is chosen, it will not be efficient for the battery of the vehicle to cover the range which is not accepted. Multi-factor optimization extensions to EVPRE now enable route calculations with express trade-offs between energy efficiency and time efficiency or a trade-off between energy efficiency and distance efficiency.
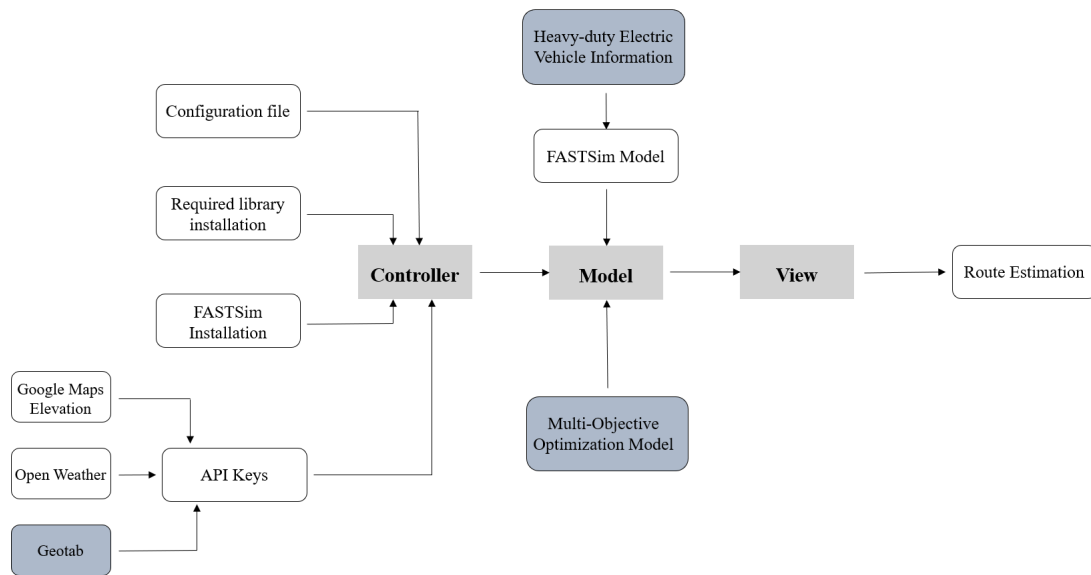
Fig. 5.3: New EVPRE System Design. Blue indicates the added components needed to expand EVPRE to operate heavy-duty freight vehicles. The significant addition of Multi-Objective optimization is necessary for balancing the needs of freight operators.

Fig. 5.3 is showing the added elements of the software in the bluish color. Initial development integrated HDV information into the FASTSim module as described in section 4.1. The information displayed in Table 4.5 is given as the input of FASTSim using a CSV ingestion. Whenever needed, the file is loaded and exported into the FASTSim model to do the simulation and required calculations. Then comes the Geotab integration. Geotab is a telematics company that provides data and analytics for fleet management. Geotab collects data from vehicles equipped with its GPS tracking devices, including location, speed, fuel usage, idling time, and other vehicle-specific information. This data is then transmitted to the Geotab cloud platform where it is processed and analyzed. Geotab's data can be

used by fleet managers to improve the efficiency and safety of their operations. Geotab also offers a range of software integrations and APIs that allow its data to be integrated with other fleet management systems. Geotab's data has been used for a variety of research projects, including studies on the impact of congestion on air quality and the effects of weather on vehicle performance. The company has also partnered with organizations such as Smart Cities Council and the American Lung Association to promote sustainable and healthy transportation.

In recent years, Geotab has been actively involved in electric vehicle (EV) research, leveraging its extensive data resources to gain insights into EV usage patterns and performance. Geotab has access to data from over 2 million connected vehicles globally, including a growing number of electric vehicles. This data includes information on vehicle location, speed, acceleration, charging activity, and other metrics that can be used to analyze EV performance and usage [69]. One area of Geotab's EV research has been focused on understanding the impact of weather on EV performance. By analyzing data from EVs in different climate zones, Geotab has been able to identify patterns in battery performance and range under different temperature and weather conditions. This information can help EV manufacturers and fleet managers better understand how their vehicles will perform in different regions and climates [70]. Geotab has also conducted research on the total cost of ownership (TCO) of EVs versus traditional gas-powered vehicles. By analyzing data on fuel costs, maintenance costs, and other factors, Geotab has found that EVs can have a lower TCO than gas-powered vehicles in many cases [71]. This research can help fleet managers and other businesses make informed decisions about switching to EVs. In addition to its own research, Geotab has made its data available to researchers and organizations interested in studying EV performance and usage [72]. This data can provide valuable insights into EV adoption and help inform policies and programs aimed at promoting sustainable transportation.

Geotab has been integrated into EVPRE using the API key. The 'TravelTime_Avg' has been extracted throughout the whole path using Geotab so that the traffic can be estimated

using this. 'TravelTime_Avg' gives the data of average travel time in seconds of the road segment with the associated traffic data. This will help in the optimization. This will help the optimization model to redirect the vehicle to follow other routes depending on the travel time requirements.

5.3 Software Components and Ease of Use

The new EVPRE software has the capability of providing single-factor optimized routes as well as multi-factor optimized routes for heavy-duty electric vehicles. For doing so, a graph object is highly needed that represents all the road segments and the locations along with the road characteristics. Following the selection of one geographical area of interest, Open Street Map (OSM) has been used to download the graphical representation of all the roads. This downloaded data includes street speed, grade, latitude, longitude, length of the road, etc. The Google Maps API is used in conjunction with OSMnx for the elevation information of each node of the graph. OpenWeatherMap API will give the necessary weather information like temperature, humidity, visibility, wind speed, etc. Geotab API is incorporated into the software so that we can use the traffic information for route estimation for more coverage. All these data will be associated with the node and edges in the graph object. Finally, the customization for HDV requires specification details on the physical vehicle as given in the input to the FASTSim model (see Fig. 5.4).

The heavy-duty vehicle has been chosen to be the Kenworth T680E model. Its information helps FASTSim in this software to simulate the performance of heavy-duty electric vehicles in an energy calculation module. Two options are provided and tested in this software base:

1. Single Factor Optimization Framework: This framework optimizes one single objective between energy, time, or distance.

2. Multi-Factor Optimization Framework: This framework makes a trade-off between the objectives. The trade-off could have been between energy-time or energy-distance or energy-distance or energy-time-distance.
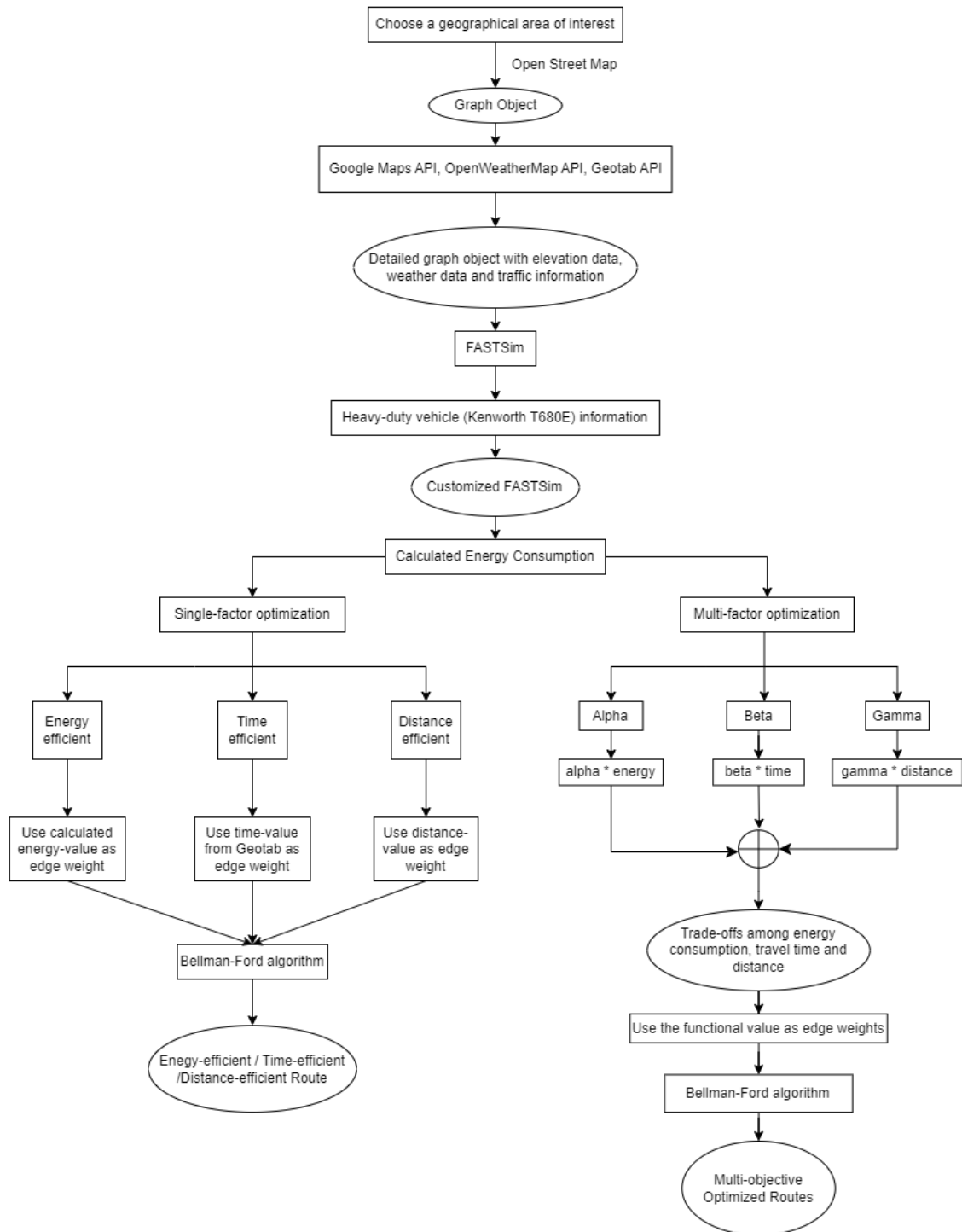
Fig. 5.4: Work Flow of New EVPRE software

The single-factor optimization framework gives either one of the following:

1. Energy-efficient route: The route takes the most energy-optimal route. The user can consume the least energy value following this path.

2. Time-efficient route: The route takes the user to the destination fastest. The time consumption of this route is the smallest compared to others.

3. Distance-efficient route: The route is the traditional distance optimal route. Following this, the user can use the shortest route within the two locations.

If the user wants an energy-efficient route within the selected start and end point, the calculated energy value is used as the edge weights in the graph. And if the efficiency factor is time, the edge weights will be the time value gathered from the Geotab API. Likely, the distance value as the edge weights will give distance-efficient routes. But all these shortest routes will be selected using the Bellman-Ford algorithm in the weighted graph where the factors would be either energy, time, or distance depending on the edge weights.

But, if the user wants a trade-off between energy, time, and distance or any two of them, the multi-factor optimization framework is chosen. Three coefficients are used there:

1. Alpha: Corresponds to the weightage associated with the energy consumption by EVs.

2. Beta: Corresponds to the weightage associated with the traffic time value gathered from Geotab.

3. Gamma: Corresponds to the weightage associated with the distance traveled.

The value of these coefficients depends on the percentage of the trade-offs. If the alpha is increased, this states that the energy optimization will have more importance compared to others. And, if the beta value is increased, it denotes that the user wants time optimization more than energy or distance optimization. As described in Section 6.3, if the user wants the route to be 80% energy efficient and 20% time efficient, the values of alpha and beta would be 0.8 and 0.2 respectively. Finally, these functional values are given to the edge weights

instead of a constant value for the multi-objective optimized routes. Then, Bellman-Ford will choose the shortest path according to the edge weights between the two points giving a multi-objective optimized path.

CHAPTER 6

SIMULATION SCENARIOS

The new EVPRE software helps EV users to get energy-efficient, time-efficient, and distance-efficient routes and also there is an added option of doing some trade-offs among them for getting multi-objective optimized routes. But it is important to note that electric-vehicle energy efficiency is different than ICE efficiency. First, it's essential to understand that EVs operate using electricity stored in batteries, while ICE vehicles use fuel like gasoline or diesel. Electric vehicles are significantly more energy-efficient than ICE vehicles because they convert more of the energy stored in their batteries into motion. Electric motors are very efficient and can convert over 90% of the battery's stored energy into motion. In contrast, ICE vehicles only convert about 20-30% of the energy in the fuel into motion, with the rest being lost as heat or through friction. Acceleration is faster at less power for EVs and it does not mind stop-and-go traffic as much which is not the case for ICE-based vehicles. They require more energy for higher acceleration and frequent stopping leads to more energy consumption. Weight matters much more for freight EVs. If the cargo weight is increased, the battery efficiency and size need to be increased simultaneously because it will require more energy for operation. Also, downhill early or later on a route can have a significant impact on electric vehicles' energy requirements. In this case, the ICE-based freight vehicles can carry bigger cargo weights with less increment in energy consumption. It is also crucial to consider the time impact with energy for truck logistics and limited fleet assets.

6.1   Choice of Location

Choosing a geographical area is the first step to moving forward with the new EVPRE software. The new EVPRE software simulates heavy-duty electric vehicles within a chosen area. We started looking for a suitable place near or within Utah being associated with

Utah State University. The main criteria of the suitable area were that the area should have been a big hub for the distribution of deliveries from where most of the goods are taken out and delivered to Utah global markets. Usually, the communities around these big ports or hubs of transportation are affected the most because of the dangerous emission from ICE-based heavy-duty vehicles.

The Utah Inland Port seemed to be a good fit for the simulation work. The Utah Inland Port is a project aimed at creating an inland port in Utah, United States. The inland port is planned to be located on approximately 16,000 acres of land west of the Salt Lake City International Airport, with a portion of the land being owned by the Utah State government. The project involves developing an area of land in Salt Lake City to serve as a hub for the transportation, warehousing, and distribution of goods from both domestic and international sources. The proposed port is located in the northwest quadrant of Salt Lake City and is designed to connect multiple modes of transportation, including rail, truck, and air cargo. The project has been controversial since it was first proposed in 2018, with many concerned about its potential impact on the environment, air quality, and local communities. They have also criticized the lack of public input in the development process and the potential for the project to exacerbate climate change. Despite these concerns, the project continues to move forward with the support of the state government and private investors.

On January 22, 2020, Dr. Kirtly Jones has spoken at the port report press release about the negative health impact the port would have with the increase of air pollution. The report [73] was released outlining the potential environmental harms of the proposed Utah Inland Port. The report has questioned the choice of the site for constructing an inland port to be critical in determining whether it will offer a viable solution or worsen the situation. Unfortunately, some areas, particularly the vulnerable shores of Great Salt Lake, have been earmarked for Utah's inland port project, despite being deemed the most unfavorable location for the well-being of people and the ecosystem. According to the report in [73], the primary environmental worry for the public is air quality, particularly the impact

of additional truck and rail traffic on the already inadequate air quality along the Wasatch Front.

There is another potential area of interest in salt lake city and that is the newly constructed Amazon regional warehouse which is on the 180,000-square-foot land located in Marriott-Slaterville at Interstate 15 and 400 North. It has been stated in [74] that over 1,600 vehicles are estimated to be entering and exiting the facility daily. Most of these vehicles are ICE-based heavy-duty freight vehicles which means that the air pollution rate is going to increase heavily. But these hubs are creating lots of job opportunities as said by the supporters of the projects. Also, it cannot be denied that such bug hubs or ports are essential as delivering heavy goods is also important.

All these concerns are being created because of diesel-based heavy-duty vehicles. One solution could have made a bridge between the supporters and opponents of the project and that could have been the electrification of heavy-duty freight vehicles. For the fast adaptation of the electrification of freight vehicles, this thesis work will help enormously as this shows the path of using a comparatively smaller size of the battery in EVs covering more range. This also provides an optimized solution to route estimation which makes heavy-duty electric vehicle users content and comfortable.

6.2   Single-Factor Optimization Framework

It has been stated in section 5.3 that the new EVPRE software consists of two optimization frameworks; one is single-factor optimization and another one is multi-factor optimization. Single-factor optimization framework gives the users routes optimizing one single factor which can be energy consumption by the vehicle or the time required for traveling or the distance required within two user-selected locations. This framework is highly beneficial for users who usually drive light-duty EVs where they can choose the energy-efficient route so that they can keep the batteries in healthy operating regions as well as reduce range anxiety. The optimization framework works within a graph object. The nodes denote the locations of Northern Salt Lake City and the edges are the routes or roads of those locations. This big graph has been downloaded using the Open Street Map. In this software, users can

choose whether they want an energy-efficient or time-efficient, or distance-efficient route by choosing the weights of the edges. If the weights are the calculated energy consumption by the vehicles, the software will provide routes that are optimized by the energy value. But if the weights are the time value that has been gained using the Geotab API, the routes will be optimized by the time required to reach the destination starting from the source location. Users have another choice which is to choose the weights to be the distance parameter. This will allow the software to provide the routes which are optimized by the distance value which is the length of the total route within the start and end locations.

	Energy Value (kJ)	Time Value (s)	Distance Value (m)
Energy-efficient	21.03	2799.05 (46% more)	48654.13 (6% more)
Time-efficient	26.11 (20% more)	1512.05	49432.08 (8% more)
Distance-efficient	22.26 (6% more)	2440.93 (38% more)	45631.59

Table 6.1: Statistical Analysis of energy consumption, time requirement, and distance traversed for the route in Fig. 6.1. In this route, 13% energy savings, 42% time savings, and 7% distance savings have been achieved on average.

In Fig. 6.1a, three routes are generated in three different colors within the start and end locations with markers. The blue marker denotes the starting location which is the Utah Inland Port and the red marker is for the destination. Among the three routes, the green route will give the most energy-efficient route. The red route will help users to reach their destination within the shortest time possible. And, the blue route will take the shortest distance within the two markers. Users can choose any one of the routes to reach the destination. If any user chooses the green route, s/he will expect his vehicle to consume the least amount of battery comparing the other routes without caring for time and distance. Then again, if any user chooses the red route, s/he will expect to reach the red location in the shortest amount of time considering the traffic condition as this new EVPRE software is using the traffic data from Geotab. To validate this, Fig. 6.1b has been generated. In Fig. 6.1b. the green bars are giving the energy value consumed following three different paths from the software. The red bars are for the time value and the blue bars are for
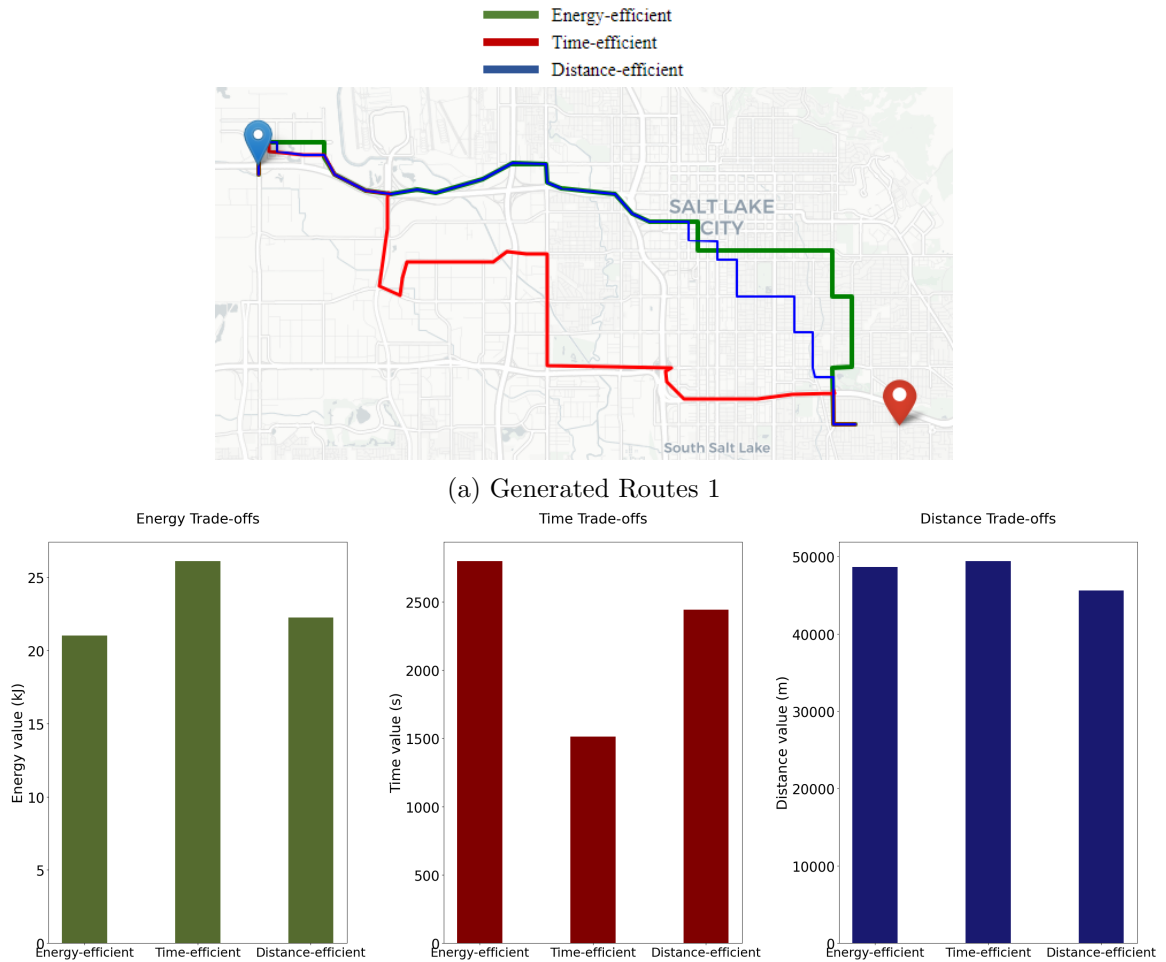
(a) Generated Routes 1

(b) Green bars: Energy consumption by the three routes, Red bars: Time required for the three routes, Blue bars: Distance covered by the three routes.

Fig. 6.1: Energy-efficient route (Green), Time-efficient route (Red), and Distance-efficient route (Blue) have been produced using the EVPRE software integrating the traffic time data. The route covers a distance of around 45630 meters. The energy-efficient route uses ∼ 21.03 kJ energy and the time-efficient route reaches the destination in ∼ 1512.05 seconds or ∼ 25 minutes.

the distance value for the three routes with three objectives. Looking at the green bars, it has been confirmed that the energy-efficient route is consuming the least amount of energy. The time-efficient route is also taking the user to the destination in the least amount of time, as the distance-efficient route. Looking at the statistics of Table 6.1, it is visible that the energy-efficient route is saving around 13% energy consumption on average. The time-efficient route is taking around 42% less time to reach while the distance-efficient route is

efficient in saving distance 7% on average.

(a) Generated Roues 2

(b) Green bars: Energy consumption by the three routes, Red bars: Time required for the three routes, Blue bars: Distance covered by the three routes.

Fig. 6.2: Energy-efficient route (Green), Time-efficient route (Red), and Distance-efficient route (Blue) have been produced using the EVPRE software integrating the traffic time data. The route covers a distance of around 38800 meters. The energy-efficient route uses ~ 18.39 kJ energy and the time-efficient route reaches the destination in ~ 1549.42 seconds or ~ 26 minutes.

Similarly, Fig. 6.2a gives an energy-efficient route in green, a time-efficient route in red, and a distance-efficient route in blue starting from Utah Inland Port. Fig. 6.2b is showing the comparisons among them to prove their efficiency with visualization. The stored statistics of Fig. 6.2 in Table 6.2 states that the energy-efficient route is efficient 3% on average in energy consumption in these locations when the time-efficient route will

	Energy Value (kJ)	Time Value (s)	Distance Value (m)
Energy-efficient	18.39	2121.23 (27% more)	43236.42 (10% more)
Time-efficient	18.99 (3% more)	1549.42	39766.77 (3% more)
Distance-efficient	18.91 (3% more)	1931.53 (20% more)	38814.27

Table 6.2: Statistical Analysis of energy consumption, time requirement, and distance traversed for the route in Fig. 6.2. In this route, 3% energy savings, 23.5% time savings, and 6.5% distance savings have been achieved on average.

redirect the user to the destination with 23.5% less amount of time. Now, if Table 6.1 and Table 6.2 are compared, even though the route in Table 6.1 was about 6000 meters longer than the route of Table 6.2, the energy-efficient route could save around 13% energy consumption for the earlier route (Table 6.1).

	Energy Value (kJ)	Time Value (s)	Distance Value (m)
Energy-efficient	16.29	1386.07 (2% more)	34228.93 (0.27% more)
Time-efficient	17.08 (5% more)	1363.83	35132.22 (3% more)
Distance-efficient	17.49 (7% more)	1468.82 (7% more)	34138.82

Table 6.3: Statistical Analysis of energy consumption, time requirement, and distance traversed for the route in Fig. 6.3. In this route, 6% energy savings and 4.5% time savings have been achieved on average while the distance-efficient route saves 1.6% distance than others.

	Energy Value (kJ)	Time Value (s)	Distance Value (m)
Energy-efficient	19.49	1870.75 (8% more)	40503.69 (0.14% more)
Time-efficient	21.09 (8% more)	1722.63	43700.33 (7% more)
Distance-efficient	20.41 (5% more)	1859.88 (7% more)	40446.26

Table 6.4: Statistical Analysis of energy consumption, time requirement, and distance traversed for the route in Fig. 6.4. In this route, 6.5% energy savings and 7.5% time savings have been achieved on average, and around 3.6% distance can be saved using the distance-efficient route.

Looking at Figure 6.3 and 6.4, we can see that the energy-efficient route is saving
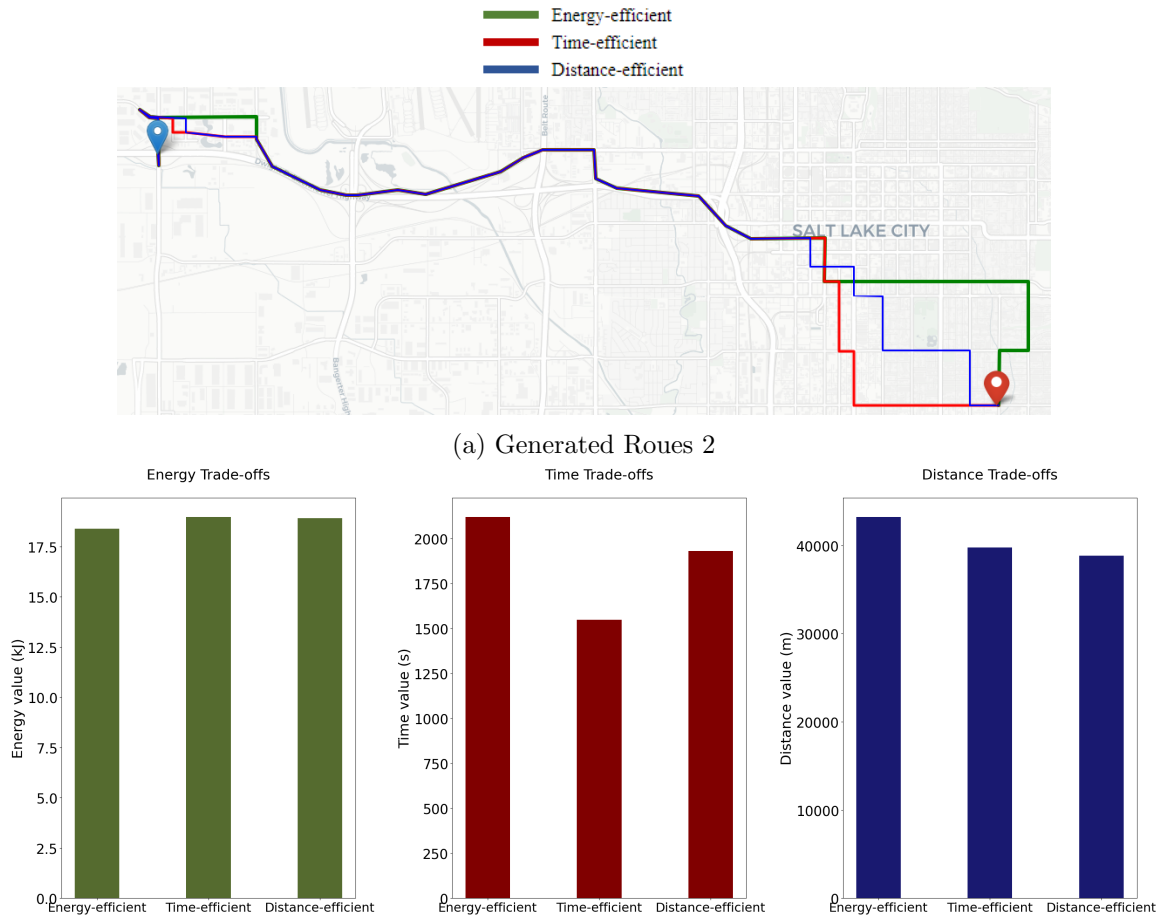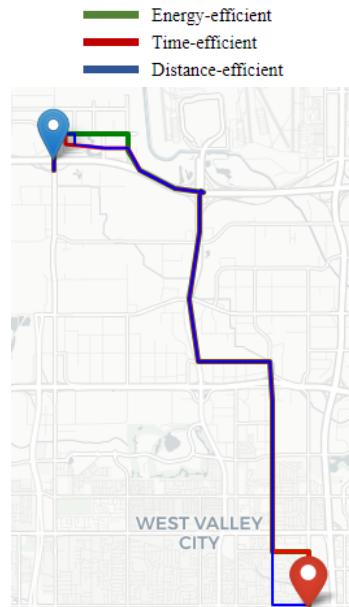
(a) Generated Routes 3
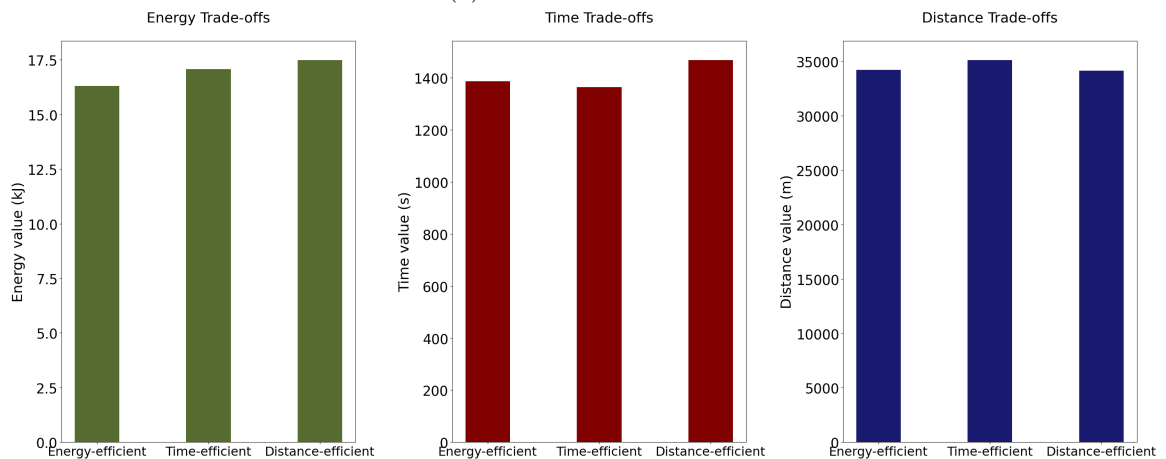
(b) Green bars: Energy consumption by the three routes, Red bars: Time required for the three routes, Blue bars: Distance covered by the three routes.

Fig. 6.3: Energy-efficient route (Green), Time-efficient route (Red), and Distance-efficient route (Blue) have been produced using the EVPRE software integrating the traffic time data. The route covers a distance of around 34100 meters. The energy-efficient route uses ∼ 16.29 kJ energy and the time-efficient route reaches the destination in ∼ 1363.83 seconds or ∼ 23 minutes.

energy as well as it is following the closest to the shortest distant path. In Figure 6.3, the energy-efficient route is saving around 6% energy consumption while it takes about 22 seconds more and just 0.3% more distance to reach the destination. In Figure 6.4, the

(a) Generated Routes 4

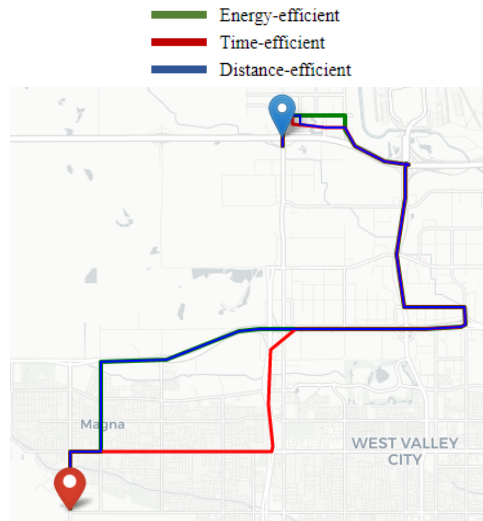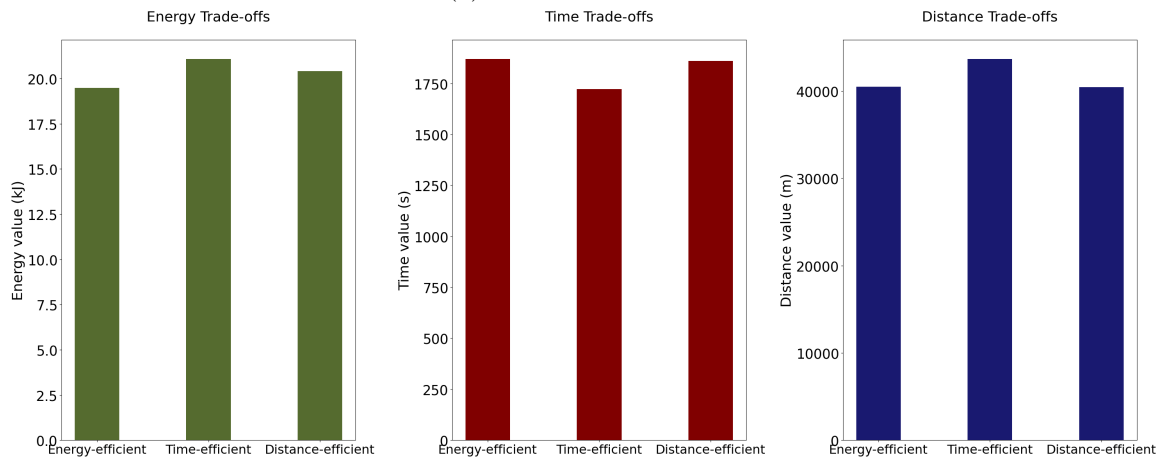(b) Green bars: Energy consumption by the three routes, Red bars: Time required for the three routes, Blue bars: Distance covered by the three routes.

Fig. 6.4: Energy-efficient route (Green), Time-efficient route (Red), and Distance-efficient route (Blue) have been produced using the EVPRE software integrating the traffic time data. The route covers a distance of around 40400 meters. The energy-efficient route uses ~ 19.49 kJ energy and the time-efficient route reaches the destination in ~ 1722.63 seconds or ~ 29 minutes.

energy-efficient route is saving around 7% energy consumption and it is taking 3 minutes more with 0.1% more distance for the travel. This says that the energy-efficient route can be great also to save energy consumption as well as following a time-efficient route which helps the Freight EV users to keep their battery life healthy along with maintaining fast deliveries.

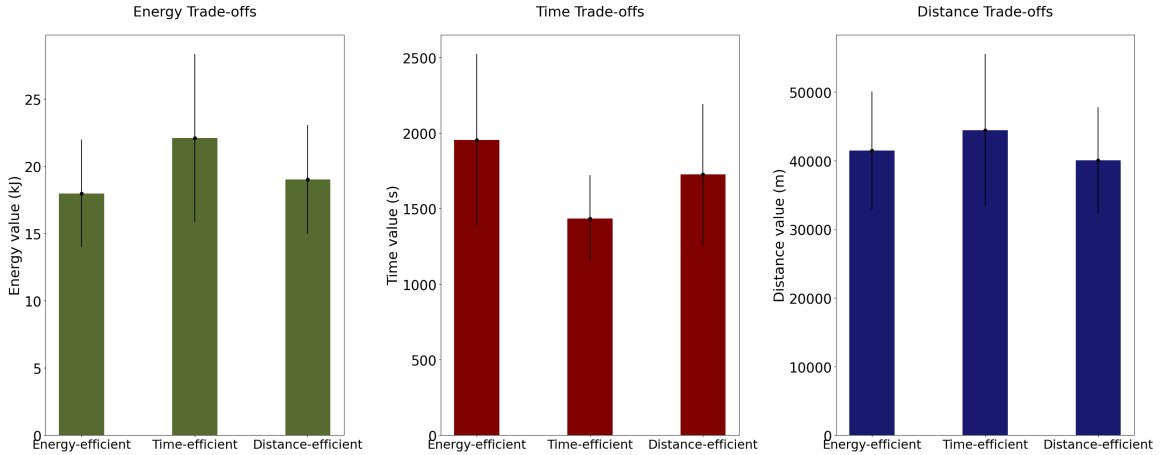Fig. 6.5: Average energy consumption, time requirements, and distance traversed of 30 different routes starting from the Utah Inland Port. The green bars are denoting the simulated energy consumption values for following the three different routes. The red bars are for visualizing the time requirements to reach the destinations and the blue bars are for the distance covered for the three routes.

	Avg Energy (kJ)	Avg Time (s)	Avg Distance (m)
Energy-efficient	17.98	1953.52 (27% more)	41432.59 (3% more)
Time-efficient	22.09 (23% more)	1434.15	44440.94 (10% more)
Distance-efficient	19 (5% more)	1725.06 (17% more)	40020.96

Table 6.5: Statistical Analysis of energy consumption, time requirement, and distance traversed for the route in Fig. 6.5. These are the records for the average statistics showing the efficiency of 30 generated routes from Utah Inland Port. It is evident that overall 14% energy savings, 22% time savings, and 7% distance savings have been achieved.

Now, it is necessary to look at the average efficiency of the algorithm which can be visualized with Fig. 6.5. 30 different routes have been chosen while all of them started at the Utah Inland Port. We have tried to visualize the average efficiency of the generated routes to reach different delivery locations starting from the Utah Inland Port. The bars are showing that the optimal routes are giving the optimal result on average. This has been recorded in Table 6.5. Table 6.5 states that the energy-efficient route consumes 22% less energy on average and the time-efficient route reaches the destination 14% faster on average. It is visible that there could have been around 5% error in the estimation. So, it can be promised that it is efficient to follow the generated routes to fulfill the user's optimization.
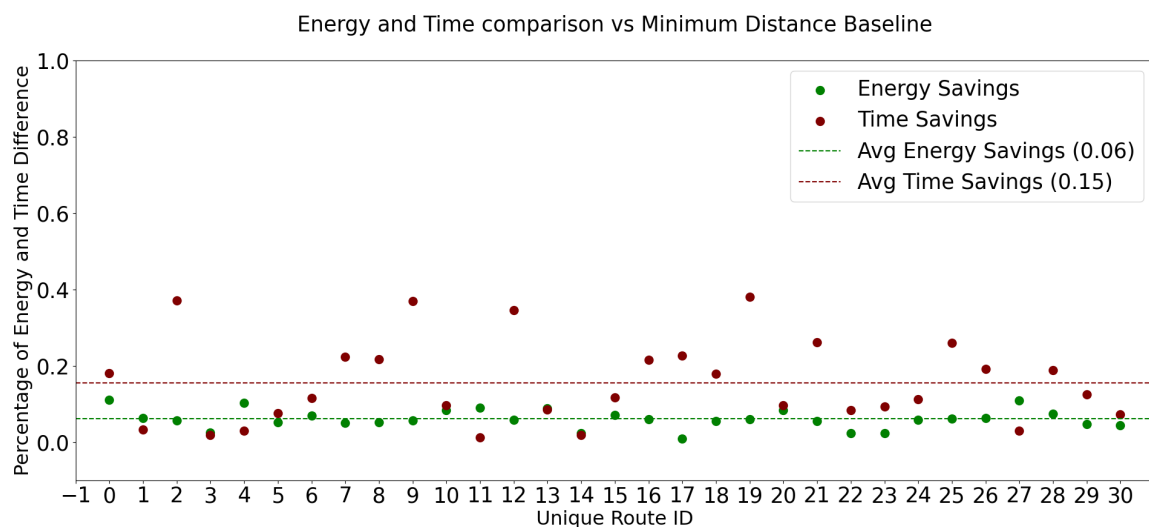
Fig. 6.6: On average 6% of energy savings and 15% of time savings have been achieved from 30 routes starting from Utah Inland Port. These energy and time-efficient routes have been compared with the traditional distance-based routes.

Fig. 6.6 is a great visualization of the fact that the single-factor optimization framework is saving around 6% of energy consumption compared to the general distance-efficient routes which are usually designed for the ICE-based vehicles for fuel consumption efficiency. We have compared the energy-efficient and time-efficient routes with the baseline route which is the distance-efficient route. There are 30 routes that have been used in Fig. 6.5. The comparison between the energy values of the energy-efficient route with the baseline one is giving them a saving of around 6%. This is a great achievement as savings in energy consumption are a must while using EVs on a daily basis. If around 5% of the time, we can save energy consumption, the adoption of EVs can be increased in a significant amount of time because we can rely on the range coverage and we can assure that the battery life can be improved to 5% at least.

But it is also visible in Table 6.1 that an energy-efficient route consumes 46% more time and 6% more distance to reach the destination. This cannot be always acceptable. Also, the time-efficient route is consuming 20% more energy which is not good for the battery health and the range coverage of EVs. Even in table 6.2, it is non-negligible that the energy-efficient route takes 27% more time which is around 10 minutes of extra time. To

overcome this, if the user chooses the time-efficient route, it will consume 3% more energy. This has been a great motivation for the multi-objective optimization work of the thesis.

6.3 Multi-Factor Optimization Framework

Multi-factor optimization framework has been designed so that users can choose a trade-off among the objectives; energy, time, and distance. It is practical to choose some trade-offs rather than just ignoring one objective and optimizing another one. In a single-objective optimization framework, it is not guaranteed that the energy-efficient path can reach the user to the destination on time. It just ensures that following the resulting path will consume the least amount of energy by the vehicle. This is evident in Table 6.1, 6.2, 6.3, 6.4 and 6.5. The energy-efficient route takes 27% more time on average to reach the destination which means around 9 minutes more time will require following the energy-efficient route than the time-efficient one. But if users want to reach on time following the time-efficient route, it is not guaranteed that the vehicle can cover the range with one full charge or that the path will be optimized for the battery which can arise range anxiety within the driver. From the Tables 6.1, 6.2, 6.3, 6.4 and 6.5, it can be estimated that on average 23% more energy will be consumed to reach on time.

Our balanced parameter weight-based optimization technique can solve the dilemma in a comfortable state. In this multi-objective optimization framework, some trade-offs have been offered to the users so that they can have the routes optimized like 80% of energy consumption and 20% of time value. This will ensure that following the route the user can get 80% less energy consumption while there will be a 20% chance that this route can get him to the destination on time. In this framework, three coefficients have been used; alpha, beta, and gamma. Alpha denotes the weightage to the energy consumption while beta tends to the weight of time value and gamma has been used for the distance metric. The values of these coefficients give the weights to the objectives. The values can be changed according to users' choice. If any user chooses alpha to be 0.7, beta to be 0.2, and gamma to be 0.1, this will generate a route considering 70% weight to the optimization of energy consumption, 20% weight to the time optimization, and 10% for the distance optimization.

So, the user can expect that the route can get him to the destination with around 5% less energy consumption and 2% faster than the regular route on average.
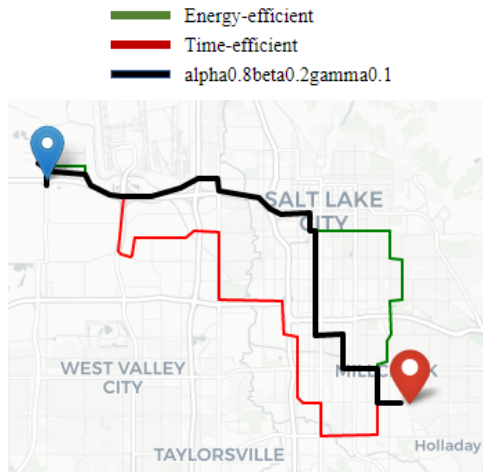

Fig. 6.7: Multi-objective Optimization route. Green route: Energy-efficient, Red route: Time-efficient, Black route: alpha0.8beta0.2gamma0.1. The route is 80% energy efficient and 20% time efficient. The route is consuming 1.22 kJ more energy than the energy-efficient one. The time required for the route is 5 minutes more than the time-efficient route and 21 minutes less than the energy-efficient route.

The route in Fig. 6.7 is a multi-objective optimized route. The route has 80% weight to the energy efficiency and 20% weight to the time efficiency. The starting location is the Utah Inland Port. The route is consuming 25.20 kJ of energy which is 1.22 kJ more than the energy-efficient route. The route is taking the user to the destination in 36 minutes which is 5 minutes more than the time-efficient route but this route is 21 minutes faster than the energy-efficient route. This route is the most sufficient one because the time-efficient route consumes 6.76 kJ more energy with just 5 minutes less time when this route is energy-efficient as well as time-efficient compared to the other two.

The route in Fig. 6.8 is another multi-objective optimized route where energy is 80% optimized and time is 20% optimized. The multi-factor optimized route consumes about the same energy as the energy-efficient route but 8.16 kJ less than the time-efficient one. This route takes around 32 minutes to reach the destination which is 5 minutes more than the time-efficient one and 6 minutes less than the energy-efficient one. The multi-objective
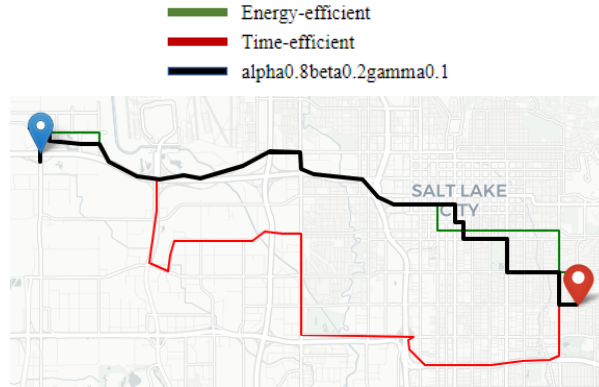
Fig. 6.8: Multi-objective Optimization route. Green route: Energy-efficient, Red route: Time-efficient, Black route: alpha0.8beta0.2gamma0.1. The route is 80% energy efficient and 20% time efficient. The route is consuming 1.22 kJ more energy than the energy-efficient one. The time required for the route is 5 minutes more than the time-efficient route and 21 minutes less than the energy-efficient route.

	Energy Consumption (kJ)	Time Requirement (s)
alpha0.8beta0.2gamma0.1	25.20	2201.39
Energy-efficient	23.98	3165.01
Time-efficient	31.96	1861.69

Table 6.6: Statistical Analysis of multi-objective optimization route (80% energy-efficient and 20% time-efficient) of Fig. 6.7. The route is consuming 1.24 kJ less energy. The time required for the route is 5 minutes more than the time-efficient route and 20 minutes less than the energy-efficient route.

	Energy Consumption (kJ)	Time Requirement (s)
alpha0.8beta0.2gamma0.1	17.96	1937.16
Energy-efficient	17.94	2265.85
Time-efficient	26.12	1598.59

Table 6.7: Statistical Analysis of multi-objective optimization route (80% energy-efficient and 20% time-efficient) of Fig. 6.8. The route is consuming the same energy as the energy-efficient one. The time required for the route is 5 minutes more than the time-efficient route and 6 minutes less than the energy-efficient route.

optimized route is a good choice for this travel because it is getting a route with some trade-offs but it is efficient enough in terms of energy consumption which is essential for EV users and also the time requirement is not too high. The time-efficient route is consuming way more energy and the energy-efficient route is taking a long time than expected. So,

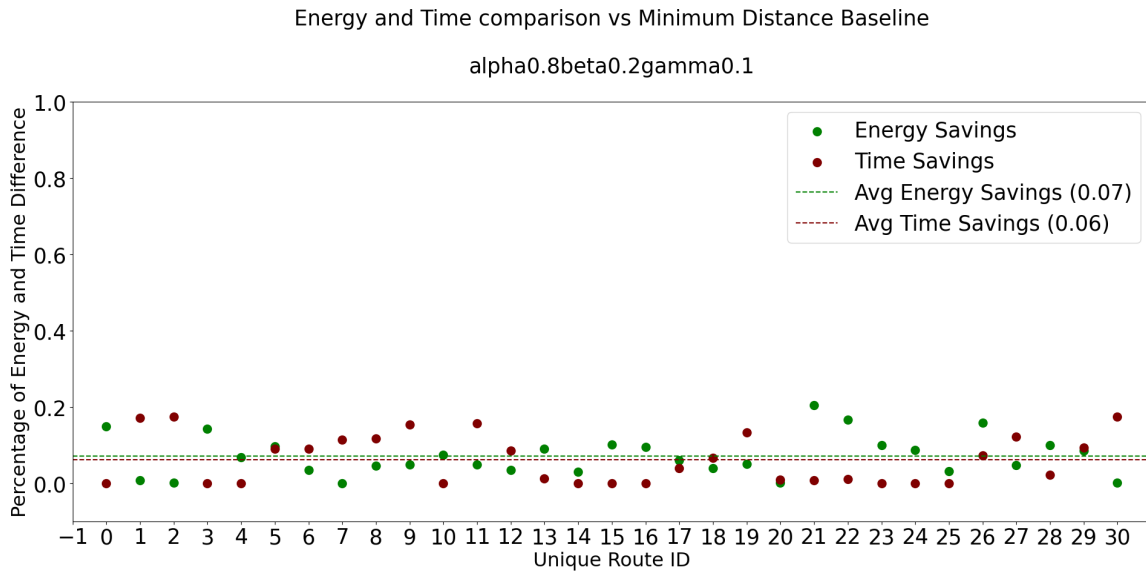this new optimized route is doing a bridge balancing these requirements.

Energy and Time comparison vs Minimum Distance Baseline

alpha0.8beta0.2gamma0.1

Fig. 6.9: On average 7% of energy savings and 6% of time savings have been achieved from 30 multi-objective optimized routes starting from Utah Inland Port. These routes are 80% energy-efficient and 20% time-efficient. These energy and time-efficient routes have been compared with the traditional distance-based routes.

Fig. 6.9 and 6.10 have been generated to show the energy and time savings using the multi-objective optimization framework with the comparison of the regular distance-efficient route. In Fig. 6.9, the alpha and beta have been considered to be 0.8 and 0.2 respectively which states that the weights have been given 80% to the energy consumption efficiency and 20% to the time efficiency. These weights generate routes optimizing around 7% of energy consumption and around 6% of time requirements.

In Fig. 6.10, the weights are 0.7 and 0.4 for alpha and beta respectively which resulted in routes optimizing around 11% of energy consumption and around 3% of time savings.

All these routes have been generated considering the traffic information gathered from Geotab API. Traffic impacts are not directly simulated as many non-highway roads do not have data associated, but all routes are considering specific factors for heavy-duty freight (i.e.: travel time including anticipated traffic and acceleration/deceleration from making turns, energy costs of accelerating a filled freight trailer, and difficulty of making turns in

Energy and Time comparison vs Minimum Distance Baseline

alpha0.7beta0.4gamma0.1
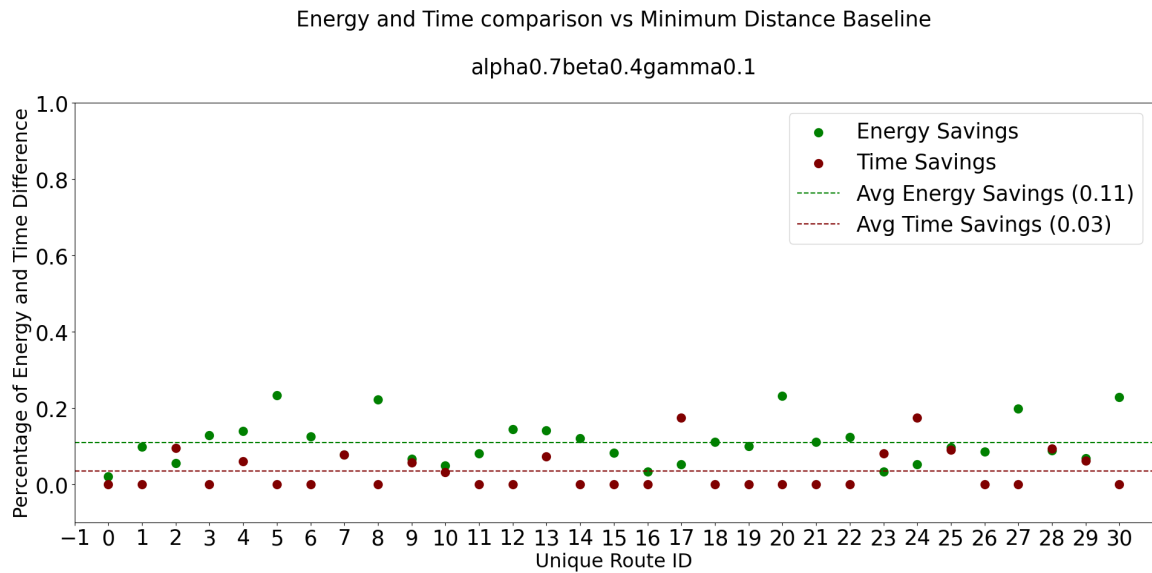
Fig. 6.10: On average 11% of energy savings and 3% of time savings have been achieved from 30 multi-objective optimized routes starting from Utah Inland Port. These routes are 70% energy-efficient and 40% time-efficient. These energy and time-efficient routes have been compared with the traditional distance-based routes.

intersections). Some traffic constraints do exist here, and some routes (i.e.: energy-efficient routes) may involve vehicles driving on smaller roads. However, all roads are viable for heavy-duty trucking (as per Geotab).

CHAPTER 7

CONCLUSION AND FUTURE WORKS

Over the past few years, the price of electric freight vehicles has been gradually dropping as battery technology has improved and production costs have decreased. As the demand for more efficient transportation options continues to grow, more and more manufacturers are entering the market, which is driving competition and further price reduction. But the adoption of heavy-duty freight electric vehicles is still not increasing as it is needed because of some factors like range anxiety, lack of charging infrastructure, cargo size, etc. While the range of electric vehicles is improving, many freight operators are concerned about the distance they can travel on a single charge and the availability of charging infrastructure along their routes. Many freight operators are concerned about the availability and reliability of charging infrastructure, particularly in rural areas or along remote routes. Without a robust and reliable charging network, businesses may be reluctant to invest in electric vehicles.

The main concern associated with the decreasing interest in adopting heavy-duty freight electric vehicles is the battery charge. Smaller batteries are faster to charge and the tool designed in this thesis allows systems to operate with $\sim 20\%$ smaller batteries or smaller freight capabilities for deliveries. The software is designed to deliver optimizing routes based on three objectives; energy, time, and distance. These objectives can be optimized one at a time and also there is an option for multi-factor optimization. Traffic information has also been associated with the calculation of energy consumption so that efficiency can be increased. In the single-factor optimization framework, users can choose from energy-efficient, time-efficient, or distance-efficient routes, and in the multi-objective optimization framework, users can do some trade-offs between energy or time, or distance so that they can get the routes with mixed optimization. A balanced parameter weight-based optimization technique has been introduced here where three coefficients; alpha, beta, and gamma have

been used in consideration of the weights to the objectives. On average, the energy-efficient routes can save $\sim 6\%$ to 10% of energy consumption and time-efficient ones can be $\sim 3\%$ to 6% faster compared to the traditional distance-based routes. In multi-objective optimized routes, the energy savings and time savings are $\sim 11\%$ and $\sim 6\%$, respectively. All these savings will help in reducing battery usage and thus, it will maintain good battery health. It will also help to increase the average range coverage of the heavy-duty freight EVs as smaller batteries can cover comparatively longer routes if the routes could have been efficient enough for energy consumption. This can eventually increase the adoption of electrified heavy-duty freight vehicles by reducing range anxiety. Electrification impacts can significantly improve health at even a 5% adoption increment as it will help cut back the fuel exertion caused by conventional motor vehicles.

7.1 Future Works

The new EVPRE software is able to provide energy-efficient, time-efficient, and distance-efficient routes with some options for trade-offs among them in a simulated world. The testing and validation of the software with real-life data from the Kenworth truck company is the next work to be done. The software can also be tested with some other optimization techniques like particle swarm optimization (PSO), ant colony optimization (ACO), etc.

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