The Benefits of EcoRouting for a Parallel Plug-In Hybrid Camaro

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Abstract

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EcoRouting refers to the determination of a route that minimizes vehicle energy consumption compared to traditional routing methods, which usually attempt to minimize travel time. EcoRoutes typically increase travel time and in some cases this increase is constrained for a viable route. While significant research on EcoRouting exists for conventional vehicles, incorporating the novel aspects of plug-in hybrids opens new areas to be explored.

A prototype EcoRouting system has been developed on the MATLAB platform that takes in map information and converts it to a graph of nodes containing route information such as speed and grade. Various routes between the origin and destination of the vehicle are selected and the total energy consumption and travel time for each route are estimated using a vehicle model. The route with the minimum energy consumption will be selected as the EcoRoute unless there is a significant difference between the minimum time route and the EcoRoute. In this case, selecting a sub-optimal route as the EcoRoute will increase the probability that the driver uses a lower fuel consumption route. EcoRouting has the potential to increase the fuel efficiency for powertrains designed mainly for performance, and we examine the sensitivity of the increased efficiency to various vehicle and terrain features. The reduction in energy consumption can be achieved independent of powertrain modifications and can be scaled using publicly available parameters.

General Audience Abstract

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The automotive industry faces increasingly strict government regulations and standards for fuel economy while maintaining the safety, performance, and consumer appeal of the vehicle. Hybrid Vehicles are cars that run on a combination of fuel an electricity. Plug-In hybrid vehicles are a subset of hybrid vehicles that have a large battery pack that can be charged externally. These vehicles therefore are a relatively cleaner form of energy and provide more mileage for the same amount of fuel. It is however important to consider the source of electricity generation when evaluating the environmental impact.

Though hybrid vehicles typically have better fuel economy than their conventional counterparts, further improvements can be made on total energy consumption. EcoRouting is a step towards achieving the high standards set for a sustainable future.

EcoRouting refers to a fuel efficient route that is still a viable alternative over the shortest Travel Time (TT) route, typically selected by routing applications and users alike. The major goal of the EcoRouting module developed here is to find a fuel efficient route which still has a viable travel time for it to be considered by the user. Maintaining a balance between the commute time and fuel consumption of the vehicle is key to ensure that drivers actually select EcoRoutes to fulfill their commuting requirements. This thesis lays out a method considering traffic conditions and the way the vehicle is driven. This method is be applied to applied to road networks in Detroit and San Francisco to gather extensive quantitative data. The data is used to analyze scenarios in which taking an EcoRoute will actually be a viable alternative for drivers of plug-in hybrids. The results show that EcoRouting is definitely viable for PlugIn hybrids and it depends highly on driver behavior and their priority of commute time. Furthermore, EcoRouting for PHEVs is more suited to city driving compared to highway driving. The EcoRoute varies and needs to be customized to the driving style of the user.

Dedication

Dedicated to my parents Krishnakali Dutta and Devapratap Baul

Acknowledgments

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Contents

List of Figures

List of Tables

Chapter 1

Introduction to EcoRouting

Corporate Average Fuel Economy (CAFE) standards are government regulations that attempt to increase the overall fuel economy in the United States. These standards are regulated by the Department of Transportation. The 2025 standards established in 2011 pushed for an overall fleet economy of 54.5 MPG for a certain size and footprint [6]. Newer studies indicate that a more realistic number for average fleet economy for automotive manufacturers lies between 50 and 52.6 MPG [7]. Since this mileage applies to a fleet of vehicles, there is increased incentive amongst vehicle manufacturers to increase the production and sales of vehicles with an electrified powertrain, which have higher MPG ratings than their conventional counterparts. From a consumer perspective there has also been a rising interest in Plug-In Hybrid Electric Vehicle (PHEVs) amidst the interest for increasing savings on fuel consumption and the impact of conventional vehicles on climate change [8].

A hybrid vehicle has two sources of energy : fuel and electric energy. Both sources are taken into consideration for the calculation of fuel consumption. The focus of this thesis is on a quantitative study to investigate fuel efficient routing for a PHEV. The Energy Independence and Security Act of 2007 [9] defines a PHEV "as a a light-, medium-, or heavy-duty motor vehicle or non road vehicle which draws motive battery with a capacity of at least 4 kWh and can be recharged from an external source of electricity." Hybrid Vehicles have been around for over two decades and there is a push for innovative technologies that improve the baseline fuel economy of hybrid vehicles. One of the innovative automotive technologies is EcoRouting and the application of this technique for hybrid vehicles is what this thesis focuses on.

EcoRouting can be defined as the routing methodology that minimizes vehicle fuel consumption compared to the more traditional routing engines that compute the shortest time route. The shortest route is also known as the Travel Time (TT) route in EcoRouting literature. Travel time when not abbreviated refers to the commute time of the route. EcoRouting may not be the TT route but the potential increase in travel time still needs to be feasible for drivers to actually use it. Any routing technique minimizes a cost or objective function.

In the case of EcoRouting , the objective function to be minimized is fuel consumption, with a constraint on the travel time. Total fuel consumption in this thesis is calculated by converting the electric energy consumption to an equivalent to balanced SOC corrected fuel consumption metric and adding it to the fuel required to drive the engine.

This thesis discusses a developed EcoRouting system that pre-processes geographical data into 4 inputs: distance, target velocity, road grade and idle time. Distance between two successive points on a route is obtained by applying Cartesian coordinate geometry principles after converting the GPS coordinates. The two geographical coordinate systems used for this computation are discussed in Section 1.3. Target velocity for the roads are obtained from open map data sources.

The drive cycle used to model driver behavior uses a simplified speed profile shaped like trapezoids. The drive cycle at any point in time has one of the four phases: Idle, acceleration, cruise and braking. Constant preset acceleration and deceleration values are used to construct the trapezoids that make up the drive cycle. These trapezoidal drive cycles are discussed further in Section 3.4

Idle time is computed using an active signal model that determines the number of traffic signals that turn red during a route commute. Each active traffic signal turns red for a fixed time that is randomly generated from typical probability distributions of signal cycles. The details of the active signal and idle time considerations are discussed in Section 3.3.2. These four inputs are then fed to the scalable powertrain model as discussed further in Section 1.5 The analysis of EcoRouting is done on the route by considering the cost function as the fuel consumption of the vehicle. The EcoRoute is selected by considering both travel time and energy consumption. In that sense, a feasible EcoRoute is a sub-optimal solution. EcoRouting helps to increase fuel efficiency without any modifications to the vehicle powertrain and can be customized to any vehicle. The presence and absence of road grade is studied through a quantitative analysis where real world routes from Detroit and San Francisco are used. The acceleration value is varied along with the speeds in congested conditions to model real world driving and test cases of driver aggression.

1.1 Current State of Technology

A niche area exists for developing an EcoRouting module for plug in hybrid vehicles that can be customized to each vehicle for accurate consumption measurements. This thesis attempts to fill that niche with extensive quantitative study and investigate the benefits of EcoRouting for PHEVs. EcoRouting has been implemented in conventional vehicles such as Ford's EcoRouting which lets the driver choose between the fastest, shortest and EcoRoute. Ford's MyTouch$^{\mathrm{TM}}$technology has an "Eco-Route" mode that lets users select choose the most fuel efficient route based on real time traffic information such that drivers can avoid congested roads and drive at fuel efficient speeds.

EcoRouting is currently a hot topic for research and a wide variety of companies have implemented some form of energy management based around the 'Eco' terminology. For example, Nissan has an app called CARWINGS™for its Leaf platform that lets a driver choose a route based on available charging stations. The Toyota Prius and Hyundai Sonata have an 'eco' mode that changes the pedal map to improve the fuel economy. The Garmin Mechanic is a device that connects to the On Board Diagnostics (OBD) port in the vehicle that attempts to improve your driving habits using fuel and mileage reports. The ecoroute™HD technology collects vehicle data and provides drivers with suggestions to imrpove their mileage. The Chevrolet Volt has a 'Mountain Mode' that forces the control strategy of the vehicle from charge depleting (CD) to a charge sustaining (CS) mode and engages the engine in providing additional power to climb up steep hills. GM filed a patent for a PHEV control strategy based on route selection [10]. Honda has an Eco-Assist™system which was originally developed for the 2010 Honda Insight. This technology uses positive reinforcement techniques to award good driver behavior. For example, the display projects images of green leaves over time if the driver incorporates high efficiency driving practices. The examples of current EcoRouting technology in conventional and electrified vehicles have a common theme of approaching the problem of solving fuel efficient routing by considering only route conditions. These technologies do not take into account the powertrain of the vehicle. The powertrain of every vehicle determines how it burns fuel for commmuting needs. A scalable powertrain model is used in this thesis which was developed by Courtney Tamaro [1] which uses publicly available data to estimate energy consumption for conventional, battery electric and hybrid vehicles.

1.2 Path planning terminology

A road network is mathematically visualized as a connected graph, an example of which can be seen in Figure 1.1. The three nodes are connected by directional arrows which represents the direction of traffic flow. The constituent parts of any road network are nodes and links.

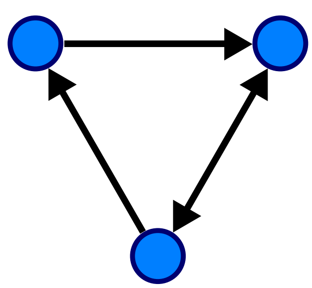

Figure 1.1: Directed graph visualization taken from Directed Graph Wikimedia (Public Domain)

A node is a geographic location through which traffic can pass indicated by the blue dots in the figure. A link or way is a connection between two nodes and can either be directional as shown in the figure or bidirectional depending on the nature of the road. A route is a path traversed between the origin node and the destination node and is characterized by an ordered pair of links. Figure 1.2 shows an example route with the basic terms like nodes and links.

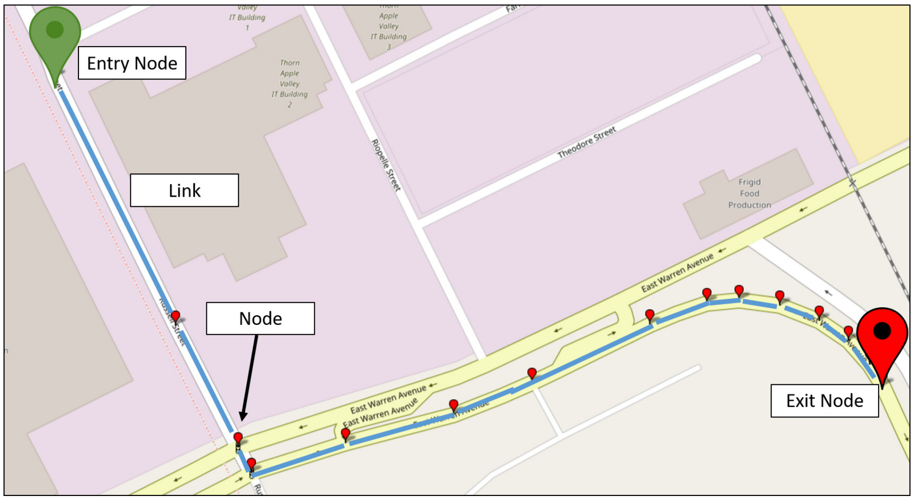

Figure 1.2: Visualization of basic route terminology

1.2.1 Traffic Assignment

Traffic Assignment is defined as the process by which paths are assigned traffic in such a way that the objectives of the path are achieved. In other words, it is methodology to assign vehicles on roads keeping in mind preset goals or conditions. One example of such a goal is ensuring that the capacity of the highway is not exceeded during peak rush hours. It is the process by which route selection is done for a vehicle and is a commonly occurring term in traffic engineering literature especially at the network level. These objectives are mathematically expressed in the form of a cost or objective function. Path planning therefore is an optimization problem where the optimal solution minimizes the cost which can either be time, distance, energy consumption or a mix of all three parameters depending on the end goal. The two basic routes generated from current routing software are the shortest time route and the shortest distance route. The shortest time route is a a more practical metric for real world driving since drivers typically care about spending the shortest amount of time commuting when done for non recreational purposes. For this reason, the TT route is considered the baseline and the two major metrics of travel time and energy consumption are compared relative to the shortest time route. The shortest distance route is also used for comparison but is not the baseline. The reason for also considering the shortest distance route is that the lowest energy route is typically the shortest distnace route.

1.3 Geographic Coordinate Systems

A Geographic coordinate system (GCS) is used to define parameters to describe locations on earth. A set of numbers, letters or numbers are used for this purpose [11]. The most common set of geographic coordinates is latitude, longitude and elevation. GCS are critical to EcoRouting because any route study would involve the extraction of geographical information about the route. GCS are used to standardize the geographical information so that they can be used worldwide across difference platforms. In this thesis two GCS are used for route input and distance calculation respectively.

Two types of geographic coordinates are used for the development of the necessary inputs for the powertrain model: The World Geodetic System (WGS84) and the Earth Centered Earth Fixed (ECEF) coordinate system. A brief overview of both is given below. The WGS84 coordinate system is used for GPS navigation. The ECEF is a Cartesian coordinate frame of reference which allows the use of Cartesian geometric principles to be used for geographical coordinates. The ECEF has been mainly used to compute distances in this thesis.

1.3.1 WGS84

The WGS84 is the standard used for GPS navigation. It comprises a standard coordinate system, a reference ellipsoid or datum, and a geoid. The geoid is an irregular surface used to model the earth at zero elevation since it is not a perfect sphere. All points on a geoid are therefore considered to have equal gravitational force. So by using the reference ellipsoid, defining a sea level on the geoid and a coordinate system, any point on the earth can be given three dimensions: latitude, longitude, and elevation. The elevation is measured from the geoid.

The WGS84 therefore approximates the shape of the earth as an ellipsoid, and a geoid is then used to mark the sea levels on the ellipsoid. The official diagram of the WG84 coordinate system can be seen in 1.3 .

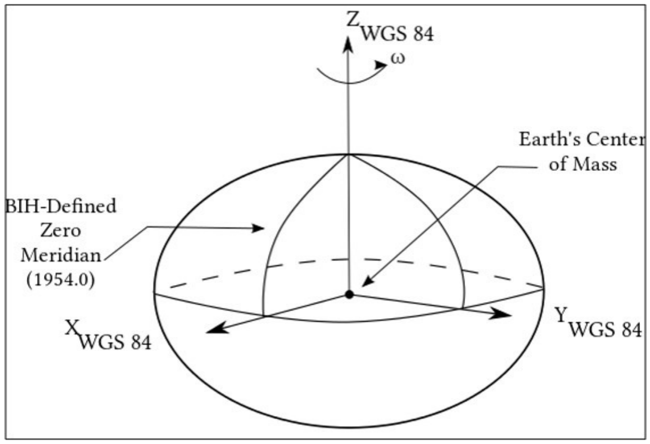

Figure 1.3: WGS84 coordinate official diagram taken from **DoD WGS 84 Technical Report** (Public Domain)

1.3.2 ECEF

ECEF is an XYZ cartesian coordinate system where [0,0,0] represents the center of the earth. Converting GPS coordinates from WGS84 to ECEF allows the use of cartesian coordinate geometry for distance computation which is one of the inputs used in the powertrain model. The Z axis passes through the North Pole and the plane of the equator is the same as the XY plane. The X axis passes through the intersection of the prime meridian and equator (0^0 latitude , 0^0 longitude) and the Y axis is located at 0^0 latitude and 90^0 West longitude. The Y axis of the ECEF coordinate is in alignment with the International Earth Rotation and Reference Systems Service (IERS) reference pole. The "Earth Fixed" portion of the ECEF is termed based on the fact that coordinates do not change with the rotation of the earth. Coordinates on the surface of the earth do not change as a result of this property. Figure 1.4 shows the relation between ECEF coordinates, latitude and longitude. As noted by James Clynch [12] the ECEF coordinate system is also for satellite applications because only the center of the earth and the axes orientation are required for geolocating precise values.

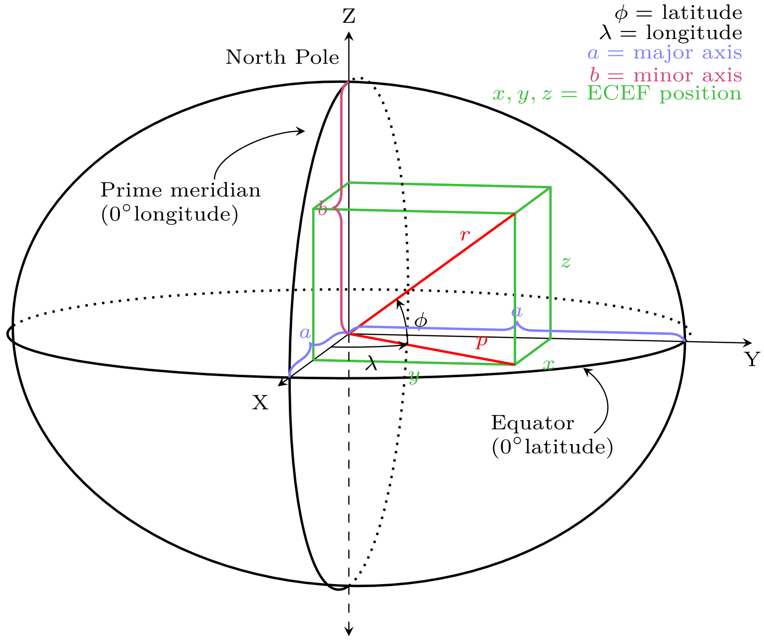

Figure 1.4: Relation between ECEF coordinates, latitude and longitude taken from **the ECEF Wikipedia page** (Public Domain)

1.4 Open Data sources and Formats

The backend of all open mapping data sources is OpenStreetMaps, a community driven open source GPS database that makes map information easily available to the public. Using publicly available sources of data is critical to ensuring reproducibility of results by anyone looking to further the state of the art in the field of EcoRouting. OpenRouteService.org is used to generate travel routes and navigation information which is used to calibrate the drive cycles used for EcoRouting. The geospatial services offered by this website use the community generated OpenStreetMap data for its backend database. The route service determines travel routes and navigation information according to diverse criteria.

Routes are exported and processed in the form of GPS exchange format (GPX files). This format is modeled around the extensible markup language (XML) and is commonly used in software for GPS applications. GPX files can be used to represent waypoints, tracks and routes. Waypoints are a collection of individual markers that are independent of each other. Track points are individual markers which are used to define a path on which travel occurs. A line drawn by joining the ordered trackpoints results in the route taken by the vehicle. The format is open and can be used without the need to pay license fees. Location data (and optionally elevation, time, and other information) is stored in tags and can be interchanged between GPS devices and software. The units of latitude and longitude is decimal degrees, while elevation is expressed in meters both using the WGS84 coordinate system.

1.5 Powertrain Model

This section of the powertrain model serves to give the reader a brief summary of the powertrain model used to compute energy consumption parameters. A more detailed description can be found in the thesis written by Courtney Tamaro [1].

The purpose of this powertrain model is to determine the energy consumption using vehicle characteristics that are openly available to the public. This approach is in contrast to more sophisticated vehicle models that assume the availability of proprietary vehicle data which isn't always ideal. This model can determine energy consumption for BEVs, HEVs, PHEVs and conventional vehicles. The model uses scaled data of powertrain components for parameter estimation. This scaling methodology allows for a model with a reduced number of inputs for faster computation.

The powertrain requires four inputs which need to be appropriately processed so that the model can generate accurate results. The four inputs to the model are distance from the origin, grade, idle time and target velocity. Each of these four parameters are discussed below along with the basic route properties.

1.5.1 Route

A route is a combination of ways as discussed in Section 1.4. Each input node to the model is a geographical coordinate with information about velocity, grade, and idle time processed in a GPX file. A distance based model is used to emulate a real world scenario where traffic data is spatially collected. The model can evaluate the tractive effort required at the wheels of the vehicle to complete such a route given the four inputs. Figure 1.5 is a visual representation of the relationship between nodes and their velocities relative to distance. A constant acceleration is used to change velocities between nodes since each node has its own target velocity.

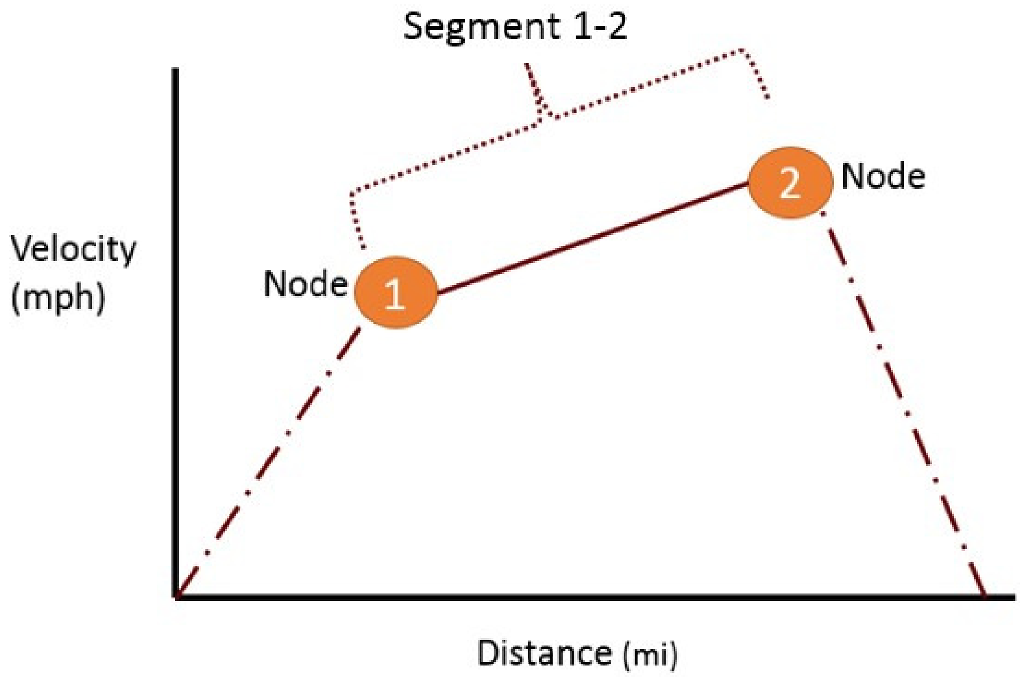

Figure 1.5: Node Segment Characteristics taken from [1] (Used With Author's Permission)

1.5.2 Origin Distance

The first node for each route is the origin and the distance for each node is computed as the absolute distance from the origin node. This way, the vehicle moves forward continuously resulting in an increase in the distance traversed. This method is similar to real world driving on highways where mile markers continuously inform the driver of the increased distance commuted.

1.5.3 Grade

Grade is a physical feature of a route that is defined as the tangent of the angle of the surface to that of the horizontal. For small angles the tangent is equal to the sine and that formula is often used for road load calculation [13]. The average grade of the entire segment is used as an input to the powertrain model. It is important to keep in mind that the nodes used should be sufficiently high in resolution to account for any grade variations.

1.5.4 Target Velocity

Target velocity for each node is the velocity which the vehicle should obtain by the next node or the desired mode-end velocity. The target velocity is used with the current vehicle velocity to find an average acceleration that the vehicle must maintain during that mode. Looking forward allows the vehicle to correct for any prior changes. Target velocity encapsulates traffic data. The target velocities received by the vehicle are average velocities of recent vehicles at the same location. In moments of high traffic, vehicles will travel at a slow velocity between distance nodes. When the vehicle is anticipated to stop, each nearby node leading up to the stop has a progressively slower target velocity. The purpose of this research is to model the vehicle as the vehicle is expected to drive, not determine a methodology to approximate how the vehicle should be driven.

1.5.5 Idle Time

A vehicle is idle when both the velocity and acceleration are zero. As the nodes in this model are based on distance, there is no way to know how long a vehicle may idle at a particular node other than to specifically input idle time at that node.

1.6 Thesis Outline

The objective of the work is to conduct a quantitative study to understand the benefits of EcoRouting for a PHEV Camaro model. This thesis will proceed as follows. First, a literature review discusses the current research done in EcoRouting, along with the powertrain models, effect of driver behavior and benefits for hybrid vehicles.

Next, the methodology for pre-processing the powertrain model inputs is discussed along with the drive cycle estimation strategy. The methodology is also validated within a 5-10 percent error margin using real world vehicle data from the US Environmental Protection Agency(EPA)[14] and the Downloadable Dynamometer Database(D3)[15] from Argonne National Labs (ANL).

This section is followed by results and analysis where the validated mehthod is applied to a variety of different routes with varying traffic levels and driver aggression based on varying constant acceleration. The thesis concludes with with recommendations where EcoRouting could prove to be viable for PHEVs along with recommended future areas of exploration.

Chapter 2

Literature Review

An introduction to the review is followed by EcoRouting done on conventional vehicles. The powertrain models used for this EcoRouting is then discussed and compared to the scalable powertrain model discussed in 1.5. The static and dynamic parameters critical to energy consumption are examined to determine the inputs for the scalable powertrain model. Driver influence and behavior has shown to be immensely important, the details of which are in Section 2.5 . Finally, current literature relevant to EcoRouting in electrified powertrains is discussed and the unique approach taken by the research done in the thesis is clearly differentiated. Finally, all the sections are summarized to make a case for investigating the benefits of EcoRouting for PHEVs using a quantitative study.

2.1 Introduction

A paper written by Kubička et al. titled [16], "Performance of current eco-routing methods" gives a comprehensive oversight into the world of EcoRouting. The focus of the paper was to conduct a study that compares EcoRoutes to the shortest and quickest routes. Conclusions of the study were drawn from the shortest routes on the basis of the fundamental principle that trading extra travel time would result in greater fuel economy. The study however does not put an upper bound on the travel times therefore the feasibility of the EcoRoutes cannot be accurately gauged. It is still a good starting paper to navigate through the vast available literature on the topic of EcoRouting.

One of the contemporary foundational papers on the topic was written by Ericson et al. [17]. The aim of their project was to optimize route choice based on the lowest fuel consumption. This project is the forerunner of what is widely called EcoRouting today.

The major conclusion was that 46 percent of the trips chosen by the drivers were not the most fuel efficient. 8.2 percent was the average fuel efficiency increase determined by them if a navigation system designed to save fuel was used. An inference can also be made from the paper that traffic information and driving behavior have a huge impact on the fuel consumption of a vehicle.

2.2 EcoRouting In Conventional Vehicles

Two seminal papers in EcoRouting laid the foundation of this thesis research. Rakha et al. [2] compared the effects of route choice decisions of a conventional powertrain vehicle. The arterial(green) and highway(red) routes used can be seen in Figure 2.1. A total of 39 trips were recorded between these two routes. 21 trips were on the highway route while 18 were of the arterial route.

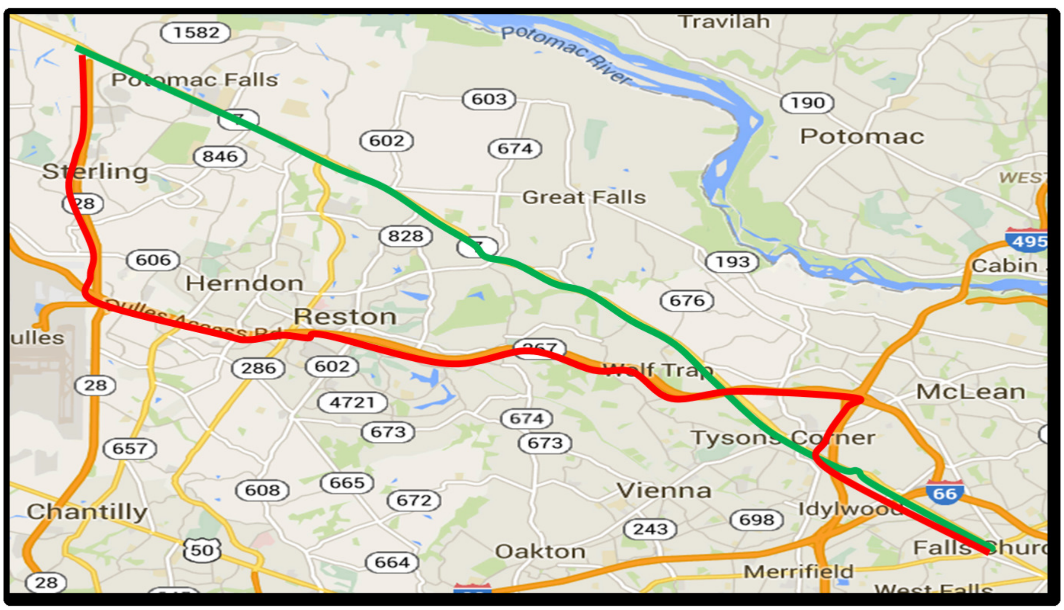

Figure 2.1: Arterial and highway routes used for Energy Consumption in [2](Fair Use)

As seen in Figure 2.1 from the paper, GPS data such as the coordinates and vehicle speed were collected for a highway and arterial route. The results showed that using the arterial route took 16 percent more time, and it consumed 18 percent less fuel compared to the highway route. The major takeaway from this paper was that the shortest time or TT route is not necessarily the most fuel efficient route and choosing an alternate route could lead to long term savings in energy consumption.

Rakha et al. [18] also quantified the impact of implementing EcoRouting from a systems level perspective on an entire road network. Parameters such as the traffic congestion, level of market penetration, and fuel efficiency of the vehicle were used over the simulated road networks of Cleveland and Columbus. The results showed that EcoRouting works better with increased adoption of the platform, more congested networks and has slightly lesser fuel savings for fuel efficient vehicles. The maximum average fuel savings was 9.3 percent compared to the shortest time route. Since the control strategy for hybrid vehicles makes it more fuel efficient, it can be concluded that the overall fuel savings for a hybrid vehicle will be less than a conventional vehicle.

2.3 Powertrain Models and Traffic Assignment for Eco-Routing

A powertrain model based on instantaneous velocity and acceleration used to estimate vehicle fuel consumption is also developed by Rakha et al. [19]. This powertrain model was typically used in the integration model in cases where historical traffic data was not available. This powertrain had only two input parameters and was developed for conventional vehicles only. The two parameters were velocity and acceleration only. The cost function for fuel consumption is a polynomial combination of velocity and acceleration. This approach works well for a fleet of vehicles but not for specialized powertrains like HEVs and PHEVs Since the hybrid has two modes of operation, a control strategy to manage the torque split is absolutely critical. This split needs to be taken into account for total vehicle energy consumption.

Rakha et al. [20] developed a software called INTEGRATION that simulates traffic on road networks and is capable of estimating fuel consumption and traffic flow. This software assigns routes to vehicles based on the fuel consumption measures using the powertrain model from [19]. The inclusion of the transient behavior was critical because similar macroscopic or network level traffic assignment tools have been shown to provide inaccurate results. Transient behaviour refers to sudden changes in velocity and acceleration. A comparison on competing macroscopic tools has been done in the Route choice paper [2] discussed in the previous section. The software can however only deal with fuel consumption at a network level and no hybrid vehicles were considered for this study because the relatively low market penetration compared to conventional vehicles [21].

This thesis uses the powertrain model developed by Tamaro [1] which uses a total of 30 inputs used to scale powertrains to suit vehicle models for conventional, EVs and hybrids. All inputs are sourced from publicly available data.

2.4 Static and Dynamic Parameters

Wisniewski et al. [22] conducted a study to understand the effectiveness of EcoRouting on automobiles. EcoRouting per their definition was limited to regen routing wherein the path is determined a fuzzy based control strategy based on the parameters of the route.

Regen routing is the determination of energy efficient routes by focusing on the recapturing of energy from regenerative braking.

A study of this paper gives a clear insight into the different types of parameters required for an EcoRouting module. Static parameters can be collected and kept offline ahead of the commute while dynamic parameters have to be collected in real time. A dichotomy exists between static parameters like speed limits and road grade and dynamic parameters like traffic and construction. In comparison, the powertrain model used for the thesis uses distance, velocity, road grade and idle time as inputs.

However, the paper deals with EcoRouting as the control strategy of the vehicle instead of choosing a fuel efficient route. On the contrary, the primary focus of this thesis is the determination of fuel efficient routes for hybrid electric vehicles with an assumed driving behavior.

2.5 Effect of Driver Influence

The focus of this thesis is EcoRouting however the way the car is driven i.e. EcoDriving plays a huge role in fuel consumption metric. EcoDriving generally refers to good driving practices to improve the long term fuel economy of the vehicle. Therefore, the driver behavior has a large effect on the end fuel efficiency of a vehicle. This effect was studied by Franke et al. [23] who interviewed 39 drivers of HEVs who had above average fuel efficiency achievements as a result of their driving. The study concluded that there is a large variance of fuel efficiency even amongst drivers who are highly motivated to uphold the general motivations of good EcoDriving practices. This variance occurs mainly because of the varying opinions of drivers and their perceived impact on the baseline. A study of EcoRoutes by varying driver aggression can reveal the specific scenarios in which EcoRoutes are viable alternatives to the shortest time routes.

Bart Saerens [24] in his PhD thesis approached EcoDriving as an optimal control problem. He developed a method to evaluate fuel efficient routes based on driving behavior. The system model consisted of a fuel consumption and vehicle model. Multiple optimal control methods are then used to solve typical problems in driving such as acceleration, deceleration and driving in between stop lights. The simulations run by him resulted in a set of driving recommendations and guidelines that help improve the vehicle fuel economy. Recommendations include maintaining a constant velocity at the highest gear, keeping a 3 second headway, and using cruise control on level roads.

The use of technology in modifying driver behavior has some negative implications as well. The National Highway Traffic Safety Administration(NHTSA) conducted a study on the impact of driver inattention on the risk of crashing. The base dataset used is the 100 Car Naturalistic Driving Study [25]. The study conducted by the Virginia Tech Transportation Institute collected driving data from a 100 vehicles which has sensors and instruments installed in them.

Two of the major identified reasons for inattention were the engagement of the driver in secondary tasks and glancing away from the road. The knowledge gained from the results of the study will be critical when building the hardware EcoRouting module which will be installed in a prototype PHEV Hybrid Camaro as part of the EcoCAR 3 competition. The module should be designed in such a way that the driver would only need to input the destination of the vehicle from a stationary/idle position so that driver distraction is minimized. It is important to keep in mind that safety considerations are not directly relevant to this thesis but will be an important part of the future work done to implement EcoRouting on a hardware level.

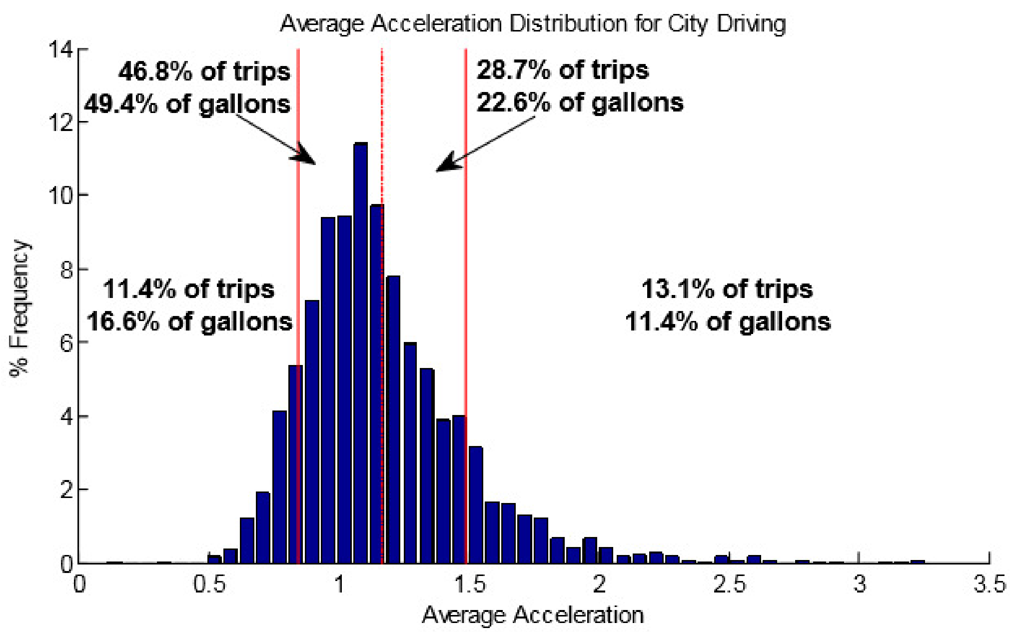

Figure 2.2: Acceleration distribution for city driving from [3] (Fair Use)

The National Renewable Energy Laboratory (NREL) published their findings in a report [3] where they attempted to quantify the the fuel savings resulting from influencing driver behavior through feedback systems to drive in a more sustainable manner. This study reported up to 20 percent fuel savings for aggressive or high acceleration driving styles in real world driving, and 5 to 10 percent savings for moderate driving styles. The distribution of acceleration profiles of city driving can be seen in Figure 2.2. This data was used to determine the acceleration values in the simplified speed profile trapezoids explained further in Section 3.4 under the Methodology chapter.

The executive summary of this NREL report does point out that the savings which are considered marginal may be insufficient to influence drivers into modifying their behavior. An EcoRouting module would therefore need to have a reasonable travel time estimate. This step ensures that the route selected by the module is indeed feasible compared to the shortest time route.

The major recommendation for drivers to operate the vehicle efficiently from the study is to hold the speed at a steady state value. The drive cycle construction used for the EcoRoutes uses a simplified speed profile as seen in Figure 2.3. These trapezoidal drive cycles also hold the speed at a steady state or cruise value and happen to be in line with the aforementioned recommendations. The vehicle accelerates at a constant value, cruises at the speed limit and then decelerates at a constant rate to arrive at the traffic signal.

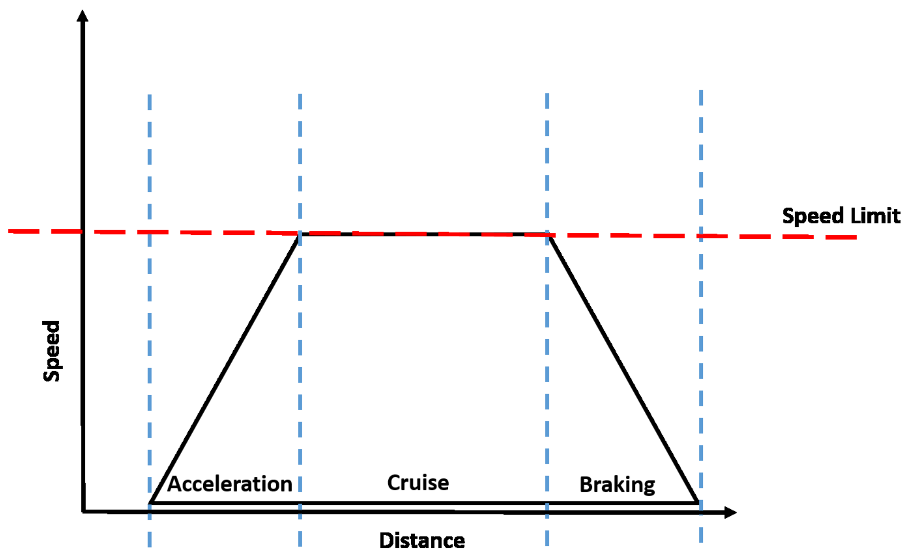

Figure 2.3: Simplified speed profile for drive cycle construction

2.6 EcoRouting in Hybrid and Electric Vehicles

Richter et al. [5] compared EcoRoutes and Time efficient routes in terms of the potential energy savings for EVs, HEVs and conventional vehicles. The street topology, traffic and vehicle powertrain were the important factors that were considered for the comparison of Eco and time routes. The results showed that the BEV model had the highest energy saving of 22.7 percent as seen in Table 2.1 using the shortest route as the baseline. The travel time increase was also the largest out of the three powertrains.

The increase in both energy saving and travel time was attributed to the fact that the BEV model skewed the EcoRouting algorithm to favor routes with longer downhill or negative grade profiles to capture regenerative braking. The major takeaway from this paper is that there are major differences for EcoRouting strategies for conventional vehicles, HEVs and BEVs and consideration of the powertrain setup of each vehicle is critical.

Table 2.1: Energy Saving and Time Increase vs Shortest Time Route from [5](Fair Use)

	Energy Saving vs shortest time route(%)	**Time Increase vs shortest time route(%)**
ICEV	9.1	22.4
BEV	22.7	27.1
PHEV	12	22.9

Larson et al. [26] designed a simulation study in Autonomie to create an Energy Management system for Hybrid Electric Vehicles where the routing algorithm has apriori knowledge of the road network. Commuter routes were generated using historical traffic data. The results showed a 4-9 percent improvement in fuel consumption. These results were very important to the research done in this thesis because the simulation used a post transmission parallel hybrid vehicle which is the powertrain of the PHEV Camaro from the scalable powertrain model used for the analysis of EcoRoutes in this thesis. Post transmission refers to the position of the motor in the powertrain. A parallel hybrid vehicle is one that is capable of being both the engine and motor independently and in a combined configuration depending on the vehicle control strategy. The developed powertrain model is quite detailed and has a high fidelity. The downside is that the model parameters are not scalable to other powertrains and vehicles plus a lot of proprietary data is used to improve model fidelity. The authors have also openly acknowledged that use of the energy management system developed by them would be feasible only if a Vehicle to Infrastructure (V2X) is already setup. A large amount of computation is needed to obtain real time route data continuously along with the historical traffic data.

Li et al. [27] in their paper did a study on the benefits obtained through advanced driver information. The motivation behind this study was to reduce haphazard acceleration and braking by modifying driver behavior. Prior information about signalized intersections would lead to a driver decelerating slowly to a complete stop at the traffic light leading to improved fuel metrics. Dilemma zones have been identified as a major issue for safety and errant driver behaviour. A dilemma zone refers to an event where the driver is unable to make a good estimation of a yellow light and has to brake hard when the light turns to red. This kind of braking causes energy losses through heat dissipation. An EcoRouting module could get real time traffic information and the geolocated traffic signal information can be made available to the driver so that acceleration and braking events are not made as a result of split second decisions. The thesis developed here uses trapezoidal drive cycles which can be scaled and used as building units for either a standard drive cycle like the Urban Dynamometer Driving Schedule(UDDS) or model driving behaviour by changing the acceleration and deceleration values.

Gonder et al. [4] analyzed the energy efficiency benefits of connectivity-enhanced route selection and adaptive cruise control methods on the Chevrolet Volt. Connectivity-enhanced refers to leveraging the use of Vehicle to Infrastructure (V2x) networks to obtain route data and enable the driver to make more energy efficient route choices. This project was a collaboration between General Motors and NREL. The identified candidate routes are broken up into road segments with its individual road characteristics with traffic and driver aggression accounted for. A drive cycle model is also used to make the kinematic predictions over each segment. This paper has an approach similar to the methods developed and validated in this thesis which is why the results of this study are quite relevant.

The results showed that out of the 43,000 Origin-Destination (OD) pairs , the fastest route is not the most energy efficient route 37 percent of the time. These are the cases where green or EcoRouting offers an alternative to the driver in terms of potential savings in energy. The extreme case as seen in Figure 2.4 shows a reduction in energy use by 12.3 percent but at a cost of 14.4 percent increase in travel time. The figure was generated by plotting the percentage change of time, cost and energy as a function of the perceived value of the time of the driver. The top line is the increase in travel time relative to the shortest time route and the bottom line plots the corresponding decrease in energy and cost.

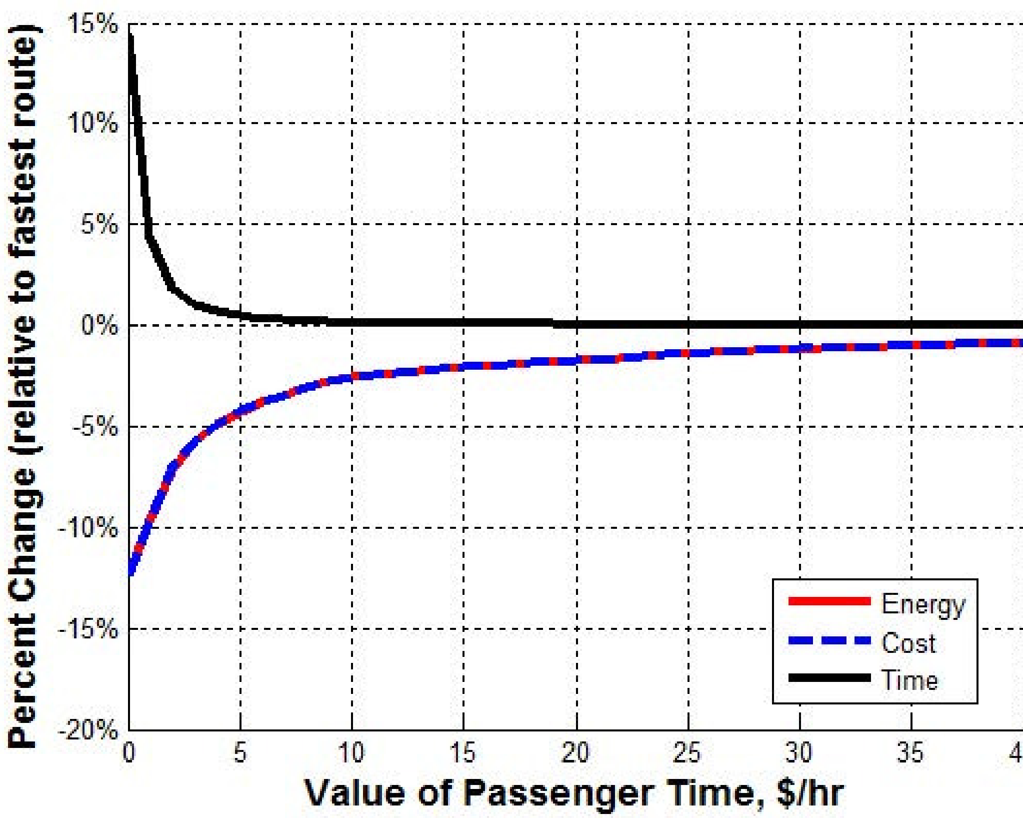

Figure 2.4: Percentage change of Energy and time vs Passenger value time from [4](Fair Use)

On the other end of the spectrum, a passenger or driver who values their time at $35/hr would reduce energy consumption by 1 percent for a trivial increase in travel time. Overall fuel savings are near 5 percent assuming a low value of passenger time. A conclusion can be drawn from the study that drivers would be more inclined to use EcoRouting when their perceived value of time is relatively less. This state of mind would allow them more options for energy efficient routing.

2.7 Summary of Literature Review

To summarize the literature review, the viablity of EcoRouting in the specific context of PHEVs has been investigated. The unique approach this thesis takes is to use a developed scalable powertrain model and apply it to different scenarios and come up with conclusions that will aid early adopters in understanding when and where an EcoRoute is a viable alternative to a conventional travel time route.

The literature review covered six sections. An introduction to EcoRouting was given through a review paper [16] that comprehensively covers the basics and the paper largely considered the foundational EcoRouting literature [17]. The second section covered the work done in conventional vehicles from a transportation point of view which was the seminal work leading to selection of this topic for this thesis. This section gave a general idea of how the problem is typically approached and set primary baseline expectations for improvement in fuel consumption.

The third section covered the powertrain models that have been used for conventional powertrains and how a simple velocity acceleration model with basic scaling parameters is used to classify large sections of vehicles. This approach is definitely beneficial from a top down network level approach. A scalable powertrain model which can be used to model any vehicle with publicly available parameters is more beneficial to implement EcoRouting modules at the hardware level for specific vehicles.

The fourth section talks about the static and dynamic parameters that are used as inputs for EcoRouting models. Through a study of the existing models, static parameters for our study were determined to be distance and grade, and speed limits, while the dynamic parameter modeled is idle time which is done using a probability distribution curve for traffic lights and the time spent waiting at stop signs.

The importance of driver behavior and and its influence is discussed. The study done by Bart Saraens [24] helped identify good driving behavior patterns which led to the development of the simplified speed profile used to construct drive cycle similar to the NEDC drive cycle. A report published by NREL was used to set the acceleration parameters for the vehicle to match real world driving. Finally, the last section covers the literature in Hybrid and Electric Vehicles and differentiates how the research done in the thesis is different from the what has been done. A study on a vehicle powertrain similar to the PHEV Camaro model shows a 4-9 percent improvement in fuel consumption which narrows the base expectations set in Section 2.2. A very novel method to evaluate the viability of EcoRoutes has been shown by [5] where the available EcoRoutes to a driver is a function of how valuable his time is at that point.

EcoRouting can therefore be potentially viable for Plug-In hybrids, even though the improvements in fuel consumption may not be as much as conventional vehicles. The next section of the thesis will cover the methodology used to set up the EcoRoutes and compare metrics against the set baseline of shortest time routes (TT routes).

This thesis develops a methodology keeping these two parameters in mind, in addition to grade and the focus is on applying the concept of EcoRouting to PHEVs.

Chapter 3

Methodology

Based on the review of current literature in the field of EcoRouting, a case can be made for a quantitative approach to the application of EcoRouting in Plug-In hybrid vehicles, so that the benefits can be analyzed for different scenarios and a conclusion made on the effectiveness of EcoRouting for Plug-In hybrids. Data collection was primarily driven by the input parameters of the powertrain model namely distance , grade, target velocity and idle time. All data is obtained from open sources to ensure easy reproducibility of results and keeping the financial costs of the experiments to a bare minimum.

The methodology of the experiments conducted can be broken down into 4 major steps: Route export, Grade Calculation, Traffic Signal Estimator and Drive cycle construction. Following these 4 steps results in the production of the four previously aforementioned input parameters which are then used to obtain results for fuel consumption for each route.

3.1 Route Export

Routes are exported from GPS Exchange (GPX) files from the OpenRouteService.org which is an website offering geospatial services using the OSM as the backend. The latitude and longitude of each node is contained within the exported GPX files. The total length of the route is obtained by converting the GPS coordinates from the WGS84 system to ECEF. Both these systems are discussed in detail in Section 1.3 Figure 3.1 shows a screenshot of an exported GPX file from the OpenRouteService website.

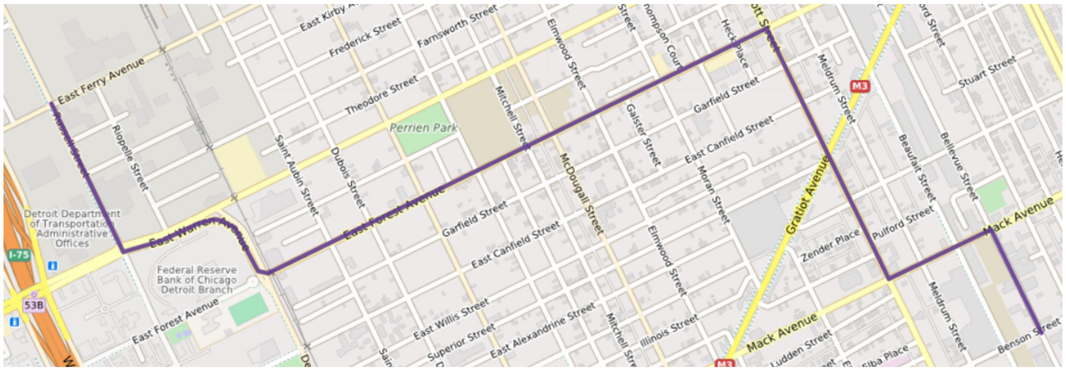

Figure 3.1: Screenshot of Detroit Route from OpenRouteService

3.2 Grade Calculation

The road grade of a route is defined as the ratio of rise over the run (horizontal distance). The road grade between two nodes is an input to the powertrain model and is a key factor to differentiating between scenarios for EcoRouting. San Francisco has a higher variability in grade compared to Detroit which is relatively flat which causes a difference in fuel consumption results for similar driving style and distance. Elevation data is obtained from the GPS visualizer website [28] which has an online elevation look-up tool. Elevation is appended to each geographic coordinate or node in the GPX file obtained from the previous step. The base elevation dataset comes from NASA's Satellite Radar Topography Mission (SRTM) which has nearly 80 percent of the earth's land surface [29]. The formula for grade is given in Equation 3.1

$$\%/Grade = \frac{((h_1 - h_2) * 100}{d} \tag{3.1}$$

where, h_1 is elevation at previous node, h_2 is elevation at current node, and d is the distance between nodes. An important mathematical property used in the equation above is the use of small angle approximation which is commonly used to estimate road grade [13]. For practical purposes in transportation engineering, the sine and tangent of the angle of inclination are approximately equal. Figure 3.2 illustrates a steep road with the rise, run, and distance labeled.

Using the small angle approximation, we get Equation 3.2.

$$Grade = \frac{rise}{run} = tan(\theta) = sin(\theta) = \frac{Rise}{Distance} \tag{3.2}$$

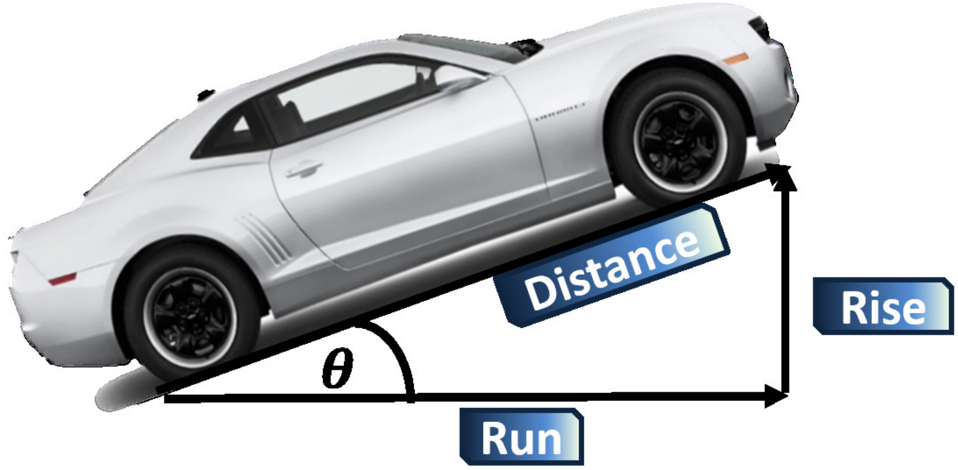

Figure 3.2: Road Grade Visualization

3.3 Traffic Modeling

An initial approach to the EcoRouting problem involved using the average velocity over the route and the travel time, given the travel time and distance parameters from OpenRouteService. Further investigation of this approach revealed that it was too simplistic to generate realistic results that can be used to draw conclusive inferences. Using an average velocity approach ignores the actual driving style which make a big difference in the fuel consumption of a vehicle. The idle time and target velocity at each node were not accounted for. These two parameters are inputs to the powertrain model and the absence of them caused the model to be unreliable.

3.3.1 Traffic Signal Finder

The new approach developed and currently used in this methodology uses the location of traffic signals as points where the vehicle comes to a complete stop. A MATLAB script was developed to match the geographic coordinates of the traffic signals upto six significant figures yielding an accuracy of 11 meters. This level of accuracy was chosen because consumer GPS units also use the same precision.The Poisson probability distribution curve was found to be the most suitable for sampling the traffic signals based on traffic flow and modeling. The idle time was on each active traffic signal was determined by a random sampling of stop times between 60-90 seconds which is the usual amount of time vehicles stop at a traffic signal based on empirical data provided by the department of transportation. An important requirement for conducting the simulation was that the vehicle would need to start decelerating in a way that it hits the stop sign at zero velocity while crossing it.

The coordinate matching for traffic signal location proved to be very inaccurate based on the incorrect assumption that the traffic signal will lie only on a node. In reality, a traffic signal can be present anywhere within a route. Therefore, this is an extension of the problem of determining whether a point (traffic signal coordinate) lies between two other points (nodes). A threshold of reasonable accuracy was determined through trial and error as well as calibrating the parameter to adjust real world consumer gps units, which are usually 11 meters. This approach while more accurate was found to be extremely sensitive to the threshold value of the minimum perpendicular distance and each route had to be separately adjusted. Custom adjustments for each route proved to be extremely time consuming.

The traffic signal data for many major cities is openly available through open source data provided by Socrata Technologies. The traffic signal locations and type is exportable through GPX files. Traffic signal points are independent of each other and are therefore stored as waypoints which have been discussed in Section 1.4. All the routes are plotted along with the traffic signal data using GPS visualizer. An example of such a map can be seen in Figure 3.3.

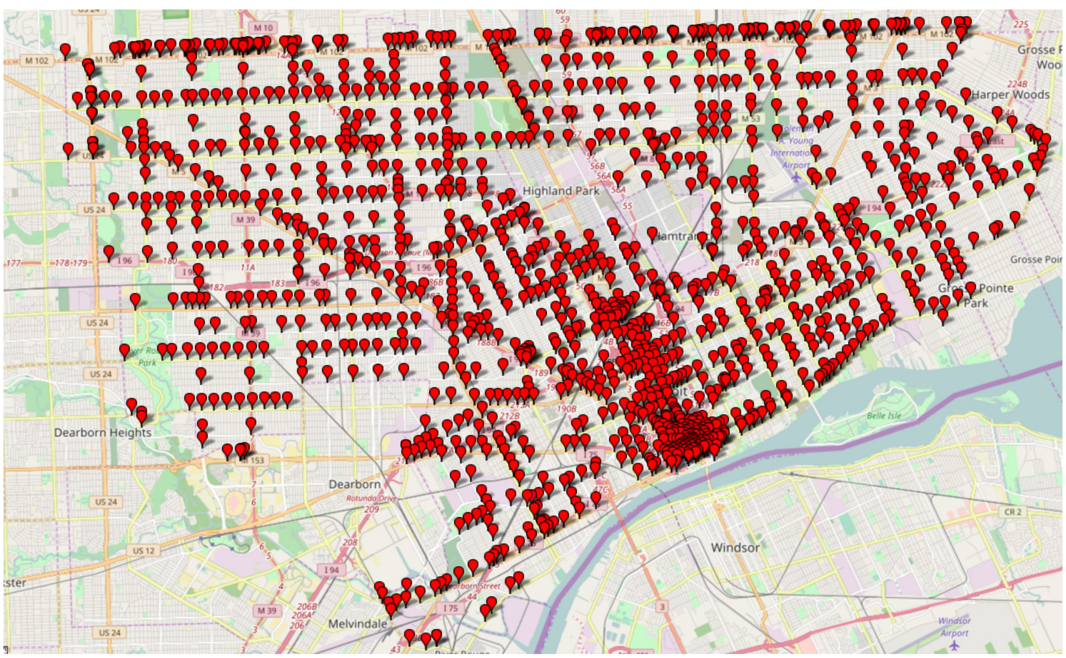

Figure 3.3: Route Map in Detroit with Signal Data

3.3.2 Active Signal Model

An active signal within the scope of this thesis can be defined as a signal that turns red or is red when the vehicle arrives at it. The active signal model uses a Poisson distribution curve to estimate the number of active traffic light signals. A Poisson distribution curve was chosen because of the vast amount of literature in traffic engineering that use it as a base function [30] [31] [32]. Poisson distribution is used to model traffic flows in discrete time models and In this thesis, it has been used to estimate the number of active signals for traffic modeling.The general form of the Poisson distribution function can be written as seen in Equation 3.3

$$P(k,\lambda) = \frac{((\lambda^k) * exp^{-k})}{k!} \tag{3.3}$$

where k refers to the number of traffic signals on the route and λ refers to the average value of the total number of active signals. For the purposes of the method, λ is parametrized 10, 30 and 50 percent of the active lights. The histogram and fitted Poisson curve can be seen in Figure 3.4.

The experiment run to obtain these histograms involves making three major steps. In the first step, the traffic data for the city is obtained and the total number of signals are obtained. The second step involves finding out how many active signals are present and low, medium, and high traffic levels are modeled by parameterizing λ. The third and final step involves figuring out which of the traffic signals in the route are active by randomly sampling from the Poisson distribution obtained in the previous step.

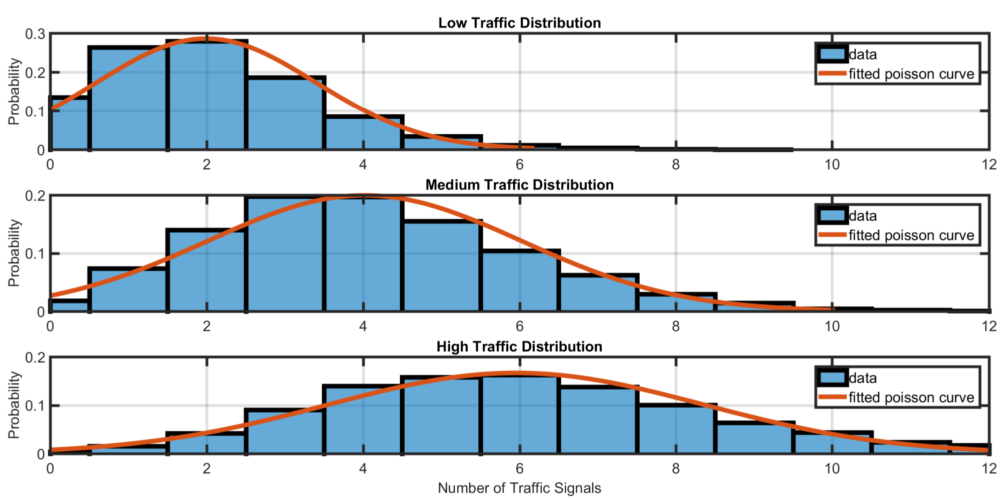

Figure 3.4: Probability distribution of active traffic signals

3.3.3 Sample Size Requirements

Adequate sample size selection for estimating traffic signal data is crucial to obtain results that can be trusted. Figure 3.5 shows a scenario where only 20 samples were collected. As a result of the undersampling, the data does not adequately fit a poisson distribution curve and a bias is introduced with respect to which signals get turned on.

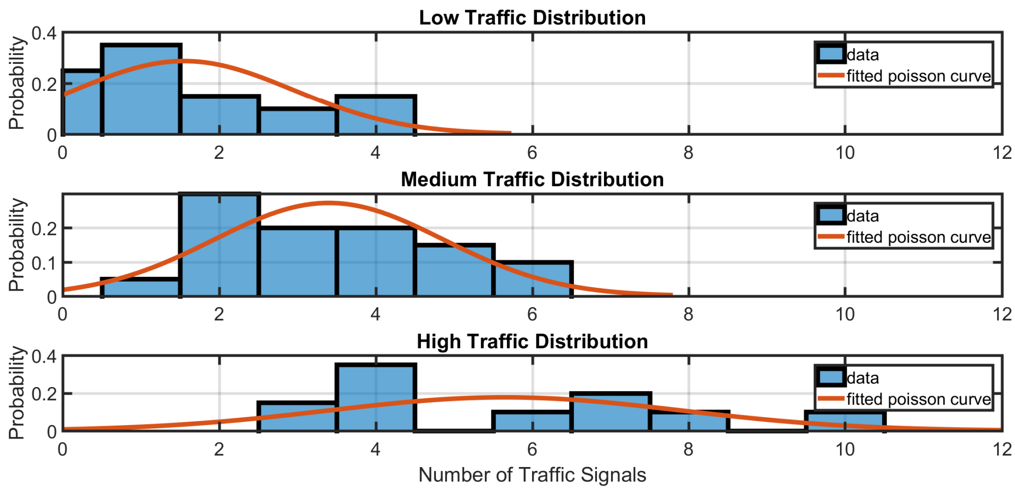

Figure 3.5: Probability distribution of active traffic signals with 20 samples

3.3.4 Idle Time Model

Idle time is a state when both velocity and acceleration of the vehicle are zero. Idle time typically occurs while waiting at traffic signals. American drivers have reportedly been delayed by 6.9 billion hours resulting in a net lost amount of fuel of 3.1 billion gallons per the 2015 Urban Mobility Scorecard [33]. So it is important to have a reasonable estimate on idle time because of the impact idle time has on fuel consumption [34]. Idle time is determined by two factors: signal cycle length and traffic delay. Per the traffic signals control handbook released by the DOT [35], Signal Cycle Length is defined as "The time required for one complete sequence of signal intervals". Traffic delay is caused by the time required to clear queues that form while waiting at traffic signals [30]. A cycle is therefore a combination of Red, Yellow and Green lights. The formula for optimum cycle length is given in Equation 3.4

$$C_T = \frac{(1.5 * L + 5)}{(1 - Y)} \tag{3.4}$$

where L is the lost time per phase, Y is the effective green cycle time percentage for the signal. Calculations for these three cases are done using the University of Florida's Transportation Course as a guideline [36]. The Highway Capacity Manual and Traffic Signal Timing Manual

[37] are also used as references. The idle times used for the simulation can be seen in Table 3.1. A range of 10 seconds is added to the calculated red light time to account for queueing

Table 3.1: Idle Time settings for different traffic levels

Traffic Level	Lost Cycle Time(s)	Optimum Cycle Length(s)	Red Light Time(s)	Idle Time Range(s)
Low	10	133	53.3	(48.3, 58.3)
Medium	10	80	32	(27,37)
High	10	40	16	(11,21)

and variability in traffic conditions. The final value of idle time is picked randomly from that particular range. The distribution of idle times in low traffic conditions can be seen in Figure 3.6.

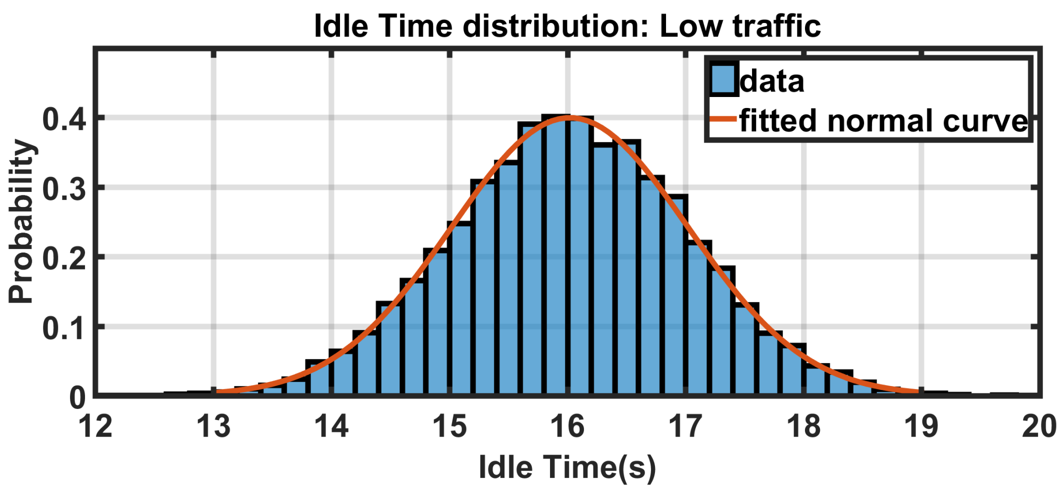

Figure 3.6: Distribution of Idle Time in Low Traffic Conditions

3.4 Drive Cycles

The basic unit of the drive cycle is a trapezoidal velocity vs time profile with a constant acceleration, which was chosen because the powertain model uses constant acceleration for velocity changes. The vehicle starts from zero velocity, accelerates to the allowable speed limit and then decelerates at a constant rate to come to a stop at the traffic signal. The same process is repeated for every traffic signal which was randomly selected to be turned on. This shape of the drive cycles resembles the New European Drive Cycle (NEDC) which is used to evaluate energy consumption for hybrid and electric vehicles. A common criticism of such drive cycle based on trapezoidal units is that such cycles do not represent real world driving conditions [38] and the same limitation does apply here. The NEDC drive cycle is going to be replaced by the Worldwide harmonized Light vehicles Test Procedure (WLTP) as a result of these shortcomings. The results obtained, however are accurate in the sense that the cruise speeds are the speed limits of that particular route and the acceleration and deceleration values are realistic to the PHEV Camaro powertrain model with validated components. Further more, the acceleration and deceleration values can be modified to create various levels of driving aggression.

The travel time is calculated from the drive cycle since vehicle velocity and distance are known at every point of time. The travel time is compared to the travel time of the Open-RouteService routing engine which is then used to calibrate the drive cycle to a real world expectation of commute times. The vehicle ramps up to the speed limit before entering an area with a new speed limit to mirror real world conditions where a driver would change the speed on seeing the speed limit marker instead of after crossing it.

3.5 Fuel Consumption Calculation

A hybrid vehicle has two sources of energy, fuel and electric energy. Both sources are therefore taken into consideration for the calculation of fuel consumption. Calculating total fuel consumption is challenging because 1 kJ of gasoline energy is not the same as 1 kJ of electric energy. The fuel economy of a vehicle is typically done on standard drive cycles where the initial battery State of Charge (SOC) is chosen such that the final SOC is close to the initial value. This iterative process of adjusting SOC values is called charge balancing. Real world routes are however not charge balanced and so a different approach is required to equate the electric energy consumption and gasoline consumption to a total fuel consumption metric.

An SOC correction factor was developed by Tamaro et al. [1] to compute the fuel consumption for real world routes. Let the initial SOC be SOC_{init} and the final SOC be SOC_{final}. When SOC_{final} is not equal or close the value of SOC_{init}, all electric energy consumption is equated to a fuel consumption using Equation 3.5

$$\Delta E_{fuel} = k_{SOC,corr} * \Delta E_{batt_int} \tag{3.5}$$

where,
ΔE_{fuel}= Fuel needed to restore the battery to SOC_{init}
$k_{SOC.corr}$= SOC Correction Factor.(negative number)
ΔE_{batt_int}=Decrease in battery internal energy
Internal battery energy is the total available energy and it includes the losses due to internal resistance. A positive ΔE_{batt_int} indicates a decrease in internal energy. The formula for Δ E_{batt_int} is given by

$$\Delta E_{batt_int} = E_{batt,cap} * \Delta SOC \tag{3.6}$$

where,

$$E_{batt,cap} = \text{Rated Battery Capacity}$$

$$\Delta SOC = SOC_{init} - SOC_{final} \tag{3.7}$$

Note: The sign convention for ΔSOC is opposite the one used in [1]. Therefore 3.5 also has a positive sign instead of a negative sign.

As can be seen from the plot in Figure 3.7, a positive ΔE_{batt_int} is a case where the battery has been depleted and the total fuel consumption increases to account for the electric energy consumption. Conversely, a negative ΔE_{batt_int} is a case where the battery SOC increases by the end of the route and the engine was used to charge the battery. Therefore, the net energy consumption is reduced to bring the total fuel consumption to a charge balanced state. The SOC correction factor for the HEVT Camaro was empirically determined to be -2.99 and approximated to -3 for calculations. The physical implication of this value is that for 1 kJ of decrease in battery energy results in an increase of 3 kJ in fuel consumption.

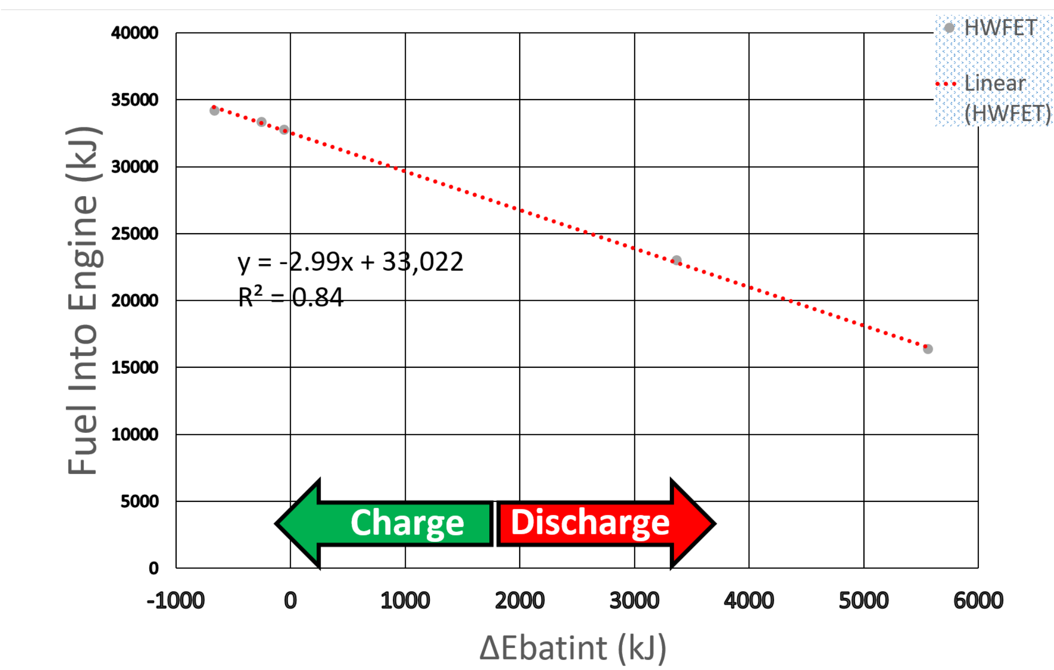

Figure 3.7: SOC Correction Plot taken from [1] (Fair Use)

3.6 Method and Powertrain Model Validation

The method described is largely quantitative and therefore requires comprehensive validation to ensure that the data and results generated are useful and can be used to build modules with real world applications. Validation for this thesis involves validation of the powertrain and use of the trapezoidal speed profiles for route synthesis. The powertrain model and its constituent parts have been extensively validated against real world data in the thesis written by Courtney Tamaro [1]. However, reproducing the validations ensures the demonstration of a clear grasp on the model parameters and how to use it. The method of using trapezoidal routes was validated using the 505 portion of the UDDS. A synthesized route of the UDDS drive cycle, specifically the part called the 505 is used to validate the method and model which is the first 505 seconds of the UDDS drive cycle. The routes were interpolated and sampled at a rate of 1 Hz to ensure model fidelity. A plot of the two routes can be seen in Figure 3.8. A 5 to 10 percent error between the drive cycle and unadjusted fuel values would

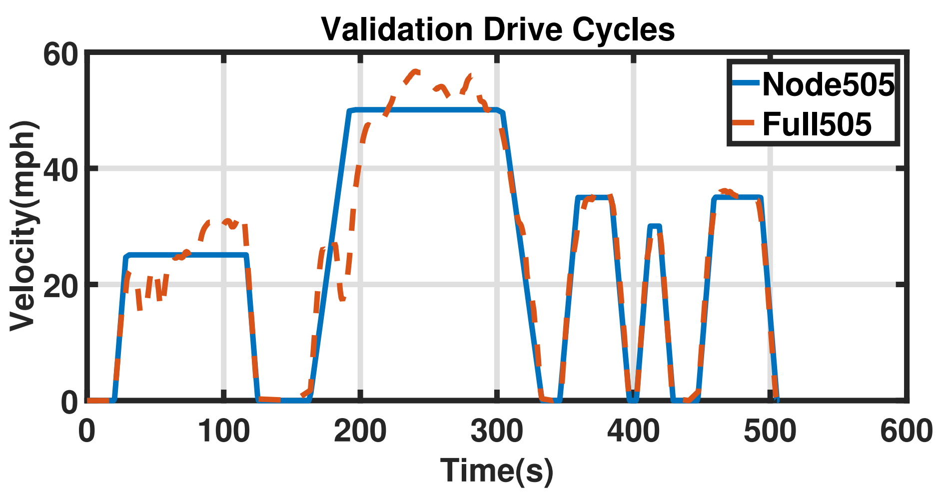

Figure 3.8: Node505 and Full505 cycles used to validate the methodology

validate the model, while the route synthesized would validate the method. Validation of the method is also done using the 2012 Ford Fusion model and the 2010 Chrysler 300 as can be seen in Table 3.2. It is important to note that both vehicles are modeled using E10 as fuel source. E10 is an ethanol fuel mixture with 10% ethanol and 90% gasoline. E10 has an energy density value of 32,305 Watt-hours per gallon (Wh/gal).

Table 3.2: Validation Results for the Full and Synthesized Drive Cycles

Routes	Vehicle Model	Total FC (Wh/mi)	Total FC (MPG)	ANL Phase 1 (MPG)	EPA Bag 3 (MPG)	Error %
Full 505	2012 Ford Fusion	1209	26.7		28.6	6.6
Synthesized 505		1283	26.2			8.5
Full UDDS	2010 Chrysler 300	1403	23.0	24.1		4.5
Synthesized UDDS		1469	22.0			8.8

3.7 Cost Function

The travel time is an important metric to evaluate the feasibility of EcoRoutes. The most fuel efficient route may not be viable for the driver if the increase in travel time is too large. Equation 3.8 describes the cost function to be minimized in EcoRoute determination. It consists of two parts, the EC metric and the travel time constraint. Watt-hours per mile(Wh/mi) is the standard metric used for total energy consumption, which is then normalized by the maximum energy consumption so that different scenarios of route distance, congestion, driver aggression, and grade can be compared.

$$Cost = \frac{EC}{EC_{max}} + \lambda * \frac{(t - t_{min})}{t_{min}} \tag{3.8}$$

where,
Cost=Cost function used to evaluate EcoRoutes.
EC=Total Energy Consumption in Watt-hours per mile.
t=Travel time of the route.
λ=Travel time penalty.
t_{min}=Time taken to traverse the shortest time or TT route.
The variation of cost with increasing λ can be seen in Figure 3.9. The travel time constraint is a weighted penalty of the difference in travel time between the route being evaluated and the TT route time for the road network in consideration. λ is the weight and it can be varied depending on the importance of commute time difference to the driver.

For the purposes of this thesis, λ is set to three values: 0.1, 0.3, and 0.5. The three values of λ result correspond to three different scenarios where the driver places a low , medium and high level of priority on the increased travel time. For the purposes of this thesis, these three values will be referred to as Case I, Case II, and Case III respectively.

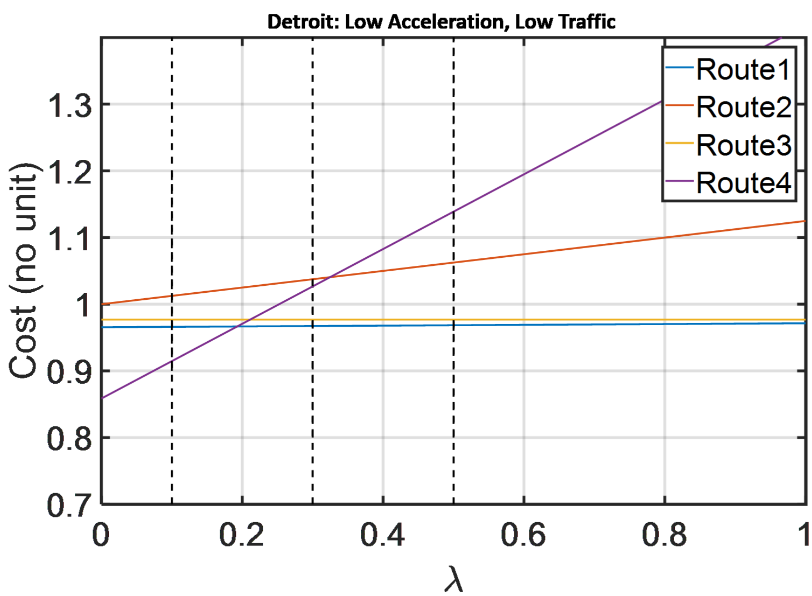

Figure 3.9: Cost Function vs λ for low traffic and acceleration conditions Detroit

Chapter 4

Results

This section of the thesis discusses the results of the quantitative study conducted using the methodology developed in the previous chapter. Routes were run in the cities of San Francisco and Detroit. Both cities were chosen on the basis of availability of extensive traffic data and grade variability. The midtown and upper eastern market areas of Detroit have a relatively even elevation profile as can be seen from the topographical map in Figure 4.1. The aforementioned areas are therefore ideal to analyze the benefits of EcoRouting on the powertrain model independent of grade.

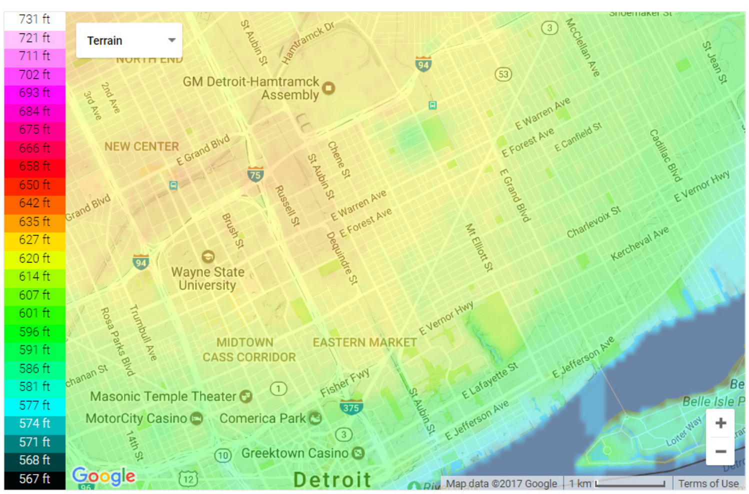

Figure 4.1: Detroit Topographical Map from **Google Maps** (Fair Use)

San Francisco on the other hand has a wide variety of deviations in terms of grade with elevations ranging from 50ft all the way to 1000 ft. The highlighted area of the city as seen in Figure 4.2, is the focus of route selection in San Francisco due to the varied choices for routes in terms of road grade.

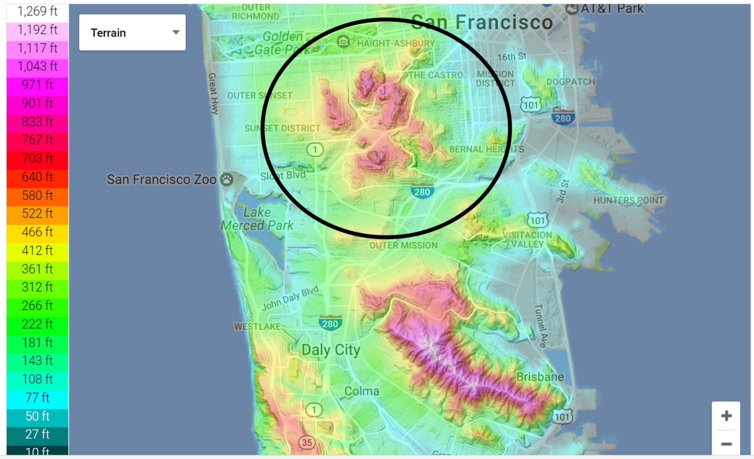

Figure 4.2: San Francisco Topographical Map from **Google Maps** (Fair Use)

4.1 Detroit network Overview: City Driving Analysis

Also known as motor city, Detroit is the most populous city in the state of Michigan and one of the largest cities in the Midwest. The city is relatively even in terms of elevation which makes it an ideal location to conduct EcoRouting studies for city driving. The scope of this study has been limited to short route distances so that they can be compared to longer routes in San Francisco. The east side of Detroit can be seen in 4.3. The origin node of the route is at the intersection of the I-75 and I-94 interstate highways on the east side of Detroit and all of it is within the fifth district.

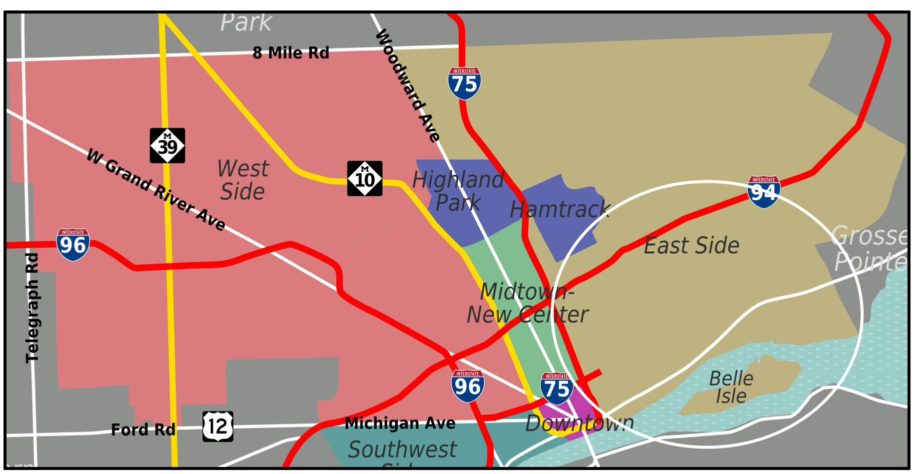

Figure 4.3: Detroit district Map taken from Wikimedia Commons (Public Domain and Fair Use)

4.2 Energy Consumption Results

Four routes as can be seen in 4.4 were used as the base routes for the quantitative study for EcoRouting. Each route was run 5 times based on the active traffic signal IDs generated by the model discussed in Section 3.3.2. A total of 4 routes are used with 2 different acceleration modes, and 2 different traffic levels (low and congested). The red markers on

Figure 4.4: The Detroit Road Network used for running routes

the map denote the position of traffic lights on the road. There is one yellow marker on Route 4 which is a stop sign, instead of a timed traffic signal. The stop sign itself doesn't affect the energy consumption of the route. However the average velocity of the route is much lower than Routes 1,2 and 3. This is the main reason why Route 4 is often the slowest of the 4 possible routes. However, the added travel time also brings in the benefit of increased fuel economy since the vehicle cannot be driven at high speeds on Route 4. Table 4.1 summarizes the route study that was done on the Detroit network. The acceleration was kept to a conservative value of 0.75 m/s^2 so drive cycles with higher acceleration could also be constructed easily. Low , midddle and high acceleration values of 0.75, 0.98 and 1.2 m/s^2 were chosen by carefully studying Figure 2.3 which is an acceleration distribution for city driving. The MPGGe values are pretty consistent with the Simulink model of the HEVT Hybrid Camaro which has target metrics of 28 MPGGe of combined Cafe 2 cycle driving along with a 4 cycle CS mode fuel economy of 24.9 MPGGe. The Poisson distribution curve was used to generate 5 random samples of active signals. These active signals were then given a randomized idle time centered around a mean based on typical signal cycle lengths as seen in Table 3.1. Active signal refers to the kth signal from the origin node out of the total number of available traffic signals. Trial number refers to the number of times that particular set of active signals is selected by the random sampling procedure.

Table 4.1: Low Acceleration and Low Traffic Conditions for the Detroit Route Study

Name	**Active Signals (Trial no.)**	**Distance (mi)**	**Engine In (kJ)**	**Δ SOC(%)**	**Batt Int(kJ)**	**Δ Efuel (kJ)**	**Efuel (Wh/mi)**	**Total FC (gallons)**	**TotalFC (MPGGe)**	**Travel Time (mins)**
Route1	None (3)	4.12	14,256	2.09	946	2,839	1273	0.14	29.3	5.04
	2 (1)	4.12	17,256	1.20	544	1,633	1420	0.16	26.5	5.80
	2,5 (1)	4.12	17,229	2.82	1279	3837	1152	0.17	23.7	6.15
Route2	None(1)	4.38	16,495	3.22	1,462	4,387	1272	0.17	25.3	5.24
	3 (1)	4.38	15,994	1.87	849	2,548	1177	0.15	28.6	6.35
	5 (1)	4.38	24,477	-3.26	-1,479	-4,438	1284	0.17	26.5	6.25
	3,6 (1)	4.38	24,816	-3.45	-1,564	-4,693	1333	0.17	26.2	7.19
Route3	None(3)	3.95	14,279	1.60	728	2,183	1159	0.14	29.1	4.65
	2,6(1)	3.95	25,861	-4.68	-2,124	-6,372	1372	0.16	24.6	6.52
	3,7(1)	3.95	27,486	-5.76	-2,612	-7,836	1383	0.16	24.4	6.44
Route4 (No Stop Sign)	None (1)	3.94	18,807	-1.15	-520	-1,560	1125	0.14	28.3	5.08
	7 (1)	3.94	13,967	0.37	167	502	1215	0.12	33.1	8.67
	2,9(1)	3.94	17,481	-1.98	-899	-2,697	998	0.12	32.4	9.94
	3,14 (1)	3.94	22,174	-5.18	-2,347	-7,042	1044	0.12	31.6	11.01
	6,12(1)	3.94	17,356	-1.02	-463	-1,390	1020	0.13	30.5	7.29

The major difference between previous research and this thesis is the stress on ensuring that the driver thinks of the EcoRoutes as a viable alternative when convenient. Computing an average of route energy consumption results in a 1230, 1274, 1245, and 1094 Wh/mi for each of the routes. Their respective travel times are 5.41, 6.05 , 5.38, and 8.4 minutes. Using the average metrics, the shortest distance route is Route 4, TT route is route 3 and the most fuel efficient route is route 4. As discussed before, the TT or shortest time route is the baseline for evaluating EcoRouting metrics. Using the cost function metric described in Section 3.7, the variation of cost with the travel time weight penalty λ is plotted in 4.5. The EcoRoute for a given λ is the route with the lowest cost. For Case I($\lambda = 0.1$), the EcoRoute is Route 4 which is the most fuel efficient and shortest distance route. For Case II, ($\lambda = 0.3$) and Case III($\lambda = 0.3$), the EcoRoute is Route 1. Route 1 and Route 3 are nearly identical routes in terms of travel time and energy consumption, which is why they are horizontal on the graph (negligible penalty).

The major conclusion that can be drawn from analyzing the table is that increased congestion causes the vehicle to have an overall lowered average velocity resulting in better fuel consumption. However, there are diminishing returns to the congestion as seen in the case of Route 4 where the improved fuel consumption metric did not make up for the huge increase in travel time. Suggesting a slightly congested road to a driver as an EcoRoute will work out as long as accurate estimates based on real time traffic data collection are made when EcoRouting is finally implemented in the vehicle. One possible implementation feature can be to let the driver select their level of preference to prioritize travel time. That way, λ can be preset before the route selection takes place.

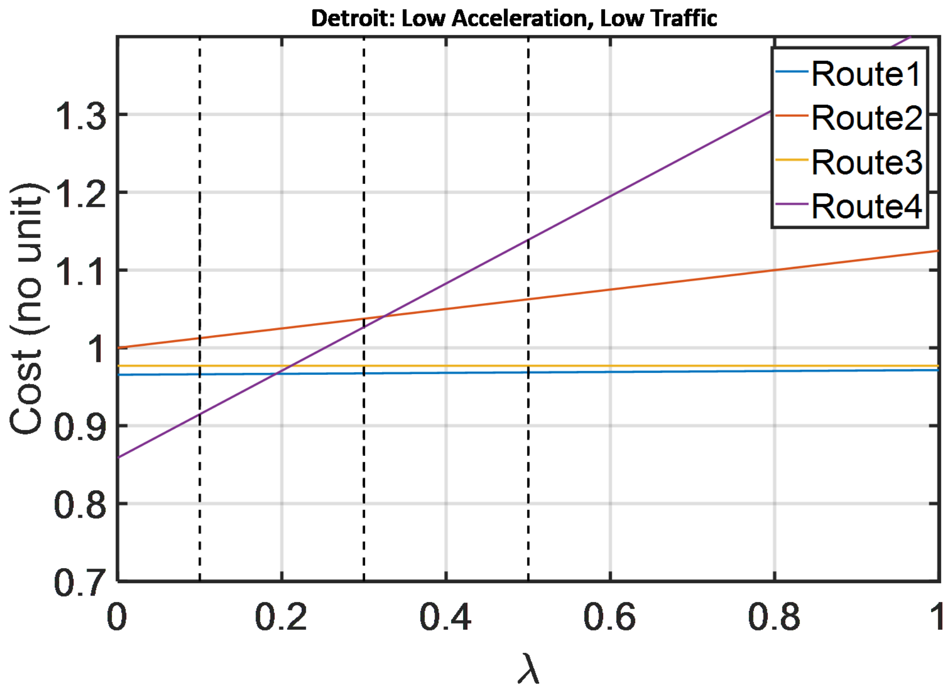

Figure 4.5: Cost vs λ for low acceleration and traffic

4.3 Effect of Acceleration on Energy Consumption

The drive cycles used to estimate driver behavior consist of trapezoidal units with constant acceleration. The major effect of changing the acceleration is the change in travel time. Table 4.2 summarizes an acceleration study that was done to evaluate how acceleration solely effects an EcoRoute. The travel time for all routes is reduced in the range of 4 to 6 percent when the acceleration is changed from 0.75 m/s^2 to 1.2 m/s^2. The fuel consumption however varies greatly and there is no direct correlation between the change in acceleration and fuel consumption for real world routes. The major reason for a lack of relation is that a high acceleration often changes the entire drive cycle. The vehicle has smaller acceleration and deceleration distances and as a result the cruise distance is larger. The cruise distance is always adjusted based on the distance traversed previous to cruise mode and and the distance travelled in the phase right after cruise mode. This case study was really useful in setting the parameters of the larger high acceleration study which is the main focus of this section. Since acceleration by itself does not have a direct effect on fuel consumption, an aggressive driver behavior model was developed using the fact that the set speed limit on the road is usually the 85th percentile speed [39]. At the 85th percentile, 15 percent of the drivers are believed to drive above the speed limit. Users typically drive 5 mph above the speed limit especially on the quicker lanes. An aggressive driver behavior was modeled by increasing the acceleration from 0.75 m/s^2 to 1.2 m/s^2. The target velocities for each node

Table 4.2: Acceleration study for 4 routes

	Acceleration (m/s2)	Distance (miles)	Engin In (kJ)	Δ SOC	Batt Int (kJ)	ΔEfuel (kJ)	Corrected Efuel (kJ)	Total FC (gallons)	MPGGe	Travel Time (mins)
Route 1	1.2	4.12	13557	1.86	845	-2535	11022	0.091	45.37	4.84
	0.75	4.12	16213	-1.81	-820	2459	18672	0.154	26.78	5.04
Route 2	1.2	4.35	15308	2.94	1332	-3996	11311	0.093	46.68	4.92
	0.75	4.35	15563	3.03	1376	-4129	11434	0.094	46.18	5.24
Route 3	1.2	3.95	13610	1.43	647	-1942	11668	0.096	41.02	4.65
	0.75	3.95	16322	-2.31	-1050	3149	19471	0.160	24.58	4.85
Route 4	1.2	3.94	16833	-1.20	-544	1632	18465	0.152	25.91	6.91
	0.75	3.94	15563	3.03	1376	-4129	11434	0.094	41.84	7.32

was also increased by 5 mph whenever possible.

Table 4.3 summarizes the high acceleration study performed at 25 percent SOC to evaluate total fuel consumption for CS mode. Route 2 has a large variation in energy consumption which can be explained using the ΔSOC metric. For the first two trials, *Delta*SOC is positive indicating that the battery has been charged leading to an overall lower equivalent SOC corrected fuel consumption. Conversely, for the last two trials of Rout 2, a negative ΔSOC indicates a depleted battery leading to an overall higher equivalent SOC corrected fuel consumption. In terms of average values, the energy consumption results for Routes 1,2,3, and 4 respectively are 1278, 1269, 1246, and 1080 Wh/mi for each of the routes. Their respective travel times are 4.76, 5.39, 4.71, and 7.05 minutes. Compared to the low acceleration study in 4.1, the travel time on average decreased by 11 percent. The average energy consumption increased by 4 percent and 0.1 percent respectively in Routes 1 and 3. It however, decreased by 0.5 and 1.2 percent respectively. Using the average metrics, the shortest distance route is Route 4, TT route is route 3 and the most fuel efficient route is route 4.

Table 4.3: High Acceleration Study at Low Traffic for the Detroit network

	Active Signals (Trial No.)	Distance (mi)	Engine In (kJ)	Δ SOC (%)	Batt Int (kJ)	Δ Efuel (kJ)	Efuel (Wh/mi)	MPGGe	Travel Time (mins)
Route1	None (3)	4.12	13602	2.48	1126	3377	1144	29.5	4.48
	2 (1)	4.12	16699	1.49	678	2034	1262	26.7	5.17
	2,5 (1)	4.12	16732	1.50	681	2044	1265	26.6	5.52
Route2	None (1)	4.38	15017	3.60	1632	-4897	642	52.5	4.72
	3 (1)	4.38	15473	2.17	986	-2957	794	42.4	5.63
	5 (1)	4.38	23963	-3.04	-1380	4140	1752	19.2	5.55
	3,6 (1)	4.38	24225	-2.49	-1130	3391	1751	19.2	6.31
Route3	None(3)	3.95	13639	1.74	789	2368	1127	29.9	4.31
	2,6 (1)	3.95	25125	-4.58	-2076	-6228	1330	25.3	5.33
	3,7 (1)	3.95	26002	-5.70	-2586	-7758	1284	26.2	5.28
Route4	None (1)	3.94	18479	-1.48	-670	2009	1443	23.3	4.10
	7 (1)	3.94	13488	0.64	290	-869	889	37.9	7.25
	2,9 (1)	3.94	12289	1.32	600	-1799	739	45.6	8.47
	3,14 (1)	3.94	18047	-4.88	-2211	6634	1739	19.4	9.20
	6,12 (1)	3.94	16974	-0.85	-384	1152	1277	26.4	6.23

Using the cost function metric described in Section 3.7, the variation of cost with the travel time weight penalty λ is plotted in 4.5. The EcoRoute for a given λ is the route with the lowest cost. For Case I ($\lambda = 0.1$), the EcoRoute is Route 4 which is the same as the previous scenario of low acceleration. For Case II, ($\lambda = 0.3$) and Case III($\lambda = 0.5$), the EcoRoute has now switched to Route 3 which is also the shortest time route.

This observation confirms the previous literature that places tremendous emphasis on driver behavior being fundamental to EcoRouting. The EcoRoute for a driver will hence be dependent on their driving style. Driving habits and historical information can then be used to build a driver profile. This driver profile can then be used to modify a base drive cycle to suit individual needs. This driver profile, when used in conjunction with the preset time priority level as suggested in Section 4.2 will aid in modeling accurate EcoRoutes custom to the driver and their specific needs.

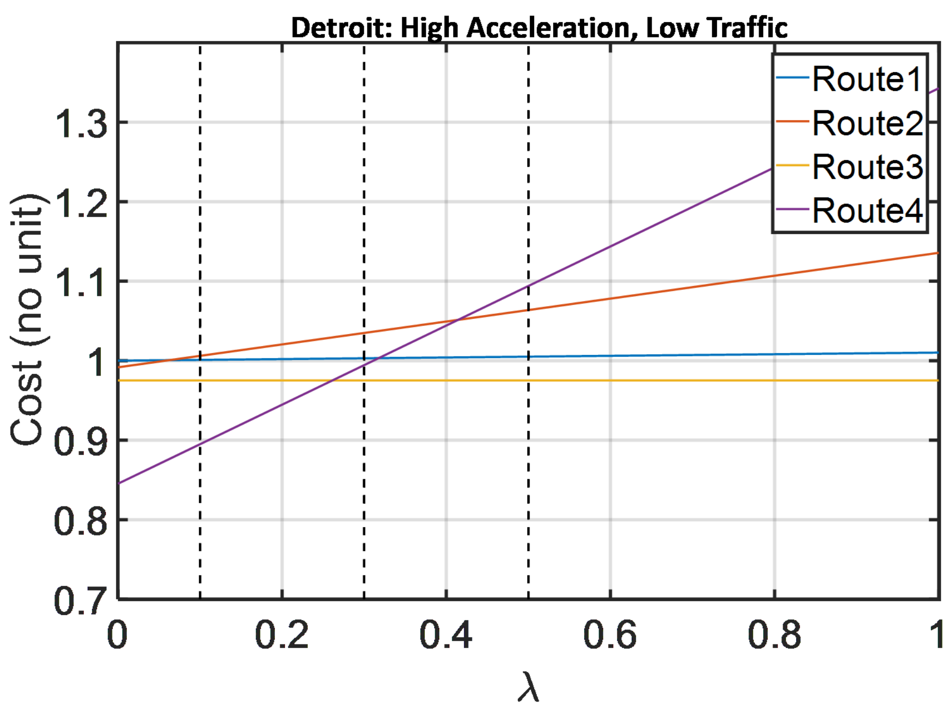

Figure 4.6: Cost vs λ for high acceleration and low traffic

4.4 Travel Time Validation

Travel time for the route is calculated using Equation 4.1

$$t_{route} = t_i + t_a + t_c + t_b \tag{4.1}$$

$t_i = IdleTime$
$t_a = Acceleration\ Time$
$t_c = CruiseTime$
$t_a = t_b = Braking\ Time$

These four variables that make up the total travel time t_{route} are highlighted on of the Detroit study routes in Figure 4.7. The idle time is determined by the traffic conditions (low vs high) and the acceleration and brake times are determined by the change in velocity between phases and the preset acceleration value for the routes. The t_c value varies depending on the time spent in cruise mode till the change of phase. The travel time calculation for the four routes in Detroit was validated using the time obtained from the routing engine of OpenRouteService. Table 4.4 lists the average travel time for each route along with the travel time provided by the OpenRouteService routing engine. The methodology used gives results close to the routing engine algorithm using simple kinematic equations. Between routes 1, 2, and 3 the maximum error is 6 percent.

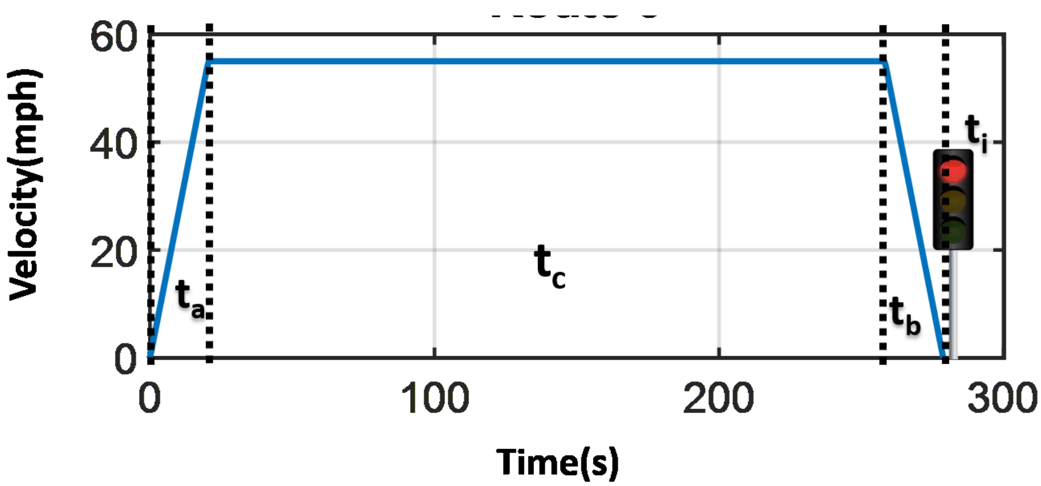

Figure 4.7: Constituent elements of travel time as seen from Route 2 of the Detroit Study

Table 4.4: Travel Time Validation Study

	Calculated Route Time(s)	**OpenRouteService Time(s)**	**% Difference**
Route 1	5.70	5.77	1.137827
Route 2	6.26	6.38	1.965169
Route 3	5.87	6.30	6.870884
Route 4	8.40	6.35	-32.2598

Route 4 is the clear outlier amongst the four routes with a difference of 32 percent between the travel time reported by OpenRouteService and the travel time calculated using the method of trapezoidal drive cycles. Therefore, a more thorough analysis of Route 4 characteristics is required to understand the reason behind this discrepancy. Table 4.5 shows the percentage difference between the calculated route distance and the OpenRouteService distance, As discussed in section 4.1, Route 4 is the only route amongst all the routes which has a stop sign. This fact has huge implications on route kinematics. While vehicles don't typically wait more than 5-10 seconds at a stop sign, the average speed around a stop sign is relatively low compared to a route that doesn't have one. The level of velocities is illustrated in Figure 4.8. The idle time incurred on that route is due to the presence of a stop sign. The vehicle cruises at the top possible speed of 55 mph for only about 25 percent of the total route. The speed around the stop sign is comparatively lower.

This level of detail is not captured by the routing engine of OpenRouteService. This observation was verified by collecting travel time data from OpenRouteService in morning, afternoon, evening and night. The travel time and route was identical regardless of the time. Therefore, an inference can be made that the OpenRouteService routing engine does not take traffic information into account.

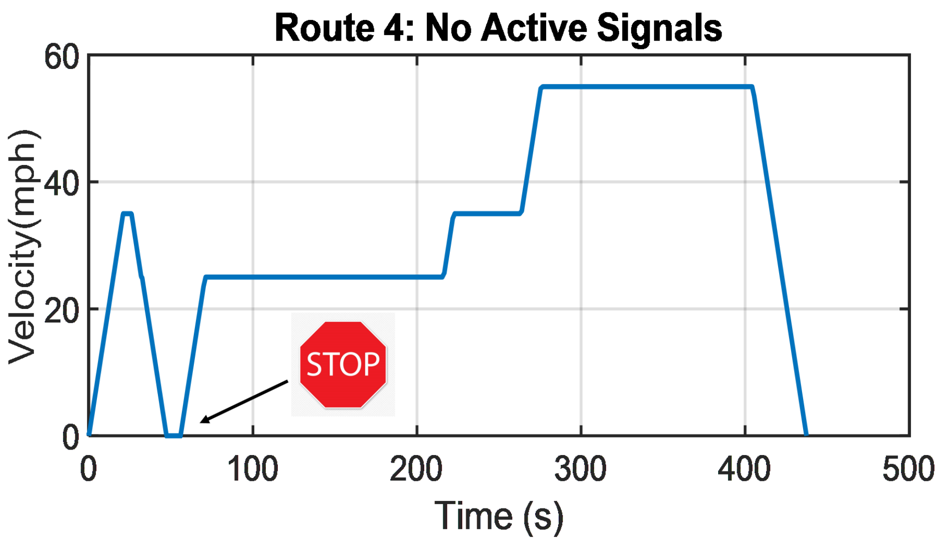

Figure 4.8: Velocity vs Time plot of Route 4 with 0 active signals

Table 4.5: Route 4 travel time values for 5 trials

	OpenRouteService Distance(mi)	Active Signals	Calculated Route Distance(mi)	% Difference
Route 4	6.35	0	5.08	-19.99
		1	8.67	36.57
		2	7.29	14.81
		2	11.01	73.37
		2	9.94	56.54

4.5 Distance Validation

Travel time for the route is calculated using Equation 4.2.

$$d_{route} = d_a + d_c + d_b \tag{4.2}$$

$Where$
$d_a = AccelerationDistance$
$d_c = CruiseDistance$
$d_b = BrakeDistance$
Figure 4.9 illustrates the three distance variables over a route trial where no traffic signals were on. The acceleration and brake distance depend on the constant preset acceleration and the difference in velocities before and after the acceleration event. The cruise distance is adjusted in such a way that the vehicle can change current speed based on the target velocity accelerating and decelerating at a constant rate. The method of distance calculation using

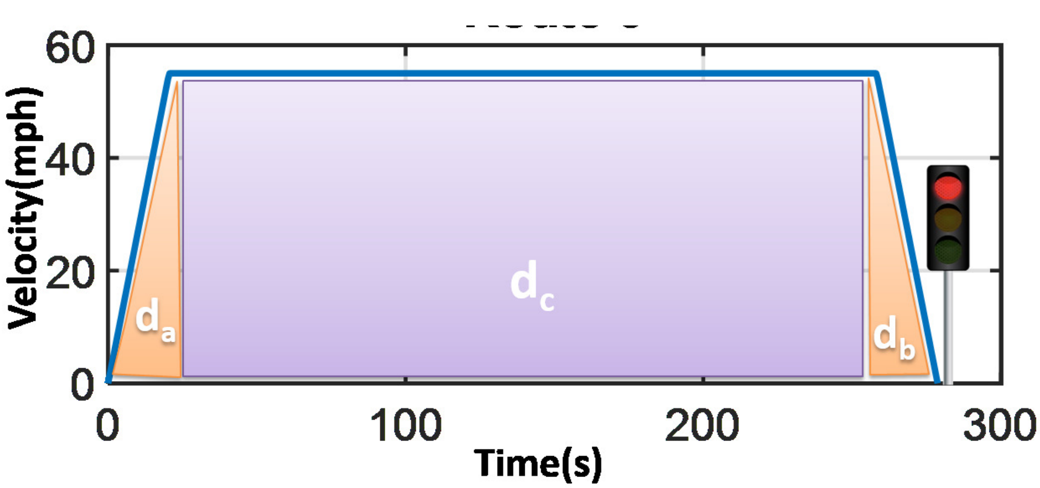

Figure 4.9: A Trapezoidal drive cycle with constituent elements to calculate distance.

the distance formula in the ECEF domain discussed in 1.3 is extremely accurate as can be seen in Table 4.6. The maximum error that occurs across the 4 routes is 3.6 percent with the other routes being within 1 percent. Distance is a static route property and is therefore easier to calculate and validate compared to travel time in the previous section.

Table 4.6: Validation table for route distance calculation

	Calculated Route Distance(mi)	**OpenRouteService Distance(mi)**	**% Difference**
Route 1	4.12	4.10	0.51
Route 2	4.38	4.23	3.60
Route 3	3.95	3.91	0.79
Route 4	3.94	3.98	-0.85

4.6 Congestion Sensitivity

Congestion is characterized by the idle time at each signal and the number of active signals. An active signal is one where the light turns red on a route which a vehicle is on. A case study can be seen in Table 4.7. The results shown are the energy consumption results for a specific iteration of Route 1 and Route 4 from the Detroit network as seen in Figure 4.4. The second row of every Route 1 and Route 4 has an increased congestion level. The idle time at each active signal is increased by 20 seconds for both routes and the results are then compared to evaluate the effect of idle time on EcoRoutes, since every other parameter is the same. As can be seen from the table the fuel consumption for Route 1 in both cases is 0.149 gallons and there is a difference of less than half a percent in the MPGGe values. In the case of Route 4, the fuel consumption value of both the regular and increased congested cases is identical at 0.142 gallons and as before. The MPGGe values for route 4 differ by 0.36 percent, which is the same as Route 1. The big difference by increasing the congestion level is on travel time. Since the idle time was increased by 20 seconds per active signal, the travel time increased by a 100 seconds for Route 1 and 60 seconds by Route 2. Therefore, an inference can be made that idle time has a negligible effect on energy consumption. However, the increase in travel time can make congested routes unviable for commute even if they happen to be more fuel efficient. For this case study, Route 4 with a travel time of 8.47 minutes is the EcoRoute. Idle time therefore has more bearing on the travel time

Table 4.7: Idle Time Case Study for Congested Conditions

	Active Signals	**Miles**	**Engine In (kJ))**	**Δ SOC(%)**	**Batt Int (kJ)**	**ΔEfuel**	**Efuel (Wh/mi)**	**FC (gallons)**	**MPGGe**	**Travel Time (mins)**
Route1	5	4.12	22139	-3.0	-1374	-4122	1214	0.149	27.8	9.82
			22244	-3.1	-1403	-4210	1215	0.149	27.7	11.49
Route4	3	3.94	22062	-3.6	-1624	-4872	1211	0.142	27.8	8.47
			22315	-3.7	-1690	-5071	1215	0.142	27.7	9.80

than the total vehicle energy consumption. It is important to note that both metrics need to be taken into account so that a driver's chances of using an EcoRoute increases. Table 4.8 is a summary of results for a congested traffic case. Congestion has been modeled using the active signal model developed and discussed in Section 3.3.2. The medium or hereafter known as congested traffic condition is used to model the traffic and the idle time per active signal is increased to a mean of 32 seconds for congested traffic. In comparison the low traffic level has a red light time of 16 seconds as can be seen in Table 3.1. One sample is taken from the Poisson distribution of traffic for Route 1 and 2 samples each for Routes 2,3 and 4.

Table 4.8: Fuel Consumption results for the Detroit network under Congested Conditions

	Active Signals	Distance (mi)	Engin In (kJ)	Δ SOC(%)	Batt Int (kJ)	Δ Efuel(kJ)	Total Efuel (Wh/mi)	FC (gallons)	FC (MPGGe)	Travel Time (mins)
Route1	5	4.12	22140	-3.0	-1374	-4122	1214	0.149	27.8	9.82
Route2	2	4.35	26163	-4.8	-2176	-6528	1253	0.162	26.9	7.12
	3	4.35	25817	-4.6	-2071	-6212	1251	0.162	26.9	8.48
Route3	3	3.95	25970	-4.8	-2173	-6518	1369	0.160	24.6	9.62
	5	3.95	27732	-5.3	-2407	-7221	1444	0.169	23.3	9.12
Route 4	4	3.94	16581	-2.1	-955	-2865	966	0.113	34.9	8.69
	3	3.94	22062	-3.6	-1624	-4872	1211	0.142	27.8	8.47

A plot of velocity vs time for 3 active signals in Route 2 can be seen in Figure 4.10. The breaks in between where velocity is continuously zero indicate idle time.

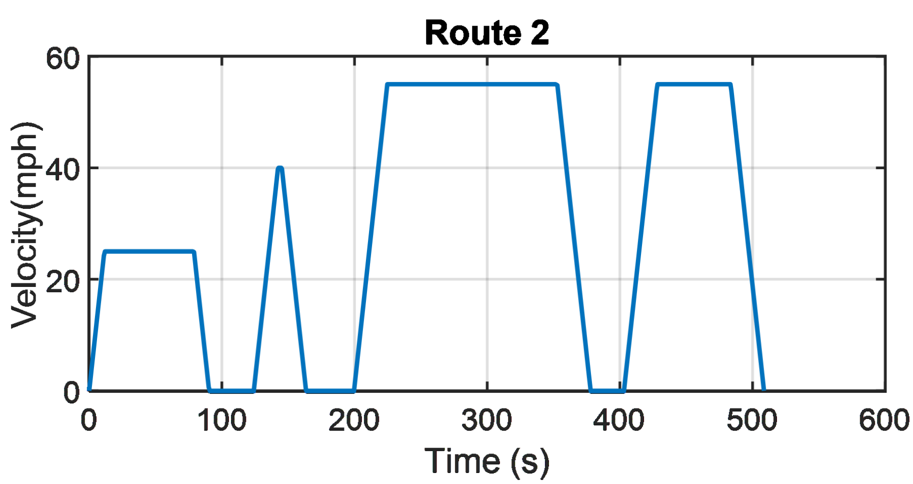

Figure 4.10: Velocity Vs Time plot for Route 2 with 3 active signals)

These breaks do not occur in a distance based drive cycle, since the distance remains constant when the vehicle is idle. The initial SOC of the battery is set to 25 percent to ensure that the battery gets depleted and both the engine and motor drive the vehicle at different points of time during the commute. As was the case before, Route 4 is still the shortest and most fuel efficient route. It is important to keep in mind that Route 4 has a stop sign in addition to the active signals.

Route 2 is the TT route for this set of trials with an average travel time of 7.8 minutes. Route 3 was previously the TT route when traffic level was low. This particular trial becomes the baseline for energy consumption to compare the alternative routes with. Figure 4.11 is a plot of cost vs λ for congested conditions in CS mode for the Detroit network. For Cases I,II and III the EcoRoute is always Route 4. This result is in agreement with previous observations made in the thesis that in increase in congestion causes fuel efficient routes to be more favorable to be EcoRoutes. Therefore, EcoRouting makes a bigger difference in city driving which is more prone to congested conditions

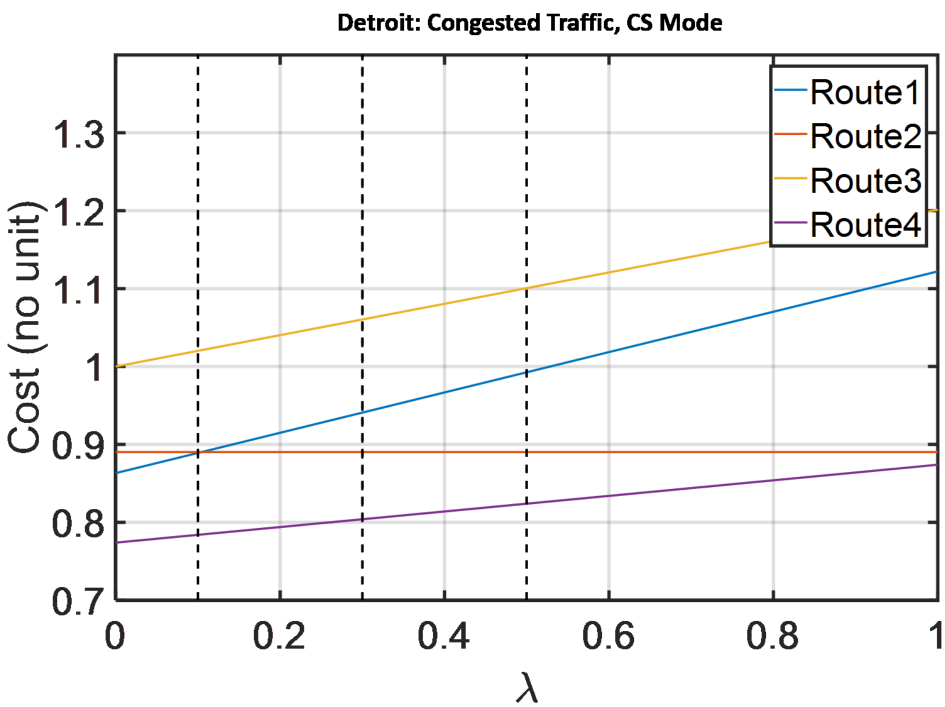

Figure 4.11: Cost vs λ for congested conditions in CS mode

4.7 Charge Depleting vs Charge Sustaining Study

The charge depleting(CD) mode of the PHEV Camaro is purely electric. When using the scalable powertrain model from [1], the PHEV Camaro needs to be run specifically in EV mode or else a general blended strategy is applied per model rules. A block diagram of the control strategy used for the powertrain model can be seen in Figure 4.12. The vehicle initially runs in CD mode which is all electric and depletes the battery pack. After the SOC of the battery hits a lower threshold (SOC_{min}), the vehicle control strategy switches to CS mode. CS mode is an engine dominant strategy where the SOC is constrained to be always within a window as seen in the figure.

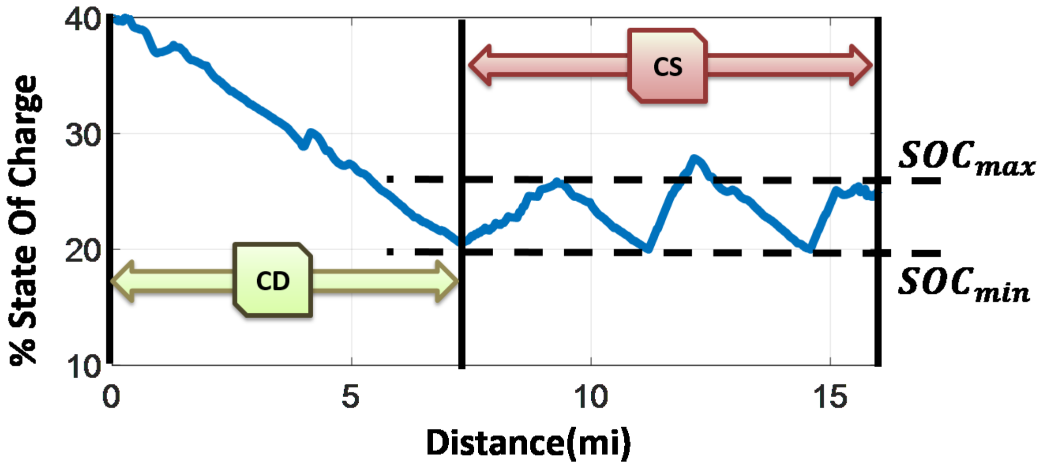

Figure 4.12: HEVT Camaro Control Strategy

Table 4.9 is a summary of route simulations where the battery SOC was set at a higher initial value of 80 percent. Doing so ensures that the vehicle now runs in CD mode, compared to previous studies where the initial SOC was 25 percent and the mode of operation was CS. The engine was not operational for these trials because the vehicle model was run in pure EV mode. The setup for comparing CD and CS modes of operation is identical to the one used in Table 4.8.

Table 4.9: Energy consumption comparison: CD vs CS modes

	Distance (mi)	Active Signals	ΔSOC (%)	AC Grid Energy (kJ)	Batt Int (kJ)	CD Electric Energy (AC Wh/mi)	Total Mileage (MPGGe)	Travel Time (mins)
Route1	4.12	5	9.9	5376	4491	362.3	93.0	9.82
Route2	4.35	2	11.5	6202	5237	395.8	85.1	7.12
	4.35	3	11.5	6183	5207	394.6	85.4	8.48
Route3	3.95	3	10.3	5593	4663	393.3	85.7	9.62
	3.95	5	11.8	6433	5333	452.3	74.5	9.12
Route4	3.94	3	10.1	5431	4574	382.9	88.1	8.47
Route4	3.94	5	10.0	5305	4519	374.0	90.1	8.69

This table does not have a fuel consumption column because when the energy consumption is all electric, there isn't any merit to discussing a hypothetical fuel consumption. A better metric to discuss energy use is the Wh/mi value or the Miles per gallon of gasoline equivalent (MPGGe). The electric energy consumption for pure EV mode is obtained from Equation 4.3

$$MPGGe = E_{cap}/(E_{grid,net}) \tag{4.3}$$

where $E_{cap} = 33700\ Wh$, which is the energy obtained by burning 1 US gallon of ideal gasoline. $E_{grid,net}$ is the AC grid electric energy measured in Wh/mi. The term ideal gasoline is used because fuel in gas stations is a blend of ethanol and gasoline. The most commonly found blend is E10 which is 10% ethanol and 90% gasoline. The travel times for the CD and CS are identical since the same drive cycles were input for both cases. In terms of comparing pure energy comparison, operating a Plug-In hybrid vehicle in charge depleting mode results in a lesser energy consumption (Wh/mi) and a greater effective mileage. Therefore, drivers should always be try to embark on a commute with a fully charged battery. However, this situation may not always be ideal depending on the availability of charging infrastructure and the inclination of the driver to charge the vehicle regularly. Figure 4.11 is a plot of cost vs λ for congested conditions in CD mode for the Detroit network. Route 2 is the TT route for this set of trials with an average travel time of 7.8 minutes. The TT or shortest time route as has been previously discussed in Section 3.7, the TT route is horizontal because $t = t_{min}$ resulting in no penalty for travel time. The EcoRoutes for Cases I, II, and III are Routes 1,4, and 2 respectively. The shortest route is therefore an EcoRoute only for the highest level of travel time priority. An observation can be made from the plot that EcoRouting offers more potential alternatives for Case II where the cost for three of the routes is almost identical. Since the motor is the prime mover during CD mode, the amount of gasoline spent during

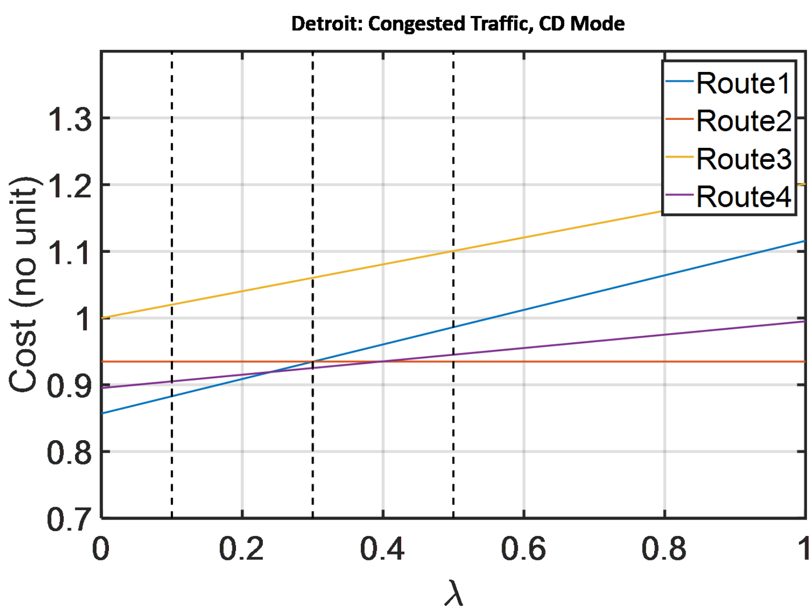

Figure 4.13: Cost vs λ for congested conditions in CD mode

the trip is also cut down significantly. Comparing just the SOC corrected fuel consumption values from Tables 4.9 and 4.8, the average mileage for corrected SOC fuel consumption is higher for the charge depleting mode compared to the charge sustaining mode by 8.4 percent. Therefore the major conclusion that can be drawn from this study is that energy efficient driving yields better results for PHEVs when the vehicle operates in a large SOC window. The presence of a large battery pack along with an engine is what makes PHEVs fundamentally different from other vehicles in the market. PHEVs allow the driver to drive the vehicle in all electric mode, provide extra torque required for high load requirements and the control strategy of the vehicle operates the engine in such a way that the overall system efficiency is maximized. In this way, PHEVs enable the driver to choose the kind of EcoRoutes they want and adjust their expectations based on the battery SOC when the commute begins.

4.8 San Francisco: Highway, Freeway and City Driving analysis

The San Francisco road network has three routes as seen in 4.14 and each of these routes has different types of road characteristics. Route 1 begins initially along State Route 1 in California and then the becomes a city route about halfway through after passing through the Golden Gate Park. Route 2 passes through one of the busiest arterial routes in San Francisco: Market street. This route also cuts through twin peaks which makes it a prime candidate for grade study.

Route 3 on the other hand goes through a combination of the I-280 and the US Route 101, an iconic and culturally significant highway. For the stretch used in the thesis, it is mostly a freeway with large stretches of road length with minimal traffic signals.

Therefore, the San Francisco Route study is a comparison between city driving (Route 2), highway driving (Route 3) and a combined city/highway (Route 1) segment. Furthermore, all three routes have different elevation profiles and road grades. Figure 4.15 is a plot of the grade of all three routes and their variation with distance. Most of the grade variation happens within the first two miles after which the grade remains relatively stable for all three routes around 0 percent. The 2 mile mark at the end of the graph is not the end of the route.

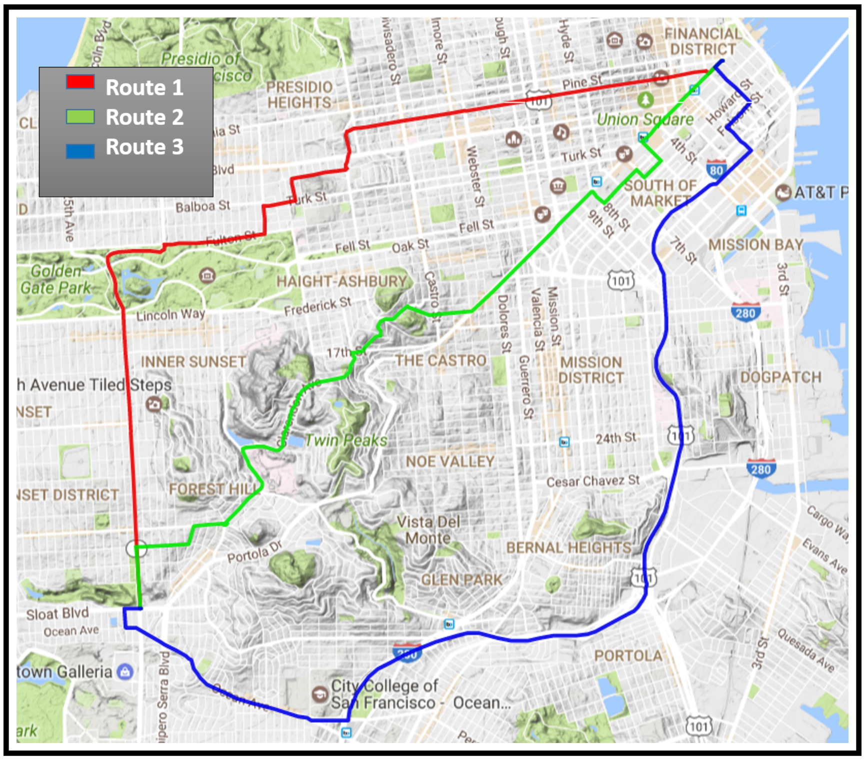

Figure 4.14: Routes used for the San Francisco Study

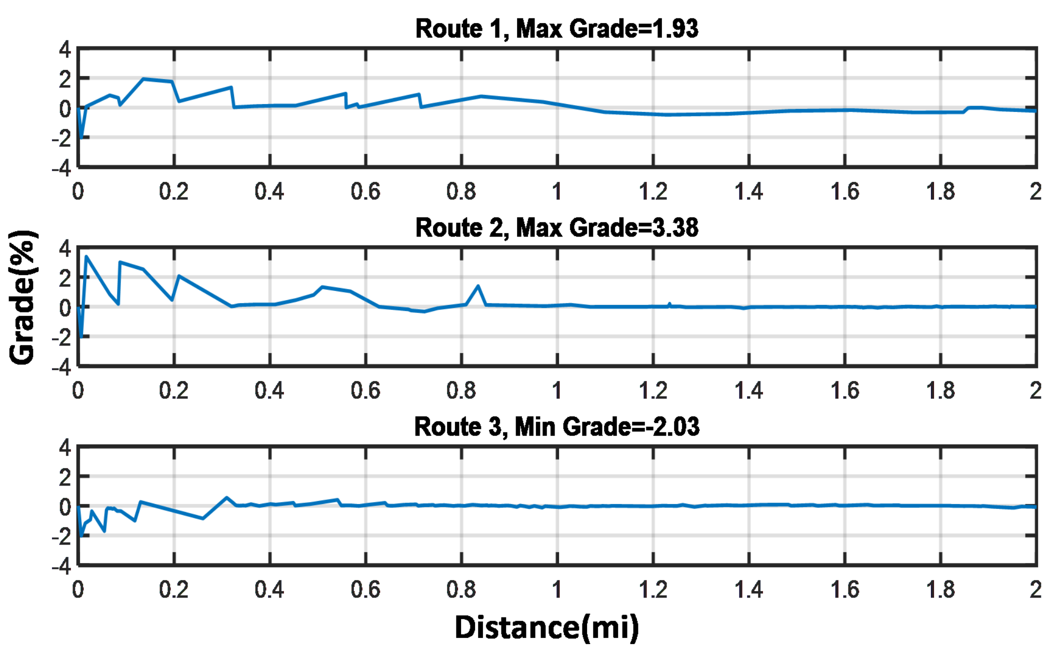

Figure 4.15: Grade vs Distance for the SF Routes

4.9 CS Mode in the San Francisco Network

Table 4.10 summarizes a single trial study for the San Francisco network. The active signals refer to the traffic signal IDs that turn red for the route. Route 2 is the shortest distance route and the most fuel efficient route. Route 3 is the TT route while Route 2 is the shortest route and the most fuel efficient route. Figure 4.16 shows the variation of cost and λ for the SF road network in CS mode. For all three cases, Route 2 is the EcoRoute in CS mode. Therefore, the more congested route is the EcoRoute. It is important to keep in mind that there is a general trend of the shortest distance route being the most energy efficient route so a person having very low priority on commute time can be automatically assigned the shortest distance route as the EcoRoute as a quick solution. Similarly, a person prioritizing travel time highly will be assigned the TT route as the EcoRoute. Another real world consideration while evaluating the viability of EcoRoutes is that the Market street is central to San Francisco and the Bay Area Rapid Transit(BART) and the San Francisco Electric trolley buses ply through it. The effect of alternative transportation and its effect on traffic congestion is outside the scope of this thesis. However, external traffic factors could be an interesting point of future work when real time traffic data is collected for an on board EcoRouting module.

Table 4.10: CS Study on the San Francisco Network. $SOC_{init} = 25 percent$

	Active Signals	**Miles**	**Engine In (kJ)**	**Δ SOC (%)**	**Batt Int (kJ)**	**Efuel (Wh/mi)**	**MPGGe**	**Travel Time (mins)**
Route1	[5,19]	7.93	32495	-5.0	-2287	898	37.5	19.5
Route2	[4,10,12]	6.90	19785	0.6	268	829	40.6	20.2
Route3	[12,16]	9.30	38221	-4.6	-2099	953	35.4	17.0

Figure 4.17 is a dual y axis plot where the SOC percentage and grade is plotted against the route distance in miles. This graph allows for a deeper analysis of how the variation in grade affects the SOC percentage. It is important to keep in mind that the vehicle switching from CD to CS mode only after the SOC hits 20 percent. The variation in grade is only shown for the first two miles is shown in Figure 4.15. The rest of the terrain (not shown in the figure) is relatively flat. The upper window or SOC_{max} as seen in Figure 4.12 is 30 percent.

The Route 1 SOC remains relatively high during the first two miles. When the vehicle goes up the hill, the SOC falls and then starts rising again when the vehicle goes downhill Furthermore, the vehicle switches to a fully charge depleting mode and the SOC drops steadily there on after. Route 2 has very positive grade values resulting in the sharp drop in SOC compared to route 1. The downward hills are unable to capture adequate regenerative braking to increase Battery SOC. Route 3 has a mostly flat grade profile as a result of which the SOC is unaffected by grade variations in Route 3.

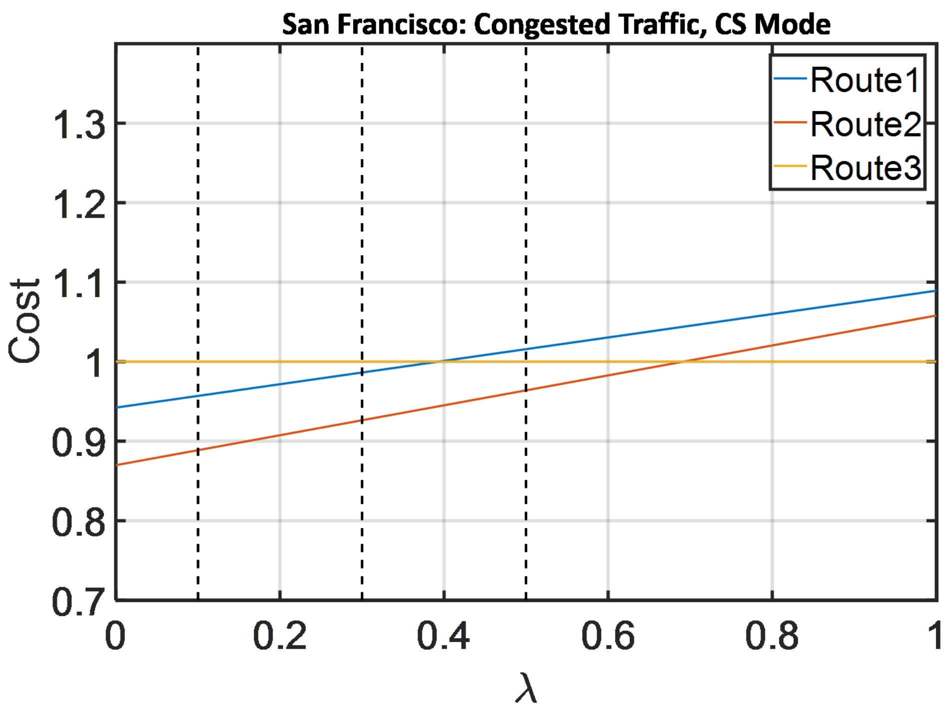

Figure 4.16: Cost vs λ for congested conditions in CS mode

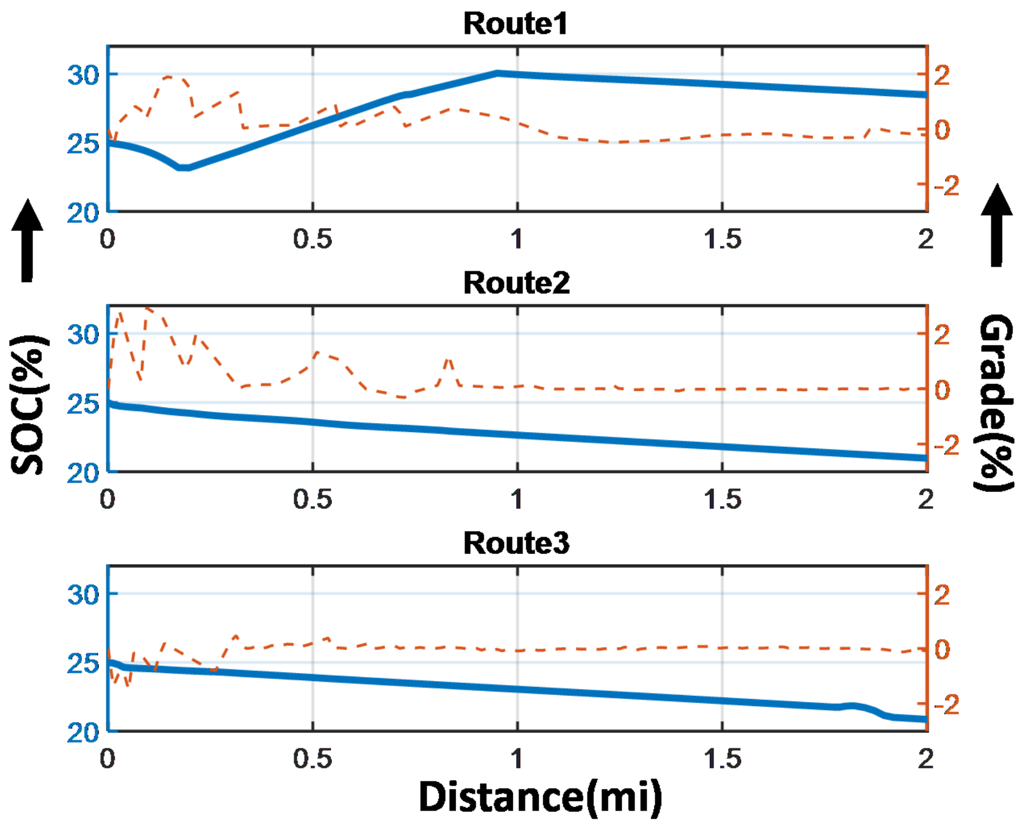

Figure 4.17: SOC and Grade vs Distance for CS Mode in the SF Network

4.10 CD Mode in the San Francisco Network

Table 4.11 summarizes a study similar to the one in the previous section but in this case the vehicle begins the route at an initial SOC of 60 percent. Similar to the previous section, Route 2 is the shortest distance route and the most fuel efficient route. Route 3 is the TT route while Route 2 is the shortest route and the most fuel efficient route.

Table 4.11: CD Study on the San Francisco Network. $SOC_{init} = 60\ percent$

	Active Signals	**Miles**	**Engine In (kJ)**	**ΔSOC**	**Batt Int (kJ)**	**AC Grid Energy (AC kJ)**	**Grid EC (AC Wh/mi)**	**MPGGe**	**Travel Time (mins)**
Route1	[5,19]	7.93	0	14.1	6407	7469	261.7	128.8	19.5
Route3	[4,10,12]	6.9	0	11.8	5343	6201	249.7	135.0	20.2
Route3	[12,16]	9.3	0	20.9	9500	11045	329.8	102.2	17

Figure 4.18 is a plot of the variation of cost vs λ for CD mode on the SF network study. Route 2 is the EcoRoute for Cases I,II and III similar to Section 4.9. What is different in this scenario is that the difference in cost between Route 1 and Route 2 is very small for all three cases. Furthermore, there is a bigger difference in the cost between the TT route and Routes 2 and 3 compared to Figure 4.16. An inference can be made from this result that EcoRouting in CD mode gives more alternative EcoRoutes to the driver when traffic conditions are congested

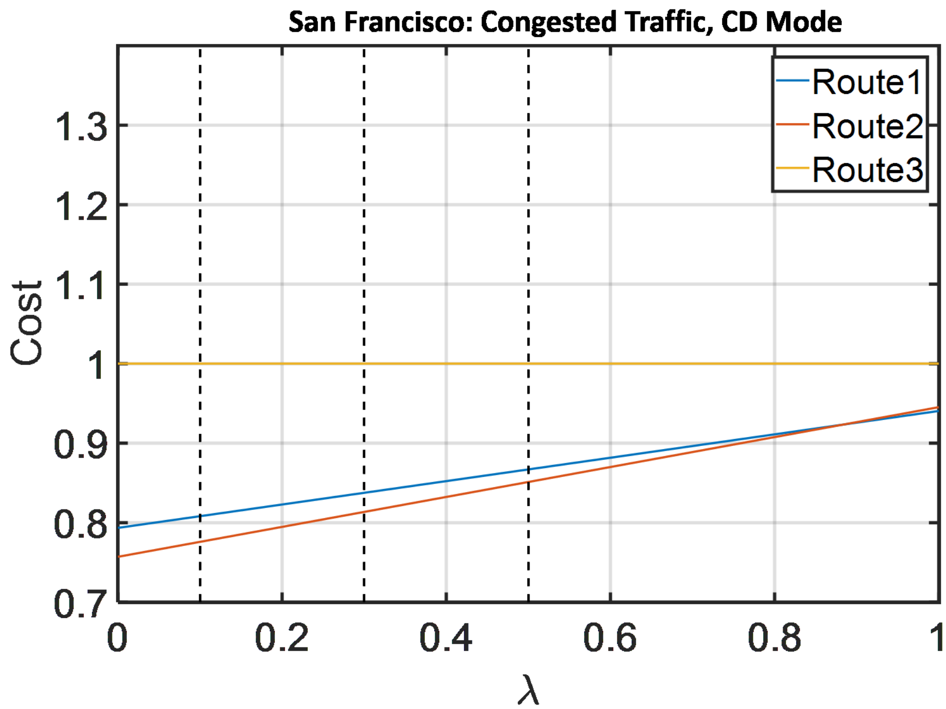

Figure 4.18: Cost vs λ for congested conditions in CD mode

The results for the Routes 2 and 3 are similar to the results in the previous section. Route 1 has a couple of local peaks in the SOC as seen in Figure 4.19 but drops overall throughout the two miles. The first local minima of the SOC coincides with a local minima of the grade. It is at that point when the grade begins to rise and the SOC rises with it. Route 1 has a higher grade over distance which the system enough of a buffer time to reflect the change in the battery SOC.

The major conclusion that can be drawn from this study is that grade can play an important part in determining the battery SOC. As inferred in Section 4.7, maintaining a higher SOC results in more energy efficient driving overall. The SOC stays at a higher level when the vehicle traverses elevation profiles where the grade steps are not very steep. Therefore, choosing a higher positive grade profile road will ensure better energy consumption from the vehicle. The average road grade over distance is very important in determining the effectiveness of a route in being a potential EcoRoute.

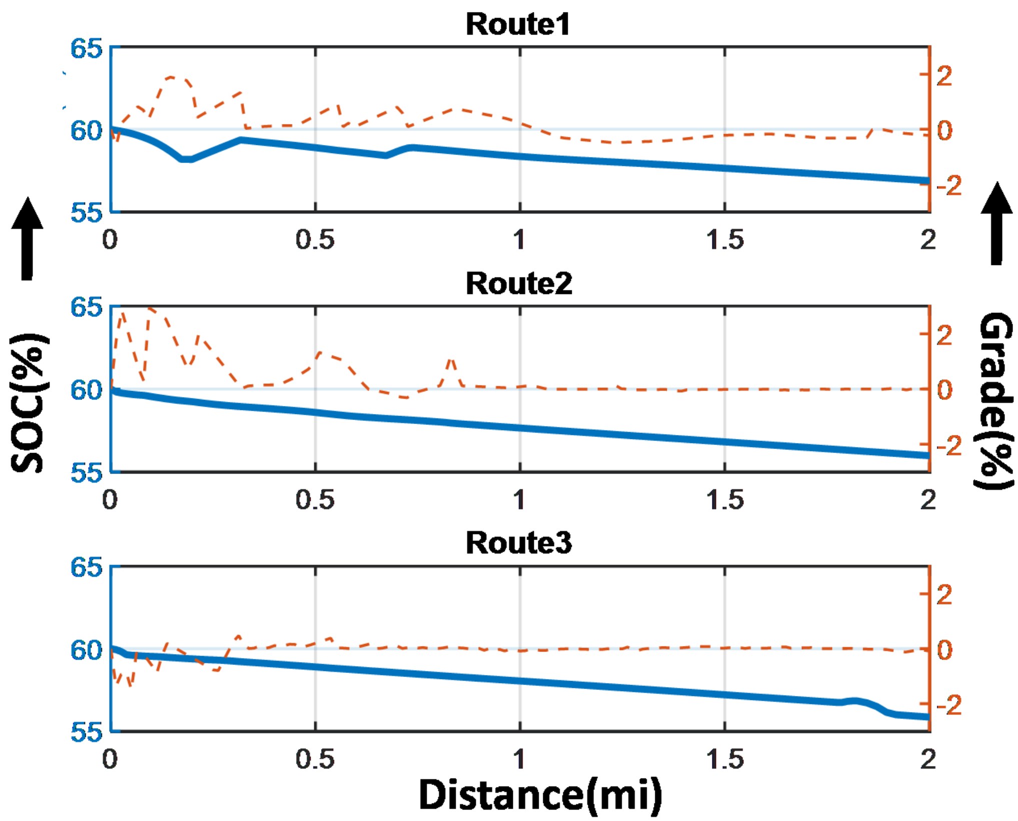

Figure 4.19: Routes used for the San Francisco Study

Chapter 5

Conclusions

In this thesis, a method has been developed to simulate real world routes and evaluate the total energy consumption for a powertrain model of a PHEV Camaro based on the HEVT Hybrid Camaro. A statistical active signal model and idle time model is developed and validated against the resulting route distance and travel time. Trapezoidal drive cycles with a constant acceleration is used to make simplified drive cycles which can be easily scaled to model driver behavior. This method of using trapezoidal drive cycles is validated against real world vehicle data taken from ANL and EPA. A normalized linear cost function is developed which minimizes total vehicle energy consumption with a constraint of travel time. Three cases of high, medium, and low priority to travel time is given so that the driver can preset their priority level and choose the EcoRoutes suitable to them.

The cities of Detroit and San Francisco are used to evaluate city and highway driving and compare energy consumption with and without the effect of grade. Detroit is a short route study while San Francisco is a longer route study.

The analysis of Detroit has offered unique insights into the benefits of EcoRouting for PHEVs and the effect of congestion and driver behavior. The San Francisco network analysis offered useful insights into the effects of road grade on SOC variation. An observation was made that traffic congestion can be affected by alternative means of transportation such as railways and bus systems.

5.1 PHEV advantage

The big question this thesis explored is where and how does EcoRouting make a difference for PHEVs. PHEVs have a large battery back which gives the driver to drive in either a motor dominant or engine dominant condition. In both cases, the EcoRoute inherently remains the same, but the amount of total energy consumption is far less when it comes to operating the vehicle in CD mode or in a mode which uses more of the energy from the battery pack. However, one thing to keep in mind is that the battery can be charged by the engine in which case more fuel is burned than necessary. The SOC has been corrected for routes which are not charge balanced. Given the vast number of options a PHEV brings to EcoRouting, it is definitely worth investing in.

5.2 Congestion: Idle Time and Traffic Signal

Traffic congestion in this thesis has been divided into the idle time stoppage at each signal and the number of signals that turn on for a given route. Idle time has been shown to have a negligible amount of impact on energy consumption but has an adverse impact on the travel time which is the deciding factor for drivers to deem a fuel efficient route and EcoRoute. An EcoRoute is one which is both fuel efficient and has a reasonable travel time estimate.

The number of traffic signals has a big impact on EcoRouting. Adding more signals initially reduces the average velocity of the route and inadvertently enforces good driving behavior leading to reduced consumption metrics. However as observed in Section 4.2 the presence of excessive traffic signals causes the travel time to increase uncontrollably leading and the heavily congested routes are not EcoRoutes. Therefore a good design practice for real time selection of EcoRoutes would be to prefer routes with low to medium levels of congestion keeping in mind that the driver isn't greatly inconvenienced by the travel time.

5.3 Grade Considerations

Grade is the primary factor that drove the choice of cities for route study. Detroit is relatively flat all over and San Francisco is well known for its steep hills. SOC has been shown to vary with grade and an important conclusion was drawn that grade can help improve energy consumption only when a high value of road grade is spread over a large distance. High road grades over small distances result battery pack depletion regardless of the actual value of the road grade. This inference should be another important point of design consideration for the EcoRouting module because grade is one of the 4 primary inputs to the scalable powertrain model used to calculate energy consumption from the modeled routes.

5.4 Driver Aggression

EcoRouting is sensitive to driver behavior as seen in Section 4.3 and that makes the concept of an EcoRoute personalized to specific requirements. As seen in the Detroit Route study, an regular driver and an aggressive driver can have different EcoRoutes given their environment.

Therefore, a learning algorithm that can pick up the driving habits of a driver and modify drive cycles to effectively calculate EcoRoutes for different scenarios would be useful.

5.5 Future Work

The future work in EcoRouting is happening right now. The constant acceleration model has been replaced by a constant jerk model. Jerk is the rate of change of acceleration. A constant jerk model allows modeling of driver behavior since real world driving has variable acceleration. Driver behavior can therefore be modeled more accurately. The traffic model currently selcts active signals and there exists scope to increase the model fidlity and incorporate traffic vehicle flows, highway capacities and modeling traffic control. Voice XML (VXML) can be used as a voice standard so that the driver does not have to type their address. Drive cycles can be customized based on either individual profiles or cluters of driver behavior. Implementing EcoRouting modules for PHEVs is definitely beneficial in the long run. These modules can be scaled to different powertains using publicly available parameters. With the increased penetration of V2X communication system, real time traffic data can be collected more accurately leading to higher fidelity EcoRouting models.

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Appendices

Appendix A

Implementation Code

A.1 Interpolator

Contents

- Plots

```
% Description: This script interpolates the data so that it can be fed into
% the scalable powertrain model
clc
clear all
close all
set(0,'DefaultFigureWindowStyle','docked')
set(0,'defaultlinelinewidth',5);
set(0,'defaultaxeslinewidth',2);
set(0,'defaultaxesfontsize',20);
set(0,'DefaultAxesXGrid','on','DefaultAxesYGrid','on')
set(0,'DefaultFigureWindowStyle','docked')
set(0,'DefaultLineMarkerSize',20);

load('r1.mat',Route1)
load('r2.mat',Route2)
load('r3.mat',Route3)
load('r4.mat',Route4)
```

Plots

```
figure
x1=[0 2]
y1=[20 32]
y2=[-3 3];
subplot(3,1,1)
yyaxis left
plot(Route1(1,:),Route1(2,:));
xlim(x1)
ylim(y1)
ylabel('SOC (%)')
yyaxis right
plot(Route1(1,:),Route1(4,:),'--','LineWidth',2);
xlim(x1)
ylim(y2)
ylabel('Grade (%)')
title('Route1')
subplot(3,1,2)
yyaxis left
plot(Route2(1,:),Route2(2,:));
xlim(x1)
ylim(y1)
yyaxis right
plot(Route2(1,:),Route2(4,:),'--','LineWidth',2);
xlim(x1)
ylim(y2)
title('Route2')
subplot(3,1,3)
yyaxis left
plot(Route3(1,:),Route3(2,:));
xlim(x1)
ylim(y1)
yyaxis right
plot(Route3(1,:),Route3(4,:),'--','LineWidth',2);
xlim(x1)
ylim(y2)
xlabel('Distance(mi)')
title('Route3')
```

```
x1 =
```

```
     0     2


y1 =

    20    32
```

A.2 Cumulative Distance Calculator

```
clc
clear
% *Find the cumulative distance value of a route*
route=gpxread('Detroit_Route2_4_Elevation');

lat=deg2rad(route.Latitude); %Lattitude is the y coordinate;
lon=deg2rad(route.Longitude); %Longitude is the x coordinate;
ele=route.Elevation;
earth=wgs84Ellipsoid;
[x,y,z]=lla2ecef(lat,lon,ele);


dist_m=sqrt(diff(x).^2+diff(y).^2+diff(z).^2);
dist_m=[0 dist_m];
cum_dist=cumsum(dist_m);
dist_miles=cum_dist*(0.000621371);
dist_miles=dist_miles';
```

A.3 WGS84 to ECEF Conversion

```
% LLA2ECEF - convert latitude, longitude, and altitude to
%            earth-centered, earth-fixed (ECEF) cartesian
%
% USAGE:
% [x,y,z] = lla2ecef(lat,lon,alt)
%
% x = ECEF X-coordinate (m)
```

```
% y = ECEF Y-coordinate (m)
% z = ECEF Z-coordinate (m)
% lat = geodetic latitude (radians)
% lon = longitude (radians)
% alt = height above WGS84 ellipsoid (m)
%
% Notes: This function assumes the WGS84 model.
%        Latitude is customary geodetic (not geocentric).
%
% Source: "Department of Defense World Geodetic System 1984"
%          Page 4-4
%          National Imagery and Mapping Agency
%          Last updated June, 2004
%          NIMA TR8350.2
%
% Michael Kleder, July 2005

function [x,y,z]=lla2ecef(lat,lon,alt)

% WGS84 ellipsoid constants:
a = 6378137;
e = 8.1819190842622e-2;

% intermediate calculation
% (prime vertical radius of curvature)
N = a ./ sqrt(1 - e^2 .* sin(lat).^2);

% results:
x = (N+alt) .* cos(lat) .* cos(lon);
y = (N+alt) .* cos(lat) .* sin(lon);
z = ((1-e^2) .* N + alt) .* sin(lat);

return
```

A.4 Idle Time Sampler

Contents

```
% Description: This code samples the idle time a vehicle waits for at
% Each traffic signal using a normal distribution curve
close all
set(0,'DefaultFigureWindowStyle','docked')
set(0,'defaultlinelinewidth',5);
set(0,'defaultaxeslinewidth',3);
set(0,'defaultaxesfontsize',35);
set(0,'DefaultAxesXGrid','on','DefaultAxesYGrid','on')
set(0,'DefaultFigureWindowStyle','docked')
set(0,'DefaultLineMarkerSize',20);
set(gcf,'color','white')
```

Begin

```
clc
clear
num=16;
pd=makedist('Normal','mu',num);
sample=random(pd,10,1000);
sampleHist=histfit(reshape(sample,1,[]));
sampleCurve=[sampleHist(2,:).XData;sampleHist(2,:).YData];
```

Plots

```
figure
histogram(sample,'Normalization','pdf','LineWidth',5);
hold on
% Normalize Fitted curve
plot(sampleCurve(1,:),sampleCurve(2,:)/trapz(sampleCurve(1,:),sampleCurve(2,:)));
xlabel('Idle Time(s)');
ylabel('Probability');
xlim([12 20])
title('Idle Time distribution: Low traffic')
legend('data','fitted normal curve')
```

A.5 Idle Time Sampler

```
%This program determines if a traffic signal lies within a route. The
%perpendicular distance of the signal is computed for each way between
```

```
%consecutive node pairs and the signal is assigned to the way, if it falls
%below a certain threshold

%The coordinates need to be converted from a WGS84 to ECEF, so that
%cartesian geometry can be applied to them

%Let P1 = [x1,y1,z1] be
%the point, and let P2 = [x2,y2,z2] and P3 = [x3,y3,z3] be two points on
%the line. Then the orthogonal distance from the point to the line is:
%d = norm(cross(cross(P2-P1,P3-P1),P3-P2))/norm(P3-P2)^2;

% P3 and P2 will be looped over the entire route. Therefore, if there are n
% nodes, then the loop runs from 1 to n-1
% dlmwrite('qq.txt',Signal); is the command required to write the text
% file

%NOTE: This code does not work as intended, unfortunately. The intent of
%putting it here is to give the reader an idea as how signal location on a
%route can be automated
clc
clear all
thresh=4;
% Step 1 : Import the data: Load the gpx file and traffic signals
Route=gpxread('Detroit_Route1_1_Elevation.gpx');
Signal=gpxread('detroitSignals.gpx');
routeSize=length(Route);
sigSize=length(Signal);
% % Convert the data into ECEF coordinated
[cartRoute.x,cartRoute.y,cartRoute.z]=lla2ecef(Route.Latitude,Route.Longitude,Route.Elev
[cartSig.x,cartSig.y,cartSig.z]=lla2ecef(Signal.Latitude,Signal.Longitude,Signal.Elevati
%Step 2:Run two loops: 1 for each traffic signal and 1 for each node pair
for j=1:1:sigSize
    P1=[cartSig.x(j),cartSig.y(j),cartSig.z(j)];
   for k=1:1:routeSize-1
         P2=[cartRoute.x(k),cartRoute.y(k),cartRoute.z(k)];
         P3=[cartRoute.x(k+1),cartRoute.y(k+1),cartRoute.z(k+1)];
        d(k+(j-1)*(routeSize-1))=norm(cross(cross(P2-P1,P3-P1),P3-P2))/norm(P3-P2)^2;
   end

end
% Step 3: Evaluate perpendicular distances, see what you come up with
distSig=reshape(d,sigSize,routeSize-1); % The reshaped array contains  all the traffic s
```

```
[sortSig,Idx]=sort(distSig,1);
[row,col]=find(distSig<thresh);

% Now that the traffic signals have been located they also need to be
% placed in the route somewhere. woo
```

A.6 Active Signal Model

Contents

- Create the PDF
- Choose how many signals will turn on.
- Plots: Probability vs Total Number of Red Lights
- Plots: Probability vs Traffic Signal Number

```
set(0,'DefaultFigureWindowStyle','docked')
set(0,'defaultlinelinewidth',5);
set(0,'defaultaxeslinewidth',3);
set(0,'defaultaxesfontsize',20);
set(0,'DefaultAxesXGrid','on','DefaultAxesYGrid','on')
set(0,'DefaultFigureWindowStyle','docked')
set(0,'DefaultLineMarkerSize',20);
set(gcf,'color','white')
```

Create the PDF

```
clc;
clear;
close all
sigNum=13;
lam_low=ceil(.1*sigNum);
lam_medium=ceil(.3*sigNum);
lam_high=ceil(.5*sigNum);
sampleSize=10000;
% Total number of route traffic signals
% Make Poisson Distribution Objects
low_traffic=makedist('Poisson',lam_low);
medium_traffic=makedist('Poisson',lam_medium);
high_traffic=makedist('Poisson',lam_high)
```

```
%1000 Random Samples
low=random(low_traffic,sampleSize,1);
medium=random(medium_traffic,sampleSize,1);
high=random(high_traffic,sampleSize,1);
% Range fitter
low(low>sigNum)=sigNum;
medium(medium>sigNum)=sigNum;
high(high>sigNum)=sigNum;
% Fitted curve
lowHist=histfit(reshape(low,1,[]));
lowCurve=[lowHist(2,:).XData;lowHist(2,:).YData];
medHist=histfit(reshape(medium,1,[]));
medCurve=[medHist(2,:).XData;,medHist(2,:).YData];
highHist=histfit(reshape(high,1,[]));
highCurve=[highHist(2,:).XData;,highHist(2,:).YData];


high_traffic =

  PoissonDistribution

  Poisson distribution
    lambda = 7
```

Choose how many signals will turn on.

```
% Low Traffic
for k=1:1:length(low)
traffLow(k,:).sigON=sort(randperm(sigNum,low(k)));
end
  % Zero Signals On Checker
  emptyIndex_low = find(arrayfun(@(traffLow) isempty(traffLow.sigON),traffLow));

% % Medium Traffic
for k=1:1:length(medium)
traffMed(k,:).sigON=sort(randperm(sigNum,medium(k)));
end
  % Zero Signals On Checker
  emptyIndex_Med = find(arrayfun(@(traffMed) isempty(traffMed.sigON),traffMed));

% % High Traffic
```

```
for k=1:1:length(high)
traffHigh(k,:).sigON=sort(randperm(sigNum,high(k)));
end
  % Zero Signals On Checker
  emptyIndex_High = find(arrayfun(@(traffHigh) isempty(traffHigh.sigON),traffHigh));

% Concatenate all data to get an array with all the signals turned on
low_ON=cat(2,traffLow.sigON);
med_ON=cat(2,traffMed.sigON);
high_ON=cat(2,traffHigh.sigON);
```

Plots: Probability vs Total Number of Red Lights

```
figure
subplotfill(3,1,1)
set(gca,'LooseInset',get(gca,'TightInset'));
histogram(low,'Normalization','probability','LineWidth',5);
hold on
plot(lowCurve(1,:),lowCurve(2,:)/trapz(lowCurve(1,:),lowCurve(2,:)))
ylabel('Probability');
title('Low Traffic Distribution')
legend('data','fitted poisson curve')
xlim([0 12])
subplotfill(3,1,2)
set(gca,'LooseInset',get(gca,'TightInset'));
histogram(medium,'Normalization','probability','LineWidth',5);
hold on
plot(medCurve(1,:),medCurve(2,:)/trapz(medCurve(1,:),medCurve(2,:)))
ylabel('Probability');
title('Medium Traffic Distribution')
xlim([0 12])
legend('data','fitted poisson curve')
subplotfill(3,1,3)
set(gca,'LooseInset',get(gca,'TightInset'));
histogram(high,'Normalization','probability','LineWidth',5);
hold on
plot(highCurve(1,:),highCurve(2,:)/trapz(highCurve(1,:),highCurve(2,:)))
xlabel('Number of Traffic Signals');
ylabel('Probability');
xlim([0 12])
title('High Traffic Distribution')
```

```
legend('data','fitted poisson curve')
```

A.7 All paths between two nodes

```
% This is a nifty bit of code, and Hrusheekesh Warpe came up with it
% It basically takes a connectivity matrix of a road network and generates
% All possible paths between two nodes.
child_handles = allchild(0);
names = get(child_handles,'Name');
k = find(strncmp('Biograph Viewer', names, 15));
close(child_handles(k))
set(0,'DefaultFigureWindowStyle','docked')
DG = sparse(connectivity_matrix)
g1 = view(biograph(DG))
from4 = graphtraverse(DG,886); % Traversals from origin
DG_from=DG(from4,from4);
g2 = view(biograph(DG_from,cellstr(num2str(from4'))))
to1 = graphtraverse(DG',305);
DG_to=DG(to1,to1); % Traversals to destination
g3 = view(biograph(DG_to,cellstr(num2str(to1'))))
h = intersect(from4,to1)
DG2 = DG(h,h);
g4 = view(biograph(DG2,cellstr(num2str(h'))))
[Dist, Path]=graphkshortestpaths(DG,886,305,5)
DG3=DG(Path{1},Path{1})
g5 = view(biograph(DG3,cellstr(num2str(Path{1}'))))
```