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VEHICLE-INFRASTRUCTURE INTEGRATION (VII) ENABLED PLUG-IN HYBRID ELECTRIC VEHICLES (PHEVS) FOR TRAFFIC AND ENERGY MANAGEMENT

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VEHICLE-INFRASTRUCTURE INTEGRATION (VII) ENABLED PLUG-IN HYBRID ELECTRIC VEHICLES (PHEVS) FOR TRAFFIC AND ENERGY MANAGEMENT

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ABSTRACT

Vehicle Infrastructure Integration (VII) program (also known as IntelliDrive) has proven the potential to improve transportation conditions by enabling the communication between vehicles and infrastructure, which provides a wide range of applications in transportation safety and mobility. Plug-in hybrid electric vehicles (PHEVs) that utilize both electrical and gasoline energy are a commercially viable technology with potential to contribute to both sustainable development and environmental conservation through increased fuel economy and reduced emissions. Considering positive potentials of PHEVs and VII in ITS, a framework that integrates PHEVs with VII technology was created in this research utilizing vehicle-to-vehicle and vehicle-to-infrastructure communications for transmitting real time and predicted traffic information. This framework aims to adjust the vehicle speed at each time interval on its driving mission and dynamically optimize the total energy consumption during the trip. Equivalent Consumption Minimization Strategy (ECMS) was utilized as the control strategy of PHEVs energy management for minimization of the equivalent energy. It was found that VII traffic information has the capability to benefit energy management, as presented in this thesis, while supporting the broader national transportation goals of an active transportation system where drivers, vehicles and infrastructure are integrated in a real time fashion to improve overall traffic conditions.

DEDICATION

This thesis is dedicated to my family and friends for their love and support...

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CHAPTER ONE

INTRODUCTION

The increasing demand for travel on highways in the United States is causing the transportation system to reach the limits of its existing capacity, which in turn has resulted in increased fuel demand and congestion, and degrading air quality. Today, nearly 60% of total U.S. petroleum consumption is satisfied by imported oil, and more than 60% of the petroleum is dedicated to transportation. In addition, the rapidly expanding petroleum consumption rates in developing countries may also threaten the sustainability of petroleum in the future (Markel and Simpson 2006). Based on 2007 Urban Mobility Report, congestion is getting worse in regions of every size in the U.S., which caused Americans an extra 4.2 billion hours in travel time and an extra 2.9 billion gallons of fuel consumption. The total cost of nationwide congestion amounts to$78 billion (Schrank and Lomax 2007).

Considering significant traffic increases anticipated in the coming decades, the United States and other countries have been working on technologies that can reduce the congestion and energy demand, and also maintain and improve the environmental condition. During the last few years, there has been an increasing concern over vehicle fuel efficiency in developed countries. There are several alternatives to petroleum for automobile use including hydrogen, ethanol, biodiesel, and electricity. Plug-in hybrid electric vehicles (PHEVs), which utilize both electrical and gasoline energy, is one of the commercially available options that may potentially contribute to a sustainable development of fuel resources, and improve the environment by increases in fuel economy and reductions in emissions.

PHEVs are considered a significant advancement of hybrid vehicle technology (Zorpette 2004). The biggest benefit of PHEVs is its advanced dual-fuel power train technology that combines the benefits of pure electric vehicle and hybrid electric vehicles (HEVs). Conventional HEVs are charge-sustaining, which means batteries are maintained at a roughly constant state of charge (SOC) (e.g., SOC = 0.3) while driving, and they are recharged only from on-board electricity generation by their respective internal combustion engines and the recapture of kinetic energy through regenerative mode of braking. PHEVs can operate in either charge-sustaining or charge-depleting mode, and they have a high energy density battery pack that can be externally charged and operated solely on electric power for a range longer than conventional HEVs, which results in a better fuel efficiency. (Williamson et al. 2006). Compared with other new vehicle technologies, the ability of PHEVs' dual-fuel power train technology has contributed significantly to energy utilization efficiency within the vehicle by reducing the consumption of liquid fuels. According to Environmental Protection Agency (EPA) data, PHEVs could reduce the consumption of fuel by at least 70 percent compared with other conventional vehicles.

Recently, highway congestion is not only the recurring "rush hour" delays in major cities, more than half of all congestion is non-recurring, caused by crashes, disabled vehicles, adverse weather, work zones, special events and other temporary disruptions to the highway transportation system. Reducing the number and severity of congestion is one of the major top priorities facing by the US Department of Transportation. Intelligent Transportation Systems (ITS) applications have been contributing to ease those increasing transportation limitations with modern information technologies and communication systems. Vehicle Infrastructure Integration (VII) program (also known as IntelliDrive) has the potential to improve transportation conditions by enabling the communication between vehicles and infrastructure, which provides a wide range of applications in transportation safety and mobility. As envisioned, a VII system involves equipping vehicles and roadside infrastructure with wireless communication interfaces that provide constantly changing data, such as speed, acceleration/deceleration, and position, to the traffic surveillance system, which can contribute to an accurate assessment of existing and predicted travel conditions.

Many existing studies have examined the feasibility of Dedicated Short Range Communication (DSRC) for VII. DSRC is one of the promising communication technologies for ITS. It is a short to medium range wireless protocol based on IEEE 802.11p (Chen and Cai 2005). It is considered as an accepted wireless communication technology for enhancing transportation safety and highway efficiency in VII application (Bai and Krishnan 2006). DSRC technology for ITS applications works at 5.9 GHz to support information transmission between vehicles and roadside devices. DSRC also enables any two DSRC-equipped vehicles to exchange information via ad-hoc networks that are set up spontaneously between vehicles as the need arises; examples include traffic signal violation warning, emergency brake notification, and cooperative collision avoidance (Chen and Cai 2005). Most existing studies have mainly focused on traffic safety applications. For examples, Chan (2005) and the California VII research group have come up with an on-board VII pedestrian safety system that enables vehicle-to-vehicle and vehicle-to-infrastructure communication for transmitting a pedestrian detection signal. Servin et al. (2006) studied different vehicle speed adoption strategies under various freeway congestion conditions and found that intelligent speed adoption technologies can lead to lower fuel consumption and pollutant emission.

Because of the current battery technology limitation, PHEVs can only sustain limited all electric range. Based on prototypes from the last decade, the all-electric range (AER) of PHEVs is in the range of 10 to 60 miles. The 2001 national household travel survey (NHTS) indicates that the majority of daily mileages are around 30 miles. However, the utility factor (UF), which indicates the fraction of total vehicle miles traveled (VMT) and occurs within the 30 miles of daily travel, is approximately 43%. This means that a PHEV which has 30 miles of AER can displace petroleum consumption equivalent to 43% of VMT. Higher AER can be obtained by using larger battery packs, however, further occupied in-vehicle space and total weight will result in higher energy consumption. Therefore, research is needed to optimize the power management strategies for PHEVs because of the limitations of space and vehicle weight.

As previously discussed, the difference of PHEVs from HEV is the added capability to recharge the battery with electricity from an off-board source. Energy management strategy is one of the most important issues in PHEV research. The basic strategy of energy management is to optimize the total energy in the vehicle, i.e., electric power and gasoline. The strategy also determines the power distribution between the fuel converter and electricity storage system at any time for different vehicle speeds.

The basic strategy of PHEVs is to optimize the charge-depleting mode which means to assure optimal utilization and regeneration of the total energy in PHEVs. A very simple strategy is operating PHEVs in the charge-depleting mode until energy system reaches a pre-defined threshold of SOC. Then PHEVs are operated in the charge-sustaining mode for maintaining the SOC until the end of the trip (Gong et al. 2008).

Recently, many power management studies have been conducted by using the global optimization approach that aims at minimizing the cumulative energy loss through the entire trip. A study by the Argonne National Laboratory on PHEVs power management with the approach of global optimization showed that a significant improvement in fuel economy is achieved when the global optimization method is applied (Karbowski et al. 2006). However, global optimization approach relies on the prior knowledge of the driving cycle. Therefore, this method is not applicable for real-time implementation. Another power management approach is called adaptive equivalent consumption minimization strategy (A-ECMS) (Musardo et al. 2005). This strategy is developed based on the online adaptive estimation of an equivalence factor which requires current and past driving information, which makes this method more suitable for charge-sustaining operation.

According to the power management strategies previously described, traffic information takes an important role in most of them. Traffic information such as travel speed, travel time, acceleration and deceleration, and roadway geometric information can be can be easily obtained by the traffic surveillance systems. With the assistance of ITS technologies, people are able to make smart travel choices through utilizing these information. For example, travelers can get geometric information of their intended route, such as spatial profile, from Traffic Management Center (TMC) or roadside units by vehicle to infrastructure communication. Meanwhile, drivers can send and receive traffic information such as travel time, and speed. Then the alternative routes can be calculated based on the travel cost in terms of travel time and energy consumption. All the historical or real time traffic information will contribute greatly to PHEVs for optimizing the power management strategy. Many studies have been undertaken to develop PHEVs power management strategies based on traffic information provided by ITS technologies. Gong et al. (2007, 2008) concluded that with the assistance of on-board Global Positioning System (GPS), PHEVs can predict traffic by utilizing real time and historical traffic information. Then PHEVs may attain a nearly global optimal power management with least fuel consumption. Manzie et al. (2006) analyzed fuel economy of hybrid vehicles and telematics-enabled vehicles, which receive real time traffic information to adjust their drive cycle, through a simulation analysis. The telematics-enabled vehicles are equipped with on-board sensors and are able to communicate with roadside units to receive traffic flow information. They found that hybrid vehicles improve fuel economy about 15% to 25% compared to baseline vehicles, whereas vehicles with telematics capabilities had improved fuel economy similar to that of hybrid vehicles with less than 60 seconds preview of traffic information. The vehicles with telematics capabilities exhibited improved fuel economy up to 33% compared to the baseline vehicles with a preview of traffic flow information up to 180 seconds.

A reliable analysis of historical trend and real-time data of traffic condition is an important element to a traffic management and control system. Over the last decades, traffic condition prediction has played an important role for various ITS applications. There are three different types of traffic condition forecasting: long-term traffic forecasting, short-term traffic forecasting and mid-term traffic forecasting. In this study, short-term traffic prediction is considered to determine the traffic volume, travel speed, and travel time in the next time window, which means predicted traffic conditions. With the increasing deployment of ITS, the demand for the accurate short-term traffic condition forecasting is increasing. Relying on the historical and real-time data of the traffic system obtained by traffic infrastructure, traffic management centers have the ability to predict future traffic conditions on the roadways.

VII has been evaluated in the U.S. for traffic condition monitoring, emergency message dissemination, dynamic route scheduling, and safe driving through field operational tests. It has also provided an opportunity to directly collect the historical and real-time traffic data and process those data for traveler information system. In a VII system, the equipped vehicles and roadside infrastructure with wireless communication interface will make it possible to constantly sample the travel time, flow, and density of the travel population (Ma et al. 2009). The expected availability and quality of the traffic information would in turn increase the performance and capability of the traffic condition prediction system. It is obvious that the VII coverage depends on the deployment of roadside infrastructure over the network. In this thesis, it is assumed that roadside equipment (RSE) is installed in the entire network and that the VII information can be transferred to RSE without error and loss.

In this thesis, artificial neural network (ANN) is utilized for a VII based short-term online travel speed and time prediction. Travel time prediction is becoming increasingly important in traffic operations (Chen and Chien 2001). Providing travel time information on available alternative routes to travelers is believed to be an effective factor on influencing driver behavior and route/departure time decisions, which in could contribute to overall time savings and the reliability of predicted travel times on the travel network (Lint 2008). Thus, travel time prediction is an important function of the VII system for generating the alternative routes between origins and destinations. In the past, various approaches have been developed to predict traffic conditions. Some algorithms are based on statistical analysis of historical and real-time data with linear models (Zhang and Rice 2003) or Kalman filtering theory (Rice and Van Zwet 2004, Chen and Chien 2001), simulation based dynamic traffic assignment model (Ben-Akiva et al. 2002, Mahamassani 2004), and neural network models (Park et al. 1998, Vanajakshi and Rilett 2004, Van Lint 2005, Yasdi 1999). In this thesis, a multi-layer perception artificial neural network (ANN) with back propagation algorithm is used in the prediction model because of its excellent predictive capacity with learning capability. Various traffic variables can be used as input to the ANN in the short-term traffic condition prediction problems. The short-term prediction is based on the current incoming data which treats historical data or real-time data as the input of the ANN for prediction of the future traffic condition. The first predicted output value is used as one of the lagged inputs for the next prediction. This procedure is continued until the end of predictions.

Considering the positive potentials of PHEVs and VII in ITS, a framework that integrates PHEVs with VII technology will be created, which utilizes vehicle-to-vehicle and vehicle-to-infrastructure communications for transmitting real time traffic information. Such a system would actually guide these vehicles dynamically to optimize the total energy consumption during the trip. At the same time, the VII enabled PHEVs are expected to receive predicted traffic information for adjusting the vehicle speed at each point on its driving mission. Corresponding to the predicted travel time and energy consumption, PHEVs can be able to take the optimized traffic routes with the continuous knowledge of real-time changes in traffic loadings.

Therefore, the objective of this thesis is to derive a flexible and easy-to-implement in-vehicle energy management control strategy that uses microscopic online trip data derived through VII to optimize vehicle fuel and energy consumption to minimize total trip costs. The remaining chapters of the thesis are organized as follows. Chapter 2 presents a literature review related to this thesis. Chapter 3 describes the research methodology and the development of the integrated framework of the proposed VII-enabled PHEVs traffic prediction and energy management systems. Chapter 4 presents the results from a case to evaluate and analyze the performance of the proposed framework. The last chapter presents conclusions derived from this study and recommendations for the further research.

CHAPTER TWO

LITERATURE REVIEW

The capability of obtaining traffic information is expected to improve the performance of PHEVs by reducing energy consumption, emissions, and travel time from their origins and destinations. In this chapter, the first section provides a review of the previous studies of the applications of the VII system. The second section discusses different power control strategies of PHEVs. The third section presents previous research on traffic condition prediction. Finally, a summary of the previous studies on integrating traffic management with power management is provided.

2.1 Vehicle Infrastructure Integration (VII)

Since 2003, FHWA has sponsored several Vehicle Infrastructure Integration (VII) projects nationwide. Many states have participated in the VII program. California and Michigan have conducted field tests for evaluating the feasibility of different applications of VII, and identifying the architecture of a full-scale VII deployment.

VII California has tested various VII applications for on-line traffic condition assessment (VII California 2006). Under the California Partners for Advanced Transit and Highways (PATH) program, an on-board VII safety system has been implemented that enables vehicle-to-vehicle and vehicle-to-infrastructure communications for transmitting a pedestrian detection signal (Chan and Bu 2006) and a cooperative active safety warning system for slippery road warnings (Misener 2005). VII Michigan proposed a VII Data Use Analysis and Processing (DUAP) system that includes a framework for identifying usages of the VII data in management and operation of the transportation system in Michigan.VII enabled vehicles are expected to collect location, speed, and headway data, and transmit the data through the supporting VII and private networks. Under this framework, other data, such as braking status, accelerations, and weather conditions, can be provided by vehicle sensors. The DUAP system receive and process the information with a consistent set of traffic, environmental, and asset data, which is then merged with traditional traffic data used for providing traveler information (Cole 2007).

Some studies focused on vehicle-to-vehicle communication for generating travel time information. Xu and Barth (2006) evaluated different algorithms that estimated travel times through inter-vehicle communication (IVC). Relying on vehicle-to-vehicle DSRC-based communication, link travel time estimation is updated by the vehicle when it exits that link. This research found that 97% of the links in the network have estimated link travel time errors of less than 10%. Wunderlich et al. (2007) performed experiments utilizing vehicle trajectory data from the field to simulate the VII probe process and characterize the capability of using VII probe data to estimate travel time. The trajectory data is a snapshot that contains a record of vehicle position, current speed, and vehicle status information. The snapshots are generated at various rates depending on the current speed of VII-enabled probe vehicles. This experiment revealed that severe congestion can impact the availability of snapshot data for travel time calculation. The accuracy of travel time estimation decreases with a reduced snapshot rates.

Currently, VII is called IntelliDirve, and it combines advanced wireless communications, vehicle sensors, GPS navigation, on-board computer processing, and smart infrastructure that give vehicles the capability to identify threats and hazards on the roadways and give alerts and warnings to drivers (IntelliDrive^{SM} 2009). The core concept of IntelliDrive is an intelligent network operation that supports high speed data transmission among vehicles, and between vehicles and infrastructure components, or hand held devices. IntelliDrive has the potential to improve transportation safety and mobility, and reduce environmental impact (IntelliDrive^{SM} 2009).

2.2 Energy Management Strategies of Plug-in Hybrid Electric Vehicle (PHEV)

Plug-in hybrid electric vehicles' fuel economy and emission rate not only depend on battery capacity, but also rely on the energy management strategy. The basic function of energy management is to assure optimal use and regeneration of the total energy in the vehicle. At any time and for any vehicle speed, the control strategy has to determine the power distribution between primary fuel converters (FC)—internal combustion engine (ICE) and renewable electrical storage system (ESS) or the battery (Pisu and Rizzoni 2007).

Basically, there are two constraints in energy management. First, the motive power requested by the driver must always be satisfied up to a known maximum power demand. Secondly, the state of charge of the ESS must be maintained within preferred limits, allowing the vehicle to be charge-sustaining. A charge-sustaining strategy is an energy management scheme such that the energy stored in the ESS at the beginning and at the end of the trip is the same, while a charge-depleting strategy is such that the energy stored in the ESS at the end of the trip is less than at the beginning of the trip. Within these constraints, the first objective is to operate the power train to achieve the maximum fuel economy. Ideally the motive power must be split between ESS and fuel converter at each time to minimize the overall fuel consumption over a given trip according to the Equation (2.1).

$$\min_{\{P_{fc}(t), P_{el}(t), \gamma(t)\}} \int_0^T \dot{m}_f(\tau)\, d\tau \tag{2.1}$$

$$\text{subject to: } \left\{ \begin{array}{c} P_{req}(t) = P_{fc}(t) + P_{el}(t)\ \forall t \\ 0 < SOC_{MIN} \leq SOC \leq SOC_{MAX} \leq 1 \\ 0 \leq P_{fc}(t) \leq P_{fc_{MAX}} \\ P_{el_{MIN}} \leq P_{el}(t) \leq P_{el_{MAX}} \end{array} \right\}$$

where: *T* is the duration of the trip,

$\dot{m}_f(t)$ is the fuel flow rate at time *t*,

$\gamma(t)$ is the gear selection,

$P_{el}(t)$ is the power provided by the ESS at time *t*,

$P_{fc}(t)$ is the power provided by the fuel converter (engine only, engine plus generator or fuel cell depending on the configuration) at time *t*,

$P_{req}(t)$ is the power requested by the driver and

SOC is the state of charge of the ESS.

Generally, energy management strategies can be classified into three types: global optimization methods, heuristic methods, and instantaneous optimization methods. Global optimization methods are based on dynamic programming (DP) technology. It seeks a global optimal solution for the complete driving trip. However, prior knowledge of the driving cycle for global optimal solution is required. Thus, the application of this method is very limited. Many studies implemented various methods to make up this limitation of global optimization. Lin et al. (2003) designed a rule-based controller that extracts rules from DP control results. Rule-based power management strategy aims to find the optimal power split between the engine and motor for a parallel hybrid electric truck during charge sustaining mode. A power split ratio is defined as $PSR = P_{eng}/P_{req}$, where P_{eng} is the power from the engine and P_{req} is the power requested from the driver. Different values of PSR correspond to different operating modes including motor only ($PSR=0$), engine only ($PSR=1$), power-assist ($0<PSR<1$), and recharging mode ($PSR>1$). This study demonstrated that the power management strategy for HEVs, by extracting rules from the Dynamic Programming, has the clear advantage of being near-optimal, accommodating of multiple objectives.

Heuristic methods are more oriented to real-time implementation and have the advantage of not requiring precise equations or models for the system. They are often non-portable, require extensive calibration, and do not provide a global optimal solution. Schouten et al. (2002) provided a fuzzy logic controller (FLC) for parallel hybrid vehicles. The power controller first converts the accelerator and brake pedal inputs of the driver into a driver power command. Then the driver power command, state of charge of the battery, and electric motor speed are used by a fuzzy logic controller to compute the optimal generator power and a scaling factor for the electric motor. The driver power command, optimal generator power, and scaling factor are used to compute the optimal ICE and EM power. Furthermore, the efficiency of the ICE for a given power level is optimized by using an optimal speed-torque curve, and gear shifting to control the speed of the ICE. The efficiency of FLC was compared to the default controller without intelligent control strategy, which indicated that FLC could improve the efficiency of power train.

Instantaneous optimization methods, based on the local minimization of a fuel consumption function, are advantageous in deriving a local optimal solution that is charge-sustaining, easy to implement, portable and easy to calibrate. The complexity is shifted to off-line calculations and the challenge arises in the correct formulation of the fuel consumption function, especially when several objectives must be optimized simultaneously (e.g. fuel consumption, emission, and battery life) for the energy minimization. Equivalent Consumption Minimization Strategy (ECMS) (Paganelli et al., 2002; Sciarretta et al., 2004; Pisu et al., 2007) is one of the instantaneous methods. Because it is intrinsically charge-sustaining and requires only current and past driving information, this strategy is widely applied for optimizing HEVs energy consumption.

In ECMS approach, the global criterion given in Equation (2.1) is replaced by a local criterion (Equation 2.2), thusly reducing the problem to minimized an equivalent fuel consumption function $\dot{m}_{f,eq}(t)$, which contains information regarding actual fuel consumption and future fuel saving/cost.

$$\min_{\left\{P_{fc}(t), P_{el}(t), \gamma(t)\right\}} \dot{m}_{f,eq}(t) \quad \forall\, t \tag{2.2}$$

Although, the global minimization problem represented in Equation (2.1) is not strictly equal to the local minimization shown in Equation (2.2). However, local minimization results in a formulation amenable to real-time control, while the use of the equivalent fuel flow rate indirectly accounts for the non-local nature of the problem. In this thesis, ECMS is utilized as the control strategy of PHEVs energy management for minimization of the equivalent energy consumption as given by Equation (2.2).

2.3 Online Traffic Condition Prediction

With the development of ITS, there has been an increased interest in the use of predicted traffic conditions to positively influence travelers' departure time and route choice. Many approaches have been developed on short-term forecasting algorithms. Some methods are based on statistical methods such as time series analysis (Sun et al. 2005), the Kalman filtering method, and linear regression techniques (Kwon et al. 2000, Zhang and Rice 2003). Kwon et al. (2000) explored using linear regression and advanced statistical methods for prediction of travel time based on historical and real-time traffic flows and densities. They derived a simple linear regression model to provide appropriate short-term travel time forecasting by collecting the current travel time of probe vehicles. Similarly, Zhang and Rice (2003) proposed a short-term freeway travel time prediction method based on a linear regression model. The implementation of this methodology included off-line computation and storage of the estimated model coefficients for different departure time and prediction horizons. The model was able to predict the travel time utilizing the incoming data and model coefficients. However, this linear regression travel time prediction model used linear relationships between measured speed at each sensor location and travel time between two installed loop detectors. Thus, the accuracy of those applications is limited by the availability and reliability of loop detectors.

Artificial intelligent techniques have been extensively used in traffic flow, speed and travel time prediction. Vanajakshi and Rilett (2004, 2007) presented travel time and speed prediction models by means of artificial neural network (ANN) and support vector machine (SVM) methods. The authors found that ANN prediction models have the disadvantage of providing no information about the relative importance of the various parameters, unlike statistical models. ANN prediction models depend strongly on the amount of available data for training the network. For limited or missing data, the trained ANN data cannot represent all situations. To address these problems, the authors explored support vector regression (SVR) model, which combines pattern classification and regression techniques. Vanajakshi and Rilett (2004, 2007) demonstrated that traffic speed and travel time prediction for the next two minutes using SVR performed better than ANN. Van Lint et al. (2005) proposed freeway travel time prediction framework using a state-space neural network (SSNN) that predict travel time in each roadway section to derive the future travel time of the entire route. They found that SSNN is not sensitive to missing data, and is robust to either random or structural absence of input data. They concluded that the SSNN model can provide satisfactory results in real-time applications even though part of the data is missing.

Previous studies demonstrated that SVR is applicable to travel time predictions. Wu et al. (2004) proposed to use SVR for short-term travel time prediction. They found that SVR requires less computational resources, and can rapidly converge without local minimization. An effective prediction algorithm must consider both recurring traffic patterns and non-recurring spontaneous traffic events. Castro-Neto et al. (2008) provided an on-line support vector regression (OL-SVR) model to predict traffic flow under typical and atypical traffic conditions. They pointed out that OL-SVR has the advantage to predict nonrecurring traffic compared with other algorithms. Park (2002) employed a hybrid neural-fuzzy methodology that used fuzzy C-mean (FCM) to classify traffic patterns into clusters, and then used radial basis function (RBF) NNet to predict future traffic conditions within clusters.

Typically travel time prediction method uses historical mean traffic flow variables, such as speed, flow and density being measured by inductive loop detectors or by other roadside sensors as input variables to predict travel time. The indirect estimation of travel time by those inputs may introduce additional errors into the travel condition prediction.

The majority of existing travels condition prediction methods use densely-placed traffic sensors, such as video and loop detectors, to estimate travel time (Zou, 2007). These sensors are typically placed at a spacing ranging from every half mile to a quarter of a mile. With these methods, travel time is predicted indirectly based upon traffic sensor measurements, such as volume, density and speed, which may introduce additional errors into the travel condition prediction. In addition, existing travel time prediction models perform poorly under the impact of unexpected incidents (Van Lint, 2005).

Oak Ridge National Lab (ORNL) energy division researchers along with researchers at the University of Texas at Austin and the Massachusetts Institute of Technology developed a real-time Traffic Estimation and Prediction System (TrEPS). TrEPS uses traffic surveillance data to estimate and predict traffic network conditions, and to provide information that helps travelers to select the best routes, and TMCs to anticipate and avert traffic congestion. Using real-time traffic data from roadside sensors, TrEPS can be utilized predict short term traffic conditions and traffic flow patterns to assist TMCs in producing proactive traffic control actions that reduce congestion.

2.4 Integration of Traffic Management with Power Control Management

Many studies have been undertaken to develop PHEVs power management strategies based on traffic information provided by ITS. Gong, Q., et al (2007) (2008) developed a global optimization scheme of PHEV power management under a trip modeling framework that implemented ITS technology, such as communication between

PHEV and transportation infrastructures. With the assistance of an on-board Global Positioning System (GPS), PHEVs can predict the travel/driving profile by utilizing real time and historical traffic information sent by roadside sensors. Manzie et al. (2006) analyzed the fuel economy of hybrid and telematics-enabled vehicles, through a simulation analysis, which receive traffic flow information to adjust their drive cycle. The telematics-enabled vehicles are equipped with on-board sensors, and are able to communicate with roadside units. They found that hybrid vehicles had an improved fuel economy of 15% to 25% compared to baseline vehicles, whereas vehicles with telematics capabilities had an improved fuel economy similar to that of hybrid vehicles with less than 60 seconds preview of traffic information. The vehicles with telematics capabilities exhibited improved fuel economy up to 33% compared to the baseline vehicles with a preview of traffic flow information up to 180 seconds.

National Renewable Energy Laboratory (NREL) implemented an approach that employs route-based control to improve HEV efficiency at minimal additional costs (Gonder 2008). Gonder evaluated a range of route-based control approaches and identified look-ahead strategies (using input from “on-the-fly” route predictions) as an area meriting further analysis.

2.5 Summary of Literature Review

The literature review revealed the following limitations related to research on energy management of PHEVs using real time traffic data. First, previous studies on PHEVs power control strategy utilized standard driving cycles that can not reflect the real operating conditions on roadways. Although the global optimization method has demonstrated great potential for achieving good fuel economy, it is difficult to know all of the trip information in advance. Another difficulty is the computational load for global optimization algorithms in the microprocessor of PHEVs. Considering the feasibility of online PHEVs energy management control, ECMS is a better control strategy for VII enabled PHEVs because of its characteristic of local minimization control.

Most travel time prediction approaches were based on historical and real-time macroscopic traffic data collected by loop detectors. Limited research has been undertaken on using VII generated microscopic traffic data to predict roadway conditions. This study propose to utilize historical and real-time traffic data collected by VII enabled vehicles to predict travel time and traffic speed. For predicting speed profile, VII generated speed data has been proven to be more accurate in presenting the real driving conditions, which in turn provides better energy management for VII-enabled PHEVs.

CHAPTER THREE

METHODOLOGY

This chapter discusses the methods employed to conduct the study on VII enabled PHEVs. As shown in Figure 3.1, the methodology has two main parts; VII transportation system modeling for predicting traffic condition, and PHEV QSS modeling for optimizing energy consumption.

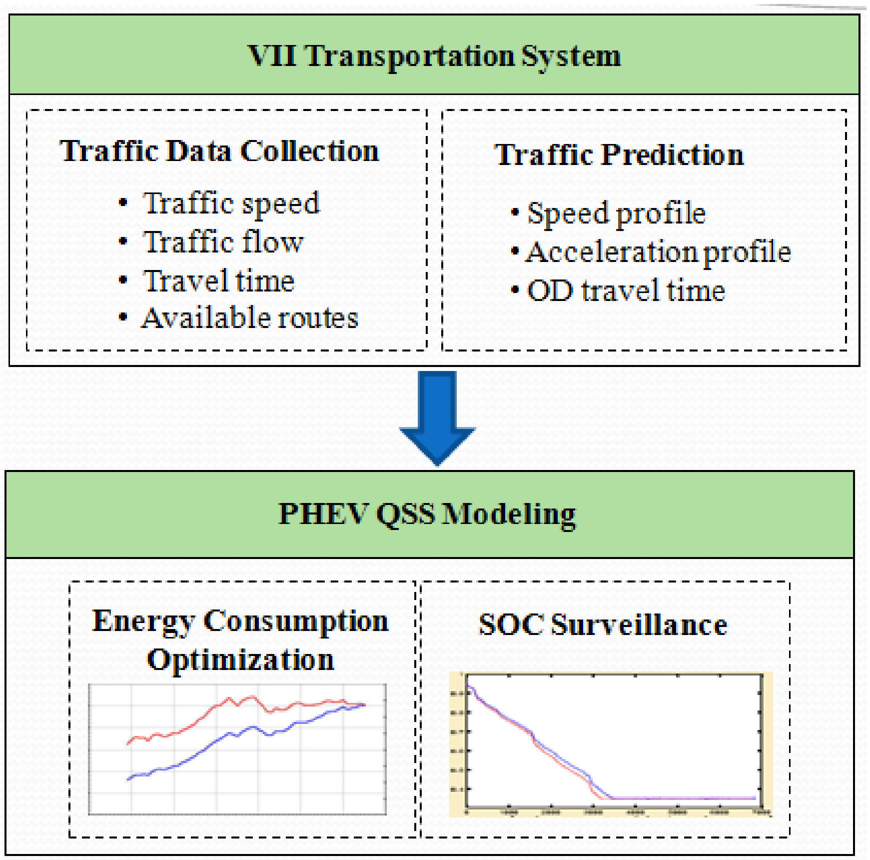

Figure 3.1 Research Methodology

3.1 Traffic Condition Prediction Model

To achieve an effective and economic trip, the prior knowledge of traffic conditions is quite useful. In this thesis, a short-term prediction of traffic conditions is developed by utilizing artificial neural network (ANN).

ANN is an intelligent computing technique that is composed of a hierarchy of processing units, which organized in a series of two or more mutually exclusive sets of neurons or layers. Particularly, multilayer feed forward artificial neural networks (MLFF-ANN) that utilize a back propagation algorithm have been applied successfully to solve some complex problems by training them in a supervised learning environment. As shown in Figure 3.2, a MLFF-ANN model consists of one input layer for distributing a set of input data into the next layer, one output layer to point the overall mapping results of the available inputs, and one or more hidden layers to process the back propagation algorithm by adjusting weights between all neurons repeatedly until the actual output maps the desired target in a certain error range. The repeating process is called training, which aims to solve several issues for the MLFF-ANN. One of them is selecting the number of hidden layers and neurons in the hidden layers. Another issue is finding globally converging solution to avoid local minimization in a reasonable period of time. At last, validating the MLFF-ANN is necessary by inputting the testing data set.

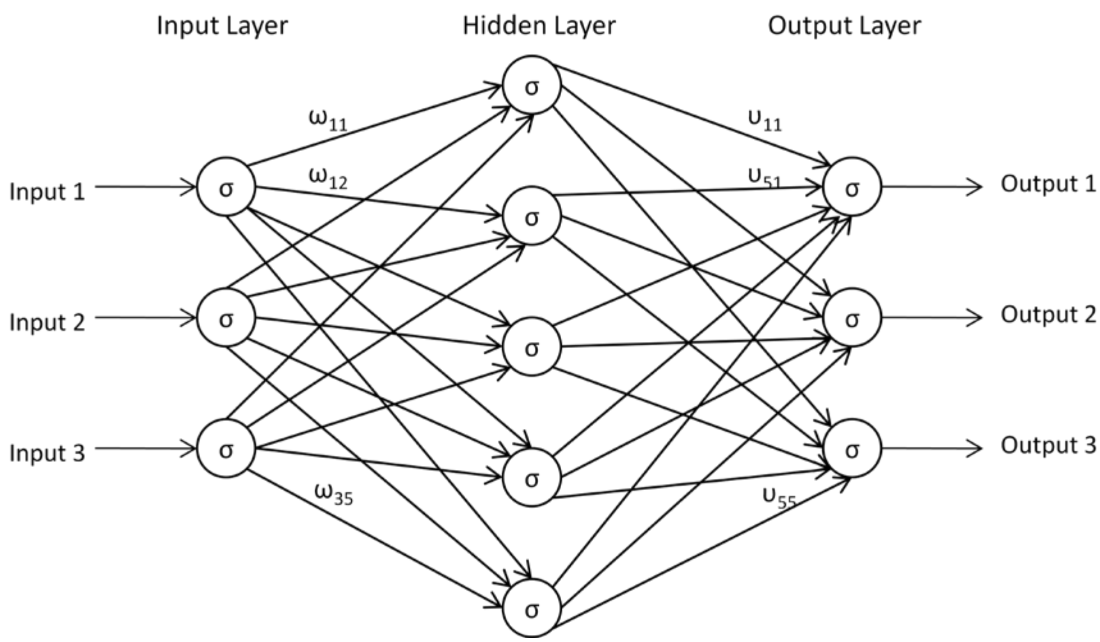

Figure 3.2 Multilayer Feed Forward Artificial Neural Networks Structure

With the learning capability, ANN model is suitable for solving problems like prediction of traffic parameters (e.g., travel time, flow and speed). Hence, in this thesis, a MLFF-ANN with back propagation algorithm was considered to predict travel time and speed.

For predicting travel time, the architecture of MLFF-ANN was composed as follows: five neurons in the input layer, single hidden layer with 10 neurons and 1 output neuron for output layer. A typical online time series prediction procedure was used with a prediction horizon time step of 1 minute. Given the travel time in a time series $x(t)$, $t = 1, 2, \dots$ and the prediction target $x(t+1)$ that is generated, a set of training samples were used to train the MLFF-ANN model. The MLFF-ANN training procedure was done in the following fashion:

In each of the travel time profiles from origin to destination (OD), the first 5 data points (OD travel time departure at 16:00, 16:01, 16:02, 16:03, 16:04) were used as input, with the 6th data point (OD travel time departure at 16:05) being the target. Then the 5 data point input window moves ahead, incorporating the 6th data point to generate a new 5 data points input (OD travel time departure at 16:01, 16:02, 16:03, 16:04, 16:05). Meanwhile, the 7th data point (OD travel time departure at 16:06) is considered the target. This procedure continues until the last data point (OD travel time departure at 19:00) becomes the target. The OD travel time profiles of each route during three days were utilized to train the MLFF-ANN model. The model was tested on the 4th day of OD travel time data.

To evaluate the prediction performance of the MLFF-ANN model, absolute percent error (APE) and mean absolute percent error (MAPE) were employed (Equations 3.1and 3.2, respectively).

$$\mathrm{APE}(\%) = \frac{|y_i - \hat{y_i}|}{y_i} \times 100\% \qquad (3.1)$$

$$\mathrm{MAPE}(\%) = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y_i}|}{y_i} \times 100\% \qquad (3.2)$$

where $\hat{y}_i$ is the predicted OD travel time for observation i; y_i is the actual OD travel time for observation i; n is the number of predictions.

Since the driving cycle input of PHEV QSS model is functioned in one second time step, the speed profile prediction should be also in one second time step. It is impossible to get speed data in each second along the roadways by loop detectors economically. In this thesis, VII generated speed data was considered as the traffic data source. VII enabled vehicles are viewed as mobile sensors that can collect real-time traffic data in every time step. The data will be stored and send in package in every prediction time window from VII enabled vehicles to roadside infrastructure agents.

Similar to OD travel time prediction model, speed profile prediction model also utilizes a typical online time series prediction procedure to predict traffic speed. The architecture of this MLFF-ANN speed profile prediction model has 60 neurons in the input layer, 50 neurons in single hidden layer, and 120 output neurons. Assuming the current time is t, the input neurons include a set of speed data *f(t), f(t-1), …, and f(t-59)* at time *t, t-1, …, t-59* respectively. Based on these historical and real-time data, the future speed values of $f(t+1), f(t+2), \ldots, f(t+120)$ can be predicted. Then the predicted speed values of $f(t+61), f(t+62), \ldots, f(t+120)$ will be used as the input data for next prediction step to predict speed values *of* $f(t+121), \ldots, f(t+240)$. This procedure continues until the last speed of the trip is predicted. The author utilized 80% of the speed samples in training and the remaining samples were used in the testing the MLFF-ANN model.

3.2 PHEV QSS Modeling

In this section, a series PHEV model was built up using QSS Toolbox (QSS-TB). QSS-TB is MATLAB/Simulink based software that contains general structures of common elements of vehicles, such as the internal combustion engine, electric motor, battery system, etc. It is quite flexible in combining different energy components to feature the drivetrain of any types of existing vehicle model.

3.2.1 Series PHEV

In series PHEVs, traction force is provided by the electric motor. The power sources of this motor are an engine-generator set and electricity storage system as shown in Figure 3.3. The arrows indicate the energy flows among all the components of a series PHEV. There are two forms of energy, mechanical power and electric power. The double-headed arrows signify that it is possible for the electric power flowing in both directions at different times. The energy flow from the internal combustion engine (ICE) is unidirectional because it represents the irreversible engine process (Pisu and Rizzoni 2005). The output of the generator is connected to the electric motor through a Power Converter. The electric storage system can be recharged by the off-board power grids or by the ICE to extend the range of charge depleting mode. While the vehicle is driven at low speeds, the electricity from the battery system draws power to drive the electric motor that is in full electric vehicle mode. During acceleration or high speed driving, in addition to the power drawn from the battery system, the generator, which is powered by the ICE, also provides extra energy to drive the vehicle.

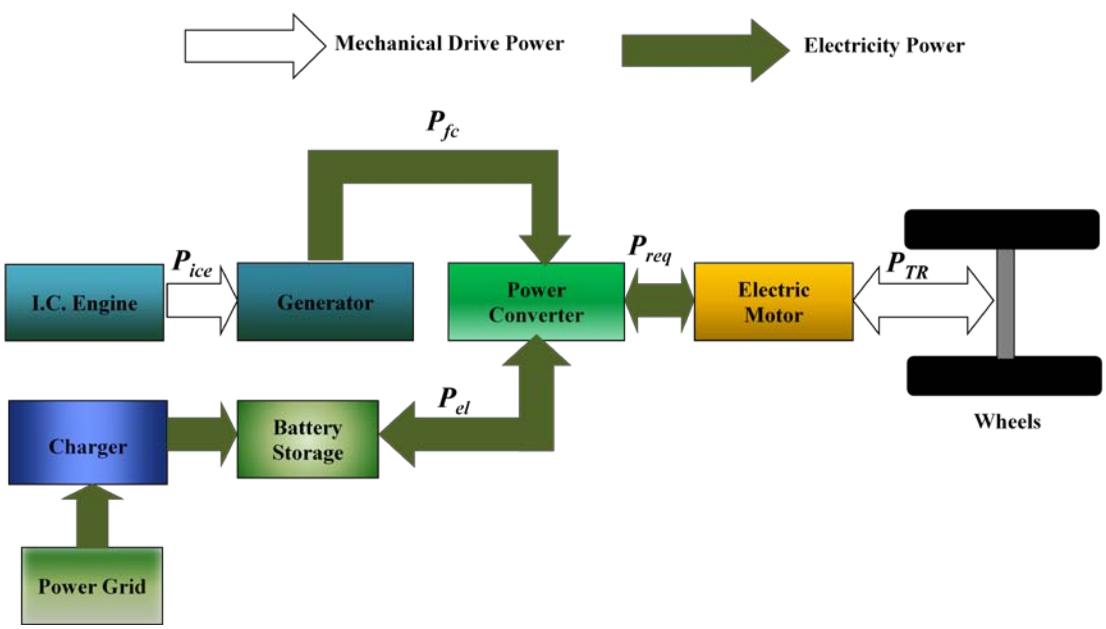

Figure 3.3 Series PHEV Components and Power Flows

Table 3.1 indicates the main specifications used in the PHEV model. The model is characterized as mid-size sedan with 70 horse power (hp) of engine and 8.11 kilowatt hour (kWh) battery system. The battery system is constructed by 18 packs that is 2.23 Ah current and 201.6 voltages. Each of battery pack is combined by 61 cells in series. Thus, the total energy that the battery system can provide is 8.11kWh.

Table 3.1 Parameters of Resistance and Vehicle Model Specifications

Total weight (M)	1256 kg
Projected frontal area (A_f)	2.16 m^2
Aerodynamic drag coefficient (C_d)	0.26
Ambient air density (ρ_a)	1.18 kg/m^3
Rolling friction coefficient (C_r)	0.007
Transmission efficiency	0.98
Final gear ratio	3.5
Engine power	70 hp
Motor/Generator power	67 hp
Motor/Generator efficiency	0.95
Battery construction	61 cells of 2.23-Ah cylindrical battery in series for each pack
Battery packs	18
Battery capacity	8.11 kWh
SOC window	30% ~ 80%

Assume a vehicle moves on a straight roadway with speed *v* and acceleration *a*, the tractive force to propel the vehicle forward must overcome the opposing forces that are air resistance, rolling resistance, grade resistance, and inertial resistance as shown in Figure 3.4 and Equation 3.3.

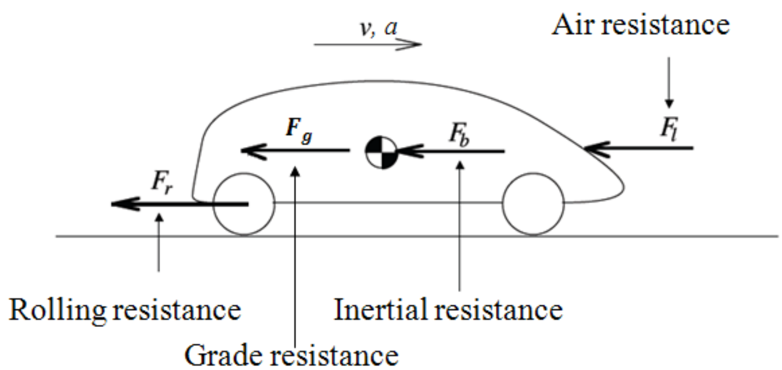

Figure 3.4 Force Diagram of Vehicle

$$F(t) = F_l + F_r + F_g + F_b \tag{3.3}$$

Based on the predicted velocity and acceleration profiles over the desired driving route by the in-vehicle processors and the known road grade, it is possible to determine an estimate of the vehicle power demand at the wheels expressed as Equation 3.4,

$$\hat{P}_{TR}(t) = F(t)\hat{v}(t) = \frac{1}{2}\rho_a C_d A_f v^3(t) + Mg\cos\alpha(t)C_r v(t) + Mg\sin\alpha(t)v(t) + Ma(t)v(t) \tag{3.4}$$

where ρ_a is the ambient air density, C_d is the aerodynamic drag coefficient, A_f is the projected frontal area of the vehicle, C_r is the rolling friction coefficient, M is the vehicle total mass, g is the gravity, $\alpha(t)$ is the road grade, $\hat{v}(t)$ is the predicted vehicle velocity, and $\hat{a}(t)$ is the predicted vehicle acceleration. Table 3.1 indicates the values of those parameters.

The power required during each time step is calculated directly from the estimated drive cycles. The required power is then translated into torque and the required speed of the electric motor. Taking into consideration the losses of the electric motor and transmission losses between each energy component, like the generator and ICE, the power flow is calculated backward through the drive train. Lastly, the use of fuel or electric energy is computed for the given drive cycle.

As the engine-generator set contributes most of the power for the propulsion system, it is reasonable to focus on optimizing the engine and generator efficiencies (Baumann et al.). The mechanical power P_{ice} and electric power P_{fc} generated by the engine-generator set can be expressed by Equations 3.5 and 3.6.

$$P_{ice} = \omega_s T_s = \eta_e(\omega_s T_s)\, P_{TR} = \eta_e(\omega_s T_s)\, \dot{m} H_{LHV} \tag{3.5}$$

$$P_{fc} = \eta_g(\omega_s T_s)\, P_{ice} \tag{3.6}$$

where T_s and ω_s are the engine output torque and speed respectively, $\eta_e(T_s, \omega_s)$ and $\eta_g(T_s, \omega_s)$ are the efficiency maps of the engine and generator respectively, $\dot{m}$ and H_{LHV} are the fuel mass flow rate and the corresponding fuel low heating value. The torque and speed of the engine have the constraints as follows.

$$\begin{cases} 0 \leq T_s \leq T_{max}(\omega_s) \\ \max(\omega_{e,min}, \omega_{g,min}) \leq \omega_s \leq \min(\omega_{e,max}, \omega_{g,max}) \end{cases}$$

where $T_{max}(\omega_s)$ is the maximum engine torque output as a function of the engine speed, $\omega_{e,min}$ and $\omega_{e,max}$ are the minimum and maximum angular speeds respectively of the engine, and $\omega_{g,min}$ and $\omega_{g,max}$ are the minimum and maximum angular speeds respectively of the generator (Gao et al. 2009).

For the power of a 80kW engine and 80kW generator, within the operational space defined by Equations 3.3 and 3.4, the engine efficiency map $\eta_e(T_s, \omega_s)$ can be presented in the speed-torque plane as shown in Figure 3.5.

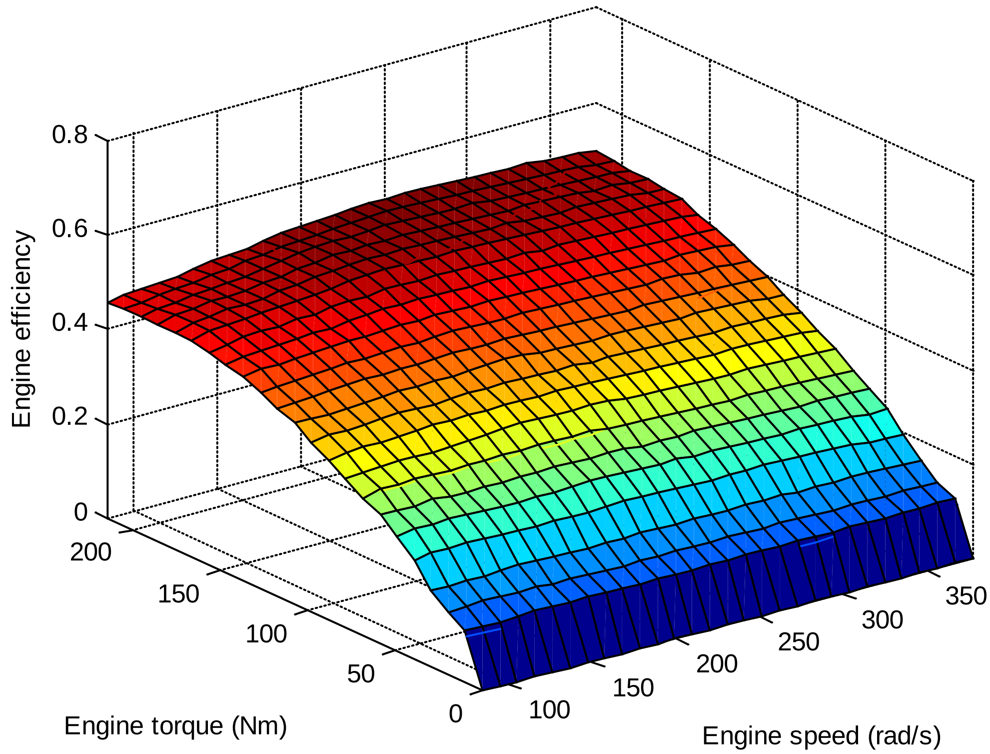

Figure 3.5 Engine Efficiency Map

The torque and speed of the engine associated with the best efficiency curve defines the optimal engine operating points that implies the minimum fuel consumption of the engine under certain speeds. Figure 3.6 indicates the optimal efficiency curve that defines the optimal speed and torque of the engine that operates under a most efficient situation.

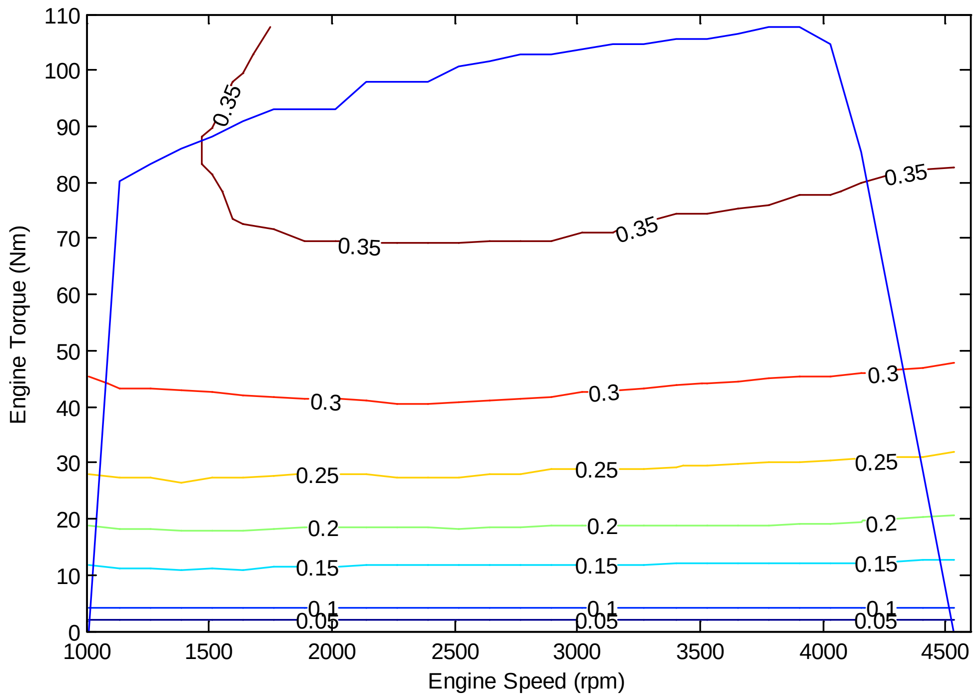

Figure 3.6 Optimal Engine Torques vs. Speeds Curve with Best Efficiencies

3.2.2 PHEV Energy Management Strategy

In this thesis, the PHEV energy control was designed using ECMS algorithm. PHEV control strategy is similar to the one used in HEV. The main difference between PHEV and HEV is that the battery system of PHEV is depleted to the minimum state of charge (SOC) and then sustained by the ICE as a conventional HEV. As described in the previous chapter, ECMS control strategy solves the local optimization problem of HEV considering the total energy consumption. It is based on the fact that the energy consumption from the battery of a hybrid vehicle is replenished by running the engine. Therefore, the battery discharge at any time is equivalent to some fuel consumption in the future (Tulpule et al. 2009). Given a power demand at the wheels, the ECMS algorithm searches for the best power split between the engine and battery that minimizes the equivalent fuel consumption. The basic function of ECMS algorithm can be expressed as Equation 3.7 and 3.8.

$$\dot{m}_{f,eq}(t) = \dot{m}_{f,FC}(t) + \dot{m}_{f,ESS,eq}(t) \tag{3.7}$$

$$\dot{m}_{f,ESS,eq}(t) = \left(s_{chg} \cdot \gamma \cdot \frac{1}{\eta_{el,dis}(P_{el}(t))} + s_{dis} \cdot (1-\gamma) \cdot \eta_{el,chg}(P_{el}(t)) \right) \cdot \frac{P_{el}(t)}{Q_{LHV}} \tag{3.8}$$

where, P_{el} : power provided by the electricity storage system,

$\gamma = \begin{cases} 1 & if \quad p_{el} \geq 0 \\ 0 & if \quad p_{el} < 0 \end{cases}$,

$\dot{m}_{f,ESS,eq}(t)$: equivalent fuel consumption,

s_{chg}, s_{dis} : equivalent factors,

$\dot{m}_{f,FC}(t)$: fuel flow rate at time t,

$\dot{m}_{f,eq}(t)$: equivalent cost/saving associated to battery,

η_{el} : efficiency of the electrical path, values are different between charge mode and discharge mode.

The equivalence factors s_{chg} and s_{dis} are determined by the future driving conditions. Generally speaking, they can be seen as parameters to be optimized in order to obtain optimal fuel consumption and charge sustaining behavior. Therefore, the total fuel consumption of a series PHEV at a given moment can be expressed as the sum of actual fuel consumption of the engine-generator set and the equivalent fuel consumption of the battery pack (Gao et al. 2009). The objective of ECMS energy control is to determine a mechanism for the adaptation of the equivalence factors based on the traffic data provided by the VII network and predicted by the PHEV-VII in-vehicle processors.

3.2.3 QSS Modeling

As previously discussed, this study used a backward approach to model vehicle energy flow. Generally, backward model begins from a given driving cycle at the wheels. The tractive power is calculated in terms of the known parameters. Then the needed power flow is traced back through the power train to find how much power that each involved component has to provide. In backward model, driver behavior is not required. Thus, the power required at the wheels of the vehicle through the time step is calculated directly from the known drive cycles. The required power is then translated into the torque and speed of electric motor, and moves up stream to estimate the power required at the power source, ICE and battery at the end. Figure 3.7 shows the backward PHEV simulation modeling.

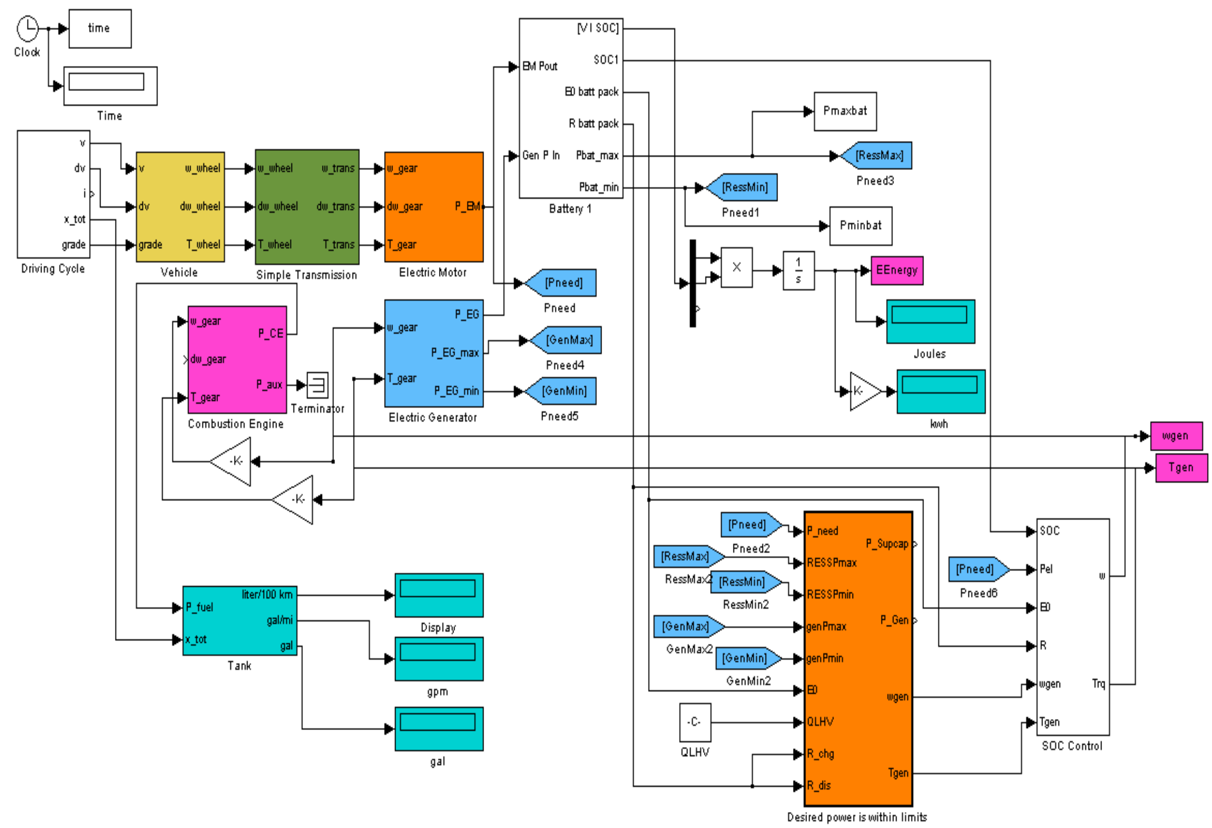

Figure 3.7 QSS Model of Series PHEV

In this model, the “Desired power is within limits” block is used for identifying the optimal choice of the equivalent factors that minimizes the fuel consumption under charge-sustaining conditions. This backward modeling assumes that the future vehicle power is equal to the driver power request in the future driving conditions. The optimal equivalent factors can be pre-computed off-line based on the predicted driving profiles.

3.3 Integrated Simulation

In this section, the integration of PHEV energy control with VII systems is discussed. Since traffic conditions may change with time, an accurate traffic condition prediction system should be adopted within a prediction horizon *k*. Every *k* seconds, the calculation of the equivalence factors will be repeated using the new prediction of velocity and acceleration for the remainder of the road trip.

One major objective of the VII transportation system considered in this thesis is to provide traffic information to VII-PHEV to minimize the overall fuel consumptions and costs. To achieve this target, the integrated system not only calculates the equivalent factors to reach the minimum energy consumption, but also keeps track of the battery's SOC every *k* seconds to sustain the charge depleting range as long as possible for the trip.

Simulation is a comparatively cost-effective process for evaluation due to the complexity and cost in conducting a field test. In this study, the actual driving conditions were generated by Paramics microscopic simulation tool, which is a time step and behavior-based microscopic traffic simulation software (Quadstone 2008). The real traffic condition of the selected study site was simulated by Paramics, which covers interstate highways and urban streets in the North Charleston area, South Carolina. The travel time and speed profiles of three available routes between an origin and destination were predicted using historical and real-time information supplied by VII enabled vehicles and traffic infrastructure agents. By knowing the future traffic information, the PHEV model will give the final SOC of the battery, amount of fuel consumed, and travel time between alternate travel paths of the PHEV-VIIs.

CHAPTER FOUR

VII-PHEV ANALYSIS

This chapter presents the analysis of an ANN algorithm based traffic prediction model, energy consumption impact, and traffic impact of PHEVs. The performance of the ANN model was evaluated with the prediction of travel time and speed profile between the selected origin and destination. The energy management strategy of PHEVs was evaluated by comparing SOCs and fuel consumptions by utilizing QSS PHEV simulink modeling in different optimization scenarios on three alternative routes.

4.1 Traffic Prediction Model Performance

In this section, the travel times and traffic speed profiles between the origin and destination along three different routes were predicted using the ANN-based prediction model. The predicted results were evaluated with the actual traffic data of the selected study site, which was obtained by microscopic traffic simulation. Figure 4.1 shows the study site located in North Charleston. Three alternative routes were selected: Route 1 is a major route along I-26, Route 2 is an alternate route along US 78 and Route 3 is a combination of the first two routes along I-26 and US 78.

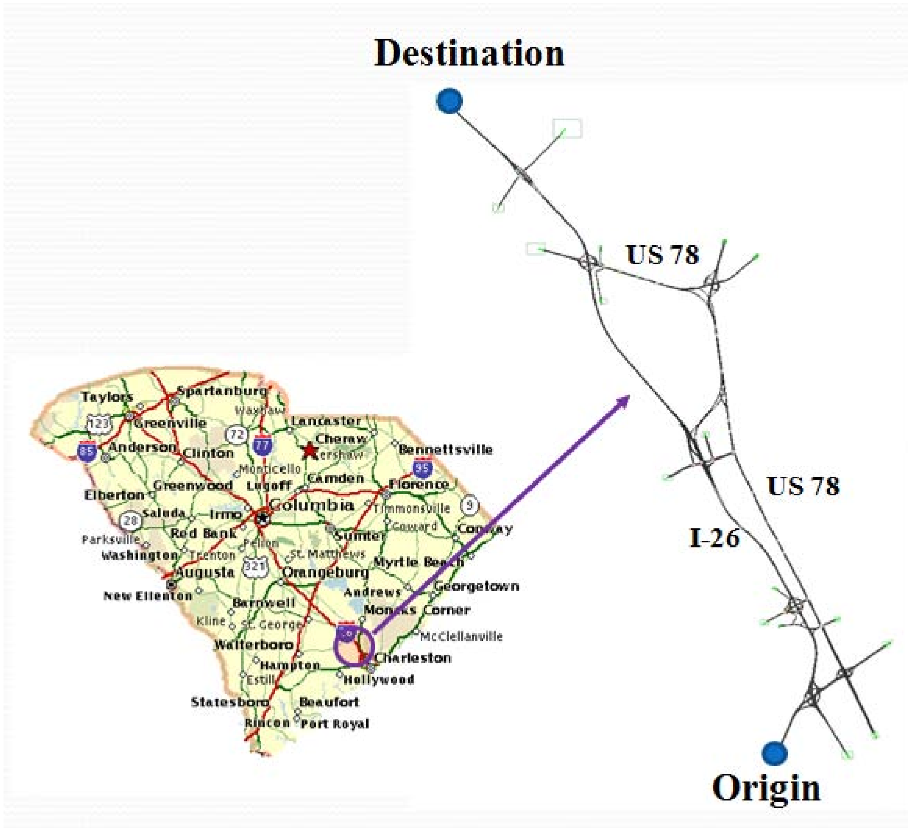

Figure 4.1 Traffic Network of Study Site

4.1.1 Travel Time Prediction

This section presents the performance of travel time prediction model which was built utilizing an ANN algorithm. Utilizing microscopic traffic simulation, the variations of the OD travel time between departure times 16:00 to 19:00 for four days were obtained. Those data were grouped into a training data set and a testing data set as described in chapter 3. Figures 4.2 to 4.4 present the testing results by comparing the actual and predicted OD travel times on Routes 1, 2 and 3, respectively. APE values of all the routes are shown in Figure 4.5. The OD travel time prediction method indicates that using the previous travel time intervals of 5 minutes to predict the next 5 minute travel time interval an accurate prediction can be made. Figure 4.2 indicates that the travel time prediction for Route 1 at time 18:00 to 19:00 has relatively large error. This is due to the large amount of traffic flow on the interstate highway during the peak hour. Therefore, a different traffic pattern should be compared to the previous period to attain a more accurate prediction.

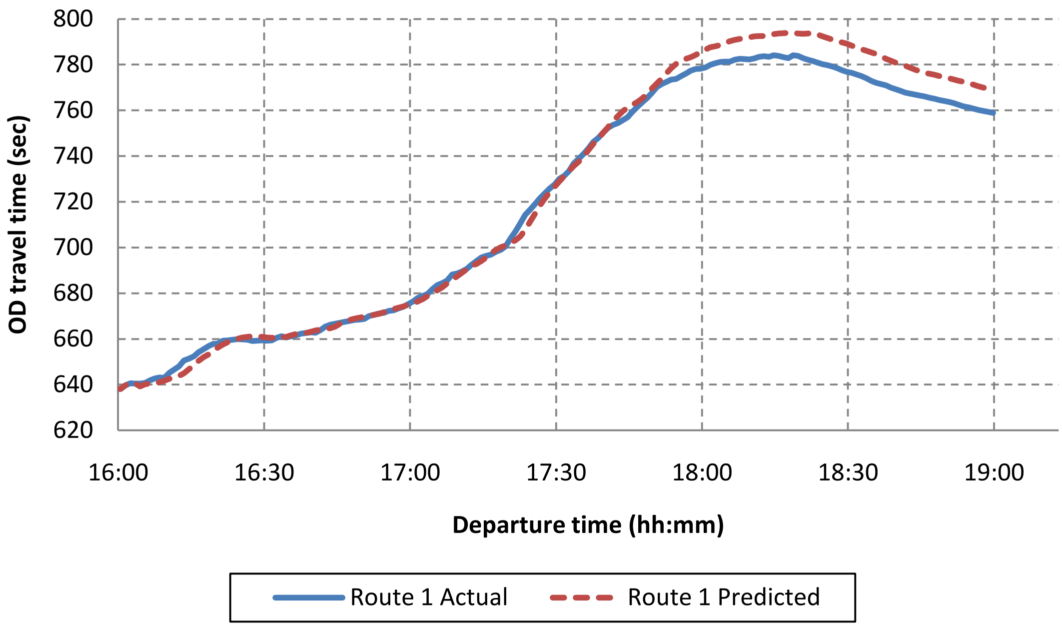

Figure 4.2 Actual and Predicted Travel Time for Route 1

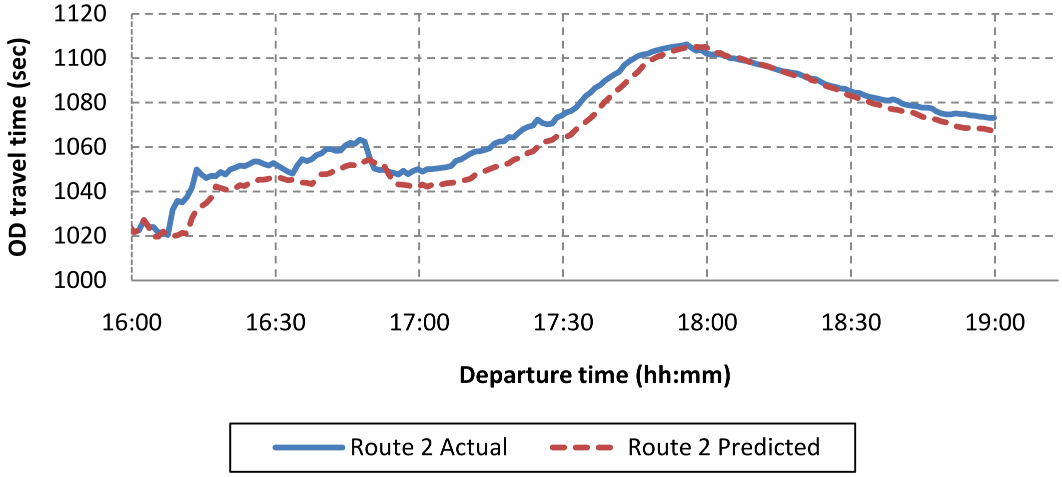

Figure 4.3 Actual and Predicted Travel Time for Route 2

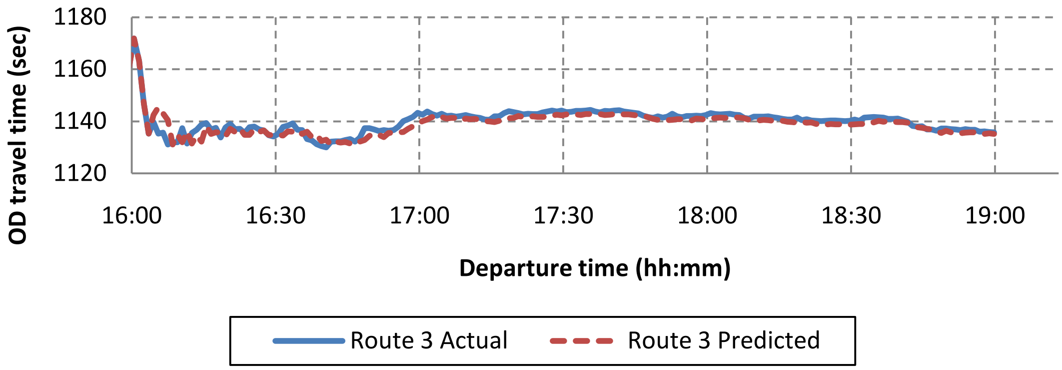

Figure 4.4 Actual and Predicted Travel Time for Route 3

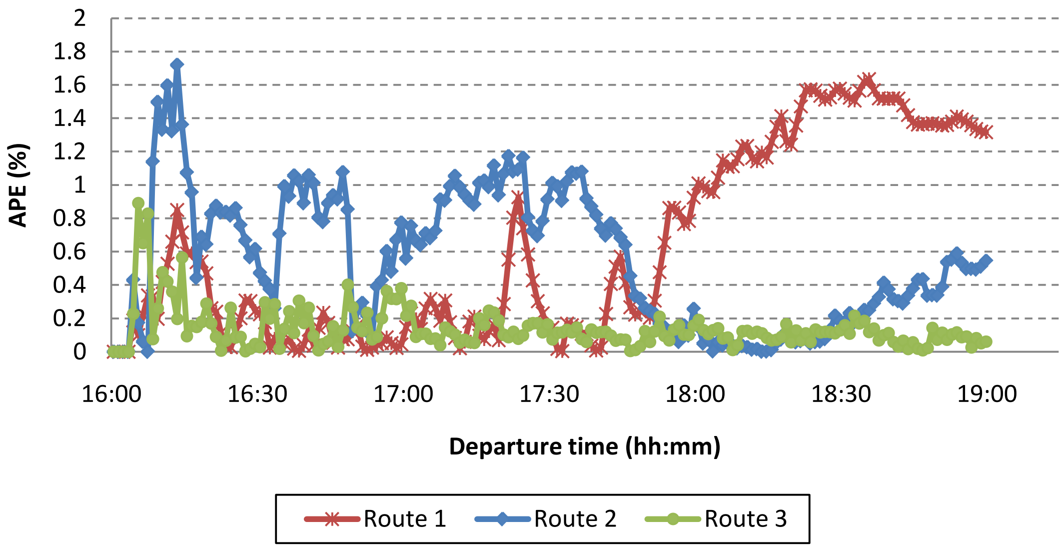

Figure 4.5 Travel Time Prediction Performance Measured by APE

For each route, mean absolute percent error (MAPE) was computed by simply averaging the absolute percent error (APE) over all the predicted data points. The MAPE values are shown in Table 4.1. Route 3 has better prediction performance compared to Routes 1 and 2. This is because Route 3 is a low volume street and has limited travel time variations during the peak hour.

Table 4.1 Travel Time Prediction Performance Measured by MAPE

Route	MAPE (%)
1	0.62
2	0.55
3	0.14

4.1.2 Speed Profile Prediction

This section presents the performance of the speed profile prediction model developed utilizing an ANN algorithm Variations of speed profiles from day to day in the afternoon peak hour were obtained through a microscopic traffic simulation PARAMICS . The speed profile reflects vehicles driving speed in each second on the roadways. In this thesis, speed profiles for three available routes were predicted and all speed observations are based on normal traffic conditions.

Figures 4.6 to 4.7 show the actual and predicted driving speed profiles for Route 1 and 3. As shown in Figures 4.6 and 4.7, the predicted speeds are close to the actual conditions. It indicates that using a 60 second prediction horizon window of speed data to predict the future speed can achieve almost accurate performance.

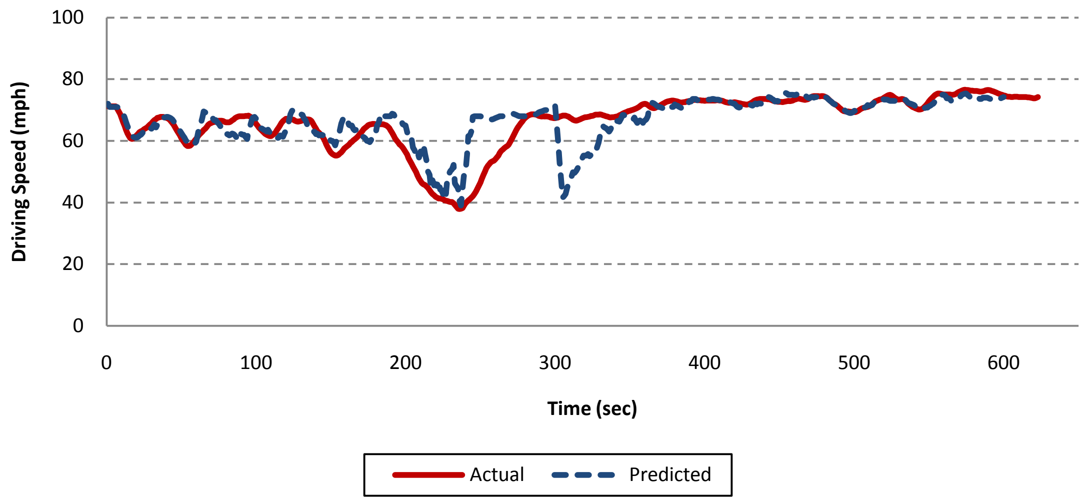

Figure 4.6 Actual and Predicted Traffic Speed Profile for Route 1

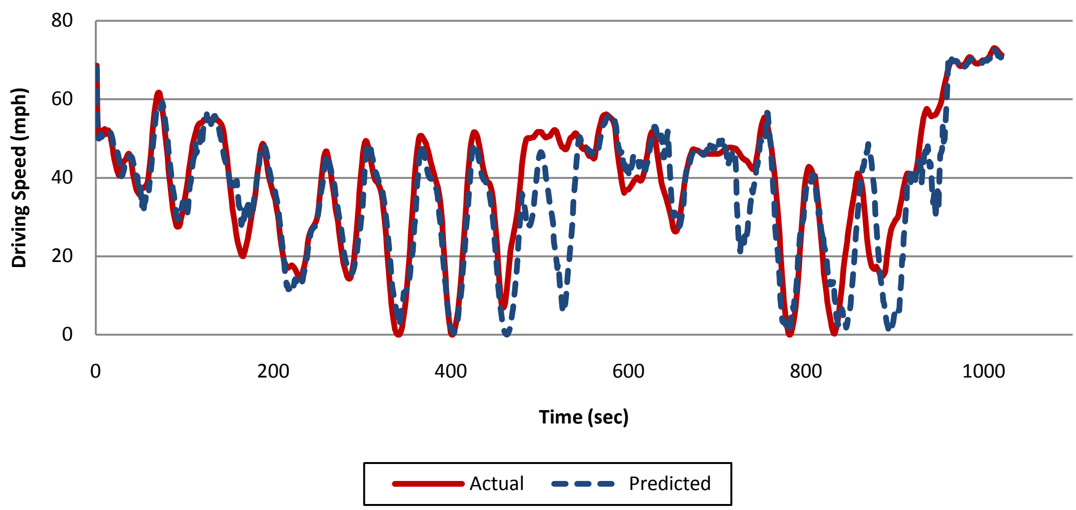

Figure 4.7 Actual and Predicted Traffic Speed Profile for Route 3

With the comparison of the MAPEs of all routes as shown in Table 4.2, the accuracy of speed predictions for Route 1 is the best since variations of speed in interstate highways, such as in Route 1, is less when compared with that of urban streets, such as in Routes 2 and 3. The sudden changes in speeds occur on urban streets due to the stops at signaled intersections.

Table 4.2 Traffic Speed Prediction Performance Measured by MAPE

Route	MAPE (%)
1	6.2
2	8.02
3	30.8

4.2 Impact Assessment

In this section, the traffic and energy consumption impacts are discussed. Different scenarios of VII enabled PHEVs were considered in the analysis, such as with and without an ECMS optimization algorithms.

4.2.1 PHEV Energy Consumption Impact Assessment

This section discusses the performance of VII enabled PHEVs integrated with ECMS energy control strategy. By utilizing PHEV QSS model, the fuel and electricity consumptions of VII-PHEVs with ECMS control strategy were compared with the baseline PHEVs. Baseline PHEVs are those types of vehicles being operated under default energy control strategy. In such a case, PHEVs firstly run in the mode of consuming only electricity and try to avoid turning internal combustion engine on only when extra power is needed to assist driving vehicles. Thus, charge depleting time is shorter than other cases. Based on the predicted speed profiles introduced in the previous section, the driving cycles were created as the input of the PHEV QSS model. One way to analyze the performance of VII-PHEVs and baseline PHEVs is examining the SOC of the electricity storage system versus travel distance. Figures 4.8 to 4.10 present the SOC of the electrical storage system for driving on Route 1, 2 and 3 respectively. Figure 4.9 and 4.10 indicate that the battery systems of the baseline PHEVs do not perform well. On one hand, the charge depleting rate of the baseline PHEVs is too fast. On the other hand, the SOC for Route 3 oscillated aggressively. However, the VII-PHEVs with energy management control have better performance relative to the baseline PHEVs. Since the driving cycles of the three routes are short, SOCs do not reach charge sustaining threshold. In order to observe the performance of battery in both charge depleting and charge sustaining modes, the driving cycles were extended by repeating an additional cycle for all the routes.

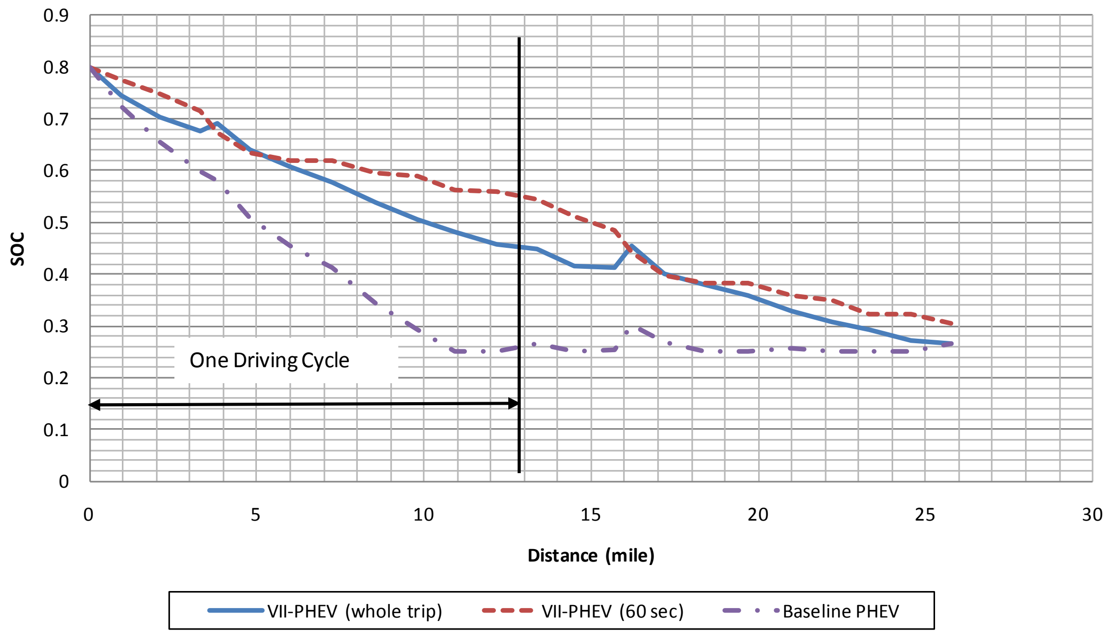

Figure 4.8 Comparisons of SOCs of VII-PHEV and Baseline PHEV on Route 1

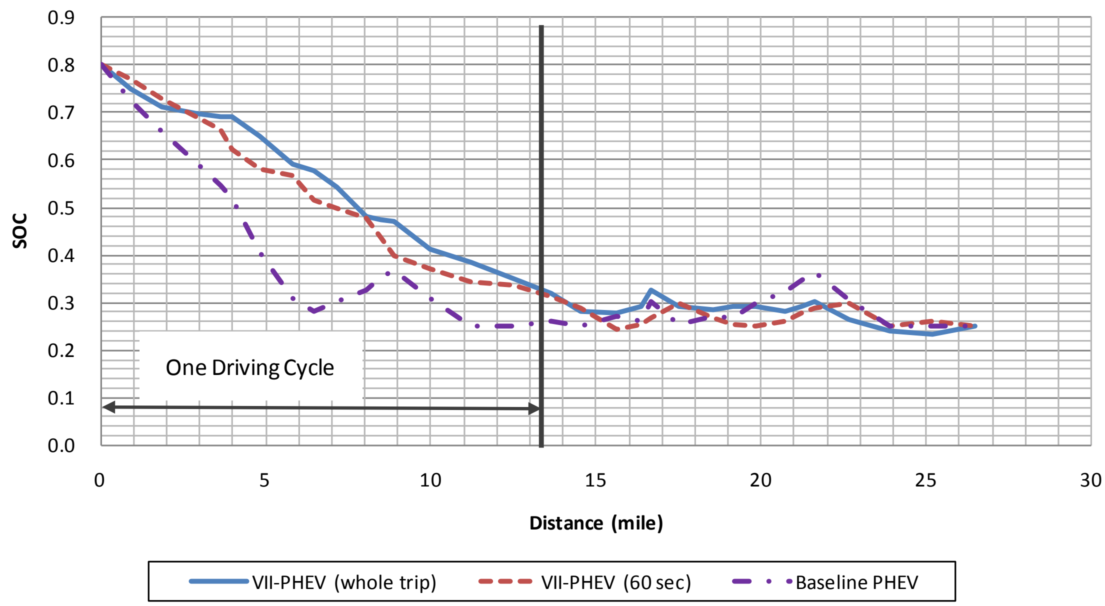

Figure 4.9 Comparisons of SOCs of VII-PHEV and Baseline PHEV on Route 2

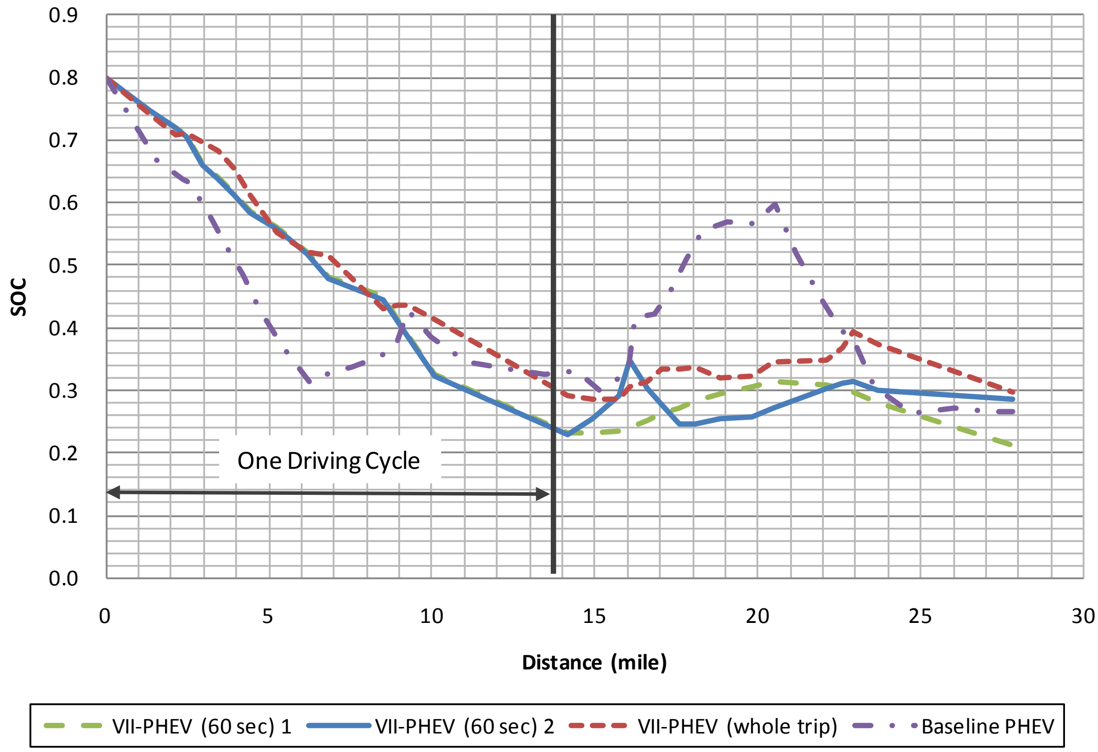

Figure 4.10 Comparisons of SOCs of VII-PHEV and Baseline PHEV on Route 3

For assessing the energy consumption impact of the VII-PHEVs, two different optimization methods were implemented for each of the driving cycles: entire trip optimization and 60 sec window size optimization. Both optimization methods for VII-PHEVs were compared with baseline PHEVs in the end. For whole trip optimization, a constant pair of equivalent factors was utilized for the entire trip. Otherwise, the equivalent factors in the 60 sec window size optimization scenario were changed every 60 sec with the known predicted future speed profile, and the adjusted in terms of SOC changing rate. It can be seen in Figures 4.8 to 4.10 that the whole trip optimization and 60 sec window size optimization have much better performance than baseline PHEVs without ECMS energy control. The slow discharging behavior of the two optimization methods is due to the blended control of battery energy with engine power. Since the three routes considered in this study have different travel distances, the discharge rates varies accordingly.

In Figure 4.10, two types of 60 sec window size optimizations for VII-PHEVs associated with different groups of equivalent factors are shown. It can be seen that, different pairs of equivalent factors can cause the performance of the battery system to vary. Hence, finding the best pair of equivalent factors is the key point in ECMS control strategy. Table 4.3 lists the equivalent factors for the 60 sec window size optimization and the whole route optimization scenarios.

Table 4.3 Equivalent Factors in Different Optimization Scenarios for Route 3

Window Sequence #	**Equivalent Factors ($s_{chg} = s_{dis}$)**		
	60 sec Window Size Optimization 1	**60 sec Window Size Optimization 2**	**Whole Trip Optimization**
1	0.450	0.450	0.470
2	0.430	0.430	0.470
3	0.990	0.990	0.470
4	0.810	0.790	0.470
5	0.450	0.450	0.470

6	0.510	0.510	0.470
7	0.010	0.010	0.470
8	0.490	0.490	0.470
9	0.640	0.640	0.470
10	0.780	0.790	0.470
11	0.500	0.500	0.470
12	0.990	0.990	0.470
13	0.760	0.760	0.470
14	0.790	0.790	0.470
15	0.470	0.470	0.470
16	0.350	0.460	0.470
17	0.360	0.460	0.470
18	0.360	0.600	0.470
19	0.810	0.490	0.470
20	0.740	0.490	0.470
21	0.710	0.470	0.470
22	0.490	0.460	0.470
23	0.430	0.420	0.470
24	0.470	0.450	0.470
25	0.500	0.530	0.470
26	0.450	0.480	0.470
27	0.550	0.630	0.470
28	0.600	0.640	0.470
29	0.460	0.470	0.470
30	0.430	0.460	0.470

In addition, fuel consumptions of Route 1, 2, and 3 were calculated by the QSS PHEV model in different scenarios. As shown in Figure 4.11, fuel consumption of the VII-PHEVs with ECMS control saves more energy than the baseline PHEVs without ECMS control. The simulation result also indicates that the longer traveling, the more percent of fuel consumption saving.

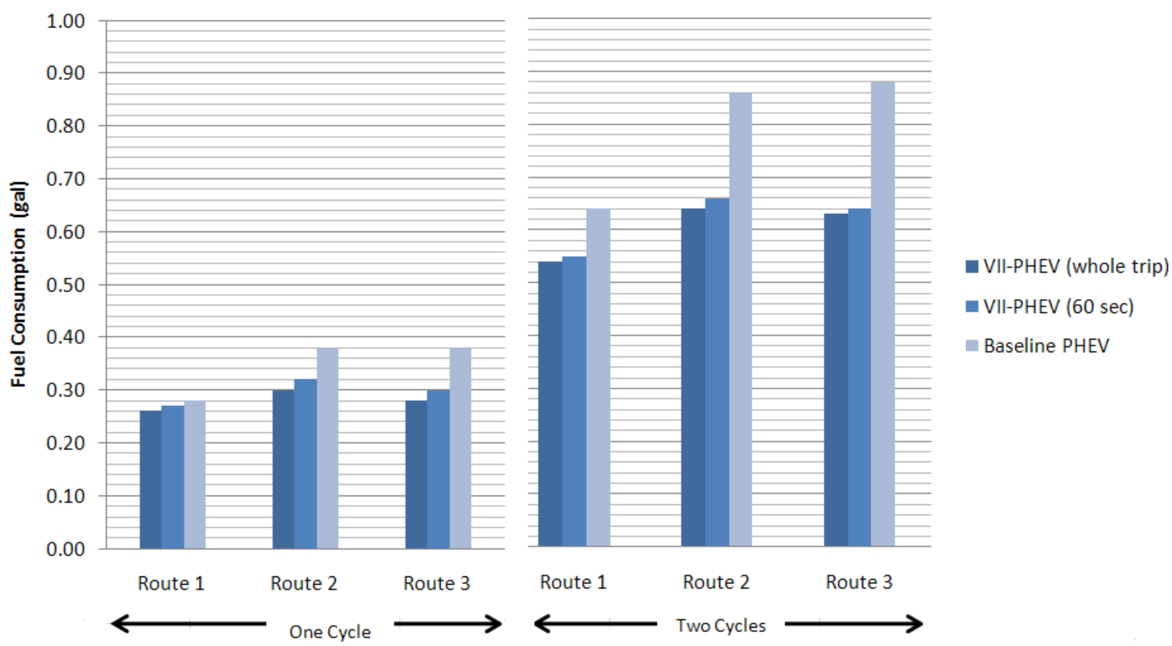

Figure 4.11 Fuel Consumptions for One and Two Driving Cycle in Different Scenarios

The whole trip optimization strategy has slightly less fuel consumption relative to the 60 sec window size optimization, however, it is based on the entire known route speed information and it's difficult to implement in the real world. Thus, the 60 sec window size optimization is easy to process given the 60 second predicted speed profile.

4.2.2 Traffic Impact Assessment

In this section, the analysis of traffic impacts of the VII enabled PHEVs is analyzed. As discussed in previous sections, advanced knowledge of traffic information plays a very important role for optimizing PHEVs energy consumption and rerouting PHEVs to save travel time, even to avoid traffic incidents. In this study site, three available routes connect the origin and destination. Route 1 is an interstate highway, so travel along this road is much faster. Route 2 is half interstate highway and half urban street and Route 3 is entirely an urban street. Table 4.4 demonstrates the travel distance and travel time for driving along the three routes. The economic cost for different energy control scenarios were calculated by assuming costs of $2.5 per gallon of gasoline and $0.1 per kWh of battery charging.

Table 4.4 Travel Times and Economic Costs for Different Routes

	Distance (mile)	**Travel Time (sec)**	**Cost (dollar)**		
			VII-PHEV (whole trip)	**VII-PHEV (60 sec)**	**Baseline PHEV**
Route 1	12.89	678	0.697	0.711	0.831
Route 2	13.17	918	0.812	0.865	1.084
Route 3	13.84	1160	0.768	0.826	1.058
Route 2 (10 min incident)	13.17	1518	0.868	0.837	N/A

In regular traffic conditions, Route 1 is the best choice because of the travel time and lower cost of operations. However, incidents or congestion may occur on a high density interstate highway during peak hours. Thus, advanced knowledge of traffic conditions is quite valuable for travelers. Figures 4.12 and 4.13 indicate the battery SOC and fuel consumption by taking Route 2 when a 10 min congestion occurs in the middle of the travel way. In this case, assume PHEVs have run into a congested traffic network in result of a small accident. Since the traffic is interrupted, upstream PHEVs have to be stopped until the incident is handled and cleared. The obstructed PHEVs should work more efficiently if the prior traffic information can be obtained. As shown in Table 4.4, PHEVs with the 60 sec window size optimization costs less fuel than whole trip optimization with constant equivalent factors. However, the whole trip optimization keeps charge depleting mode for a longer distance, which is the preferred battery working condition.

Therefore, in order to achieve time and fuel consumption savings, integrating VII traffic information with the intelligent energy control strategy will contribute more compared to separate implementation of each.

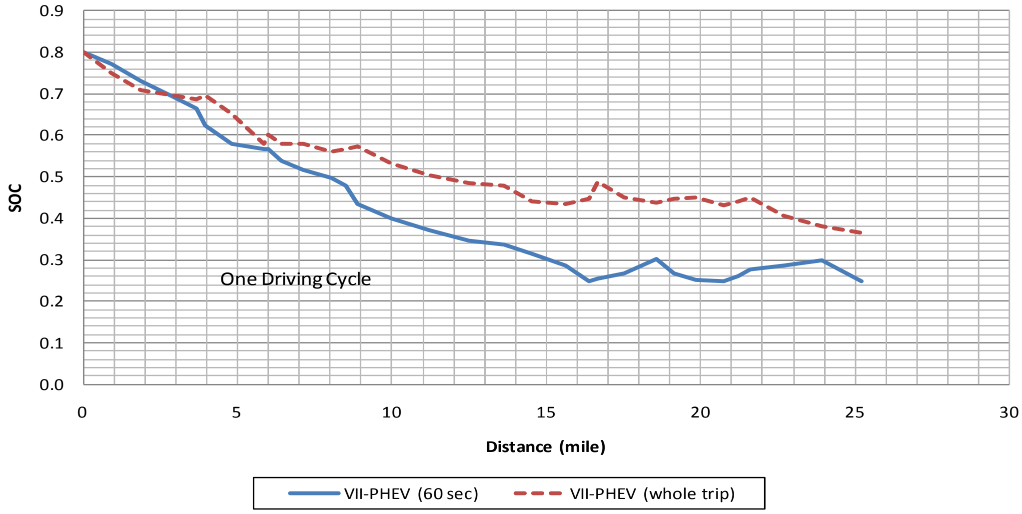

Figure 4.12 SOC vs. Driving Distance with 10 min Incident

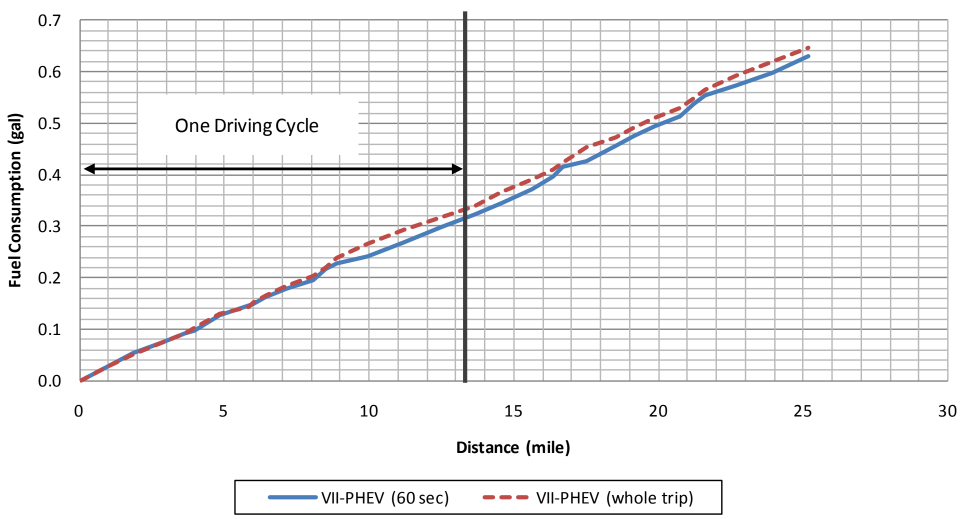

Figure 4.13 Fuel Consumptions with 10 min Incident

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

The first section of this chapter presents the conclusions developed from the research. The second section lists recommendations for future work.

5.1 Conclusions

Connecting PHEVs with highway infrastructure to benefit energy management, as presented in this thesis, supports the broader national transportation goals of an active transportation system where drivers, vehicles and infrastructure are integrated in a real time fashion to improve mobility. The benefit of such an active transportation system is revealed in this research where vehicles and infrastructure are connected though a real time system to improve energy consumptions and trip predictability.

The ANN algorithm based traffic prediction models, which utilize VII generated data, proposed in this research were found suitable for predicting OD travel time and traffic speed. Only a minor difference of errors existed between the prediction on freeways and urban streets. The analysis suggests that ANN based prediction model can be applied to the entire roadway network that includes roads of different functional classes. It was found that a 60 second speed profile could be predicted with small error under an earlier knowledge of 60 second traffic information.

The look-ahead traffic estimation is expected to be shared between VII-PHEVs and traffic infrastructure, which can highly improve traffic efficiency. Based on the predicted traffic information, VII-PHEVs have ability to adjust the speed profiles and optimize the power split between electricity and gasoline. The analysis revealed that PHEVs integrated with VII system improves energy consumption compared to PHEVs without VII and energy optimization capabilities.

It was found that fuel consumptions of VII-PHEV could be improved between 17% and 25% relative to the baseline PHEVs on roadways of different functional classes. Fuel consumption of VII-PHEV on urban driving has relatively more savings than on freeway driving. The simulation results indicated that local optimization in 60 seconds interval based on VII predicted traffic information performs similarly under global optimization, and it performs better under unpredictable traffic conditions, such as those results in due to incidents. The reliability of predicted traffic information enables ECMS energy controller to optimize PHEVs energy consumption in real time, which improves the PHEVs' energy management performance.

5.2 Recommendations for Future Work

The following work is recommended to expand the research presented in this thesis:

- This research used a series PHEV power configuration, which translates to a larger engine and relatively smaller electricity storage system. This limits the range of all electric-mode and reduces the economic efficiency when compared with larger electricity storage system and smaller engine. The follow-up research should include a revised PHEV model configuration that considers a larger electrical storage system. This will improve economic efficiency of PHEVs as this will support the extension of charge depleting range.

- This research considers one type of PHEV system, which is a series PHEVs. The author did not consider other two types of PHEVs, which are parallel and series-parallel. Future research can include many diverse types of PHEVs.

- The traffic prediction model developed in this research could be improved by considering diverse traffic conditions that are expected on different types of roadways. For predicting accurate future driving speeds, a roadway feature recognition method is recommended that identifies different roadway characteristics, such as ramps, curvature, and distance to signal controlled intersections. The existing ANN model needs to be further expanded and evaluated for saturated traffic conditions.

- This research did not include dynamic assignment of PHEVs in the network based on traffic and energy demands. Future research should include dynamic assignment of PHEVs based on available routes, traffic and energy demands, and driver preferences regarding energy and travel time savings.

- The author utilized ANN algorithm to predict traffic conditions. Other Artificial Intelligence (AI)-based tools, such as SVR, SVM, Bayesian NN, genetic algorithms, could also provide reliable predictions of traffic conditions. Future research should evaluate the performance of ANN with other AI tools in predicting traffic conditions.

- Field experiment of the research presented in this paper would validate the estimated benefit derived through computer simulations. The author proposes future field experiments with PHEVs equipped with VII capabilities for operational verifications of the concept presented in this thesis. This will expedite the deployment of the PHEV-VII system.

APPENDICES

Appendix A

Codes

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