Validation of EcoRouting and an Analysis of the Impact of Traffic on Route Choice

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ABSTRACT

Battery Electric Vehicles and Plug-in Hybrid Vehicles are increasingly becoming more popular in recent years. Stricter regulations from government agencies to curb emissions and reduce impact on climate have led to automobile makers adopt electric powertrains. EcoRouting is one such method to reduce energy usage in personal transport.

EcoRouting is a methodology that determines the route with the least energy consumption between two points. Standard navigation systems often determine the shortest or the fastest route, emphasizing travel time. EcoRouting considers an alternative criterion - energy consumption. In this thesis, an automation methodology is presented that determines the EcoRoute among given route alternatives based on route distance, speed limits, road grades, traffic signs, driver aggression and the powertrain.

There are three major objectives in this thesis: Developing the automation methodology for the determination of EcoRoute for use in on-board applications, validating the EcoRouting methodology on actual driving conditions and studying the impact of traffic on the choice of EcoRoute.

The automation methodology has been developed on the Android framework for use with on-board applications on Android mobile devices. The automation methodology used to conduct sensitivity studies show that factors such as driver aggression, distance and conditional stops impact energy consumption. The comparison of results of simulation using the automation methodology against results from actual driving to validate the methodology on

actual driving conditions show that transient traffic conditions can have significant impact on energy consumption. Finally, route energy consumptions for various traffic conditions are estimated using simulation to understand the impact of traffic on energy consumption and EcoRoute choice. Results that are obtained show that apart from traffic affecting the energy consumption, travel times can have an impact on choice of EcoRoute.

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GENERAL AUDIENCE ABSTRACT

Government agencies have been introducing tighter regulations in order to improve fuel economy and reduce emissions. These regulations are targeted at reducing the impact of vehicle usage on climate. Automobile manufacturers have increasingly adopted electric powertrains to meet these regulations. Battery Electric Vehicles and Plug-in Hybrid Vehicles are more popular than ever. Other methods in reducing environmental impact by automobiles are also being conducted. EcoRouting is one such method. EcoRouting determines the route that consumes the least energy between two locations.

EcoRouting requires no modifications to be done on the vehicle or its powertrain. A methodology has been developed in this thesis that takes into account various factors such as traffic signs, speed limits, road grades, powertrain and driver aggression to determine the route that consumes the least energy.

Research in this thesis has been divided into three major parts: development of the automation methodology, validating the methodology for actual driving conditions and understanding the impact of traffic on energy consumption. Results of case studies show that the input parameters affect energy consumption significantly. Traveling speeds affect the energy consumption and since transient traffic conditions can affect traveling speeds, transient traffic conditions can have a significant impact on energy consumption. Since energy consumption alone is not considered in determining the EcoRoute and the travel times are also considered so as to not inconvenience the user, traffic conditions impact the choice of EcoRoute both due to differences in energy consumption and travel time

Dedication

Dedicated to my parents

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I would like to thank Sidhant for assisting me in my research and being a great friend.

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Last but not the least, I would like to thank my parents, for being there for me always. No words can do justice to the sacrifices they have made for me to reach this position.

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Chapter 1

Introduction

The last few years have seen government agencies introduce stricter regulations on fuel economy and emissions as a measure to reduce impact on the climate. Automobile manufactures have increasingly adopted electrified powertrains in order to meet these regulations. A technology once reserved for economy vehicles has seen increased adoption on performance vehicles in recent years. The most prominent examples of such high performance vehicles employing electrified powertrains include the Porsche 918, the McLaren P1 and the Ferrari LaFerrari. With electrification and hybridization, manufacturers have been able to claim higher fuel economies than their fuel powered counterparts. Another popular example is the Toyota Prius, which is able to achieve high gas mileage with a hybridized powertrain. Research efforts on reducing fuel consumption are not limited to powertrain. Powertrain agnostic methods have also been studied to reduce fuel consumption. EcoRouting is one such method that helps reduce fuel consumption without altering the powertrain or the vehicle.

EcoCAR 3 is a four year North American collegiate automotive engineering competition in the U.S. Department of Energy (DOE) Advanced Vehicle Technology Competition series. EcoCAR 3 challenged 16 North American university teams to redesign a 2016 Chevrolet Camaro into a technologically advanced, energy efficient, high performance vehicle while retaining the iconic design. Student teams implemented energy innovations across various technical swimlanes [3]. EcoRouting was chosen as the topic of research under the Innovation swimlane.

EcoRouting is a methodology to determine the route with the least energy consumption between a source and a destination. EcoRouting differs from traditional routing methods in that traditional routing strives to determine the fastest or the shortest route. EcoRouting tries to determine a route with the least energy consumption while constraining travel times. An optimum EcoRoute is the route option that minimizes energy consumption chosen by setting a maximum threshold for an increase in travel time, if any, over the fastest route.

Falling fuel prices have failed to encourage adoption of hybrid vehicles in recent years [12]. However, the drop is forecast to be temporary and fuel prices are expected to increase [11]. While this has been one deterrent in the adoption of hybrids, other factors such as range anxiety and lack of incentives in the form of fuel economy have also impacted hybrid cars.

Hybrid cars intend to provide the benefits of both electric vehicles and fuel powered vehicles under one package. Due to added complexities in design and considerations of cost and weight, hybrid cars tend to get smaller electrical energy storage systems. Smaller batteries result in lower ranges that are not encouraging for the users. EcoRouting attempts to help alleviate this problem by determining the path with the least energy consumption. The potential benefits include increased fuel economy and lowered emissions as hybrid vehicles are used more in electric modes.

In this thesis, research is conducted on electric vehicles or battery electric modes of hybrid vehicles. The objective of this thesis is split into three parts: developing an automated methodology for determining the EcoRoute for use with on-board applications, validating the proposed EcoRouting methodology on actual driving conditions and finally, studying the impact of traffic on the choice of EcoRoute. The proposed automation methodology determines the EcoRoute from a set of available alternative routes rather than performing the routing. It thus becomes a path-planning problem.

The thesis progresses as follows. A brief summary of background information and terminology is presented further in this section, followed by a review of literature in the next chapter. A chapter is then dedicated to each of the three major parts of the thesis.

1.1 Background Information

Tamaro developed a scalable powertrain model for HEVT research on EcoRouting in [25]. The model uses publicly available powertrain data to calculate energy consumption estimates for each specified route. The velocity profile required by the powertrain model is synthesized using the methodology developed by Moniot [22].

Certain route parameters and data are required for synthesizing the velocity profiles for a given route. Data specific to each route are obtained from on-line databases by means of queries and requests. The retrieved data is then processed and stored inside the program. The terminology used in the automation methodology is described here.

1.2 Terminology

The origin is denoted the source and the terminating point is denoted the destination. A route is any path that connects the source and the destination nodes. The time taken to traverse the fastest route is tt (travel-time) and the fastest route is called the travel-time route or the tt route.

Each route is composed of edges, called segments, and placeholders, called nodes, connecting the edges. Each node is uniquely identified using GPS coordinates i.e the latitude and longitude geographic coordinate system. A visualization of nodes and segments is presented in 1.1.

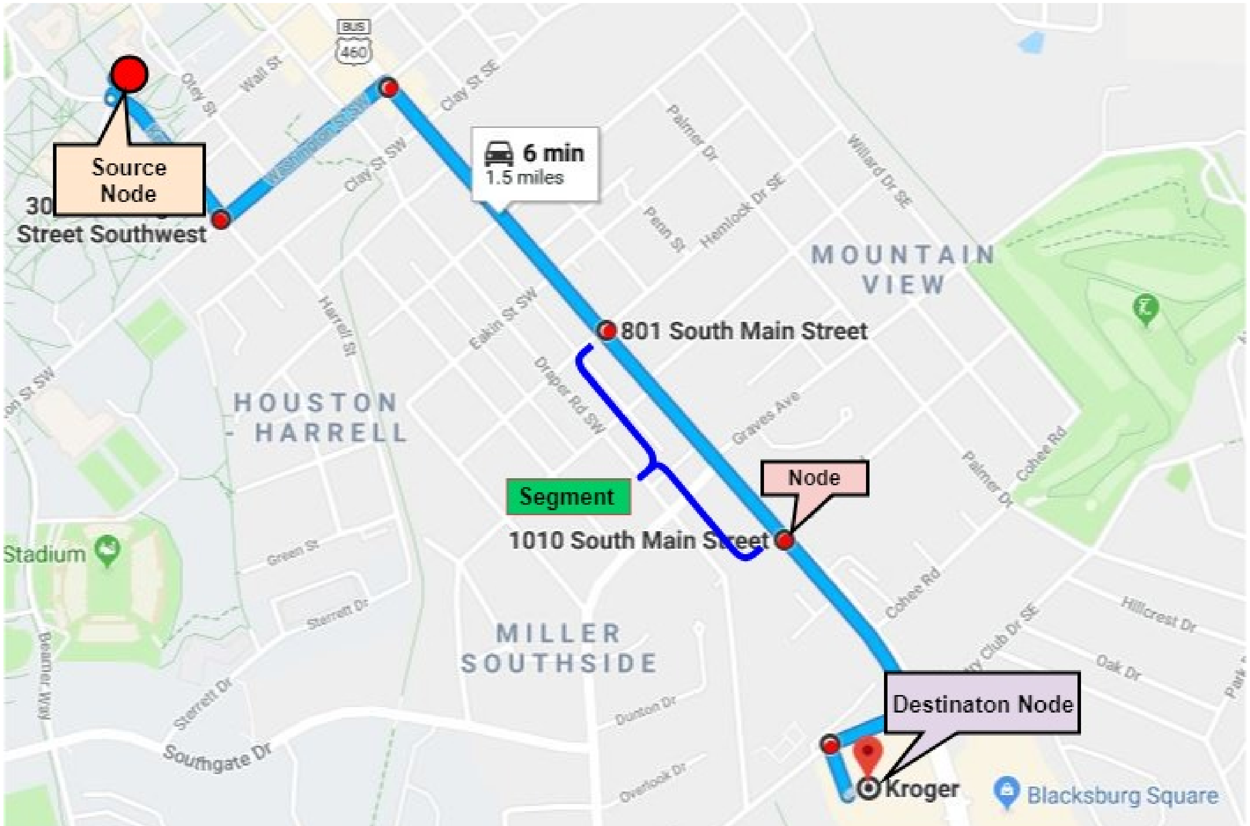

Figure 1.1: Visualization of terminology

1.3 Android SDK

The EcoRouting software has been developed using the Android framework. Android is an operating system based on a modified linux kernel typically available on mobile and hand-held devices [2]. The Android operating system allows custom user applications to be built and run on a variety of devices, along with the in-built applications. Applications for an android device are written in the Java programming language and run on a virtual machine. The Android system software components themselves are written in Java, C and C++.

Programming in Java for Android carries forward most of the features found in regular Java programming. Java programs are portable and platform independent. It was built with the WORA (Write Once Run Anywhere) concept. This allows Android applications to be developed agnostic of the target device and compatible on multiple devices. This is particularly advantageous for EcoRouting software as extra hardware or installation is not required and users can simply install the EcoRouting application on their Android devices. Additionally, Android applications can be adapted to work with vehicles that support Android Auto with little modification. Android Auto is a technology that allows Android devices to extend an interface into the multimedia and the infotainment console system of a vehicle.

Programming in Java for Android presents several advantages over regular java programming. Android devices provide a continuous link to the internet while being mobile and portable. A major influencing factor for the choice of Android is the rich source of in-built libraries accessible through the Android SDK (Software Development Kit) that are absent in JDK (Java Development Kit). The Android framework provides abstracted access to web-services, device sensor data and UI (User Interface) rendering services specifically for routing and mapping applications. Lastly, the Android SDK allows applications to be tested on an Android device emulator running on the host system. This ensures robust testing of applications prior to being installed onto an actual Android device.

1.4 Geospatial Data

As mentioned previously, several route parameters are required in synthesizing a velocity profile for modeling the energy consumption. These route parameters are obtained through API (Application Programming Interface) calls to various web services. The required data is obtained by parsing the server responses to the API calls. The route parameters required are: route alternatives, road grades, stop sign locations, signal light locations and speed limits. While parameters like stop sign locations, signal light locations and speed limits decide the driving speeds and acceleration along the routes, road grades affect the power requirements at the powertrain to attain the required velocities. The impact of road grades on driver behavior is not studied in this thesis.

1.4.1 Google Maps Platform

The Google maps platform, available on the Android SDK, allows the addition of maps based on the Google maps data to an application. The SDK provides APIs to download data from Google servers, display maps, draw graphics on maps and handle UI responses to gestures [6].

Google Maps Directions API

The Google maps directions API is used to obtain route alternatives between any two locations through HTTP (Hypertext Transfer Protocol) URL (Uniform Resource Locator) requests. The two locations are obtained by geocoding the source and the destination addresses input by the user. The HTTP request takes several parameters as inputs along with the source and destination locations. A URL is then constructed with all the required input parameters based on the user inputs prior to making the HTTP GET request. The server responds by returning an output file containing data on multiple routes along with directions to traverse the routes in the form of either a JSON (JavaScript Object Notation) file or an XML (Extensible Markup Language) file, specified as a parameter in the request. The routes are composed of legs. Legs are further broken into smaller steps [7]. Individual steps are represented by encoding the collection of coordinates making up the step into a polyline. A polyline is a string of characters formed by encoding the numerical values of latitude-longitude pairs of a series of coordinates [5].

1.4.2 Discussion on routes returned by Google Maps API

The EcoRouting methodology in this thesis was developed as a path-planning problem. Construction of routes between a source and destination is possible but not approached given the high computational resource requirements and general difficulty in obtaining map data. The EcoRoute is determined from a set of routes returned by the Google Maps Directions API.

It is possible that the true EcoRoute may not be present in the set of routes determined by Google Maps Directions server between a given source and destination. However, the Directions API tries to determine the fastest routes between a source and a destination. Since travel-time is also considered in determining the optimal EcoRoute in the proposed methodology, a slower EcoRoute may not be the optimal route always since it is possible that such routes will be rejected due to higher travel-times.

The route data obtained from Directions API also contains the overall route travel times and travel times for the individual route segments, estimated by Google maps servers. Historically collected data obtained from users is used by Google Servers in predicting the fastest routes [13]. It is however unclear as to how exactly Google Maps servers determine routes between a source and a destination given the lack of literature and the proprietariness of methods used.

Google Maps Elevation API

The grade information for the routes are obtained using the Google Maps Elevation API. Using the collection of coordinates obtained by decoding the individual polylines for each step in a route, a URL is constructed and a HTTP GET request is made through the Google Maps Elevation API to obtain elevation data for all the coordinates making up the route [4].

1.4.3 OpenStreetMap (OSM)

Speed limits, stop signs and signal lights constrain the velocities attained by a vehicle on a route. OpenStreetMap offers several services to query its database to obtain various geospatial information. Using OpenStreetMap API services the data needed for velocity profile synthesis are obtained.

1.5 Previous work used in this thesis

A brief introduction to the Velocity Profile Synthesis methodology developed by Moniot [22] and the powertrain model developed by Tamaro is presented here.

1.5.1 Velocity Profile Synthesis

Moniot developed a Velocity Profile Synthesis Methodology based on the Hill Model for use with EcoRouting for HEVT [22]. Several methods for velocity profile synthesis use a constant acceleration model. Constant acceleration models require powertrains to produce unrealistic levels of power. Moniot implemented a piecewise jerk constant, where jerk represents the rate of change of acceleration per time, to produce a variable acceleration rate model to synthesize velocity profiles that more closely match real world driving.

The model, also called the full Hill model, takes into account several factors: maximum acceleration, minimum acceleration, maximum jerk, minimum jerk, initial velocity, final velocity, cruise velocity and distance in generating the velocity profile for all the modes of the route. The model can be calibrated to suit drivers of various levels of aggression through the use of tuning constants.

The full model for a mode comprises seven regions of piecewise jerk expressions. The 7 regions are shown in Figure 1.2

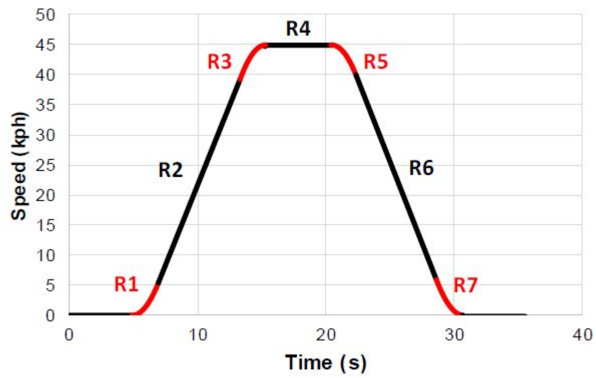

Figure 1.2: Velocity profile comprising of 7 regions [22]

The profile begins with maximum jerk at region 1, reaches maximum acceleration at the end of region 1, accelerates at the maximum rate in region 2, jerks to the cruising velocity in region 3 and then maintains the cruising velocity at zero acceleration in region 4. Regions 4,5 and 6 are symmetrical to regions 1, 2 and 3 with the jerk and acceleration being negative. The maximum acceleration/deceleration and jerk are derived from the maximum acceleration of the vehicle using the tuning constant for a particular driver's aggression level. In this thesis, a route is broken down into segments. A segment is the part of a route between stops. A segment here is the equivalent of a mode in Moniot's model.

1.5.2 Powertrain Model

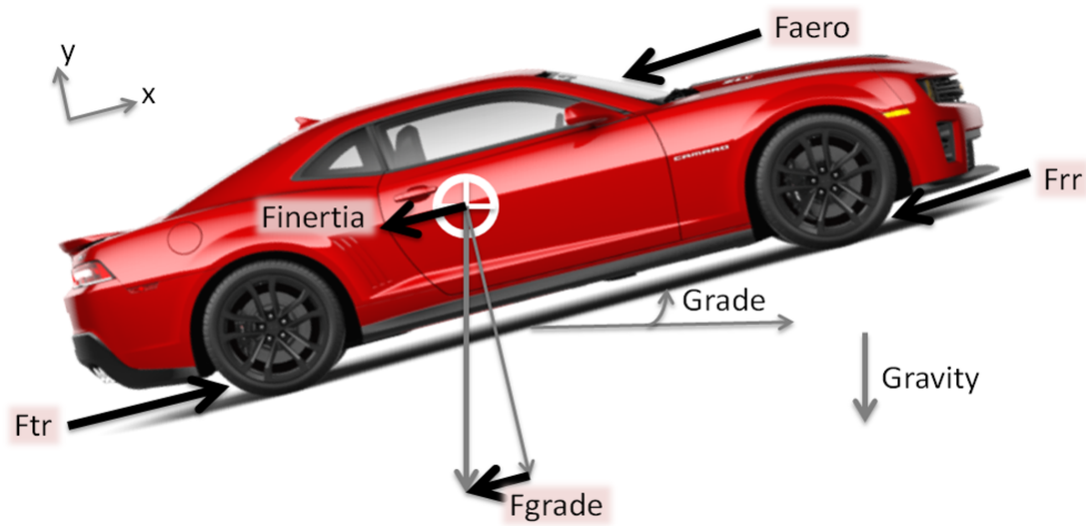

Figure 1.3: Tractive forces acting on a vehicle [25]

The velocity profile synthesis determines the velocities along the route at discrete points. This is input to the powertrain model [25] for energy consumption estimation. The powertrain model is backwards facing as energy and power are first calculated at the wheels and traced backwards through the powertrain components, all the way up to the energy storage system. By adding up energy estimates at each discrete point in the route, the total energy estimate is calculated. The tractive forces acting on a vehicle are shown in the free-body diagram in Figure 1.3.

1.6 Contributions of this thesis

An automation methodology to calculate the optimum EcoRoute based on existing data has been developed as part of this thesis. The automation methodology was implemented on the Android framework to be used as an on-board application on a mobile device in a vehicle. The methodology considers traffic lights, stop signs, speed limit signs and road grades between a user entered source and destination addresses in calculating the EcoRoute. Methods and sources for obtaining the required data automatically are also detailed. The methodology is verified against results of previously conducted studies and used to conduct further tests to determine the impact of various factors on energy consumption.

Existing research on EcoRouting automation or applications available in the market have been found to be closed-sourced and cannot be used to conduct further tests. The software methodology in this thesis was developed in a modular fashion for several reasons. The modular architecture makes addition of newer components easier while making it also suitable for modifications. The modules can be extended by modification to suit specific requirements. The methods described here use data from sources that are openly available on the internet and hence eliminates the need to collect data or obtain access to proprietary data. The methodology described can be programmed using any suitable language for any capable device. The developed software can also be modified to work on Java capable workstations for conducting further tests.

It was observed that existing research in literature generally published simulated results without providing an idea as to how proposed models would work in the real-world. To find the efficacy of the proposed methodology in actual driving conditions a study was conducted as part of this thesis to compare results of methodology simulation against measured energy consumption in actual driving. Studies were conducted to determine other factors that could affect energy consumption. A comparison of the synthesized velocity profiles generated in simulation to actual driving speeds and a study of the impact on energy consumption was also conducted. A main goal of this section is to determine how the proposed EcoRouting methodology compares to actual results, the accuracy of obtained data as compared to ground truth and to find any external factors that may or may not be captured in software methodology simulation but are present in real world affecting the energy consumption.

A traffic impact analysis was conducted to understand the impact of traffic on energy consumption. Using the HEVT Camaro as the basis simulations were conducted for different traffic conditions in determining the impact of traffic on travel time and energy consumption. A comparison study between results of simulation on the software methodology developed in this thesis and the results of traffic simulation for the HEVT Camaro was conducted to correlate between the prevailing traffic conditions and the conditions in software methodology. This study helps in understanding trade-offs between energy consumption and travel time in determining the optimal EcoRoute.

Chapter 2

Review of Literature

Current research on EcoRouting deals with conventional, hybrid and electric vehicles. EcoRouting research is aimed at reducing emissions and improving fuel economy for conventional vehicles, control strategies for hybrid vehicles and range maximization in electric vehicles typically.

2.1 Research on EcoRouting models

In this section, the research on EcoRouting models is discussed. A brief overview of current trends in EcoRouting is presented here.

Formulating a precise model for prediction of energy consumption is the major part of analysis in [20]. A macroscopic reformulation of a standard microscopic model is introduced which predicts consumption based on travel time, speed profile and speed profile skew. The analysis in this paper found consumption to be sensitive to input parameters, strongly dependent on the departure time and weakly sensitive to the characteristics of traffic information system processing.

The authors try to address three questions: Impact of input parameters to the model on energy consumption, dependence of energy consumption on the time of departure and the impact of traffic information systems on energy consumption prediction error. The energy consumption in the model is estimated from the tractive requirements at the wheels for the vehicle to overcome tractive forces encountered using input parameters: the travel time, velocity profile, road grades and vehicle specific parameters. Historically collected traffic data is used for traffic simulation and obtain the veocity profile. The number of vehicles in a road network for various times in a day is used to determine the dependency of consumption on time of departure. The authors note that consumption is chaotic, especially with respect to traffic conditions. Also, travel time predictions were found to be unreliable for congested traffic conditions. The model however, is not suitable for adoption on realistic vehicles as lossless vehicles are assumed in the model. Also, the model does not account for driver aggression.

A comparison of performance of existing EcoRouting methods is presented in [19]. Three EcoRouting methods are compared against the ability to lower energy consumption in simulated urban traffic. The methods were chosen from published literature such that the ideas used to achieve EcoRouting were different. The authors observed that the methods showed potential for energy savings and require better consumption estimates to attain.

The authors compared eco-routes to the fastest and shortest routes in order to determine trade-offs between travel time and energy consumption in an experiment consisting of a set of randomized trip source and destinations. The Eco-route, shortest route and the fastest routes are simulated separately such that the initial conditions remain same. It was found that models that use average vehicle characteristics as opposed to vehicle specific calibration did not work well in practice. Some models were found to favour shorter routes to be more economical always. Finally, it was found that the model that used a physical model of the vehicle resulted in most accurate estimates. This shows that tuning of models to suit the specific vehicle results in more accurate prediction of energy consumption, travel time and subsequently, an optimal EcoRoute.

A study of performance of models in predicting vehicular environmental impact is conducted in [17]. The authors have developed EcoMark, a framework for evaluating vehicular environmental impact models. Using the framework, the authors were able to classify models on suitability for EcoDriving or EcoRouting.

EcoMark uses GPS coordinate trajectories to correlate with map databases in building a spatial network as the input to the consumption model. 11 consumption models in existing literature are simulated within EcoMark. Instantaneous models that respond to real-time inputs were found to be suitable for EcoDriving. Aggregated models that depend on historically collected traffic and network data were found to be suitable for EcoRouting, suggesting that EcoRouting is more of a path-planning problem. The authors also found that models that considered road grades in estimation to be more accurate.

2.2 EcoRouting research in electric vehicles

Driving range has been one of the main obstacles to electric vehicle adoption. EcoRouting research on electric vehicles is mostly focussed on maximizing driving range. Typical areas of research include climate and HVAC system control optimization, powertrain modelling, charge scheduling etc. This section discusses the EcoRouting research on BEVs.

In [26], the authors propose model-based strategies to maximize driving range and optimize energy consumption by leveraging advanced driver assistance systems. An energy efficient route is suggested prior to the start of the trip using EcRouting strategies and during the trip, driving range prediction and optimal speed suggestion is suggested to the driver using EcoCoaching strategies. An overview of the system architecture is shown in Figure 2.1.

The EcoRouting solution between an origin and a destination is achieved by modeling the road network as a weighted directed graph. Energy and time weights are assigned to each route arc. The driving range is predicted by searching along the suggested path from the vehicle's current position in the graph. Real-time range prediction can also be achieved taking real-time traffic conditions and infrastructure into account in the model. Driving speed is one of the main inputs to the model. The authors observed reduction in energy consumption using this approach.

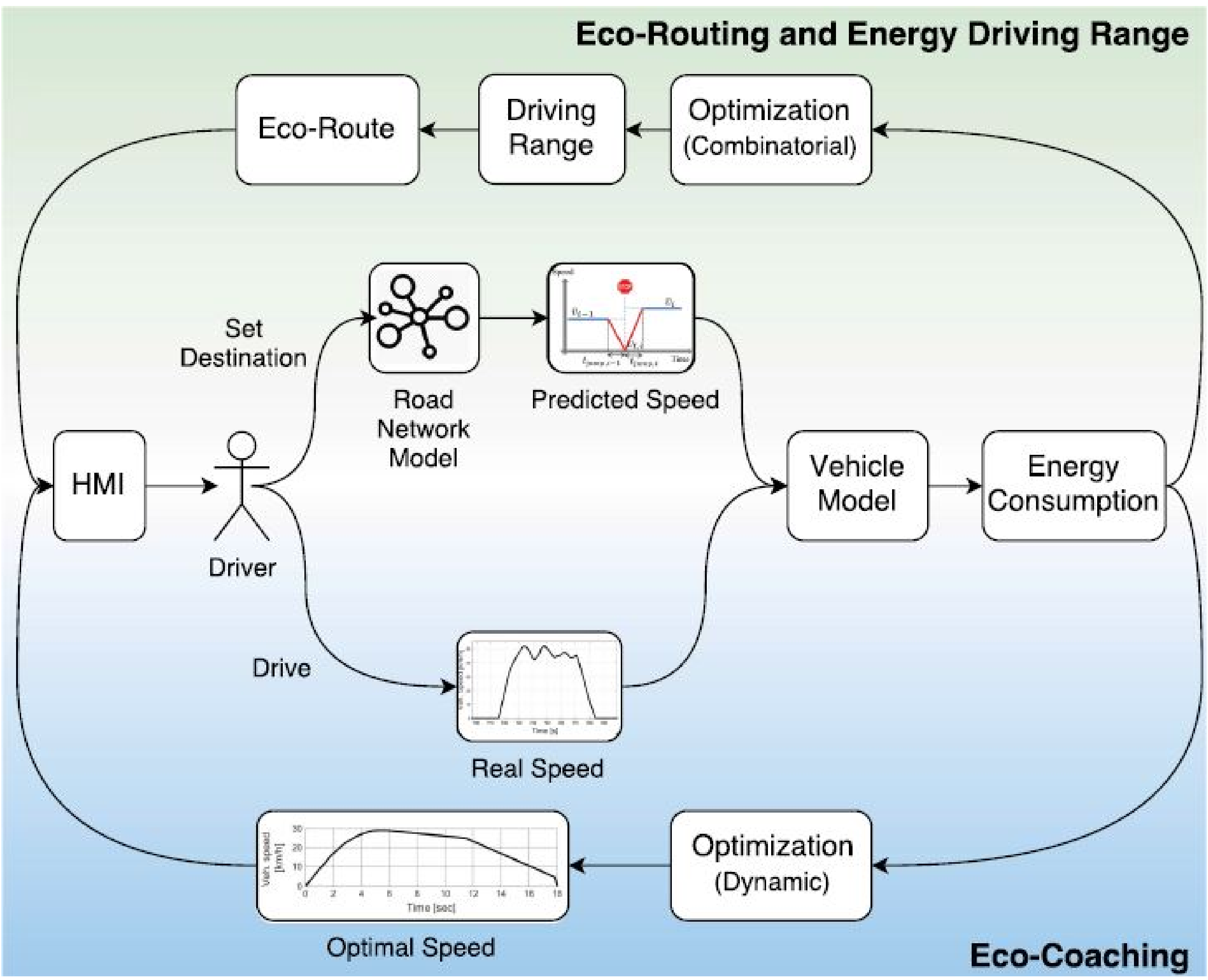

Figure 2.1: EcoRouting and EcoCoahing for range maximization [26]

The authors have not considered the impact of driver aggression in the modeling approach. Also, methods for obtaining data to construct the road network are also not studied.

In [28], the authors address difficulties faced by electric vehicles such as poor driving range that arise due to limitations in battery packs and battery lifetime degradation by optimizing the Heating, Ventilation, and Air Conditioning (HVAC) power consumption. The authors observed that the HVAC system alone could consume nearly 40% of total energy during a trip as shown in Figure 2.2. A methodology integrating navigation system and climate control is proposed.

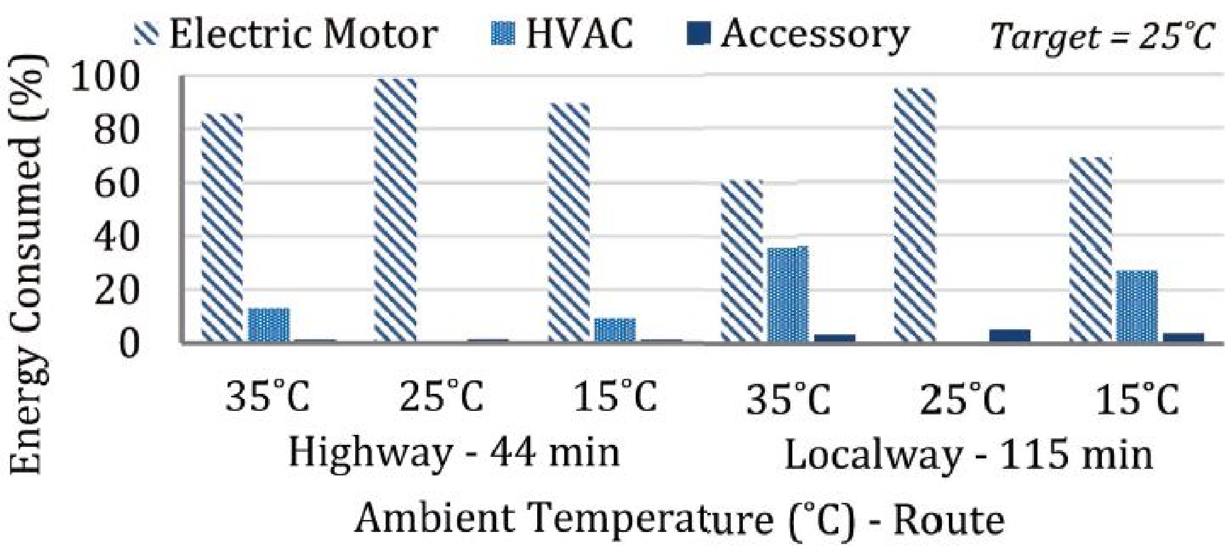

Figure 2.2: Energy consumption sources for different routes [28]

By integrating the navigation system and HVAC system into a model and utilising system components: Map database, route behavior and electric vehicle components: motor, accessories and HVAC, the authors observed upto 24% improvement in battery lifetime and 17% reduction in energy consumption.

While the authors have successfully utilized existing map database in determining the EcoRoute, a comparison of simulation results to actual driving was not conducted. A real-world test of the proposed system can provide a better idea about the efficacy of the model and also determine other factors that may or may not have been considered in the methodology. Also, the compromise on travel-time due to EcoRouting was not considered by the authors in the model. A compromise on travel-time to favour routes consuming lesser energy might inconvenience drivers.

Electric vehicle charging is a major issue faced by BEVs and has hindered EV adoption. The authors in [14] propose a charge scheduling and routing mechanism for a set of electric vehicles. A deviation of 24.22% and 20.15% from optimal results in average time and energy consumption respectively were observed under initial testing of the heuristic algorithm.

2.3 EcoRouting research in conventional vehicles

Typically, research on EcoRouting in conventional vehicles has been conducted in trying to reduce fuel consumption and emissions. This section of the literature review discusses the research on EcoRouting in conventional vehicles.

An average fuel savings of 3.3% to 9.3% as compared to traditional routing was observed by using EcoRouting on Cleveland and Columbus road networks in [9]. Similarly, reduction in HC, CO, NOx and CO2 emissions were also observed. The network-wide impact of EcoRouting was quantified on the two metropolitan networks by simulating on the INTEGRATION traffic simulation software. The authors concluded that the benefits of EcoRouting would increase with increased market penetration.

INTEGRATION can also be tweaked to simulate electric vehicles or hybrid vehicles by including the specific powertrain model. Also, a model specific to the vehicle can also be created for simulation. The authors have validated the EcoRouting models for light duty vehicles. The simulation software and the methodology, however, cannot be used on on-board applications as the road network has to constructed manually for every set of source and destination addresses.

Using historical link speed data, velocity profiles are recreated to calculate link fuel costs in [21]. The authors note that the speed profiles synthesised differ from actual driving speeds. However, the authors also conclude that map based attributes possess the potential in calculating EcoRoutes as route characteristics are influenced by location-based attributes. Fuel savings of upto 45% were observed in the field test and the factors influencing fuel consumption are speed profiles and accelerations.

Fuel savings of up to 33% at an expense of 3% increase in travel time was observed in experiments conducted by the authors in [15]. Developing a macroscopic, non-iterative algorithm to estimate fuel consumption forms the major part of research in this paper. The model takes into account route parameters such as stops, engine parameters obtained from the automaker, gearbox efficiency, average speed and air-resistance in estimating fuel consumption. The authors also report that proper gear shifting strategies in the case of manual cars can result in up to 25% fuel savings.

Analysing the impact of road grades on fuel consumption forms the major part of research in [29]. The fuel consumption difference between slope and flat road surfaces is observed to be higher in the 0 - 25 km/h range and a lesser gap is observed at higher speeds. Also, peak variance in fuel consumption is seen when the grade is 2.6% by the authors.

2.4 EcoRouting research in hybrid electric vehicles

Hybrid vehicles present additional difficulties as compared to conventional or electric vehicles. Hybrid vehicles typically aim to combine the best of both conventional and electric vehicles in one package. This creates the need for complicated control strategies. Research on EcoRouting in hybrid vehicles while trying to minimize energy/fuel consumption also focuses on the power-train control strategy. This section of the literature review discusses EcoRouting research on hybrid vehicles.

A semi-analytical solution of powertrain energy management is derived for hybrid electric vehicles (HEVs) based on a predicted speed model in [23]. The fuel consumption is predicted as a function of the trade-off between fuel economy and battery usage for each road segment. The novel road network model introduced by the authors takes into account the battery charge variation that is feasible at the road segment level. The model was able to achieve a desired final battery charge by determining an optimal power split. In [18], the authors propose a Combined Routing and Power-train Control (CRPTC) algorithm which calculates the optimal powertrain along with the optimal energy route. Unlike traditional approaches, the control strategy does not operate under the Charge Depleting First (CDF). CRPTC was shown to perform better than CDF by the authors. CRPTC selects either Charge Depleting (CD) mode or Charge Sustaining (CS) mode for each link based on the energy costs for the link in each mode. CRPTC was simulated using historical traffic data and compared against simuation on CDF. The comparison results are shown in Figure 2.3.

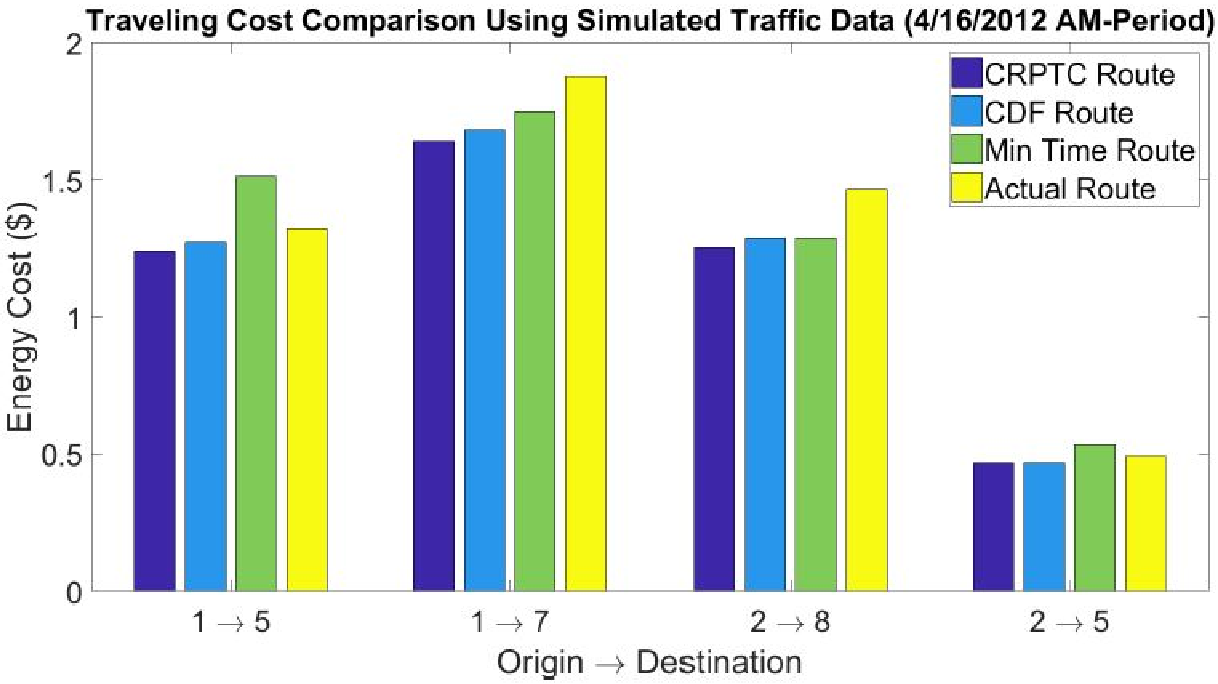

Figure 2.3: Perfromance of CRPTC against other routes [18]

The results show that typically, minimum travel-time rutes suffer from higher energy consumption. Actual energy consumption results were found to be usually greater than simulated estimates due to the presence of unforeseen circumstances or factors that are difficult to be captured in simulation. Also, traffic was found to play an impact on energy consumption as different traffic conditions at different times of the day resulted in different energy consumption estimates and results. Generally, energy consumption was found to be higher during times when traffic was more congested. However, the ranking of routes based on energy consumption remained the same for all traffic conditions. The variance of results between the routes was found to be least in the case of uncongested traffic.

2.5 Research on EcoRouting algorithms and solution computation

Various methods have been employed in literature for computing EcoRoutes. EcoRouting is typically a computationally resource intensive and requires many sources of data. This section of literature discusses the current state of challenges and difficulties faced due to complexity of EcoRouting algorithms and resources required in processing data for EcoRouting computation.

In [10], the authors discuss the challenges faced by EcoRouting services due to Spatial Big Data, which is defined as data of large volume and/or velocity incapable of being processed by current computing technologies. Typical examples of spatial big data are GPS track data of vehicles, roadmap data and engine data. Challenges faced by EcoRouting services include: Violation of non-stationary ranking of candidate solutions across departure times which can be addressed by a critical-time-point based approach, Lossless non-decomposability of some properties of n-ary relations between datasets into binary relations which can be solved by using Lagrangian Xgraphs. A difference between obtained data and the ground truth was found to affect the accuracy of energy consumption estimation. The authors also discuss future directions for addressing challenges faced in processing Spatial Big Data.

Crowd sourced data collected from on-board computers of vehicles and drivers can enhance the efficacy of EcoRouting systems substantially. The issue of privacy in data collection, as personal data of drivers can be misused without consent is addressed in [27]. Crowd-sourced data can be used to significantly improve accuracy of Distance-To-Empty predictions on vehicles. The framework for crowd-sourced data collection is shown in Figure 2.4. The authors propose a solution of matrix factorization from collaborative filtering to enhance privacy of crowd-sourced data.

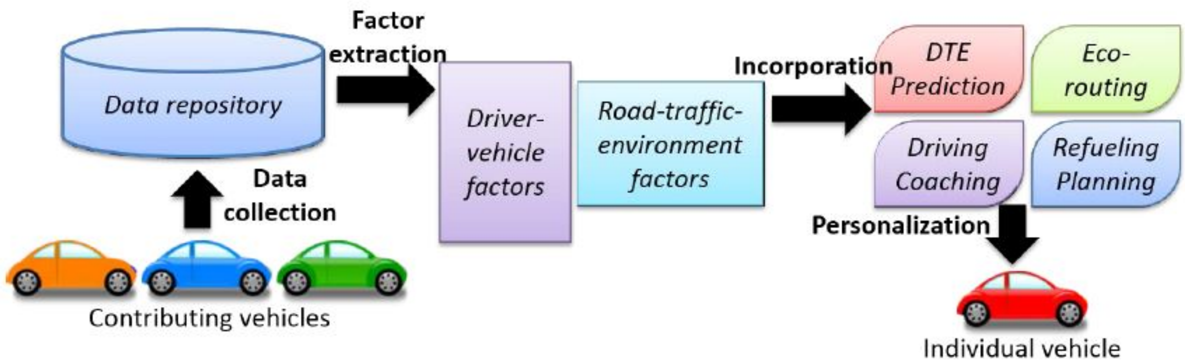

Figure 2.4: Framework for crowd-sourced data collection [27]

The authors introduce energy consumption prediction models based on privacy enhanced data. Laplacian mechanism is implemented to unsettle sensor data. Three levels of privacy settings for the application of laplacian mechanisms: Complete privacy, Type-revealing privacy and Identity-revealing privacy are implemented. The estimation errors of both models based on type-revealing privacy settings: Comparison with average and Matrix factorization were found to be within 10%.

2.6 Summary of Literature Review

The five sections of the literature review discuss the current state of technology and past research on various areas related to EcoRouting. Section 1 talks about research on EcoRouting models. General trends on EcoRouting models, the performance and their evaluation was studied and summarised here.

Sections 2, 3 and 4 discuss EcoRouting research specific to electric, conventional and hybrid vehicles respectively. Powertrain modeling methods, challenges and factors affecting the energy consumption of vehicles were studied. Driving range optimization, battery life optimization, various factors both internal and external, affecting the energy consumption and range prediction are some of the major topics of current research. Strategies that combine EcoDriving with EcoRouting are also studied and summarised here. Reducing fuel consumption and emissions are the major areas of research on conventional strategies. Fuel savings and emission reductions of different strategies are summarised in section 3. Other factors affecting fuel consumption, emissions and modeling approaches to estimating fuel consumption emissions were also studied. Section 4 focuses on existing research on EcoROuting strategies for hybrid vehicles. Apart from individual challenges affecting both conventional and electric vehicles pertaining to hybrid vehicles, a major area of research on hybrid vehicles is on designing and studying control strategies to obtain an optimum balance between powertrains while gaining fuel and energy savings.

Section 5 discusses the computational approaches and challenges faced in collecting and processing data for EcoRouting. Processing huge amounts of data, maintaining security and privacy of data sourced from users are some of the factors affecting widespread adoption of EcoRouting. Approaches that result in efficient processing of large data and secure data privacy are studied and the results are summarised.

A complete literature review of research on powertrain modeling and velocity profiles is presented by Tamaro [25] and Moniot [22] respectively.

Chapter 3

Automation Methodology

A major goal of the year 4 of EcoCAR3 competition was for teams to have fully integrated Camaros. This section discusses the details of the proposed methodology for automating the determination of the EcoRoute for usage in on-board applications.

The process of determining the EcoRoute is carried out in three major steps: route data import and processing, synthesizing the velocity profiles based on the route parameters, and calculating the energy consumption estimates using the specified powertrain model. An overview of the EcoRouting methodology is shown in Figure 3.1.

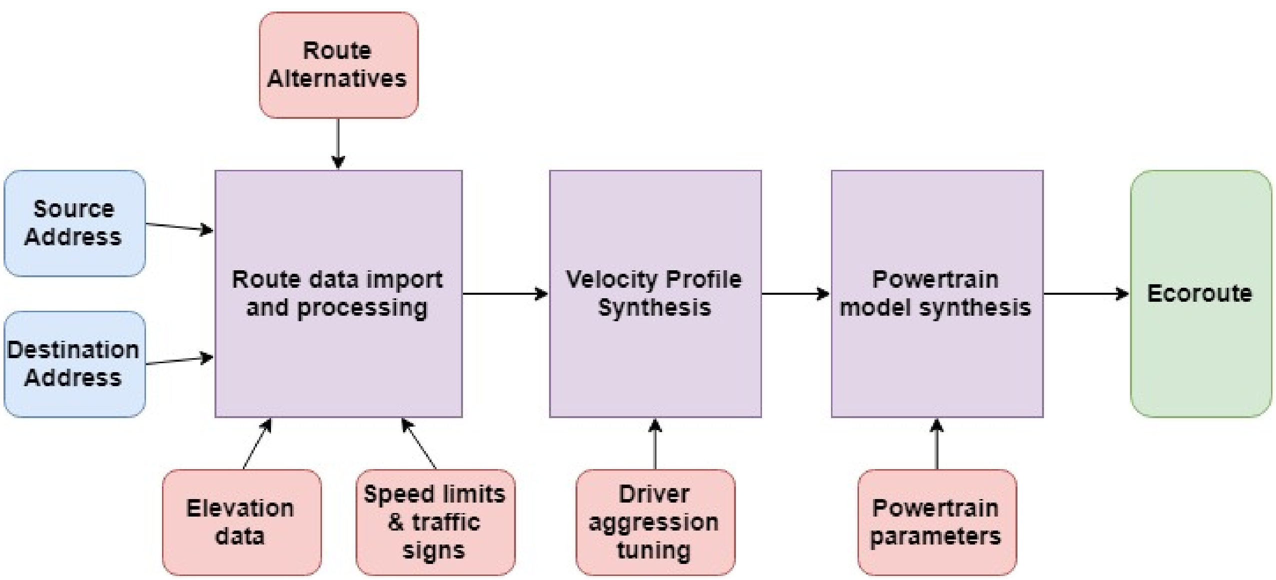

Figure 3.1: Software methodology overview

3.1 Route data import and processing

As mentioned in the earlier sections, several route parameters are required to synthesize the velocity profiles over each route alternative. The required data is imported by making API calls to various services. Usually the resulting data is in a form that is unusable directly in the code. The resulting data is therefore parsed, processed and stored in the program memory.

3.1.1 Maps Activity

At the front end of the software, the UI file gets inputs and displays outputs to the user. The file that interacts with the UI in the background is called maps activity. This is the main file where the program execution is started. When the user enters the application on a device, a screen is presented with textboxes to enter the source and the destination addresses as shown in Figure 3.2.

As soon as the user enters the source and destination addresses and presses the search button, the function linked to the search button retrieves the string data from the respective fields. Reverse geocoding is then performed using the Google Maps Geocoder API to obtain the latitude and longitude coordinates for the source and destination addresses. Using the source and destination coordinates the directions API request URL is constructed. A HTTP GET request is then performed using the constructed URL to obtain route alternatives from the source to the destination.

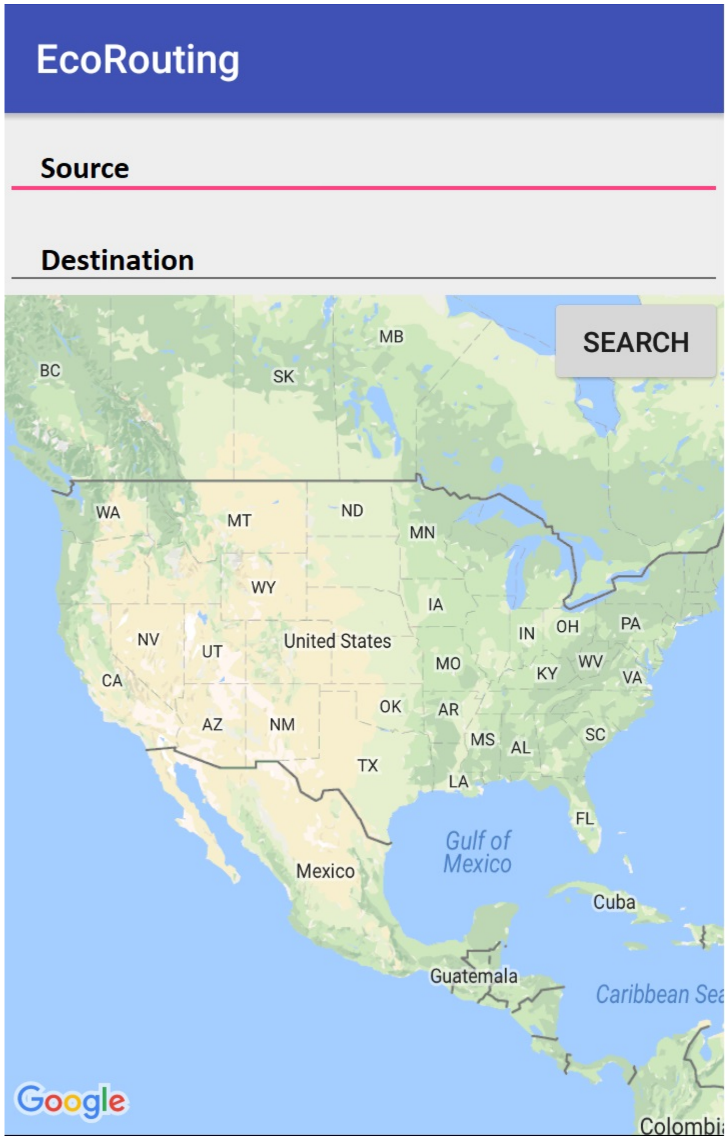

Figure 3.2: EcoRouting android application UI: start page

After parsing the JSON file resulting from the direction API HTTP request, the route alternatives are separated into route objects for parallel processing. At this point control is transferred to individual threads of operation spawned from the main program to process each route object. After the threads complete processing their respective route objects, control is transferred back to maps activity with the energy consumption estimates. The routes are then rendered on the UI to the user with different colors based on the energy consumption estimation values as shown in Figure 3.3.

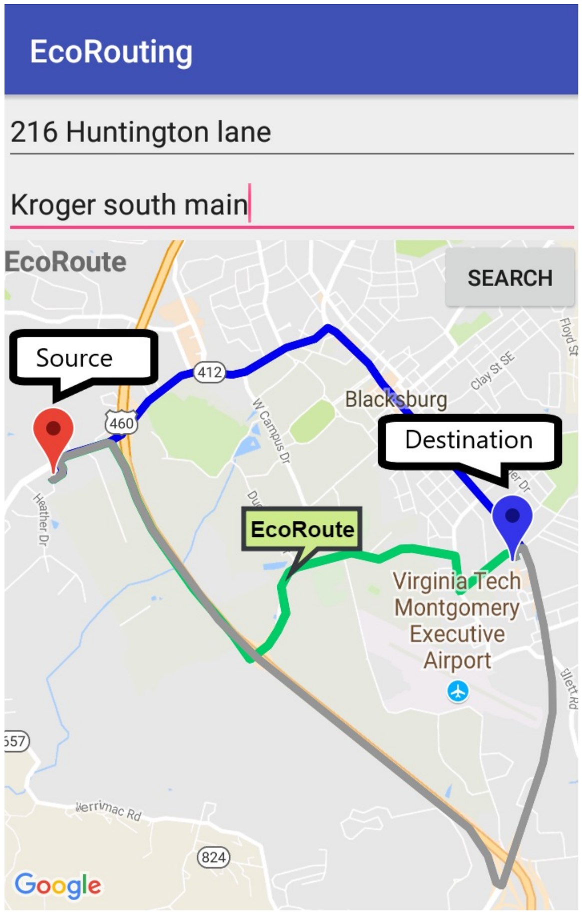

Figure 3.3: EcoRouting android application UI: output page

3.1.2 Route object

The maps activity file creates a thread for each route alternative. At the time of thread creation, the route object is initialized with the JSON object from the processed directions API result file. Maps activity then initiates the thread execution. The steps carried out to determine the energy consumption across each thread are same. Since the route alternatives are independent of each other, processing is parallelized to yield results faster.

When execution starts in a route object, the first step is to get speed limits, stop sign locations, traffic sign locations and elevations over the route. As mentioned earlier, OpenStreetMap services are used for this purpose, the Overpass API in particular. The API takes a rectangular bounding box of coordinates comprising the north, south, west and east bounds as input and returns an XML file containing various datasets. In the dataset a node uniquely corresponds to a latitude-longitude coordinate on the road network, identified by a unique node identifier. All the nodes within the bounding box are first listed with the coordinates and the node Id. Nodes corresponding to traffic signs and stop signs are identified with special tags that have key-value relations. Figure 3.4 shows a sample section of the XML file containing a list of nodes.


```
<node id="216380165" lat="37.2275952" lon="-80.4405313"/>
<node id="216396543" lat="37.2129310" lon="-80.4066518"/>
<node id="216396566" lat="37.2141690" lon="-80.4076282"/>
<node id="216398366" lat="37.2248976" lon="-80.4248795"/>
<node id="216412107" lat="37.2208961" lon="-80.4230185">
  <tag k="crossing" v="uncontrolled"/>
  <tag k="highway" v="crossing"/>
</node>
<node id="216425695" lat="37.2258237" lon="-80.4433441"/>
<node id="216427601" lat="37.2210552" lon="-80.4228502"/>
<node id="216428685" lat="37.2203529" lon="-80.4076808"/>
<node id="216432017" lat="37.2191765" lon="-80.4026531"/>
<node id="216432513" lat="37.2256215" lon="-80.4252140"/>
<node id="216438920" lat="37.2155627" lon="-80.4062752"/>
<node id="216440123" lat="37.2091506" lon="-80.4050309"/>
<node id="216441656" lat="37.2173421" lon="-80.4191600">
  <tag k="highway" v="traffic_signals"/>
</node>
```


Figure 3.4: List of nodes: sample

OpenStreetMap identifies a segment of a road as a way. Each way is uniquely identified using a way ID. A way is an ordered collection of nodes from the road map making up the segment of the road [1]. The placement of nodes along the way is such that when nodes are joined end to end, it follows the geometry of the road. The line joining any two nodes is a straight line. A straighter section of a way will be made up of lesser number of nodes as compared to a curved section as a curved section needs to be broken into much smaller straight line segments to represent the geometry of the road more accurately. This is shown in Figure 3.5

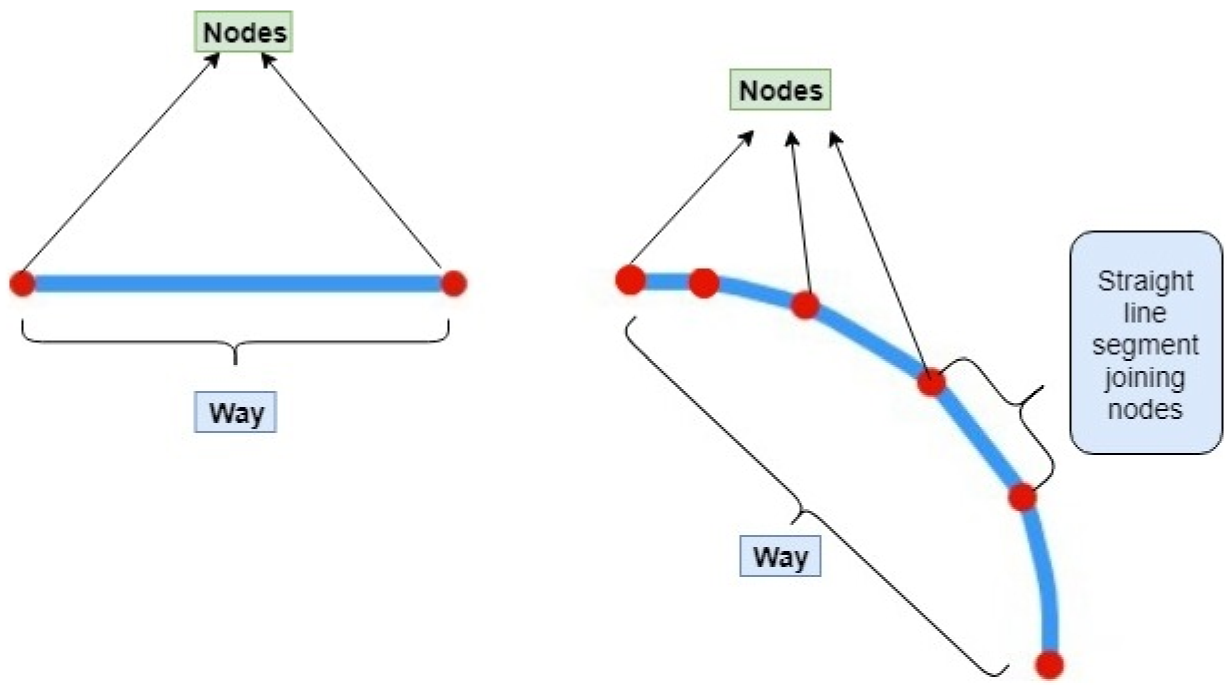

Figure 3.5: Road geometry: a) straight section b) curved section

The XML file output contains only ways and sections of ways present within the bounding box. Along with the nodes making up a way, additional information about the way are given in tags. Examples of additional information include speed limit, number of lanes, type of road etc. Figure 3.6 shows typically how the information about a way is organized in the XML file. The way, identified by the unique ID: 131420406, has four nodes: 712707650, 712707025, 726763676 and 726760572. The speed limit is given in the value field of the tag ”maxspeed”. The speed limit for this particular way is 35mph. Regional speed limits around the way are given as values for the tag ”bburg:maxspeed”.

```xml
<way id="131420406">
  <nd ref="712707650"/>
  <nd ref="712707025"/>
  <nd ref="726763676"/>
  <nd ref="726760572"/>
  <tag k="bburg:dataset" v="rcl"/>
  <tag k="bburg:id" v="438;438;757;785;805;818;852;868;888;905;726;667;674;694"/>
  <tag k="bburg:maint" v="Blacksburg"/>
  <tag k="bburg:maxspeed" v="25.0;25.0;35.0;35.0;35.0;35.0;35.0"/>
  <tag k="bburg:name" v="MAIN"/>
  <tag k="bburg:type" v="ST"/>
  <tag k="highway" v="primary"/>
  <tag k="lanes" v="4"/>
  <tag k="lanes:backward" v="2"/>
  <tag k="lanes:forward" v="2"/>
  <tag k="lit" v="yes"/>
  <tag k="maxspeed" v="35 mph"/>
  <tag k="name" v="South Main Street"/>
  <tag k="ref" v="US 460 Business"/>
  <tag k="sidewalk" v="both"/>
</way>
<way id="133434564">
  <nd ref="216441656"/>
  <nd ref="721784659"/>
```


Figure 3.6: Example: Way data

Figure 3.7 shows a visual representation of nodes and ways inside a bounding box plotted on a map. The XML file is parsed and data is organized into node and way objects. A node or a way object encapsulates the data required by the program in a form accessible by code using placeholders and variables, visualized in Figure 3.8. Hashmaps storing node and way object data as key-value pairs are constructed to retrieve data from a node or a way by querying using the unique ID as key value.

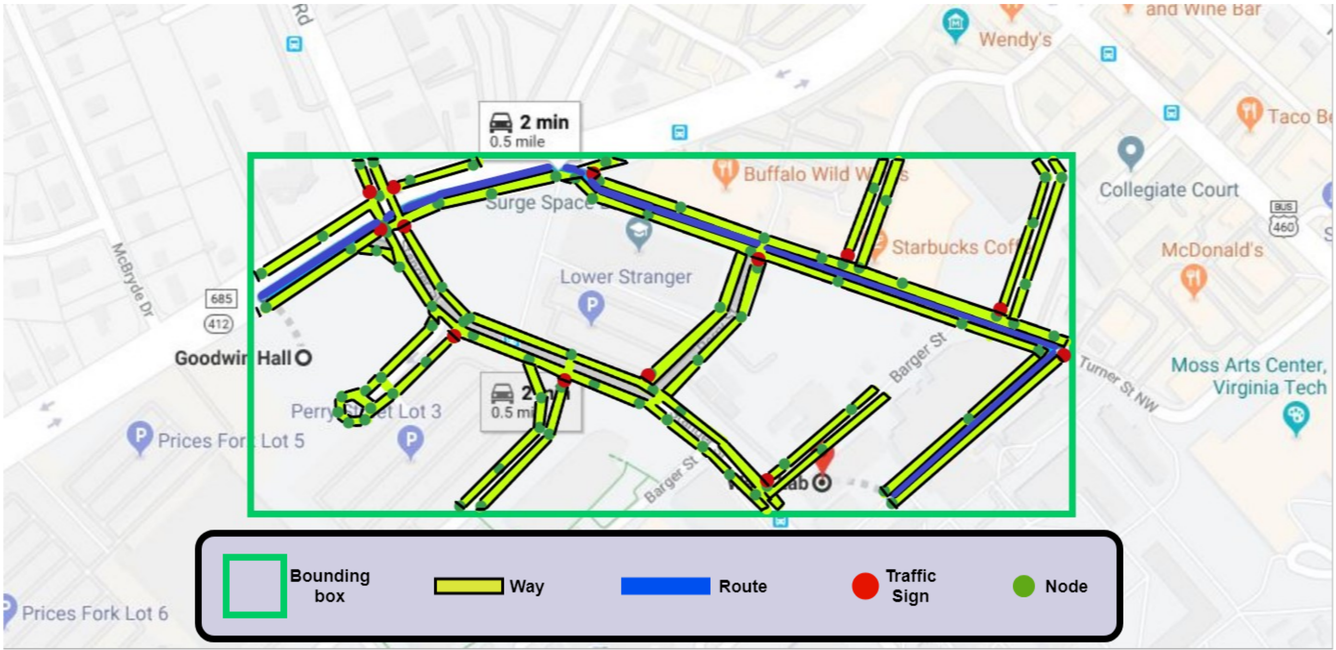

Figure 3.7: Representation of nodes and ways inside a bounding box on a map

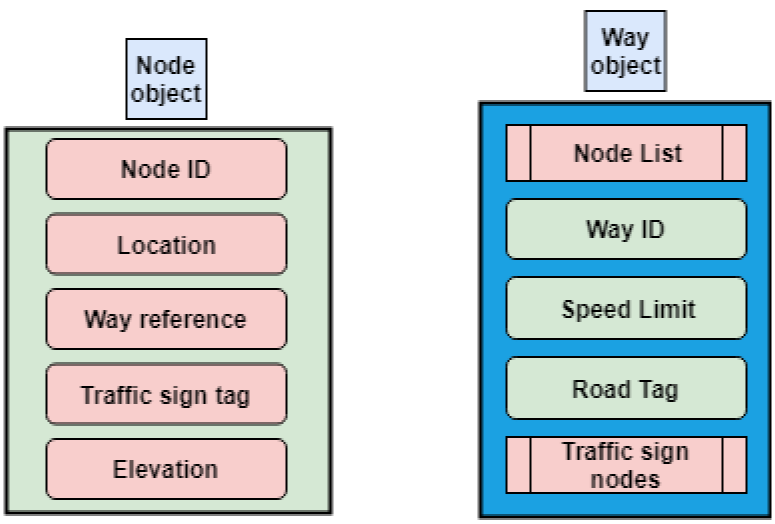

Figure 3.8: Node and way placeholders: a) Node object b) Way object

.

As seen in the Figure 3.7, the XML file contains comprehensive data on all the nodes and ways within the bounding box area. The actual route is only comprised of certain nodes and ways within the bounding box. It is thus required to filter out nodes and ways corresponding to the route from the hashmaps. More precisely, since a route is represented as a polyline when data is obtained from the Google maps directions API, the series of coordinates obtained from the decoded polyline string need to be matched with the nodes and ways in the OpenStreetMap dataset. This presented a problem since the same way is represented using a different series of coordinates in the Google polyline as compared to the coordinates of the nodes making up the way in the OpenStreetMap dataset. Figure 3.9 shows a set representation of the disjoint between the Google polyline coordinates and the OpenStreetMap nodes for the same way.

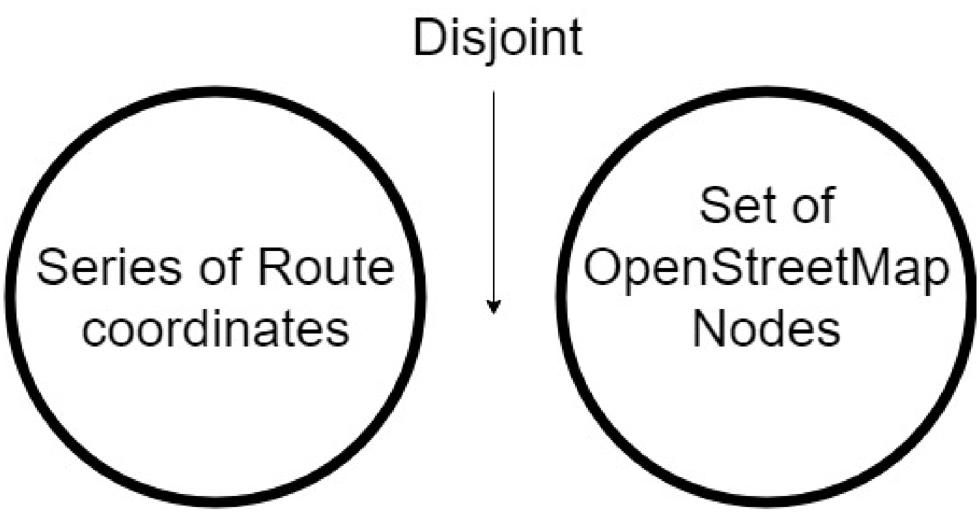

Figure 3.9: Disjoint subsets of route coordinates and OpenStreetMap nodes

Figure 3.10 shows the geographical representation of a way on a map using: a) Google polyline points and b) OpenStreetMap way nodes.

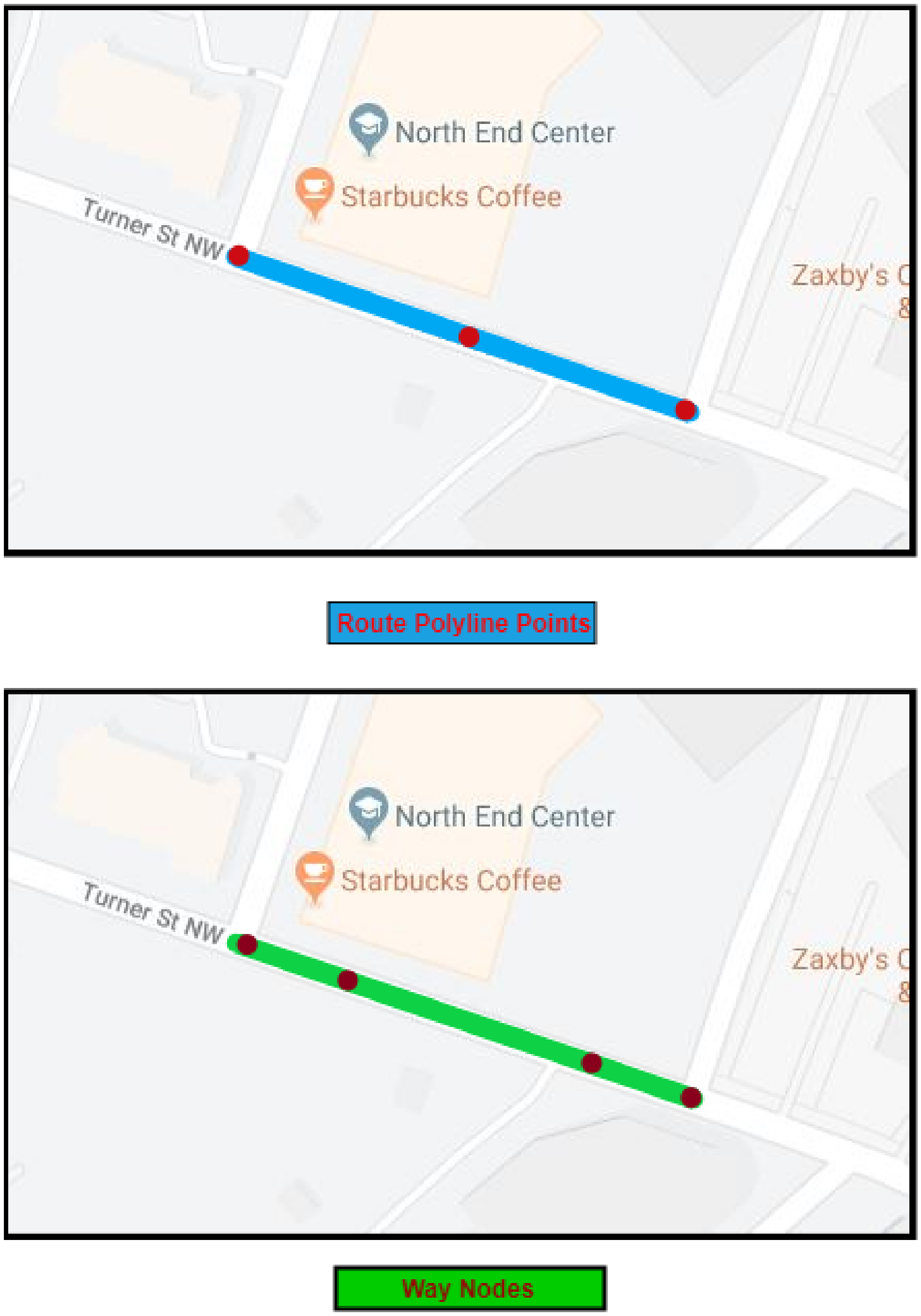

Figure 3.10: Route points and way nodes: a) Route polyline points b) Way nodes

Route Matching and Match objects

OpenStreetMap provides a matching service that takes a series of GPS points as input and snaps it to its road network of nodes and ways [8]. This service is used on the series of coordinates from the decoded route polyline. The matching service returns the equivalent or the nearest OpenStreetMaps node IDs for the route polyline points in an ordered matchings array. The node IDs in the matchings array are used to query the node hashmap constructed to retrieve node data. However, it was found that certain nodes obtained through the matching service were absent in the hashmap dataset obtained from the overpass API. It was also found that these nodes particularly belonged to residential roads and freeway ramps. The set representation is shown in Figure 3.11.

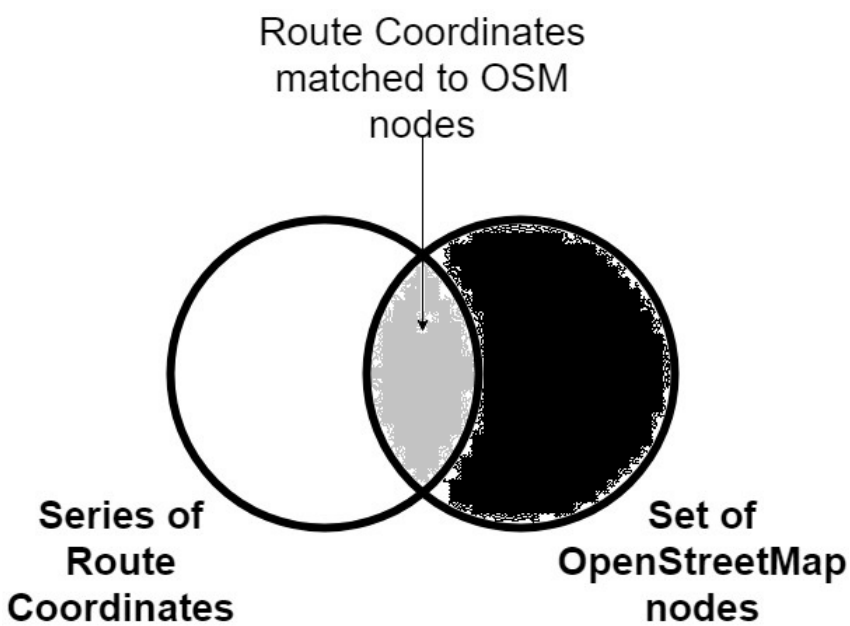

Figure 3.11: Union between subsets of route coordinates and OpenStreetMap nodes

Since the matching service returned only the node IDs and no corresponding node data, it was not possible to obtain node data for the matchings nodes that were absent in the hashmap. It was also observed that such nodes appeared together in order and were not randomly scattered along the route. By querying OpenStreetMap specifically for such nodes, data on traffic sign placements are obtained. An OpenStreetMap query for data on the first appearance of an absent node also yields data on the way the node is part of, along with other nodes in the way. This prevents further, separate HTTP API calls for data on each consequent absent node as the node and way hashmaps would be updated with data on nodes in the vicinity of the first node, hence eliminating the need to make costly API calls. Separate API calls for each absent node was prevented. It was particularly useful since the number of such absent nodes were significant and each API call created a bottleneck.

Average time taken for an API call	746 ms
Max Time recorded for an API call	1562 ms
Number of absent nodes	122
Total number of calls made	9

Table 3.1: Analysis of API calls for absent nodes

From Table 3.1, it can be seen that by keeping the number of calls made to only 9, nearly 85 seconds of computational time was saved on average for processing a particular route.

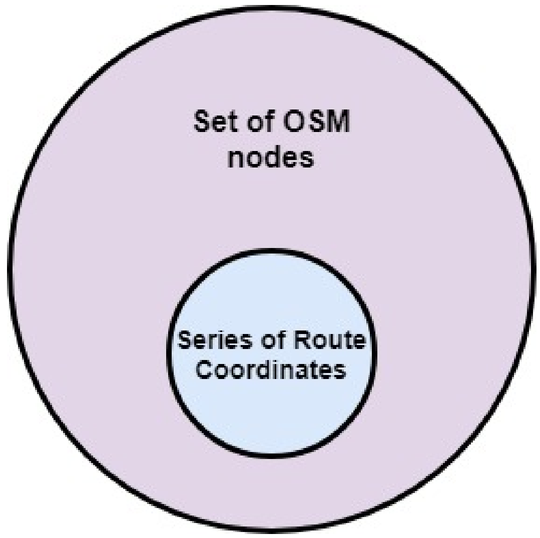

Figure 3.12: Route coordinates completely matched to OpenStreetMap nodes

With the route coordinates now associated with OpenStreetMap nodes, the only remaining piece of data yet to be retrieved is the elevation data to calculate road grades. The series of coordinates are passed as input to Google maps Elevation API. The resulting JSON file of results is parsed and the corresponding elevation value is filled in the associated match object, thus encapsulating all data pertaining to a node inside the same object.
The resulting array of matchings nodes obtained by parsing the output JSON file is encapsulated with the route coordinate in a match object as shown in Figure 3.13

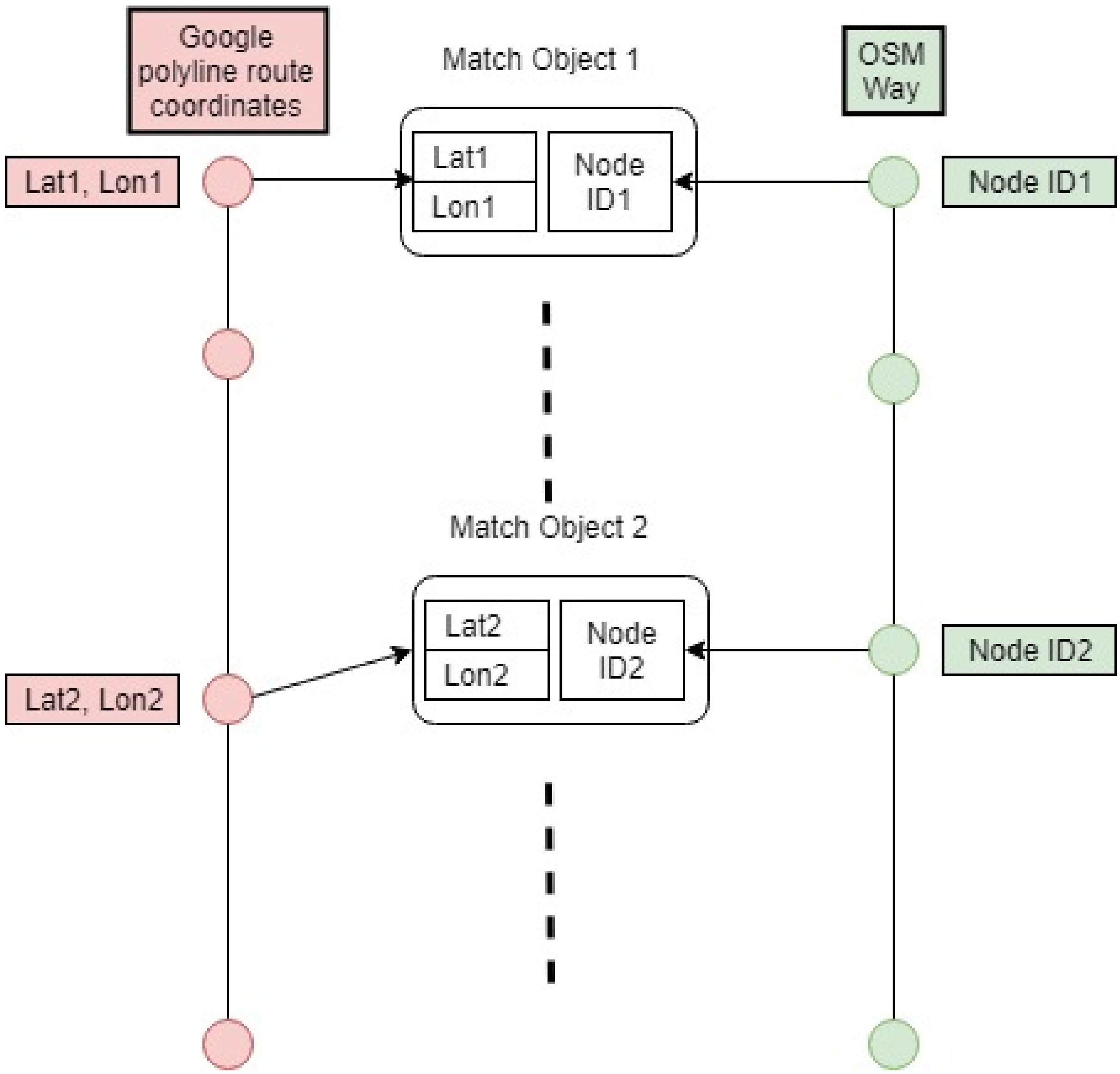

Figure 3.13: Match object encapsulating coordinates and node ID

3.1.3 Grade Computation

Road grades over the route are computed from the elevation data of match objects. The grade is calculated over a distance resolution of 40 meters between two match objects. This is done to account for errors in accuracy of elevation data. The grade between two match object nodes is calculated as shown below.

$Grade(\%) = (Rise/Run * 100)$

where, Rise = Difference in elevation between the nodes, and Run = Distance between the two nodes.

A sample plot of grade and elevation changes over the distance of a route is shown in Figure 3.14.

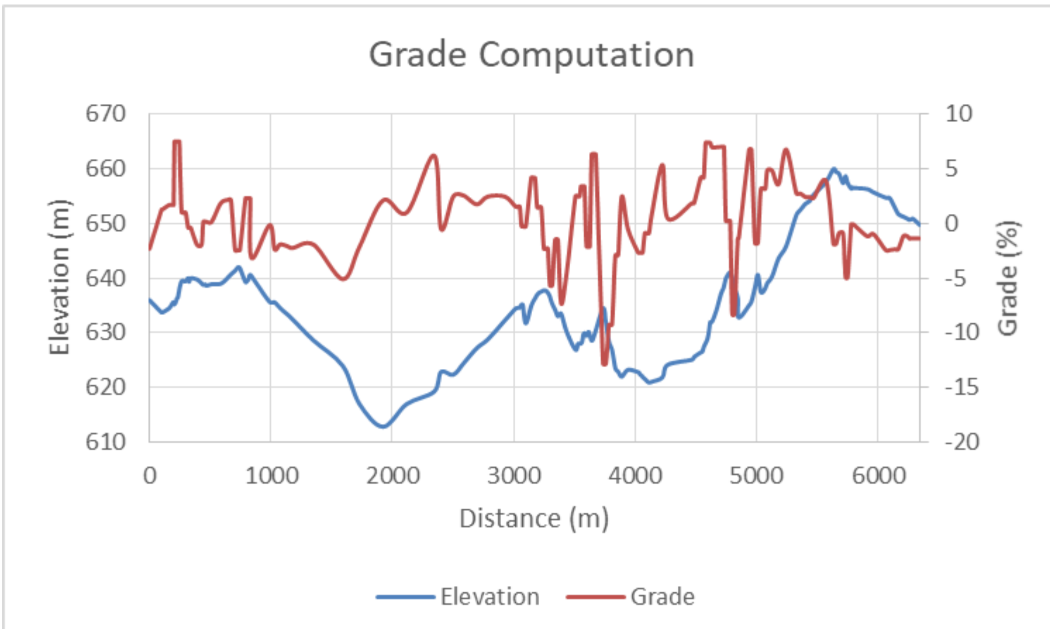

Figure 3.14: Grade and Elevation vs Route Distance

Speed Limit association

Speed limits over the route are associated with the nodes by tracing the way the node is part of and then retrieving the speed limit of the corresponding way object. For this purpose, during parsing and creation of a way object, all the nodes inside the way are referenced in order in an array inside the way object. Additionally, inside each node the way objects the node is part of are also referenced. Hence it is possible to access both the way objects a node is part of, from the node object and, all the nodes in a way, from the way object. Also, nodes corresponding to traffic lights or stop signs are specifically marked inside the node object. Some nodes, particularly ones corresponding to road intersections will be part of more than one way. It is important to pick the right way for a node to avoid discontinuities and inconsistencies in associating speed limits with the node. Figure 3.15 demonstrates a scenario where picking the wrong way for a node results in associating the wrong speed limit and hence creating inconsistencies. Here, the nodes on Way 1 correspond to the route being considered. Data and nodes for Way 2, which is present inside the bounding box for the route, is also present in the stored dataset, along with data and nodes for Way 1. Way 1 has a speed limit of 35mph, the speed limit for the route and way 2 has a speed limit of 25. Ways 1 and 2 have a node common in the intersection.

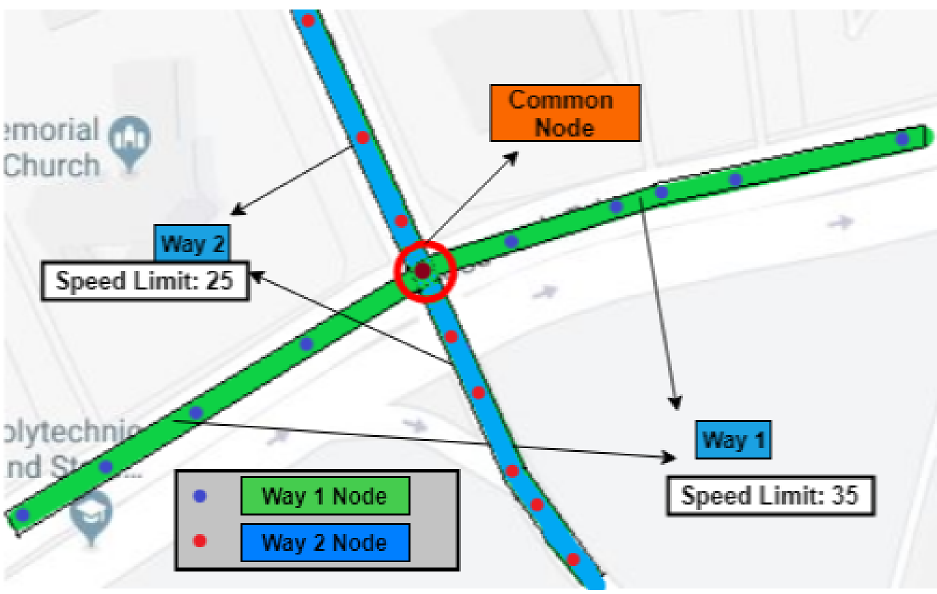

Figure 3.15: Node common between two different ways

Speed limits for the route are processed by accessing the nodes on way 1 in order, and associating the node with the speed limit of the corresponding way. While associating the speed limit for the common node, a choice of either associating it with the speed limit of way 1 or the speed limit of way 2 is presented. Associating the common node with the speed limit of way 2 would be incorrect and create an inconsistency. To solve this problem, while retrieving the way for the nodes of a route in order, a count of the number of times a way is accessed is maintained. For each way access from a node, the way access count is incremented. The count of number of way accesses for all the nodes in the route are first updated, prior to associating speed limits. The nodes are then accessed in order and the speed limits are associated. While associating the speed limit for a common node, the speed limit of the way with the higher count is chosen. In the scenario shown in Figure 3.15, way 1 will have an access count of 10 and way 2 will have an access count of 1. While choosing the way for the common node to associate speed limit, way 1 will be chosen since it has a higher access count than way 2.

Traffic sign node insertion

A list of nodes marked for both traffic signs: traffic signals and stop signs, are maintained for each way object. When determining the ways for the nodes along the route, the positioning of the traffic sign nodes in the route is also determined. The traffic signs nodes are then inserted in the appropriate positions along the route.
Finally, with all the data required for synthesizing the velocity profile for a route imported, the route has to be broken down into smaller segments for velocity profile synthesis.

3.1.4 Route segments

A segment is the equivalent of a mode in [ref], the reference used for velocity profile synthesis. The series of match objects making up the route is divided into segments. Splitting of the route is done at positions corresponding to traffic signals or stop signs. A segment of nodes is encapsulated within a segment object. Each segment carries additional data about the segment along with the nodes: the initial velocity, determined from the velocity of the first node, the cruise velocity, determined from the speed limit and the final velocity determined from the velocity of the final node or a speed limit change, if any.

3.2 Velocity profile and powertrain model synthesis

After the processed route data is organized into segments, velocity profiles are generated for each segment. A full mode is made up of 7 regions. In constrained cases synthesizing all 7 regions for a segment may not be necessary. The dynamics of each region in a segment are calculated first. The regions are spaced and acceleration timed such that an upcoming speed limit is reached as the sign is passed.

3.2.1 Model description

Prior to synthesizing the velocity profiles a few parameters need to be defined specific to driver aggression and the vehicle.

a_{max} = Maximum acceleration

a_{min} = Maximum deceleration rate = $-1 \cdot a_{max}$

α = Acceleration tuning constant

j_{max} = Maximum acceleration = $\alpha \cdot a_{max}$

n = Jerk tuning constant

j_{min} = Maximum negative jerk = $-1 \cdot n \cdot j_{max}$

Parameters α, n, a_{max} and a_{min} are driver aggression specific. An aggressive driver will accelerate and decelerate at a higher rate and is reasoned that, will also jerk between acceleration rates sharply. In other words, the vehicle will not only accelerate at a higher rate but also attain the maximum acceleration sooner in the case of an aggressive driver. A higher value for α, n, a_{max} and a_{min} should be chosen for aggressive drivers. The segment parameters,

$V_0 =$ Initial Velocity

$V_c =$ Cruise Velocity

$V_f =$ Final Velocity

With these parameters defined the dynamics for regions are next set as follows.

$\Delta\_tR1 = a_{max}/j_{max}$

$\Delta\_tR3 = (-1 \cdot a_{max})/j_{min}$

$\Delta\_tR5 = a_{min}/j_{min}$

$\Delta\_tR7 = (-1 \cdot a_{min})/j_{max}$

$\Delta\_vR1 = j_{max} \cdot (((\Delta\_tR1)^2)/2)$

$\Delta\_vR3 = (j_{min} \cdot (((\Delta\_tR3)^2)/2)) + (a_{max} \cdot \Delta\_tR3)$

$\Delta\_vR5 = j_{min} \cdot (((\Delta\_tR5)^2)/2)$

$\Delta\_vR7 = (j_{max} \cdot (((\Delta\_tR7)^2)/2)) + (a_{min} \cdot \Delta\_tR7)$

$\Delta\_tR2 = ((V_c - \Delta\_vR1 - \Delta\_vR3 - V_0)/a_{max})$

$\Delta\_tR6 = ((V_f - \Delta\_vR5 - \Delta\_vR7 - V_c)/a_{min})$

$\Delta\_xR1 = ((j_{max} \cdot (\Delta\_tR1^3))/6) + (V_0 \cdot \Delta\_tR1)$

$v\_1 = ((j_{max} \cdot (\Delta\_tR1)^2)/2) + V_0$

$v\_2 = (a_{max} \cdot \Delta\_tR2) + v\_1$

$\Delta\_xR3 = ((j_{min} \cdot (\Delta\_tR1^3))/6) + (a_{max} \cdot (\Delta\_tR3^2)/2) + (v\_2 \cdot \Delta\_tR3)$

$\Delta\_xR2 = (a_{max} \cdot ((\Delta\_tR2)^2)/2) + v\_1 \cdot \Delta\_tR2$

$\Delta\_xR5 = ((j_{min} \cdot (\Delta\_tR5^3))/6) + (V_c \cdot \Delta\_tR5)$

$v\_5 = ((j_{min} \cdot (\Delta\_tR5)^2)/2) + V_c$

$v\_6 = (a_{min} \cdot \Delta\_tR6) + v\_5$

$\Delta\_xR7 = ((j_{max} \cdot (\Delta\_tR7^3))/6) + (a_{min} \cdot (\Delta\_tR7^2)/2) + (v\_6 \cdot \Delta\_tR7)$

$\Delta\_xR6 = (a_{min} \cdot ((\Delta\_tR6)^2)/2) + v\_5 \cdot \Delta\_tR6$

$\Delta\_xR4 = X - (\Delta\_xR1 + \Delta\_xR2 + \Delta\_xR3 + \Delta\_xR5 + \Delta\_xR6 + \Delta\_xR7)$

$\Delta\_tR4 = \Delta\_xR4/V_c$

$v\_3 = ((j_{min} \cdot (\Delta\_tR3^2)/2) + (a_{max} \cdot \Delta\_tR3) + v\_2)$

$v\_4 = V_c$

$v\_7 = ((j_{max} \cdot (\Delta\_tR7^2)/2) + (a_{min} \cdot \Delta\_tR7) + v\_6)$

$\Delta\_tR6 = ((V_f - \Delta\_vR5 - \Delta\_vR7 - V_c)/a_{min})$

where,

$\Delta\_tR1 =$ Region 1 time difference

$\Delta\_tR3 =$ Region 3 time difference

$\Delta\_tR5 =$ Region 5 time difference

$\Delta\_tR7 =$ Region 7 time difference

$\Delta\_vR1 =$ Region 1 velocity difference

$\Delta\_vR3 =$ Region 3 velocity difference

$\Delta\_vR5 =$ Region 5 velocity difference

$\Delta\_vR7 =$ Region 7 velocity difference

$\Delta\_tR2 =$ Region 2 time difference

$\Delta\_tR6 =$ Region 6 time difference

Δ_xR1 = Region 1 distance difference

v_1 = Velocity at the end of Region 1

v_2 = Velocity at the end of Region 2

Δ_xR3 = Region 3 distance difference

Δ_xR2 = Region 2 distance difference

Δ_xR5 = Region 5 distance difference

v_5 = Velocity at the end of Region 5

v_6 = Velocity at the end of Region 6

Δ_xR7 = Region 7 distance difference

Δ_xR6 = Region 6 distance difference

Δ_xR4 = Region 4 distance difference

Δ_tR4 = Region 4 time difference

v_3 = Velocity at the end of Region 3

v_4 = Velocity at the end of Region 4

v_7 = Velocity at the end of Region 7

Δ_tR6 = Region 6 time difference

The full description of the velocity profile synthesis model can be found in [22]. Using the region dynamics described above, a velocity profile is synthesized for each segment by interpolating points between the segment nodes. The interpolated points are spaced with a time resolution of 0.1 seconds. The velocity profile outputs synthesized for each interpolated point are fed as input to the backwards facing powertrain model described in [25] to estimate energy consumption.

3.2.2 Verification and validation

Warpe, in [30] conducted a case study and calculated the energy consumption estimates on three routes in the city of Blacksburg, Va. In the case study a 2013 Nissan Leaf is selected as the vehicle for powertrain model simulation. The software methodology described in this thesis is validated against the results from [30]. Warpe used OpenRouteService, a cartographic platform that provides routing information, to obtain routes between the source and destination, GPS Visualizer to obtain elevation data, and, OpenStreetMaps to obtain positions of traffic signals, stop signs and speed limits in his case study. The process for determining the EcoRoute in the study involved manual intervention in several stages. To validate the automation methodology proposed in this thesis, a comparison of results against Warpe's study was made for the same set of source and destination addresses, choice of aggresission and driver aggression calibration.

Figure 3.16 shows an overview of the routes selected for the validation study. The routes are the same, albeit with a slight difference in route 3. Route 3 in the validation study differs from Warpe's case study due to the construction of a new exit in place of a traffic signal, thus changing the geometry. While having become longer it now also has one mandatory stop less. The source and the destination addresses for the routes however, remained same for both Warpe's case study and the validation study in this thesis. The summary of routes is shown in Table 3.2.

Route	Length (Old)	Max Speed	No. of Stops (Old)
1	3.6 miles	40	15
2	5.6 miles	65	11
3	3.9 miles (3.5)	65	8 (7)

Table 3.2: Summary of Routes for validation

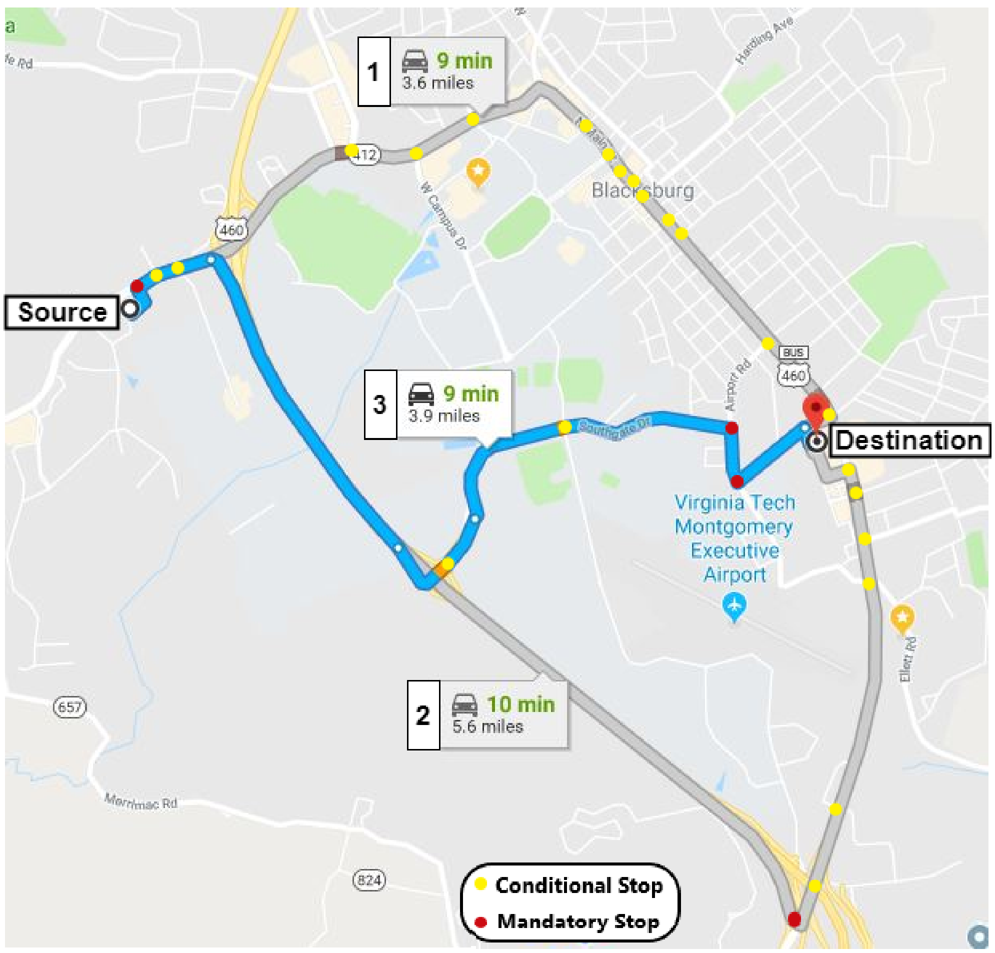

Figure 3.16: Overview of routes in the Blacksburg case study

Route 1 consists of urban driving and thus encounters 15 mandatory and conditional stops. Route 2 consists of mostly highway driving over a distance of 5.6 miles. Route 3 is a mixture of both highway and urban driving.

Results of Validation

Using the aforementioned source and destination addresses as input to the software, the energy consumption estimates were calculated over the three routes. The parameters used for synthesizing the velocity profile are shown in Table 3.3. Values of 0.5 and 0.3 for α and n, respectively, were chosen since the values resulted in velocity profiles that closely matched real world driving behavior [22]. Also, as the study in this thesis was aimed at validating against the case study conducted by Warpe, it was important to choose these values as the same values were chosen by Warpe in his case study as well.

Parameter	**Value**
a_{max}	1.5
a_{min}	-1.5
α	0.5
j_{max}	0.75
n	0.3
j_{min}	-0.225

Table 3.3: Parameters for validation

Simulation was done on the routes for 2 cases: A) considering all conditional stops (traffic signals) as mandatory stops and, B) considering only mandatory stops (stop signs). Table 3.4 shows the comparison of travel times and average speeds for the three routes for both cases A and B between the two studies. Table 3.5 shows the comparison of results of wheel energy and the predictive terminal energy estimation on the two case studies. The wheel energy, or the tractive energy is the energy required at the wheels to overcome the tractive forces encountered by the vehicle due to forces of: aerodynamic resistance, rolling resistance, inertia and grade. The values from Warpe's case study are given in the column labeled 'W' and the values from the validation study conducted in this thesis are given in the column labeled 'V'.

	Distance		**Stops**		**Time**		**Average Speed**	
	miles		**#**		**s**		**mph**	
	W	**V**	**W**	**V**	**W**	**V**	**W**	**V**
Route 1A	3.49	3.58	15	15	784	796	16	16
Route 1B	3.49	3.58	3	3	448	460	28	28
Difference	-	-	-12	-12	-42%	-42%	75%	73%
Route 2A	5.45	5.54	11	11	757	769	26	26
Route 2B	5.45	5.54	3	3	489	499	40	40
Difference	-	-	-8	-8	-35%	-35%	55%	54%
Route 3A	3.34	3.90	7	8	509	563	24	25
Route 3B	3.34	3.90	5	4	441	492	27	28
Difference	-	-	-2	-4	-13%	-13%	15%	18%

Table 3.4: Validation: Time and average speed

	Distance		Wheel Energy		Terminal Energy	
	miles		kJ		kJ	
	W	V	W	V	W	V
Route 1A	3.49	3.58	1199	1235	2450	2541
Route 1B	3.49	3.58	1316	1350	2145	2205
Difference	-	-	8.9%	8.5%	-14.2%	-15.2%
Route 2A	5.45	5.54	3263	3327	4799	4888
Route 2B	5.45	5.54	3550	3599	4706	4815
Difference	-	-	8.1%	7.5%	-2.0%	-1.5%
Route 3A	3.34	3.90	1719	2006	2647	3080
Route 3B	3.34	3.90	1778	2071	2640	3117
Difference	-	-	3.3%	3.1%	-0.3%	1.2%

Table 3.5: Validation: Wheel and Terminal energy

The software methodology described in this thesis was able to estimate similar values for travel times, average speed, wheel energy and terminal energy on routes 1 and 2 for both cases A and B. The route distances were slightly higher in the validation study since the software methodology in this thesis used different sources to obtain route information between the source and destination. Due to longer distances, the travel times, naturally, were also higher. The average speed values for all three routes in both the cases in the validation study were within 0.99% of the values in Warpe's case study. The differences in wheel and predictive terminal energy values between the two studies are shown in Table 3.6

Route	Wheel Energy Difference	Terminal Energy Difference
#	%	%
1A	2.96	3.74
1B	2.54	2.78
2A	1.97	1.86
2B	1.36	2.31
3A	16.68	16.34
3B	16.47	18.08

Table 3.6: Differences in energy estimates between studies

A maximum wheel energy difference of 2.96% was observed on route 1 for case A and a maximum predictive terminal energy difference of 3.74% for the same case. These differences can be attributed to the slightly longer distances and differences in other data between the two different sets of sources of information used in routing.

Route #	Wheel Energy (Wh/mile)		Terminal Energy (Wh/mile)	
	W	**V**	**W**	**V**
Route 1A	95	96	195	197
Route 1B	105	105	171	171
Route 2A	166	167	245	245
Route 2B	181	180	240	241
Route 3A	143	143	220	219
Route 3B	148	147	219	222

Table 3.7: Wh/mile comparison between studies

Table 3.7 shows a comparison of wheel and terminal energy between the studies in Wh/mile. The results obtained in the validation study are consistent with values obtained in Warpe's study.

In the case of route 3, higher average speeds were observed in the validation study as compared to Warpe's case study. The absence of a traffic light while transitioning from a highway to urban roads resulted in higher speeds. The section of route 3 that was changed since Warpe conducted the case study is shown in Figure 3.17.

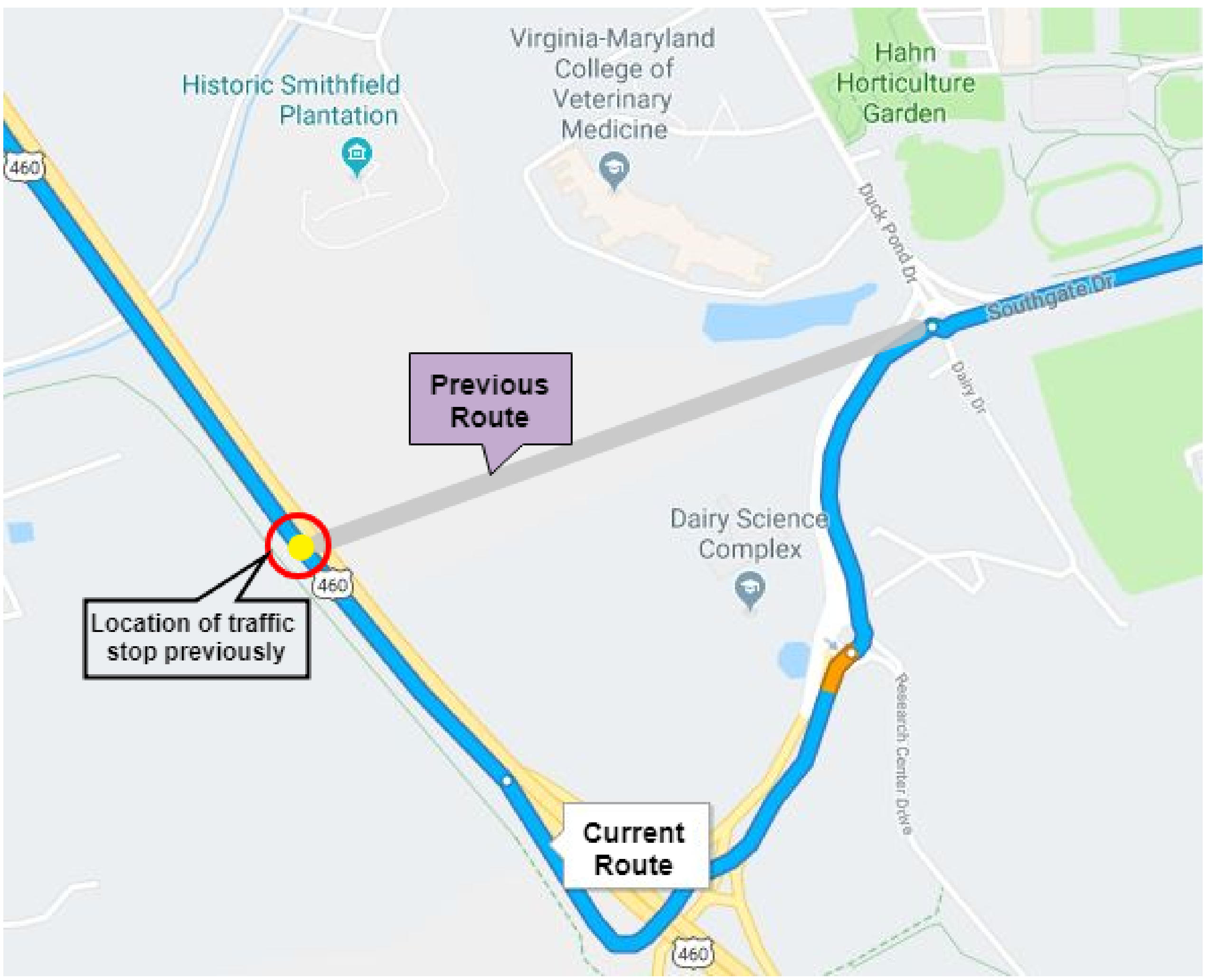

Figure 3.17: Difference in route 3 sections

The values from simulation results for route 3, as predicted, were different and in the case of energy consumption, higher. To analyze the impact of route changes in route 3 on the overall energy consumption, two simulations were conducted on a part of route 3: the new part, comprising the current section that has changed and the old part, comprising the previous section. The simulation captured values between 2 points on the route chosen such that the current section and old section would fall in between the points.

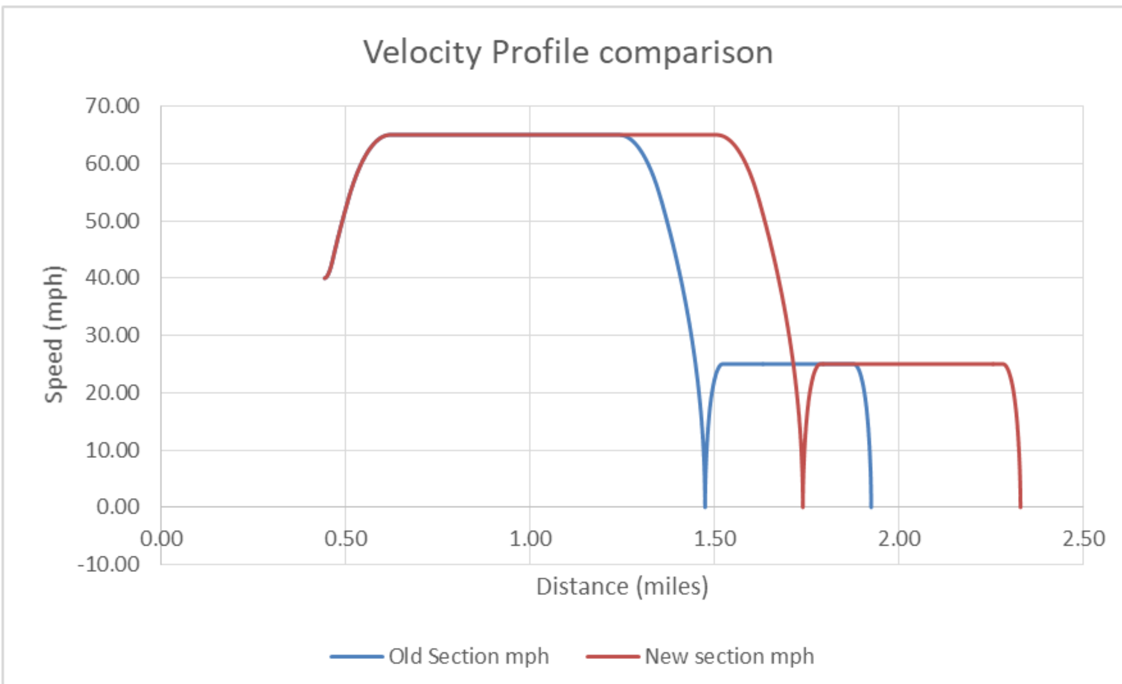

Figure 3.18: Velocity profile comparison in route 3: differences

A comparison of velocity profiles on the old and the new sections is shown in Figure 3.18. The section between the two points is longer in the current route. In Table 3.8, it can be seen that the changes in route 3 contribute to the differences in values between the previous case study and the current one. The differences in Table 3.8 account for majority of the differences seen in Table 3.4 and Table 3.5. The difference in distance accounted by the changes in route 3 was 0.4 miles out of the total difference of 0.56 miles. A time difference of 34.8 seconds was accounted by the route changes, out of the total 54.5 seconds. 273.53 kJ out of 287kJ in wheel energy difference and 384.17kJ out of 432.56kJ in predictive terminal energy differences were similarly accounted for due to the changes in route 3. The rest of the differences can be accounted for due to differences in route data sources, similar to routes 1 and 2.

	Previous section	**Current Section**	**Difference**
Time (s)	114	149	35
Distance (metres)	3098	3750	651
Wheel energy (kJ)	187	460	273
Terminal energy (kJ)	533	917	384

Table 3.8: Difference in values on the changed section of route 3

3.3 Results

With the software methodology validated on a 2013 Nissan leaf to predict the EcoRoute among a choice of route alternatives, the software was put to test under various inputs to better understand the impact of factors influencing total energy consumption along a route. The impact of factors like road grades, driver aggression tuning, cruising speed and acceleration are studied in this section. A route segment of total distance 1000 meters was chosen for simulation under various input conditions. The powertrain model of the 2013 Nissan leaf was chosen for this simulation.

3.3.1 Sensitivity study: Driver aggression vs energy consumption for different cruise speeds

To better understand the impact of driver aggression at different speed limits on energy consumption, simulations were performed to estimate the energy consumption for different speed limits over a combination of different values of driver aggression tuning, acceleration rates and road grades. Values of a_{max} simulated were $3m/s^2$, $2m/s^2$ and $1m/s^2$. An a_{max} value of $3m/s^2$ corresponds to a 0 to 60mph acceleration time of 8.94 seconds while an a_{max} value of $1m/s^2$ corresponds to a 0 to 60mph acceleration time of 26.82 seconds. a_{min} for all cases was set to $-a_{max}$. Driver aggression tuning constants α was kept same as n. The values of α simulated were 0.75 and 0.5.

This study was conducted to determine whether lower driver aggression levels resulted in higher energy consumption due to the longer times spent by the vehicle in overcoming the tractive forces.

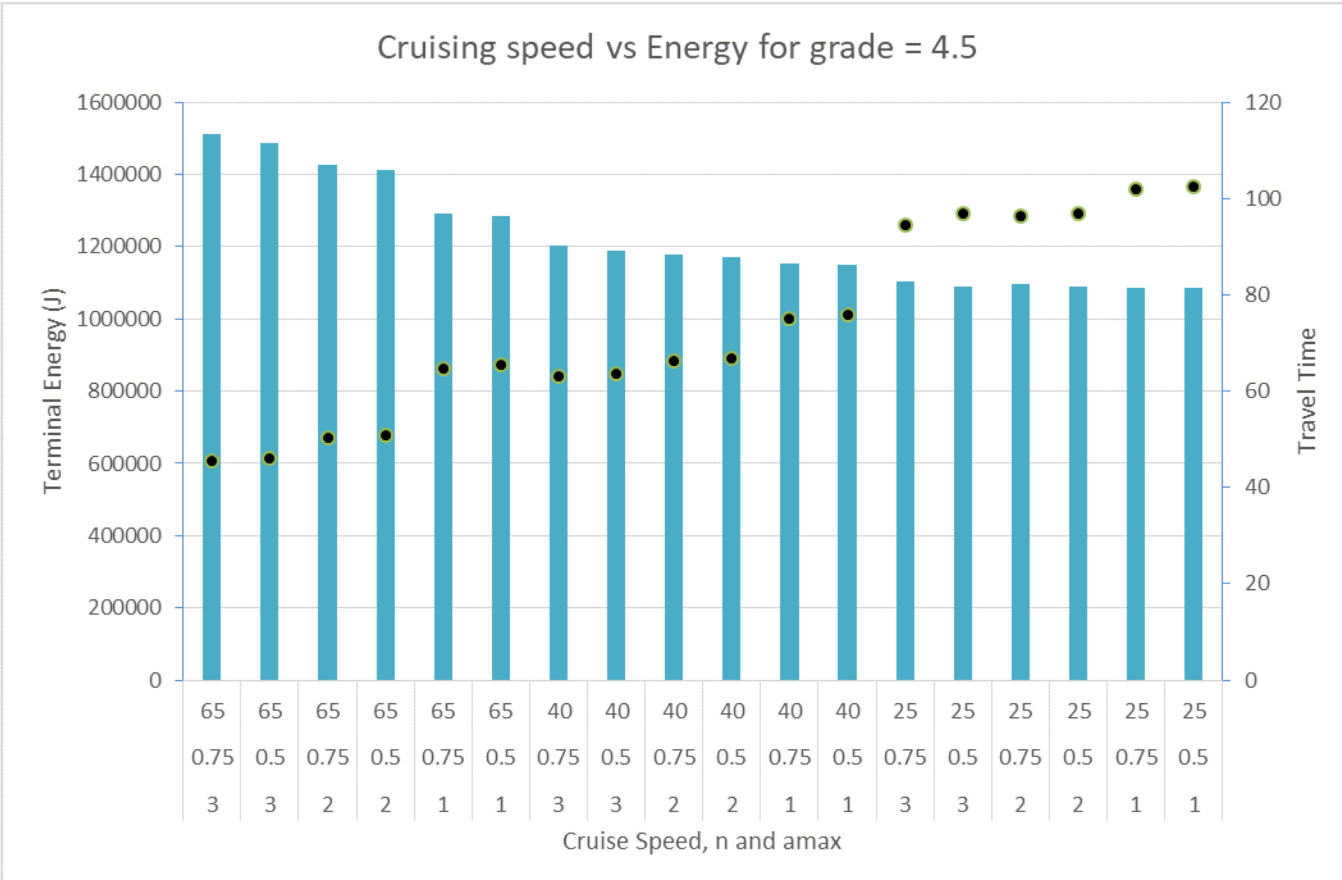

Figure 3.19: Cruise speed vs energy consumption at grade = 4.5%

Figures 3.19, 3.20, 3.21, 3.22 and 3.23 show plots of terminal energy consumption versus different cruising speeds when grade is kept constant at 4.5%, 3.0%, 1.5%, 0% and -1.5% respectively. The solid blue bars represent the energy consumption estimate for a particular case while the green dots represent the travel time in seconds. While an increase in speed limit, driver aggression level or acceleration rate generally resulted in lower travel times and higher energy consumption values, it can be seen that in some cases this ordering does not hold. The energy consumption estimates for a speed limit of 40mph at $a_{max} = 3$ and $\alpha =$ 0.75 or 0.5 are lower than the estimates when the speed limit was 65 at a lesser acceleration rate of $a_{max} = 1$ and similar aggression levels of $\alpha = 0.75$ or 0.5.

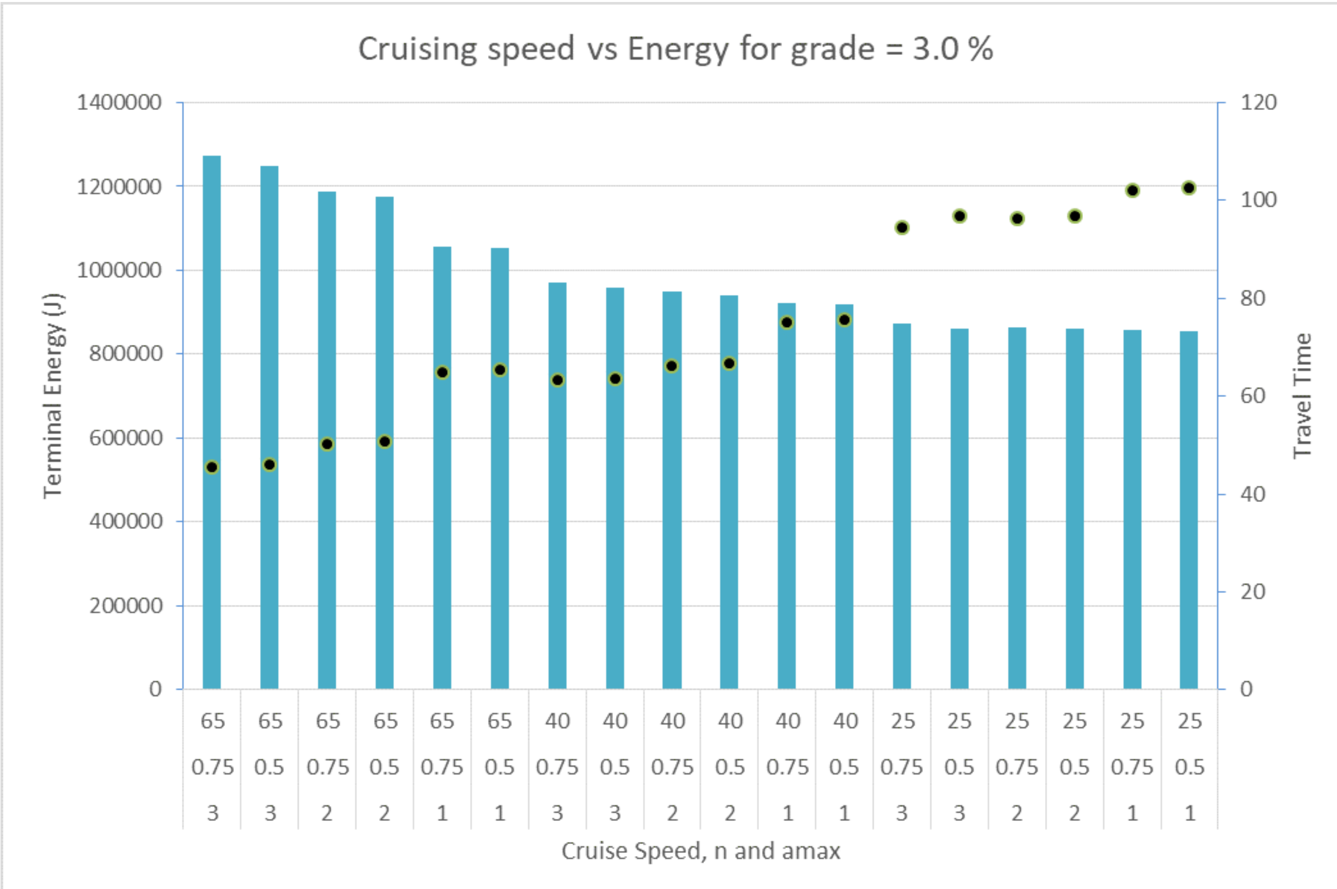

Figure 3.20: Cruise speed vs energy consumption at grade = 3.0%

Similar observations can be made for any value of grade. A route choice with a higher speed limit does not always necessitate shorter travel times if the driver employs different levels of aggression between routes.

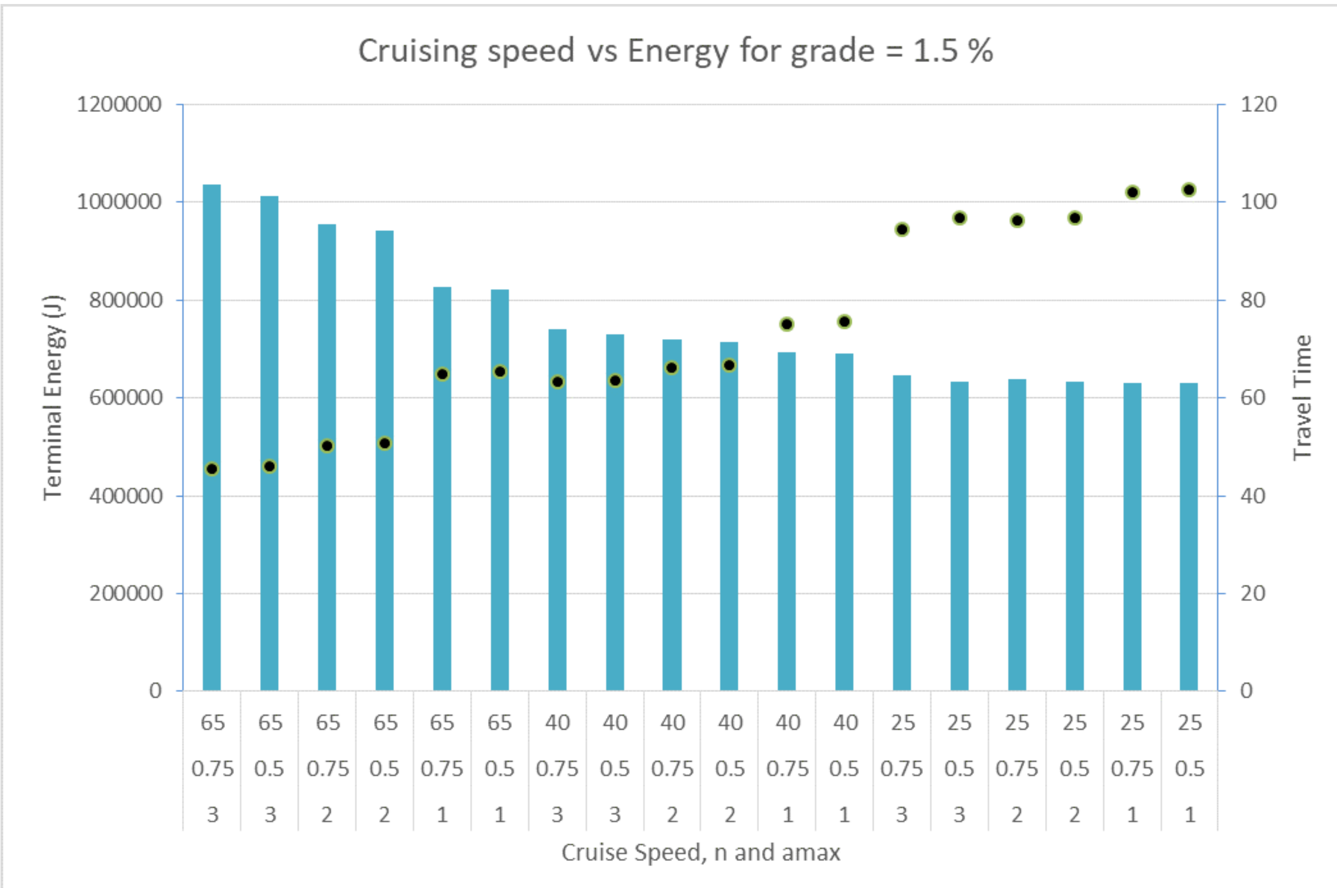

Figure 3.21: Cruise speed vs energy consumption at grade = 1.5%

For any given speed limit and road grade, lower aggression levels generally resulted in lower energy consumption estimates and higher traveling times. The difference in energy consumption estimates for different aggression levels for a particular cruising speed were higher in the case of higher speed limits as compared to lower speed limits.

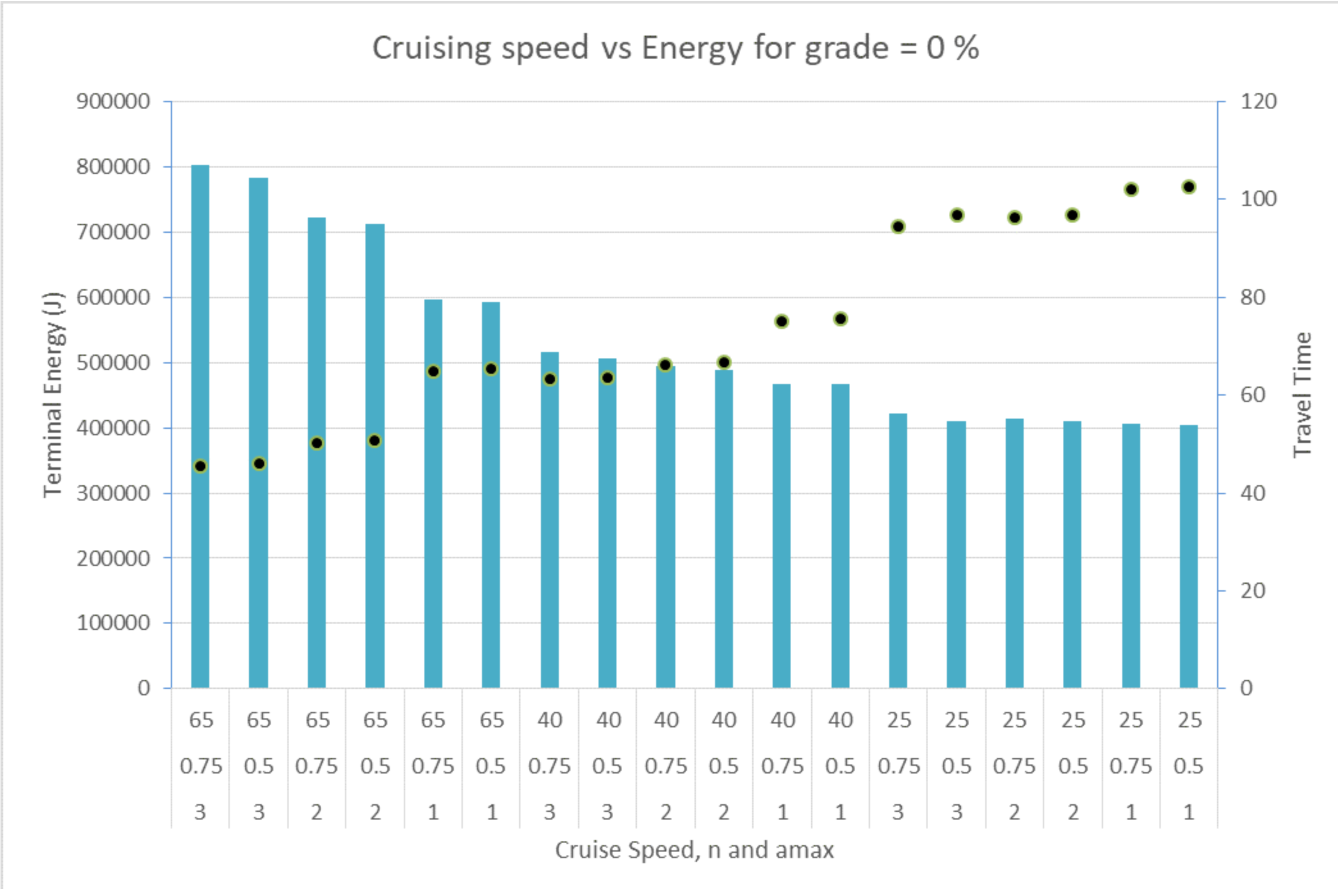

Figure 3.22: Cruise speed vs energy consumption at grade = 0.0%

For any value of road grade, in the case of cruising speed of 25mph, a higher jerk rate corresponding to $\alpha = 0.75$ resulting from quicker pedal adjustments by the driver but a lower acceleration rate of $a_{max} = 2$ resulted in a slightly higher energy consumption estimates than the estimate for $\alpha = 0.5$ and $a_{max} = 3$.

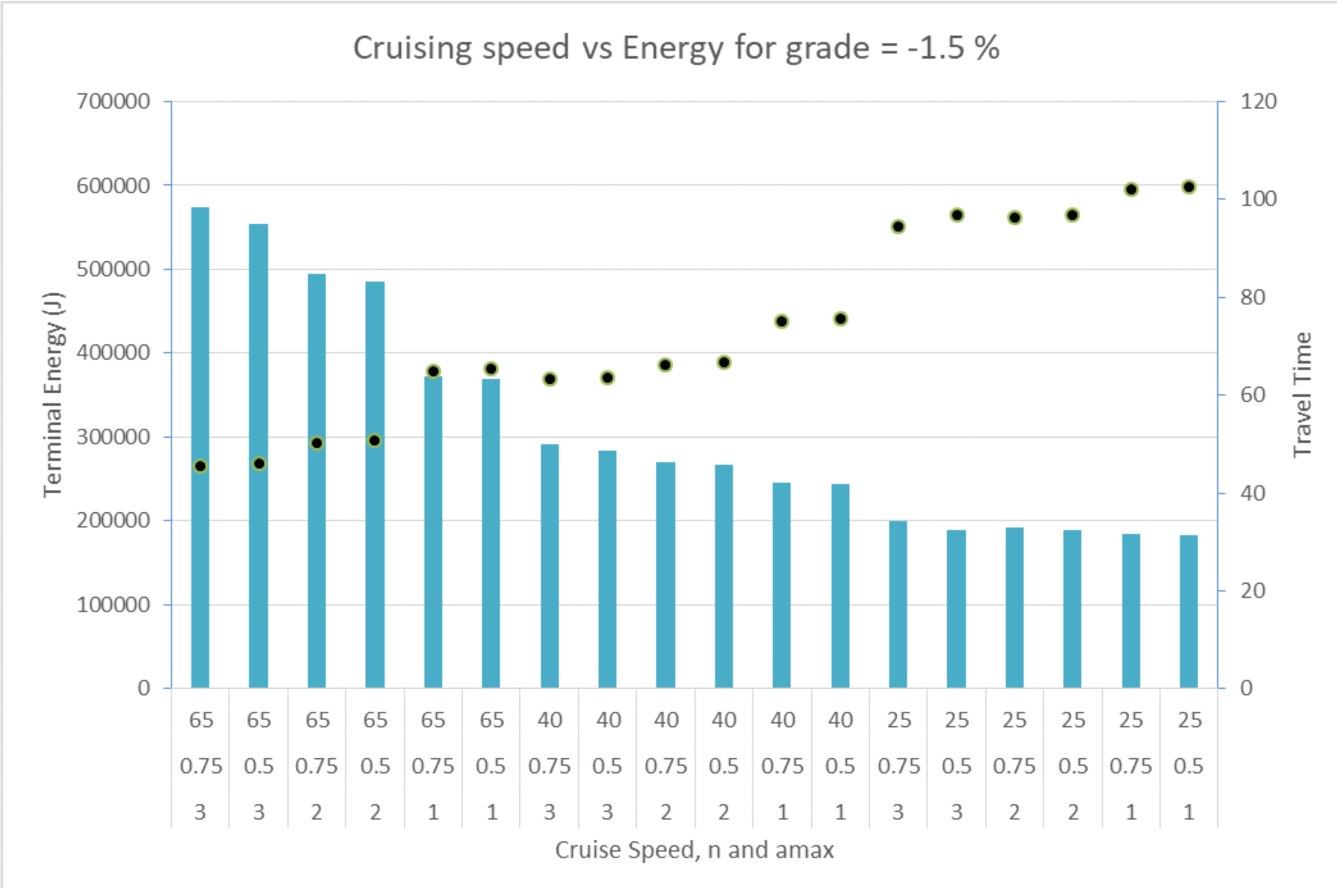

Figure 3.23: Cruise speed vs energy consumption at grade = -1.5%

In a real world driving scenario, traffic, especially on urban routes where speed limits are generally low might result in frequent acceleration-deceleration events. A driver employing sharper pedal adjustments but lower acceleration rates might experience significantly higher energy consumption if such acceleration-deceleration events are large in number. This case study thus shows the importance of tuning the driver aggression constants appropriately. Incorrect calibration of these constants can result in either a sub-optimal route or a route of longer travel duration to be chosen.

3.3.2 Distance vs Energy Consumption

Often, the shorter route tends to be the EcoRoute. However, as we have seen so far, several factors affect the choice of EcoRoute. A simulation was done to demonstrate that the shorter, faster route may not always be the EcoRoute. For this purpose two routes: route 1 and route 2 of different lengths were synthesized. Route 1 is shorter at 850m and route 2 is 900m long. The speed limit on route 1 is 65mph while the speed limit on route 2 is 40mph. Table 3.9 shows the results of simulation. Road grades were kept the same for both the route simulations.

Route	**Distance**	**Cruising Speed**	**Travel Time**	**Terminal Energy**
#	**m**	**mph**	**s**	**kJ**
1	850	65	50	552
2	900	40	64	427

Table 3.9: Distance vs Energy consumption

Naturally, route 1 with a higher speed limit and shorter distance has a shorter travel time compared to route 2. However, route has a lower energy consumption estimate. On route 2, in spite of the longer traveling times the vehicle has to expend less energy overall to overcome the tractive forces at the wheels due to the lower speed limit. On route 1, the force due to rolling resistance, force due to aerodynamic resistance and force due to inertia are all higher since the vehicle has to accelerate for longer and travel at a higher speed. This is shown in Figure 3.24.

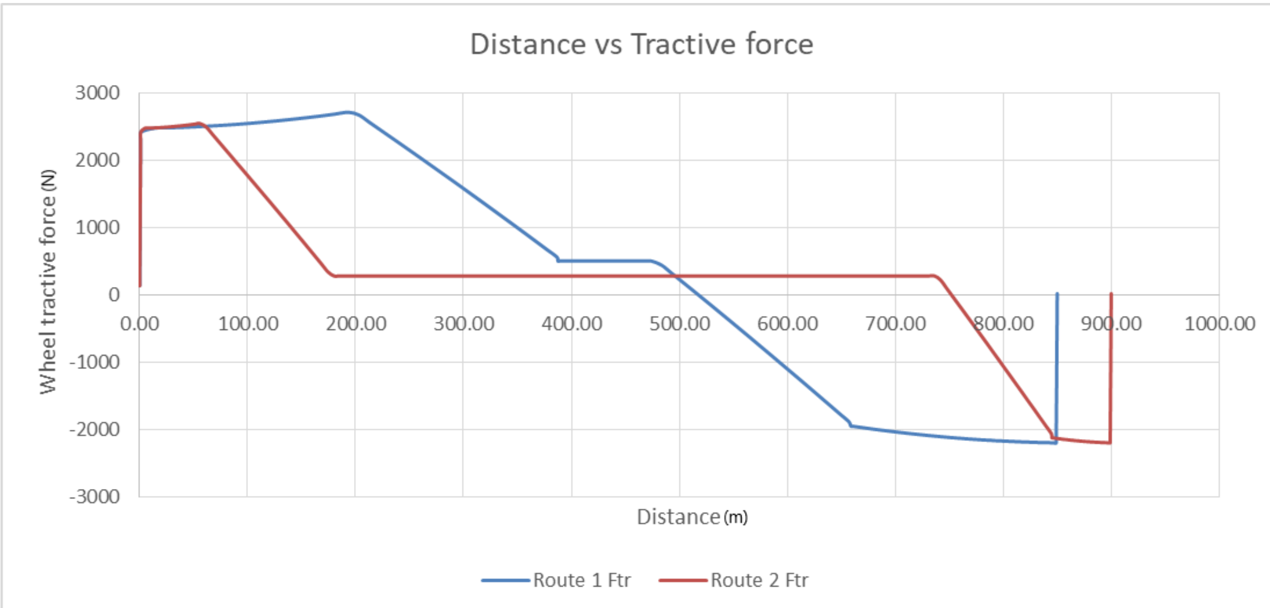

Figure 3.24: Distance vs Tractive force at wheels

3.3.3 Conditional stops vs Energy consumption

Stops along a route affect the energy consumption since extra energy is expended in stopping and accelerating the vehicle back to speed as opposed to cruising at constant speed. When a vehicle is cruising at a constant speed, since the force required to overcome the inertia is minimal to zero, less energy is expended to cover the same distance as opposed to accelerating from a lower speed to a higher speed. At higher speeds, however, the force required to overcome the aerodynamic drag becomes significant and contributes to energy consumption. While vehicles can capture energy through regenerative braking, some energy is wasted through various losses and cannot be recaptured. It thus results in a overall net energy expenditure during the stopping-acceleration event. A typical route consists of several stops, both conditional and mandatory. Stop signs are mandatory and cannot be avoided. Traffic signals constitute conditional stops and can be avoided. To understand the impact of conditional stops on the overall energy consumption, route 1 in the blacksburg case study from Figure 3.16 is used in simulation for a varying number of conditional stops. The total number of conditional stops occurring along this route is 15. By randomly considering a different combination of stops out of the total 15 stops, the energy consumption along the route is calculated by synthesizing the velocity profile. For example, 10 out of the 15 conditional stops are randomly chosen to be mandatory stops while the rest are not considered. In a total of 3 iterations, two other different combinations of 10 stops out of 15 are considered for simulation. The simulations similarly are repeated by varying the number of stops considered to 7 and 5. The results of the simulation are shown in Figure 3.25, Figure 3.26 and Figure 3.27. The predictive terminal energy consumption for a set of conditional stops in kJ is plotted against the number of stops in the test case.

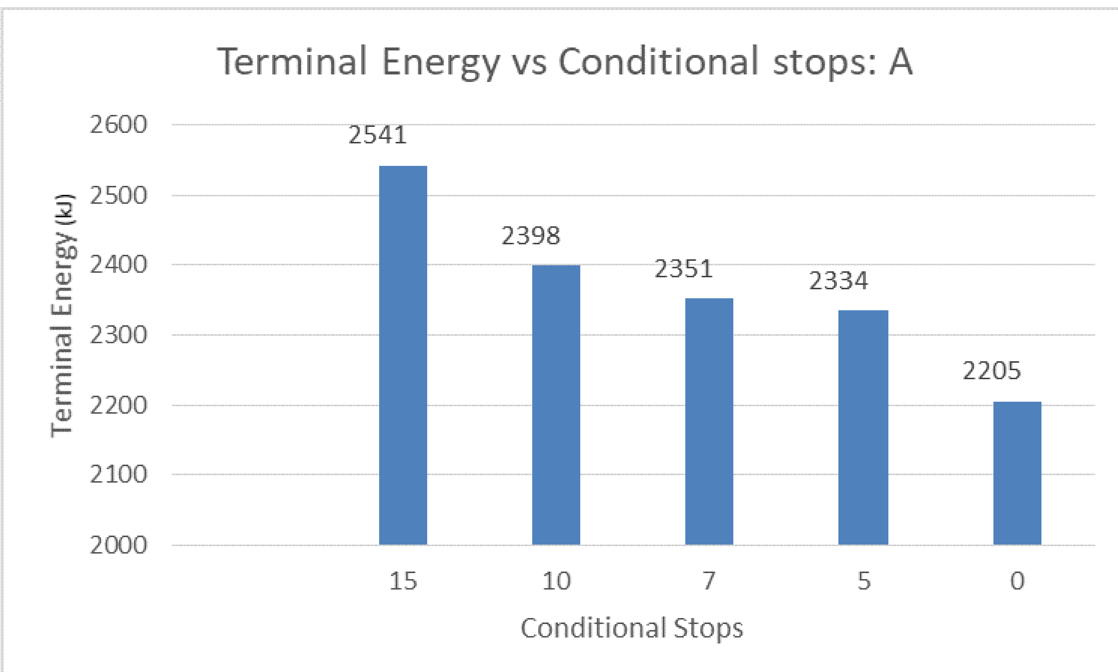

Figure 3.25: Conditional stops vs energy consumption: case A

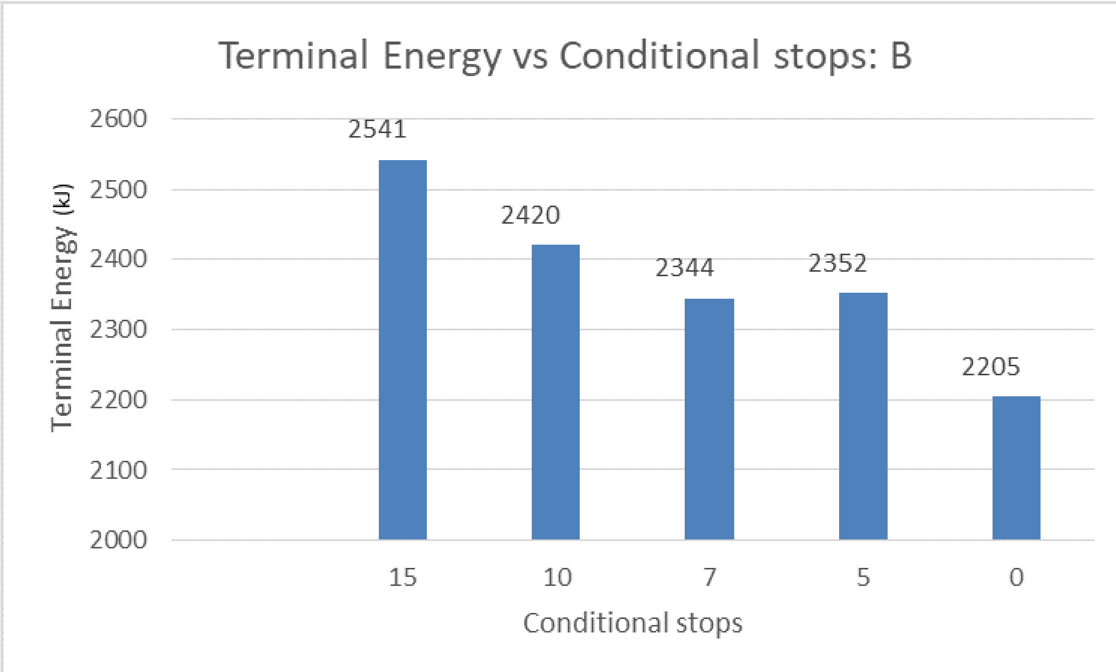

Figure 3.26: Conditional stops vs energy consumption: case B

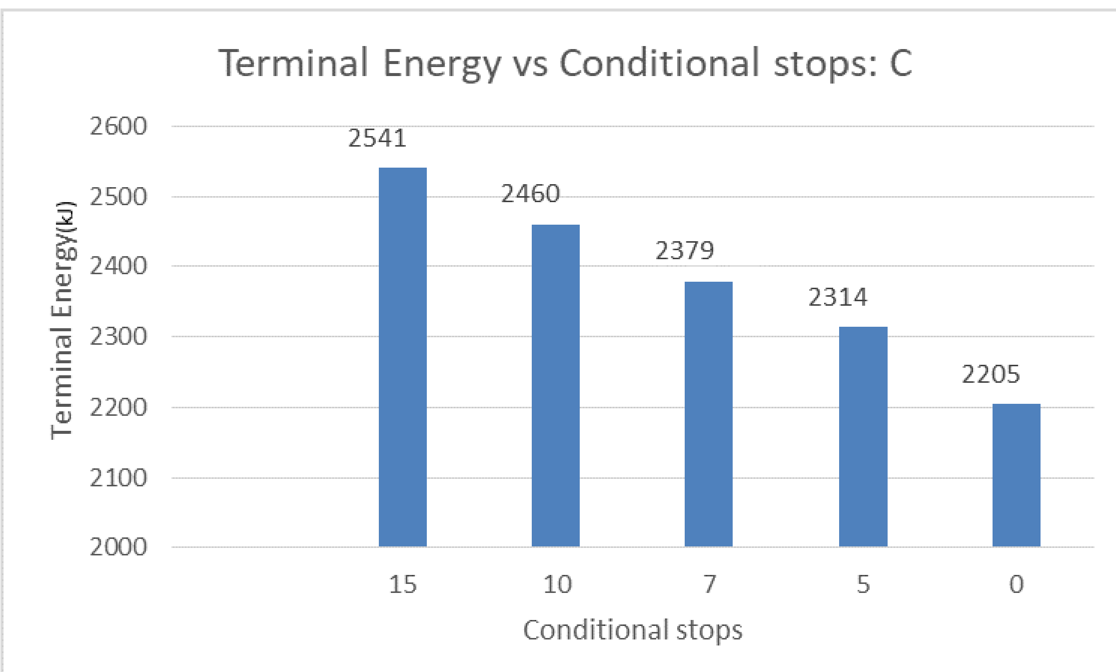

Figure 3.27: Conditional stops vs energy consumption: case C

A general trend in decreased energy consumption as the number of stops decreases can be observed. However, depending on the placement of the stop along the route and the speed limits before and after the stop and grades, the energy consumption can be higher for a lower number of stops as compared to a higher number of stops. This can be seen in case B where a particular combination of 5 stops had a higher energy consumption than 7 stops.

3.4 Case Study: Michigan

An EcoRouting analysis case study was conducted in the state of Michigan, for routes between Rochester Hills and Farmington Hills. Three routes between the source and destination were studied, consisting of a mix of highway and street driving. A summary of the routes considered is presented in Table 3.10. The travel time predictions obtained from Google directions API are shown here.

Route Number	**Mandatory Stops**	**Conditional Stops**	**Travel Time (min)**	**Route Distance (miles)**	**Max Speed Limit (mph)**
1	2	29	34	23.3	70
2	3	24	37	21.7	70
3	2	16	36	29.8	70

Table 3.10: Summary of Routes: Michigan Case Study

Route 1 is a mixture of city and highway driving, route 2 is mostly urban driving and route 3 is mainly highway driving. Similar to the blacksburg case study. An overview of the routes is shown in Figure 3.28.

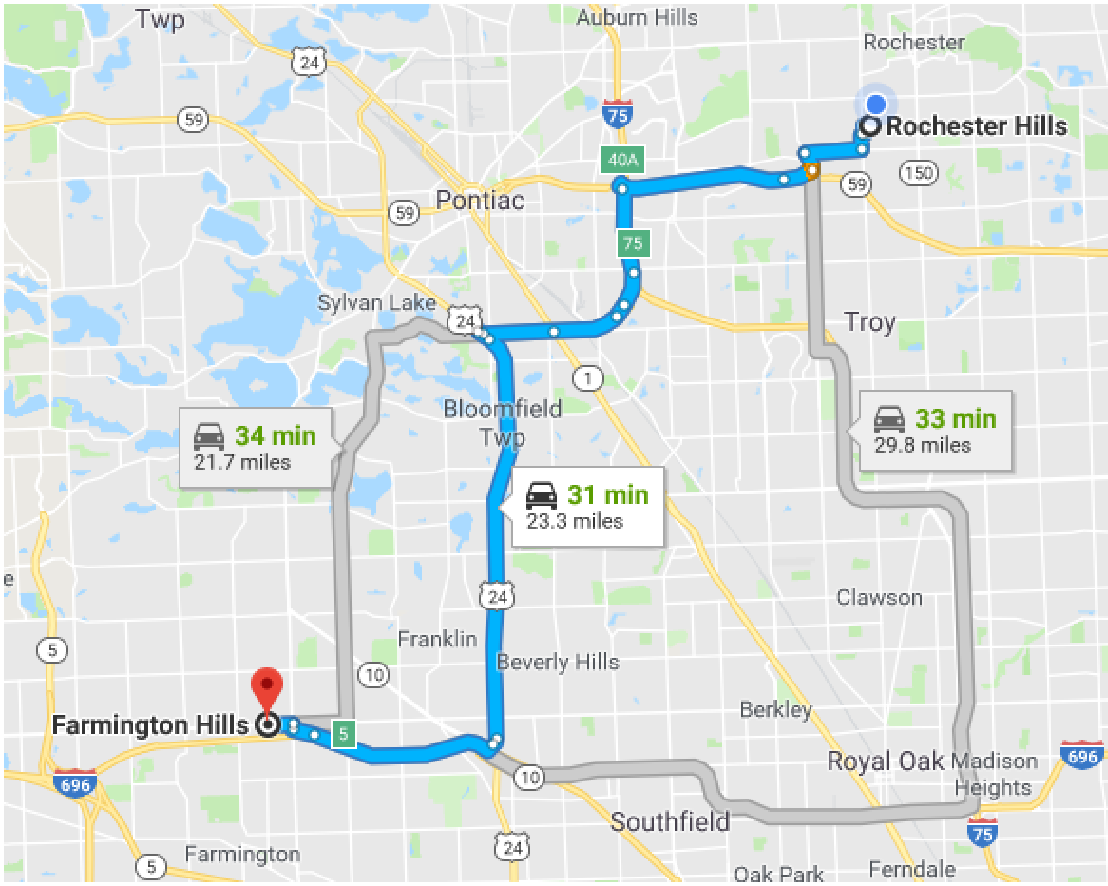

Figure 3.28: Michigan case study: Routes overview

Simulation was conducted for the 2013 Nissan Leaf with parameters from Table 3.3. Three scenarios were considered for simulation: Considering only mandatory stops, considering all stops and considering 50% of conditional stops randomly. The travel time predictions made using the automation methodology is shown in Table 3.11. The travel time predictions while considering only mandatory stops were found to be close to the predictions by Google maps directions API during times between 12:00 AM and 6:00 AM. The travel time difference between the case where only mandatory stops were considered and case where all stops were considered was similar for routes 1 and 2 at 353 and 355 seconds respectively. Route 3, being mostly driven on the highway saw a much smaller difference at 234 seconds.

Route Number	**Travel Time (seconds)**		
	Mandatory Stops	**All Stops**	**50% of Conditional Stops**
1	2049	2402	2169
2	1966	2321	2046
3	1956	2190	2038

Table 3.11: Michigan Case Study: Travel Time Prediction

Table 3.12 shows the terminal energy prediction for the three cases on the three routes. A threshold of 10% increase in travel time over the fastest routes is fixed for choosing the optimum EcoRoute. It can be reasoned that similar conditions would prevail on all three routes at the same time: i.e if no conditional stops are encountered on route 1, it is unlikely that driving on route 2 or 3 would encounter all the stops at the same time. Thus, route 2 will be chosen as the EcoRoute since least energy is consumed here. In the improbable case where all stops are encountered on route 2 but none are encountered on routes 1 or 3, route 1 will be the optimum EcoRoute as it offers the next best balance between travel time and energy consumption. If, however, it is assumed that 50% of conditional stops are encountered on an average, route 2 will be chosen as the optimum EcoRoute.

Route Number	**Terminal Energy (kJ)**		
	Mandatory Stops	**All Stops**	**50% of Conditional Stops**
1	14259	16473	15145
2	13562	15558	14213
3	18029	21158	19221

Table 3.12: Michigan Case Study: Terminal Energy Prediction

This study shows the importance of stops in determining the travel time and energy consumption. Typically, users might be tempted to use route 3 for this commute as it will most likely always be the fastest routes between the source and the destination and avoids several conditional stops. However, it can be seen that route 2 has a significant potential of 26% energy savings with a compromise of only about 6% on travel time.

Chapter 4

Validation in Actual Driving Conditions

This chapter discusses the results of validating the EcoRouting methodology in actual driving conditions. An experiment was conducted in Blacksburg, Virginia on the routes described in Figure 3.16. The HEVT Camaro in battery electric vehicle (charge depleting) mode was used in the experiment. This chapter is divided into three parts. In the first part, using the software methodology described in chapter 3, the predictive terminal energy on the three routes for the HEVT Camaro is calculated for three scenarios: a) considering all stops, both conditional (traffic signals) and mandatory (stop signs), as mandatory stop signs , b) considering only mandatory stops where all the traffic signals are assumed to be green, and c) considering all the mandatory stops and only the conditional stops encountered in the actual driving test. In the second part the results of terminal energy consumption measured while the HEVT Camaro was driven along the simulated routes is described. The third part describes the results of simulation using the velocity profiles captured during driving. Finally, the results of the three sections are compared and summarized.

4.1 Simulation: HEVT Camaro

In the first test case (case a), all 15 stops on route 1, 11 stops on route 2 and 8 stops on route 3 are considered as mandatory stops. In the second test case (case b), only mandatory stops on routes 1, 2 and 3 are considered. In the third test case (case c), the stops encountered in actual driving are considered. The velocity profiles on the routes for the three scenarios are generated using the parameters shown in Table 4.1.

Parameter	**Value**
a_{max}	1.5
a_{min}	-1.5
α	0.5
j_{max}	0.75
n	0.3
j_{min}	-0.225

Table 4.1: Velocity profile synthesis parameters: HEVT Camaro

Route		**Distance**	**Stops**	**Travel time**	**Average speed**
#		**miles**	#	**s**	**mph**
1	a	3.58	15	784	16
	b		3	449	29
	c		6	646	20
2	a	5.54	11	757	26
	b		3	489	40
	c		5	699	28
3	a	3.90	8	593	23
	b		4	501	28
	c		5	540	26

Table 4.2: Travel time and Average speed prediction: HEVT Camaro

The power train parameters of the HEVT Camaro in charge depleting mode were then used in the power train model synthesis using the generated velocity profiles. Table 4.2 shows the travel time and average speed predicted in the simulation for the three test cases.

While synthesizing the velocity profiles over the three routes in scenario c), since all the mandatory stops and only the conditional stops encountered in the actual driving trip are enabled, the other conditional stops are disabled and the corresponding nodes are processed the same way regular, non-traffic sign nodes are treated. Table 4.3 shows the wheel energy and the predictive terminal energy for all three test cases. An important observation to be made here is that the ranking of the routes based on predictive terminal energy consumption is similar to the results from simulation of the 2013 Nissan leaf in Table 3.5.

Route		**Distance**	**Wheel energy**	**Predictive terminal energy**
#		**miles**	**kJ**	**kJ**
1	a	3.58	1666	4313
	b		1838	3397
	c		1673	3819
2	a	5.54	4481	7953
	b		4877	7409
	c		4634	7438
3	a	3.90	2364	4986
	b		2443	4224
	c		2408	4404

Table 4.3: Wheel energy and predictive terminal energy: HEVT Camaro

4.2 Energy consumption in an actual driving scenario

The EcoCar3 competition required teams to have data logging systems setup to log various CAN messages. HEVT used GL1000, a data logger unit developed by Vector Informatik GmbH for logging data on the HEVT Camaro. The data logger can be setup to log data at set intervals. The data logger was setup to log messages corresponding to the energy storage system such as the terminal voltage and current at 100ms intervals. With the data logging setup in place and enabled, the HEVT Camaro was driven along the three different routes between the source and destination. Care was taken to drive normally, like in any driving scenario, to make sure the results reflected typical driving conditions. After the HEVT Camaro was driven along the three routes, the logged data was retrieved and filtered to get data pertaining to the three routes. The results are shown in Table 4.4

Route	**Distance**	**Stops**	**Travel time**	**Average Speed**	**Terminal energy**
#	**miles**	#	**s**	**mph**	**kJ**
1	3.60	6	673	19	4421
2	5.58	5	706	28	7462
3	3.95	5	695	20	5011

Table 4.4: Travel time, average speed and Terminal energy: HEVT Camaro

4.3 Powertrain model synthesis on measured velocity profile

In the driving test conducted in section 4.2, the HEVT Camaro was also setup to log GPS based data such as speeds, elevation and location. The performance box data logger device developed by race logic was used to log data in 100ms intervals. This data was used in place of the velocity profiles as the input to the powertrain model to estimate the energy consumption. The results were compared to the simulated data and the measured data from actual driving to assess the efficacy of the software methodology. The results of powertrain model synthesis on captured velocity profiles in actual driving is shown in Table 4.5. The travel time and average speeds shown here are the same as in Table 4.4.

Route	**Distance**	**Stops**	**Travel time**	**Average Speed**	**Wheel energy**	**Predictive terminal energy**
#	**miles**	#	**s**	**mph**	**kJ**	**kJ**
1	3.60	6	673	19.25	1654	4362
2	5.58	5	706	28.45	4452	7452
3	3.95	5	695	20.48	2413	5009

Table 4.5: Powertrain model synthesis on recorded velocity profile

4.4 Comparison of results

In this section, the results of simulation, actual driving and energy consumption modeling on measured velocities are compared. This gives us an idea on the efficacy of the software methodology in selecting the optimal route. Comparisons are done on travel time, average speed, tractive energy requirement at wheels, terminal energy consumption and velocity profile.

Inaccuracy in predicting the travel time may result in choosing a suboptimal route as the EcoRoute. This is particularly undesirable as the route requiring least amount of energy may not always be optimal if the travel time is significantly longer than the fastest route. On the other hand, a route with less energy consumption but a travel time within the threshold for travel time increase over the fastest route may also be rejected due to inaccuracy in predicting the travel time. The software methodology assumes a stop time of 0 seconds for mandatory stops such as stop signs and a stop time of 25 seconds for traffic signal stops. Figure 4.1 shows the comparison of travel times between simulation and actual driving for the three routes.

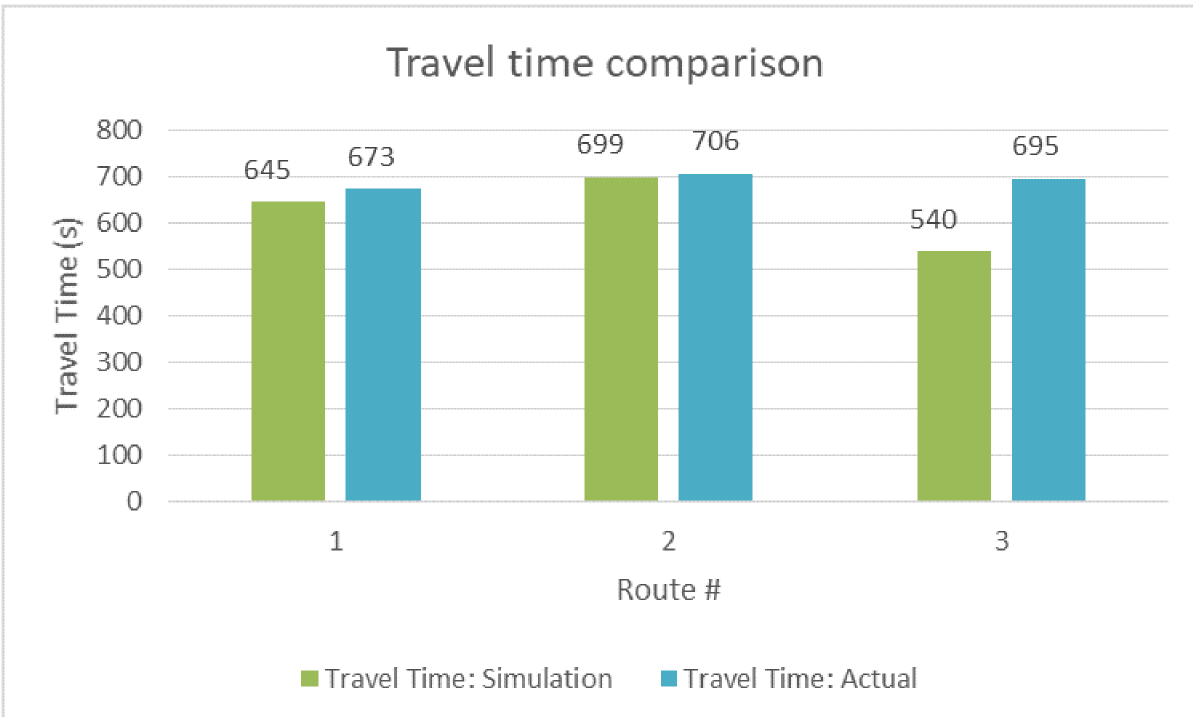

Figure 4.1: Travel time comparison: Simulation vs actual

The travel time difference for route 1 is -4.11% , -0.96% for route 2 and -22.3% for route 3. In the actual driving test for route 3, additional stop times of 75 seconds and 47 seconds were separately recorded in two different instances while complying to stop for a stopped school bus. Although such stops are mandatory, they are geospatially transient and cannot be predicted accurately. It is, however, important to note that such transient conditions in an actual driving scenario contribute significantly to the travel times. While majority of the travel time differences on route 3 can be attributed to transient conditions, the rest of the difference is the result general traffic encountered while driving. A comparison of actual driving distance and distance in simulation is shown in Figure 4.2.

Figure 4.2: Distance comparison: Simulation vs actual

It should be noted that users may enter approximate addresses for source and the destination while the actual source and destination might vary slightly. For example, in the case of route 3, an approximate destination address ”Kroger, South Main, Blacksburg” was entered. The route data obtained for this string covered the route until a nearby traffic signal while the actual driving involved crossing the traffic signal and entering the parking lot. Due to differences in travel time and distance, differences in average speed predictions were observed as shown in Figure 4.3. The smaller travel times and smaller distances as predicted in simulation resulted in larger average speed being predicted overall across all the routes.

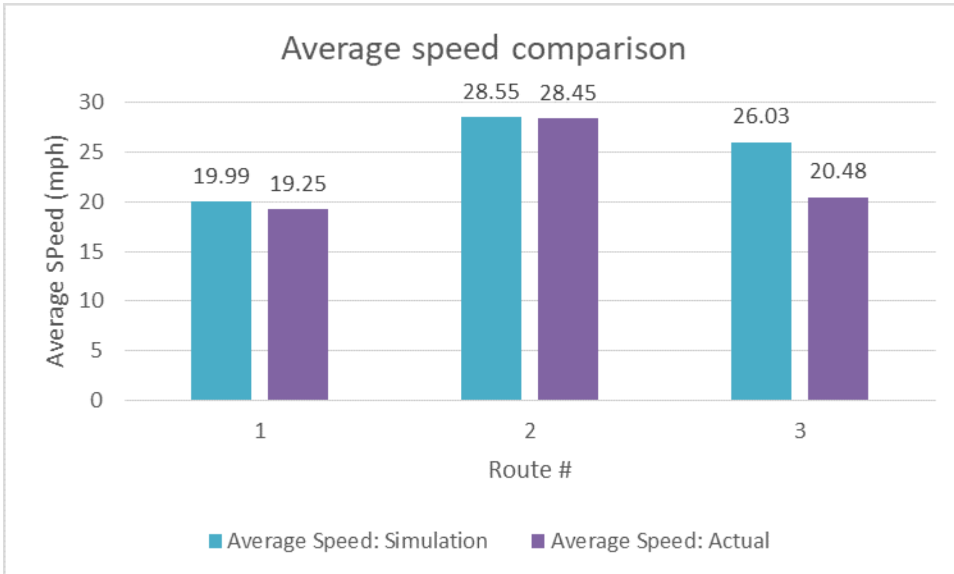

Figure 4.3: Average speed comparison: Simulation vs actual

Since no actual wheel energy is required to be overcome by the powertrain while the vehicle is stopped and the difference in distance is minor, differences of -1.13%, -4.08% and 0.2% were observed on the three routes respectively, as shown in Figure 4.4.

The wheel energy estimated by simulation was generally higher than the wheel energy calculated by energy consumption modeling on captured velocity profiles. The wheel energy estimation for route 3 in simulation was however, lower than the wheel energy estimated from captured velocities due to the differences in the route explained earlier. The terminal energy predicted in simulation was lower than the actual terminal energy consumed as shown in Figure 4.5. The backwards synthesized terminal energy values, calculated by modeling the energy consumption on captured velocity profiles, are much closer to the actual values. The differences between the backwards synthesized terminal energy values calculated from modeling the energy on measured velocity profiles and actual terminal energy consumption values are -1.35% for route 1, -0.12% for route 2 and -0.04% for route 3.

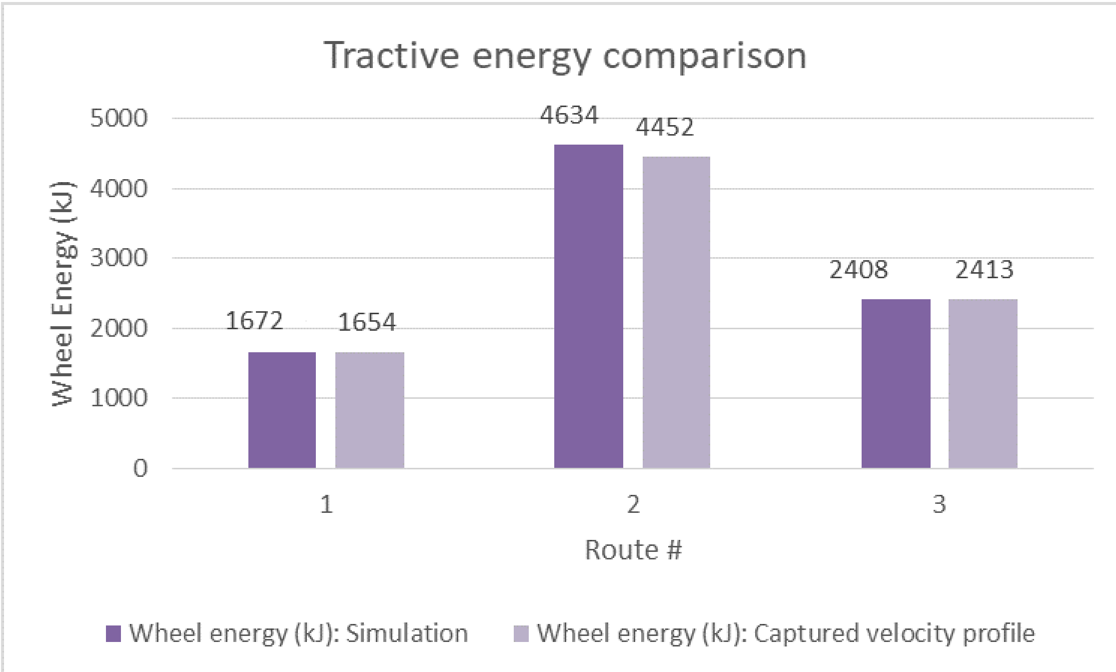

Figure 4.4: Tractive energy comparison: Simulation vs actual

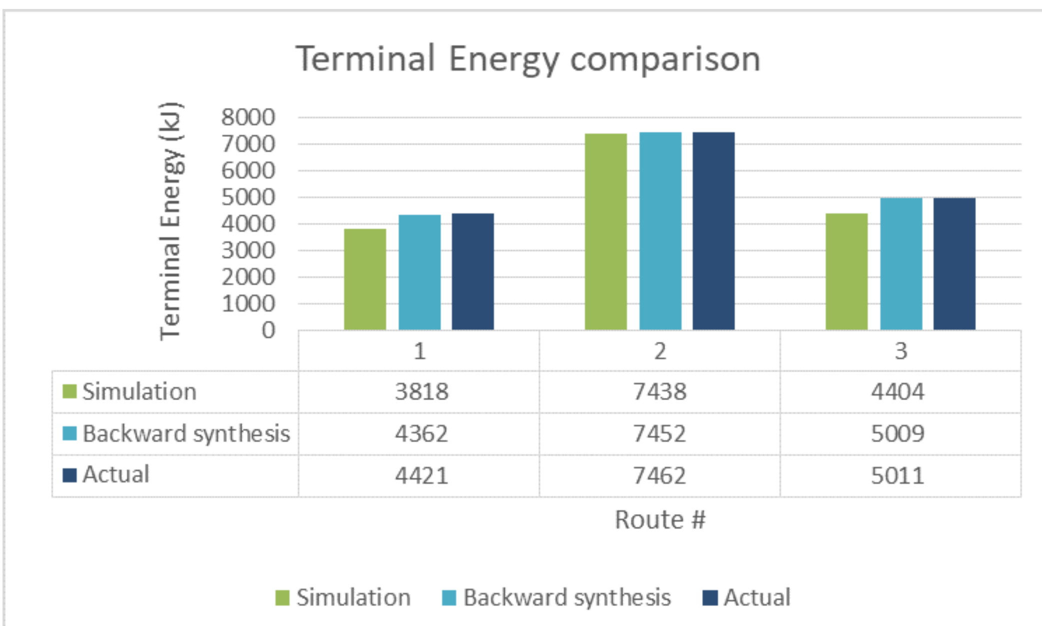

Figure 4.5: Terminal energy comparison: Simulation vs actual

A closer look at a comparison of velocity profiles and measured velocities on the three routes provides a possible explanation for the differences observed between predictive terminal energy consumption values and actual values. In general it can be observed that there are significantly higher number of acceleration/deceleration events as compared to the simulated velocity profile due to traffic conditions.

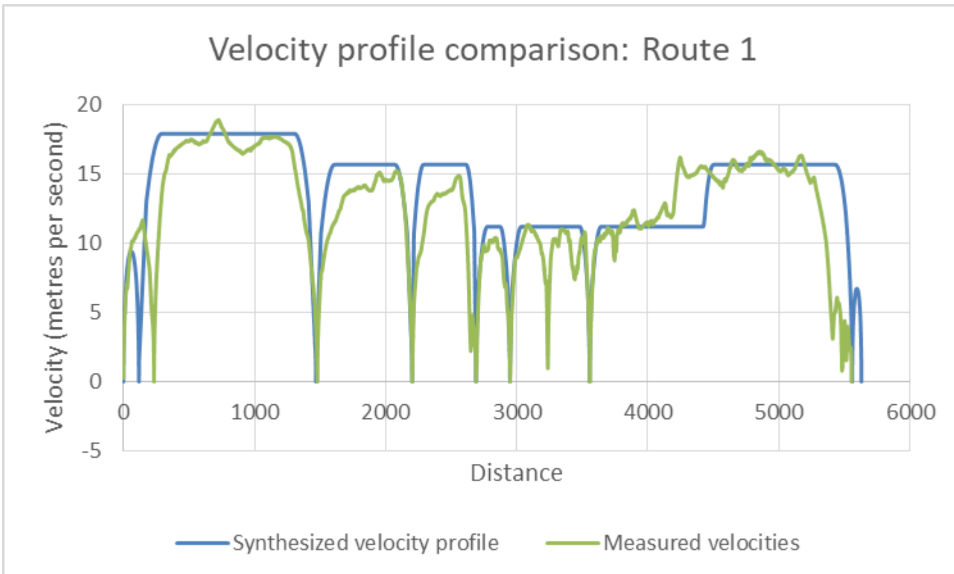

Figure 4.6: Velocity profile comparison on route 1: Simulation vs actual

In the comparison of velocity profiles on route 1 as shown in Figure 4.6, in some segments the vehicle has failed to achieve continuous, constant cruising speeds. It can also be observed that the vehicle has decelerated within segments after having achieved the cruising speed. Between 3000 to 3500 meters from the start the vehicle can be seen almost coming to a stop in spite of no stop being present. These differences result in energy consumption being higher than what was predicted. A mismatch between route data used in simulation and ground truth was also observed

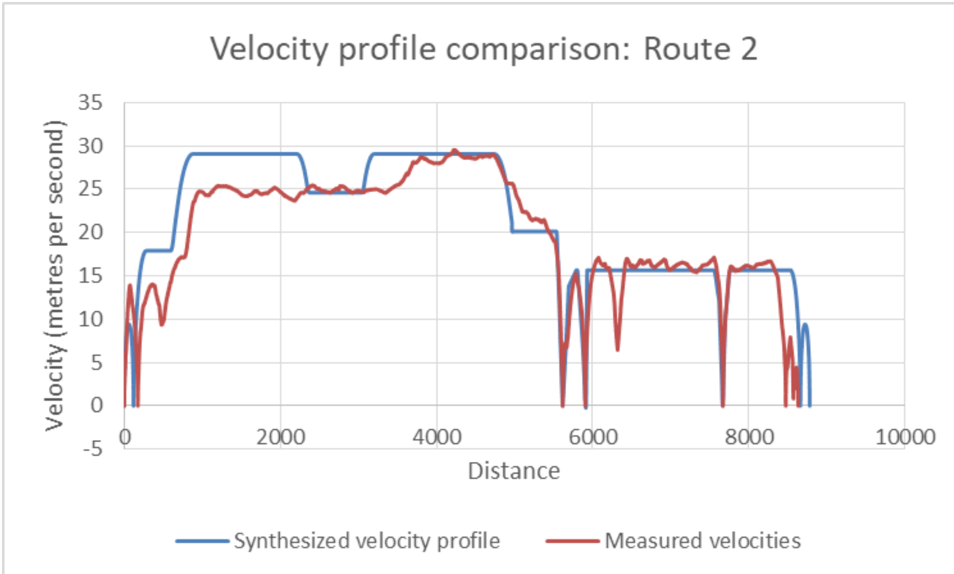

Figure 4.7: Velocity profile comparison on route 2: Simulation vs actual

In the case of route 2, as shown in Figure 4.7, the vehicle maintained better cruising speeds as compared to route 1 since a significant distance involved driving on the highway. However it can be seen that the vehicle fails to achieve a cruising speed of 29.0576 m/s (65 mph) in between 300 to 2200 meters. A speed limit drop from 29.0576 m/s to 24.5872 m/s at the 2200 meter mark results in the traffic slowing down and propagating backwards, resulting in vehicles slowing down in spite of being in the 65mph zone. When the speed limit increases again at the 2600 meter mark, traffic resulted in the vehicle not being able to accelerate immediately. In the simulation, a vehicle is assumed to accelerate and attain a higher speed limit as the speed limit sign is passed. As we have seen earlier, for a particular route higher traveling speeds result in increased consumption. Similarly, stops and acceleration events also increase energy consumption. The higher energy consumption predicted by the simulation in between the 100m mark and 2200m mark due to higher traveling speeds compensate for the higher energy consumed in the acceleration events and energy consumed due to transient traffic conditions. In the end the predicted terminal energy and the actual consumption values are similar.

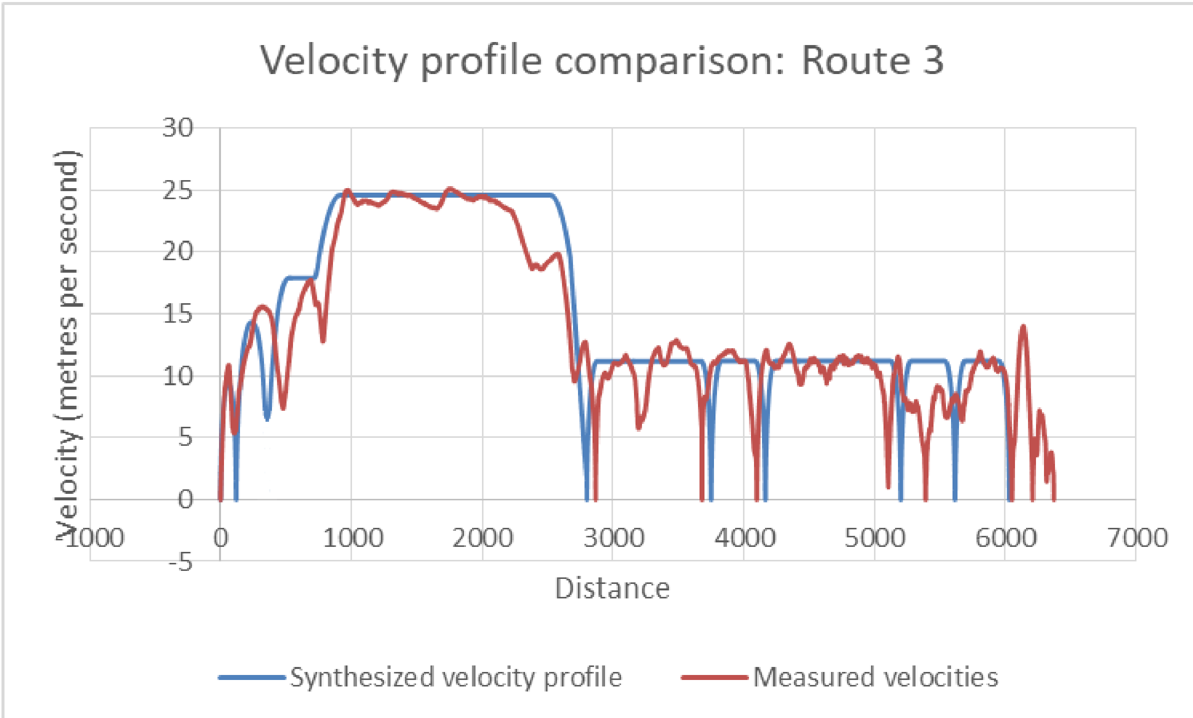

Figure 4.8: Velocity profile comparison on route 3: Simulation vs actual

On route 3, as mentioned earlier two stops were encountered while complying for a stopped school bus, one at the 5300m mark and the other, at the 6100m mark. This resulted in an additional deceleration - acceleration event shown in Figure 4.8, at the second stop. The first stop for a stopped school bus did not result in an additional deceleration-acceleration event as the stop was near a signal light, at the 5500m mark, and the vehicle continued to remain stopped for the signal after the school bus moved, albeit, at a distance from the location of the traffic signal. Additionally, the vehicle was slowed below the cruising speeds due to traffic on two other occasions, one between the 500m and 1000m marks and the other in between the 3000m and 3500m marks. Generally there were several other fluctuations in the driving speeds along the route. Such variances in driving speeds combined with the additional distance covered in the end mentioned earlier contribute to higher energy consumption.

Despite the differences between the estimated energy consumption values and the actual consumption values the ranking of the routes based on route energy consumption remains consistent with the measured results. Also transient traffic conditions were present on urban routes more prominently as compared to highways. Traffic results in more deceleration-acceleration events on urban routes as compared to highways, where traveling speeds are much more constant. The software methodology assumes the vehicle to come to a stop exactly at the location of the traffic sign. This is not always the case in actual driving conditions as the vehicle might come to a stop a certain distance behind the traffic sign due the presence of other vehicles stopped ahead at the same traffic sign. Also, the methodology assumes a vehicle to start accelerating at maximum jerk rate from a stop before attaining the maximum acceleration rate. This may not always be possible due to the presence of traffic ahead, in which case a vehicle would accelerate at a lower rate experiencing frequent periods of jerks while trying to maintain safe commuting distances. Given accurate velocity profiles, as seen in Figure 4.5, the energy consumption can be accurately modeled with minor errors. Synthesizing velocity profiles based on transient traffic conditions was not considered and is out of scope of this thesis.

Chapter 5

Traffic Impact Analysis

As seen in the previous section, traffic conditions affect the energy consumption as the traveling speeds of a vehicle are affected. In this section the impact of traffic flow rate, defined as the number of vehicles passing a point in a given time period, on the total energy consumption of a vehicle is studied. Simulation using the software methodology described in this thesis assumes free flow traffic and hence vehicles are assumed to travel at free flow speeds or at the speed limits. From the actual driving test and upon observing the measured velocity profiles it was noted that the vehicle could not achieve cruising speeds or speed limits due to presence of traffic. This resulted in the energy consumption estimates being different from the actual values.

5.1 Simulation Description

The study on the impact of traffic density is carried out for three different values of flow rate: flow rate for uncongested traffic conditions, flow rate at saturation, where saturation is defined as the maximum rate at which vehicles can travel at reasonable speeds, and flow rate at congested conditions, where the flow rate exceeds the rate at saturation and nears jam density, which is defined as the maximum vehicles per unit length achievable under congestion. Simulation runs were conducted in the INTEGRATION microscopic traffic assignment and simulation software [24].

INTEGRATION is a microscopic simulation model that can track behavior of vehicles at a resolution of 100ms in a road network. Traffic phenomena like incidents, lane changes, signal lights etc. are modeled in the simulation software. The domain of the application is to model decisions taken by drivers en route to their destination once the trip is started. The simulation provides various statistics and outputs for later analysis. For the purpose of this thesis, a network of nodes and links was constructed for the routes described in Figure 3.16 for simulation. The inputs given to the simulation model are described below.

Node Characteristics: The nodes making up a route are specified in this input. The node data along with their GPS coordinates were obtained using Google maps API and OpenStreetMaps. The nodes were chosen such that they represented the geometry of the roads precisely. All nodes received unique identification numbers based on the order of appearance on the route.

Link Characteristics: This input defines the individual links making up the routes. INTEGRATION software represents a route as a collection of links joined end-to-end. The input data provided here include: upstream and downstream node of the link, length of the link and traffic characteristics such as saturation flow rate, free-flow speed, speed at saturation and jam density. The link capacity is calculated by multiplying the number of lanes in the link, retrieved from OpenStreetMap data, with the saturation flow rate per lane, obtained from the Virginia Tech Transportation Institute (VTTI). Additionally, information about traffic signs and signal lights are provided here. Each link is uniquely identified using a link ID in the link characteristics definition input file.

Grade Inputs: Simulations in INTEGRATION are performed by default assuming 0 grades. Optionally, grades can be provided as inputs. The grade inputs, if provided, require an average grade to be provided for each link. The average grade for each link was calculated using the distance between the upstream and downstream nodes and the change in elevation.

Signal timing plans: INTEGRATION allows specification of a timing plan for each signal light present on the route, described in the link characteristics input file. The default timing plans provided within INTEGRATION are used.

Traffic Demands: The number of vehicles traversing the network per unit time and the network entering times are specified in this input file. INTEGRATION has a predefined set of vehicle classes that traverse the network. While the general traffic demand was made up of the default vehicle classes available, a new vehicle class with the specifications of the HEVT Camaro was created in a separate input file described below. The traffic demands are specified as a time series of departures, with an offset from the simulation start time for each traffic demand. To ensure the network was populated prior to the demand containing the HEVT Camaro class entering the network, a demand of vehicles of other classes was specified to enter the network first. A demand comprising the HEVT Camaro vehicle class is specified to enter the network, after the demand for vehicles of other classes populate the network, later in the series of demands. Also, the demand comprising of the HEVT Camaro class was provided a time interval greater than the predicted travel time for the route to ensure the vehicle completed the trip and exited the network.

Vehicle Characteristics Input: INTEGRATION allows users to define custom vehicle classes based on a vehicle's specifications. These inputs are used to estimate energy consumption over the trip. The VT_CPEM (Virginia Tech Comprehensive Power-based Energy Consumption Model), a microscopic backwards facing model [16], is used for estimating energy consumption for electric vehicles in the network. The model computes the tractive power required at the wheels from the aerodynamic, rolling and grade resistance forces based on the vehicle parameters defined in this input file. The model description can be found in

[16] and computes the tractive power requirement similar to the computational method in [25].

From the node and link characteristics inputs, INTEGRATION performs traffic assignment using the default Dynamic Traffic Assignment (DTA) mechanism. By predicting the travel times for each vehicle in the links from the times at which the vehicle is anticipated to enter the link, the minimum path of a vehicle's scheduled departure is calculated in this method. The anticipated travel time for each link is estimated based on the predicted link traffic volumes and queue sizes are used to estimate the travel times for each link. With all the inputs for simulation provided, upon start of simulation, INTEGRATION computes a summary and statistics of the simulation for all vehicles that exit the network at the end of simulation period. Statistics such as the number of vehicles that complete trips, the number of trips completed per vehicle, average trip times, average stops encountered and the average electrical energy consumed for each class of vehicle is computed and populated in the output file.

5.2 Results of Traffic Simulation

The simulations for this thesis were carried out for three test cases on all the three routes. In all the test cases for all the routes, a traffic demand of 1000 veh/h was loaded to populate the network at first. The traffic demands for the HEVT Camaro vehicle class were provided in three steps: 800 veh/h (vehicles/hour) for uncongested traffic conditions, 1300 veh/h to simulate flow rate conditions at saturation and 2000 veh/h for congested traffic conditions. The statistics retrieved upon completion of the simulation were: average travel time per route, average number of stops per route and the average energy consumption per route, for the HEVT Camaro class of vehicle.

5.2.1 Travel Time vs Traffic

The results of simulation on travel time versus traffic flow rate for the three routes are shown in Figure 5.1.

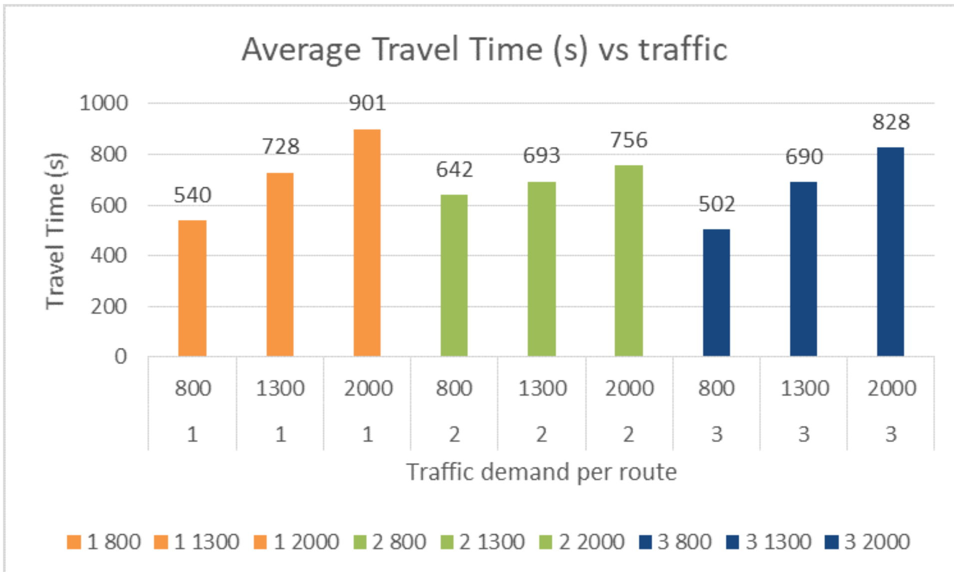

Figure 5.1: Average Travel Time versus Traffic Demand per Route

As expected, the travel times increased as the number of vehicles in the network increased. Routes 1 and 3 saw higher increases in travel times as the flow rate was increased as compared to Route 2. Route 2 has a majority of links on the freeway and since freeways have higher capacities as compared to urban roads, the travel time increase with traffic flow rate was less compared to routes 1 and 2 which are mostly traversed through urban roads. To better understand what level of traffic the travel time prediction by the software methodology presented in this thesis and the actual travel times correspond to, a comparison with the travel times predicted in INTEGRATION was made, as shown in Figure 5.2.

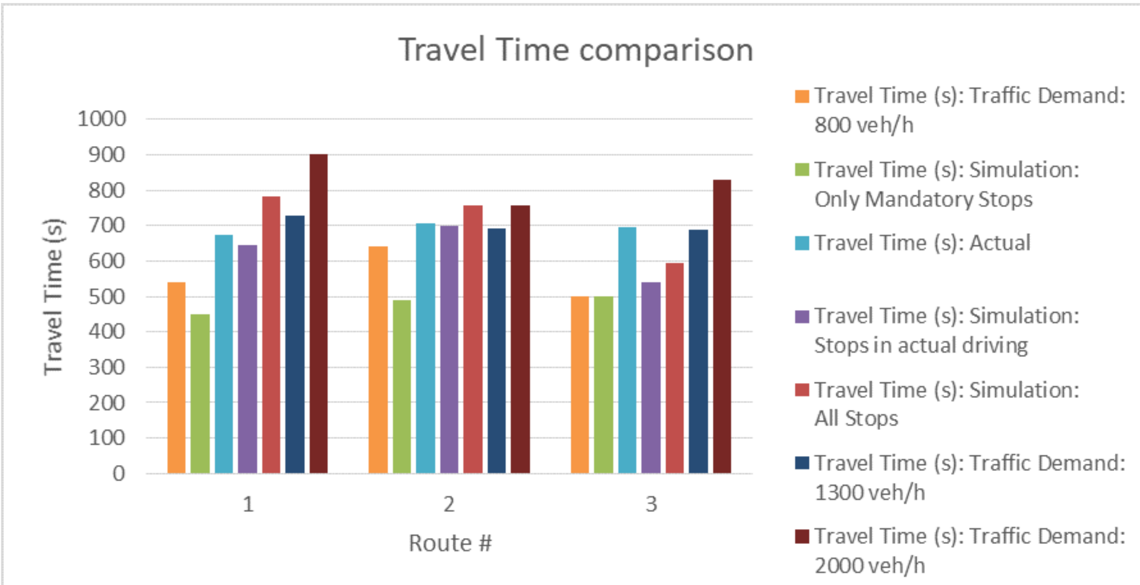

Figure 5.2: Travel Time comparison for traffic levels

The average number of stops encountered for each route for the different traffic conditions, predicted by INTEGRATION is shown in Figure 5.3. The number of stops considered for the simulation in the software methodology and the number of stops in actual driving for the three routes are shown in Table 5.1. In all the three routes, the travel times predicted by simulation and the actual travel times were within travel times at free flow and travel times at congested traffic conditions. The travel times calculated by considering only mandatory stops by the software methodology were lower than the free flow traffic condition travel times in all three routes. In both routes 1 and 2, the travel times and the average stops encountered in actual driving were closer to traffic conditions at saturation, suggesting that traffic conditions close to saturation traffic conditions prevailed in the actual driving case. This argument is especially strengthened as the actual driving was conducted in conditions close to peak hour traffic. The travel times predicted in simulation by the software methodology considering the stops encountered in actual driving were lower than actual times but, closer to travel times at saturation than travel times in free flow conditions. A possible explanation is that the number of stops considered were closer to the average number of predicted stops at saturation than free flow. On route 3, if the total extra stopping time of 122 seconds due to additional stoppage for 75 and 47 seconds each while complying to stop for a stopped school bus, mentioned previously are not considered, the travel time would be in between travel times at free flow conditions and travel times at saturation flow, suggesting moderate traffic conditions.

Route	**Stops Considered**		
#	**Simulation: All Stops**	**Simulation: Only mandatory stops**	**Stops encountered in actual driving**
1	15	3	6
2	11	3	5
3	8	4	5

Table 5.1: Number of Stops considered

5.2.2 Average Number of Stops vs Traffic

Similar to travel times, the number of stops encountered by the vehicle per trip increased as it spent more time in the network. This is shown in Figure 5.3. When a vehicle spends more time on a network, the probability of encountering signal lights increases. Also, the number of stops encountered is greater than the number of mandatory stops at the least.

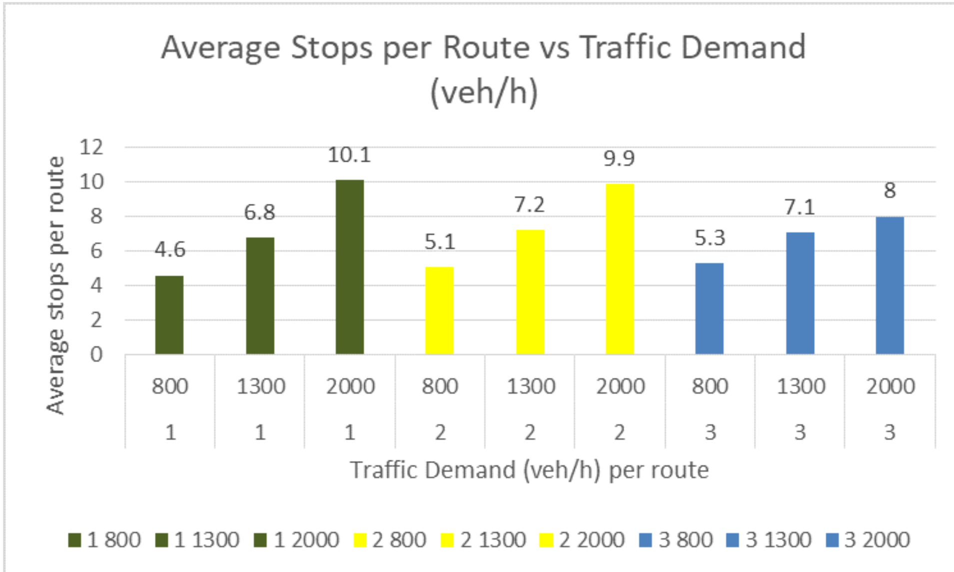

Figure 5.3: Average Number of Stops versus Traffic Demand per Route

5.2.3 Average Energy Consumption vs Traffic

The average energy consumption per trip of a route, as predicted in simulation on INTEGRATION generally saw a decline on all the three routes with increase in traffic flow rate. A possible explanation is as the flow rate increases, the average traveling speeds and the cruise speeds attained decrease, hence resulting in the vehicle expending lesser energy to overcome tractive requirements at the wheels.

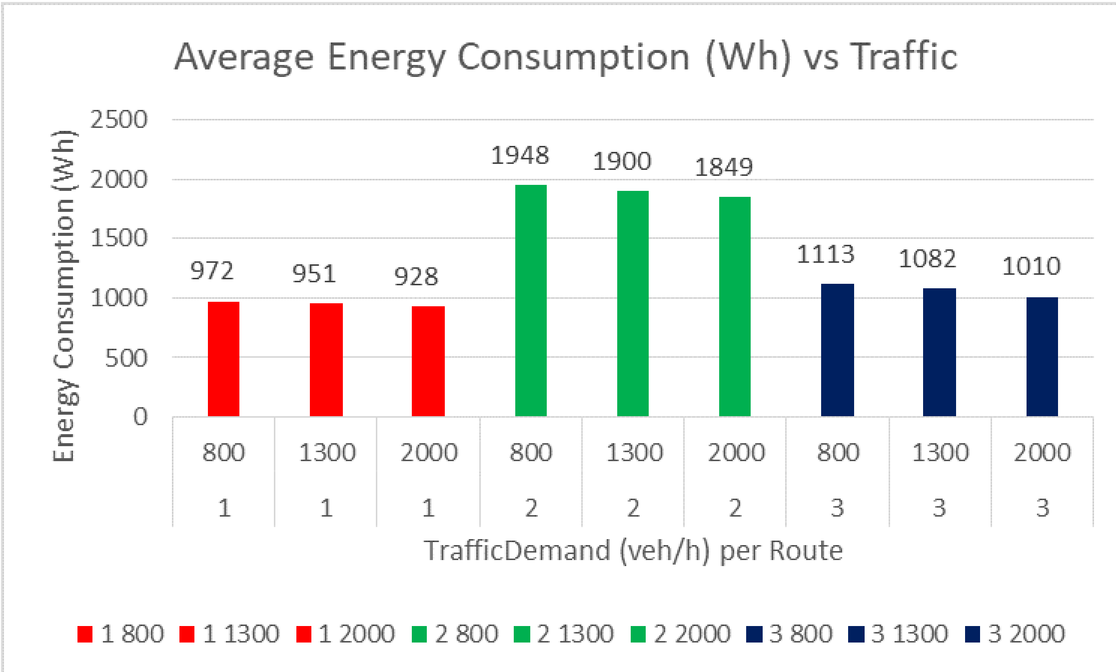

Figure 5.4: Average Energy Consumption versus Traffic Demand per Route

5.3 Discussion

We have thus seen so far that higher traffic may result in lower energy consumption. While it would be tempting to choose a route with lesser energy consumption as a result of higher traffic, an optimal solution may not be achieved as it also results in a significant increase in travel times. In this particular case study, while the ranking of routes based on energy consumption remains the same for any combination of traffic flow rates, the choice of optimal route will change depending on the difference in travel times. Under uncongested traffic flow rates on all the three route choices, for a maximum travel time increase threshold of 10%, Route 1 will be chosen as the EcoRoute since it consumes the least amount of energy while being 7.56% slower than the fastest route. For the same maximum travel time increase threshold, a flow rate of 1300 veh/h or more on Route 1, 1300 veh/h or less on routes 2 and 3 would result in Route 3 being chosen as the optimal route. The only scenario where Route

2 would be optimum is if both routes 1 and 2 have flow rates of 2000veh/h or higher and route 3 had a flow rate of 1300 veh/h or less.

Chapter 6

Conclusions

This thesis is divided into three major parts. The first part of the thesis constitutes analyzing and verifying the automation methodology to be used on on-board applications. Validation of the automation in actual driving conditions is carried out in the second part. Impact of traffic on the choice of EcoRoute is studied in the third part. The results of each part are presented.

6.1 Automation Methodology

The methodology to import and process route data for constructing velocity profiles is presented in this thesis. Methods for obtaining route parameters and correcting for corner cases are also presented. The processed route data is then used to synthesize velocity profiles. The synthesized velocity profiles are then fed into the powertrain model of a 2013 Nissan Leaf and the results are verified against previously obtained results on the same routes. The results of case study conducted on three routes in Blacksburg, Virginia are presented and an analysis of change in results due to change in route geography is also presented. The results show that the proposed automation methodology was successfully able to predict energy consumption in accordance with previously obtained results. The verification study comparing results from the automated methodology to the results of previous studies that were validated on a 2013 Nissan Leaf show that the methods proposed here can be successfully used to predict EcoRoute between a source and destination.

A change in route geometry between the same source and destination can result in the energy consumption to change. A longer route consisting of a higher number of stops resulted in higher travel time and energy consumption. Although the average speed increased, due to addition of stops and a longer distance, the travel time was higher. This also shows the importance of obtaining the latest map data as road networks can undergo changes over time and processing outdated data can result in inaccurate results. Since both travel time and energy consumption are affected due to changes in a route, the choice of EcoRoute may also change. An analysis on the changed section of route 3 in the Blacksburg case study showed that the changes between the current and the previous route accounted for the overall differences between the results for the route.

Sensitivity studies conducted on cruise velocity, road grades, distance and conditional stops versus energy consumption show the importance of the various factors affecting energy consumption and demonstrates that the fastest or the shortest route may not always be the EcoRoute. Generally, the shorter route is assumed to be the EcoRoute. However, the shorter or the faster route may not always be the route with the least energy consumption as energy consumption is not dependent on the distance or travel-time alone. Other factors like stops, road grades and speed limits affect the energy consumption and it is possible for the shorter or the faster route to not be the EcoRoute.

Stops generally increase the energy consumption. However it cannot be taken as a thumb rule that the route with the higher number of stops will have higher energy consumption. For any particular route, a higher number of stops encountered generally results in higher energy consumption. Stops induce additional acceleration-deceleration events and in-spite of regenerative braking, there is a net loss of energy in the acceleration-deceleration event. However, given the placement of stops, type of stops and other road network characteristics, it is possible for the same route to have a lower energy consumption for higher stops as compared to lower stops.

6.2 Validation in actual driving conditions

Validation of the automated software is done by comparing the results of simulation to results of an actual driving test and powertrain model synthesis on measured velocities during the driving test. Extensive analysis on travel time and energy consumption predictions are conducted. Comparative studies on synthesized velocity profiles to actual driving speeds are conducted to understand the impact of vehicle kinematics on energy consumption. Transient traffic conditions were found to significantly affect energy consumption. Conditions that cannot be predicted were found to cause mismatch between predicted and actual energy consumption. Mismatch between route data obtained for software simulation and ground truth was observed in general and found to cause error in prediction. Overall, generating accurate velocity profiles is most important to predict energy consumption accurately, however, given the feasibility and complexity of such models and also since consistently ranking routes based on energy consumption is much more practical and useful, the EcoRouting problem can be solved using the velocity profile synthesis based on Hill model used in this thesis.

Actual driving conditions may not usually match the smooth driving profiles generated in simulation. Actual driving conditions contain a lot more acceleration-deceleration and stop-go events that may be impossible to predict. Several times, due to the presence of traffic vehicles may fail to achieve the posted speed limits as predicted and result in stops at places where it is not legally required to stop. All this affects the overall energy consumption. The differences between predicted and the actual results may even be large enough to affect the choice of EcoRoute.

6.3 Traffic Impact Analysis

The impact of traffic on the travel time and energy consumption for the HEVT Camaro is studied. Analysis of comparison of travel times and energy consumption of three routes in Blacksburg, Virginia for varying traffic conditions show that while energy consumption over routes may not change the selection of optimal route, the choice of EcoRoute is mostly affected by travel time predictions.

While prediction of energy consumption can be made more accurate by modeling and capturing transient real-time conditions, such conditions did not have an impact on the ranking of routes based on energy consumption alone.

For any particular route, with an increase in traffic, the average number of stops encountered generally increases. The energy consumption and travel time also increases with traffic. The choice of optimal EcoRoute between a choice of routes for different traffic conditions can be different not only based on the energy consumption, but also the travel-time.

Chapter 7

Future Work

The focus of research for EcoRouting in this thesis was on automation, validation in actual driving and traffic impact analysis. The analyses was conducted on a battery electric vehicle. The studies need to be expanded to other battery electric vehicles, conventional vehicles and hybrid vehicles. A comparison of the effectiveness of the EcoRouting methodology on different powertrains needs to be conducted.

EcoRouting can be combined with ADAS (Advanced Driver Assistance Systems) to coach the driver on better driving strategies to maximize energy/fuel savings with prior route knowledge.

The performance of the EcoRouting methodology when applied to several vehicles in the same network and the further adoption and modification to obtain network wide energy savings needs to be studied.

Mechanisms for collecting data while EcoRouting systems are employed on board and further processing it to find patterns need to be looked upon. The collected data can help better predict travel times, generate more accurate velocity profiles and help tune constants and parameters used in modeling. Additionally, such data can help tune the model specific to routes and the driver. Also, the prediction of conditional stops and the stop times specific to both the routes and driver can be made more accurate with collected data. Machine learning algorithms could especially be very useful for finding patterns in collected data.

A velocity profile synthesis model that accounts for traffic and also considers road grades as input could be very useful for predicting energy consumption more accurately. Studies on how traffic impacts traveling speeds and research on mechanisms for obtaining real-time traffic data need to be conducted. With real-time traffic incorporated into the software methodology, appropriate modifications can be done to the algorithm to calculate updated optimum EcoRoutes in real-time on the move based on live traffic data.

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