A Predictive and Intelligent Environmentally Friendly Vehicle Navigation System

A Dissertation Submitted to the Graduate Faculty of the

University of Detroit Mercy

In Partial Fulfillment of the requirements for the Degree of

DOCTOR OF ENGINEERING

Department of Electrical and Computer Engineering

College of Engineering and Science

By

Mohamad Abdul-Hak

University of Detroit Mercy

October 31st, 2013

Acknowledgments

I am especially grateful to my advisor, Professor Nizar Al-Holou, for all the guidance, support and suggestions I received during my research. His availability and accessibility, including holding late and weekend office hours, have contributed to the progress of this research in a timely and gratifying manner.

Furthermore, I would like to sincerely thank my co-advisor, Professor Youssef Ahmad Bazzi, for his assistance and guidance in keeping my graduate study goals in focus. I will always cherish his insight and comprehensive knowledge.

I am also indebted to Dr. Luca Delgrossi, Dr. Utpal Dutta and Dr. Utayba Mohamad for their valuable feedback. They have been particularly kind, and patient with me. Besides I would like to thank my manager at Mercedes Benz Research and Development Oliver Cordes for his motivational support and for his attendance of my final defense.

I would like to thank my affectionate wife, Assma, and loving kids, Sara and Omar, for their quiet patience while I prepared this research. Their tolerance for my occasional tense mood is a statement in itself for their firm devotion and love.

I would like to thank my father, Abdul-Raouf, and my mother, Nawal, for setting an example of hard work and persistence; my father had infused in me the will to stay the course. His loss during the process of my research was extremely difficult and caused an immense and memorable scar in my life. He was always proud and very supportive of my educational achievements. Envisioning the happiness my dad would have experienced for this progress helped me stay the course to pursue this research.

I would like to thank the following organizations for supporting this work, University of Detroit Mercy, Mercedes Benz Research and Development, Chrysler Corporation, AVL GmbH, Professor Valentin Cristea and Professor Liviu Iftode at University Politehnica of Bucharest, and the iTETRIS consortium.

Some of this work was partially funded by Michigan Ohio UTC program supported through the U.S. Department of Transportation (USDOT), Research and Innovative Technology Administration (RITA) and Michigan Department of Transportation (MDOT).

Abstract

The field of Intelligent Transportation System (ITS) has been experiencing a remarkable growth in a wide range of vehicle applications research, categorized into safety to reduce or eliminate crashes, mobility to mitigate congestion and environmental impact, and convenience to provide driver connection to media and social network services. This research focuses on the mobility application and aims to provide drivers the least congested transportation route choices enabled by the ITS Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I) and Infrastructure to Vehicle (I2V) envisioned communication platforms. This research presents an in-vehicle navigation methodology with the prospect of being implemented in a new progressive vehicle navigation system.

Recent research in vehicle navigation systems has proposed energy consumption/emission optimized routing methodologies using historical traffic data modeling. More than 50% of congestion in U.S. cities is nonrecurring congestion [1]. Nonrecurring congestion reduces the availability of the traffic network, thus rendering historical traffic data-based systems insufficient in more than 50% of the cases. Real-time traffic data modeling provides an enhanced performance in traffic congestion assessment; however, greater performance is expected with a predictive traffic congestion model with increased certainty.

This research starts by reviewing the conventional shortest path and fastest path vehicle routing methodologies. It also reviews key search algorithms, namely the well-known unidirectional search algorithm Dijkstra and the bidirectional search algorithm A*.

Having presented the enhanced performance of eco-routing, the research introduces the predictive traffic information assessment and integration approach. Additionally, the approach aims to offer the driver the flexibility to optimize travel costs such as energy consumption, emission and travel time. The assessment of predictive traffic information modeling using wireless communication data has been limited due to the difficulty in objectively and quantitatively evaluating energy and emission reduction effects using ITS technology. The capabilities of Petri Net extend beyond other similar mathematical modeling languages, such as neural networks, to include analysis control and graphical representation. It is natural to model the optimal problem on a cost-dependent petri net graph where the travel costs are: energy consumption, emission and travel time. We propose an algorithm based on Dijkstra's unidirectional search algorithm and introduce speedup techniques that may be applied to the cost-dependent network. Our methodology deals efficiently with the accuracy of the solution in a dynamic environment where selective travel cost is dynamically updated to enable optimal route solution.

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Chapter 1

1 Introduction

1.1 Motivation

Without the balanced greenhouse gas GHG effect, the planet would not be warm enough to sustain life in the form it is known to us today. Carbon dioxide (CO_2) is the largest contributor to the overall GHG concentration, with a growth of 42% from 1950 to 2010 [2]. In 1896 Arrhenius, the Swedish and Nobel Prize winner, was the first to mathematically correlate CO_2 increased concentration levels in the atmosphere to Earth's increased surface temperature [3]. One hundred and eleven years later in February 2007 under the Intergovernmental Panel on Climate Change (IPCC), thousands of scientific researchers collectively concluded that industrialization causes global warming through the acceleration of CO_2 emissions. Increased earth surface temperature is causing extreme weather changes such as droughts, floods, heavy rain and excessive heat that cause fires. By investing in technologies that reduce GHG emissions, we can reduce future climate change threats.

In 2011, U.S. greenhouse gas emissions totaled 6,702 million metric tons of CO_2, 84% of overall GHG emissions [4]. CO_2 can stay in the atmosphere for nearly a century, so the earth will continue to be warm in the coming decades. The warmer it gets, the greater the risk is for more severe changes to the climate and the earth's system. Our choices to reduce GHG emission today will shape the world in which future generations will live. Although no single industry has been fully responsible for the GHG emissions, it has become clear that the transportation industry is a key contributor, with 28% of total GHG emissions [4]. Thus reduction in vehicle energy consumption and emissions is critical.

The U.S. Department of Transportation's (DOT) investment in the Intelligent Transportation System (ITS) platform will lead to the second U.S transportation industry revolution. ITS confirmed the use of wireless communication technology in enhancing transportation system efficiency and its environmental impact. A new wave of environmentally aware transportation technology research has been spurred in the United States, targeting different areas of renewable energy sources and improved energy efficiency machinery. The Electric Vehicle (EV) is a state-of-the-art technology vehicle that addresses the continually pressing energy and environment concerns. Recent development in vehicle electrification brings substantial benefits to vehicle operating efficiency. Overall electric propulsion and charging efficiency is approximately 68%, compared to conventional internal combustion propulsion vehicles at around 25% [5]. U.S. electricity generation and production accounted for 40% of GHG emissions in 2011 [6]. It is clear that while the electrification of the vehicle has offered an emission reduction to the vehicle, it has also shifted the emission generation from being on-board the vehicle to being off-board at the electric utility companies. Another field of vehicle efficiency research has proposed an optimal Speed-Advising methodology to reduce vehicle fuel consumption and emissions [7]. The optimal speed advisory eco-driving system is rendered less practical in congested areas and when not combined with an energy-efficient travel route selection. None of the eco-driving advisory systems deals with optimizing the drive profile while optimizing the route profile; when combined, this provides the true benefits of environmentally friendly transportation, as represented in Figure 1.

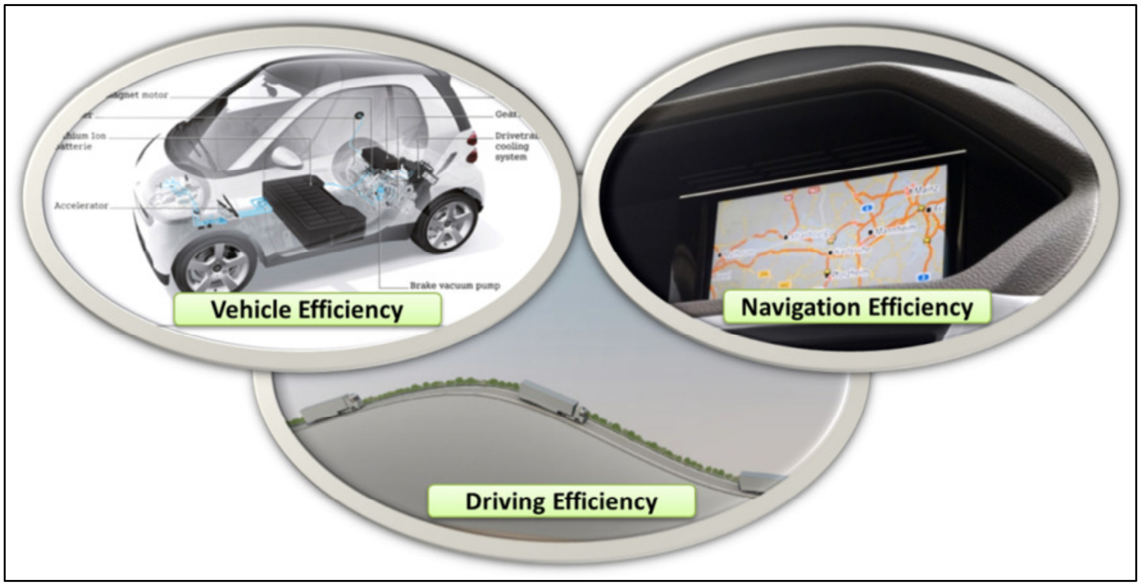

Figure 1: Environmentally Friendly Transportation

Other proposed solutions include static- and dynamic-based vehicle routing systems that would guide drivers through a minimized energy consumption travel route, formerly recognized as "Environmentally Friendly Routing/Eco Routing." Recent navigation system research has proposed energy consumption/emission routing methodology using historical traffic data modeling. More than 50% of congestion is nonrecurring congestion, which 25% percent of the time is caused by accidents, 15% by weather conditions, and 10% by temporary construction [8]. Nonrecurring congestion reduces the availability of the traffic network, rendering historical traffic data-based systems insufficient in more than 50% of the cases. Real-time traffic data modeling [9] provides an enhanced performance in traffic congestion assessment; however, greater performance is expected with a predictive traffic congestion model that has increased certainty. The assessment of predictive traffic information modeling using wireless communication data has been limited due to the difficulty in objectively and quantitatively evaluating energy and emission reduction effects using ITS technology. The nation's largest non-profit association that advocates for smart transportation technology solutions is the ITS of America, which has invested in the development and deployment of ITS services that rely on wireless communication technology, formerly known as Dedicated Short Range Communication (DSRC). The original intent of DSRC 5.9 GHz frequency band allocation by the Federal Communications Commission (FCC) in vehicle safety applications has been extended to include energy and emission optimization navigation applications as well. By adopting DSRC technology; ITS will spur a new revolution in U.S transportation system applications, the first revolutions since the construction of the Interstate Highway System in the 1970s. The field of ITS is experiencing remarkable growth and a wide range of vehicle applications research, categorized into Safety to reduce or eliminate crashes, Mobility to mitigate congestion and environmental impact, and Convenience to provide driver connection to media and social network services. This research focuses on the mobility application and aims to provide drivers the least congested transportation route choices enabled by the ITS Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I) and Infrastructure to Vehicle (I2V) envisioned communication platforms. This research presents an in-vehicle navigation methodology with the prospect of being implemented in a new progressive vehicle navigation system.

This research is inspired by the USDOT's vision of the Connected Vehicle [10] and aims to introduce a vehicle routing methodology that reduces the effect of traffic congestion by integrating a predictive mechanism for traffic congestion assessment and mitigation. This research proposes an Eco Predictive Dynamic Routing methodology that advises a driver of travel paths with the least travel cost based on predictive traffic congestion assessment. This research identifies the significance of routing policies based on predictive traffic data and incorporates this information as a key factor in the routing policy.

The proposed methodology offers an extended application to the conventional Internal Combustion Engine (ICE) propulsion technology to further include the Electric Drive (ED) propelled vehicle technologies such as the Electric vehicle (EV) and the Plug-In Hybrid Electric Vehicle (PHEV). This research is concerned with putting the design of ICE and ED technologies into a broader efficiency perspective by proposing a vehicle navigation system which will be referenced in this research as Predictive Intelligent Energy Management System (PIEMS). The PIEMS is to offer an enhanced overall navigation performance and user experience of ICE and ED propelled vehicles, relative to energy consumption and emissions through optimized navigation using the ITS wireless communication platform. Finding the optimal route in a road network from a current start location to a given destination is an everyday problem that most drivers have to tackle when planning a trip for a new target point. Many applications were designed to provide route search service using different platforms, ranging from vehicle navigation devices, to cell phones, to web-based navigated maps. The term “optimal,” in a routing algorithm, may refer to a range of objectives that end-users can choose from to optimize the route, such as fastest route, shortest route, fastest route given a preference to various road characteristics, or fuel-efficient route. These navigation algorithms also differ in the way they deal with the changing traffic conditions over time, and they can be divided into three main categories:

1. Static modeling
2. Dynamic real-time modeling
3. Dynamic predictive modeling

In the static planning model, all travel times and traffic conditions are considered constant over time, resulting in less realistic driving costs for road segments. The static model was improved on with the extended deterministic model, in which certain properties of road networks are considered to change as a function of the time, per day; week or even season (e.g. some roads may be closed during specific time periods) thus the accuracy of the route cost estimation is increased. The extended deterministic planning model is currently used by the most of commercial navigation systems. However, more accurate representation of the traffic flow, and hence responsive routing, can be achieved with dynamic routing model. In dynamic routing, real-time traffic information is integrated into the planning model. The optimal route to the destination is calculated before the start of a trip and it is updated dynamically to adapt to new traffic conditions during the travel. Theoretically, the resulting optimal route of the dynamic routing approach outperforms the static and time-dependent routing approaches in terms of accuracy and efficiency. However, in order to compare different route-planning methodologies, a clear classification of those methodologies is needed which will be provided in later section. Our research proposes a dynamic routing methodology that addresses the following issues:

a) The question to address is how to describe a dynamic multi-objective vehicle routing methodology. To the vast extent of our extensive literature survey, no one has yet considered this problem. Shortest path or fastest travel time does not necessarily provide emission optimized routing in all traffic conditions. A determination of routing methodology based on energy consumption and emission prediction needs to be identified and compared to existing shortest path and fastest time optimization constraints.

b) In the proposed dynamic routing methodology, a large amount of traffic information is anticipated to be exchanged. To enhance performance accuracy, simplified representation assumptions for traffic condition representation shall be excluded. How to define traffic information and transform into travel time, energy consumption and emission costs, maintaining and conceivably improving the certainty of traffic congestion prediction assessment.

c) When multiple travelers make dynamic routing decisions to the same alternative route, an additional research question to address is the congestion impact that will be introduced on the alternative route and the proposed solution to maintain the cost-benefit in vehicle dynamic routing.

1.2 Scope of the Proposed Research

The work in this research is motivated by the USDOT's vision of Connected Vehicle [10] and is to introduce a vehicle routing methodology that reduces the effect of traffic congestion by integrating a predictive mechanism for traffic congestion assessment and mitigation. This paper proposes an Eco Predictive Dynamic Routing methodology advising driver of path with the least emission based on predictive traffic congestion assessment. The Eco Predictive Dynamic Routing depicted in

Figure 2 as optimal routing is evaluated with the Real-time Dynamic Routing, which dynamically advises driver of path with least emission based on real-time (current) traffic information. In addition the evaluation is extended to include the conventional Static Routing methodology, which advises driver a path with least emission once at start of trip based on historical traffic information. This research identifies the significance of routing policies based on predictive traffic data and incorporates this information as a key factor in the routing policy.

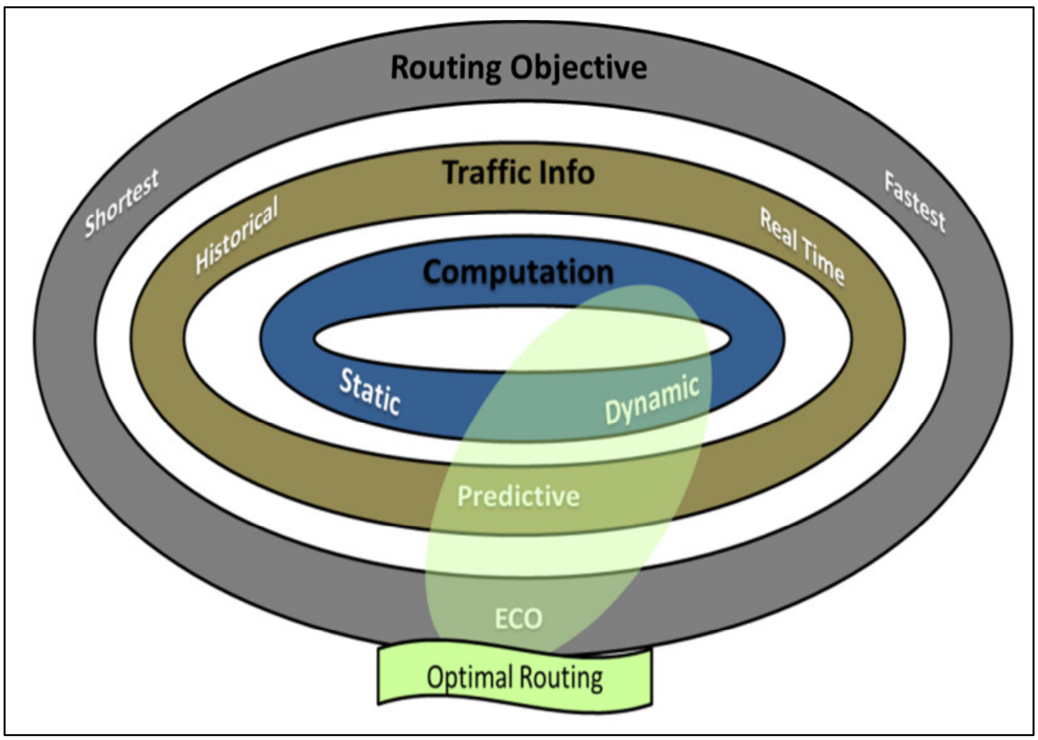

Figure 2: Eco Predictive Dynamic Routing

This research specific contribution to the knowledge based of vehicle routing methodologies in cost-dependent networks is summarized as follows:

1. Establish a framework for environmentally friendly routing in a dynamic cost dependent network.
2. Extend the study of environmentally friendly routing policies to strategies based on predictive traffic information.
3. Propose a multi-objective (travel time, energy consumption and emission) vehicle routing methodology.
4. Propose a hybrid traffic data communication platform.

The proposed methodology will benefit from employing DSRC based real-time traffic information and will integrate a state-of-art Well-To-Wheel (WTW) emission model extending the application of the proposed methodology to plug in technology vehicles such as the EV and the PHEV.

1.3 Hypothesis

The hypothesis being investigated is:

"Developing an Eco Predictive and Dynamic vehicle routing system architecture will provide a greater efficiency in vehicle energy and emission travel costs compared to traditional shortest distance and shortest time vehicle routing systems." This problem is of current interest because of the imminent impact on the environment and quality of living, the vehicle transportation system is presenting.

1.4 Research Contribution

The contribution of the research to the knowledge based of vehicle routing methodologies in cost-dependent networks is summarized as follows:

1. Establish a framework for environmentally friendly routing in a dynamic cost dependent network. Various descriptions have been made in the literature to define environmentally friendly routing. This dissertation research identifies the resemblances and establishes the state of art framework.
2. The study of environmentally friendly routing policies has been restricted to methodologies based on real-time traffic data. This research develops a routing methodology based on predictive traffic information.
3. Develop a multi-constraint cost function that supports tunable optimization criteria to present optimal routing relative to emission, travel time and energy consumption.
4. Develop a dynamic re-routing methodology to accommodate continued travel cost optimization in sudden traffic changes such as accidents.
5. Model the transportation problem via Petri Net, link travel cost and develop a routing solution algorithm.

6. Integrate individualized vehicle fuel/energy and emission modeling based on vehicle kinematics offering a more reliable evaluation of road network energy and emission travel costs.

7. Extend the concept of vehicle routing methodology to emission cost. This research recognizes the significant role of the emission factor in routing policies and includes it as a key factor in the routing policy. Emission cost is particularly important in plug in electric vehicle applications, where vehicle emission to a large extent does not exist and thus energy source emission shall be incorporated.

1.5 Research Issues

This section describes the main research issues:

a) How to model a dynamic multi-objective vehicle navigation system. In the surveyed literature, single cost such as travel time, energy consumption or path length are defined as respectively single target cost objective for route optimization. The static, dynamic real-time and the proposed dynamic predictive routing methodologies will be evaluated and compared. Consideration to curse of dimensionality is incorporated in the selection between the following three main modeling categories:

    - Static modeling

- Dynamic real-time modeling
- Dynamic predictive modeling

b) How to define predictive traffic information and transform into travel costs avoiding high computation power needs and loss of prediction certainty. Furthermore, when evaluating ED vehicle route optimization methodology traffic information would need to include new aspect of road and infrastructure variables such as electrical vehicle charging location and associated energy source emission.

c) How to develop a dynamic efficient routing algorithm, based on the multi-objective cost function in a dynamic traffic network; where efficiency is extended beyond the conventional route travel time and route distance to also include energy consumption and emission.

d) How to validate the concept of the proposed research. For the proposed methodology validation, Petri Net modeling tools shall be reviewed evaluated and selected. Furthermore the final results are validated through a traffic network simulation tool combining vehicle, communication and a traffic simulator which is to be investigated, reviewed and selected for the proposed routing algorithm evaluation and validation.

1.6 Research Outline

The remaining chapters in this research are organized as follows: Chapter 2, a literature review, key concepts and the related work of the research are introduced to show that the proposed research undertaken is original work while closely relating to other research in the field. In Chapter 3 the wireless communication technology IEEE 802.11.p is evaluated and its potential role in traffic information communication is stated. Chapter 4 presents the development and application of the Eco predictive dynamic vehicle routing system including the routing methodology, architecture and modelling approach. We include the proposed concept for mitigating the curse of dimensionality phenomena with the Predictive Traffic Congestion Index (PTCI), describe with illustrative examples and state the PTCI properties. In the same Chapter 4 we extend the frame work and algorithms developed to alternative plug in vehicle technologies through the integration of the WTW emission model. We then present the simulation results of the routing policy in real-life traffic network to study and compare the performance of the proposed environmentally friendly routing to shortest time and shortest distance routing. Chapter 5 concludes with highlights of the proposed dissertation and proposes future directions of research work.

Chapter 2

2 Literature Review

2.1 Background

The overall section is to show that the research undertaken is original work while closely relating to other research in the field. The first part of this chapter provides an overview of necessary basic concepts and definitions important for the reader to be familiar with in order to recognize the nuances of the research. The second part of this chapter gives an overview of the related work, focusing mainly on Environmentally Friendly Navigation Routing Methodologies.

2.2 Vehicle Navigation Technology

There are several vehicle routing algorithms offering a shortest distance or shortest time routing. However none have been identified in the field of eco predictive dynamic navigation to exist to date. The literature survey revealed few vehicle onboard algorithms employing simplified modeling techniques which may not be suitable for providing a true energy/emission optimized route. The existing routing system does not use dynamic routing to allow driver to avoid abrupt traffic changes such as traffic accident. Furthermore the current routing algorithm considers real-time traffic information and no predictive traffic information. Since the traffic condition is relevant at expected time of arrival of navigated vehicle, predictive traffic information should be considered to find an enhanced performance in travel time, energy consumption and emission travel costs. The reader is to establish a profound understanding of the difference between real-time and predictive traffic information in Section 4.3.1. In order to overcome the shortcomings of the existing environmentally navigation systems, our proposed methodology will adapt predictive traffic information to dynamically find an energy and emission efficient route.

2.2.1 Related Work

A navigation system that searches for an energy, emission and travel time costs optimized route based on predicted traffic information assessment and calculation; guiding drivers through emission efficient routes is essential for providing true environmentally friendly navigation. ITS wireless technology connectivity allows for developing traffic congestion mitigation techniques through traffic condition communication. The transportation system is to operate more efficiently with an overall source to destination optimization in travel time, energy consumption and emission. It is feasible to apply environmentally friendly navigation, when monitoring and estimating the state of the traffic system using heterogeneous sensors. The realization of the DSRC wireless communication technology has motivated and enabled the main directions of this research for estimating traffic congestion with an increased certainty. The majority of the surveyed modeling methods focused on macroscopic traffic congestion methodology and link-level travel time estimation. Optimizing emission and fuel consumption are increasingly important design parameters when designing navigation systems. This section provides an overview of the work related to this research.

Table 1 summarizes the literature surveyed in the proposed research. The table shows the research group, applied algorithm, modeled parameters, navigation service and the applicable vehicle type. Over time, efforts to address fuel efficiency improvements have been pursued in two dimensions:

a) The first area of research focuses on eco-driving to reduce vehicle's energy consumption and emission in conventional Internal Combustion Engine (ICE) vehicles. Optimization algorithm to minimize fuel consumption by employing Global Positioning System (GPS) data and analysis of vehicle operating parameters has been presented by Neiss [11]. This methodology is limited to the cruise control function of the vehicle's system and consequently has a disadvantage in minimizing the overall route operating cost of the operator overriding the cruise control direction. Wu [12] presents a method to reduce emissions through an advisory drive profile at traffic signals. Zegeye [13] presents a control method to determine the optimal speed limit control measures based on a predictive emission model. Nevertheless these methodologies are not able to adapt to continuously changing traffic conditions, causing poor performance of energy and emission optimization due to the natural stochastic form of traffic conditions and unpredictable traffic congestion conditions. The eco-driving system is rendered less practical if it is not combined with a fuel-efficient route selection. Several researchers have proposed optimal speed advising algorithms [14][15][16][17]. None of these eco-driving advisory systems deals with optimizing the drive profile while optimizing the route profile/path. A navigation system that searches for an optimized energy-consumption route based on predicted emission calculations that guide drivers through emission efficient routes is essential for providing true eco-navigation.

b) The second area of research emphasizes route planning to reduce vehicles' energy consumption and emissions; energy and emissions optimization algorithms are proposed to provide eco-routing.

Shahzada [18] applied the A* algorithm on a heuristic-based cost estimation function to find the shortest path to the destination using a mobile phone application. This resulted in a macroscopic determination of traffic and weather conditions. Barth [9] applied a comprehensive modal emission model that can predict fuel consumption and emissions of several vehicle types. The research applies real-time traffic parameters (five minute loops) to determine road segment congestion. Barth's approach utilizes field experiments to build the vehicle speed and emission models employed in Dijkstra's route optimality algorithm. Kono [19] proposes an ecological route search, which generates routes of optimized fuel consumption using traffic information, geographic information, and vehicle parameters. Kono applies Dijkstra's algorithm on a conventional vehicle emission model with predicted fuel consumption costs, thereby proving through a driving experiment that a time-priority route is not necessarily an eco-route with reduced emissions. Wu [20] proposed a fuel consumption predictive model utilizing the adaptive learning ability of back-propagation neural networks to refine the accuracy and minimize forecasting errors. Wu's proposed predictive process goes through two phases: Data acquisition and training of the predictive model's neural network.

Research Group	Optimization Technique	Parameters Modeled	Application	Vehicle Type
Neis et al. [11]	Metaheuristic	Travel time, fuel	Eco-Driving	ICE
Wu et al. [12]	Probabilistic	Fuel, emission	Eco-Driving	ICE
Zegeye et al. [13]	Not determined	Emission	Eco-Driving	ICE
Shahzada et al. [18]	A* Algorithm	Travel time, traffic, weather, emission	Eco-Routing	ICE
Barth et al. [9]	Dijkstra	Travel time, traffic, emission	Eco-Routing	ICE
Kono et al. [19]	Dijkstra	Fuel, emission	Eco-Routing	ICE
Wu et al. [20]	Back prorogation neural network	Fuel consumption, emission, traffic conditions	Eco-Routing	ICE
Proposed Method [21][22][23]	Petri Net unidirectional unfolding search algorithm "Arc Cost Constant" (ACC)	Travel time, energy, consumption, WTW emission	Eco-Routing	ICE, EV, PHEV

Table 1: Environmentally Friendly Navigation Literature Survey

Although the body of literature survey is extensive, little of what has been published pertains directly to providing the driver with dynamic assistance guidance that helps them select energy and emission efficient routes based on predictive traffic information. This research will focus on the second dimension of energy efficiency improvements, as established in the literature survey and identified as the environmentally friendly route planning. This research further contributes to the success of energy optimization and emission reduction by presenting the design and development of an energy and emission vehicle routing navigation system. What further differentiates this research from previous eco-routing work is that while the dimensionality problem that results from real-time traffic communication still needs to be understood, the more important aspect of real-time routing is to enable a predictive traffic congestion index as a means to reduce traffic data communication bandwidth and, by extension, computation speed. In addition this research will implement a novel predictive traffic information calculation, defined differently from the general broad predictive traffic information definition.

If a predictive and dynamic rather than a real-time and static model of traffic density is made available to the navigation system, the available optimal routes can be computed, thereby facilitating an enhanced certainty performance in traffic congestion assessment. To utilize the full potential of predictive traffic information system, it is critical to combine it with the lowest latency speed communication median available for VANET, which is offered by DSRC.

2.3 Basic Concepts

The concepts explained in this section familiarize the reader with the nuances of the research.

2.3.1 Vehicle Routing Problem

Vehicle routing problem (VRP) in transportation systems was first formulated by Dantzig and Ramser [24]. The VRP problem applies the optimal control theory to search for a minimum cost route that connects a source node to a destination node. The VRP illustrated in Figure 3 is defined on a graph $G = (P, L)$, where $P = (P_1 \dots, P_n)$ the set of places and $L = (L_1 \dots, L_n)$ the set of links connecting places. Each link L_i has an associated cost C_i, representing travel costs such as distance, travel time, energy consumption or emissions. Where P_S and $P_D \in P$. P_S denote the source place and P_D denotes the destination place, all other places P_i represent network connections. The VRP is generally classified as finding the set of routes connecting P_S to P_D, with an optimized link cost C_i and where each of the links L_i is traversed only once.

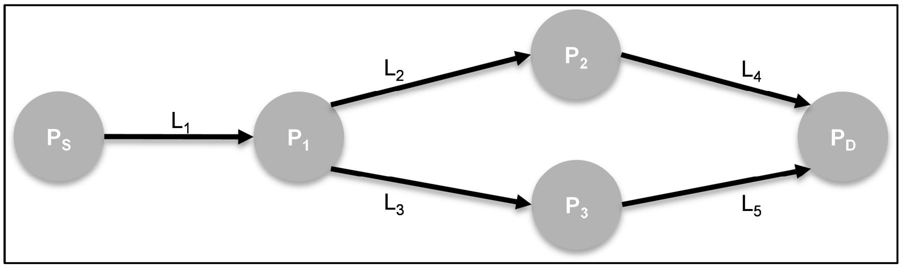

Figure 3: Network Illustrating Vehicle Routing Problem

In contrast to the classical definition of the VRP, real-world vehicle navigation application shall take into respect two important aspects: evolution and quality of traffic information. Evolution relates to the fact that traffic congestion varies during the execution of a route; and example of this is when a traffic accident occurs, yielding a sudden traffic congestion. Quality of information reflects the uncertainty of the traffic information due to voluntary mechanism such as approximation or involuntary uncertainty due to delay in the traffic data communication; an example of this is when traffic congestion is classified based on cellular phone users [25].

2.3.2 Optimal Control

Researchers have extensively studied the Calculus of Variations and Optimal Control theory; exemplar studies include those of Gelfand and Fomin [26] Touzi [27], Athans and Falb [28], Lewis et al. [29], and Kamien and Schwartz [30]. The history of optimal control dates back to antiquity (c. 356-260 BC) with reference to Queen Dido, formerly also known as Alyssa. When queen Dido pursued refugees in North Africa, she was permitted to select a land to stay in based on the perimeter that she encloses with an oxhide cut into thin pieces. Queen Dido selected a hill that allowed her to have more land surface area covered with the same perimeter if she selected a flat surface. This is recognized in modern mathematics as the Isoperimetric Problem. The isoperimetric problem was studied intensively by several mathematicians, such as Fermat, Galileo, Newton, Johamm and Jacob Bernoulli, Leibnitz, l'Hopital, Tschirnhaus, Tonelli, and Euler. The resulting ideas were collected and generalized by Bellman in the context of dynamic programing. In principle, Euler formulated the optimal problem in general terms of finding the curve $\boldsymbol{u}(\boldsymbol{t})$ over a bounded interval $\boldsymbol{a} \leq \boldsymbol{t} \leq \boldsymbol{b}$, with specified values $\boldsymbol{t}(\boldsymbol{a})$ and $\boldsymbol{t}(\boldsymbol{b})$ for a nonlinear, dynamic system described by

$$f(u, \dot{u}; t) \; where \; \dot{u} \equiv \frac{du}{dt} \tag{2.1}$$

Subject to:

$$\frac{d}{du} f_{\dot{u}}(u(t), \dot{u}(t); t) = f_u(u(t), \dot{u}(t); t) \tag{2.2}$$

$$t \in (a, b) \tag{2.3}$$

$$u(t) \in R^n \tag{2.4}$$

The optimal control problem is then to find an admissible minimum J such that

$$J = \int_a^b f(u(t), \dot{u}(t); t) dt \tag{2.5}$$

The integrand in this expression is a function $\boldsymbol{f}$ depending on a single function $\boldsymbol{u}(\boldsymbol{t})$, on its partial derivative $\dot{\boldsymbol{u}}(\boldsymbol{t})$, as well as on one independent variable $\boldsymbol{t}$.

The solution is denoted by the function $\boldsymbol{u_0(t)}$; let's consider a second arbitrary twice differentiable function $\boldsymbol{L(x)}$ over the same bounded interval $\boldsymbol{a} \leq \boldsymbol{t} \leq \boldsymbol{b}$, thus

$$\ddot{u}(t_a) = \ddot{L}(t_a) = 0 \tag{2.6}$$

Clearly illustrated in Figure 4 , the linear combination becomes

$$u(t,\alpha) = u_0(t) + L(t,\alpha) \tag{2.7}$$

The new function $\mathrm{L(t,\alpha)}$represents the paths between the boundaries $\mathrm{(a,b)}$, where the integral in (2.5) is minimized when $\alpha = 0$ and $\mathrm{u(t)}$is minimal.

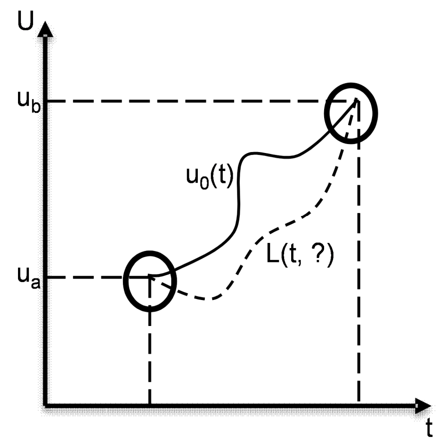

Figure 4: Minimum and Maximum of a Function

2.3.3 Multi Variable Optimal Control

The VRP in focus of this research attempts to solve for connecting a source and destination in a minimum cost approach that relies on three independent parameters: energy, emissions and travel time. The integral in 2.5 shall be extended to include three independent variables incorporating the respective first order derivative.

Let $\boldsymbol{f}(\boldsymbol{t}, \boldsymbol{c}, \boldsymbol{e}, \boldsymbol{x}, \boldsymbol{a}, \boldsymbol{b})$ be differentiable with respect to all six variables

The integral equation from 2.5 then becomes

$$J|x| = \iiint_R f(c, e, t, x, x_c, x_e, x_t) dc, de, dt \tag{2.8}$$

where R is a bounded region between points $(\boldsymbol{a}, \boldsymbol{b})$, and $\boldsymbol{x_t}, \boldsymbol{x_c}, \boldsymbol{x_e}$ is the partial derivatives of time $(\boldsymbol{x})$ with respect to the three independent variables: energy consumption$(\boldsymbol{c})$, emissions $(\boldsymbol{e})$and travel time$(\boldsymbol{t})$. The problem is then to find the function

$$x(t, c, e) \tag{2.9}$$

Where the following conditions are met:

1. Function is continuously differentiable with respect to $(\boldsymbol{c}), (\boldsymbol{e})$ and $(\boldsymbol{t})$ in the bounded region R;
2. Boundary values are defined in R; and
3. Yields a minimum of the equation 2.8.

2.3.4 Path Multiplicity

If there are *n* nodes in a network, then there are *n-1* links. There may be several routes connecting a source place to a destination. If all cumulative weights of links in a given network are the same, then every route of that graph is a minimum travel route. This scenario is very unlikely in traffic network where cost to travel a path is not identically the same due to the variance in road and traffic attributes.

2.3.5 Path Uniqueness

If there is one distinct weight for each identified route in a network, then there will be only one optimal solution. Mathematical contradiction can be used to prove that uniqueness exists.

1. Assume network A is identified with an optimal solution connecting a source node to a destination node through a route defined as R with minimal link cost defined as L
2. Assume network A is not unique, that there exists another network B with equal link weights
3. Let link L1 with cost C1 be a link that is in network A but not in network B
4. As network B offers an optimal solution, $\{L1\} \cup B$ shall contain an optimal route R
5. Then network B shall include at least one link L2 that is not in network A and lies on route C
6. Assume the weight of L1 is less than that of L2

7. Replace L2 with L1 in network B to produce the optimal solution {L1} ∪ B – {L2}, which has a smaller solution compared to network B

This applies the generic contradiction law [31] as derived by Aristotle's law of non-contradiction that states: "One cannot say of something that it is and that it is not in the same respect and at the same time.” Thus, we assumed network B offers an optimal solution, but proof shows that it does not.

2.3.6 Curse of Dimensionality

Using multi variable cost function for vehicle environmentally friendly navigation requires an iterative algorithm for finding an optimal solution, which becomes computationally intensive when the number of vehicles and route options is large, resulting in an exponential growth of computation time. This phenomenon is formerly known as “Curse of Dimensionality,” devised by Richard Bellman [32] in reference to the optimization by exhaustive enumeration of an open-ended search spare. This phenomenon continues to be researched, and the research proposes to deal with the curse of dimensionality problem by creating a reduced set of transportation variables into a space of fewer dimensions, with the condition of maintaining traffic information assessment accuracy.

2.3.7 Curse of Modeling

Modeling of dynamic systems is extremely difficult and challenging. In the transportation system, several relations and parameters exist that require proper understanding and design to simulate real-life scenarios such as vehicle emission, and vehicle movement. Inaccuracies in models lead to misrepresentation of results and ultimately indecorous conclusions. All surveyed research in the environmentally friendly routing field has escaped addressing the curse of the modeling problem through a simplified mathematical function representation that calculates energy consumption and emissions based on road segment average speed for all types of passenger vehicles.

2.3.8 Petri Net Modeling

A Discrete Event Dynamic System (DEDS) is a dynamic system in which state transitions are triggered by the occurrence of discrete physical events occurring randomly in the system [33][34]. The ability of Petri Net (PN) extends beyond other similar mathematical modeling languages, such as neural networks, to include analysis, control and graphical representation. Since the introduction of PNs in 1962 by Carl Adam Petri, PNs have been extensively been applied to transportation systems. The characteristics of PNs are determined by a feasible transitioning path between a source and destination. The transportation system is rather complex, asynchronous and stochastic system characterized as a DEDS structure. Traffic systems can be modeled utilizing PNs. The navigation process of vehicles can be considered a discontinuous system at connecting road segments. PNs offer a graphical representation of systems consisting of places, transitions, arcs and tokens. In the transportation model, places are represented by roadside units, transitions as travel time cost, arcs as paths between roadside units and tokens by vehicle constrained travel cost i.e. travel time, energy and emission.

2.3.9 Electric Vehicle Design

Recent advancements in vehicle battery and charging technologies have allowed the Electric Vehicle (EV) to be considered the new generation of automotive transportation. However, the physical dimensions, packaging environment, cost and charging of EV batteries continues to be the main challenge and the focus of development for EVs. Battery technology selection continues to be the primary challenge in achieving the proper balance in the EV design. The EV design challenges differ from the conventional ICE vehicle and the differences are described below:

- Battery capacity: EV battery capacity is predetermined by the battery design and cell chemistry. Lithium polymer batteries are the target implementation for EV mainly due to their high power-to-weight ratio.
- Vehicle weight: EV's weight increases proportionally to battery capacity increases.

- Vehicle space: Vehicle operators favor personal use of vehicle space. EV requires more packaging space to house the battery in a safe environment. Generally, the battery is packaged in the center of the vehicle where vehicle operators conventionally utilize this space.
- Driving range: EV can only run for 100-200 miles before recharging. A gasoline vehicle can drive more than 300 miles before refueling.
- Charging time: EVs have no internal source for recharging the battery. EV charging times range between 3 to 8 hours compared to 2 to 4 minutes of refueling for gasoline vehicles.
- Range anxiety: EV operators are usually concerned with their vehicles' limited driving range, inadequate charging infrastructure and long charging time.
- Energy consumption: EV propulsion systems offer around 85% efficiency compared to about 25% efficiency for ICE
- Emission: EV emits no pollutants; however, power plants generating the EV electricity may emit them.

While battery manufacturers are still pursuing improvements in energy capacity, the navigation technology and rapid advances in wireless communication technology can be used to achieve the vehicle performance balance, described as "Target" and presented in Table 2.

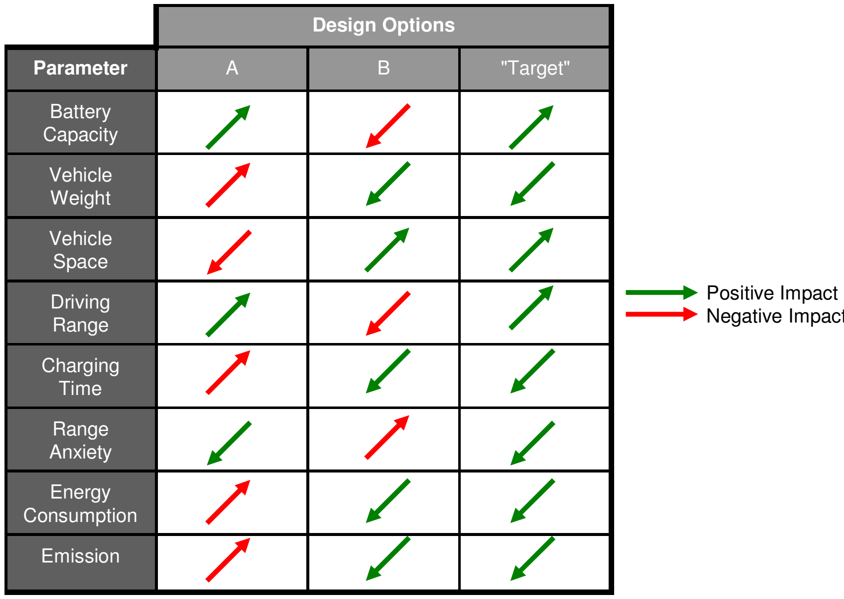

Table 2: Electric Vehicle System Design Options Evaluation

Table 2 clearly shows the limitations of using battery capacity as the only design variable for achieving a balanced EV design that is acceptable for EV operators. To realize the success of EVs, achieving the "Target" design option shall be exerted. This topic call for considering two crucial aspects in addition to battery technology: Traffic information evaluation and wireless communication technologies. The need to identify traffic conditions and the ability to transfer these conditions in real-time constitutes the success of optimizing energy consumption and emission reductions in EVs. The EV sub-systems differ from those of a conventional ICE vehicle in terms of the components illustrated in Figure 5 and listed below:

a) High voltage electric battery rather than a fuel tank to store and supply the required operational energy.

b) Electric motor rather than an ICE to propel the vehicle.

c) Gear box rather than a transmission to couple the power from the electric motor to the drive shaft and wheels.

d) On-board or off-board charger to allow for recharging the high voltage electric battery.

e) Direct current/alternating current (DC/AC) inverter to convert the DC high voltage battery into AC to drive the e-motor.

f) DC/DC converter to convert the DC high voltage battery into DC low voltage battery (conventionally identified as a 12-Volt battery).

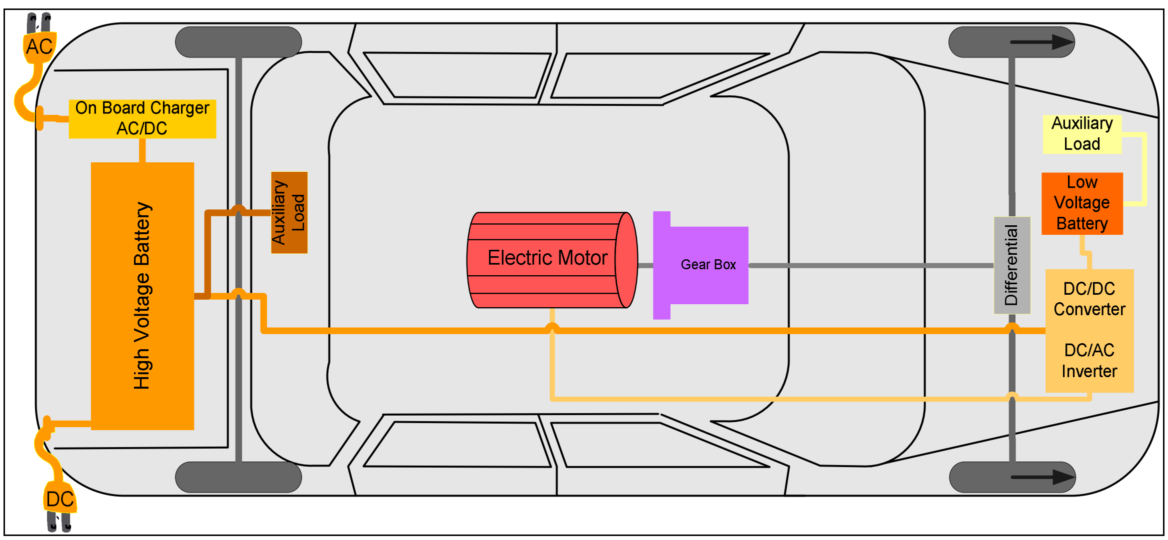

Figure 5: Electric Vehicle Model

2.3.10 Electric Vehicle Emission

An accurate assessment of EV emissions requires the inclusion of the electrical energy source associated emissions with the generation and transmission formerly recognized as Well to Wheel (WTW) analysis. Electrical energy is generated from two main sources, as illustrated in Figure 6 and listed below:

- Non-renewable sources: Coal, natural gas, nuclear and petroleum
- Renewable sources: wind, solar and geothermal

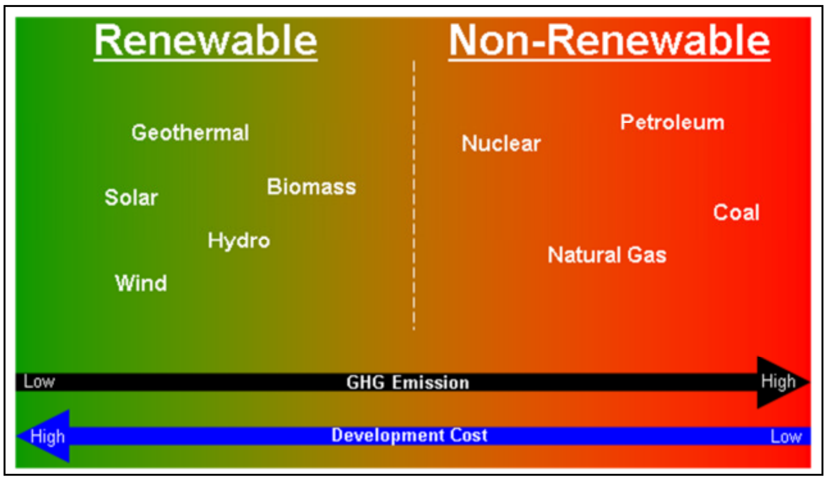

Figure 6: Electrical Energy Sources

Non-renewable energy produces elevated GHG emissions. Coal is leading all other energy sources in terms of GHG emissions. Renewable energy investments have, to some extent, been very limited due to the associated high development costs. However, government subsidiaries continue to make the renewable energy investment more affordable. EV proponents claim that this type of vehicle is a Zero Emission Vehicle (ZEV), but this depends on many factors, one of which is key and shall be highlighted: the EV operating energy emission is a function of the emission at the energy source. The upstream GHG emissions are based on power plant types and efficiency. EV technology proponents claim that this type of propulsion technology can reduce long-term GHG emissions, but this can only be verified by implementing the WTW emission model to analyze the GHG emissions associated with the electrical energy source.

2.3.11 Electric Vehicle Efficiency

The EV overall efficiency can be classified in three main categories: charging efficiency, driving efficiency and energy generation. The following section describes the categories and their respective components.

2.3.11.1 Charging Efficiency

Automotive charging standards are currently being developed worldwide to allow for DC (Direct Current) charging. In contrast, AC/DC (Alternating Current/Direct Current) charging standards have already been established and are currently being implemented in a number of alternative vehicle technology production models, such as the Chevy Volt and Spark, EV SMART, Mitsubishi MIEV, Nissan Leaf, Tesla Model S, and Fiat e500. DC charging enables the vehicle's high voltage DC battery to be directly charged from the charge station, bypassing the vehicle's on-board charger, thus further improving charging efficiency and time. DC charging is the target implementation for public charging, enabling fast charge. Due to the associated high cost of DC charging infrastructure, AC/DC charging will be the alternative and only solution for residential charging.

The EV charging efficiency is the ratio of energy transferred to the high voltage battery to the energy consumed from the AC source. Charging efficiency is highly dependent on charging power and operating temperature. Figure 7 depicts a typical EV charging efficiency operated at room temperature and that utilizes an AC/DC on-board charger with a maximum output power of 3500 Watts.

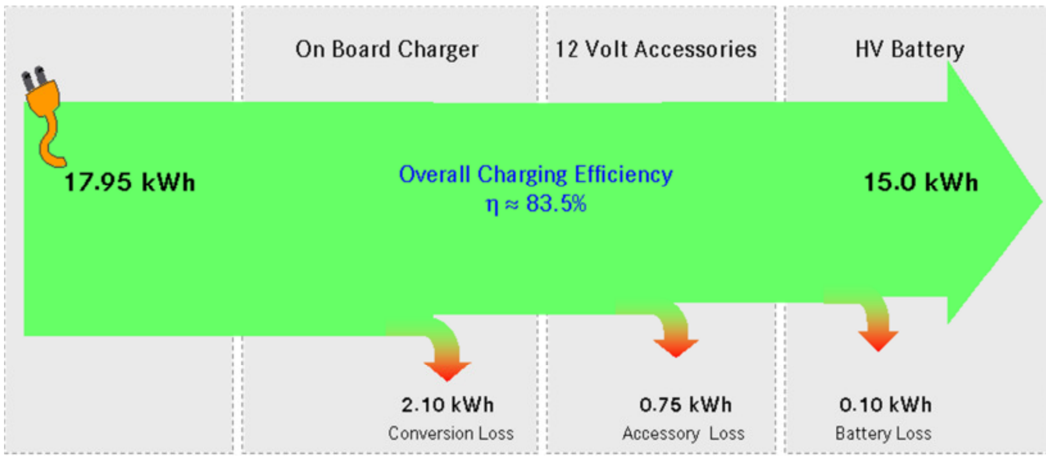

Figure 7: Electric Vehicle Charging Energy Flow and Efficiency Diagram

2.3.11.2 Operational Efficiency

Generally, the efficiency of the EV Electrical Motor (EM) is exceptionally high, roughly 85 % compared with an ICE at roughly 25%. Power losses in an EV are negligible, and in this section we will focus on power losses from key components that occur in an electrical propulsion system during driving mode due to power conversion, operation and propulsion. As illustrated in Figure 8, approximately 81.3 % of the energy stored in the High Voltage (HV) battery is used to propel the EV. Combining the EV overall charging efficiency with the EV overall operational efficiency, the EV efficiency becomes roughly 67.9 %, around four times more efficient than an ICE propelled vehicle that has an overall efficiency of roughly 14 %.

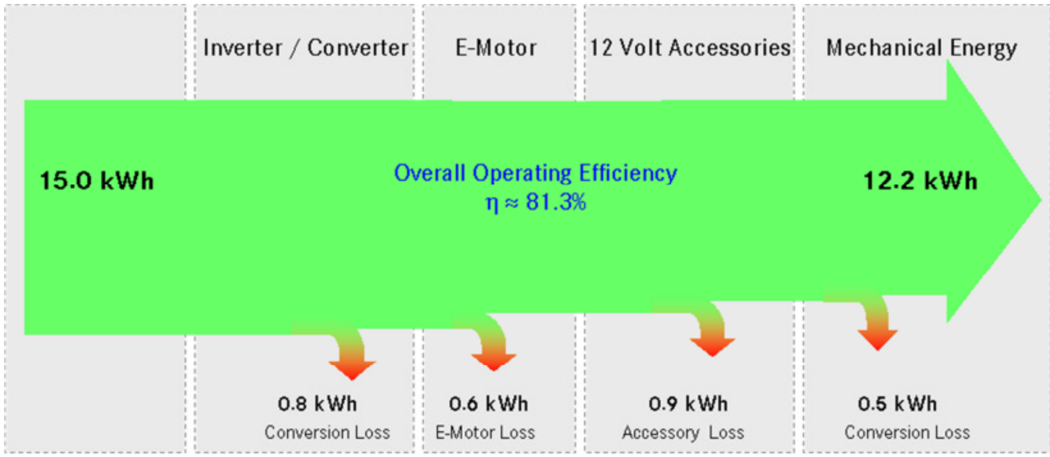

Figure 8: Electric Vehicle Operating Energy Flow and Efficiency Diagram

2.3.11.3 Power Source Generation and Transmission Efficiency

For a full representation of energy and emission calculation, it is important to consider the efficiency involved in energy recovery, processing and transportation. Complete vehicle energy-cycle analysis tools, commonly known as WTW analysis tools are needed to provide an accurate assessment of EVs' overall efficiency and emissions. The U.S Environmental Protection Agency's (EPA) offers an emission database called the "National Emissions Inventory" (NEI); the database includes annual emissions associated with electric energy generation. To fully evaluate emission impact of EV, a WTW emission model shall be considered, as depicted in Figure 9.

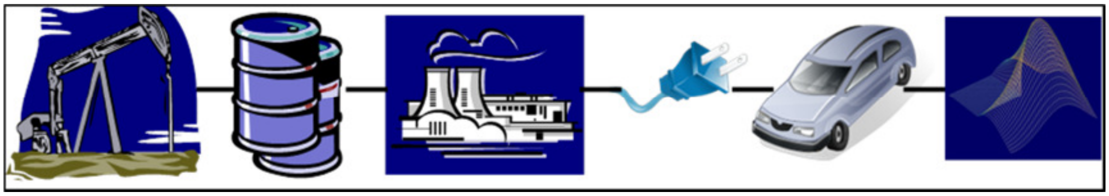

Figure 9: Well-To-Wheel (WTW) Modeling

2.4 Technologies to Enable Application

This section will provide an overview of the relevant technologies required to enable and apply our proposed research in the field.

2.4.1 Global Positioning System

One of the major revolutions in the automotive industry is the integrated vehicle navigation system made available by the global position satellite constellation. Vehicle positioning is an essential function in vehicle navigation systems. Vehicle positioning relies on a space-based satellite navigation system deployed in Earth's orbit, providing time information in all environmental conditions. This enables the computation of 3-D position information. Positioning accuracy is correlated to the availability of the positioning satellite and the vehicle's satellite receiver systems; a minimum of four satellites are required to provide minimal position accuracy. Several satellite receivers' manufacturers offer systems with a mechanism to augment satellite signals with other terrestrial signals, thereby offering an extremely superior accuracy. An example of this is the Topcon GR-5 receiver [35]. The benefits of this system is its compatibility with the U.S. satellite system GPS, the Russian satellite system GLONASS and the European satellite system GALILEO. Furthermore, the Topcon GR-5 receiver system offers a static accuracy of 3mm and a Real-Time Kinetic (RTK) accuracy of 10mm. It is important to note than in cases where satellite navigation coverage is not available due to obstructions from tunnels or high rise building areas, for example, terrestrial signals, such as those of the Differential Global Positioning Satellite (DGPS), the High Accuracy-Nationwide Differential GPS (HA-NDGPS), Real-Time Kinematic (RTK), and the Network RTK (NRTK) can be used, offering, in this case a slightly reduced accuracy. These systems primarily repeat the GPS signal and improve its accuracy by correcting for the ionospheric and tropospheric effects. The drawback of such system is that it would not to offer any solution for the multipath problem. The accuracy of such terrestrial signals could be greatly improved with the vision of Robust GPS (RGPS) [36]. RGPS for vehicle positioning enhancement is yet another benefit achieved through the DSRC technology. In the proposed research, real-time vehicle position is required with a very high level of accuracy; achieving increased vehicle positioning accuracy enables the proposed navigation system to have route optimization with both high confidence and reliability. Most importantly, it avoids the inclusion of stochastic modeling.

2.4.2 Dedicated Short Range Communication (DSRC)

The USDOT has invested in the Connected Vehicle Safety Pilot Program at the University of Michigan Transportation Research Institute (UMTRI) [37] to evaluate the DSRC technology benefits in safety applications. Based on initial results, the USDOT anticipates that DSRC connected vehicles will reduce or eliminate 80% of vehicle crash scenarios involving unimpaired drivers. In light of UMTRI's final report in late 2013, an affirmative Notice of Regulatory Intent (NRI) is expected by the National Highway and Traffic Safety Administration (NHTSA), likely to be followed by a federal mandate in 2014.

Connected Vehicle deploys the concept of a connected vehicle to the surrounding roadway attributes, thereby enabling V2V, V2I, and I2V communications. Figure 10 illustrates the vision of the connected vehicle project within the ITS frame of architecture.

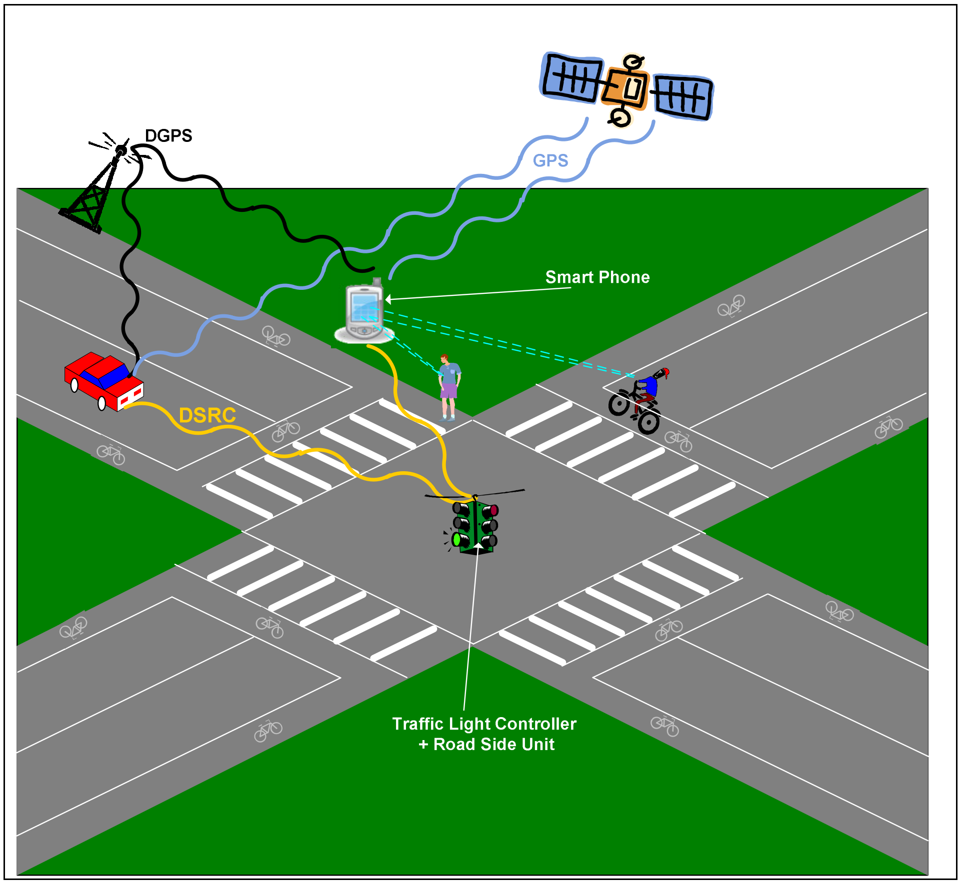

Figure 10: DSRC Networked Environment

Wireless Access in Vehicular Environment (WAVE) is the term used to describe the suite of IEEE 1609 and IEEE 802.11p standards. WAVE extension to automotive applications is described in SAEJ 2954 [38]. The WAVE protocol architecture and its major components, excluding the physical layer, are illustrated in Figure 11. WAVE is the core structure of DSRC.

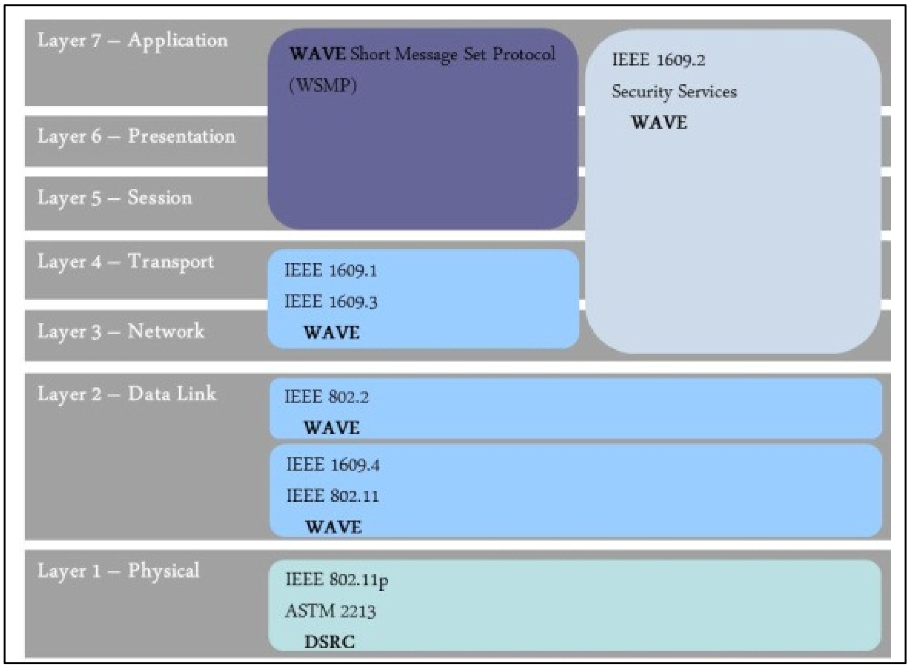

Figure 11: WAVE/DSRC Protocol Layers and Associated Standards

DSRC is, to date, the most qualified wireless standard for Connected Vehicle applications. The DSRC technology was primarily developed for the ITS vehicular safety applications to allow vehicles traveling at high speed to communicate status among other vehicles. V2V, V2I and I2V offer the highest messaging latency performance compared to the proposed alternative communication technologies: Fourth Generation Long-Term Evolution (4G LTE), its successor (5G) and Wi-Fi, as summarized in Table 3. DSRC is defined by the framework of the American Society for Testing and Materials (ASTM) and standardized by the IEEE 802.11P. DSRC is based on the Wi-Fi architecture, high-speed, two-way Line-of-Sight (LoS) short range (up to 1000 meters) wireless communication. DSRC licensed in 2004 by the FCC at 5.85 - 5.925 GHz band with a bandwidth of 10 MHz. This spectrum is not subject to any aggregation limit; each licensee will use channels in accordance to the ASTM-DSRC Standard E2213 [39]. DSRC is designed for automotive safety applications and sponsored by the USDOT Research and Innovative Technology Administration (RITA) [40]. DSRC test beds are currently being systematically deployed for evaluation throughout the U.S transportation system.

	DSRC (802.11p)	**Wi-Fi (802.11n)**	**4G LTE**	**5G**
Frequency	5.8 GHz	5.2 GHz	2 GHz	28 GHz
Bandwidth	75 MHz	20 MHz	20 MHz	Not defined
Range	< 1000 m	< 250 m	< 1000 m	< 2000 m
Data rate	< 27 Mbps	< 54 Mbps	< 75 Mbps	< 1 Gbps
Latency	< 50 ms	< 100 ms	< 100 ms	Not defined
Mobility	> 60 mph	> 60mph	> 60 mph	> 60 mph
V2V	Yes	Yes	Thru Server	Thru Server
V2I	Yes	Yes	Yes	Yes
I2V	Yes	Yes	Yes	Yes

Table 3: Comparison of Wireless Communication Technologies

USDOT continued support to DSRC, through the connected vehicle program is driven mainly by the DSRC capability to support with the required stability, transmission speed, security and privacy vehicular safety applications. USDOT envisions DSRC applications to expand beyond safety applications to include traffic management applications such as: “adaptive” traffic signals, variable message signs, and rapid response to traffic incidents that improve traffic flow, thus reducing congestion and improving air quality.

DSRC is governed by a set of industry standards classified in the following four listed categories:

1. Information: IEEE 1455, SAE J2735
2. Application: IEEE 1609.0, IEEE 1609.1, IEEE 1609.2, IEEE 1609.11
3. Transport: IEEE 1609.3
4. Sub-Network: IEEE 1609.4, IEEE 802.11p, ASTM E2213

DSRC enables the attainment of the following safety critical components for vehicle communication [41]:

- Licensed frequency: FCC-licensed bandwidth by Order FCC 03-324
- Fast Network Acquisition: Enabling immediate establishment of communication between vehicles and roadside units
- Low Latency: Resulting in least execution time
- High Reliability: Providing high level of user reliability
- Safety application priority: Multiple channel allocation to enable priority of safety message
- Security and Privacy: User privacy and protected transmission security

Traffic information can alternatively be transferred over cellular or WiMax networks that offer better coverage; however, the latency renders the wireless communication system impractical in safety applications. DSRC offers increased data capacity and reduced latency. A recent study [42] attempts to consider cellular networks, particularly the Third Generation Partnership Project Long Term Evolution (3GPPLTE), as an alternate infrastructure to DSRC technology. DSRC was designed for VANET to satisfy the vehicle safety application requirements, promising to reduce accidents by employing ITS safety application. The unique feature of low latency will secure the DSRC position as an essential safety relevant communication technology. DSRC offers, to date, single wireless communication technology for future vehicular safety applications. Increasing the existing 3.9 million miles of roadway network in the United States [43] is an expensive and environmentally destructive solution; consequently, animal habitats are lost and fragmented, air quality worsens, and there is increased human-made noise. The work proposed here further assesses the benefits of the DSRC technology in vehicular navigation applications specifically, by focusing on energy and emissions reduction. Real-time traffic information available by DSRC is expected to improve roadway efficiency and reduce congestion at a lower cost than is achievable by roadway additions. Real–time traffic conditions communication between V2I is an essential functional to achieve real-time and predictive navigation systems with enhanced traffic assessment accuracy. The dynamic nature of traffic conditions requires the employment of a high-speed communication technology. The DSRC benefits and applications are not fully exploited and tested; in our opinion, DRSC technology offers the most promising wireless technology for real and predictive traffic information communication. Our proposed research evaluates the benefits and challenges of DSRC in vehicular navigation applications.

2.5 Proof of Concept

This research evaluates two approaches: an actual physical experimental implementation and a computer-based simulation. Since the actual implementation of such a project is expensive due to costs of equipping multiple vehicles and infrastructure with DSRC technology and since software programming nowadays is a trustworthy tool to perform accurate simulations, a computer-based simulation can help avoid the jeopardy of time and funds that accompanies actual implementations. With numerous simulation tools available, choosing one that meets the requirements for validating the features of the application being developed is a major step. There are several important aspects of the real-world application; however, the most critical for the routing application is the tool's ability to enable a microscopic model implementation. This section will begin by providing the definition of the microscopic simulation tool, the process for selecting the tool and the selected tool and implemented modifications that enable the validation of the proposed routing algorithm.

2.5.1 Traffic Simulation Model

In transportation research, three major classes of traffic models exist, according to the level of details being simulated. Increased computation speed has allowed for the evolution of the different simulation approaches; the three different classes are presented below in chronological order, with the earliest developed listed first and depicted in Figure 12:

1. Macroscopic: Continuous flow simulation, utilizing traffic average flow and density characteristics.
2. Microscopic: Single vehicle simulation, utilizing vehicle behaviors relative to acceleration, deceleration, route and lane changes.
3. Sub-Microscopic: The microscopic single vehicle model is further sub-classified into components such as the engine speed and the transmission gear ratio.

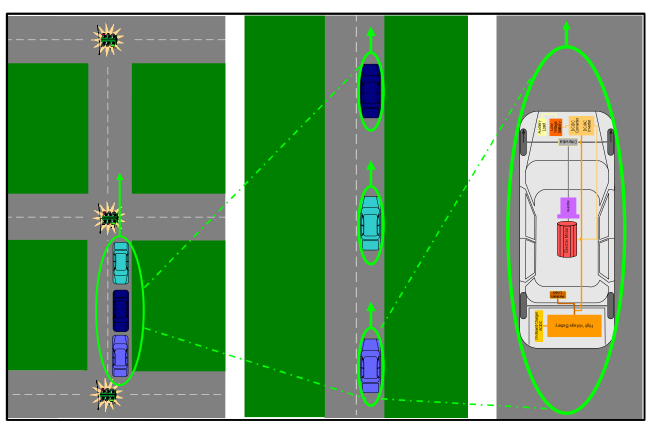

Figure 12: Classes of Simulation Tool; from left to right (Macroscopic, Microscopic and Sub-Microscopic)

2.5.2 Simulation Tool Selection

Traffic simulators are important tools to researchers and road authorities to evaluate—in terms of traffic flow—different traffic control methodologies, such as introducing new roads or changing speed limits and traffic light phases. Such simulators, which focus basically on traffic flow, are referred to as macroscopic traffic simulators. On the other hand, ITS applications are concerned with the movement of each individual vehicle, its speed, emissions and fuel consumption profiles. The traffic simulators that provide the opportunity to calculate such data are referred to as microscopic traffic simulators. The wide range of benefits that a traffic simulator can provide has led to numerous simulation tools becoming available. Some of them are sophisticated commercial products, such as AIMSUN, VISSIM and PARAMICS, and some are open source, such as MITSIMLab, INTEGRATION, SmartAHS and Simulation of Urban Mobility (SUMO). Choosing the right simulation tool can be difficult, taking into account the large number of tools available and the different sets of features that each tool provides.

2.5.3 Criteria for Selecting a Simulation Platform

For the vehicle routing application to be simulated, two simulators must be running simultaneously, a traffic simulator and a network simulator, and each must meet a specific set of requirements and communicate in a real-time manner with the other simulator. The main requirements for each of the simulators are described in this section; this is accompanied by a discussion of the interface between them. The traffic simulator should be a microscopic traffic simulator, i.e., able to provide information about an individual vehicle, such as location, speed, acceleration, route and travel time. Also, the traffic simulator should be able to import real-world maps, such as TIGER or OSM, in order to simulate realistic traffic scenarios, whose results can be reflected in the real world. Moreover, the traffic simulator should enable the incorporation of a fuel/energy consumption and pollutants emissions model, which provides the opportunity to simulate the proposed eco-friendly routing applications.

As for the network simulator, it should support wireless ad-hoc networks with dynamic topologies. Although different network simulators can provide those capabilities, it is also important that the network simulator support the new protocol stack used in the vehicular networks for exchanging the different sorts of information, upon which cooperative decisions should be made. Those protocols are as described in Section 2.4.2 DSRC in the United States, and in WAVE in Europe. The coupling (interfacing) of the two simulators can be either open loop or closed loop. The open loop coupling is a one direction connection from the traffic simulator to the network simulator. The traffic simulator is first run by generating mobility traces for all the vehicles inside the simulation environment. These traces are then fed into the network simulator to simulate the exchange of messages between vehicle nodes. This interface is not suitable for our applications because these applications should be able to affect the behavior of the vehicles based on real-time events. This approach is discussed and analyzed by Rehunathan et al. between the traffic simulator MITSIMLab and the network simulator ns2 [44]. The closed loop coupling is a bidirectional connection between the two simulators, in which both of the simulators are running side by side. The positions of vehicles are continuously being updated in the network simulator. Basically, the idea is to have a live application programming interface (API) socket connection, allowing for a real-time exchange of events between the two simulators. Such an interface satisfies the requirements needed to simulate ITS applications. However, only few simulation platforms adopted this kind of interface, including IntelliDrive simulation environment, developed at the University of Virginia [45], VGSim [46], Vehicles in Network Simulation (Veins) [47], and Integrated Wireless and Traffic Simulation Platform for Real-time Road Traffic Management Solutions (iTETRIS), funded by the European Union [48].

2.5.4 Methodology and Other Simulators

For the proposed research project, a simulation platform that meets the aforementioned criteria was needed. The methodology used to select this tool is described hereafter in detail. The main requirement for this platform was for it to be open sourced, as this will allow for further enhancements and developments as needed. Thus, the first step was to develop a partial list of the major open-sourced traffic simulators, as shown in Table 4.

Traffic Simulator	**Developer**
INTEGRATION	Transport Research Group, Queens University, Canada
MITSIMLab	Massachusetts Institute of Technology, United States
SmartAHS	University of California, Berkley, United States
SUMO	Institute of Transportation Systems at the German Aerospace Center, Germany
TRANSIM	Los Alamos National Laboratory, United States

Table 4: Open Source Traffic Simulators

Since the final goal was to select an ITS simulation platform, the ability of any of these traffic simulators to interface with a network simulator had to be investigated. The conducted review showed many attempts in the literature to achieve this purpose; most of them implemented SUMO as the traffic simulator, such as TraNS, Viens and MITSIMLab. From the conducted literature review, it was decided that none of these tools could be the proper simulation platform, especially since ITS applications are just debuting in the industry. Thus, a long-term evolution simulation platform is preferred. Our review of the simulation platforms concluded by selecting the simulation platform iTETRIS, a €4.42 million funded project with over 30 months of development.

2.5.5 Integrated Wireless and Traffic Simulation Platform for Real-time Road Traffic Management Solutions (iTETRIS)

The EU Framework Program 7 (FP7) funded project, iTETRIS, targets extending the simulation capabilities of wireless vehicular cooperative systems to evaluate road traffic management services and vehicular applications. iTETRIS addresses four important and distinct challenges:

a) Road traffic and wireless integrated open-source simulation platform

b) Large scale trials

c) Realistic V2V and V2I communication simulation

d) Dynamic, distributed and self-autonomous ITS applications based on cooperative systems

iTETRIS proposes a flexible 3-block simulation architecture, a real-time closed loop coupling between the traffic simulator, SUMO [49][50] and the Network Simulator 3 (ns- 3) [51][52], as shown in Figure 13.

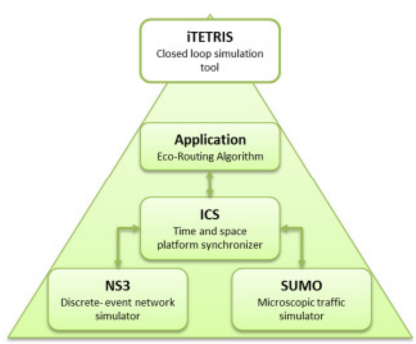

Figure 13: iTETRIS Block Diagram

The integrated system provides a central control block to realize the coupling called iTETRIS Control System (iCS). iCS provides a platform for application developers to develop and integrate their novel applications with the simulation platform. This allows the application to be developed in any programming language as long as it supports socket communication. Flexibility and extendibility are main motivations of such architecture definition.

2.5.5.1 Main Features

iTETRIS is based on two basic simulators, traffic simulator, SUMO, as well as a network simulator, ns-3 . Nevertheless, the set of features that it can provide is not limited to the combination of features provided by each of the simulators; it extends through the central block, iCS, with the ability to simulate the performance of our proposed navigation methodology supported by novel cooperative V2X communication systems.

From a traffic simulator point of view, SUMO provides the following features:

- Microscopic traffic simulator, i.e., the ability to track characteristics of an individual vehicle, such as speed, acceleration and route, and trip characteristics such as travel time, distance and delay.
- Simulation of realistic traffic flows with multiple vehicle classes (passenger, bus, ambulance, etc…).
- Emission modeling: CO_2, NOx, particles, noise, fuel consumption, etc.

As for the network simulator, ns-3 provides the following features:

- Good scalability, modularity and multi- technology support.
- Support of IEEE 802.11p.

iTETRIS identifies and defines a set of practical solutions (called strategies in the project) for both traffic condition estimation and traffic management. The first class of strategies uses dynamic V2X communications to monitor traffic situations and detect anomalous cases in a more reactive, precise and efficient way. Examples of this class are “Distributed traffic jam detection” and “Induction loop replacement.”

2.5.5.2 Enhancements on the Tool

iTETRIS is a new simulation tool. Before considering it for the simulation of our ITS applications, the tool had to be tested and evaluated to make sure that it was capable of providing the desired results. Also, testing allowed us to explore the tool in more detail, thereby enhancing knowledge of the ITS applications that can be simulated with this tool. A demo application was successfully run. The application had a very simple task, which was to increase maximum allowed speed for vehicles as they enter a specific communication zone. In the process, the tool was explored in more detail. For example, the sets of information that can be fed into the application to be simulated are:

- Information about cars in a fixed zone: the information is vehicle id, position X, position Y, and speed.

- Information about the received messages from surrounding nodes. This set of information is associated with a single node, mobile or fixed. Also, the sets of ITS applications that the tool can handle are:
    - Update maximum speed (the demo application).
    - Re-route a bus when an open lane is available.
    - Traffic jam detection.

Nevertheless, those capabilities are not enough to simulate a routing application in terms of data provided to the application, result handling and processing. The following subsections present the new incorporated enhancements.

2.5.5.3 Added Subscriptions and Result Containers

iTETRIS is designed based on server/client architecture; i.e., it allows the simulation of a wide range of algorithms, provided they can be represented by an executable (client) that can communicate with the iTETRIS controller (server) over a TCP connection. The messages exchanged over this connection fall into, from the algorithm's point of view, two axiomatic categories: input and output. For any algorithm to be run and evaluated, it requires a certain set of information that forms the algorithm's input. In the iTETRIS platform, iCS plays the role of the server, responsible for providing such information to whatever application with which it has a live TCP connection. In this server/client architecture, a notify-by-subscription configuration is used to forward event updates to the client. This means that the client (algorithm) is required to show interest in one or many of predefined events in order for the server (iCS) to send back information related to those desired events. Events are referred to as subscriptions; they are defined within the iCS, and the algorithm is required to subscribe to one of the subscriptions in case it is interested in the information this subscription provides. iTETRIS has several predefined subscriptions such as "Received CAM Messages Information" or "Return Cars In Zone." Those subscriptions are essential to simulate many cooperative ITS applications, as the information they provide is the minimum requirement for an algorithm to reach a cooperative decision. However, simulating complex algorithms requires additional information about the simulation scenario from the other two subsystems (SUMO and ns-3); those subscriptions have been expanded, and moreover, new subscriptions were defined.

2.5.5.4 Additions to Existing Subscriptions

If information about received cooperative awareness messages (CAM) at a specific node is desired, the algorithm subscribes to "Received CAM Messages Information" for the node of interest, and this information will be pushed by the iCS to the algorithm at each simulation step, provided the renewal of the subscription. CAM messages include information about the vehicle's position, speed, acceleration and direction. A complete list of information found in CAM messages includes the following: Node Id, Position X, Position Y, Message Generation Time, Station Type, Speed, Angle, Acceleration, Length, Width, Lights, Lane Id, Edge Id and Junction Id.

Sophisticated ITS applications require additional information about the surrounding environment of the node running that application. Such information can be related to the vehicle in terms of the vehicle's turning intentions or vehicle's distance to next junction, or it can be related to the road network map in terms of current lane maximum allowed speed. Subscription "Return Cars in Zone" was used to forward this information to the application. Originally, this subscription included only four parameters: node id, position X and Y and speed. Therefore, to simulate the routing application, other parameters had to be incorporated into this subscription. The following additional parameters were incorporated into this subscription along with a brief description:

- Vehicle's Emission Class: Used for calculating fuel consumption and emissions
- Vehicle's Next Edge Id on Route: Id of the next road segment this vehicle has on its route. This parameter can be used to indicate vehicles' turning intentions
- Vehicle's Next Edge Weight: The global weight of the next road segment on the vehicle's route. This weight is represented by the travel time, energy consumption and emissions

- Vehicle’s Current Edge Weight: The global weight of the current road segment
- Vehicle’s Current Lane Max Speed: Maximum speed allowed on the vehicle’s current lane
- Vehicle’s Distance to Next Junction: The distance, measured in meters, the vehicle to pass to arrive at the next junction on its route

The aforementioned parameters are retrieved at every simulation step from the traffic simulator SUMO and forwarded to the application in the subscription “Return Cars in Zone,” along with other parameters that this subscription originally provides.

2.5.5.5 New Subscriptions Defined

For the purpose of evaluating the routing algorithm, a new sort of information that was not originally provided by any of the available subscriptions was needed; this was the timing information of the upcoming traffic light on the node’s route. Traffic light schedule broadcasting is one of the first ITS applications to be proposed and tested. The information sent can be simplified to two important parameters: time-to-red and time-to-green. This information should help the driver adjust his/her speed in order to avoid stopping at a red light at the intersection. For our proposed routing algorithm, which utilizes V2V/V2I/I2V messages, such information is helpful in planning the best route to navigate from the current position to the desired destination. The challenge was how to provide information as informative as time-to-red and time-to-green for each possible turn at the intersection while respecting the structure used to define traffic lights in the traffic simulator SUMO. The phase of the traffic light is determined by two elements: integer duration and a string state. The state string defines the state of every 'Link Index' over the time specified by 'duration'. At a specific point during the run cycle of the platform, iCS should forward the subscriptions' information to the application. iCS will start processing and sending the information from each subscription, one at a time. For the new subscription, iCS starts by fetching the current lane Id of the subscribed node, and from that it will get the edge Id. Then, iCS asks the Facility Manager—an entity responsible for managing information about the map, such as lanes, edges, junctions; stations (mobile, fixed); and other parameters related to the messages exchanged—to provide it with Ids of all the lanes belonging to this edge. Then, for each lane, iCS also asks the Facility Manager for the traffic light Id controlling this lane. And after retrieving information about all the links in that traffic light from SUMO using a special API function, iCS determines lane Ids (along with the corresponding link index) that the vehicle could possibly take as an exit lane from the intersection. At this point, all the information needed to process the program of the traffic light is made available; the possible lane Id—and hence edge Id—represents possible turns that an approaching vehicle node might take; the corresponding link index for those lanes will be used to monitor the changes in the traffic light state between phases, thus calculating the time to switch.

The Traffic Light Timing Information results that are sent to the routing application includes: Next Edge ID, Time to Switch and Current State. The proposed information result informs the time-to-red and time-to-green schedule. For example, if time-to-switch is 10 sec. and current state is ‘r’, it can reasonably be deduced that time-to-green is 10 sec.

2.5.5.6 New Result Containers Defined

One major step to simulate a routing application in this platform is to create a suitable entity that will receive the results from the application logic and disseminate those results to the traffic simulator to update vehicles and surrounding objects. In real life, assuming the logic resides inside of the vehicle after the logic receives all the information from the surrounding environment and completes the required processing, it will show the results to the driver so he/she can take action. In the simulation, however, an entity should process the results from the logic to the traffic simulator, thus converting those results to actions. This entity is called a Result Container. For routing applications, regardless of the logic used to determine the best route between two points on the map, the result is always a route represented by a list of road segments that the vehicle needs to take in order to get to its desired destination. For the routing application, one new result container was defined and tested in the platform. As a result, the result container produces a whole route by executing the task to receive the new route and then requesting ordering to re-route the studied node using the new route.

2.5.5.7 Simulation Tool Summary

In this section, the methodology for selecting an ITS simulation tool was presented along with the basic set of features that such a tool should feature. Those requirements can be summarized as a microscopic traffic simulator supporting real life road maps and bi-directionally interfacing with a network simulator that supports the DSRC protocol stack. The iTETRIS was introduced and evaluated. This tool is engineered for large-scale evaluation of cooperative traffic management strategies based on V2V/V2I communication systems. To address the essential modularity requirements needed for a fully flexible development of its subsystems, a 3-Block architecture has been considered. The iCS is the central entity of the platform. It allows an efficient integration of SUMO and ns-3, two widely used open-source simulation platforms for dedicated traffic and communications simulations. iCS ensures the synchronization of events over the time and the consistency of simulation objects' positions in the two simulation platforms. Additional features of this tool were developed:

a) The ability to simulate ITS applications that implement routing algorithms.

b) The ability to simulate ITS applications that utilize traffic light information, such as time-to-green and time-to-red.

c) The ability to assess traffic conditions that is based on current and futuristic traffic information.

d) The ability to evaluate emissions of a plug-in electric vehicle, through the development and integration of a WTW emission model.

Chapter 3

3 IEEE 802.11p in VANET

3.1 IEEE 802.11p Overview

The IEEE 802.11p wireless communication protocol offers the highest potential to serve ITS applications mainly due to the low latency communication performance needed to serve road safety applications. Connected Vehicle deployment relies on evaluating several factors of the IEEE 802.11p protocol such as mobility, range, latency, and Doppler shift effect. IEEE 802.11p is an approved 2010 amendment that supports wireless communication in WAVE ITS applications. DSRC-based communication test beds have been deployed recently and exist in very limited areas in five of the nation's states (Michigan, California, Tennessee, Virginia, New York and Florida [40]. Accessibility cost and limited implementation of test beds required us to validate the IEEE 802.11p protocols in a simulation environment.

3.2 IEEE 802.11p Evaluation

In order to evaluate the potential for integrating the IEEE 802.11p in our proposed environmentally friendly navigation application, the efficiency and performance of implementing wireless communication technology shall first be analyzed. There exists a large body of interesting ongoing research that evaluates the IEEE 802.11p wireless communication in VANETs to explore and extend its vehicle application. To the broad extent of the literature survey, no research or publication was identified that addresses the packet delivery performance relative to the number of vehicles/nodes. Ensuring high performance in communication quality of service is an essential factor for providing the needed performance in traffic conditions assessment. Traffic condition assessment is one of the main factors required for providing an accurate solution in vehicle routing evaluation and optimization.

This chapter will evaluate the wireless communication network performance as a function of the number of vehicles, the communication technologies and the message characteristics. The limited availability of wireless-equipped vehicles, the cost and the complexity of empirically evaluating wireless communication technologies led us to the use of a simulator. For this evaluation, a simulation tool combining traffic and network simulation capabilities is necessary.

This study is presented in two parts:

I. Provides an overview of the study, the evaluation tool and the evaluation method.

II. Develops use cases to simulate different scenarios, analyze and discuss simulation results.

3.2.1 Related Work

A large number of recent studies have focused on the performance evaluation of wireless communication in vehicular applications. C. Gorgorin research [53] was conducted to evaluate the reliability of vehicles' ad-hoc networks using a traffic/network simulation tool (VNSim) developed by University Politehnica of Bucharest. The research results demonstrated the advantages of implementing the DSRC communication protocol rather than the IEEE 802.11n communication protocol at the physical, MAC and application layers. The research limits the average number of vehicles being evaluated to 90 vehicles/minute. Our use case extends the study beyond 90 vehicles/minute to evaluate the performance of data communication in highly congested intersections due to traffic accidents or construction zones.

Other efforts have focused on developing dynamic traffic light algorithms. A. Turky et al. [54] developed a genetic algorithm-based traffic light controller to enhance traffic and pedestrian flow performance at traffic lights. This algorithm was based on two parameters: the queue of vehicles and pedestrians at the red light, relative to the number of vehicles and pedestrians that pass through a green light. The performance comparison revealed that the proposed controller had a performance advantage relative to other dynamic traffic light algorithms. The research takes the impact of data communication performance on the proposed traffic light algorithm.

3.2.2 Simulation Tools

In order to study the efficiency of the DSRC communication protocol, traffic and network simulators are needed. In this chapter, we discuss a few simulation tools to identify a suitable tool for our simulation goals. Simulation tools such as TSIS-CORSIM and Paramics are two of several microscopic traffic simulators. This type of simulator provides accurate traffic data; nevertheless, these simulators do not include any network simulation capabilities. Integrating a network simulator is essential when evaluating the impact of the communication network performance with high user rates. High-performance network simulators such as ns-2 and ns-3 are available. ns-2 and ns-3 are open-source simulation tools that run on Linux. JiST/SWANS is yet another platform-independent network simulator with high performance in discrete evaluation simulation. These types of tools are good for network simulation; however, these tools do not include a traffic simulator, which is equally as essential for our study. ViiLab is a new traffic/network simulator whose development is still being enhanced. Further exploration was required to validate the capabilities of this tool, thus disqualifying it from this study. The evaluation of the aforementioned simulation tools led us to concentrate our efforts on utilizing VNSim, an integrated platform for network/traffic-simulating tool developed by University Politehnica of Bucharest [55]. VNSim provides traffic and vehicle information such as the maximum/average delay of vehicles, fuel consumption and emissions. Furthermore, VNSim's network simulation capabilities provide network communication data such as the number of transmitted messages, rate of received messages, cause of non-received messages, and the several source of messages as shown in Figure 14.

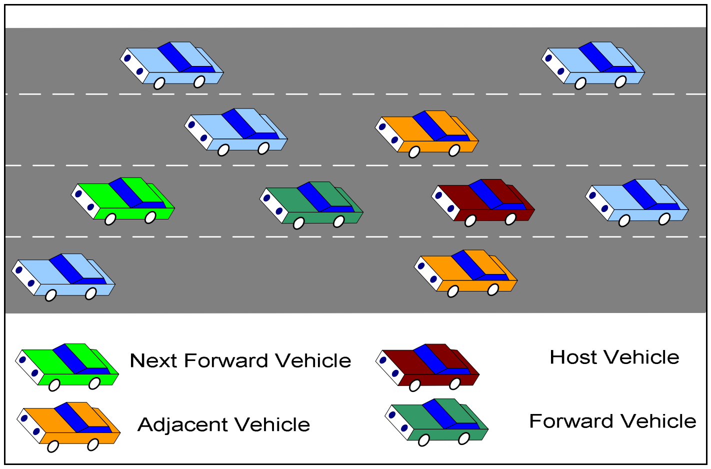

Figure 14: Communication Environment

3.2.3 Propagation Models

During wireless transmission of a signal from a transmitter to a (moving) receiver, the signal can experience fading. There are different fading effects such as shadowing or multipath propagation. Shadowing can be caused by objects (e.g., hills, tunnels) that obstruct the signal path between the transmitter and the receiver. The resulting amplitude change seen by the receiver is slow. This kind of fading is thus called slow fading and is modeled using a lognormal fading profile. Multipath propagation is primarily present in urban environments where the transmitted signal can be reflected or scattered from diverse objects such as buildings or moving vehicles. This creates multiple propagation paths. Along each path, the signal can experience a different delay, attenuation, phase shift or Doppler frequency shift. At the receiver, these signals interfere either constructively or destructively, which results in fast fluctuations of the received signal amplitude. This kind of fading is thus called fast fading and is modeled using Rayleigh or Rician fading profiles, for example.

Fading can cause poor performance in a communications system since it strongly influences the signal-to-noise ratio of the transmission channel. Bit error ratios will increase as the signal-to-noise ratio drops due to strong fading. Severe drops in the signal-to-noise ratio may even lead to a temporary failure of communications. For this reason, it is important to test receivers under fading conditions during design and conformance test stages. This requires well-known and repeatable test conditions that can be provided by fading simulators generating realistically faded test signals in the lab.

IEEE 802.11p has been designed to use Multiple Input Multiple Output (MIMO) technology. MIMO helps reduce the multipath effect between the transmitter and receiver. Therefore, deploying IEEE 802.11p in vehicular environments has the potential to enhance the performance of V2I networks. The MIMO technology relies on statistically independent fading in the multiple transmission paths to increase signal diversity. Thus, MIMO systems need to be tested under (multipath) fading conditions. As MIMO is implemented in all modern communications systems for increasing data throughput, fading simulators must also be able to provide realistic MIMO fading scenarios.

In an ideal communication medium, there is only one direct line of communication between the sender and the receiver units. In a real world application, there are random obstacles such as buildings and other radio wave communication that interfere with the communication path between a sender and a receiver. As a result, it is challenging to model the communication interference and analyze its characteristics. Several radio propagation models have been developed to model the different phenomena that influence the received signal:

- The Shadowing Model: This model seeks to solve the fading effects that occur on the signal, as well as the loss of signal power that occurs on the long distance path. The model can measure the loss in received signal power using a logarithmical equation that depends on distance. In addition, the model adds a Gaussian random variable to counteract the loss caused by obstacles in the communication medium.
- The Two Ray Ground Model: Two paths were considered in this model; the direct line of sight and the ground reflection path between the sender and the receiver, as shown in Figure 15. Therefore, the power of the received signal is simply the sum of these two paths. It is important to note that for short distances between the sender and the receiver, such as a traffic signal, this model does not provide good-quality results.

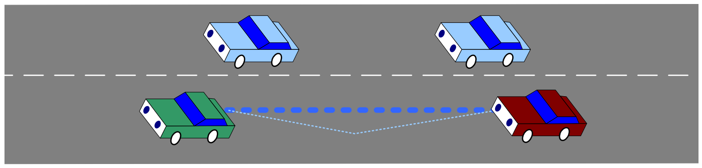

Figure 15: Two Ray Ground Model

- The Ricean Fading Model: The radio signal in this case tends to partially cancel itself out due to the multi path interference. This kind of fading occurs when the signal coming generally from the line of sight signal overpowers all other signals.

3.2.4 Data Dissemination Model

Data dissemination models in vehicle communication networks are very important to ensure effective data sharing. Three different types of data dissemination models have been developed and assessed:

1. Probabilistic Forwarding (PF)
2. Complete Forwarding (CF)
3. Neighbor Discovery (ND)

The communication data or packet is sent with a fixed period every 100 milliseconds for all three dissemination models; however, the types of packets differ among the three data dissemination models.

1. In Probabilistic Forwarding, the vehicle can send one of two packets:

- Packet with vehicle data, containing information about itself; or
- Packet with vehicle data, containing information about itself and all other vehicles in its communication range

The application will choose which packet to send in a probabilistic way depending on the size of the platoon. Another enhancement is achieved using the following model: when a vehicle stops at a red light, the vehicle sends a message indicating that it is still in the platoon but will not be active. This will ensure that the vehicle's information will stay in the platoon packet and, consequently, the number of overall packets will be reduced.

2. The Complete Forwarding model does not use different types of packets. In this model, the only packet that will be sent from each vehicle is the platoon packet, in which the vehicle broadcasts its database, which includes information about the other vehicles it identifies.

3. On the other hand, the Neighbor Discovery Model does not deal with vehicle platoons. Each vehicle sends a static packet in a static period of time. These packets contain information about the vehicle that sends it (ID, Timestamp, Speed, Road, Point, Offset, Lane, Direction, Signal, and State). The packet size is fixed to 27 bytes. The application adds two extra bytes to this packet, containing information that defines its type. Thus, the packet size becomes 29 bytes.

In summary Probabilistic and Complete Forwarding deal with large numbers of vehicles, in which drivers tend to travel as platoons (highway or intersection). In the Forwarding models, the packet contains general information about the road and detailed information about each vehicle in the platoon. Nevertheless, there are two constraints on the platoon packets: The information about each vehicle should not be outdated, and the total size of the packet should not exceed 2,300 bytes (Ethernet 802.11 frame size).

3.2.5 Performance Measures

In order to evaluate the DSRC protocol at intersections, we apply the three different data dissemination models: PF, CF and ND. In addition, we select several test cases to compare the dissemination models to communication performance in terms of the ratio of successfully received to lost packets.

For each data dissemination model, we present the ratio of successfully received/lost packets as a function of the number of nodes per simulation minute. To analyze the reasons behind losing packets, we evaluate each category:

- Collision: two packets arrive at the same time to the node, and the ratio of the first packet to the sum of the two packets is lower than the collision threshold.
- Corrupted: the received packet does not have enough power to decode the Physical and PCLP header.

- RX (Receiving): the received packet was rejected because the node is engaged in receiving another packet (receiving mode).
- TX (Transmitting): the received packet was rejected because the node is engaged in transmitting another packet (transmitting mode).
- PER: the received packet does not have enough power to decode the data.
- Weak: the received packet does not have enough power to be detected, and it is too weak to be received; it would normally be detected as noise.

3.2.6 Simulation Setup

The VNSim Simulator environment was selected to run different traffic light scenarios. These scenarios differ by number of nodes; the same simulated scenarios were repeated for the three different data dissemination models—PF, CF and ND.

The simulated road is a simple cross intersection; one crossroad has three lanes in the North/South directions and two lanes in East/West directions, as shown in Figure 16. On each side of the roads, approximately 15–25% of all traveling vehicles will turn left; similarly, the same number will turn right, and the remaining will continue straight. We ran each experiment for 60 simulation minutes. The average number of nodes varied between 35-290 vehicles per simulation minute. Modifying the number of vehicles per lane per simulation hour generated the number of nodes used in each experiment. We divided the drivers' driving behaviors equally into Very Calm, Regular and Aggressive. We selected a pre-timed traffic light controller;

the cycle's length of time was 70 seconds: Green 30 seconds, Yellow 3 seconds, and all Red on all sides of the intersection 2 seconds; hence the Red was 35 seconds long.

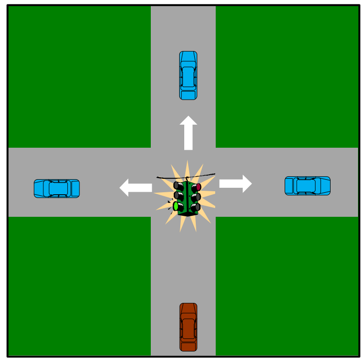

Figure 16: The Simulated Intersection

All of the simulated vehicles were equipped with a wireless device (V2V) and with the infrastructure (V2I). The communication range was set to 200 meters between the vehicles and 1,000 meters between vehicle and infrastructure. The selected radio propagation model is the shadowing model.

3.2.7 Scenario Description

We ran seven scenarios for each different data dissemination model. The number of nodes is different for each scenario and follows the possible paths that were illustrated in Figure 16:

- Vehicles/lane/hour turning left
- Vehicles /lane/hour going straight
- Vehicles /lane/hour turning right

The selected intersection's traffic flow scenarios are as follows:

- Scenario 1: 25 (Left), 50 (Straight) and 25 (Right)
- Scenario 2: 35 (Left), 70 (Straight) and 35 (Right)
- Scenario 3: 30 (Left), 100 (Straight) and 30 (Right)
- Scenario 4: 50 (Left), 150 (Straight) and 50 (Right)
- Scenario 5: 35 (Left), 180 (Straight) and 35 (Right)
- Scenario 6: 90 (Left), 180 (Straight) and 90 (Right)
- Scenario 7: 110 (Left), 220 (Straight) and 110 (Right)

The simulation time was fixed to 60 minutes, which translates into different real run-time based on the selected scenario. The real run-time varied between 10 and 60 minutes.

3.2.8 The Overall Traffic Data

We have run the simulation for all vehicles at the intersection for different data dissemination models, as illustrated in Figure 17; we establish that the average waiting time of the three dissemination models performs equally well for the first six scenarios. In scenario seven, we can clearly identify that the CF dissemination model results in an improved performance.

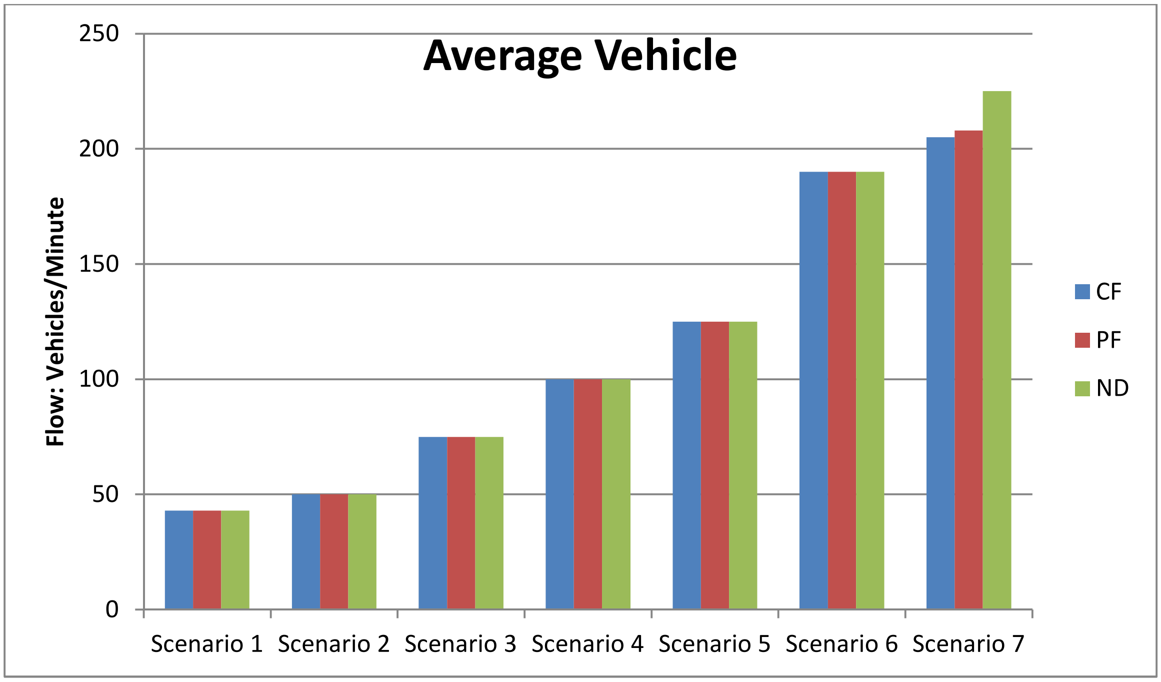

Figure 17: Total Average Number of Vehicles at the Intersection

Figure 18 presents the maximum wait; the pre-timed intersection control can no longer offer equalized volumes identified in scenario six and beyond. Furthermore, the results reflect that the PF and CF dissemination models perform equally and surpass the ND dissemination model performance.

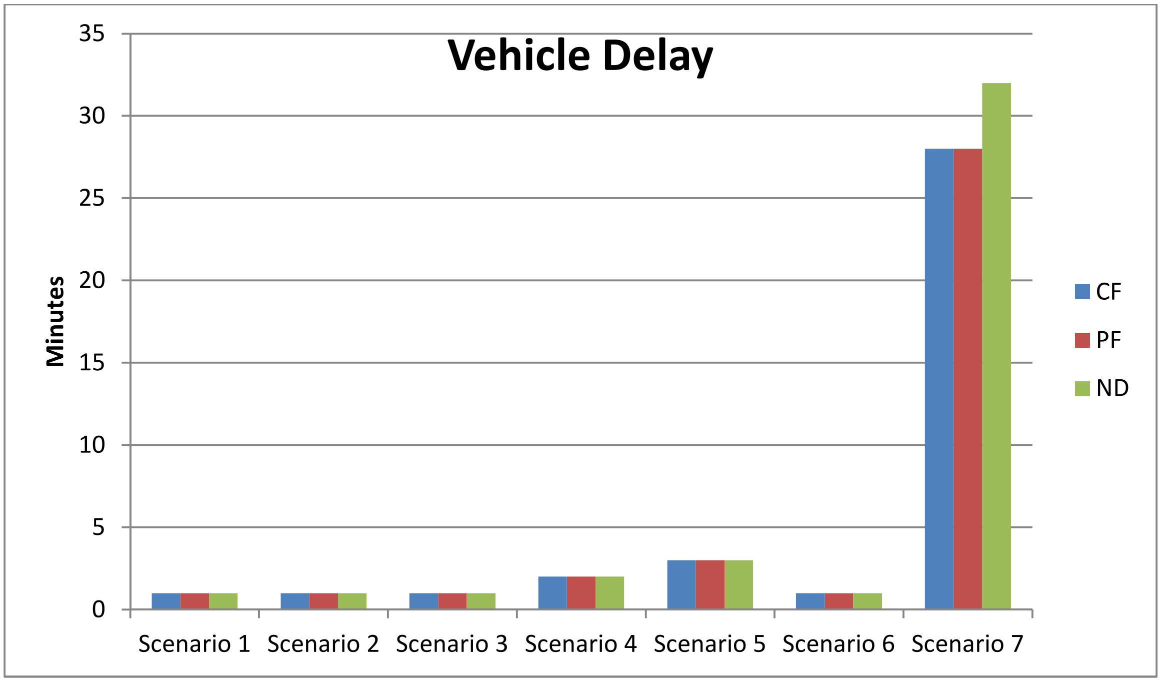

Figure 18: The Maximum Waiting Time at Intersection

An additional measure to portray the enhanced performance of the CF and PF dissemination models was "intersection average delay." We evaluated the vehicle average delay at the intersection, and the results that are reflected in Figure 19 clearly show the underperformance of the ND dissemination model.

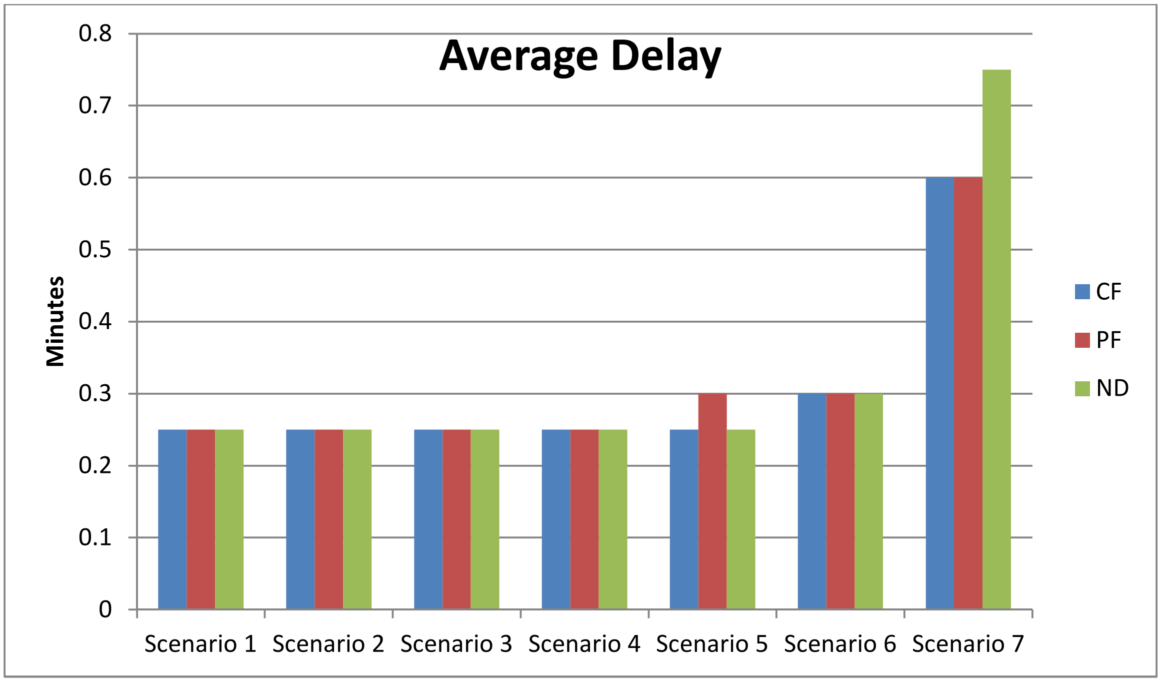

Figure 19: The Average Delay Time at Intersection

Next, the ratio of the successfully received and lost packets for each data dissemination model is discussed. This study will help identify which of the dissemination models could offer enhanced communication performance at intersections. This decision will be based on the largest number of nodes that the model can serve. The simulation results are illustrated in Figure 20. The most interesting aspect is the intersecting point of the "successfully received packet" versus the "lost packet" curves for each of the dissemination models. The representative model's plot intersection point identifies where half of the transmitted messages are getting lost. When using Neighbor Discovery and Complete Forwarding, half of transmitted packets are not received at approximately 110 nodes, while the Probabilistic Forwarding reached approximately 130 nodes before losing half of the transmitted packets. These results lead us to conclude the Probabilistic Forwarding model offers an improved performance compared to the Complete Forwarding and the Neighbor Discovery dissemination models.

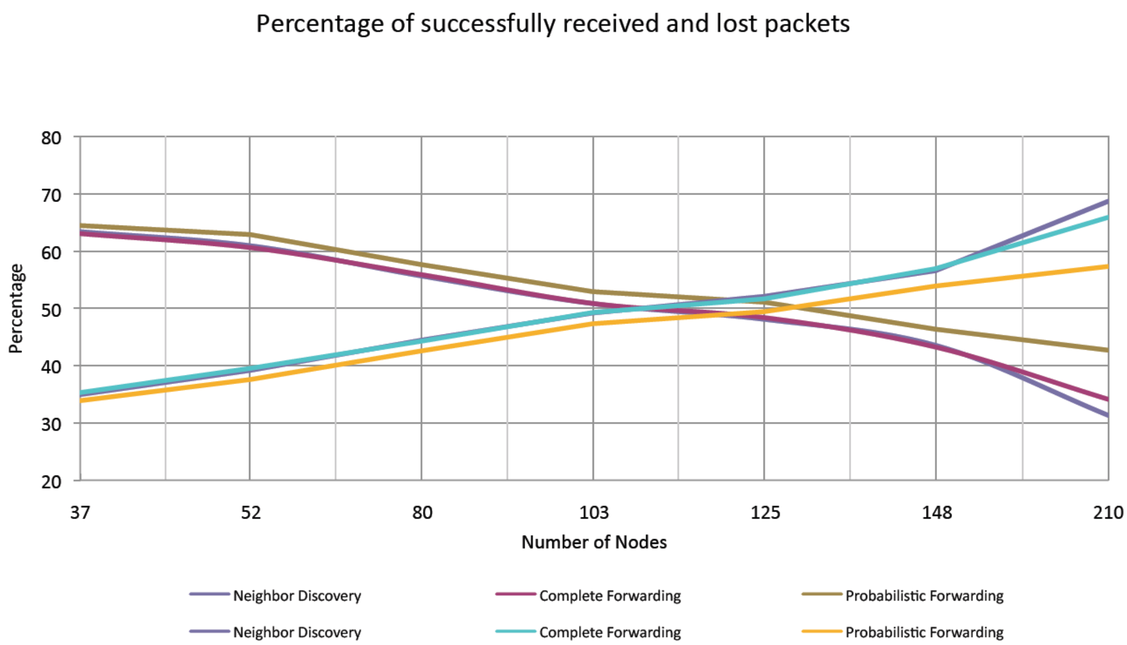

Figure 20: The Percentage of Successfully Received Packets

3.3 IEEE 802.11p Evaluation Summary

Multiple performance measures are currently under development and being evaluated by IEEE 802.11p for vehicular applications [40]. The main focus of this chapter was to evaluate the IEEE 802.11p for integration in our proposed vehicle navigation application, which is described in Chapter 4. Experimental results demonstrated the enhanced performance of the DSRC wireless communication technology with specific calibration achieving successful performance in the vehicular multipath environment.

Chapter 4

4 Environmentally Friendly Navigation

4.1 Optimal Routing Policy

In this chapter, we discuss planning optimum routing policy that reduces vehicle energy consumption, emissions and travel time. An optimal routing policy is a routing methodology implemented by a traveler who is attempting to move in a roadway network from a source node to a destination node with the least expected travel costs, where cost is defined as travel time, energy consumption and emissions. Furthermore, the aim of this chapter is to extend our proposed vehicle routing methodology to re-route vehicles in real-time and incorporate the following routing cost factors: energy consumption, travel time and emissions. In several cases the traditional navigation technology with routing policies based on shortest path or least travel time would also minimize energy consumption and emissions; however there are several cases where this routing policy is not applicable, particularly in the case where traffic jams are introduced in roadways with higher slopes.

The chapter first provides a literature survey on a broad range of traffic network routing problems. A framework is then established, in order to provide a unified view of the problem, considering the numerous variants already in the literature and the additional possibilities of new variants. This framework includes a description of the re-routing policy, the decision process in static, dynamic and predictive models. Furthermore, Section 4 outlines several case studies along with their results.

4.2 Proposed System Architecture

Finding the optimal route in a road network from a current start location to a given destination is an everyday problem that most drivers must consider when planning a trip. The term "optimal" in a routing algorithm may refer to a range of objectives from which end-users can choose to optimize the route, such as the fastest route, shortest route, fastest route given a preference to various road characteristics, or the most fuel-efficient route. These navigation algorithms also differ in the way that they address the changing traffic conditions over time, and they can be divided into the two main categories: static and dynamic, as shown in Figure 21.

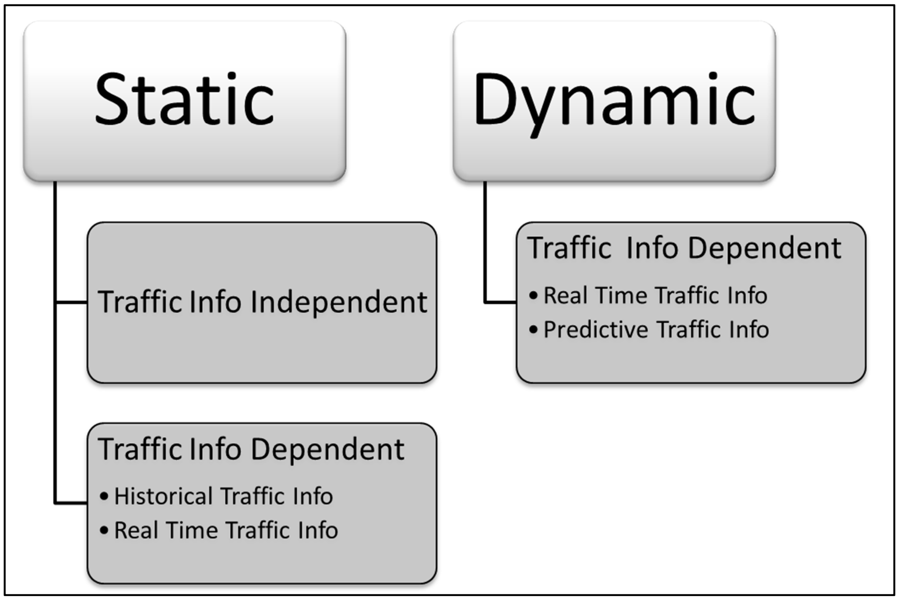

Figure 21: Routing Computation Methods

In the conventional static planning model, all travel times and traffic conditions are considered constant over time, resulting in less realistic travel costs for road segments. The static model was improved upon in the extended deterministic static model [56], in which certain properties of the traffic network are considered to change as a function of the time of day, week or even season (e.g., some roads may be closed during specific time periods); thus, the route cost estimation is more accurate. Most commercial navigation systems use the extended deterministic planning model. However, a more accurate representation of the traffic flow and responsive routing can be achieved with a dynamic routing model [57].

Environmentally friendly routing is a methodology intended to enable reductions in energy consumption and emissions to reduce global warming implications. The shortest or fastest path does not necessarily provide emission-optimized routing in all traffic conditions; vehicle energy consumption and emissions depend heavily on changing traffic conditions. A highly congested, but quick route does not offer minimum travel time or emissions. An increased number of vehicles on a limited roadway yields decreased route throughput and results in longer vehicle waiting time, formerly known as congestion. Similarly, a congested, but short path offers the minimum travel distance but does not minimize travel time, energy consumption or emissions. An emission-optimized route that incorporates traffic, vehicle and geographical information can allow the vehicle to move from the origin to the destination with the shortest travel time and least emissions. The three main routing objectives are illustrated in Figure 22.

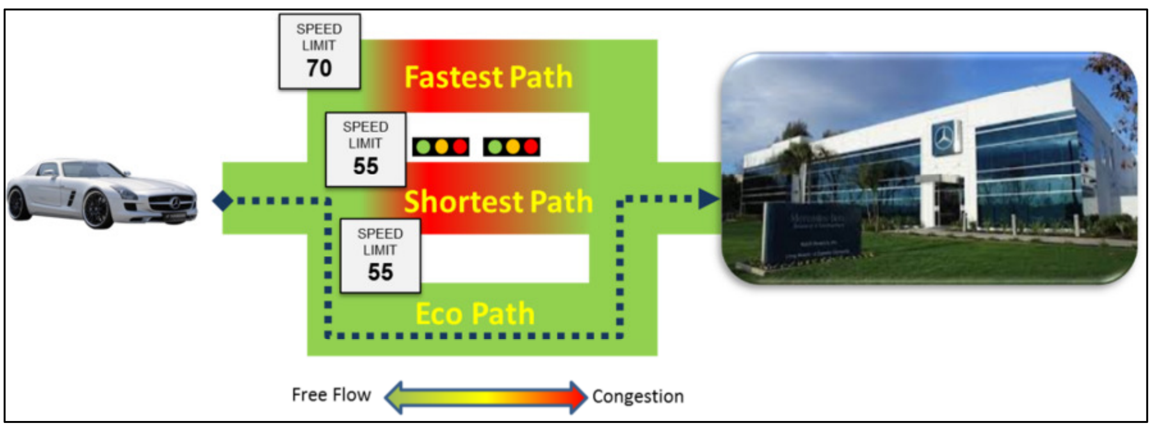

Figure 22: Vehicle Routing Objectives

The optimized navigation is achieved via wireless communication of traffic information using V2V, V2I, and I2V platforms and on-board vehicle travel route optimization application.

The overall methodology for developing eco-friendly navigation can be constructed in three phases, as depicted in Figure 23 and described below.

- Phase I is the initialization step, in which the roadway network covering the origin to the destination is partitioned and represented as a number of nodes and segments. This step uses vehicle and route parameters at the origin to advise the driver of initial drive and route profiles based on real-time traffic data.
- Phase II uses the driver input to develop the travel cost function to be optimized. For a given traffic network, segment-based travel cost factors are developed based on the traffic and roadway conditions. The segment-based factors are based on the microscopic segment characteristics, such as vehicle travel profile (speed vs. time), route profile (location vs. time), and road profile (road gradient). The segment-based factors are indexed in a Predictive Traffic Congestion Index (PTCI).
- Phase III uses travel time cost parameters to plan an optimized route and drive profiles. With the input variable PTCI, a routing policy and novel dynamic re-routing policy based on predictive traffic information are developed to enhance vehicle performance relative to emissions and travel time. The proposed method illustrates that a stochastic model does not need to be included if vehicles adhere to the drive/route profiles and if the traffic information is dynamically updated.

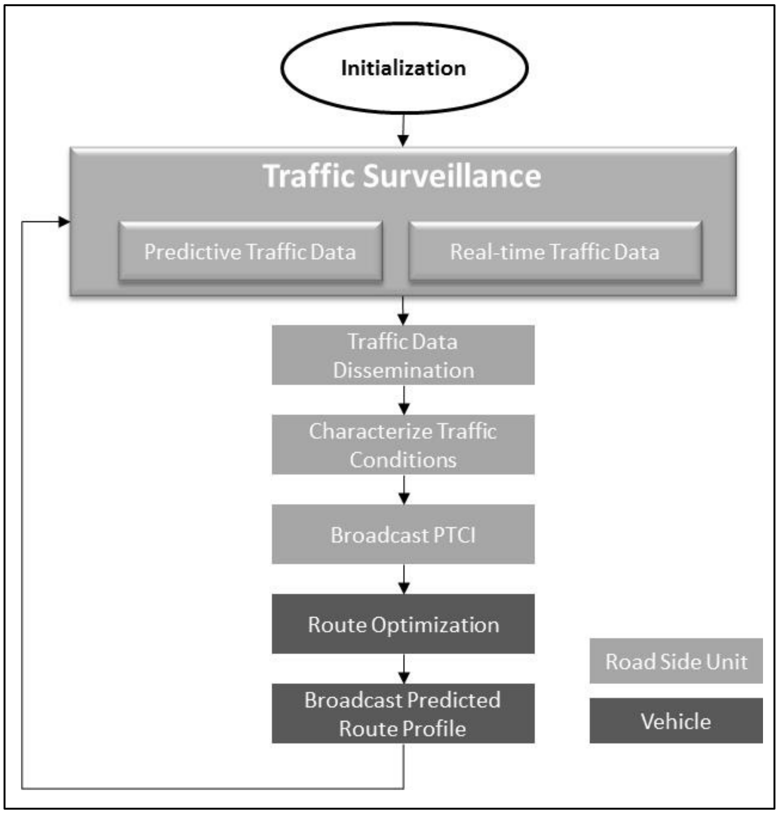

Figure 23: Eco-friendly Navigation Flow Diagram

4.3 Traffic Information Assessment and Communication

Communication of real-time traffic conditions between vehicles and infrastructures is an essential functional requirement to achieve a predictive vehicle navigation system with enhanced traffic assessment accuracy. The dynamic nature of traffic conditions requires the employment of low-latency communication technology. DSRC was primarily developed for ITS vehicular safety applications to support a vehicle traveling at highway speeds to communicate its status in V2V, V2I and I2V configurations. DSRC offers the highest messaging latency performance compared to the proposed alternative communication technologies, including Fourth-

Generation Long-Term Evolution (4G LTE), its successor (5G LTE), and Wi-Fi. Furthermore, DSRC communication allows for the essential predictive traffic modeling capability feature unlike the previously proposed approaches limited to real-time traffic information assessment listed below:

i. Optical Digital Camera [58]: this methodology is based on analyzing consecutive video images of a specific road network segment.

ii. Inductive Loop Road Sensor [59]: this methodology employs magnetic sensors embedded in the road to count the number of vehicles passing through a road segment.

Our methodology to model and estimate traffic conditions is based on the extensively used Greenshield model [60]. The model considers a linear relationship between the traveled vehicle speed and density, as illustrated in Figure 24. Applying the proposed predictive and dynamic route search algorithm requires iterative calculations to find an optimal solution. This calculation becomes computationally intensive when considering a large number of vehicles and route options, resulting in an exponentially long computation time. This phenomenon is known as the “Curse of Dimensionality,” previously explained and proposed by Richard Bellman [32], in reference to the optimization by exhaustive enumeration of an open-ended search space. To mitigate this phenomenon, it is important to develop and integrate functional approximation architecture to represent the travel costs. The approximation architecture of current and predictive traffic information is key to precise traffic condition assessment. For every roadway segment, link-based travel cost factors have been developed based on the traffic conditions. Henceforth, the link-based weight is referenced as the PTCI, which is calculated based on real-time and predictive traffic conditions. The PTCI consisting of travel cost is computed in the roadside unit (RSU) by assessing the vehicle travel cost employing the V2I and I2V communication infrastructure and given the distance of each road segment as logged. Each route segment has an equilibrium point at which free flow occurs at the vehicle speed limit; i.e., the number of vehicles arriving to the segment equals the number of vehicles leaving the segment.

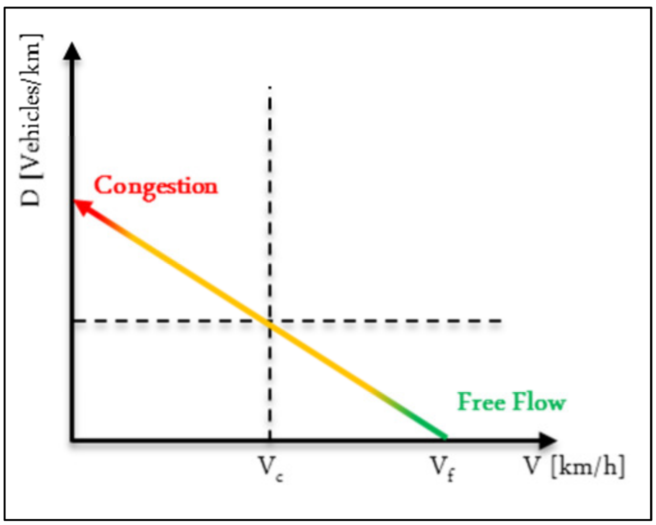

Figure 24: Traffic Density vs. Vehicle Speed

To the extent of our research, all identified route planning methodologies are based on historical or current (real-time) traffic state and not on futuristic (predictive) network conditions of when the navigated vehicle is expected to pass through an assessed edge. The dynamic nature of the traffic network requires us to implement a dynamic routing methodology. Determining how and when to re-route a vehicle includes several problems. Historical and current traffic information by itself unfortunately does not allow for an optimal routing decision because the state of the network edge has evolved; thus, the traffic condition at the navigated edge is unknown. Predicting the travel time, energy consumption and emissions is an ambitious task because of the dynamic structure of the traffic network. Furthermore, special consideration shall be given to avoid having vehicles taking the same alternative path during a traffic jam condition. Our proposed sophisticated rerouting algorithm will take all of the aforementioned challenges into consideration by developing and implementing the microscopic traffic model approach presented in Section 1.5. The recent microscopic modeling approach [61][62][63] offers our application the compulsory enhanced performance compared to other models, such as the mesoscopic or the macroscopic integrated in earlier vehicle routing policies [64][65].

This research aims to incorporate a new heterogeneous methodology to assess the microscopic traffic congestion by integrating the DSRC and GPS data to assess the real-time and predictive microscopic traffic congestion on a roadway segment. There are several techniques for traffic surveillance, and a comparative overview is provided in Table 5. The most recently implemented methodology in traffic congestion assessment, mainly due to its relatively lower cost, is the one based on the cellular network. Traffic data is collected from mobile phone networks and have been mainly implemented in travel time-based routing applications [66][67].

To the extent of our research, all identified route planning methodologies, to date, are based on historical or current (real-time) data for static navigation. Our approach proposes an extension to the vehicle navigation system to incorporate the proposed traffic information prediction and dynamic routing. In order to evaluate the potential benefits of integrating the predictive and dynamic mechanism in our proposed navigation application, the efficiency and performance of the predictive and dynamic mechanisms shall first be analyzed and compared to non-predictive systems.

Method	Quality	Cost	Concerns
Inductive loop sensors	Magnetic system compatible with all weather conditions, installation sensitive	Relatively high considering roadway installation and maintenance	Reinstallation is required when road is repaved
Video-based	Poor in condition such as rain, fog, snow, inadequate light	Relatively high to equip all roadway networks.	Complex data analysis software is needed. More expensive to incorporate infrared vision
Cell and GPS	Relatively slow communication over the cell phone network	Relatively low, considering cell phone based	Not reliable in cases where customer is not sharing location due to privacy concerns
DSRC AND GPS	Research to date reveals no issues	Recent DSRC hardware is relatively high	Public Privacy

Table 5: Traffic Surveillance Techniques

There are several traffic surveillance techniques, as introduced in Table 5; each technique has the ability to accumulate certain types of real-time traffic data. Hence, real-time traffic data is rendered less accurate the further the navigated vehicle is from the assessed roadway segment. Recent research has further enhanced the traffic congestion assessment by introducing a predictive methodology represented by a statistical model predicting travel times for a particular day of the year and time of the day based on accumulated real-time traffic data. Unfortunately, this methodology does not perform well in nonrecurring traffic conditions such as disabled vehicles, roadway construction, heavy merging traffic, traffic accidents and un-planned special events. Our solution moves one step further to introduce an effective methodology for determining predictive traffic. Accordingly, all of the prior work has been based on real-time traffic data and none on predictive traffic data collection. Thus, from this point on, the conventional predictive methodology will be referenced as hybrid-predictive, and our proposed traffic information data as predictive. The following section will describe in detail our definition of predictive traffic information.

This research leverages the emerging vehicle to infrastructure DSRC technology and existing GPS technologies for the purpose of a microscopic traffic data collection and dissemination that offers drivers a cost-optimized eco-friendly vehicle routing solution. This technique is distinctive to our research as our predictive traffic information data collection methodology, described in this section, is novel. Furthermore, the quality and reliability of this data collection system is expected to be superior compared to the other techniques given 100% penetration level. We do not see the required market penetration level as an obstacle for the scope of this research, as we anticipate a mandate by NHTSA to equip all vehicles with DSRC technology after the release and review of UMTRI final report at the end of 2013 for evaluating DSRC communication benefits in vehicular safety applications [37]. The PTCI concept is introduced to represent vehicle flow and density with an associated level of congestion and is stored in the RSU for reference by future non-navigated vehicles. This section describes the methodology for calculating the PTCI. The traffic characteristics used in the calculation of the PTCI are illustrated in Figure 25 and are described below.

- Headway (H): time between two successive vehicles (s/vehicle)

- Gap (G): time between two successive vehicles excluding the length of the leading vehicle (s/vehicle)
- Inflow (Q_{pin}): number of vehicles predicted to pass the starting point in a new segment during a specified time interval (vehicles/h)
- Outflow (Q_{pout}): number of vehicles passing the end point in a new segment during a specified time interval (vehicles/h)
- V: vehicle speed (km/h)
- V_f: free-flow vehicle speed (km/h)
- V_p: predictive speed (km/h)
- D_p: predictive traffic density, number of vehicles occupying segment space (vehicles/km)
- D_j: traffic jam density (vehicles/km)
- The inverse of flow is headway (H), which is the time between the i^{th} vehicle entering segment and the $(i+1)^{th}$ vehicle
- T_p: predictive travel time (s)
- L_i: travel segment length (m)

The traffic model considers a linear relationship between the vehicle speed, traffic density and flow; thus:

- $V_p = V_f\left(1 - \frac{D_p}{D_j}\right)$ (4.1)

- $V_p = \frac{Q_p}{D_p}$ (4.2)

- $T_p = \frac{L_p}{V_p}$ (4.3)

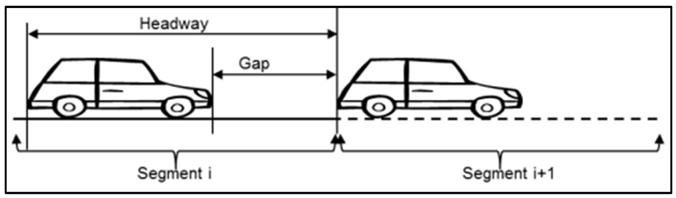

Figure 25: Traffic Characteristics

Table 6 illustrates the PTCI for a single-lane scenario, in which V_f = 50 km/h, and a fixed segment length L_i = 400 m. Under the aforementioned conditions, travel time costs are calculated for the respective segment based on equation (4.3), and a corresponding PTCI is selected and updated in the RSU to be communicated to the navigated vehicle for a decision on re-routing.

Travel Time (s)	PTCI	Description
288- 308	0	Free Flow
309-329	1	Slight Delay
330-350	2	Moderate Delay
351-371	3	High Delay
372-392	4	Significant Congestion
>392	5	Severe Congestion

Table 6: Travel Time Cost Scenario

Similarly, the predicted emission δ_p can be calculated based on the Handbook of Emission Factors (HBEFA) for the road transport emission model [68], as defined in the emission fit function [69] depicted below:

$$\delta_p(v,a) = \frac{1}{h\gamma}(P_0 + m.a_p.v_p + m.g.\mu_0.v_p + m.g.\beta.v_p + m.g.\mu_1.v_p{}^2 + \frac{1}{2}\, c_w \rho A v_p{}^3) \quad (4.4)$$

where c_w is the aerodynamic resistance; m is the vehicle mass; μ_0 is the static friction coefficient; μ_1 is the dynamic friction coefficient; P_0 is the idle power consumption; γ is the motor efficiency; A is the front area of the vehicle; h is the energy content; ρ is the air density; g is the gravitational constant; β is the road segment slope; v_p is the predictive speed and a_p is the predictive acceleration.

Table 7 illustrates the PTCI for a single-lane scenario, with V_f = 50 km/h, L_i = 400 m, and a road segment slope of 0%. Under the aforementioned conditions, emission travel costs are calculated for a respective segment based on equation (4.4), and a corresponding PTCI is selected and updated in the RSU to be communicated to the navigated vehicle for a decision on re-routing. One vehicle class weight is considered here (light-duty); however, the vehicle model could be simply extended in future work to incorporate additional vehicle classes, such as light-, medium- and heavy-duty vehicles.

CO_2 Emissions (grams)	PTCI	Description
< 165	0	Free Flow
166-180	1	Slight Delay
181-205	2	Moderate Delay
206-220	3	High Delay
221-235	4	Significant Congestion
> 235	5	Severe Congestion

Table 7: Emissions Travel Cost Scenario

4.3.1 System Architecture

Figure 26 illustrates a block diagram of the Predictive Intelligent Energy Management Sub-Systems and the interfaces to vehicle sub-systems and road infrastructure. The historical traffic data is utilized for initialization of the system, in which the vehicle has not yet established a real-time or predictive connection with the roadway infrastructure for the real-time and predictive traffic information. It should be noted that the model allows for weather data information to be integrated in the PTCI; however, this is not evaluated in this research and is left for future research. Traffic accidents and congestion due to severe weather conditions, such as icy or snowy roads, may be excluded through re-routing. An equally extensive research, if not more so, that is similar to what has been accomplished in this research is needed to evaluate the impact of weather data and to assess if modification to the route selection algorithm is necessary.

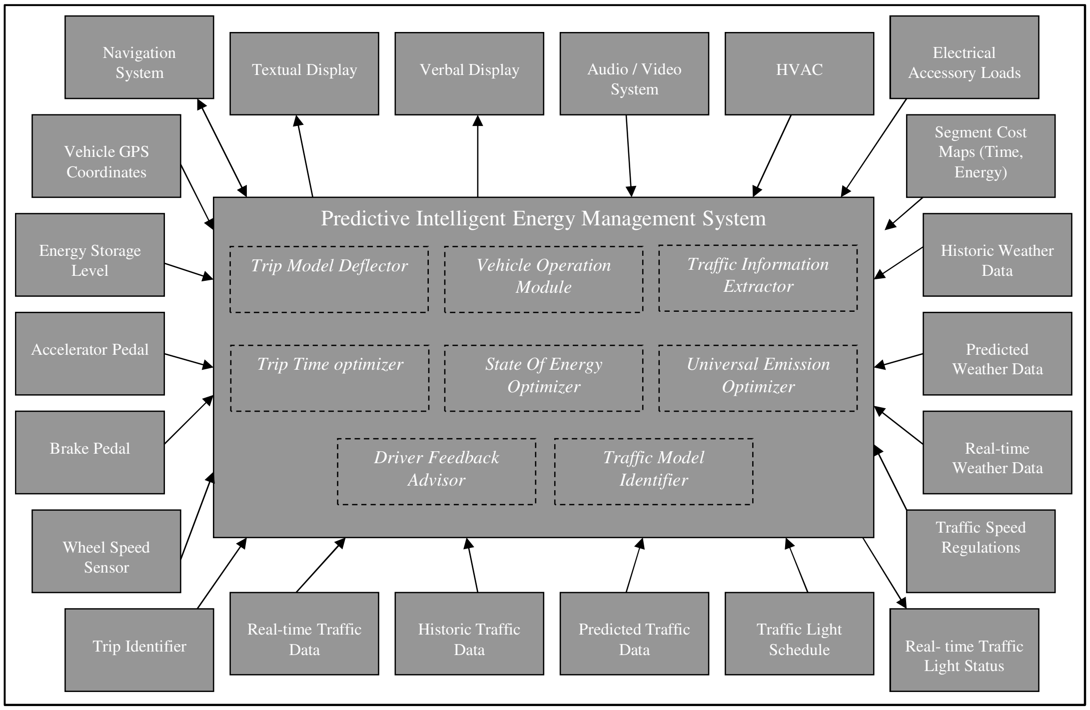

Figure 26: Predictive Energy Management System

The predictive feature of the proposed environmentally friendly system is viable through the ability to integrate the vehicular wireless communication technology (presented in Chapter 2.4.2) to communicate the traffic system information. Our vehicle navigation system is composed of six modules that are illustrated in Figure 27 and described below:

1. Traffic Data Extractor (TDE): Used to extract the predictive traffic data from the ITS network. This data is consequently used to determine if alternative routes should be considered.

2. Vehicle Operation Mode (VOM): Used to provide the vehicle's current operation modes including vehicle speed, position, fuel level, etc.
3. Trip Model Identifier (TMI): Used to learn the route road conditions, including slope and distance. This is accomplished through the use of GPS data.
4. Trip Model Deflector (TMD): Used to re-route trip as necessary following the processing of predictive traffic congestion.
5. Vehicle Operation Optimizer (VOO): Used to optimize drive operation and consisting of three sub-modules: Travel Time Optimizer, Universal Emission Optimizer and State of Energy Optimizer. The intelligent algorithm found in this module has two key features: agile and dynamic.
6. Driver Feedback Advisor (DFC): Used to provide the driver feedback relative to style, including speed, acceleration, deceleration and alternative route.

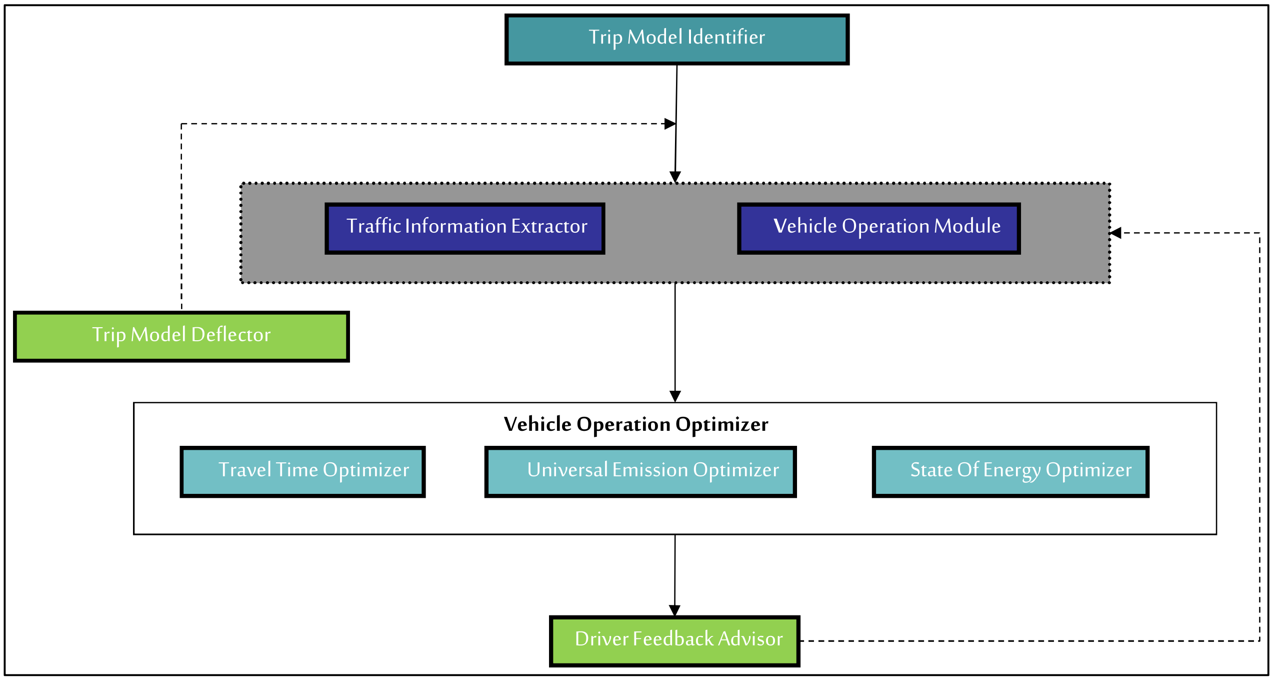

Figure 27: Predictive System Architecture

Assuming a driver is traveling from a source P_s to destination P_d over a pre-selected optimized route illustrated in Figure 28. Given the dynamically updated traffic congestion index showing an increased value reflecting congestion, the driver would favor switching to another route with continued optimized cost. However the driver could only switch to another route at nodes, or intersections. Because of this, we propose route optimization to include nodes' connection capacity.

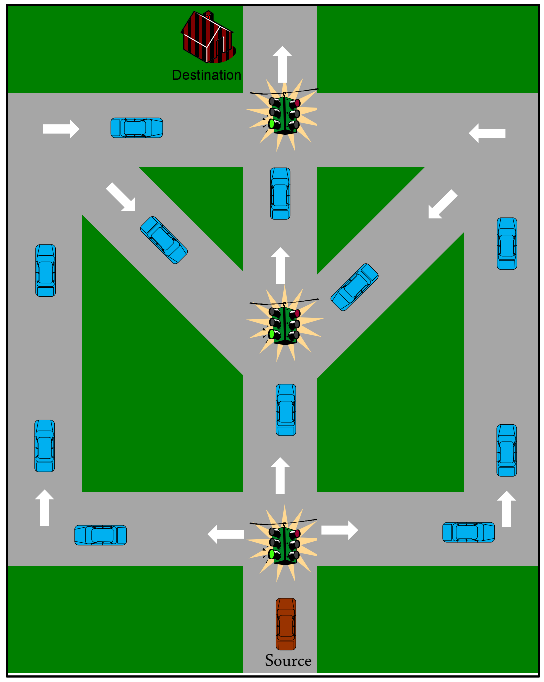

Figure 28: Vehicle Traversing in a Roadway Network

The node capacity (σ) is defined as the number of segments available from any node P_i, which represents all possible routes for a source-destination pair. The node capacity of a route is built while the source node P_i starts to identify a path to the destination node P_d. The maximal node capacity of a node P_i, denoted as σ_i, indicates the available connecting segments at next node P_{i+1}. The node capacity is a good measure of the node degree of travel freedom, providing a reliability assessment of the path. The node capacity is essential in route planning to determine how to select the path to the destination efficiently, ensuring the driver arrives at the destination at any cost in case of link connection failure due to, for example, an accident. The node capacity is determined for each node in the roadway network; the node capacity for node P_{i+1} is attached to the predecessor connecting node or nodes P_i. The cause of this is a driver traveling a segment, he/she cannot re-route until next node is reached. In cases where U-turns are allowed in a roadway network, those U-turns are to be considered separate nodes. U-turns are not reflected in this example, and are to be addressed in future work. The navigation routing methodology is planned for on-board vehicle calculation; thus, it is important to select a node search methodology using a sub search area rather than entire map in order to reduce computation time and eliminate the curse of dimensionality phenomena. The proposed node search methodology to be implemented in this case is based on a modified Greedy Perimeter Stateless Routing (GSPR) protocol [70], where node P_{i+1} is evaluated only if it is geometrically closer to destination node P_d than predecessor node P_i. Initially, the vehicle at source node P_s broadcasts a Route Request (RREQ) to discover a path that includes recorded travel costs and node capacity σ_i set to infinity, all other nodes set their respective σ_i to 0. Let G_i be the roadway network that includes all connecting node to source node Ps. All P_i, $\{N_i \in G_i\}$ and $\{|\overline{P_iP_d}| < |\overline{P_sP_d}|\}$ will have an identified node capacity σ_i between Ps and P_i. Next, as the entries of the routing table of node P_i is updated, P_i will sort the node capacity of all entries in its routing table and updates its respective σ_i selecting the maximal node capacity. Then P_i rebroadcasts the RREQ including its σ_i to all P_i, $\{N_i \in G_i\}$ and $\{|\overline{P_iP_d}| < |\overline{P_sP_d}|\}$. To reduce the unnecessary updating of the route table, the modified DRSM controls the vehicle's priority to rebroadcast an RREQ, unless the travel time, t_i, is adversely impacted due to, for example, an accident. When the RREQ reaches the destination node P_d , P_d would uni-cast to source node P_s the Route Reply (RREP), identifying the optimal route by selecting a neighboring node with maximal life capacity and minimum travel time t_i. The steps of the applied protocol are illustrated in the example of Figure 29, showing an example roadway topology; the corresponding PTCI in this case is selected based on the travel time cost factor (t_i), and node capacity σ_i for each node is labeled in the corresponding table. P_s sets in the corresponding table its pre-established travel time cost based on the traffic information to 6 and node capacity to 1 based on the connecting neighboring nodes in consideration, where $\{|\overline{P_iP_d}| < |\overline{P_sP_d}| \}$. Similarly, node P_1 sets the node capacity to the number of neighboring connecting nodes in addition to the carryover number of nodes of previous node P_s. By following the same procedure, the RREQ reaches destination node P_d. P_d looks up its routing table and select P5 as the next node to relay the RREP; in this case there is no other neighboring node. As the RREP reached node P5, P5 looks up its routing table and selects P4 as the next node to relay the RREP, as it offers the target value of $\{t^i_{min}, \sigma^i_{max}\}$. As the RREP returns to the source node P_s, the optimized route offering highest degree of travel and least travel cost P0→P1→P3→P4→P5→P7 is uncovered.

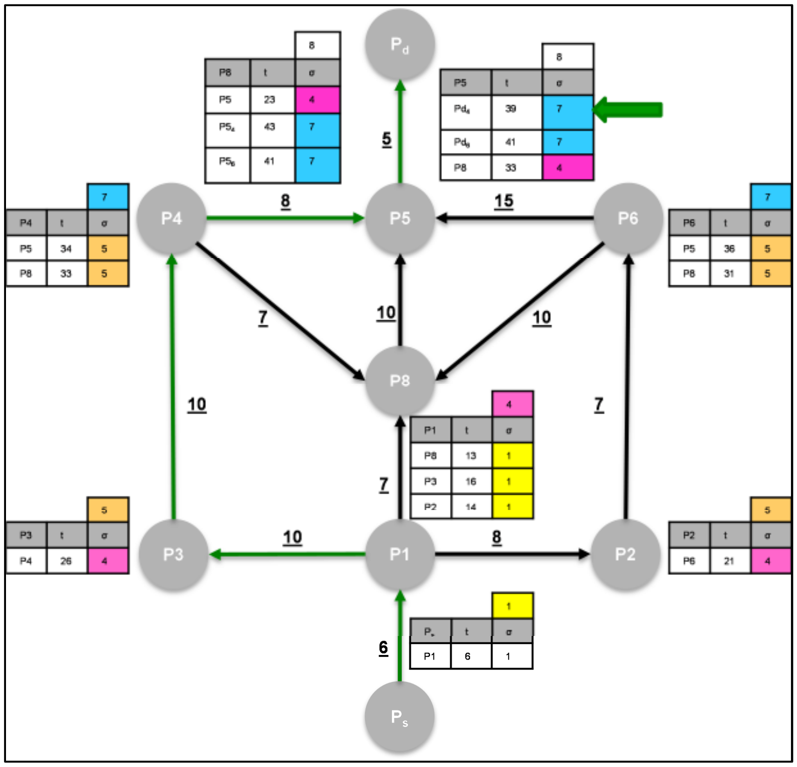

Figure 29: Dynamic Node Capacity Assessment Application to Vehicle Routing

4.4 Dynamic Re-routing

During travel, an alternative route search is performed if traffic congestion is increased, which is reflected in a higher PTCI value. In the proposed dynamic routing methodology, predictive traffic information is integrated into the planning model. The optimal route to the destination is calculated before the start of a trip and is updated dynamically to adapt to new traffic conditions during travel, as illustrated in Figure 30. When multiple travelers make dynamic routing decisions to the same alternative route, special consideration should be given to prevent vehicles from taking the same alternative path during a traffic jam. The proposed dynamic re-routing logic is activated when the updated received PTCI is worse, reflecting worsening traffic conditions ($PTCI_{new} > PTCI_{previous}$). It is important to select the proper PTCI threshold for the re-routing decision to avoid unnecessary or delayed re-routing. Furthermore, the number of re-routing events was limited to two to alleviate the computational burden. The vehicles selected for re-routing are the vehicles closest to the identified predictive traffic congestion. The distance factor is integrated in the on-board vehicle application and is assumed to be the same for all other vehicles. The union of all vehicles closest to the predicted congestion is selected and evaluated for alternative constrained paths.

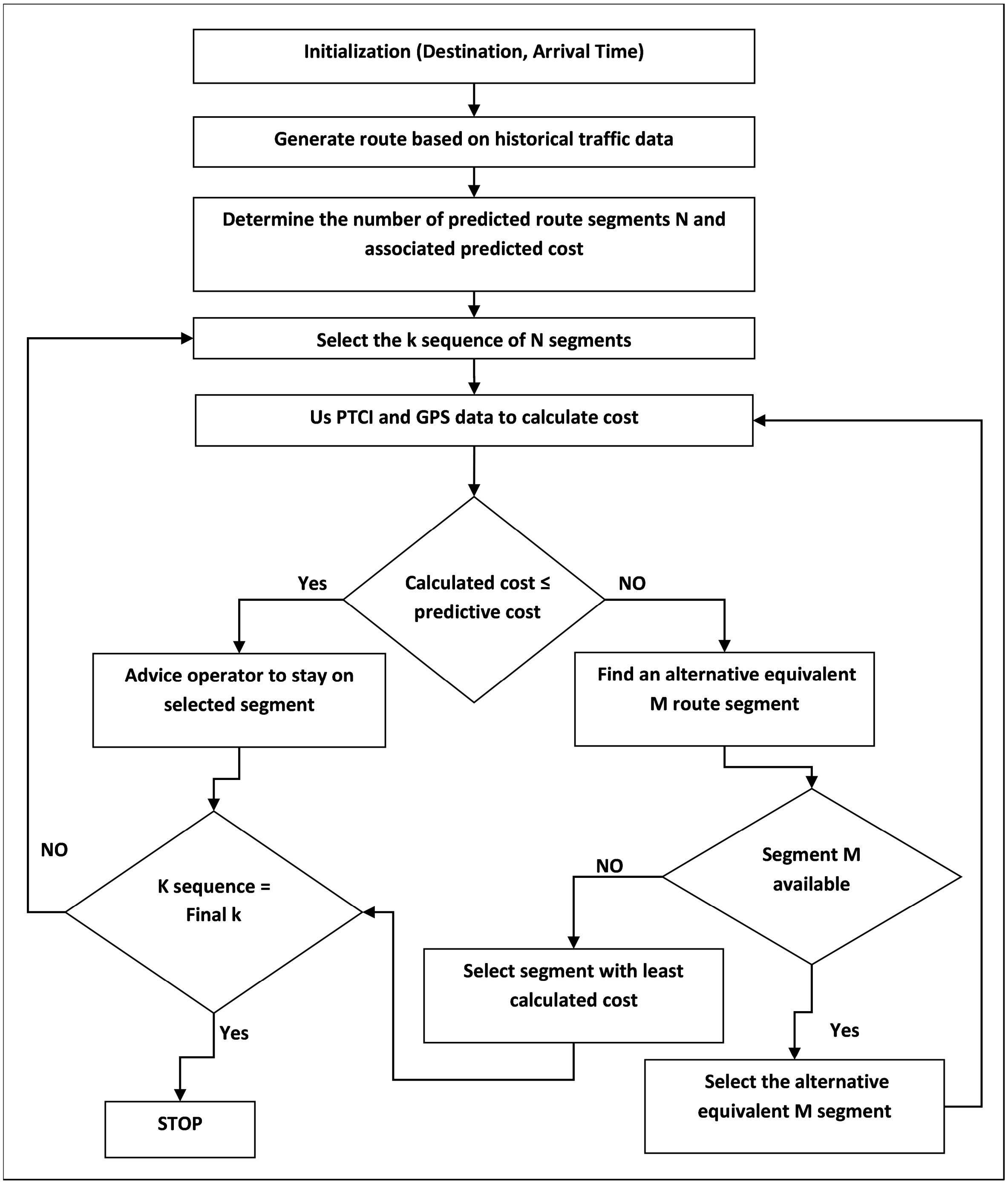

Figure 30: Operational Flow Chart Diagram

4.5 Traffic Network Model

The transportation system is a rather complex, asynchronous and dynamic system. Its structure is characterized as a DEDS [71], in which state transitions are triggered by the random occurrence of discrete physical events in the system; thus, the traffic system can be modeled by PNs. The capability of PNs extends beyond other similar mathematical modeling languages (e.g., neural networks) to include analysis, control and graphical representation. Since their introduction in 1962 by Carl Adam Petri, PNs have been extensively applied to transportation systems. A literature survey documenting all PN applications in the modeling, analysis and control of traffic systems has been presented, indicating the potential extension of PNs to transportation systems [72]. The navigation process of a vehicle can be approached as a discontinuous system of connected road segments. PNs offer a graphical representation of the system that consists of places, transitions, arcs and tokens. In the transportation model, places are represented by interconnecting points that enable re-routing; transitions represent travel costs; arcs represent paths between RSUs; and tokens are vehicle-constrained travel parameters (e.g., travel time or emissions). A petri structure is noted as PN= (P, T, F, C_0), where P= $\{P_1, P_2, P_3 \ldots P_n\}$ the finite number of traffic roadside units, T=$\{T_1, T_2, T_3 \ldots T_n\}$ the finite set of travel cost associated with road segment $(P \times T) \cup (T \times P) \rightarrow \mathbb{Z}$, where $\mathbb{Z}$ is an event based relationship between roadside unit and transitions. The notation C is the vector of the number of tokens for each roadside unit, formerly known as marking M_0In the simplified traffic network and equivalent PN model scenario, illustrated in Figure 31. It is necessary to unfold the PN to analyze the reachability of the destination by the vehicle at the origin. The unfolding approach of PN = (P, T, F, C_0) Ω = (RN, β), where RN is a resulting net, β is the monomorphic category of net N to RN, and conditions C and events E are mapped to place P through transition T.

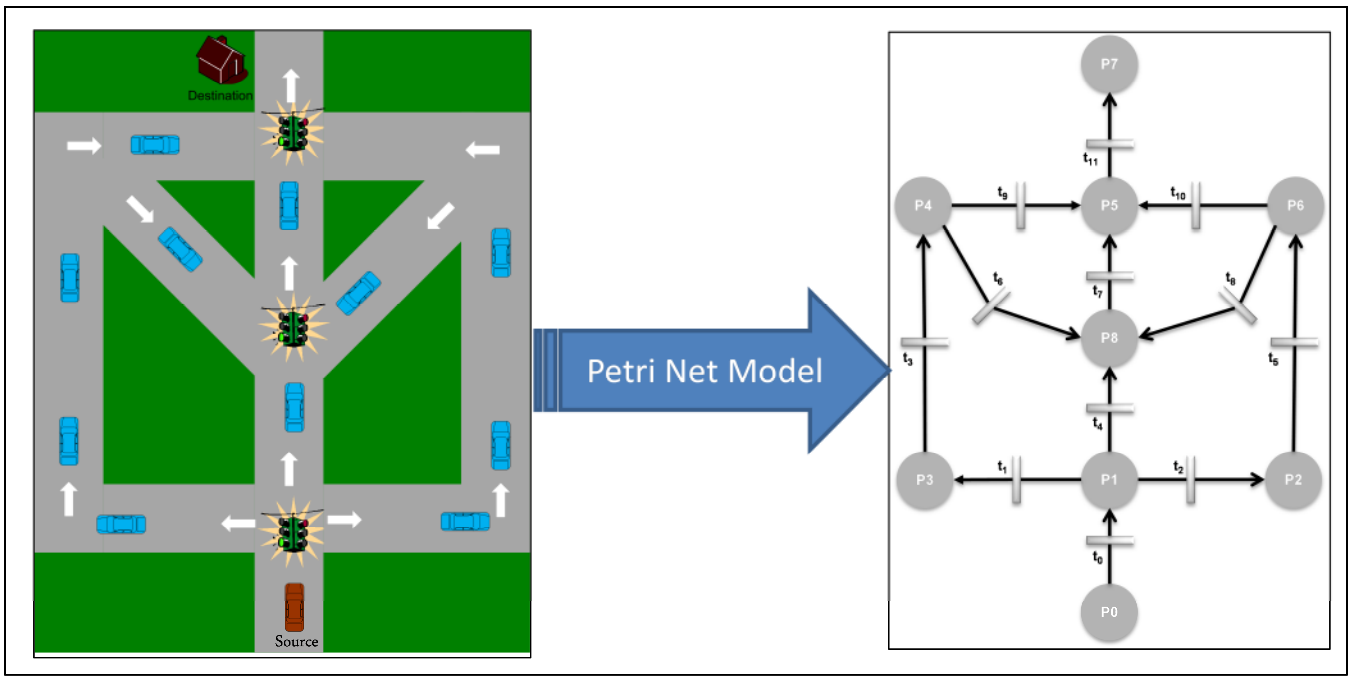

Figure 31: Traffic Network and Equivalent PN Model

The PN unfolding process first introduced by McMillan [73] is a reachability analysis and planning tool that naturally enables the identification of all possible paths from an origin to destination and allows for the determination of separate solutions for independent sub-problems. The reachability algorithm involves a search strategy but does not require a specific methodology. Typically, a breadthfirst search (BFS) algorithm is implemented. In this paper, we implemented a modified version of Dijkstra's algorithm [74] that we named the arc cost compliment (ACC) algorithm. The traditional Dijkstra algorithm implements an iterative solution-finder scheme to solve the dynamic functional equation for the shortest cost problem in (2.8) by the reaching method [75]. Researchers in the last five decades have proposed shortest path algorithms with increased computation speed through the integration of hierarchical speedup techniques; however, the surveyed algorithms A*[76], D*[77] achieved enhanced computation performance given a sub-optimal solution. The certainty of path optimization in our environmentally friendly navigation system is critical for the navigated vehicle in addition to the predictive traffic information assessment; therefore, we decided to use a PN unidirectional unfolding search algorithm with a modified Dijkstra search algorithm. Making note of computation speed capabilities has and continues to linearly increase over time due to the continued progress in the semiconductor technology.

Since the vehicle arrival time is expected to be known through the communication of the vehicle's drive and route profiles (the cost of traveling a route segment is calculated and integrated in the PTCI. Our search approach would involve a uni-directional forward search method. Our forward search is implemented on the weighted graph within non-negative weights by the bounding function $x(t,c,e)$ presented in section 2.3.3. The bidirectional search method enables faster convergence of the solution; however, we have excluded it since it does not necessarily offer the minimum cost path, as routes are independently and in parallel being computed from the source node and destination node to meet at an intersecting point. Our proposed algorithm is titled, Arc Cost Compliment algorithm (ACC), because it utilizes the conventional PN arc cost; however, in a novel compliment implementation, provided that route planning is properly coupled to the algorithm, the ACC algorithm generates optimal navigation relative to energy, emission and travel time. The forthcoming section provides the definition and notation used in the algorithm and presents the ACC algorithm in detail.

4.6 Definition

The objective of environmental navigation is to move a vehicle from an origin to a destination while avoiding traffic congestion and optimizing travel time. The problem space can be formulated as a set of places denoting vehicle positions, destinations and roadway intersections connected by unidirectional arcs that represent connecting paths, each of which has an associated travel cost. The vehicle starts at the origin and moves across arcs to other states until it reaches the destination state. The travel cost for traversing an arc from place P to P_i is the positive complement number of the arc travel cost. If P does not have an arc to P_i, then c (P,P_i) is undefined. Two places, P and P_i, are connected in space if c (P,P_i) is defined. The routing problem of minimizing the sum of the total travel cost is formulated as an optimization algorithm. The place $p_{vi,uj}$ is introduced to denote the existence of a vehicle v_i on roadside unit u_j. The firing of each transition $t_{vi,ua,ub}$ implies the traveling of a vehicle between two adjacent RSUs, u_a and u_b. Let N_t be the total number of possible paths to be evaluated for vehicle v_i. Let M_k be the initial marking at time k. Let φ be the total travel time threshold, δ be the total vehicle energy threshold, and ε be the total vehicle emission threshold. The routing problem can be formulated based on equation (2.8) as the problem to find an optimal firing sequence to minimize:

$$C = \sum_{p=}^{Pi} \alpha . \varphi_{ui} + \beta . \delta_{ui} + \omega . \varepsilon_{ui} \tag{4.5}$$

4.6.1 Optimization Algorithm

Step 1: Initialization

a) The number of travel time constraints is set as the number of tokens at P_0

b) The pre-calculated travel time cost is set as the arc weight

c) The pre-calculated emission cost is set as the arc weight

d) Starting at the initial origin node, search the markers that enable a transition

Step 2: Optimization

a) Fire a transition, and then decrease the number of tokens from its initial marker

b) Continue firing until the number of tokens is depleted or destination P_i is reached

c) Repeat for all possible paths N_t and save all possible interim solutions

Step 3: Convergence

Based on the driver's routing selection for travel time or emission, the optimal solution is the path connecting the origin to the destination with a maximum number of tokens remaining at the destination.

Step 4: Re-Optimization

The re-optimization of subnet u_j is executed on the condition that higher arc weights are received, indicating worsening traffic conditions. The objective function for re-optimization is similar to step 2, given that re-optimization begins at the current marker.

4.7 Finite Converged Search

An infinite unfolding of PN Ω will result from a transportation network in which all route segments are connected. Thus, we seek a complete finite unfolded alternative Ω'; that contains a sufficient amount of information to reach an optimal solution. The key to obtain a complete, finite prefix is to identify the unfolding cut-off event, which is the node connection capacity in our case. The node connection capacity is selected as the cutoff event, as the driver in a dynamic routing environment is capable of switching to alternative routes when a route has been taken with multiple node connections. The node capacity (σ) is defined as the number of segments available from any node P_i, representing all possible routes for an origin-destination pair. The node capacity of a route is built when the origin node P_i starts to identify a path to the destination node P_d. The maximal node capacity of node P_i, denoted as σ_i, indicates the available connecting segments at the subsequent node, P_{i+1}. The node capacity is a good measure for the node degree of travel freedom, providing a reliability assessment of the path. The node capacity is essential in route planning to determine how to select the path to the destination efficiently while ensuring that the driver will arrive at the destination at any cost in the case of a link connection failure (due to, for example, an accident). The node capacity is determined for each node in the roadway network; the node capacity for node P_{i+1} is attached to the previous connecting node or nodes P_i. The background for this approach is that when a driver is traveling a segment, he/she cannot re-route until the next node is reached. In cases where U-turns are allowed in a roadway network, those U-turns are to be considered as separate nodes. U-turns are not reflected in this example and will be addressed in future work. The unfolding action is ceased when the defined node capacity σ' is reached. Figure 32 and Figure 33 present the unfolding of nodes P5 and P8, respectively, to evaluate the reachability to the final marker P7.

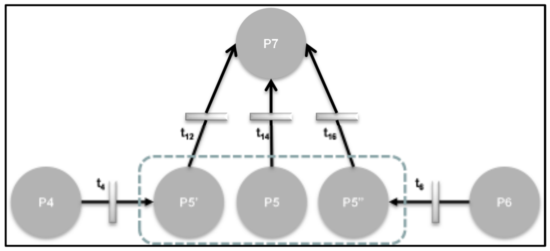

Figure 32: Unfolding P5 through P4 and P6

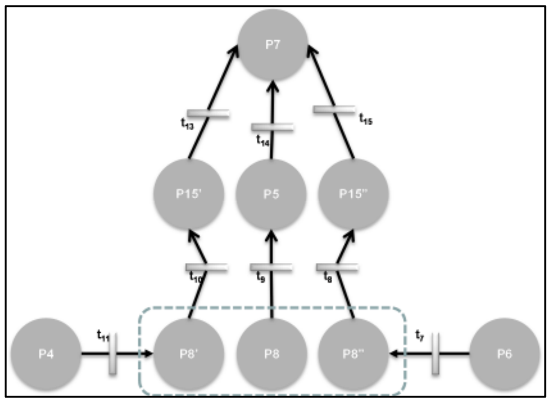

Figure 33: Unfolding: P8 through P4 and P6

Figure 34 presents the fully unfolded PN that corresponds to the traffic network given in Figure 31. All possible paths from the origin to destination are represented. Because the travel time and emissions are the target optimized travel costs, the initial marking M_0 represents the upper bound travel time and emission constraints set. In this case, the constraints are 60 seconds of time and 200 grams of CO_2, based on real-time traffic data. The marker M_{ij} is the final marker denoting the predictive travel time and emission cost compliment for the respective path j.

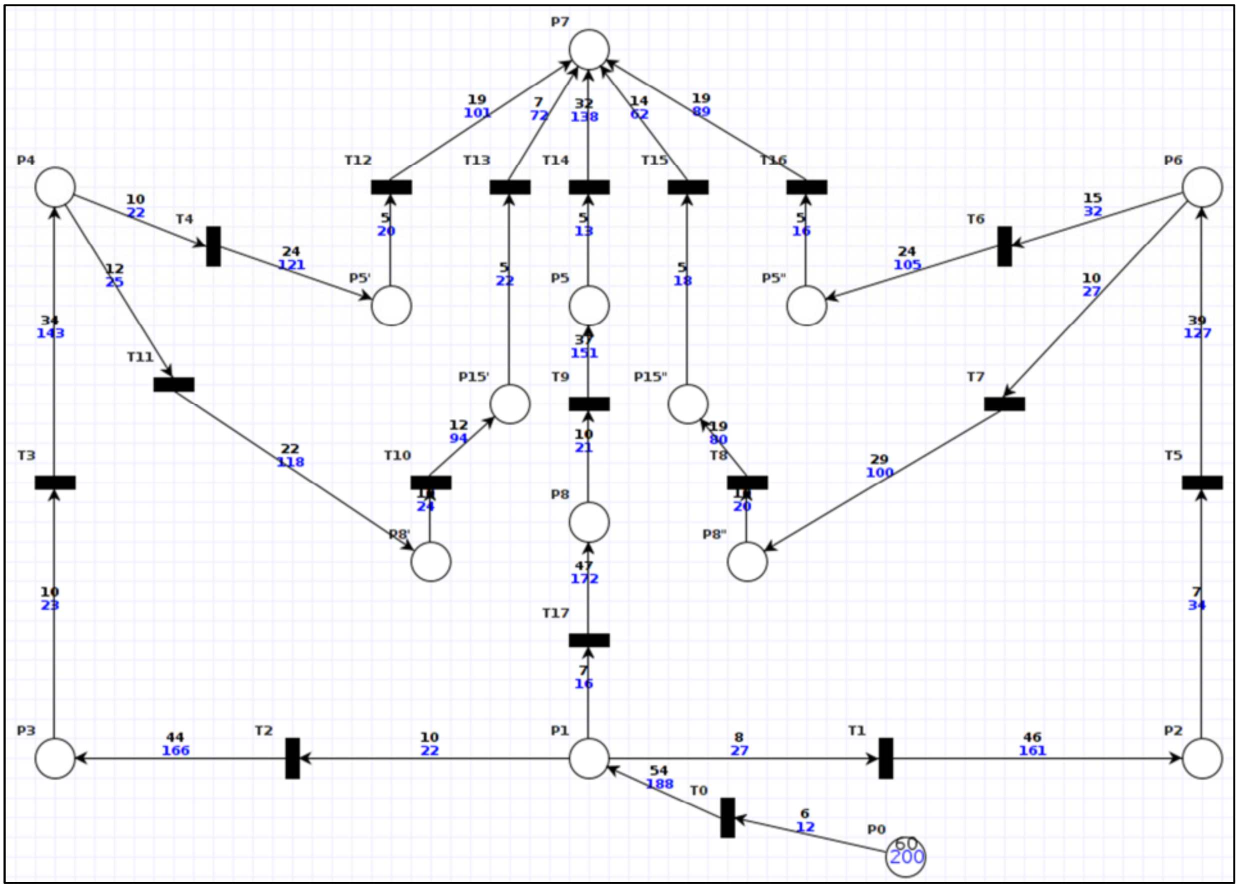

Figure 34: Unfolded PN Model

The vehicle destination P7 can be reached via different places and firing sequences. The incidence matrix depicted in Figure 35 presents all possible paths and presents the travel time cost complement of each path based on the ACC algorithm. The final destination P7 can be reached via transition T_i and respective cost C_i as T12:41, T13:53, T14:28, T15:46, or T16:41. The lowest-cost path through transitions T0→T17→T9→T14 is selected as the optimal route plan.

	T0	T1	T10	T11	T12	T13	T14	T15	T16	T17	T2	T3	T4	T5	T6	T7	T8	T9
P1_Time	54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P0_Time	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P2_Time	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P15'_Time	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P8'_Time	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P4_Time	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0
P7_Time	0	0	0	0	19	7	32	14	19	0	0	0	0	0	0	0	0	0
P5'_Time	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0
P5_Time	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37
P15"_Time	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0
P5"_Time	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0
P8_Time	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0
P3_Time	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0
P6_Time	0	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0
P8"_Time	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	0

Figure 35: Travel Time Cost Incidence Matrix

If the driver selects the emissions-based route optimization search, the reachability to the destination is calculated in a similar manner. The vehicle destination place P7 can be reached via different places and firing sequences. The incidence matrix depicted in Figure 36 presents all possible paths and presents the travel emission cost complement of each path based on the ACC algorithm. The final destination P7 can be reached via transition T_i and respective cost C_i as T12:101, T13:72, T14:138, T15:62, or T16:89. The lowest-cost path through transitions T0→T17→T9→T14 is selected as the optimal route plan. This specific scenario, where the road slope is 0%, illustrates that the emissions-based PTCI provides the same route path solution as the travel time-based PTCI solution.

	T0	T1	T10	T11	T12	T13	T14	T15	T16	T17	T2	T3	T4	T5	T6	T7	T8	T9
P1_Emisison	188	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P0_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P2_Emisison	0	161	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P15'_Emisison	0	0	94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P8'_Emisison	0	0	0	118	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P4_Emisison	0	0	0	0	0	0	0	0	0	0	0	143	0	0	0	0	0	0
P7_Emisison	0	0	0	0	101	72	138	62	89	0	0	0	0	0	0	0	0	0
P5'_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	121	0	0	0	0	0
P5_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	151
P15"_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	80	0
P5"_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	0	0	105	0	0	0
P8_Emisison	0	0	0	0	0	0	0	0	0	172	0	0	0	0	0	0	0	0
P3_Emisison	0	0	0	0	0	0	0	0	0	0	166	0	0	0	0	0	0	0
P6_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	0	127	0	0	0	0
P8"_Emisison	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0

Figure 36: Emission Cost Incidence Matrix

4.8 Electric Vehicle Travel Cost

In order to evaluate the benefits of predictive traffic information, a cost function shall first be established. The parameters to be optimized in this section are trip time φ(i) and energy δ (i)

$$C = \sum_{i-0}^{j-1}[\varphi(i) + \delta(i)] = TC \sum_{i-0}^{j-1}[x(i) + u(i)] \qquad (4.6)$$

where j is the period of the route, TC is total cost of route as well as battery energy and time, x (i) is the dynamic state vector of the vehicle such as vehicle speed, high voltage battery state of charge, motor torque, vehicle route, and u (i) is the control vector of the vehicle such as the recommended vehicle speed, the recommenced acceleration, the recommended deceleration, and the recommended route. The optimization problem becomes the search for the control vector u (i).

The cost function will be subject to the targeted vehicle model. In this unit, the EV model described in section 2.3.9 will be used for simulation, thus resulting in the following constraints:

$\delta_{min} \leq \delta\ (i) \geq \delta_{max}$ (4a)

$T_{min} \leq T\ (i) \geq\ T_{max}$ (4b)

$V_v(i)= V_{v\text{-}req}$ (4c)

$\tau_{em}(i)= \tau_{em\text{-}req}(i)$ (4d)

$V_v(i)\leq V_{v\text{-}max}$ (4e)

$V_{minlimit} \leq V(i) \geq V_{maxlimit}$ (4f)

$Acc_{v\text{-}min} \leq Acc_v(i) \geq\ Acc_{v\text{-}max}$ (4g)

$\tau_{em}(i)\leq \tau_{em\text{-}max}(i)$ (4h)

where V_v is vehicle velocity, $V_{v\text{-}req}$ is requested vehicle velocity, $V_{v\text{-}max}$ is vehicle maximum velocity, $V_{minlimit}$ is minimum speed limit, $V_{maxlimit}$ is maximum speed limit, $A_{ccv\text{-}min}$ is vehicle minimum acceleration, $A_{ccv\text{-}max}$ is vehicle maximum acceleration, τ_{em} is electric motor torque, $\tau_{em\text{-}req}$ is electric motor torque requested, and $\tau_{em\text{-}max}$ is electric motor maximum.

4.8.1 Electric Vehicle Simulation Setup and Results

The default electric vehicle model illustrated in Figure 37 was selected from the Advanced Vehicle Simulator (ADVISOR) [78] program for simulation. ADVISOR is a sophisticated vehicle systems analysis tool that integrates a backward and forward modeling approach, founded on Matlab/Simulink software environment. It is focused on providing simulation to assist in modeling vehicle performance and vehicle energy management.

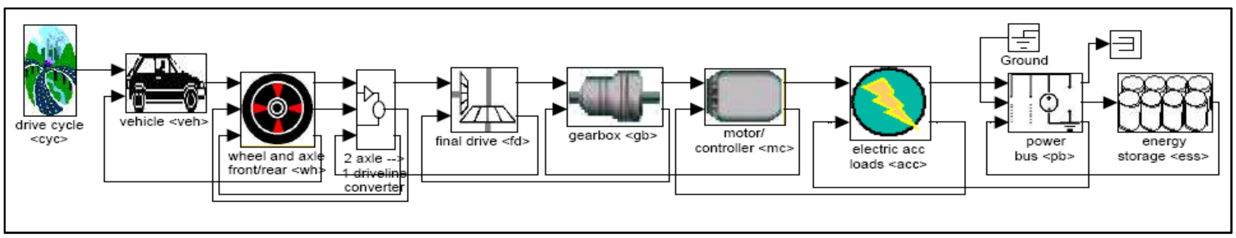

Figure 37: Electric Vehicle Model

As illustrated in Figure 38, assume the vehicle is entering a segment with a traffic signal ahead; the dynamic programming algorithm [5] is applied to the i^{th} segment, and the optimal drive cycle is obtained. The drive cycle is then provided to the driver as a recommendation to be applied. Provided the driver follows the drive cycle recommendations, the predictive vehicle achieves enhanced performance in energy efficiency and, in some cases, an enhanced arrival time.

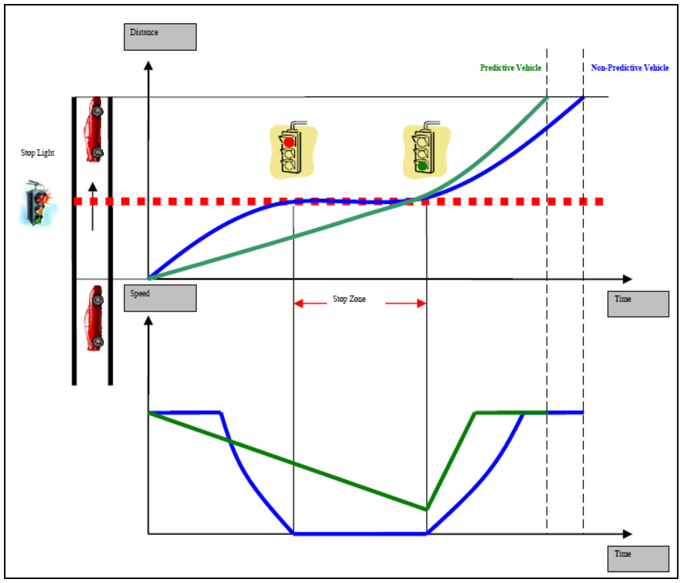

Figure 38: Predictive vs. Non-Predictive Traffic Information: Traffic Light Scenario

It should be noted that the drive profile advisory model is not further evaluated in this research and is left for future research. However, based on initial results, it is clearly shown that enhanced performance can be achieved with the integration of a vehicle drive profile advisory model. Concluding with a personal note, the drive profile advisory system performance can be as good as the driver's adherence to the advisory drive profile. Accordingly, we foresee a great benefit from a drive profile advisory system when combined with an autonomous driving system. Note that the algorithm computation is subject to all previously listed constraints including (4a) High Voltage battery energy δ (i) (4a) and trip time T (i) (4b); in a scenario where battery energy is jeopardized, which could be very critical for EV, alternative route segments with a recharge location are pursued, as illustrated in Figure 39.

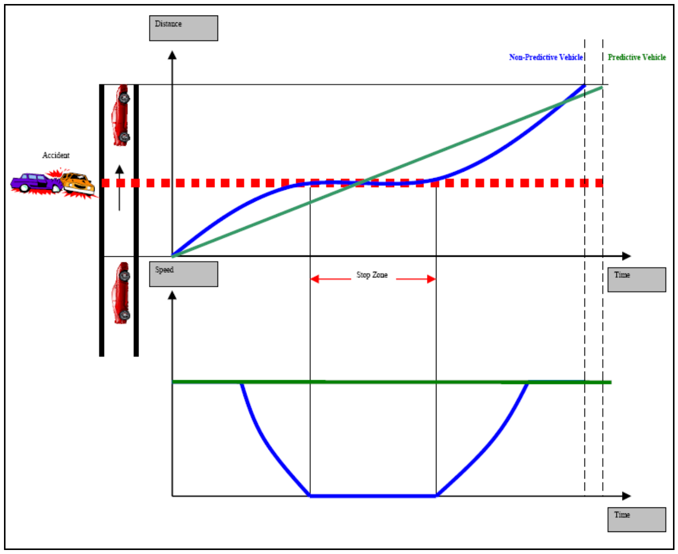

Figure 39: Predictive vs. Non-Predictive Traffic Information: Vehicle Traffic Accident Scenario

To evaluate the benefits of the proposed predictive algorithm, we use the approach of the cost function optimization in ADVISOR [78]. A single route segment of 4,000 meters is selected for comparison; the initial value of the High Voltage State of Charge is set to be at 100%. The results are shown in Figure 40 and Figure 41.

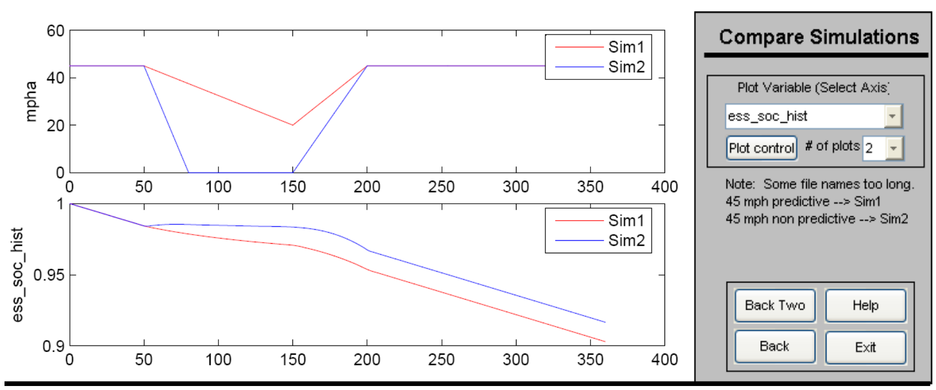

Figure 40: Traffic Light Scenario State of Charge Evaluation

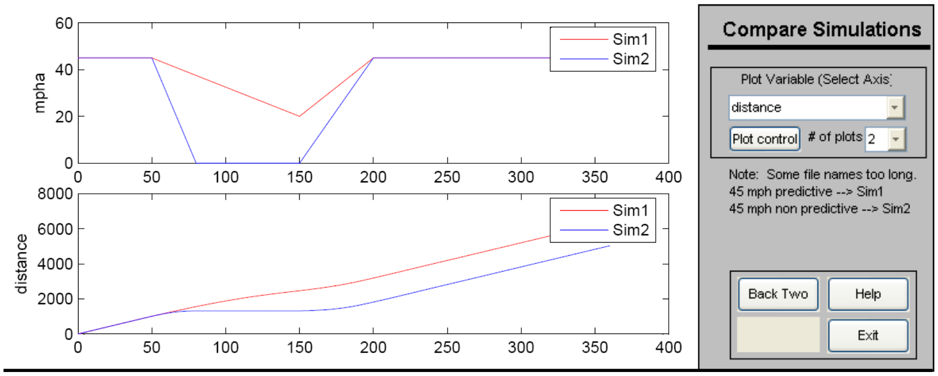

Figure 41: Traffic Light Scenario Travel Time Evaluation

In the traffic accident scenario, the PIEMS continue to provide an enhanced performance. Again a single route segment of 4,000 meters is selected for comparison; the initial value of the High Voltage State of Charge is set to 100%. The segment results are illustrated in Figure 42 and Figure 43.

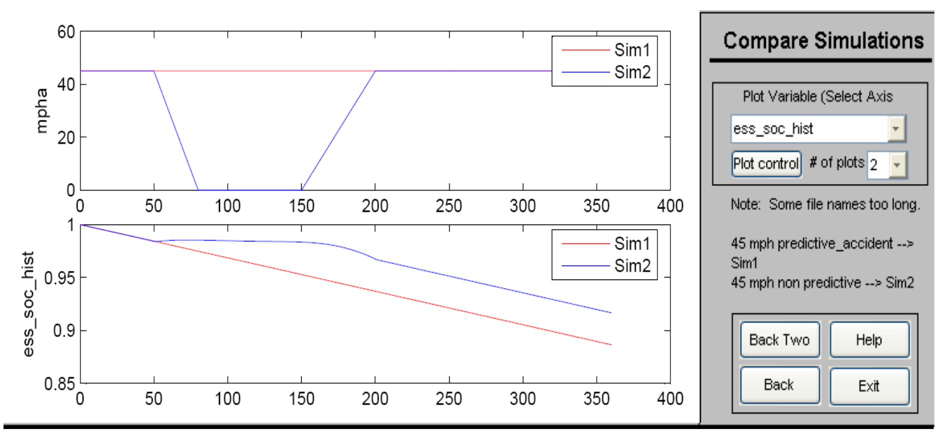

Figure 42: Traffic Accident Scenario State of Charge Evaluation

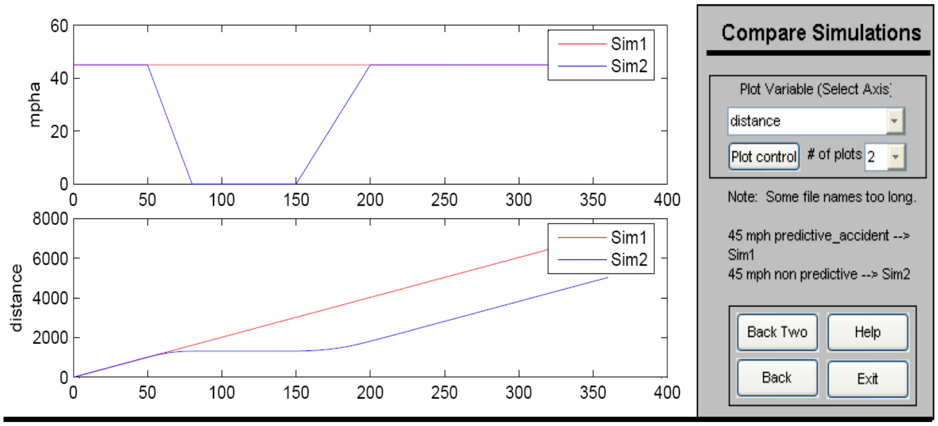

Figure 43: Traffic Accident Scenario Travel Time Evaluation

The energy consumption and travel time data of the predictive and non-predictive traffic information used by the navigated vehicle is summarized in Table 8 and Table 9.

Vehicle Type	**Segment Length**	**Travel Time**	**ΔSOC**
Predictive	4000 meters	241 Seconds	5.94%
Non Predictive	4000 meters	310 Seconds	6.7%

Table 8: Traffic Light Scenario State of Charge (SOC) and Travel Time Summary

Vehicle Type	Segment Length	Travel Time	ΔSOC
Predictive	4000 meters	199 Seconds	6.3%
Non Predictive	4000 meters	310 Seconds	6.7%

Table 9: Traffic Accident Scenario State of Charge (SOC) and Travel Time Summary

The results show the benefits of the predictive traffic information in both energy consumption reduction and, in this special case, a travel time reduction. This was achieved through the reduction of deceleration rates and avoiding vehicle stops. In this case, the predictive traffic information offers an energy consumption improvement and travel time improvement. For the traffic accident scenario, the results show the benefits of the trip model deflector proposed predictive traffic information in both energy consumption reduction and also, in this special case, travel time reduction. The energy consumption and emission benefits were achieved through re-routing while meeting the original travel time and energy consumption constraints. In this case the predictive vehicle offers an energy consumption improvement and a noticeable travel time improvement. In summary, the predictive mechanism applied in the routing policy allows for pre-selecting a route with increased travel cost accuracy. The stochastic nature of the traffic system is eliminated through the dynamic traffic information update enabled by the low latency communication technology DSRC.

4.9 A Real-World Application

This section extends the models and simulation completed in Section 4.8.1 to include a real-world map with representative route options and vehicles. Furthermore, the cost function presented in Section 4.8 will be expanded to include emission costs, thus allowing application of our proposed application to plug-in vehicles.

The focus of our discussion is routing policy in real-world application including the predictive traffic data feature described in Section 4.3.1.

4.9.1 Evaluation

The objective of our simulation-based evaluation was to analyze the performance of different vehicle routing methodologies. We will specifically analyze the following question:

- Which routing methodology offers the driver the most improved performance in terms of energy consumption, emissions and travel time?

Two approaches were evaluated to support the premise of the research: The implementation of a physical experiment and computer-based simulation. Because the actual implementation of such a project is expensive due to the cost of equipping multiple vehicles and infrastructure with DSRC technology and because software programming is a trustworthy tool to perform accurate simulations, a computer-based simulation can avoid the time and expenses that accompany physical implementations. Thus, a computer-based proof-of-concept simulation is the tool of choice for our research.

4.9.2 Simulation Scenario

To validate the proof-of-concept of the proposed predictive routing methodology, a set of simulation scenarios were carefully designed and constructed to represent real-world traffic network scenarios. The following experimental configuration settings were chosen:

Network map: A real-world map of Eichstätt City in Bavaria, Germany, (illustrated in Figure 44) was selected. The map was exported from OpenStreetMap and converted to a SUMO format using the application "Netconvert." The SUMO network file describing the traffic network includes roadway information, such as lanes, roadway slope, traffic lights, junctions and speed limits.

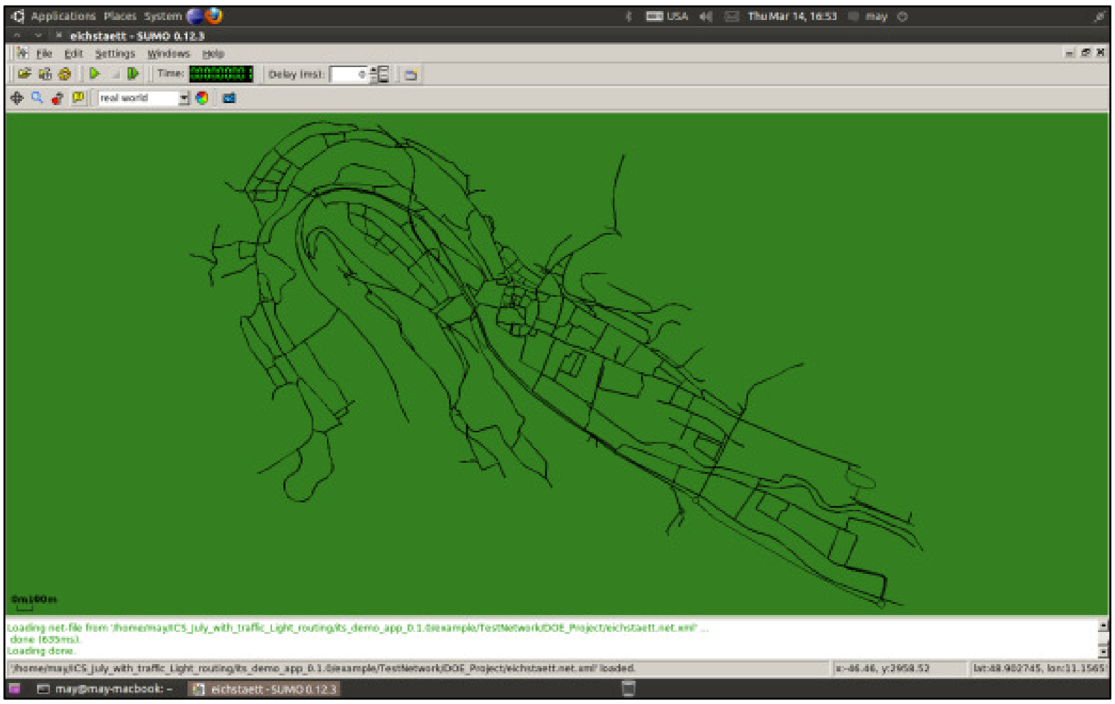

Figure 44: Map of Eichstätt City, Bavaria, Germany

Vehicle trips and traffic flow: A random trip and traffic flow file is generated by developing and running a python script entitled "randomTrips.py." A set of trips (including origin/destination, edges, and departure times) is generated with a uniform random distribution. Trips are dispatched throughout the simulation at equal intervals of one time step, starting from zero to 100 (i.e., a distinct trip is generated at each simulation time step, and a new vehicle using this trip is emitted every 100s). However, the number of vehicles that share the same trip is constrained to six, resulting in a total of 100 trips x 6 vehicles = 600 vehicles running in 1 h of simulation time.

Initial Routes: The initial path that connects the origin to its corresponding destination was computed under real-time traffic conditions. The simulation network and its vehicle movements are initialized with travel cost (travel time or emissions) as the edge weight and utilizing the proposed PN-based ACC algorithm to find the optimal path. These static routes have been generated using the modified SUMO tool DUAROUTER and include the automatic iteration to compute the presented dynamic re-routing once the simulation is started.

Hybrid Communication Platform: To implement and evaluate the proposed dynamic routing methodology, the simulation experiments are run in a state-of-the-art hybrid wireless DSRC-based communication environment that supports V2V, V2I and I2V for exchanging traffic information. The exchanged messages in our simulation environment are divided into two main types, based on the purpose of the message's payload instead of on the communication type (V2V, V2I or I2V):

- Cooperative Awareness Messages (CAMs): messages exchanged between vehicles (V2V) and from vehicles to RSUs (V2I). The broadcast area for CAM messages is dynamic, related to the mobile vehicle communication area, and set to 100 m. CAM packets comprise two data classes:

- Vehicle travel and drive profile, including vehicle data, such as speed, position and direction.
- Communication profile: transmission frequency

- Geographical Broadcast Messages (GEOBROADCASTC): messages sent from RSUs to vehicles (I2V). These messages are used to broadcast the PTCI as computed by RSUs to all vehicles in the communication range. The broadcast area is static, related to the predetermined communication radius of the RSU (set at 400 m).

Due to the slow computational processing from the increased number of RSUs and limited hardware system specifications, only eight RSUs have been implemented. Six of the RSUs were assigned to traffic light signals, and the other two RSUs were assigned to main junctions. To ensure that the majority of navigated vehicles received messages from the RSUs, these units were distributed over the center area of the city, covering the highly congested roads. Multi-hop communication was activated for all traffic data broadcasted from RSUs to compensate for the limited number of RSUs.

4.10 Results and Analysis

The eco-routing algorithm was implemented in iTETRIS, evaluated and compared with the shortest and fastest travel time. Each vehicle in the simulation was assigned a recording device that captures and stores the vehicle's instantaneous trip information, such as CO_2 emissions and fuel consumption and other static information, such as the route length and travel time. The trip information of all vehicles is then processed, and the following global performance metrics are calculated:

- Total route length (meters): the total distance traveled by all vehicles to reach their respective destinations.
- Total waiting time (seconds): the total time spent waiting at traffic lights by all vehicles.
- Total travel time (seconds): the total travel time spent by all vehicles to reach their respective destinations.
- Total fuel consumption (liter/second): The total average fuel consumption rate by all vehicles.
- Total CO_2 emissions (gram/second): The total CO_2 emission rate by all vehicles.

Figure 45and Figure 46 illustrate the advantages of a predictive dynamic travel time-optimized routing in a congested traffic network with respect to the traditional static and real-time dynamic travel time-optimized routes. In addition to the travel time, environmental performance improvements are achieved by reducing the fuel consumption and CO_2 emissions. The travel time, fuel consumption, and CO_2

emission improvements result from the predictive dynamic traffic status updates provided by the V2V and V2I communication infrastructure.

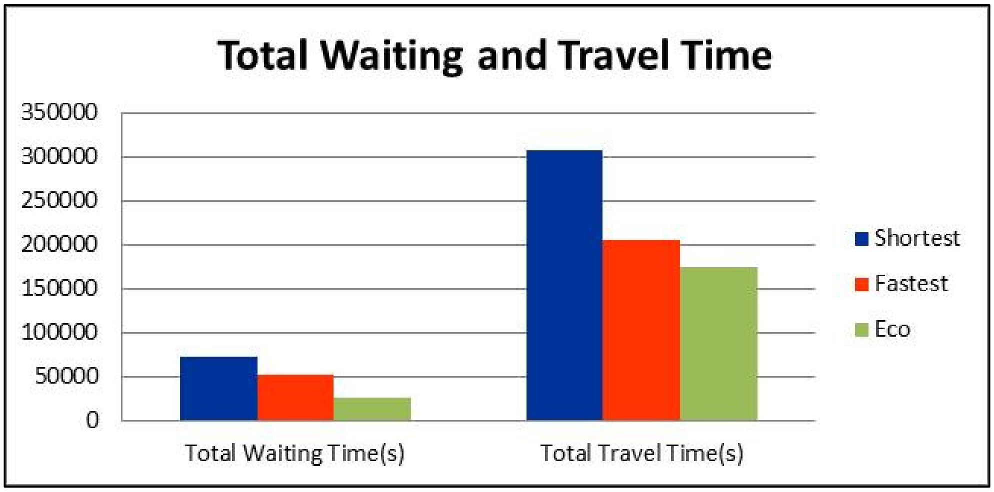

Figure 45: Shortest vs. Fastest vs. Eco (600 vehicles)

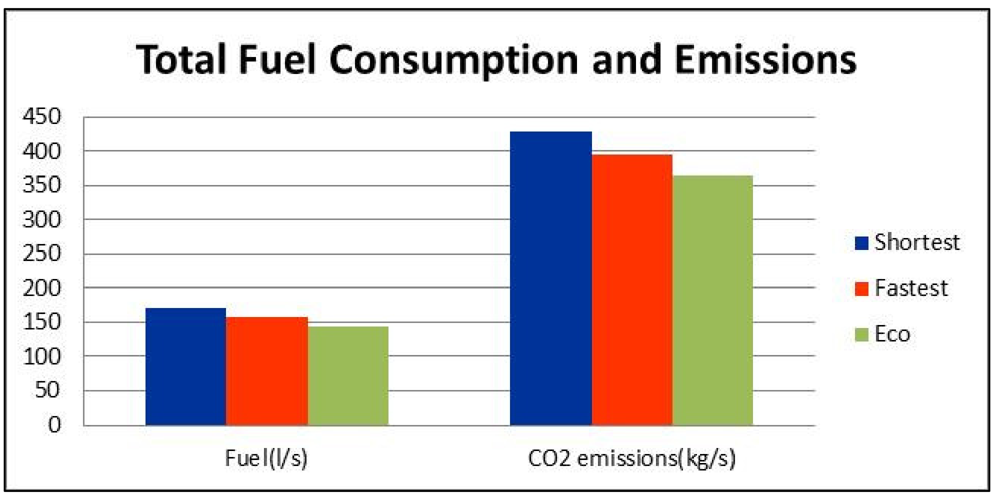

Figure 46: Shortest vs. Fastest vs. Eco (600 vehicles)

The results of the experiment are summarized in Table 10. The values are normalized to the result of the shortest-distance priority route. When comparing the three routing objectives, the eco-routing objective outperforms the shortest and fastest objectives in terms of all evaluated criteria.

Routing	Waiting Time	Travel Time	Fuel Consumption	CO_2 Emission	Evaluation
Shortest	1	1	1	1	⟷
Fastest	0.72	0.66	0.92	0.92	↓
Eco	0.37	0.56	0.85	0.85	↓

Table 10: Comparison of Experimental Results for Shortest vs. Fastest vs. Eco

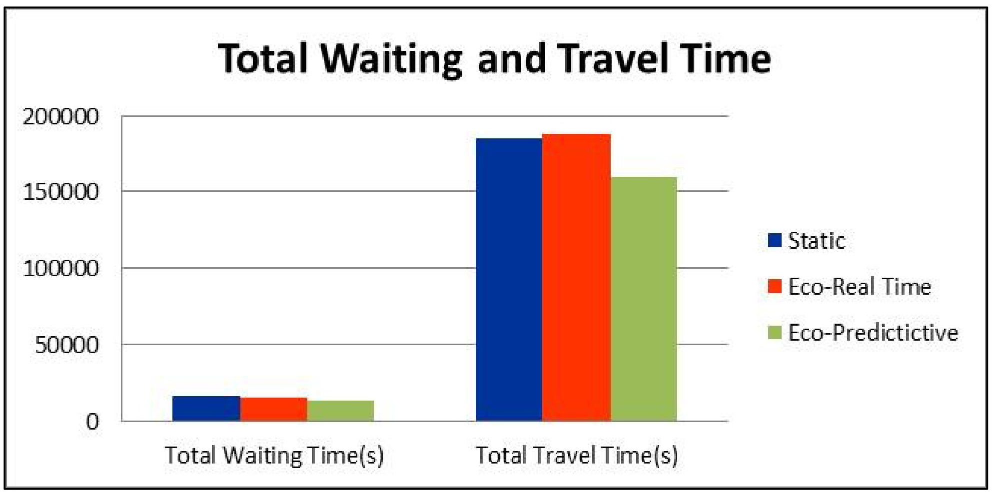

Figure 47: Static vs. Eco Real-time Dynamic vs. Eco Predictive Dynamic (600 vehicles)

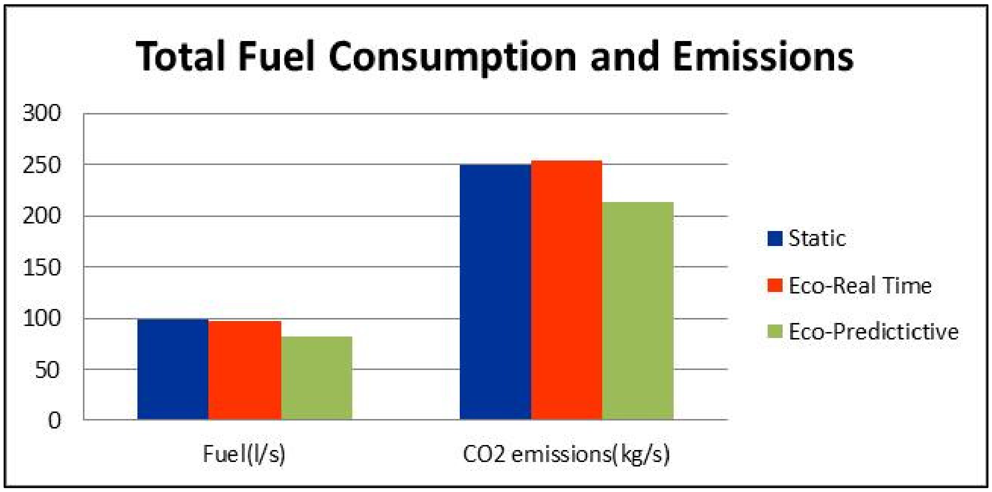

Figure 48: Static vs. Eco Real-time Dynamic vs. Eco Predictive Dynamic (600 vehicles)

The results of the experiment are summarized in Table 11. The values are normalized to the results of the shortest-distance priority route. When comparing the results of the three routing objectives, the dynamic predictive eco-routing objective outperforms the dynamic real-time eco-routing and static routing objectives. In this scenario, where traffic conditions are highly dynamic, real-time dynamic routing is rendered less effective compared to the static routing methodology, due to the rapidly changing traffic conditions.

Routing	Waiting Time	Travel Time	Fuel Consumption	CO_2 Emissions	Evaluation
Static	1	1	1	1	⟷
Real-time	0.94	1.01	0.97	1.02	⟷
Predictive	0.81	0.86	0.83	0.85	↓

Table 11: Comparison of Experimental Results for Shortest vs. Fastest vs. Eco

Experimentally, the resulting optimal route of the predictive dynamic routing approach outperforms the static and time-dependent routing approaches in terms of accuracy and efficiency. We further evaluated the proposed predictive dynamic routing methodology simulating the highest level of foreseen traffic congestion (i.e., 1,100 vehicles rather than 600) while holding all other simulation parameters constant. Figure 49 and Figure 50 illustrate the same enhanced performance in travel time, fuel consumption and CO_2 emissions for the proposed dynamic predictive eco-routing methodology.

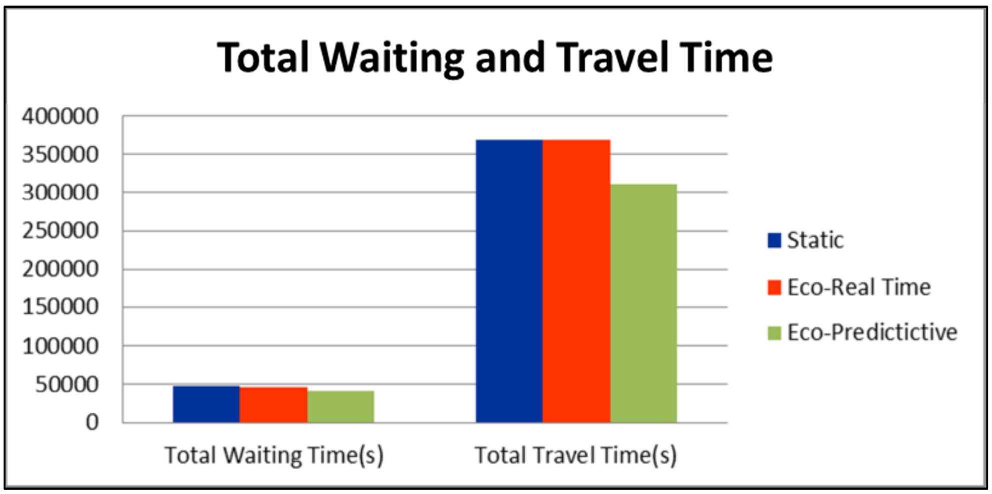

Figure 49: Static vs. Eco Real-time Dynamic vs. Eco Predictive Dynamic (1,100 vehicles)

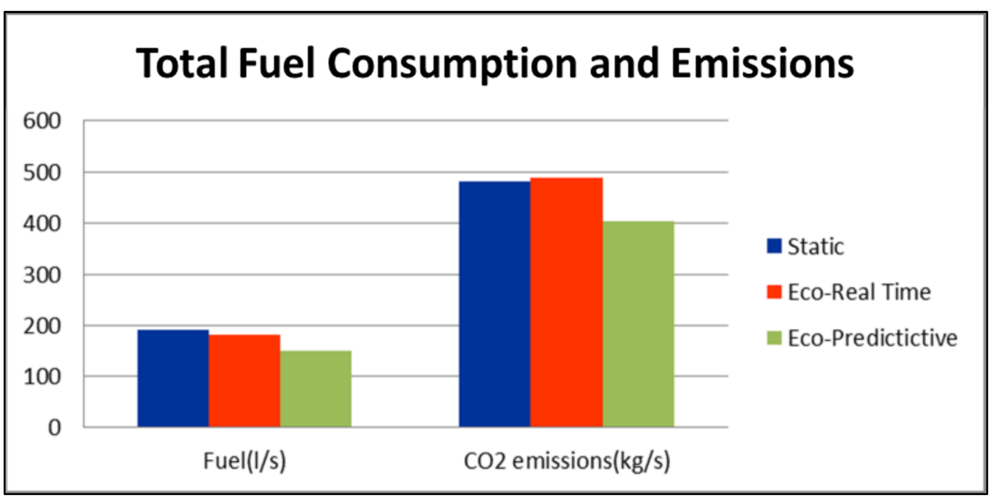

Figure 50: Static vs. Eco Real-time Dynamic vs. Eco Predictive Dynamic (1,100 vehicles)

The results of the experiment are summarized in Table 12. The values are normalized to the results of the static distance priority route. When comparing the results of the three routing objectives, the eco-routing outperforms the shortest and fastest objectives in all evaluated criteria.

Routing	Waiting Time	Travel Time	Fuel Consumption	CO_2 Emission	Evaluation
Static	1	1	1	1	↔
Real-time	0.97	0.99	0.94	1.01	↔
Predictive	0.88	0.84	0.78	0.83	↓

Table 12: Comparison of Experimental Results for Shortest vs. Fastest vs. Eco

Chapter 5

5 Conclusions and Future Research

5.1 Conclusions

In this section the product of the research is to be summarized; recommended future research is also being described.

We considered the problem of finding an optimal path between two points on a large-scale cost-dependent traffic network, which has a practical application in a progressive vehicle navigation system. The problem is traditionally solved with a shortest path or fastest path approach, which does not necessarily provide energy- and emission- optimized routing in all traffic situations. Vehicle energy consumption and emission depends heavily on changing traffic conditions. A highly congested fastest route does not offer minimum travel time or reduced emissions. An increased number of vehicles on limited roadway yields a decreased route throughput and results in longer vehicle waiting time, formerly known as congestion. Similarly a congested shortest path offers minimum travel distance, but it does not bring any benefit in minimizing travel time, energy consumption or emissions. Thus we proposed an efficient emission optimized route planning that incorporates traffic, vehicle and geographical information to enable the vehicle to move from the source to destination with the least travel time, energy consumption and emission.

First we reviewed existing static and dynamic routing methodologies and search algorithms. This allowed us to underline the necessity of an eco-friendly routing methodology with an integrated dynamic search engine. In the conventional static planning model, all travel times and traffic conditions are considered constant over time, resulting in less realistic travel costs for road segments. The static model was improved on in the extended deterministic static model, in which historical and real-time traffic information are considered in the route planning. However, more accurate representation of the traffic flow, and hence responsive routing, has been achieved with dynamic routing model. Furthermore and due to the fast changing traffic conditions historical and real-time traffic information inherently contain obsolete traffic information resulting in decreased certainty in planned route optimization performance. Therefore, we attempted to overcome this problem by proposing a routing methodology based on predictive traffic information. We further proposed a hybrid framework for processing and dissemination of traffic information, which overcomes the curse of dimensionality phenomena and its drawback of longer processing time. Moreover, our proposed algorithm is the first method to address a multi-criteria optimization through the proposed cost function, which includes a balanced approach in optimizing travel time, energy consumption and emissions. The resulting algorithm for vehicle route planning has enabled its extension to plug in electric vehicle, by incorporating the WTW emission model.

Following this approach, we are able to improve the efficiency of vehicle traveled route in terms of energy consumption, emissions and travel time. Improvement is mainly due to the pre-knowledge of traffic condition of routed vehicle. The computation experiments reported in this research, suggests that connected vehicles provides the capability of enhanced performance in route planning when combined with the low latency wireless communication technology DSRC.

We presented extensive computation experiments showing the benefits of our methodology in real world cases. The methodology was validated on a real world traffic network map. We analyzed and evaluated our route planning methodology to other methods identified in the literature survey.

In summary the product of the work is an Eco Predictive Dynamic vehicle routing methodology enhancing performance over all other routing methodologies in terms of travel time, energy consumption and emission.

5.2 Future Research

The prediction of traffic conditions is an ambitious task. Further enhancement to the performance of traffic assessment model may be made through a pre-knowledge on when traffic incident is to dissolve. Another important aspect is determining the precise relationship between the size of the unfolding PN and the planning problem, and accordingly identifying properties that guarantee completeness of the finite route.

These topics are relevant to further pursue performance enhancement to the predictive traffic assessment model. Equally extended future research is required to develop and evaluate benefits.

Chapter 6

6 Publications Related to This Research

Parts of this dissertation have appeared in the following publications:

([21][22][23][79][80][81][82][83][84][85][86][87][88]). Copyright is held by the editors, where applicable.

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