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**MODELLING FUEL CONSUMPTION OF ADVANCED TECHNOLOGY
VEHICLES IN TRAFFIC NETWORKS USING ARTIFICIAL NEURAL
NETWORKS**

by

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A thesis submitted to the
Faculty of Graduate Studies and Research
In Partial Fulfilment of the Requirements
for the Degree of

Doctor of Philosophy

Department of Civil and Environmental Engineering
Carleton University
Ottawa, Ontario
August 2004

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*The Doctor of Philosophy in the Civil and Environmental Engineering Program
is a joint program with the University of Ottawa, administrated by the
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ABSTRACT

Advanced Technology Vehicles (ATV) have been advertised to help solve transportation's oil use and environmental problems. Current traffic and transportation models are not suitable to study fuel consumption implications of using these vehicles in real traffic networks. The objectives of this thesis research were to study fuel consumption characteristics of ATV's in realistic traffic networks and to develop fuel consumption models for typical traffic facilities using Artificial Neural Networks (ANN).

To generate data for the ANN process, a methodology was established for three different facilities namely urban arterial, urban freeway, and Central Business District network. Three types of vehicles were used. These are conventional Internal Combustion Engine (ICE), hybrid ICE, and hybrid Fuel Cell. To obtain instantaneous speed/acceleration profiles, traffic conditions were simulated using the Federal Highway Administration sponsored Traffic Software Integrated System (TSIS) 5.1. Using the speed/acceleration profiles as inputs, fuel consumption data were generated using the **Advanced Vehicle Simulator** (ADVISOR) 2002 developed by the U.S. National Renewable Energy Laboratory.

A Bayesian regularization approach was applied to train a number of ANN models as noted below.

- A microscopic fuel consumption model was developed by using time, speed, acceleration, state of charge, and the battery system current as explanatory variables and,
- For macroscopic analyses of fuel consumption, a model was developed based on an aggregation of information obtained at the microscopic level, using link average speed as the explanatory variable of fuel consumption.

Quantitative and Qualitative analyses showed that all ANN models have a strong to moderately strong relationship between the predicted fuel consumption values and the fuel consumption values provided by ADVISOR.

Using coefficients provided by the ANN models, an algorithm coded in Visual Basic was developed to implement the fuel consumption models. Results obtained from this algorithm showed that the difference between the estimated fuel consumption and fuel consumption values provided by the ADVISOR and TSIS combination were always less than 5 %.

The algorithm could be used as a standalone tool or, could be integrated into traffic simulation models for the estimation of the energy consumption effects of policies and operations in an efficient manner.

ACKNOWLEDGEMENTS

I would like to dedicate this thesis to Daniella, my wife, for her patience and understanding, and to my parents Juanita and Daniel, for their support in many tangible and intangible ways.

I would like to take the opportunity to thank my supervisor, Prof. Ata M. Khan for his encouragement and support and also for guiding me through my years at Carleton University with skill and enthusiasm. I would like to thank Prof. Juan Salinas for taking the time to discuss with me many issues throughout my school years. My sincere appreciations to Prof. Roberto Narbaitz at the University of Ottawa for permitting me access to his laboratory and software systems in the initial phases of my research. Thank you also to Prof. Neal Holtz and all the members of my advisory committee, for their support and helpful suggestions.

I would also like to thank Mrs. Xiaotao Shu for her invaluable help during the construction and debugging phases of the algorithm, and the City of Ottawa's Transportation, Utilities and Public Works Department, and the Ministry of Transportation of Ontario's Planning and Design Section-Eastern Region for all the information provided.

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Glossary of Terms

ATV	Advanced Technology Vehicles
ADVISOR	Advanced Vehicle Simulator
ANN	Artificial Neural Networks
CARB	California Air Resources Board
CBD	Central Business District
CO	Carbon Monoxide
CORSIM	Corridor Simulation
ESS	Energy Storage System
FC	Fuel Consumption
FHWA	Federal Highway Administration
FTP	Federal Test Procedure
HC	Hydrocarbon
HVEC	Hybrid Vehicle Evaluation Code
HWFET	Highway Fuel Economy Test
HWY	Highway
ICE	Internal Combustion Engine
KPH	Kilometres per hour
MLP	Multilayer Perceptron
MPH	Miles per hour

NiMH	Nickel Metal Hydride
NO _x	Nitrogen Oxides
NREL	National Renewable Energy Laboratory
NTIS	National Technology Information Service
OECD	Organization for Economic Cooperation and Development
ORNL	Oak Ridge National Laboratory
PEMFC	Polymer Electrolyte Membrane Fuel Cell
POX	Partial Oxidation system
SAE	Society of Automotive Engineers
SOC	State of Charge
SSE	Sum-of-square error
STAG	Canadian Sustainable Transport Advisory Group
TRANSIMS	Transportation Analysis Simulation System
TSIS	Traffic Software Integrated System
UDDS	Federal Urban Dynamometer Driving Schedule
USDOE	U.S. Department of Energy
USEIA	U.S. Energy Information Administration
USEPA	U.S. Environmental Protection Agency
USGS	U.S. Geological Survey

CHAPTER 1. INTRODUCTION

1.1 Background

Transportation studies suggest that in the near future, in the absence of drastic policy measures, urban road traffic will continue to operate in congested conditions (Boarnet and Crane, 2001). Also under the business-as-usual scenario, the transportation sector will continue to rely on petroleum fuels and will produce increased carbon dioxide and other emissions in the future years (Goodwin, 1996). Under these adverse projected conditions, the need for a sustainable transportation system is clear. The Organization for Economic Cooperation and Development (OECD) defined sustainable transportation as the one “that does not endanger public health or ecosystems and uses renewable resources at below their rates of regeneration” (STAG, 2001).

Sustainability in the transportation sector greatly depends on technological innovations. Even though most major automobile manufacturing companies have initiated programs for the development of hybrid electric and fuel cell vehicles, it is not possible to fully comply with the concept of sustainability without an integration of these new technologies into the transportation planning and decision-making process.

Planning for transportation energy for the 2020-2030 horizons requires some knowledge as well as tools that are not available today. Consequently we have limited ability to

analyze policies and plans that feature new technology vehicles in real-world applications. This need for research in the energy consumption characteristics of advanced technology vehicles in real world applications has been highlighted by a number of authors and agencies (Wang 2002, Khan 2001). Models are required that enable the quantification of energy consumption of hybrid and fuel cell vehicles vis-à-vis conventional technology vehicles in realistic applications.

1.2 Research Objectives and Scope

This thesis focuses on the study of fuel consumption characteristics of advanced technology vehicles, and on the development of microscopic as well as macroscopic fuel consumption models based on Artificial Neural Networks (ANN) technique.

The specific objectives of this research were as follows:

1. Identify factors affecting fuel consumption behaviour of advanced technology vehicles, and currently available methods to predict it on the basis of a thorough literature review,
2. Identify explanatory variables that affect fuel consumption of conventional and advanced technology vehicles from the perspective of modelling fuel consumption,

3. Development of instantaneous and average fuel consumption models for conventional and advanced technology vehicles using Multilayer Perceptron (MLP) Neural Networks trained with Bayesian regularization,
4. Development of an algorithm to implement the fuel consumption models.

The resulting models are expected to be useful for the analysis of traffic networks used by conventional technology as well as advanced technology vehicles. Without such models, sustainable transportation policies, programs and projects cannot be fully tested. The algorithm could be used as a stand-alone tool or integrated in microscopic and macroscopic traffic models for the estimation of fuel consumption effects of policies, plans and transportation operations in an efficient way.

As for scope of this research, the following conditions were taken into consideration:

- Two conventional Internal Combustion Engine (ICE) vehicles were simulated in order to represent the passenger car fleet. Light truck vehicles (i.e. minivans and sport utility vehicles) were not included in the present research.
- In a similar manner, three advanced technology vehicles were selected to represent the advanced vehicular technology currently available (i.e. a hybrid ICE vehicle and two fuel cell vehicles with an on-board system to reform gasoline to hydrogen). Direct hydrogen or alternative fuels were not considered for simulation.

- Simulation of traffic conditions was restricted to the AM Peak period observed in three different types of urban facilities (i.e., central business district road network, urban arterial, and urban highway).
- Only road loads (i.e. rolling, gradient and acceleration resistance including idle effects) were taken into consideration for the calculation of fuel consumption. The effects of external loads such as air conditioning, power windows, and entertainment components on average or instantaneous fuel consumption are not part of this thesis.

1.3 Organization of Thesis

The thesis is organized as follows:

In Chapter 2, a brief overview is presented of the future condition of the world's oil resources and the role that advanced technology vehicles could play to reduce energy consumption in transportation. Issues related to the measurement and estimation of advance technology vehicle fuel consumption are described. Also, the use of neural network models, uncovered by the literature review is reported in this Chapter.

Chapter 3 describes the methodology used to model three different urban traffic conditions and the calculation of instantaneous and average fuel consumption of three different types of passenger vehicles: conventional internal combustion engine vehicles,

hybrid internal combustion engine vehicles, and hybrid fuel cell vehicles using a gasoline reformer as a source of hydrogen. The process used to select optimal neural network structures for every case is also presented in this chapter.

In Chapter 4, results of the neural network training process are evaluated using qualitative and quantitative techniques. Analysis of residuals of testing data are reported and used in conjunction with information found in the literature review to compare fuel consumption behaviour of advanced technology vehicles under different conditions of traffic.

Implementation of neural network models into a Visual Basic algorithm is presented in Chapter 5. This chapter also describes three examples of urban traffic conditions and the impact of using advanced technology vehicles over micro and macroscopic fuel consumption.

Finally, in Chapter 6 conclusions of this thesis are reported and recommendations are presented.

CHAPTER 2. LITERATURE REVIEW

2.1 Petroleum Resources and Sustainable Development

Fuel consumption by road vehicles has been steadily increasing in Canada since the early 1990's. In the case of diesel fuel a 175% increase in its consumption was observed between 1990 and 2000. See Figure 2-1 (Lawson, 2003). In the same period, concerns over the adverse environmental effects of transportation have been increasing.

Figure 2-1 Road fuel consumption in Canada

For a sustainability perspective, a main issue is the high rate of petroleum fuel consumption that is contributing to the rapid decline of conventional oil resources (STAG, 2001). Since the earliest discovery of oil in 1859, more than 800 billion barrels of oil have been consumed in the entire world. This amount corresponds to almost half of

the discovered conventional oil resources and, in accordance with the latest U.S. Geological Survey (USGS) assessment, approximately one fourth of the 3 trillion barrels of conventional oil reserves on earth (USDOE, 2001).

Based on the most recent estimates of conventional oil resources around the world, the U.S. Energy Information Administration (USEIA) developed a set of production-demand scenarios (USDOE, 2001). The first scenario considered a maximum world reserve to production ratio (R/P) of 10 and a mean growth of 2%. Results of these assumptions were a peak production in 2037, followed by a rapid decline in production. The second scenario used a more traditional exhaustion pattern of 2% per year decline, resulting in an earlier production peak in 2016, but a slower decline. Nevertheless, the result of both projections was a similar production in 2050. See Figure 2-2 (USDOE, 2001).

Figure 2-2 Annual global oil production scenarios

Although these particular projections were based on multiple factors (i.e. ultimate resource quantity, demand growth rate, and production decline rate) that are subject to discussion, it is certain that world oil production will be declining in the present century (USDOE, 2001). Therefore long before 50 percent exhaustion is reached, a transition to efficient and alternative fuel-based vehicles must begin.

Road vehicles are the single largest consumer of fossil fuels in Canada (Lawson, 2003, Transport Canada, 2003). It should be noted that since the early 1970's, the use of technological improvements have more than doubled the fuel economy of conventional ICE cars and light trucks. Fuel injection systems and transmissions of increasing sophistication continue to penetrate the new light duty vehicle fleet. However these new technologies have been applied to increase power and performance of new vehicles (USEPA, 2001a). Due to increase in the number of vehicles and increased power demand, gasoline fuel use by passenger cars and light trucks continues to rise in Canada. See Figure 2-3 (Lawson, 2003).

The U.S. Environmental Protection Agency (USEPA) describes the introduction of advanced technology vehicles with hybrid propulsion systems as “the most significant change to light duty vehicle fuel economy technologies of the recent years” (USEPA, 2001a). A hybrid car is a vehicle propelled by the combination of an internal combustion engine or another source of power, and an electric drive train. Although this technology has been researched since the 1900s, it was in the late 1970s when the major U.S. federal

agencies started to support the research and development of hybrid vehicles in the United States (Plotkin et al, 2001).

Figure 2-3 Gasoline consumption per year by passenger cars and light trucks in Canada

With similar comfort features as a conventional gasoline vehicle and comparable driving characteristics, a hybrid shows a better fuel economy than expected for a regular gasoline model. See Table 2-1 (Takimoto M., 2002).

Table 2-1 Fuel economy comparison between a conventional and a hybrid vehicle

	Average Speed (km/h)	Toyota Prius Hybrid	ICE
		Fuel Economy (L/100 km)	
City driving	48.2	4.9	7.6
Highway driving	77	4.4	6.5

From this perspective, most of the major automobile companies are currently developing their own line of hybrid vehicles. See Table 2-2 (Lipman and Hwang, 2003).

Table 2-2 Commercial and announced hybrid plans for the U.S. market

Vehicle	System Voltage	Motor Traction Power	Battery Type	Peak Power	Category
GMC Sierra and Chevy Silverado, Integrated Starter Alternator Damper (ISAD) system, CY2004	42 volts	na	Pb-Acid	na	Integrated Starter Generator
GMC Yukon and Chevy Tahoe, Integrated Starter Alternator Damper (ISAD) system, CY2007	42 volts	na	Pb-Acid	na	Integrated Starter Generator
Chevy Equinox (2006) and Malibu (2007), Belt Alternator System (BAS)	36 volts	na	Pb-Acid	na	Integrated Starter Generator
Dodge Ram Contractor Special, CY 2004	42 volts	na	Pb-Acid	na	Mild Hybrid
Honda Civic, Integrated Motor Assist (IMA), MY03	144 volts	10 kW	Ni-MH	14%	Mild Hybrid
Honda Insight, Integrated Motor Assist (IMA) will be discontinued after MY2003	144 volts	10 kW	Ni-MH	17%	Mild Hybrid
GM Saturn VUE Hybrid, CY 2005	300 volts	40 kW	Ni-MH	30%	Full Hybrid
Ford Escape Hybrid MY2004	300 volts 300 volts	65 kW	Ni-MH	na	Full Hybrid
Toyota Prius, Toyota Hybrid System (THS), MY2003		33 kW	Ni-MH	39% (29% battery)	Full Hybrid
Toyota Prius, Toyota Hybrid Synergy Drive, MY2004	500 volts	50 kW	Ni-MH	46%	Full+Hybrid
Lexus RX330 Hybrid, CY2004	600 volts	175 kW	Ni-MH	60%	Full+Hybrid
Examples of Recent Hybrid Fuel Cell Prototypes					
Ford Think Focus FCV Hybrid	na	65 kW	Ni-MH	100%	Hybrid Fuel Cell Vehicle
Honda FCX-V3 FCV	na	60 kW	Ni-MH	100%	Hybrid Fuel Cell Vehicle
Toyota FCHV (Fuel Cell Hybrid Vehicle)	600 volts	80 kW	Ni-MH	100%	Hybrid Fuel Cell Vehicle

Furthermore, the Canadian Sustainable Transport Advisory Group (STAG) has selected the gasoline-electric hybrid vehicles as the most viable alternative to reduce fuel consumption in the transportation sector in the short-term. For the long-term, however, a more sustainable option is available for the mainstream market offering much potential to reduce petroleum consumption: the fuel cell vehicle (STAG, 2001).

A fuel cell has the ability to take “fuel” (i.e. hydrogen) directly and following its combination with oxygen, converts it into electricity that can be used to power various applications (i.e. electric drive vehicles). If a fuel cell system is used instead of a conventional internal combustion engine as a vehicle’s power source, the theoretical energy conversion efficiency increases by almost 30 percent (Unnash and Drunert, 1999). Also, because there is no chemical combustion in the process, in theory a perfect fuel cell will produce zero emissions at the secondary energy consumption level. In such a scenario, it is assumed that emissions related to the production of hydrogen (if any) have already been taken into account in the fuel cycle.

Currently, numerous research programs are in progress to integrate fuel cell technology as a power source in light-duty and heavy-duty vehicles. For example, Daimler Chrysler, in a joint effort with Ballard Power Systems and Ford, courageously announced that they would have 100,000 fuel cell vehicles available for the mainstream market by 2005 (Unnash and Drunert, 1999).

However, it should be noted that new vehicle technologies, like hybrid electric and fuel cell vehicles, differ from an internal combustion engine (ICE) vehicle in many aspects. In a vehicle equipped with a conventional internal combustion engine as a source of power, the fuel consumption is almost inversely proportional to the average speed. This is due to the fuel consumption penalty of stop-and-go operations in traffic networks. As a result, fuel efficiency keeps on improving with increased link average speed until a certain speed is reached in which drag resistance is a major contributor to fuel use. On the other hand, this is not necessarily the case for an advanced technology vehicle. Since an advanced technology vehicle features electric drive, its regenerative braking design overcomes the disadvantage of stop-and-go operation. Additionally the power control strategy of such a vehicle can prevent the idling mode of the internal combustion engine of a hybrid vehicle.

For example, for a hybrid electric vehicle, like the Toyota's Prius, the battery provides all the power required for the motor to run the vehicle until the road loads are high enough to require the use of the internal combustion engine. However, when the vehicle comes to a stop, the system might go into "idling stop" mode, automatically shutting down the engine to prevent idling. When the vehicle starts moving again, the motor provides the initial drive force and restarts the engine. Due to its regenerative braking system, this type of hybrid vehicle also has the capability to convert braking energy into electricity that is recovered by the battery. During acceleration and other periods of heavy road load, the

vehicle uses the engine and the battery system to provide the requested power, resulting in a lower fuel consumption and powerful acceleration (USEPA, 1998).

2.2 Fuel Consumption Models

In transportation planning and engineering, estimation of energy consumption has become an essential task. Among other measures of effectiveness used to select the most desirable traffic network improvement alternative, studies of energy and emissions are frequently required. This requires tools that can model vehicle's performance in urban networks, including fuel consumption. For this purpose, some traffic micro-simulation models include fuel consumption and emissions modules for conventional ICE vehicles. Other traffic microsimulation models are used in association with energy consumption models of appropriate design. However these tools cannot be used for the calculation of instantaneous or average fuel consumption of hybrid ICE and hybrid fuel cell vehicles.

Instantaneous fuel consumption models compute a vehicle's fuel consumption based on instantaneous power as an explanatory variable. The total fuel consumed by a vehicle during a drive cycle reflects the power required along the trip. This in turn reflects the speed and acceleration/deceleration profile experienced by the vehicle (Akcelik, 1986).

This approach is the basis for the recently developed Transportation Analysis Simulation System (TRANSIMS). In TRANSIMS, the light-duty vehicle fuel consumption model

uses speed and acceleration to calculate the required power by taking into account not only the total tractive force required to drive the vehicle but also the power drained by electric accessories such as air conditioning.

With the engine power known, the calculation of fuel consumption and emissions is straightforward (Barret et al, 1999). Although data for a fleet of more than 300 vehicles were used to develop TRANSIMS's Fuel and Emission Module, none of them was an advanced technology vehicle. Therefore TRANSIMS is unsuitable to calculate fuel consumption of hybrid ICE or hybrid fuel cell vehicles.

It is possible to use the original power-based model developed by Post et al, presented in Equation 2-1, to show the differences between fuel consumption of an advanced technology vehicle equipped with an energy storage system (ESS) and the instantaneous fuel consumption of a conventional ICE vehicle. (Post *et al.*, 1984, and Biggs and Akcelik, 1986):

$$\begin{aligned} FC &= \alpha + \beta \cdot Z & Z \geq 0 \text{ kW} \\ FC &= \alpha & Z < 0 \text{ kW} \end{aligned}$$

Equation 2-1 Instantaneous fuel consumption of a conventional ICE vehicle
(Source: Post et al, 1984)

where:

FC	= Instantaneous fuel consumption; ml/min
α	= vehicle parameter; ml/min
β	= vehicle parameter; ml/min kW
Z	= Instantaneous power demand; kW

Although the instantaneous power demand (a function of vehicle's mass, drag, speed, acceleration and road gradient) is common to both kinds of vehicles, the condition limits in which the coefficients α and β are used are highly affected by the control strategy implemented in an advanced technology vehicle. For an internal combustion engine with spark ignition, the idle fuel rate α is an estimate of fuel used to maintain engine operation and could be expressed as a linear function of engine capacity. In other words, the bigger the engine, the more fuel will be consumed in idle condition.

This is not entirely valid for an advanced technology vehicle under certain battery's residual charge capacity or state of charge values (scaled from 0 to 1; 0 is empty, and 1 is full). If the battery has a state of charge (SOC) value, over a certain limit, *lim*, specified by its control strategy, the vehicle would turn off the engine in idle condition and it will work only with battery power, causing zero fuel consumption. In a similar manner, the fuel consumption rate per unit of power generated, β , is affected by the fact that over a specific power demand value Z_{max} , the engine will be assisted by the motor to overcome the power demanded (i.e. 52 kW for the U.S. Toyota Prius at 4500 rpm).

It is clear that if Equation 2-1 is used to calculate fuel consumption of an advanced technology vehicle, an overestimation will occur when $Z > Z_{max}$, and in idle conditions when $SOC > lim$. Consequently, Equation 2-1 for an advanced technology vehicle must be affected by the following conditions:

$$\begin{aligned}
FC &= \alpha + \beta_1 Z & Z \geq 0 \text{ and } Z < Z_{MAX} \\
FC &= \alpha + \beta_2 Z_{MAX} & Z > Z_{MAX} \\
FC &= \alpha & Z < 0 \text{ and } SOC < \lim \\
FC &= 0 & Z < 0 \text{ and } SOC > \lim
\end{aligned}$$

Equation 2-2 Instantaneous fuel consumption of a advanced technology vehicle

where:

FC	= Instantaneous fuel consumption; ml/min
α	= vehicle parameter; ml/min
β_1 and β_2	= vehicle parameters; ml/min kW
Z	= Instantaneous power demand; kW
Zmax	= Peak power provided by the engine; kW

One of the widely used urban traffic simulation models, the Federal Highway Administration's TRAF-series of models, including its latest version, TSIS 5.1, uses a different approach to evaluate the impacts of traffic network improvement alternatives on emissions and fuel consumption of conventional ICE vehicles. This approach is based on a set of look-up tables that relate fuel consumption and emissions with vehicle speed and acceleration. The set of look-up tables was developed by Oak Ridge National Laboratory (ORNL) from on-road and chassis dynamometer testing of a fleet of eight vehicles representing the current internal combustion engine technology (West *et al*, 1999).

Instantaneous fuel consumption could be easily calculated by interpolation or directly relating the observed speed and acceleration on a second-by-second basis with the table's values. However, to accurately calculate fuel consumption for advanced technology vehicles, not only instantaneous speed and acceleration but also the participation of the

energy storage system should be taken into account. Consequently, in order to use this analytical method of fuel consumption, several look-up tables, one for every SOC conditions (i.e. 0.80 to 0.75, 0.75 to 0.70, etc) would be needed, making the entire process cumbersome and impractical.

As for the average fuel consumption models, the most basic form of this type of model correlates fuel consumption with the average speed of the trip (Fwa and Ang, 1992). The following form of the model is not valid at speeds higher than 56 km/h (35 miles/h) because at higher speeds, air resistance affects fuel consumption.

$$F = a_0 + \frac{a_1}{V}$$

Equation 2-3 Average fuel consumption of a conventional internal combustion engine vehicle (Source: Fwa and Ang, 1992)

where

- F = average fuel consumption for a unit distance in a trip (ml/km)
- V = average speed of the trip (takes into account stops and speed changes in km/h)
- a_0, a_1 = vehicle-specific coefficients (ml/km and ml/hr respectively)

In this empirical type of equation of average fuel consumption, a_0 is a parameter associated with fuel consumed to overcome rolling resistance. It is approximately proportional to vehicle weight. a_1 is a parameter that is approximately proportional to fuel consumption while idling. However, for an advanced technology vehicle with two different sources of energy, the fuel consumption is not only dependent on the average speed along a specific trip, but also on the SOC value at the beginning of that trip and the

selected control strategy (USEPA, 1998). Therefore, the average fuel consumption model described by Equation 2-3 must be changed as follow:

$$F_{(SOC)} = a_{o(ESS)} + \frac{a_{1(ESS)}}{V}$$

Equation 2-4 Average fuel consumption of a advanced technology vehicle

where

SOC = State of Charge (SOC values: 0.8 to 0.4)

ESS = Energy Storage System, control strategy (series, parallel, parallel-series),

$F_{(SOC)}$ = represents a series of equations that describe the average fuel consumption for every different initial SOC value and/or control strategy considered.

It should be noted that not only fuel consumption models based on equations such as Equation 2-2, and Equation 2-4 for advanced technology vehicles are unavailable but also precise fuel consumption factors for these vehicles under various operating conditions are unknown (Samaras *et al*, 1998, Santini *et al*, 1999). One reason for this lack of information resides in the fact that evaluating fuel consumption of advanced technology vehicles is a complex task that involves the use of different power train configurations, power plants, battery size, and the calibration used to maintain the battery's SOC during vehicle operation.

Furthermore, the SOC depends on many variables. In turn, the assessment of these variables is quite difficult and requires special equipment that sometimes is only available through the vehicle's manufacturer (USEPA, 1998). To overcome the problem presented by the battery's SOC, the Society of Automotive Engineers (SAE) proposed the

following approach: *“Two identical drive cycles must be run in succession. Then, a window of time equal to the length of the selected drive cycle is slid along the time axis until the battery state of charge at the start and end of the sliding window cycle were equal. Within the shifted window, the vehicle has still traveled through the complete drive cycle. We can therefore divide the distance traveled within the window by the fuel consumed without regard for the battery state of charge”* (SAE, 1995).

However, this procedure is very difficult to accomplish without an enclosed testing loop and it is almost impossible in real world traffic conditions. As a result, the preferred alternative has been to subject the advanced technology vehicles to chassis dynamometer tests (USEPA, 1998).

Chassis dynamometer tests are carried out using different driving patterns for different vehicle conditions (cold start, different SOC values, etc). These driving patterns represent the driving behaviour for categorized driving situations on specific types of roads. The data derived using this procedure is considered to be representative for that certain driving situation. Information provided by chassis dynamometer tests and direct measurements allow researches to simulate the special behaviour of advanced technology vehicles through computer simulation models. Some of these models, developed to estimate vehicle performance and fuel consumption for advanced technology vehicles are discussed in the following section.

2.3 Computer Simulation Models

Computer simulation programs such as SIMPLEV and CarSim (Cuddy, 1995) accept input data to describe the physical characteristics of the vehicle (power train, battery pack, etc), and the specific speed trace. The input data may be in the form of efficiency factors or maps, with efficiency in function of explanatory variables such as torque and rotational speed. Unfortunately, due to the nature of the source code for SIMPLEV and CarSim, written specifically for electric vehicles and series hybrid ICE vehicles, implementing changes to model other control strategies or fuel cell vehicles would be very difficult.

The Hybrid Vehicle Evaluation Code (HVEC) developed at Lawrence Livermore National Laboratory eliminates this problem, making it possible to simulate a variety of vehicle types and components (fuel cell vehicles included), and to predict fuel consumption and emissions for the USEPA's Urban and Highway driving schedules. However, the code has not been properly documented, and is not available to the public (Aceves and Smith, 1995).

An alternative that allows an easier modification of computer codes in order to reflect the operation of real-world advanced technology vehicles is to build them in the user-friendly environment of MatLab/Simulink. In this case, the Massachusetts Institute of Technology's Energy Laboratory, used a simulation model running under MatLab/Simulink to study the advantage of advanced technology vehicles over

conventional ones (Weiss et al, 2003). Texas A&M University also selected a MatLab environment to develop its simulation code Versatile-Elph. This code is considerably simpler than the one from the MIT, because all the interactions between vehicle components are graphically represented using logical blocks and connecting lines (Senger, 1997).

However, according to the U.S. Department of Transportation, “*since 1995, the leading simulation model developed, validated and widely used is the Advanced Vehicle Simulator, ADVISOR*”, which was developed by the U.S. National Renewable Energy Laboratory (NREL) at Golden, Colorado. Running in MatLab/Simulink, it has the capability to model the operation of conventional, hybrid, electric and fuel cell vehicles. Moreover, since this model can produce estimates of fuel consumption and emissions of current or future vehicles, ADVISOR has been used to provide estimates of vehicle performance in circumstances when there are no data available or when performance analysis for future vehicles are desired (FHWA, 2001, Plotkin *et al*, 2001, Wipke *et al*, 1999)

ADVISOR uses a backward-forward version similar to the modelling approach developed by Barth et al, in 1996 for conventional ICE vehicles (Figure 2-4). In this type of model, all the physical processes involved in fuel consumption and the consequently emission of contaminants are individually modelled analytically (Barth *et al*, 1996). The addition of sub-modules for battery control strategy and motor assist operation into the process presented in Figure 2-4 (Barth et al, 1996), would allow the use of the physical

modelling approach to the calculation of fuel consumption of advanced technology vehicles.

Figure 2-4 Physical model approach

The last public domain version of the Advanced Vehicle Simulator, ADVISOR 2002, included several types of conventional ICE, hybrid ICE vehicles (e.g. Toyota Prius and Honda Insight), and hybrid or direct fuel cell vehicles. Performance information, such as efficiency maps for the engine, motor and fuel cell system, emissions contours and performance graphs for the battery system is available (Plotkin *et al*, 2001). Even though ADVISOR is capable of calculating fuel consumption and tailpipe emissions for specific speed profile, it has been mostly used by several researchers to analyze vehicle power-trains, many different conceptual vehicles, and new test procedures under standardized drive cycles (An *et al*, 1999, Santini *et al*, 1999, An *et al*, 2001, and Markel *et al*, 2002).

More information about the capabilities and operation of ADVISOR is presented in Appendix B.

2.4 Integration of Fuel Consumption and Computer Simulation Models

An interesting approach, from the perspective of the present thesis, is to develop and use microscopic and macroscopic models in order to eliminate or minimize the acquisition of field data that could be expensive or almost impossible to obtain (Frechette and Khan, 1998). In the case of conventional ICE vehicles, J. Y. Park (Park *et al*, 2001) explored the relationships between fuel consumption, emissions, speed and acceleration changes for various driving conditions by using two different microscopic models, VISSIM and MODEM. VISSIM is a micro-simulation package developed by PTV System that simulates vehicle movements on a second-by-second basis using car following and lane changing logic. MODEM is a database of fuel consumption and exhaust emissions values for conventional ICE vehicles. It was designed as a part of a European Commission project with the objective of analyzing fuel consumption and exhaust emissions for conventional ICE vehicles operating in different traffic conditions (congested urban road, motorway, etc), and are subject to different driving behaviours.

In Park's research, VISSIM was used to generate files containing second-by-second data (speed and acceleration) of vehicles running in a simulated network based on data from the city of Maidstone in the United Kingdom. These data were used as an input to

MODEM to calculate instantaneous fuel consumption and emissions. From outputs, regression models were developed which relate emissions with speed and acceleration levels. Park's work is similar to that carried out between 1998 and 2001 by Ahn et al, who developed the same type of relationships using higher order quadratic terms for conventional ICE vehicles, based on data collected at the ORNL (Equation 2-5). Several types of models based on polynomial combinations of speed and acceleration levels (e.g. linear, quadratic, and cubic terms), were developed and tested against the ORNL fuel consumption values (Ahn, 1998).

$$F = (a_1 + b_1S + c_1S^2) + (a_2 + b_2S + c_2S^2)Acc + (a_3 + b_3S + c_3S^2)Acc^2$$

$$F = (a_1 + b_1S + c_1S^2) + (a_2 + b_2S + c_2S^2)Acc + (a_3 + b_3S + c_3S^2)Acc^2 + (a_4 + b_4S + c_4S^2)Acc^3$$

$$F = (a_1 + b_1S + c_1S^2 + d_1S^3) + (a_2 + b_2S + c_2S^2 + d_2S^3)Acc + (a_3 + b_3S + c_3S^2 + d_3S^3)Acc^2$$

Equation 2-5 Instantaneous fuel consumption of conventional internal combustion engine vehicles (Source K. Ahn, 1998)

where

F	= fuel consumption (milligrams/s) for a certain speed or acceleration per one second
a	= intercept
b, c	= coefficients of equation
S	= speed (ft/s)
Acc	= acceleration (ft/s ²)

Subsequent versions of these relationships were used as a subroutine in the traffic simulation model INTEGRATION. Although the final model, shown in Equation 2-6, fits

the ORNL data accurately for high speed and low acceleration levels ($R^2 = 0.9969$), it was less accurate at low speed and high acceleration levels (Ahn *et al*, 2002)

$$F = (a_1 + b_1S + c_1S^2) + (a_2 + b_2S + c_2S^2)Acc + (a_3 + b_3S + c_3S^2)Acc^2$$

Equation 2-6 Instantaneous fuel consumption of conventional internal combustion engine vehicles (Source K. Ahn, 1998)

Akcelik *et al*, indicate that the use of polynomial speed and acceleration terms in fuel consumption regression models may result in a problem of multi-collinearity since relevant traffic variables are highly correlated. As a result, if all model coefficients are determined by regression analysis, the model results for idle, cruise and acceleration conditions are unlikely to share the same level of effectiveness (Akcelik *et al*, 1983). It is therefore necessary to use separate functions for idle, cruise, and other travel conditions, or to apply another approach that overcomes the problems mentioned above.

2.5 Artificial Neural Network Models

In recent years, a specific kind of artificial neural network known as Multilayer Perceptron (MLP) Neural Network has been applied with highly accurate results to transportation problems in which the input/output relationships are nonlinear, and/or involve high-order correlations among the input variables (Dougherty, 1995; Wasserman, 1993). The success of MLP neural networks can be attributed to the fact that rather than

solving for the relationship between input and output variables, as is done in regression analysis, a MLP neural network is trained to recognize relevant patterns between the input and output variables included in a “training” data set. Given that MLP neural networks simply learn the relationship between input and output variables, it can handle problems where the relationship between variables are highly non-linear and non-stationary (e.g., changing over time) or when the independent variables can be correlated. These conditions cause linear statistical techniques considerable difficulty. Although there is a diverse range of neural networks in terms of structure and mode of operation, all neural networks can be viewed as non-linear functions or systems that perform the same task: mapping input vectors to output vectors (Wasserman, 1993).

In Figure 2-5 (Dowla and Rogers, 1995), the input to the system is denoted by the vector x and the output denoted by the vector y . Therefore the input-output relation can be written as $y = f(x, w)$, where w denotes the weights of the network.

Figure 2-5 Neural Network as a nonlinear system

If only two weights in a network are considered, it is possible to use a graphical interpretation of this operation to better understand the results of the training process. In

Figure 2-6 (Wasserman, 1993), the rubber sheet represents the error surface where the height of the sheet at each point represents the error at that (x, y) position. Thus the objective of training the network is to identify and optimize the weights so that the error in the output is minimized (Wasserman, 1993).

Figure 2-6 Rubber sheet analogy for error

2.5.1 Back-Propagation Algorithm

By far the most common approach to train an MLP network is non-linear local optimization of the network weights. In the late 1980s simple gradient-based learning rules were used, such as Equation 2-7:

$$w_{k+1} \leftarrow \left[w_k - \mu \frac{\partial E_D}{\partial w_k} \right]$$

Equation 2-7 Iterative weight update rule. Gradient Method (Source: Dowla and Rogers, 1995)

where w_k is the weight vector containing all network weights at the k step, μ is a fixed step size called the learning rate, and $\partial E/\partial w_k$ is the partial derivative of the objective function with respect of the weight w_k . For the objective function E_D the sum of square error (SSE) was normally used (Equation 2-8).

$$E_D = \sum_{i=1}^n (y_i - a_i)^2$$

Equation 2-8 Sum-of-square error function (Source: Foresee and Hagan, 1997)

where a_i represents the neural network response, y_i is the correspondent output value for the input vector i , and n is the number of input vectors. The basic backpropagation algorithm changes each weight in a direction that minimizes the error. In other words, it is expected that after each iteration, $E_{k+1} < E_k$. See Figure 2-7 (Dowla and Rogers, 1995).

However, in many cases, this is not the direct route to a minimum, and when the back-propagation algorithm is applied to large sets of data, poor results and lengthy training times could be expected (Dowla and Rogers, 1995).

Figure 2-7 Graphical interpretation of the gradient descent learning rule

2.5.2 Newton's Based Optimization Algorithms

Another alternative to achieve fast optimization is the use of Newton's method. The iterative weight update rule of Newton's method is graphically described in Figure 2-8 (Dowla and Rogers, 1995), and expressed by:

$$w_{k+1} \leftarrow \left[w_k - \frac{\left[\frac{\partial E_D}{\partial w_k} \right]}{A_k} \right]$$

Equation 2-9 Iterative weight update rule. Newton's method (Source: Ham and Kostanic, 2001)

where A_k for a multiple-variable case is the Hessian matrix element (second derivative) of the objective function at the current values of the weights. Although Newton's method

often converges faster than gradient methods (Ham and Kostanic, 2001), it is complex and expensive to compute the Hessian matrix for MLP neural networks.

Figure 2-8 Graphical interpretation of the Newton's Method

However it is possible to express the elements of the Hessian matrix for a linear neural network, with a single output and a sum-of-square error used as objective function, as the second derivatives with respect of the weights (i.e. weights w_r and w_s), as follow:

$$\frac{\partial^2 E}{\partial w_r \partial w_s} = \sum_i \frac{\partial e_i}{\partial w_r} \frac{\partial e_i}{\partial w_s} + \sum_i (y_i - a_i) \frac{\partial^2 e_i}{\partial w_r \partial w_s}$$

Equation 2-10 Hessian Matrix's element (Source: Bishop, 1995)

where $\partial e_i / \partial w$ is the first derivative of the network errors with respect to the weights. For a non-linear neural network in the limit of an infinite data set the difference between the neural network outputs and the target values will be small and the second term could be neglected (Bishop, 1995).

$$\frac{\partial^2 E}{\partial w_r \partial w_s} = \sum_i \frac{\partial e_i}{\partial w_r} \frac{\partial e_i}{\partial w_s}$$

Equation 2-11 Approximation of Hessian Matrix's elements (Source: Bishop, 1995)

State-of-the-art training algorithms specifically designed for minimizing a sum-of-square-error function, such as the Levenberg-Marquardt algorithm, use this approximation to the Hessian as follows:

$$w_{k+1} \leftarrow \left[w_k - \frac{\frac{\partial E_D}{\partial w_k}}{\left(\sum_i \frac{\partial e_i}{\partial w_{kr}} \frac{\partial e_i}{\partial w_{ks}} \right) + \lambda I} \right]$$

Equation 2-12 Levenberg-Marquardt's iterative weight update rule (Source: Bishop, 1995)

where the parameter λ governs the step size, and I is the unit matrix. When the scalar λ is zero, this algorithm becomes an example of Newton's method, using the approximated Hessian matrix. When λ is large, this becomes gradient descent with a small step size (the learning rate μ). Due to the reason that Newton's method is faster than the gradient descent method, the goal of the iterative process is to decrease the value of λ after each successful step (i.e. reduction in performance function), and increase only when a tentative step would increase the performance function. In this way, the performance function will always be reduced in every iteration of the algorithm (Fine, 1999).

A neural network using the Levenberg-Marquardt algorithm was selected by Ahn (1998), as a good candidate to estimate fuel consumption and emission rates of conventional

internal combustion engine vehicles at the microscopic level, due to the following arguments:

- *“Data are heavily non-linear with several oscillations along the speed axis”,*
- *“Data are to be fitted with a fast computational procedure for later implementation in micro simulation model”, and*
- *“The accuracy of the algorithm needs to be enough to support second-by-second simulations”*

When trained with the same information used to develop the regression models discussed in Section 2.4 (i.e. speed and acceleration as explanatory variables of instantaneous fuel consumption), this neural network model showed a correlation coefficient of 0.9998 (Ahn, 1998).

Wang (1998) confirmed that it is also possible to use neural networks with an optimized back-propagation learning algorithm as an efficient tool for modelling emission rates of conventional internal combustion engine vehicles at the macroscopic level. When three different neural networks were trained to learn the relation between five input variables (percentages of delay, queue and stop time, average speed, and volume) and one output variable (i.e. CO, HC and NO_x one at a time) from a set of data created with TRAF-NETSIM, all of them showed greater coefficient of determination values (R^2) than those generated by regression models (Wang, 1998).

In a similar approach, Arsie et al (2000), used experimental data from two different internal combustion engines as a training dataset for a MLP neural network with a structure composed of four input variables (torque, rpm, air-fuel ratio, and spark advance) one hidden layer with five hidden units, and one output variable (fuel consumption).

Although R^2 values were not included in their paper, Arsie et al reported lower values of an error index (Equation 2-13) for the neural network model than the corresponding value of a regression model.

$$\text{Error} = \frac{\sqrt{\sum_{i=1}^{N_t} (y_i^* - y_i)^2 / N_t}}{\tilde{y}^*}$$

Equation 2-13 Error index (Source: Arsie et al, 2000)

where y_i are the predicted data, y_i^* are the measured data, $\tilde{y}^*$ is the mean of the measured data and N_t is the number of data points used. However, their research also showed that an overlycomplex neural network overfits the data and generalizes poorly.

In other words, the error on the training set is driven to a very small value, but when new data are presented to the network, the error is large. The network memorizes the training examples, but it has not learned to generalize to new situations (Arsie *et al*, 2000).

2.5.3 *Bayesian Regularization*

A method referred to as regularization improves the neural network generalization by constraining the size of the network weights. In other words, if a network just large enough to provide an adequate fit is used, the network response will be smooth (Foresee and Hagan, 1997). This technique is based on the addition of a new term and two parameters to the sum-of-square error, changing the objective function to:

$$S(w) = \beta E_D + \alpha E_w$$

Equation 2-14 Modified Objective Function (Source: Foresee and Hagan, 1997)

where E_D is the sum-of-square error, E_w is the sum-of-square of the network weights, α and β are the parameters of the objective function that represents the inverse variance of the distributions (Nabney, 2002). The size of the objective function parameter α with respect to β dictates the emphasis on training, i.e., if α is much lower than β the training algorithm will tend to make the errors smaller. On the other hand, for values of α much bigger than β , the training process will reduce the weight size at the expense of network errors in an attempt to soften the network response.

The major problem in this approach resides in the adequate selection of values for the objective function parameters (Foresee and Hagan, 1997). In search for an optimal solution to this problem, David MacKay (1994) has applied Bayes's rules to neural network learning using a Gaussian prior distribution for the neural network parameters

(MacKay, 1994). A brief description of his approach is presented in Appendix A, and only the main results of this approach are included in the present section.

Under this approach, the weights of the network are considered as random variables, and before any data are collected, any knowledge about these weights can be represented as the prior distribution $p(w)$. Once a data set D has been observed, the posterior probability distribution for the weights can be expressed according to Bayes's rule as follows:

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)}$$

Equation 2-15 Posterior probability distribution of weights (Source: Bishop M.C., 1995)

In this equation, $p(D|w)$ is the probability that the dataset D occurs, given the weights w , and $p(D)$ is a normalization factor included to reassure that the total probability is 1. The result of this Bayesian technique is a new expression for the posterior probability distribution for the weights:

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)} = \frac{1}{Z_s(\alpha, \beta)} \exp(-S(w))$$

Equation 2-16 Modified posterior probability distribution of weights (Source: Bishop M.C., 1995)

where $S(w)$ corresponds to the modified objective function, and Z_s is a normalization factor. The following equations express the optimized parameters α_{MP} and β_{MP} .

$$\alpha_{MP} = \frac{\gamma}{2E_w} \quad \beta_{MP} = \frac{N - \gamma}{2E_D}$$

where γ is the effective number of parameters and N is the number of input vectors in the data set. As observed in Equation 2-16, when the regularized objective function $S(w)$ is minimized, the posterior probability reaches its maximum value. This expression satisfies the proposed Bayesian framework, in which the optimal weights should maximize the posterior probability $P(w|D)$ (Foresee and Hagan, 1997). The MacKay's Bayesian techniques (Mackay, 1994) allow the optimal setting of the regularization parameters, and when used in conjunction with the Levenberg-Marquardt algorithm (discussed in Section 2.5.2) are able to produce networks with excellent generalization capabilities (Foresee and Hagan, 1997).

CHAPTER 3.METHODOLOGICAL FRAMEWORK

3.1 Introduction

Over the years, simulation models have been developed to study vehicle performance and fuel consumption when experimental or field data were absent or when projections for future vehicles were desired. These types of simulation models, based on external loads and relevant engine and vehicle characteristics and performance, have the capability to simulate existing untested or as yet un-built conceivable vehicles (FHWA, 2001).

In the same way, traffic simulation has proved to be an excellent support to traditional traffic engineering analysis methods in fully understanding the dynamics of traffic movement and control operations, allowing the evaluation of complex traffic situations that cannot be analyzed directly by other means (Clark and Daigle, 1997).

The subject of this research is one of these complex traffic situations in which detailed information about speed and accelerations is hard to obtain and reproduce without using expensive instrumented vehicles or dedicated laboratory equipment. To avoid the risk, expense, and in the case of advanced technology vehicles, the impossibility of extensive field experimentation, the FHWA's microscopic traffic simulation model CORSIM (CORridor SIMulation) included in the latest version of TSIS 5.1, was selected for use in conjunction with the NREL's advanced vehicle simulator ADVISOR (Appendix B).

Their application produced traffic flow on three different types of facilities (i.e. Downtown Urban Network, a single Urban Arterial, and an Urban Freeway facility), and the corresponding fuel consumption behaviour of three different classes of vehicles: conventional ICE, hybrid ICE and hybrid fuel cell.

Please see Figures 3-1 to 3-3 for representative facility types used in this research. Using this representation of reality, artificial neural network models at two different levels (microscopic and macroscopic) were trained to learn the fuel consumption characteristics of selected vehicular technologies when used on real world facilities. Figure 3-4 presents the general methodology used in this research.

Figure 3-1 Central Bussiness District network (Downtown)

Figure 3-2 Urban signalized 4-lane arterial (Bronson)

Figure 3-3 Urban freeway (HWY 417)

Figure 3-4 General Methodology

3.2 Microscopic Traffic Simulation

CORSIM, developed through FHWA's sponsored research as part of the TRAF family of simulation software, is the most widely used microscopic traffic simulation program in the U.S. and elsewhere around the world. It has become the standard in recent years with thousands of applications. It combines two different types of simulation models: NETSIM for non-freeway traffic and FRESIM for freeway traffic conditions. In both models, the state of each vehicle is updated every second according to the logic of car following, and lane changing algorithms. The vehicle and driver units react to their surrounding environment, as well as control devices (i.e. incidents, parking) in a stochastic manner (Clark and Daigle, 1997).

This stochastic process operates on the basis of random number seeds, which are used to generate a sequence of random numbers on which the model bases its decisions when determining random vehicle arrivals and assigning characteristics. This means that if a different random number seed is used, CORSIM will generate a different traffic stream (Rathi and Santiago, 1990). The driver and vehicle characteristics are assigned to each unit as it enters the network. Although the microsimulator of traffic has default values of parameters that affect the driving behaviour, it is logical to calibrate and validate the simulator prior to its use. In the present research, the procedure presented in Figure 3-5 was implemented to calibrate and validate the model, so as to find the most accurate representation of traffic flow on selected facilities.

Figure 3-5 Microscopic traffic simulation

3.2.1 Calibration and Validation Process

3.2.1.1 Geometric and traffic data collection

Traffic data and aerial photographs of every facility were obtained from the City of Ottawa's Transportation, Utilities and Public Works Department, the Ministry of Transportation of Ontario's Planning and Design Section-Eastern Region, and the City of Ottawa's Geographic Information System (E-Maps). From the aerial photographs and field inspections, all the information required to reproduce the physical characteristics of the network (i.e. data on roadway measurements, traffic lane characteristics, the number and type of secondary lanes, and network orientation) were collected. To complete the data collection process, other data such as traffic signal timing, information for the non-freeway facilities, and snapshots of selected locations of the freeway facility were also gathered. From these data, a link-node network structure was coded in CORSIM. Traffic volumes and traffic signal timings for the A.M. Peak Period provided by the City of Ottawa and the Ministry of Transportation of Ontario were also coded into the models (Clark and Daigle, 1997).

3.2.1.2 Selection of CORSIM parameters

Although CORSIM includes several parameters that could be calibrated so as to describe more precisely the actual traffic characteristics, Wang and Prevedouros (1998) suggested

that CORSIM's NETSIM component is capable of simulating traffic flow in non-freeway networks and facilities, with a good level of agreement with reality, using its default model parameters. Therefore, these parameters were used as the starting point for model calibration (Wang and Prevedouros, 1998, Prevedouros and Wang, 1999).

Although changes in the car-following parameters of earlier versions of CORSIM's FRESIM (i.e., 1994) were necessary for the simulation of freeway traffic, the latest version of CORSIM included in TSIS 5.1, has a default car-following sensitivity array of 12 to 3 (see Appendix B), which can be used to improve its capability to adequately simulate traffic volumes (Payne *et al.*, 1997).

3.2.1.2.1 Vehicle Entry Headway

A part of the calibration process is the specification of traffic flow (in vehicles per hour) at all arrival nodes, as well as the statistical distribution that the vehicle inter-arrival times follow, i.e., uniform, normal or Erlang distribution. Traffic flows for every node were specified in accordance with the information provided by the City of Ottawa and the Ministry of Transportation of Ontario. However, this information contains only vehicle counts and does not include any information about the distribution of the vehicle arrivals.

On non-freeway facilities with heavy traffic volume, a vehicle in a traffic stream interacts with other vehicles. For a casual observer, the time headway appears to be almost

constant, making the use of a normal distribution appropriate enough to reproduce the inter-arrival times distribution. Due to the effect of the traffic signals, the vehicles circulating on both non-freeway facilities (analyzed in the present thesis) show this kind of interaction and a normal distribution was selected to reproduce its time headway distribution (May, 1990). As for the freeway facility, in order to establish the most appropriate inter-arrival distribution, data from 3 different locations on Highway 417 were collected and analyzed. Snapshots of the A.M. Peak period traffic conditions for three different weekdays between January and March 2003 were taken by using a digital camera as follows:

- An elevated position, from which an adequate length of the facility could be observed without obstruction, was selected to mount the camera.
- A video of 10 seconds length was taken every 3 minutes, capturing all the vehicles that crossed under the observation point during that time.

With this method, 60 snapshots of the A.M. Peak period traffic conditions on Highway 417 were collected.

Traffic flow theory explains that if N cars cross a line in a time T , the flow is computed as: $q = N/T$, and the measure of time between the arrival of successive vehicles can be derived from the following relationship (Gerlough and Huber, 1975):

$$q = 1/h, \text{ and } h = T/N$$

Using the last equation and grouping the data from the videos, it was possible to construct a histogram of observed vehicle headways for Highway 417 using the Microsoft's Excel DATA ANALYSIS tool. It is possible to observe in Figure 3-6 that the frequency values show a right-tailed distribution and the use of a normal distribution to reproduce the vehicle entry headways would not be appropriate. (Clark et al, 2000).

Figure 3-6 Example of the observed vehicle headway in HWY 417

In his book, May (1990) suggests that when traffic volume is high, but not close enough to capacity, an Erlang distribution will provide a closer fit than the normal distribution. The value of K, the Erlang shape parameter, was estimated by dividing the square mean of the observed headways by its variance (Gerlough and Huber, 1975). When using all collected data, the estimate of K was found to be 1.8997. Since in CORSIM the shape parameter must be an integer it was set equal to 2. Once the existing conditions were recreated in CORSIM, the replication method proposed by Benekohal and Abu-Lebdeh (1994) was used to test the calibration process.

3.2.1.3 *Testing the Calibration Process (Replication Method)*

The replication method consists of the generation of several independent simulation runs using the same network and traffic conditions. Each run was created using a different random number seed, and for every run, after a specific period of time (always longer than the initialization time), traffic volume data at specific locations in the simulated facility were collected. The advantage of this method resides in the fact that using different random number seeds the independence between simulation runs is secured and the risk of autocorrelation could be eliminated. Therefore only an adequate number of replications must be estimated. Benekohal and Abu-Lebdehn (1994) suggest starting the replication process by using 10 runs of reasonable length that represents real-world conditions. Next, the mean and variance of those observations are found and a confidence level is selected to calculate the required number of observations (n) using the following equation (Benekohal and Abu-Lebdehn, 1994).

$$n = \frac{(ts)^2}{e^2}$$

Equation 3-1 Required number of observations

where

s = standard deviation of observations,

e = tolerable error, and

t = critical t-value from a t-distribution table for $(n-1)$ degrees of freedom and selected confidence level.

The tolerable error depends on the desired accuracy, which in turn depends on the distribution of data around the mean. Benekohal and Abu-Lebdehn suggest 5 to 15

percent of the range when a data set does not have extreme values. If n is larger than the initial number of runs, the process requires a few more runs until n is less than the total number of runs. After that, it is possible to build confidence intervals using the results from n runs (Microsoft, 2001):

$$\text{Confidence interval} = \bar{x} \pm \frac{ts}{\sqrt{n}}$$

Equation 3-2 Confidence interval function

where

s = standard deviation of n observations,

$\bar{x}$ = mean of n observations

t = critical t-value from a t-distribution table for $(n-1)$ degrees of freedom and selected confidence level.

Independence between runs was assured using numbers created by MICROSOFT's Excel function RAND as the random number seed for every run. The aforementioned process was used for the three different types of facilities discussed in the present thesis and their results are presented in Table 3-1.

Table 3-1 Calibration Process Results

Location	Downtown Network	Highway 417 Eastbound	Bronson Ave.
	Albert and O'Connor	Between Highway 416 and Greenbank Rd.	Albert St.
Number of independent simulation runs	14	13	14
Sample size	70	65	70
Sample standard deviation	16.62	16.90	37.24
Sample mean	718 vph	1287 vphpl	630 vph
t value	1.96	1.96	1.96
Confidence 95%	3.89	3.31	9.05
Confidence 99 %	5.11	4.35	11.89

These results suggest, with an adequate level of confidence, that the parameters selected in the calibration process enable CORSIM to simulate traffic that matches the observed traffic conditions in the real world, for facilities studied in this research. After completion of the calibration process, the traffic simulations were validated by comparing outputs of the calibrated model with the corresponding field observations. Milam and Choa (2000) indicate that the most common traffic flow characteristics used in validation include: traffic volume, average travel speed, queue length, and density. In this case, due to the nature of the available information, the volume served was selected as the validation parameter. See Table 3-2 (Milam and Choa, 2000).

Table 3-2 Microscopic Traffic Simulation. Validation Criteria

Parameters	Description	Validation Criteria
Volume Served	Ratio between input volume and CORSIM output or assigned volume	0.95 to 1.05 of observed value

The validation process was implemented, as described next:

- Using the calibrated model for every facility, five 30-minutes independent simulations (i.e. using different random seed numbers) were developed and traffic volumes at a specific location were noted on a regular basis. For the entire set of results, minimum, maximum and average traffic volumes were extracted, and the ratio between them and the real world's traffic volume was calculated.

Figures 3-7 to 3-12 show the comparison between maximum, minimum and average values of traffic volume against the real world's traffic volume at a specific location for

every type of facility. It is possible to observe that traffic volumes in all the simulated facilities fulfill the selected validation criteria.

Figure 3-7 Ratio between actual volume and CORSIM output. HWY 417-A

Figure 3-8 Ratio between actual volume and CORSIM output. HWY 417-B

Figure 3-9 Ratio between actual volume and CORSIM output. CBD - A

Figure 3-10 Ratio between actual volume and CORSIM output. CBD - B

Figure 3-11 Ratio between actual volume and CORSIM output. Bronson - A

Figure 3-12 Ratio between actual volume and CORSIM output. Bronson - B

3.2.2 *Data Extraction*

CORSIM produces several output forms. Although it is possible to include different measures of performance into an ASCII file or to print these, actual throughput measures (as speed or delay) are computed in aggregate form for specified measurement points or for the entire network. It is not possible to directly extract individual vehicle information. For this reason, in order to extract instantaneous speed of individual vehicles from the CORSIM output file “*.tsd”, the following procedure was used:

- A 15-minute period was simulated to allow a proper initialization.
- After the initialization period, a 15 to 45 minutes period was simulated, depending on the size of the network.

Individual vehicle information from the “*.tsd” file was extracted using an Excel add-in developed at the Georgia Institute of Technology by John D. Leonard II, named CORTOOLS (Leonard, 2000). It is included in Appendix B.

By using this approach, information on an average of 20 vehicles for every simulated network was extracted and used to create representative speed traces of non-freeway and freeway facilities under AM Peak period traffic conditions. These speed traces were exported to MatLab to be used as inputs for ADVISOR. The procedure is described next:

- From the information extracted by CORTOOLS, instantaneous speed (in feet per second) of individual vehicles was converted to miles per hour, and one Excel worksheet was created for every speed trace,
- Using MatLab's Import Wizard, every speed trace contained in the aforementioned Excel file, was individually imported into MATLAB and a new MATLAB variable named "cyc_mph" was created that contained the information for every speed trace (time and speed on a second-by-second basis),
- Finally, a set of two different MatLab files, a "*.mat" file containing the speed trace information, and a "*.m" file containing instructions that allow the use of this information in ADVISOR, were created for every speed trace and added to ADVISOR's data library.

3.3 Advanced Vehicle Simulation

In words of the US Department of Transportation, "*the leading simulation model developed, validated and widely used since 1995 is ADVISOR (ADvanced VehIcle SimulatOR)*" developed by the U.S. National Renewable Energy Laboratory of Golden, Colorado. This model not only can simulate the performance of current vehicles, but also can be used to estimate performance of un-built vehicles after these are conceived and designed (FHWA, 2001). ADVISOR is a computer program that works in MatLab/Simulink environment. It is capable of estimating fuel consumption on a second-by-second basis for a conventional or advanced technology vehicle, following a specific

speed trace. Speed traces are defined through second-by-second profiles of vehicle speed. Each profile determines the second-by-second power requirement of the vehicle, which in conjunction with the vehicle's efficiency determines the vehicle operation regimes and vehicle's fuel economy. To simulate a vehicle following a speed trace, ADVISOR uses a two-step approach (Plotkin *et al*, 2001).

In the first step, the simulated vehicle is presented with a speed trace that must be followed. Based on this information, the model calculates the force that is required at the wheels and the participation of all the power-train components to move the vehicle at the required speed and acceleration without slipping. After that, the speed reached by the vehicle is obtained. If all is correct, the requested and achieved speeds will be the same. If not, ADVISOR utilizes the achieved speed to quantify the vehicle's performance. The model uses look-up tables and detailed maps of efficiency of several explanatory variables (i.e. fuel consumption against output-torque and speed) as a basis for the estimates of the capabilities and efficiency of key components. Although, these tables and maps are normally based on experimental test reflecting conditions after warm-up, ADVISOR is also capable of simulating the effect of the engine and catalytic converter warming-up process (Plotkin *et al*, 2001).

In this thesis, the operation of five different vehicles under non-freeway and freeway A.M. Peak period traffic conditions was simulated using ADVISOR 2002, in order to collect information about vehicle's performance and fuel consumption on a second-by-

second-basis under realistic traffic conditions. With this objective in mind, similar aerodynamics characteristics, structure, materials, and wheel/tire system were used. The simulated vehicles can be classified as follows:

- Two conventional internal combustion engine vehicles (ICE), one comparable with a compact vehicle like Toyota Echo and the second, with similar capabilities as a large vehicle like Chevy Lumina, were simulated to generate a baseline for comparison,
- A hybrid vehicle was defined based on the Japanese Toyota Prius, a currently available advanced technology vehicle featuring an internal combustion engine and an electric motor, and
- Two hypothetical hybrid fuel cell vehicles with advance technology were specified. These use a Polymer Electrolyte Membrane Fuel Cell (PEMFC) to convert chemical energy to electrical energy, and an on-board Partial Oxidation system (POX) to reform gasoline to hydrogen. According to automobile manufacturing company press releases, such vehicles are likely to enter large-scale mass production phase within 5 to 10 years (Hoffmann, 2001).

The procedure implemented in the present thesis (Figure 3-13), follows the guidelines to specify different vehicles and to simulate their performance, using ADVISOR (An *et al.*, 1999; Santini *et al.*, 1999)

Figure 3-13 Conventional and advance technology vehicle simulation

3.3.1 Calibration Process

One of the main advantages of ADVISOR 2002 is the ability to define several drivetrain types not only for conventional internal combustion engine, but also for electric, series and parallel hybrid, and fuel cell hybrid models into a graphical user interface, or GUI,

based in MatLab/Simulink. This allows an easy manipulation of data files, input files, test routines, and output plots to represent new or unique vehicle components.

3.3.1.1 Vehicle Configuration

3.3.1.1.1 Conventional ICE vehicles

In order to simulate the conventional internal combustion engine vehicles, inputs presented in ADVISOR's graphical user interface for files CONV_27MPG_IN and SMALL_CAR_IN (large and small ICE respectively), were calibrated using technical specifications of a Chevy Lumina for the large car file, and a Toyota Echo for the small ICE car. See Figure 3-14 (NREL, 2002)

Figure 3-14 Simplified internal combustion engine vehicle system

Only a few modifications were required to meet the maximum power and requirements of physical characteristics (i.e. coefficient of aerodynamic drag, frontal area and vehicle's mass and scaling maximum power) of both vehicles. Most of the default values provided by ADVISOR for these types of vehicles were used without change.

3.3.1.1.2 Hybrid ICE vehicle

The hybrid ICE vehicle was simulated with the default values of ADVISOR's data file VEH_PRIUS_JPN. This file contains fuel use and vehicle performance data, obtained from calibration work carried out by the U.S. National Renewable Energy Laboratory, using test data from dynamometer testing at the U.S. Argonne National Laboratory. See Figure 3-15 (NREL, 2002)

Figure 3-15 Simplified ICE hybrid electric vehicle system

3.3.1.1.3 Hybrid Fuel Cell vehicles

Two opposite configurations of a hybrid fuel cell vehicle were simulated. The first, named Hybrid Fuel Cell Dominant is a fuel cell powered vehicle with a small battery that provides peak acceleration power while the fuel cell provides most of the power to meet the road load. The second one, referred to as Hybrid Fuel Cell Battery, has a small fuel cell and a large battery that serves the driving load. Both vehicles were simulated using a model of an ambient pressure reformed gasoline fuel cell system created for the U.S.

Argonne National Laboratory (ADVISOR's file FC_ANL50GAS). See Figure 3-16 (NREL, 2002)

Figure 3-16 Simplified fuel cell vehicle system with on-board fuel processor

Physical characteristics and battery configurations were based on vehicle configurations presented in Chapter 4 of the report entitled "Evaluation of Fuel Cell Reformer Emissions" prepared by the California Air Resources Board (CARB) and the South Coast Air Quality Management District published in 1999 by the U.S. Department of Commerce's NTIS (Unnasch and Drunertu, 1999). The coefficient of aerodynamic drag and the frontal area were the same as the calibrated values for the simulated small ICE vehicle. With respect to the vehicle's mass, the mass calculated by ADVISOR's graphical user interface was overridden to take into account the vehicle's configuration evaluated by CARB. The default ADVISOR's model of a Fuel Cell vehicle (FUEL_CELL_DEFAULTS_IN) utilizes a set of sealed valve-regulated lead-acid batteries as an energy storage. However, the vehicle's configuration evaluated by CARB indicates the use of a nickel metal hydride (NiMH) battery set with a net power of 19 kW for a Fuel Cell Dominant and 64 kW for a Fuel Cell Battery vehicle.

To validate the required number of battery modules (by weight) to fulfill the power requested (90 and 300 kg for a Fuel Cell Dominant and Fuel Cell Battery vehicle, respectively), the specific power values (in kW/kg) and the efficiency of a NiMH battery reported by CARB were used as follows:

$$\text{Number of modules} = \left[\frac{\text{Battery Net Power (kW)}}{\text{Specific Power (kW/kg)}} \right] * \text{Efficiency (\%)}$$

Results for both vehicles are presented in Table 3-3:

Table 3-3 Hybrid Fuel Cell vehicles - Battery Requirements

Vehicle	Battery Net Power (kW)	Specific Power (kW/kg)	Efficiency %	Number of Modules
Fuel Cell Dominant	19	0.25	87	87
Fuel Cell Battery	64	0.25	87	294

ADVISOR specifies a weight of 1 kg per each NiMH battery module, which results in a Battery Net weight of 87 kg for the Fuel Cell Dominant and 294 kg for a Fuel Cell Battery vehicle. Since the calculated weight values were much closer to those described by the CARB, the former were used as inputs into the ADVISOR graphical user interface.

3.3.1.2 Vehicle Control Strategy

In theory, the computer system installed in an advance technology vehicle like Toyota Prius controls the amount of power provided by the engine and the energy storage system, taking into account the road loads and the requested speed, in order to keep the vehicle operating near an optimal level. This optimum level is a predetermined function of energy use and emissions. ADVISOR simulates this behaviour following a specific control strategy for every type of vehicle to predict current, voltage, state-of-charge (SOC), and temperature of the battery using power request as an input. ADVISOR simulates the control strategy of a hybrid electric vehicle, like Toyota Prius using the power-train control and continuously variable transmission parameters, included in the data file PTC_PRIUS_JPN (NREL, 2002).

With respect to a fuel cell vehicle, the energy strategy in ADVISOR is simulated using a set of variables (cs_lo_soc and cs_hi_soc) to control the operation range in which the fuel converter is turned on or off following a similar behaviour to the series-hybrid-electric vehicle (NREL, 2002). This operating range is a compromise between the maximization of the battery's life, which might require a high SOC range (e.g. 0.5 to 0.6) to avoid damaging the battery pack for low charge conditions, and the maximization of the fuel economy, which would require a low SOC range (e.g. 0.2 to 0.3).

Theoretically, Toyota's Prius battery SOC has control limits of 0.4 to 0.8; however tests developed by National Renewable Energy Laboratory, showed that Prius tends to

maintain SOC values around a narrow band centered on 0.56, for standard drive cycles like the Federal Urban Dynamometer Driving Schedule (UDDS) and the Highway Fuel Economy Test (HWFET) (Kelly and Rajagopalan, 2001). As a result, a conservative value of 0.55 to 0.60 for the SOC range was used in the present thesis.

3.3.1.3 Initial Conditions

ADVISOR allows the selection of initial conditions in which the vehicle starts the speed profile. In this case, the Environmental Protection Agency's MOBILE family of models defines two types of start conditions i.e., cold start in which the engine starts after 12 hours of soak, and a hot start in which the engine start is done after 10 minutes of soak (USEPA, 2001b).

Considering that the number of engine starts per day for an average passenger vehicle provided by EPA's MOBILE6 is 3.85 and that a hot start is the most likely type of start to happen along the day, only hot initial conditions were used in this thesis for all the drive cycles and facilities.

In a similar way, although ADVISOR is capable of simulating air conditioning and other types of external electric loads, their effects over fuel consumption were not taken into account for any of the simulated vehicles.

3.3.2 Validation Process

To evaluate the accuracy of the calibration process, all the simulated vehicles were tested on two standardized drive cycles used to measure official vehicle fuel consumption, i.e. UDDS and HWFET. Both drive cycles are included in ADVISOR's data library making its use very straightforward. If accurate input data are employed, good agreement may be expected between simulation results and test data. Fuel consumption in miles per gallon calculated by ADVISOR and fuel consumption values from different sources are presented in Tables 3-4 to 3-8 for comparison purposes.

Table 3-4 Fuel Consumption of Conventional ICE Vehicles (a)

Large ICE vehicle	Drive Cycles	
	UDDS (mpg)	HWFET (mpg)
USEPA's 1999 FUEL ECONOMY GUIDE	20	29
USEPA (Lab test)	22	36
ADVISOR	22	39
EPA/ADVISOR	1	0.9230

Table 3-5 Fuel Consumption of Conventional ICE Vehicles (b).

Small ICE vehicle	Drive Cycles	
	UDDS (mpg)	HWFET (mpg)
USEPA's 1999 FUEL ECONOMY GUIDE	22	28
USEPA (Lab test)	27	34
ADVISOR	26.7	35
EPA/ADVISOR	1.011	0.9714

Note that USEPA lowered the UDDS fuel consumption value by 10 percent and the HWFET estimate by 22 percent from the laboratory test results (EPA, 1998)

Table 3-6 Fuel Consumption of an Hybrid ICE Vehicle

Hybrid ICE Vehicle	Assumed initial condition (SOC – start)	
	0.80 - Cold start	0.5 – Hot start
Test	UDDS (mpg)	HWFET (mpg)
NREL (Lab tests)	54.7	57.2
ADVISOR	53.2	57.4
NREL/ADVISOR	1.028	0.9965

Note that initial conditions for State-of-Charge and temperature were not included in NREL report (Kelly J. K., and Rajagopalan, 2001)

Table 3-7 Fuel Consumption of Hybrid Fuel Cell Vehicles (a)

Fuel Cell Dominant	Assumed initial SOC condition	
	0.50 – Cold Start	0.50 – Hot Start
Test	UDDS (mpg)	HWFET (mpg)
CARB	35.3	41.8
ADVISOR	34.1	42.8
CARB/ADVISOR	1.035	0.9766

Table 3-8 Fuel Consumption of Hybrid Fuel Cell Vehicles (b)

Fuel Cell Battery	Assumed initial SOC condition	
	0.50 – Cold Start	0.50 – Hot Start
Test	UDDS (mpg)	HWFET (mpg)
CARB	38.4	43.6
ADVISOR	36.2	45.4
CARB/ADVISOR	1.060	0.9603

Note that CARB calculated fuel consumption for both types of vehicles considering an average system efficiency of 0.3566 and a SOC value of 0.5 (Unnasch and Drunert, 1999)

Examination of these sheets reveals that the simulation and test results always agree within about 10%, and in most cases, within 2 to 5%.

3.3.3 Data Collection

Based on these results, around 60 speed traces from CORSIM were simulated into ADVISOR in order to collect the required number of data samples, for all vehicles and facilities, taking into consideration the minimum number of samples required for every facility. The following equation, based on the central limit theorem, was used to calculate the minimum number of samples required to comply with the desired confidence level, for every simulated facility used in this thesis.

$$n = \left(\frac{z^* \sigma}{\epsilon} \right)^2$$

where

- n is the sample size required to draw conclusions at the desired confidence level,
- z^* is a number listed in tables of standard normal probabilities
- σ is the standard deviation, and
- ϵ is the maximum tolerable error in our estimate of the population mean

Results are presented in Tables 3-9 to 3-11 using instantaneous fuel consumption values provided by ADVISOR as variable of interest.

Table 3-9 Minimum Number of Samples, CBD

Downtown Ottawa	Mean (g/sec) [a]	Std dev	Tolerance [b]	Confidence Level	ε $2*[a]*[b]$	n
Large ICE	0.67	0.77	$\pm 1 \%$	95%	0.0134	12684
Small ICE	0.51	0.50	$\pm 1 \%$	95%	0.0102	9231
Hybrid ICE	0.38	0.36	$\pm 1 \%$	95%	0.0076	8619
Fuel Cell Dominant	0.27	0.31	$\pm 1 \%$	95%	0.0054	12660
Fuel Cell Battery	0.19	0.08	$\pm 1 \%$	95%	0.0038	1702

Table 3-10 Minimum Number of Samples, HWY 417

Highway 417	Mean (g/sec) [a]	Std dev	Tolerance [b]	Confidence Level	ε $2*[a]*[b]$	n
Large ICE	1.53	1.13	$\pm 1 \%$	95%	0.0306	5238
Small ICE	1.58	0.75	$\pm 1 \%$	95%	0.0316	2164
Hybrid ICE	1.07	0.83	$\pm 1 \%$	95%	0.0214	5778
Fuel Cell Dominant	0.89	0.41	$\pm 1 \%$	95%	0.0178	2038
Fuel Cell Battery	0.74	0.34	$\pm 1 \%$	95%	0.0148	2027

Table 3-11 Minimum Number of Samples, Bronson

Bronson Ave	Mean (g/sec) [a]	Std dev	Tolerance [b]	Confidence Level	ε $2*[a]*[b]$	n
Large ICE	0.69	0.76	$\pm 1 \%$	95%	0.0138	11651
Small ICE	0.56	0.54	$\pm 1 \%$	95%	0.0112	8930
Hybrid ICE	0.37	0.41	$\pm 1 \%$	95%	0.0082	9604
Fuel Cell Dominant	0.40	0.31	$\pm 1 \%$	95%	0.008	5768
Fuel Cell Battery	0.22	0.10	$\pm 1 \%$	95%	0.0044	1984

Finally, results for several ADVISOR variables describing the vehicle's behaviour were extracted from ADVISOR outputs and stored in an Excel spreadsheet. The procedure used is as follows:

- After a simulation has been completed, every variable of interest was exported from ADVISOR to MatLab's workspace,
- A matrix was created containing all the variables of interest, and saved as an "ascii" file, and
- The "ascii" file was exported to Excel and saved for future use.

3.4 Neural Network Modelling

Taking advantage of the artificial neural network's properties discussed in Section 2.5, and following an approach similar to that one used by the United States Environmental Protection Agency for its New Generation Vehicle Model (USEPA, 2001c), neural network models capable of predicting fuel consumption of conventional and advanced technology vehicles were developed at two different levels i.e., microscopic fuel consumption and macroscopic fuel consumption (Figure 3-17 and Figure 3-18).

3.4.1 Microscopic Level

3.4.1.1 Problem Formulation

The literature review showed that vehicle's instantaneous fuel consumption can be calculated based on instantaneous measurements of explanatory variables (i.e. from field data or micro-simulation models).

Figure 3-17 Microscopic neural network modelling

Figure 3-18 Macroscopic neural network modelling

For conventional ICE vehicles, the most common of these explanatory variables is the power requested on a second-by-second basis, which in turn depends on the physical characteristics of the vehicle, its speed and acceleration/deceleration profile (Akcelik, 1986). Some studies (Ahn, 1998, Arsie *et al*, 2000) have demonstrated that it is possible to predict accurately instantaneous fuel consumption of conventional ICE vehicles, with neural network models trained using information based on look-up tables of speed, acceleration, and fuel consumption. In this case, the problem can be expressed in the following mathematical form:

$$Inst\ FC = f(speed, accel)$$

Equation 3-3 Instantaneous fuel consumption function for ICE conventional vehicles

where

speed, is the instantaneous speed in kilometres per hour,
accel, is the acceleration calculated from the collected speed values, and
Inst FC, is the fuel consumption rate in g/sec

For advanced technology vehicles, such as Hybrids ICE and Hybrids Fuel Cell, in which not only another source of power (i.e. energy storage system (ESS)), is available but also the amount of power provided by the ESS overtime depends on the battery's SOC, the addition of more explanatory variables are required to take into account the particular characteristics of these vehicles. However, SOC is not an absolute but a relative term and it is mathematically highly non-linear. It depends not only on the rate of discharge/charge but also on external and internal resistance, battery voltage, and current.

Therefore it is a term that is very difficult to calculate accurately. ADVISOR handles this problem by calculating current in and out of the ESS second-by-second, based on the power requested, and the amount of energy remaining in the battery (Bhatikar *et al*, 2000, Johnson, 2002). A general scheme representing this process is shown in Figure 3-19 (NREL, 2002)

Figure 3-19 ADVISOR's SOC calculation process

Where Max_Capacity and ESS_current are ADVISOR variables that represent the maximum battery capacity and electric current respectively. As a result, Equation 3-3 was changed for a set of two different equations, in order to account for the particular characteristics of advanced technology vehicles:

$$ESS\ Current = f(time, speed, accel, SOC)$$

Equation 3-4 Instantaneous current flow in amperes

$$Inst\ FC = f(time, speed, accel, SOC, ESS\ Current)$$

Equation 3-5 Instantaneous fuel consumption in grams per second

where

time is in seconds,

SOC, is the state of charge of the battery, and

ESS Current, is the battery's discharging or charging current.

3.4.1.2 Data Transformation

The relation between the selected input and output variables and the information extracted from ADVISOR is presented in Table 3-12.

Table 3-12 Input and Output Variables

<i>Input and Output Variables</i>		
	Definition	ADVISOR
time	Time (sec)	t
speed	Speed (km/h)	kpha
accel	Acceleration (km/h per second)	
SOC	State of Charge	ess_soc_hist
ESS Current	Current (A)	ess_current
Inst FC	Fuel Consumption (g/sec)	fc_fuel_rate

Due to the requirements of neural network computation algorithms, it is a common practice to scale input variables, through data transformations. Theoretically, if all the inputs are equally important, all network weights will have similar values and it can be randomly initialized (Nabney, 2002). Shi (2000) categorized the existing data transformation in three different groups:

- Linear transformations, in which the data are pre-processed so that the minimum is -1 and the maximum is 1 . MatLab uses the original data range as scalar and the function “premnmx” through the following algorithm:

$$pn = 2 * \frac{(p - \min p)}{(\max p - \min p)} - 1$$

where

pn is the transformed value of the input variable p , $\min p$ is the minimum value of the input variable p , and $\max p$ is the maximum value of the input variable p

- Statistical standardization, in which the input's mean and standard deviation are used to rescale the training data set as follow:

$$\tilde{x}_i^n = \frac{x_i^n - \bar{x}_i}{\sigma_i}$$

where

$\tilde{x}_i^n$ is the i^{th} transformed input variable,

x_i^n is the i^{th} input variable,

$\bar{x}_i$ is the input variable's mean, and

σ_i is the input variable's standard deviation

- Mathematical functions, in which a mathematical function is applied to the dataset.

Shi (2000) also indicates that the selection of the best transformation algorithm could be done contrasting the network performance under various transformations. Nonetheless Foresee and Hagan (1997) suggested that, if the Levenberg-Marquardt algorithm is used

to train the neural network, the best results are obtained if a linear transformation of inputs and outputs is selected.

3.4.1.3 Model Development

A Multi-Layer Perceptron Neural Network structure was selected to solve the problem expressed in Equations 3-3 to 3-5, due to the fact that “*such networks have the property that the outputs can be expressed as deterministic functions of the inputs and, as a result, the entire network represents a multivariate non-linear function mapping*” (Bishop, 1995).

Development of a neural network model for Equation 3-3 was straightforward (Figure 3-20):

- Speed values (ADVISOR variable *kpha*) previously collected are used to calculate acceleration values on a second-by-second basis,
- The corresponding vector [speed, acceleration] is transformed in order to improve the neural network training process,
- Transformed fuel consumption values (ADVISOR variable *fc_fuel_rate*) are used as targets to train the neural network to reproduce the instantaneous fuel consumption behaviour of a conventional engine vehicle.

Figure 3-20 ANN model for instantaneous fuel consumption (ICE)

However, in order to solve Equation 3-4 and Equation 3-5, the system, composed of two different neural network models, presented in Figure 3-21, was required:

- Time and SOC (ADVISOR variable t and ess_soc_hist respectively) were added as explanatory variables to create the input vector [time, speed, accel, soc]. The initial SOC value was specified as 0.60,
- In the neural network training process, input vector values and the current values calculated by ADVISOR (ADVISOR variable $ess_current$) were transformed and used as input and target variables, respectively.

- The first neural network was trained to reproduce the vehicle's control strategy and the corresponding battery's discharge/charge process. The second neural network used an input vector composed of [time, speed, accel, soc, ESS_current]. This neural network was trained to reproduce the instantaneous fuel consumption behaviour of advanced technology vehicles based on the values of the ADVISOR variable *fc_fuel_rate*.

Figure 3-21 ANN model for instantaneous fuel consumption (ATV)

It should be noted that the objective of the neural network training process is not to find or to create an exact representation of the training data, but rather to build a statistical model of the process that generates the data. In other words, the goal of neural network training is to obtain a model capable of reproducing the results of the training data set not only with a small margin of error, but also that adequately responds to novel inputs (Murata *et al*, 1994, Foresee and Hagan, 1997). In the present thesis the Bayesian framework of learning in neural networks was used in two steps: First to obtain the most adequate neural structure to solve the problem, and second, to calculate the most optimal number of hidden units in that particular structure (MacKay, 1994)

3.4.1.3.1 Neural Network Structure

It was found in the literature review that two different neural network structures have been applied to calculate fuel consumption of conventional ICE vehicles: a 3-layer neural network and a 2-layer neural network (Figure 3-22). In order to find the most adequate structure for this research, the next procedure was followed:

- Several neural network structures were created into MatLab's Neural Network Toolbox with hidden unit values from 5 to 20,
- The training process was carried out using MATLAB's Neural Network Toolbox, with MATLAB's algorithm TRAINBR as the network training function, and with an initial value of the learning rate $\mu=0.005$. MATLAB's default factor of 10 was considered for the variation of the μ value in every step.

- Two independent data sets, the training set and the testing set, were used to monitor the error behaviour during the training process. The neural network structure with better generalization capabilities will show similar error behaviour for both data sets.

Figure 3-22 Examples of neural network structures

Figure 3-23 and Figure 3-24 shows the error behaviour for a 3-layer and a 2-layer neural network respectively, when a dataset of four explanatory variables, i.e. time, speed, acceleration and SOC, was used to predict the amount of energy provided by the ESS to the system. It is possible to observe that the error on the training set that corresponds to the 3-layer neural network is driven to a very small value, but when new data were presented to the network, the error become large. Therefore, in order to be consistent and to reduce the amount of computational requirements in both, the neural network training and the implementation process, the same neural network structure, a 2-layer neural network, was selected to solve Equations 3-3 to 3-5.

Figure 3-23 Error behaviour of a 3-layer neural network

Figure 3-24 Error behaviour of a 2 layer neural network

3.4.1.3.2 *Optimal Number of Hidden Units*

The optimal number of hidden units for the selected 2-layer neural network was calculated as follows:

- Using a training data set, a 2-layer network was trained by minimizing a sum-of-squares error function with isotropic Gaussian regularizer, employing a scaled conjugate gradient optimizer algorithm developed by Nabney (2002)
- The activation function selected was a tan-sigmoid transfer function for the neurons belonging to the hidden layers while at the output layer a linear activation function was considered.

$$z_j = \tanh\left(\sum w_{ji}x_i + b_j\right)$$

Equation 3-6 Hidden Layer Activation Function

where

x_i represents the i^{th} input value
 w_{ji} represents the elements of the first layer weight matrix, and
 b_j represents the bias parameters associated with the hidden units

- A different number of hidden units were used every time and its “evidence” was calculated. A brief description of this approach is presented in Appendix A.
- Network structure with the highest “evidence” and less hidden units was selected as optimum. Table 3-13 to 3-18 shows the results of this process for Downtown Ottawa, Bronson Avenue, and Highway 417 respectively.

Table 3-13 CBD, log-evidence. [ESS]

Hidden Units	5	10	20	50	100
Vehicles	Log-Evidence (e+003)				
Hybrid ICE	-0.878	-0.902	-0.832	-0.950	-1.126
Fuel Cell Dominant	-1.141	-1.090	-1.132	-1.242	-1.440
Fuel Cell Battery	1.191	1.389	1.555	1.401	1.073

Table 3-14 CBD , log-evidence. [FC]

Hidden Units	5	10	20	50	100
Vehicles	Log-Evidence (e+003)				
Large ICE	0.637	0.677	0.611	0.667	0.332
Small ICE	1.277	1.330	1.422	1.245	0.944
Hybrid ICE	-0.210	-0.168	-0.155	-0.183	-0.519
Fuel Cell Dominant	1.198	2.606	3.063	3.021	2.500
Fuel Cell Battery	-0.551	0.0302	0.457	0.620	0.455

Table 3-15 Bronson, log-evidence. [ESS]

Hidden Units	5	10	20	50	100
Vehicles	Log-Evidence(e+003)				
Hybrid ICE	-4.427	-4.402	-4.400	-4.427	-4.605
Fuel Cell Dominant	-4.194	-4.099	-4.078	-4.144	-4.254
Fuel Cell Battery	-3.102	-2.991	-2.923	-2.995	-3.102

Table 3-16 Bronson. log-evidence. [FC]

Hidden Units	5	10	20	50	100
Vehicles	Log-Evidence(e+003)				
Large ICE	-2.305	-2.099	-2.056	2.106	-2.179
Small ICE	-2.453	-2.314	-2.315	-2.353	-2.422
Hybrid ICE	-4.428	-4.326	-4.189	-4.233	-4.470
Fuel Cell Dominant	-4.330	-3.998	-3.685	-3.665	-3.998
Fuel Cell Battery	-4.630	-4.479	-4.201	-3.868	-4.029

Table 3-17 HWY 417, log-evidence. [ESS]

Hidden Units	5	10	20	50	100
Vehicles	Log-Evidence(e+003)				
Hybrid ICE	-0.630	0.295	0.324	0.073	-0.350
Fuel Cell Dominant	1.942	2.382	2.344	2.086	1.682
Fuel Cell Battery	2.256	3.084	3.065	3.041	2.735

Table 3-18 HWY 417, log-evidence. [FC]

Hidden Units	5	10	20	50	100
Vehicles	Log-Evidence(e+003)				
Large ICE	3.699	3.696	4.057	4.236	4.297
Small ICE	-3.355	-2.951	-2.582	-2.551	-2.694
Hybrid ICE	0.041	0.025	-0.034	-0.135	-0.381
Fuel Cell Dominant	-2.232	-2.265	-2.095	-2.246	-2.434
Fuel Cell Battery	-1.497	-0.944	-0.439	-0.475	-0.723

3.4.2 Macroscopic Level

As it was discussed in Section 3.4.1, an instantaneous fuel consumption model uses measurements of explanatory variables on a second-by-second basis in order to predict the vehicle's fuel consumption. Although this type of model is ideal for detailed studies of traffic management, it requires detailed traffic information that is not usually available.

On the other hand, macroscopic fuel consumption models only use average speed as the explanatory variable, making it more suitable for assessing the impact of transportation management schemes (Akcelik *et al*, 1983).

3.4.2.1 Problem Formulation

For all the simulated vehicles, the problem could be expressed in the following mathematical form:

$$Ave\ FC = f(length, ave_speed, t_time)$$

Equation 3-7 Average fuel consumption function

where

length, is the considered link's length,
ave_speed, is the average speed along the considered link, and
t_time, is the travel time by link.

In the aggregation process average link length of 80 m for non-freeway facilities and 1000 m for freeway facilities were considered. This allowed the elimination of the link length as explanatory variable. In the same way, due the fact that average trip time per unit distance is the reciprocal of the average speed, Equation 3-7 was simplified as follows:

$$Ave\ FC = f(ave_speed)$$

Equation 3-8 Simplified average fuel consumption function

3.4.2.2 Data Collection

The US Environmental Protection Agency proposed an approach in which an integration of analysis scales is considered in order to develop a new generation modelling approach. Under this approach, the estimation process is the same for all analysis scales, and only

its level of aggregation changes (USEPA, 2001c). Following this approach, the same information used to develop all microscopic fuel consumption models was subjected to the following aggregation process:

- From the Excel files containing ADVISOR's simulation results, values of instantaneous distance travelled, fuel consumption, and speed for every simulated vehicle and facility were accumulated using Excel's function ROUND for average links of 80 m length (for non-freeway facilities), and 1000 m length for freeway facilities,
- With the use of Excel's Conditional Summatory Function, average fuel consumption (lt/100 km), average speed (km/h), and travel time, were calculated for every link.

Once the data for all vehicles and traffic conditions were integrated in a macroscopic way, a statistical analysis was performed in order to generate only the most statistically representative values into the data sets, minimizing the presence of outliers and reducing the variation in the final data sets. This procedure involved the following steps:

- Average speed and average fuel consumption values collected in the aggregation process were sorted in groups of 10 kph each (0 to 9 km/h, 10 to 19 km/h, etc), from lower to higher average speed,
- Using Microsoft Excel's DATA ANALYSIS function, a histogram of average fuel consumption values for every group was created, and its total amount of occurrences was calculated,

- Only the average fuel consumption values with a frequency value above 5% of the total amount of occurrences per group were selected,
- Using Microsoft Excel's IF and AND functions, the average fuel consumption values that satisfied this criterion were found and used to create the final datasets.
- A matrix for every vehicle and facility was created containing the collected information, exported to MatLab, transformed, and used as dataset for the neural network training process.

3.4.2.3 Model Development

Once again, a MLP neural network was selected to solve the problem expressed in Equation 3-8. It should be noted that due to the aggregation process, the average size of the original training datasets shrunken almost by a factor of 10, from 10 000 vectors to around 1 000 vectors. Consequently, the number of parameters had to be controlled to avoid overfitting. So as to do this, the Bayesian framework of learning was used not only to train the neural networks models, but also to calculate the effective number of parameters, as follows (Bishop, 1995):

- Several 2-layer neural networks with hidden unit values from 5 to 25 were trained by minimizing a sum-of-squares error function with isotropic Gaussian regularizer, employing a scaled conjugate gradient optimizer algorithm developed by Nabney (2002)

- Once again, the activation function selected was a tan-sigmoid transfer function for the neurons belonging to the hidden layers while at the output layer a linear activation function was considered.
- After training, the “evidence” value and the effective number of parameters for all different neural network structures were collected. Tables 3-19 to 3-21 shows results of this process for Downtown Ottawa, Bronson Avenue, and Highway 417 respectively.

The neural network structure with the lower effective number of parameters and higher “evidence” value was trained to solve Equation 3-8 for every vehicle and type of facility.

Table 3-19 CBD. Effective number of parameters and log-evidence values

Hidden Units	5	10	15	20	25
Vehicles	Effective Number of Parameters [log-evidence(e+003)]				
ICE Large	13 [-1.1842]	18 [-1.1920]	16 [-1.9728]	15 [-1.9637]	22 [-1.9587]
ICE Small	13 [-0.9689]	17 [-0.9508]	26 [-0.9491]	21 [-0.9498]	35 [-0.9598]
ICE Hybrid	12 [-1.1782]	15 [-1.1635]	21 [-1.1512]	18 [-1.1327]	29 [-1.1342]
Fuel Cell Dominant	12 [-1.703]	17 [-1.6866]	20 [-1.6908]	17 [-1.6903]	18 [-1.6774]
Fuel Cell Battery	12 [-1.2901]	21 [-1.2848]	26 [-1.2874]	29 [-1.2793]	26 [-1.2395]

Table 3-20 Bronson. Effective number of parameters and log-evidence values

Hidden Units	5	10	15	20	25
Vehicles	Effective Number of Parameters [log-evidence(e+003)]				
ICE Large	13 [-1.4677]	22 [-1.4357]	26 [-1.4017]	33 [-1.3972]	37 [-1.3858]
ICE Small	12 [-1.4336]	22 [-1.4330]	26 [-1.5019]	28 [-1.4801]	38 [-1.4692]
ICE Hybrid	13 [-1.778]	20 [-1.7589]	25 [-1.7519]	31 [-1.7538]	35 [-1.6798]
Fuel Cell Dominant	12 [-2.2688]	20 [-2.2437]	20 [-2.2739]	26 [-2.223]	32 [-2.3676]
Fuel Cell Battery	13 [-1.3663]	20 [-1.332]	31 [-1.3338]	35 [-1.3378]	35 [-1.2156]

Table 3-21 HWY 417. Effective number of parameters and log-evidence values

Hidden Units	5	10	15	20	25
Vehicles	Effective Number of Parameters [log-evidence(e+003)]				
ICE Large	14 [-1.4202]	22 [-1.3984]	31 [-1.3836]	35 [-1.3792]	43 [-1.3607]
ICE Small	14 [-1.5591]	22 [-1.5212]	29 [-1.4669]	33 [-1.4767]	39 [-1.4307]
ICE Hybrid	11 [-1.561]	17 [-1.5321]	19 [-1.5415]	21 [-1.559]	26 [-1.5318]
Fuel Cell Dominant	13 [-1.5426]	22 [-1.5109]	25 [-1.5373]	28 [-1.5379]	31 [-1.4990]
Fuel Cell Battery	11 [-1.5773]	18 [-1.5404]	22 [-1.5907]	31 [-1.6054]	29 [-1.6206]

3.4.3 Neural Network Training Process

After selecting the optimal neural network structure for every type of vehicle and facility for both levels of modelling (i.e. microscopic and macroscopic), the training process was carried on using MatLab Neural Network Toolbox. To do this process, two main parameters were considered:

- Training Function. As discussed in Chapter 2, the main goal of neural network training is to adjust the weight vector w such that the objective function $S(w)$ is minimized.

$$S(w) = \beta E_D + \alpha E_w$$

Due to the fact that the error $S(w)$ is a nonlinear function of w , the use of an iterative algorithm was required to explore the weight space and find the optimum values of w , α , and β . In this thesis, MatLab's algorithm TRAINBR was selected. TRAINBR is a network training function that uses Bayesian Regularization to update the weight and bias values according to Levenberg-Marquardt algorithm.

- Learning rate. For the Levenberg-Marquardt algorithm an initial value of μ (the learning rate) must be chosen and this value should vary appropriately during the minimization process (Bishop, 1995). In this context, Esposito et al (2001) suggested that the optimal initial value of μ varies within the range of [0.009 - 0.002] values. Therefore an initial value of $\mu=0.005$ was used in the present work.

MatLab's default factor of 10 was considered for the variation of the value of μ in every step.

Once the neural network structures were generated and the respective training function and learning rate were selected, the training process was developed for every type of vehicle and facility. Results of this process are presented and discussed in the following chapter.

CHAPTER 4. MODEL ASSESSMENT AND COMPARISON

For the assessment of the models, their results were compared with the ADVISOR generated estimates. The correlation coefficient R and its square value, the coefficient of determination R^2 , are commonly selected according to the literature as “goodness-of-fit” measures. These were used in the present thesis, since they quantitatively measure the degree to which the predicted value (i.e. the fuel consumption predicted by the neural network model) fits the fuel consumption estimate provided by ADVISOR. The interpretation of the R and R^2 values is very subjective. However some researchers have provided guidelines, e.g. Younger (1979) stated that a correlation coefficient value between ± 1.0 to ± 0.75 reflects a strong to moderately strong relationship between variables. All trained neural network models were subjected to this assessment process in order to measure the extent to which the model output matches the initial data. It should be noted that all R and R^2 values were presented in this thesis using four significant figures because this is the regular format for these values in both, MATLAB and Microsoft’s Excel.

4.1 Microscopic Fuel Consumption Models

The level of agreement, expressed by the R and R^2 values in Tables 4.1 to 4.3, between the fuel consumption predicted by the neural network and the fuel consumption values contained in the training data set shows that, after the training process was completed, the

neural network models were able to solve the problem expressed by Equations 3-3 and 3-5 (Tables 4.1 to 4.3). With respect of ESS current (Equation 3-4), although the correspondent R and R^2 values suggest that a moderately strong relationship exists between the neural network outputs and the ADVISOR outputs included in the training data set for all the facilities, it is possible to observe that a higher variation between both results could be expected under certain driving conditions.

Table 4-1 Quantitative Analysis of Training Dataset - CBD

ESS	R	R^2
Vehicles		
Hybrid ICE	0.9406	0.8849
Fuel Cell Dominant	0.9214	0.8490
Fuel Cell Battery	0.9968	0.9938

FC	R	R^2
Vehicles		
Large ICE	0.9838	0.9679
Small ICE	0.9914	0.9830
Hybrid ICE	0.9886	0.9775
Fuel Cell Dominant	0.9988	0.9978
Fuel Cell Battery	0.9896	0.9795

Table 4-2 Quantitative Analysis of Training Dataset - Bronson

ESS	R	R^2
Vehicles		
Hybrid ICE	0.9192	0.8451
Fuel Cell Dominant	0.9468	0.8965
Fuel Cell Battery	0.9964	0.9930

FC	R	R^2
Vehicles		
Large ICE	0.9883	0.9768
Small ICE	0.9855	0.9713
Hybrid ICE	0.9840	0.9684
Fuel Cell Dominant	0.9990	0.9981
Fuel Cell Battery	0.9981	0.9964

Table 4-3 Quantitative Analysis of Training Dataset – HWY 417

ESS	R	R ²
Vehicles		
Hybrid ICE	0.9868	0.9739
Fuel Cell Dominant	0.9550	0.9122
Fuel Cell Battery	0.9915	0.9832

FC	R	R ²
Vehicles		
Large ICE	0.9964	0.9929
Small ICE	0.9969	0.9939
ICE Hybrid	0.9801	0.9606
Fuel Cell Dominant	0.9973	0.9947
Fuel Cell Battery	0.9995	0.9991

With the purpose of gaining knowledge about the possible origins of this variation and to explore the possible consequences over the “goodness of fit” of the neural network models, an independent set of data not previously used in the training process, named testing data set, was presented as inputs to the trained neural network models and their corresponding results were evaluated.

4.1.1 Evaluation Process

The neural network training process with Bayesian Regularization does not require separate training and testing data sets. Nevertheless with the intention of improving the level of confidence in the generalization capabilities of the neural network models, the network performance was evaluated with a testing data set not used for training. This testing data set was created by retaining a random sample of the training data before starting the training process. Flood and Kartam (1994) suggested two different ways to

perform this evaluation process i.e. qualitatively and quantitatively. The qualitative method involves the evaluation of the network's validity through the collection and plotting of the sum of square error values for both data sets (training and testing) along the entire training process.

If the error curve that corresponds to the testing data set shows a similar pattern to that followed by the training data set, it is possible to assume that the network is learning an accurate generalized solution to the problem. If the opposite is observed, the network is only memorizing the training patterns.

Another qualitative method makes use of the fact that the model ($\hat{Y}$) does not generate an exact representation of the testing outputs (Y) and the differences between them can be represented by the following equation:

$$e_i = Y_i - \hat{Y}_i$$

Equation 4-1 Model's Residuals

in which the residuals e_i , can be defined as the difference between what is actually observed, and what the trained network predicts. Several authors indicate that, if the model under inspection is correct, the residuals should exhibit tendencies that allow the confirmation of the assumptions initially made about the errors or at least they should not show a trend that defy these assumptions (Zapranis and Refenes, 1999, Draper and Smith 1998).

For mathematical models of the form: $y = f(x, w) + \varepsilon$ as the neural network models, the error term ε is assumed to be normal with mean zero and constant variance (Lee, 1998). Finally, the second type of evaluation makes use of the correlation coefficient R and its square value, the coefficient of determination R^2 to compare, in a quantitative manner, the testing target values and the values produced by the neural network model.

4.1.1.1 Conventional Internal Combustion Engine Vehicles

Figures 4.1 and 4.2 present in a graphic form, the error between the neural network results and the ADVISOR estimates in a logarithmic scale (vertical axis), against the number of epochs required for the entire training process (horizontal axis) for all training and testing data sets.

It is clear that all neural network models were capable not only to learn the training patterns but also to generalize enough to minimize the error between the predicted fuel consumption values and the ADVISOR estimates of fuel consumption included in all testing data sets for conventional ICE vehicles.

In the same way, it is possible to observe in Table 4-4 that a strong relationship exists between the neural network outputs and the ADVISOR outputs included in the testing data set.

Table 4-4 Quantitative Analysis of Testing Data Set – ICE vehicles

Type of Facility	Conventional Vehicle			
	Small ICE		Large ICE	
	R	R ²	R	R ²
CBD Ottawa	0.9821	0.9647	0.9858	0.9719
Bronson Ave.	0.9831	0.9665	0.9853	0.9709
Highway 417	0.9969	0.9940	0.9962	0.9925

Figure 4-1 Sum-of-square errors, Small ICE vehicle

Figure 4-2 Sum-of-square errors, Large ICE vehicle

Predicted against ADVISOR values of fuel consumption and its corresponding coefficient of determination are presented in a graphical form in Appendix C. This level of agreement between the fuel consumption predicted by the neural network and the fuel consumption values contained in the testing data set shows that the neural network model

was able to adequately predict the fuel consumption behaviour, not through the memorization of the training data, but rather through modelling of the underlying generator of the data. As a result, when fuel consumption values from ADVISOR and the trained neural network models were plotted against the explanatory variables, *speed* and *acceleration*, on a second-by-second basis, a great resemblance between both graphics was observed along all the simulated traffic conditions for both types of conventional internal combustion engine vehicles (Figures 4-3 to 4-14).

The trend observed in the 3-D graphics adequately represents the effects of speed and acceleration of fuel consumption of conventional ICE vehicles discussed in the literature: at low speed without acceleration or in idle conditions, the fuel consumed second-by-second is low and only increases when the vehicle increases its speed or is subjected to higher accelerations.

4.1.1.2 Hybrid Internal Combustion Engine Vehicles

Modelling fuel consumption of Hybrid ICE vehicles, like Toyota Prius, is a more complicated process in which the interaction of two different sources of power and a specific energy control strategy must be taken into account. As was discussed in Section 3.3, the simulated Hybrid ICE vehicle is capable of operating on electricity, gasoline, or a combination of both, to accommodate the requested driving power.

Figure 4-3 ADVISOR fuel consumption. Small ICE vehicle, CBD

Figure 4-4 Predicted fuel consumption. Small ICE vehicle, CBD

Figure 4-5 ADVISOR fuel consumption. Small ICE vehicle, Bronson

Figure 4-6 Predicted fuel consumption. Small ICE vehicle, Bronson

Figure 4-7 ADVISOR fuel consumption. Small ICE vehicle, HWY 417

Figure 4-8 Predicted fuel consumption. Small ICE vehicle, HWY 417

Figure 4-9 ADVISOR fuel consumption. Large ICE vehicle, CBD

Figure 4-10 Predicted fuel consumption. Large ICE vehicle, CBD

Figure 4-11 ADVISOR fuel consumption. Large ICE vehicle, Bronson

Figure 4-12 Predicted fuel consumption. Large ICE vehicle, Bronson

Figure 4-13 ADVISOR fuel consumption. Large ICE vehicle, HWY 417

Figure 4-14 Predicted fuel consumption. Large ICE vehicle, HWY 417

Figure 4-15 and 4-16 presents graphically the error behaviour along the entire training process for training and testing data sets corresponding to the Energy Storage System (ESS) and fuel consumption (FC).

Figure 4-15 Sum-of-square errors. ESS - Hybrid ICE

From the results presented in the charts, it can be inferred that the neural network models trained to solve Equations 3-4 and 3-5 will have good generalization capabilities.

Figure 4-16 Sum-of-square errors. FC- Hybrid ICE

Also, adequate level of agreement between the original output data set and the neural network's output should be expected. This was corroborated when results provided by all the neural network models for the testing data set were related with their corresponding data set outputs (Appendix C). In order to analyze quantitatively this level of agreement, correlation coefficients and coefficients of determination values for all neural network models were calculated and are presented in Table 4-5.

Table 4-5 Quantitative Analysis of Testing Data Set. Hybrid ICE

Type of Facility	ICE Hybrid			
	ESS		FC	
	R	R ²	R	R ²
CBD Ottawa	0.9406	0.8849	0.9886	0.9775
Bronson Ave.	0.9192	0.8451	0.9840	0.9684
Highway 417	0.9868	0.9739	0.9810	0.9606

Although these values suggest that a moderately strong relationship exists between the neural network outputs and the targets of the testing data set for all the facilities, a more detailed examination was done by plotting the corresponding residual values against the input variables for all the neural network models. Due to the number of explanatory variables in Equations 3-4 and 3-5, a set of three-dimensional plots was used in order to analyze the residuals.

4.1.1.2.1 Downtown Driving Conditions

When the ESS residuals were plotted against the input variable, *time*, most of the residual values tended to follow a horizontal band along the speed axis, a signal of no abnormality in the model (Draper and Smith, 1998). With regard to the input variable, *state of charge*, or SOC, Figure 4-17 shows that after a fast depletion of the SOC from its initial value of 0.60, SOC levels were maintained around 0.50, where only a small variation in the ESS residual values could be observed. Based on these results, it is suggested that no appreciable abnormality could be attributable to those components of the model.

For the other two explanatory variables, *speed* and *acceleration*, Figure 4-18 illustrates that the difference between the outputs of the trained neural network and the outputs included in the testing data set shows no appreciable variation along the entire speed range. In relation to the acceleration component of the model, Figure 4-19 shows that, although the residuals tend to follow a horizontal band between all values of deceleration and low acceleration values, the trained neural network overestimates or underestimates the participation of the ESS in high acceleration conditions. However, it should be noted that this particular driving condition represents less than 4% of the entire testing dataset.

Figure 4-17 ESS Residual vs time and SOC. Hybrid ICE - CBD

Figure 4-18 ESS Residual vs speed and acceleration. Hybrid ICE -CBD

For the neural network model trained to solve Equation 3-5, there are 5 explanatory variables in the equation: time, State of Charge, speed, acceleration, and ESS. However, based on the results discussed previously, the analysis of residuals was only performed for the *speed*, *acceleration* and *ESS* explanatory variables. Figures 4-20 and 4-21 show that no abnormality should be expected from the ESS explanatory variable. Also, it is possible to observe in Figure 4-20 that most of the residual values are grouped in two narrow bands along the entire speed range, indicating the ESS participation in the driving process (positive values when the energy storage system provides energy to the electric

motor, and negative values when the vehicle uses the electric motor and/or the generator to recharge the battery system).

Figure 4-19 ESS Residual vs acceleration and speed. Hybrid ICE – CBD

Figure 4-21 shows the relationship between acceleration levels and the ESS values and its influence on the residuals of the fuel consumption model. Once more, it is possible to observe that a higher variation of the residuals only appears when the acceleration values are in a zone between 5 and 10 kph/sec, indicating that the initial assumptions of the model do not seem to be violated.

Figure 4-20 FC residual vs speed and ESS. Hybrid ICE – CBD

4.1.1.2.2 Urban Arterial Driving Conditions

Residuals for the neural network trained to simulate the responses of the energy storage system were plotted against all the explanatory variables included in Equation 3-4. In Figure 4-22 the effects of *time* and *state of charge* over the ESS residuals follows a similar trend than that observed for the CDB Ottawa model i.e., following the Prius's

control strategy, the battery's energy is depleted from its initial value of 0.60 to a SOC value around 0.50 where the charge/discharge process is smoother.

Figure 4-21 FC residual vs acceleration and ESS. Hybrid ICE – CBD

Nevertheless, the residuals tend to follow a horizontal band between the values -20 and 20 with a small percentage of points outside this band over the SOC and time axes, implying that no abnormality could be detected.

Figure 4-22 ESS residual vs time and SOC. Hybrid ICE – Bronson

As was expected, because of the ESS neural network model coefficient of determination value, a greater presence of residuals outside a horizontal band with limits $(-20, 20)$ could be observed when the speed and acceleration components of Equation 3-4 were plotted against the ESS residual values.

The variation observed in the residual values for acceleration episodes around 5 to 10 kph/sec suggests that either the charge/discharge behaviour in that particular region was too complex or the training data set did not include enough occurrences of this type of

episodes for the neural network to provide a full approximation of the targeted surface (Figure 4-23 and Figure 4-24, respectively).

However, this variation is not enough to indicate that the model shows signs of abnormality. The same assumption of normality could be used with respect to the fuel consumption neural network model (Figures 4-25 and 4-26).

Figure 4-23 ESS residual vs speed and acceleration. Hybrid ICE – Bronson

Figure 4-24 ESS residual vs acceleration and speed. Hybrid ICE - Bronson

Figure 4-25 FC residual vs speed and ESS. Hybrid ICE - Bronson

Figure 4-26 FC residual vs acceleration and ESS. Hybrid ICE - Bronson

4.1.1.2.3 Highway Driving Conditions

Driving on a highway represents higher and more sustained speeds and less variation in acceleration values than those observed for the CBD Ottawa and Bronson Avenue scenarios. Under the Prius's control strategy point of view that means less use of the energy provided by the battery and smoother charge/discharge behaviour. Figure 4-27 shows the effect of the explanatory variables, *time* and *state of charge*, over the ESS residuals for highway driving conditions. It should be noted that even though the battery's energy is also depleted in the initial 400 seconds of driving, from its original

SOC level of 0.6 to a region around 0.5 SOC, its effect in Figure 4-27 is not that important as in previous traffic scenarios.

Figure 4-27 ESS residual vs time and SOC. Hybrid ICE – HWY 417

Furthermore, since the main source of discrepancies between the output data set and the trained neural network results for Equation 3-4 could be attributable to episodes of high acceleration at instantaneous speed values lower than 60 kph, it is not surprising that plotting the ESS residual values against the explanatory variables, *speed* and *acceleration*, a more compact and narrow band of residuals is present on both axes (Figures 4-28 and 4-29).

Figure 4-28 ESS residual vs speed and acceleration. Hybrid ICE – HWY 417

Figure 4-29 ESS residual vs acceleration and speed. Hybrid ICE – HWY 417

On the other hand, the main variation in the fuel consumption residual values is observed in two different regions i.e., one, when the instantaneous speeds are higher than 80 kph with low or no acceleration, and two, at speeds lower than 40 kph. The former effect could be explained as a result of the control strategy according to which the battery is recharging when the vehicle is subjected to cruise driving conditions and energy from the engine is available. The latter effect is possible to be the result of not enough information to fully train the neural network for this particular condition. However, this variation is not large enough to indicate that the initial assumptions of the model do not hold (Figures 4-30 and 4-31).

Figure 4-30 FC residual vs speed and ESS. Hybrid ICE – HWY 417

Figure 4-31 FC residual vs acceleration and ESS. Hybrid ICE – HWY 417

With the evaluation process completed, it was possible to plot the original and predicted instantaneous fuel consumption values against the explanatory variables, *speed* and *acceleration*, and to compare the results, not only one against the other, but also against the information sourced from the literature about the fuel consumption behaviour of Hybrid ICE vehicles such as Toyota Prius. In 1998, the USEPA discussed the vehicle operating strategy published by Toyota for its Hybrid ICE Prius under different driving conditions. In its report, the EPA included Toyota's claim about the capability of Prius to "shut-off" its engine at startup and at light load. Kelly and Rajagopalan (2001) also discussed this particular characteristic of Toyota Prius after observing that, for the

standard Federal Test Procedure (FTP) cycle, the vehicle was able to run in all-electric mode during low speeds and low load conditions, but none of them includes a specific threshold in which the vehicle is unable to maintain its all-electric driving. More detailed information was published by the Automotive Engineering International (2001), in which 45 km/h was indicated as the speed at which stop-and-go operation of the engine is permitted. In speed conditions over 45 km/h, the Prius's gasoline engine is always on and its power is diverted to the wheels to drive the vehicle and supply energy to the motor or, if it is necessary, to charge the battery. Only when the power demand exceeds the maximum power of the engine, the battery is used to provide additional power.

Figures 4-32 to 4-35 show the effect of speed and acceleration over instantaneous fuel consumption predicted by ADVISOR and the trained neural networks, for simulated traffic conditions of CBD Ottawa and Bronson Avenue. It is possible to observe that the fuel consumption behaviour follows the trend described in the literature for congested “stop-and-go” urban traffic conditions (USEPA, 1998): for low speed and accelerations or idle conditions, the battery system supplies all the power required to drive the vehicle, and only when the speed increases or more power is required to accelerate the vehicle, the engine increases its participation in the energy process and more fuel is consumed. For highway driving conditions, in which few or no total stops were considered, Kelly and Rajagopalan (2001) report that Toyota Prius was able to “shut-off” its engine for only 4% of the HWFET cycle. This situation is reflected in Figures 4-36 and 4-37 that show fuel consumption for Highway 417 against speed and acceleration values.

Figure 4-32 ADVISOR fuel consumption. Hybrid ICE vehicle, CBD

Figure 4-33 Predicted fuel consumption. Hybrid ICE vehicle, CBD

Figure 4-34 ADVISOR fuel consumption. Hybrid ICE vehicle, Bronson

Figure 4-35 Predicted fuel consumption. Hybrid ICE vehicle, Bronson

Figure 4-36 ADVISOR fuel consumption. Hybrid ICE vehicle, HWY 417

Figure 4-37 Predicted fuel consumption. Hybrid ICE vehicle, HWY 417

The average time in which the vehicle was in “all-electric” mode is only 7%, resulting in higher fuel consumption not only for acceleration episodes but also for cruise traffic conditions.

4.1.1.3 Hybrid Fuel Cell Vehicles

Contrary to conventional ICE vehicles and Hybrid ICE vehicles, where the power required is provided by burning fuel, advanced technology vehicles equipped with a fuel cell system generate electric power through an electrochemical reaction using hydrogen as the energy carrier. Although both types of simulated fuel cell hybrid vehicles have the same configuration, their differences in fuel cell and battery sizes change the way that the vehicles respond to the road loads. See Figure 4-38 (Unnasch and Drunert, 1999)

Figure 4-38 Simplified fuel cell system with on-board fuel processor

4.1.1.3.1 Hybrid Fuel Cell Battery

As was described in detail in Section 3.3, in a hybrid fuel cell vehicle with a battery dominant system, the primary source of drive power is the energy storage system where the fuel cell system is maintained in a quasi-steady-state operation providing a constant energy output (TRB, 2000, Pettersson and Westerholm, 2001). This particular characteristic of the fuel cell battery vehicle and the fact that the battery's capacity is larger than that observed for a Toyota Prius, reduces the SOC effects over the training data set, and a better performance of the neural network could be expected after the training process.

Figure 4-39 and 4-40 shows the error values for the training and a testing dataset along all the training process. It can be observed that both lines, representing the error behaviour for the training and the testing dataset, follow the same trend. This observation leads to the implication that, in a qualitative way, the trained neural network should be able to solve Equations 3-4 and 3-5 with good generalization capabilities. In order to evaluate how well the results provided by the trained neural networks represent statistically the outputs provided by ADVISOR, the testing data set was used as inputs to the trained neural network.

The correlation coefficient and the coefficient of determination were calculated from its outputs (Table 4-6).

Table 4-6 Quantitative Analysis of Testing Data Set – Hybrid Fuel Cell Battery

Type of Facility	Hybrid Fuel Cell Battery			
	ESS		FC	
	R	R ²	R	R ²
CBD Ottawa	0.9967	0.9935	0.9859	0.972
Bronson Ave.	0.9925	0.9851	0.9927	0.9855
Highway 417	0.9907	0.9815	0.9994	0.9989

Figure 4-39 Sum-of-square errors. ESS - Hybrid Fuel Cell Battery

Figure 4-40 Sum-of-square errors. FC - Hybrid Fuel Cell Battery

Based on the interpretation of the R and R^2 values stated by Younger (1979), all the results show a moderately strong to strong relationship, minimizing the residual's variation for all the explanatory variables. This suggests that no abnormality could be expected from the models (Figures 4-41 to 4-55).

Figure 4-41 ESS residual vs time and SOC. Fuel Cell Battery – CBD

Figure 4-42 ESS residual vs speed and acceleration. Fuel Cell Battery – CBD

Figure 4-43 ESS residual vs acceleration and speed. Fuel Cell Battery – CBD

Figure 4-44 FC residual vs speed and ESS. Fuel Cell Battery – CBD

Figure 4-45 FC residual vs acceleration and ESS. Fuel Cell Battery – CBD

Figure 4-46 ESS residual vs time and SOC. Fuel Cell Battery - Bronson

Figure 4-47 ESS residual vs speed and acceleration. Fuel Cell Battery - Bronson

Figure 4-48 ESS residual vs acceleration and speed. Fuel Cell Battery - Bronson

Figure 4-49 FC residual vs speed and ESS. Fuel Cell Battery - Bronson

Figure 4-50 FC residual vs acceleration and ESS. Fuel Cell Battery - Bronson

Figure 4-51 ESS residual vs time and SOC. Fuel Cell Battery – HWY 417

Figure 4-52 ESS residual vs speed and acceleration. Fuel Cell Battery – HWY 417

Figure 4-53 ESS residual vs acceleration and speed. Fuel Cell Battery – HWY 417

Figure 4-54 FC residual vs speed and ESS. Fuel Cell Battery – HWY 417

Figure 4-55 FC residual vs acceleration and ESS. Fuel Cell Battery – HWY 417

Although a hybrid fuel cell battery vehicle has a more complicated operating system than a regular internal combustion engine vehicle, R and R^2 values presented in Table 4-6, are as good as the previously calculated correlation coefficient and coefficient of determination of neural network models for conventional ICE vehicles. For the purpose of understanding better the possible causes of this improvement in the training process, a more detailed evaluation of the fuel consumption behaviour of the simulated fuel cell battery vehicle was developed. This evaluation was based on the original outputs from ADVISOR, the trained neural network results, and the information obtained from the literature for this specific type of advanced technology vehicle.

Plotting instantaneous fuel consumption against speed and acceleration on a second-by-second basis shows two very well defined sections in all the simulated traffic conditions: the first one, where the vehicle responds to the road loads without using the fuel cell system, meaning that fuel consumption is zero, and the second one, where the fuel cell provides additional power to the electric motor (Figures 4-56 to 4-61).

The first section could be explained as follows: although the type of fuel cell used in the simulations is able to deliver between 80 to 90% of its power output immediately after the start-up, the fuel processor requires time in order to start the production of hydrogen (Barbir, 2003). While the U.S. Department of Energy has a reformer fuel cell start-up target of 60 seconds for the year 2005 (Wipke et al, 2003), ADVISOR uses a more conservative value between 90 to 120 seconds (for a hybrid fuel cell battery and a hybrid fuel cell dominant vehicle, respectively) as the period between the start-up and the moment at which the fuel cell is able to add power to the system and that was the behaviour that the trained neural network was able to “learn”.

The second section is a direct consequence of the series hybrid system used by the simulated vehicle. In theory, in order to minimize losses and inefficiency, the fuel cell system is operated at a minimum power level in idle and low load conditions, and during the rest of the drive cycle the fuel cell system is able to operate at its peak efficiency in order to increase the overall efficiency of the vehicle (Unnasch and Drunet, 1999).

Figure 4-56 ADVISOR fuel consumption. Fuel Cell Battery vehicle, CBD

Figure 4-57 Predicted fuel consumption. Fuel Cell Battery vehicle, CBD

Figure 4-58 ADVISOR fuel consumption. Fuel Cell Battery vehicle, Bronson

Figure 4-59 Predicted fuel consumption. Fuel Cell Battery vehicle, Bronson

Figure 4-60 ADVISOR fuel consumption. Fuel Cell Battery vehicle, HWY 417

Figure 4-61 Predicted fuel consumption. Fuel Cell Battery vehicle, HWY 417

Figures 4-62 and 4-63 show a histogram of the power provided by the fuel cell and the efficiency of the fuel cell stack for downtown and urban arterial driving conditions, respectively. Here, it is possible to observe that ADVISOR's outputs follow the behaviour described by the literature, and three different sections are well defined i.e., zero power output at warm-up time, minimum power output around 3 kW to reduce losses, and maximum power output between 5 to 10 kW where the efficiency of the fuel cell is higher so as to minimize the consumption of fuel.

Figure 4-62 Fuel cell output power vs efficiency. Fuel Cell Battery – CBD

However, in order to meet the high load expected during highway driving conditions, the fuel cell is forced to work at peak power most of the time, in a region where the fuel cell efficiency is lower, and as a consequence, the consumption of fuel increases (Figure 4-64).

Figure 4-63 Fuel cell output power vs efficiency. Fuel Cell Battery - Bronson

Figure 4-64 Fuel cell output power vs efficiency. Fuel Cell Battery – HWY 417

4.1.1.3.2 Hybrid Fuel Cell Dominant

For a fuel cell dominant vehicle where the fuel cell system provides most of the power along the drive cycle, the energy storage system and its control strategy are the main source of variation between ADVISOR's outputs and the values predicted by the trained neural network. See Figure 4-65 and 4-66.

Figure 4-65 Sum-of-square errors ESS – Fuel Cell Dominant

Figure 4-66 Sum-of-square errors. FC – Fuel Cell Dominant

Even though Figure 4-65 and 4-66 shows qualitatively, that good generalization capabilities are expected for both models, it is possible to observe that the level of error expected for the model trained to solve Equation 3-5 is higher than that previously calculated for a hybrid fuel cell battery vehicle. Correlation coefficient and coefficient of determination values calculated for all the models corroborate in a quantitative manner, the assumption noted above (Table 4-7 and Appendix C).

Table 4-7 Quantitative Analysis of Testing Data Set - Hybrid Fuel Cell Dominant

Type of Facility	Hybrid Fuel Cell Dominant			
	ESS		FC	
	R	R ²	R	R ²
CBD Ottawa	0.9221	0.8503	0.9977	0.9955
Bronson Ave.	0.9434	0.8901	0.9943	0.9887
Highway 417	0.9517	0.9058	0.9795	0.9895

A possible explanation for this particular behaviour could be found through an inspection of the way that the control strategy manages the energy interchange between the fuel cell system and the battery. On this matter, ADVISOR uses the following strategy for the simulation of fuel cell vehicles (NREL, 2002):

- *“To maintain charge in the battery, the fuel converter turns on when the SOC reaches the low limit, cs_lo_soc ”,*
- *“The fuel converter turns off when the SOC reaches the high limit, cs_hi_soc ”,*
- *“The fuel converter operates at the most efficient level”*

Although this strategy is followed by both types of vehicles (i.e., Hybrid Fuel Cell Battery and Hybrid Fuel Cell Dominant), the differences in the battery size and fuel cell stacks change the way in which this strategy is implemented. Due to its lower capacity, the battery of a Hybrid Fuel Cell Dominant vehicle is charged more frequently than the battery system in a Hybrid Fuel Cell Battery vehicle under similar circumstances.

Figure 4-67 shows the SOC behaviour for both vehicles in a section of the CBD of Ottawa data set used in the training process.

Figure 4-67 State of Charge under downtown traffic conditions

A direct consequence of this behaviour is the higher variation observed in Figures 4-68 to 4-70, where the explanatory variables, state_of_charge and time, were plotted against the ESS residual values.

Similarly, the use of a bigger fuel cell stack increases the complexity of the process expressed in Equation 3-4 for a hybrid fuel cell dominant vehicle in comparison with a hybrid fuel cell battery vehicle under similar driving conditions.

Figure 4-68 ESS residual vs time and SOC. Fuel Cell Dominant – CBD

Figure 4-69 ESS residual vs time and SOC. Fuel Cell Dominant - Bronson

Figure 4-70 ESS residual vs time and SOC – Fuel Cell Dominant – HWY 417

Figures 4-71 and 4-72 show the power provided by the fuel cell along part of the downtown data set used in the neural network training process for a hybrid fuel cell dominant and a hybrid fuel cell battery vehicle, respectively. Although under idle and low load conditions both vehicles maintained the fuel cell operation at certain minimum levels (2 to 4 kW for a hybrid fuel cell battery vehicle and 5 to 10 kW for a hybrid fuel cell dominant vehicle), the hybrid fuel cell dominant vehicle was also able to turn-off the fuel cell system, increasing the complexity of the response surface which the neural network was trained to emulate. This results in a higher variation between ADVISOR outputs and the values predicted by the trained neural network (Figures 4-73 to 4-78).

Figure 4-71 Fuel cell power output for a fuel cell dominant vehicle - ADVISOR

Figure 4-72 Fuel cell power output for a fuel cell battery vehicle - ADVISOR

Figure 4-73 ESS residual vs speed and acceleration. Fuel Cell Dominant – CBD

Figure 4-74 ESS residual vs acceleration and speed. Fuel Cell Dominant – CBD

Figure 4-75 ESS residual vs speed and acceleration. Fuel Cell Dominant - Bronson

Figure 4-76 ESS residual vs acceleration and speed. Fuel Cell Dominant - Bronson

Figure 4-77 ESS residual vs speed and acceleration. Fuel Cell Dominant – HWY 417

Figure 4-78 ESS residual vs acceleration and speed. Fuel Cell Dominant – HWY 417

As in the case of the simulated fuel cell hybrid battery vehicle, in this case, ADVISOR outputs were combined with information from literature sources in order to understand better how the hybrid fuel cell dominant vehicle responds to the road loads (Figures 4-79 to 4-81). In a hybrid fuel cell battery vehicle, because of the small size of the fuel cell stack, the power provided to the system and the consequent fuel consumption in idle and low load conditions were below 3 kW and 0.3 g/sec, respectively. These values were sufficient to make it unnecessary for the fuel cell shutdown in order to accomplish ADVISOR's control strategy. It should be noted that even if shutting down the fuel cell system under idle conditions reduces the consumption of fuel, very little information is available about the effects of this operation over the gas reformer and the fuel cell system itself (Markel *et al*, 2003).

Figure 4-79 Fuel Cell output power vs Efficiency. Fuel Cell Dominant - CBD

Figure 4-80 Fuel Cell output power vs Efficiency. Fuel Cell Dominant - Bronson

Figure 4-81 Fuel Cell output power vs Efficiency. Fuel Cell Dominant – HWY 417

Since for a hybrid fuel cell dominant vehicle, the desirable minimum power level and corresponding fuel consumption were 3 times higher than that observed for a hybrid fuel cell battery vehicle, a compromise between fuel consumption optimization and the reduction of losses in the battery and gas reformer systems was necessary.

Nonetheless, a comparison of Figure 4-64 and Figure 4-81 shows that a hybrid fuel cell dominant vehicle has a more efficient behaviour (in terms of power provided by the fuel cell system) than the hybrid fuel cell battery vehicle under highway conditions (TRB, 2000). Finally, a comparison of the model results against the fuel consumption behaviour calculated by ADVISOR is presented in Figures 4-82 to 4-87.

4.2 Macroscopic Fuel Consumption Models

Results of the process described in Section 3.4.2 are presented, for all vehicles and traffic conditions, in Tables 4-8 to 4-10 (goodness of fit), and in Figures 4-88 to 4-92 in form of link average speed against average fuel consumption diagrams. Here, it is interesting to note that fuel consumption predicted by the ANN models show some oscillations in its values. This behaviour could be a consequence of several reasons such as:

- Inaccuracies of the average speed models at very low speeds and speeds higher than 60 km/h (USEPA, 1974, Ding, 2000).

Figure 4-82 ADVISOR fuel consumption. Fuel Cell Dominant vehicle, CBD

Figure 4-83 Predicted fuel consumption. Fuel Cell Dominant vehicle, CBD

Figure 4-84 ADVISOR fuel consumption. Fuel Cell Dominant vehicle, Bronson

Figure 4-85 Predicted fuel consumption. Fuel Cell Dominant vehicle, Bronson

Figure 4-86 ADVISOR fuel consumption. Fuel Cell Dominant vehicle, HWY 417

Figure 4-87 Predicted fuel consumption. Fuel Cell Dominant vehicle, HWY 417

Table 4-8 Quantitative Analysis of Testing Data Set – Macro CBD

Vehicles	CBD Ottawa	
	R	R²
ICE Large	0.9394	0.8826
ICE Small	0.9322	0.8691
ICE Hybrid	0.9228	0.8516
FC Dominant	-	0.1401
FC Battery	0.8778	0.7706

Table 4-9 Quantitative Analysis of Testing Data Set - Macro Bronson

Vehicles	Bronson Ave.	
	R	R²
ICE Large	0.9614	0.9244
ICE Small	0.9547	0.9116
ICE Hybrid	0.9239	0.8536
FC Dominant	0.7824	0.6123
FC Battery	0.9764	0.9534

Table 4-10 Quantitative Analysis of Testing Data Set - Macro HWY 417

Vehicles	Highway 417	
	R	R²
ICE Large	0.8110	0.6578
ICE Small	0.7118	0.5067
ICE Hybrid	0.5842	0.3413
FC Dominant	0.7162	0.513
FC Battery	0.6997	0.4897

Figure 4-88 Macroscopic Fuel Consumption. Large ICE Vehicle

Note that this figure does not show fitted curves. Independent values for ADVISOR and ANN model outputs are presented.

Figure 4-89 Macroscopic Fuel Consumption. Small ICE Vehicle

Note that this figure does not show fitted curves. Independent values for ADVISOR and ANN model outputs are presented.

Figure 4-90 Macroscopic Fuel Consumption. Hybrid ICE Vehicle

Note that this figure does not show fitted curves. Independent values for ADVISOR and ANN model outputs are presented.

Figure 4-91 Macroscopic Fuel Consumption. Fuel Cell Battery Vehicle

Note that this figure does not show fitted curves. Independent values for ADVISOR and ANN model outputs are presented.

Figure 4-92 Macroscopic Fuel Consumption. Fuel Cell Dominant Vehicle

Note that this figure does not show fitted curves. Independent values for ADVISOR and ANN model outputs are presented.

- The neural network capacity to “learn” the fuel consumption behaviour expressed in the aggregate data from ADVISOR, or
- Due to the fact that the oscillations observed in the values predicted by the ANN models could be a result of overfitting the data.

The generalization capabilities of the model were evaluated as follow.

4.2.1 Evaluation Process

Once again, to evaluate the generalization capabilities of the trained neural network models, the sum of square errors for the training and testing data sets were collected along the entire training process and plotted together. It should be noted that the Hybrid Fuel Cell Dominant vehicle was not subjected to this analysis because of the high variation in fuel consumption values exhibited for all traffic conditions (Figure 4-92). Although the Hybrid Fuel Cell Dominant vehicle shows fuel consumption behaviour similar to the ICE Hybrid vehicle, the number of times in which the fuel cell system is allowed to shutdown (consequently reducing its fuel consumption), is more broadly dispersed along the average speed range. This particular behaviour could be explained as the result of a couple of factors related to the control strategy implemented in this type of vehicle and to the required time to warm-up the fuel cell and gasoline reformer system. These have been previously discussed in Section 4.1.1.3. Under idle and low load conditions, a hybrid fuel cell dominant vehicle not only maintains the fuel cell operation under certain minimum power levels (5 to 10 kW), but it was also able to turn-off the fuel

cell system, increasing the complexity of the response surface which the neural network was trained to emulate. This has resulted in a higher difference between ADVISOR outputs and the values predicted by the trained neural network. For the rest of the simulated vehicles, the error curve corresponding to the testing data set shows a similar pattern to that followed for the training data set allowing the assumption to hold that all the neural networks were capable of learning an accurate and generalized solution to the problem (Figures 4-93 to 4-96).

Figure 4-93 Sum-of-square errors. Macroscopic – Large ICE

Figure 4-94 Sum-of-square errors. Macroscopic – Small ICE

Figure 4-95 Sum-of-square. Macroscopic – Hybrid ICE

Figure 4-96 Sum-of-square errors. Macroscopic – Fuel Cell Battery

Similarly, residual values of average fuel consumption were plotted in a time-ordered manner and against predicted values for the two non-freeway traffic conditions (Figures 4-97 to 4-100).

The basis of this analysis was explained in Section 4.1 and only results are discussed in this section. In this respect, for all the simulated vehicles, the presence of a narrow

horizontal band along all the time steps suggests that no apparent long-term time trend is affecting the model. However for advanced technology vehicles, a higher variation in the residual values at the beginning of the drive cycle is observed. This variation is a direct consequence of the control strategy implemented for both types of advanced technology vehicles. In a Hybrid ICE vehicle, the control strategy discussed in Chapter 3 uses the energy stored in the battery system to drive the vehicle, minimizing the fuel consumed until a low value of SOC is reached. For a Hybrid Fuel Cell Battery vehicle, the reason behind the variation in the residual values is the period between the start-up and the moment at which the fuel cell is able to add power to the system. Along this period, the battery system is required to provide all the energy required to drive the vehicle.

Hence, it is clear that a higher variation between the results of a neural network model, (that was trained to predict the average fuel consumption of advance technology vehicles using link average speed as the only explanatory variable) and the results provided by ADVISOR, could be expected at the beginning of every cycle.

Finally, when residuals of average fuel consumption are plotted against predicted values for both non-freeway traffic conditions, no abnormality is observed indicating that the initial assumptions explained in Chapter 4 had not been violated (Figures 4-101 to 4-104). However, it is interesting to note that for a Hybrid Fuel Cell Battery vehicle, the higher variation in the residual values is generated in the warm-up period, when the fuel consumed is zero.

Figure 4-97 Residuals plotted in time order. Large ICE vehicle

Figure 4-98 Residuals plotted in time order. Small ICE vehicle

Figure 4-99 Residuals plotted in time order. Hybrid ICE vehicle

Figure 4-100 Residuals plotted in time order. Fuel Cell Battery vehicle

Figure 4-101 Residuals plotted vs predicted values. Large ICE vehicle

Figure 4-102 Residuals plotted vs predicted values. Small ICE vehicle

Analysis of Residuals

Figure 4-103 Residuals plotted vs predicted values. Hybrid ICE vehicle

Analysis of Residuals

Figure 4-104 Residuals plotted vs predicted values. Fuel Cell Battery vehicle

In order to study the average fuel consumption behaviour of simulated advance technology vehicles for non-freeway facilities, equations of the type represented by Equation 2-3 were developed by using regression analysis. This equation is attributed to Fwa and Ang (1992)

$$FC = a_0 + \frac{a_1}{V}$$

where

FC = average fuel consumed for a unit distance in a trip
V = average speed of the trip

As explained in Chapter 2, in this equation, a_0 and a_1 are vehicle-specific parameters (Table 4-11). For conventional ICE vehicles, a_0 represents fuel consumed to overcome rolling resistance (approximately proportional to vehicle weight), and a_1 is a parameter approximately proportional to fuel consumed while idling (Fwa and Ang, 1992, Chang *et al*, 1977).

Table 4-11 Linear Regression Coefficients a_0 and a_1

Facilities	CBD Ottawa		Bronson Ave.		Highway 417	
Vehicles	a_0	a_1	a_0	a_1	a_0	a_1
ICE Large	3.752	269.03	3.0	251.90	-	-
ICE Small	3.250	186.50	2.391	195.60	-	-
ICE Hybrid	2.818	139.50	1.659	141.80	-	-
FC Dominant	-	-	-	-	-	-
FC Battery	0.855	77.40	0.874	86.40	-	-

However, it is possible to observe in Figure 4-105 and Figure 4-106, that simulated advanced technology vehicles do not exactly follow this relationship.

Figure 4-105 relates the values of the coefficient a_I , in grams per second, with the average idle fuel flow rate extracted from ADVISOR outputs for Downtown Ottawa and Bronson Avenue.

This graph shows that for all vehicles, a_I is approximately proportional to the idle fuel flow rate, because for a conventional ICE vehicle, the fuel consumed during idle conditions is used just to overcome mechanical losses and because these losses are directly related with the engine's size, therefore a_I is independent of the type of traffic conditions (Chang et al, 1979).

Figure 4-105 Relationship between linear coefficient a_1 and Idle Fuel Flow rate

In order to minimize losses and inefficiency due to idling and low load conditions in a Fuel Cell Hybrid Battery vehicle, the fuel cell system is operated at a minimum power level, which is not related to the traffic conditions. As was discussed in more detail in Section 4.1.1.3.1, in a fuel cell hybrid vehicle with a battery dominant system, the primary source of driving power is the energy storage system where the fuel cell system is maintained in a quasi-steady-state operation providing a constant energy output.

It should be noted that for a Hybrid ICE vehicle this relationship between a_I and the idle fuel rate has a higher variation than the rest of the vehicles, including a Hybrid Fuel Cell Battery vehicle. This variation could be attributable to the way the Hybrid ICE vehicle handles the energy storage system, and consequently, the amount of fuel consumed in idle conditions.

Although this type of vehicle has an internal combustion engine that uses fuel to operate in idle conditions, it also has a battery storage system that can take care of the vehicle's operation, shutting down the engine and avoiding fuel consumption in idle conditions. The use of the engine or the battery system in idle conditions is a direct result of the vehicle's control strategy that, as discussed in Chapter 3, is totally dependent on the traffic conditions where the vehicle has been operating.

As for the coefficient a_0 , Figure 4-106 presents values (in lt/100 km) against the vehicle's weight (in kilograms). It is clear that, for conventional ICE vehicles the values of a_0 are

directly proportional to the weight of the vehicle. However this assumption cannot be sustained in the case of advanced technology vehicles. Although both vehicles, Hybrid ICE and Hybrid Fuel Cell Battery, are heavier than the simulated ICE vehicles, a_0 's are lower. Furthermore, the Hybrid Fuel Cell Battery vehicle is almost 200 kg heavier than the Hybrid ICE and a_0 is much lower.

Figure 4-106 Relationship between linear coefficient a_0 and vehicle weight

A possible explanation for this behaviour could be found by exploring the way the different vehicles respond to the power requirements. In Chapter 2, the power-based model developed by Post (Equation 2-1) was used to explain the differences in fuel consumption between conventional vehicles and advanced technology vehicles.

$$FC = \alpha + \beta \cdot Z \quad Z \geq 0 \text{ kW}$$

In this equation, Z represents the power required to overcome rolling resistance for a conventional vehicle and it is directly related to the vehicle's weight. This is also true for an advanced technology vehicle. But, because this type of vehicle has two sources of power, the engine will be assisted by the motor to complete the power demand, allowing a reduction in the amount of fuel consumed. Moreover, a better efficiency of the operating system in an advanced technology vehicle, represented in the equation by the parameter β , allows a further reduction in the fuel consumed, which is not affected by weight.

Therefore, it can be assumed that the aggregated data from ADVISOR reflect the expected fuel consumption behaviour not only for conventional ICE vehicles, but also for advanced technology vehicles equipped with a battery system. In this case, it is important to note that in the case of advance technology vehicles, the fuel consumption behaviour learned at the macroscopic level for the trained neural networks corresponds to one in which the vehicle starts its drive cycle with a SOC value of 0.60.

CHAPTER 5. IMPLEMENTATION OF THE MODELS

5.1 Introduction

Computational implementation of the neural network models developed in this thesis research is based on the following sequence of equations (Nabney, 2002);

$$a_j = \sum_{i=1}^N w_{ji} * x_i + b_j \quad j = 1, \dots, M$$

$$z_j = \tanh(a_j) \quad j = 1, \dots, M$$

$$a_k = \sum_{j=1}^M w_{kj} * z_j + b_k \quad k = 1, \dots, c$$

$$y_k = a_k$$

Equation 5-1

where

y	neural network model results
w and b	model coefficients (weights and bias)
x	an input vector containing the input variables
tanh	a nonlinear transfer function
N	number of inputs
M	number of hidden units
c	number of outputs

Detailed explanations of all the components of these equations are presented below.

Input vector x. Although the training process used a set of values provided by ADVISOR, the implementation of all neural network models requires only one external input vector

i.e., instantaneous speed for the microscopic fuel consumption model or link average speed for macroscopic fuel consumption model. From this input vector, the algorithm is able to calculate the rest of the required input values.

Model Coefficients w and b . Weights, together with the bias values (in the form of matrices or vectors, depending on the number of hidden units), are the results of the neural network training process. These matrices or vectors are located in a file, specific for every neural network (Appendix D).

Transfer function. Because a two-layer structure was selected for all the neural networks in the present thesis, partial results of the first layer are affected by a nonlinear transfer function $\tanh$, meanwhile the second layer results are affected for a linear transfer function.

Neural network results y . Microscopic fuel consumption, in g/sec, and macroscopic fuel consumption, in lt/100 km.

This implementation is schematically presented in Figures 5-1 to 5-4. Although both models, instantaneous and average fuel consumption, shared the same general structure, in the case of instantaneous fuel consumption for advanced technology vehicles, three different steps were added to the process:

- First, participation of the Energy Storage System is calculated by using time, speed, acceleration, and the initial SOC as inputs,
- Second, based on the calculated ESS value, the state of charge is updated and used to calculate the following ESS value. Calculations in this step were based on the internal resistance battery model (R_{int}) used by ADVISOR to estimate the State of Charge (Johnson, 2002, NREL, 2002).

$$SOC = \frac{Ah_{\max} - Ah_{used}(\eta_{Coulomb})}{Ah_{\max}}$$

Equation 5-2

where

$$Ah_{used} = \int_0^t \eta_{coulomb} A dt \quad \text{for } A < 0 \text{ Charge}$$

$$Ah_{used} = \int_0^t A dt \quad \text{for } A > 0 \text{ Discharge}$$

Equation 5-3

and

$$Ah_{\max} [\text{NiMh}] = 23,400 \text{ Ah (discharge)}$$

$$\eta_{coulomb} = 0.905$$

- Third, instantaneous fuel consumption is calculated using time, speed, acceleration, and the calculated State of Charge and ESS as inputs.

Figure 5-1 Microscopic fuel consumption model, ICE vehicles

Figure 5-2 Microscopic fuel consumption, ATV (a)

Figure 5-3 Microscopic fuel consumption, ATV (b)

Figure 5-4 Macroscopic fuel consumption model

Because the procedure described above implies only mathematical operations of matrices, it may be implemented in software platforms such as Excel, Visual Basic or C++.

In the present thesis the Suite 6.0 of Microsoft's Visual Basic Professional was used to develop an algorithm capable of creating the weights and bias file, to read and calculate the corresponding input values for every model and, based on Equation 5-1, to predict micro or macroscopic fuel consumption of conventional and advanced technology vehicles (Appendix E).

For transportation planning purposes, the advantage of this procedure resides in the fact that the same information used to calculate fuel consumption of conventional ICE vehicles (i.e., second-by-second or link average speed values), is required to calculate micro or macroscopic fuel consumption of advanced technology vehicles. This fact makes it suitable as an auxiliary tool for most traffic and transportation simulation models currently available in the market.

For example, the developed algorithm could be useful in the solution of WHAT IF, type of questions in which different alternatives are tested, i.e. what is the expected amount of fuel savings if advanced technology vehicles take the place of conventional ICE vehicles in the light-duty vehicle fleet?

5.2 Sample Model Application: Fuel Consumption Properties of Advanced Technology Vehicles versus Conventional ICE Vehicles

It is generally accepted by transportation experts that fuel savings derived due to the use of advanced technology vehicles will be higher in stop-and-go driving conditions than that expected for uncongested driving conditions. However the amount of such savings has been subjected to discussion mostly because there is not enough information to develop empirically a controlled comparison between a conventional ICE vehicle and a comparable advance technology vehicle (Santini and Vyas, 1999).

On this matter, the European Commission DG/VII built a database using several different sources in order to estimate emissions and energy consumption factors for advanced technology vehicles. However, the amount of available information was not sufficient to develop a statistical relationship between average speed and energy consumption with an adequate level of confidence. Therefore, only an average energy consumption rate for Hybrid ICE vehicles of 436 Wh/km was included in the report (Samaras *et al*, 1998).

Santini et al (2000), using statistical methods and judgment based on results of previous research, developed a relationship between in-use fuel consumption and average speed, for three different vehicles, including a Prius-type Hybrid ICE vehicle (Santini *et al*, 2000). Estimates of fuel consumption and savings based in these functions for two different vehicles, a conventional ICE vehicle like Toyota Corolla and a hybrid ICE vehicle like Toyota Prius are presented in Table 5-1 (Santini et al, 2000)

Table 5-1 Estimates of fuel consumption and savings

Speed (mph)	Corolla (gal/h)	Prius (gal/h)	Savings (Corolla – Prius) (gal/h)
5	0.41	0.15	0.26
15	0.66	0.31	0.35
25	0.92	0.52	0.40
35	1.18	0.81	0.37
45	1.43	1.14	0.29
55	1.69	1.46	0.23
65	1.95	1.66	0.29

Note: Hybrid ICE versus conventional ICE vehicle

To show the simplicity of the use of the developed algorithm, the next procedure was followed in order to replicate the analysis of Santini et al, using a small conventional ICE vehicle and a Hybrid ICE vehicle:

- Average driving speeds presented in Table 5-1 were transformed from miles per hour to kilometers per hour in an Excel spreadsheet, and a “text” file was generated and used as input for the algorithm.
- The algorithm acknowledged the text file, and using the corresponding model, average fuel consumption was calculated for every vehicle, in liters per 100 km.
- An output file was created containing both the average driving speed used as input and the predicted average fuel consumption.
- After transforming the results provided by the algorithm from liter per 100 km to gallons per hour, a fitted curve was constructed for both types of vehicles (Figures 5-5 and 5-6), and fuel savings for the entire range of speed were calculated. See Table 5-2.

Figure 5-5 Predicted and estimated fuel consumption of a hybrid ICE vehicle

Figure 5-6 Predicted and estimated fuel consumption of a conventional ICE vehicle

Table 5-2 Predicted fuel consumption and savings

Speed (mph)	Small ICE (gal/h)	Hybrid ICE (gal/h)	Savings (ICE – Hybrid ICE) (gal/h)
5	0.72	0.38	0.34
15	0.67	0.55	0.12
25	0.72	0.53	0.19
35	0.87	0.57	0.30
45	1.12	0.75	0.37
55	1.48	1.1	0.38
65	1.93	1.34	0.59

Note: Hybrid ICE versus conventional ICE vehicle (fitted values)

Even though fuel consumption predicted by the algorithm for both type of vehicles was similar to that presented in Table 5-1, the expected savings did not exactly follow the same trend discussed by Santini and Vyas (1999). A possible reason for this difference is the type of function selected by Santini et al, to calculate fuel consumption of conventional and hybrid ICE vehicles. Although these functions were not included in this study, it was possible to obtain them from the values presented in Table 5-1 (Figures 5-5 and 5-6).

Figure 5-5 shows fuel consumption predicted by the algorithm and values provided by Santini et al (2000), in gallons per hour, against average driving speed in miles per hour, for a hybrid ICE vehicle like Toyota Prius. It was observed that although the results followed the same trend, the polynomial function developed by Santini et al, produced a smoother response that in some way overshadows the effects of the state of charge over the fuel consumption behaviour, particularly under low average driving speeds.

Furthermore, the selected function for a conventional ICE vehicle is a linear function similar to that described in section 2.2 that does not represent fully the differences in fuel consumption at different average driving speeds (Figure 5-6).

Here, it is interesting to note that the effectiveness of a transportation control measure to reduce fuel consumption is normally found by using average values in two steps. In the first step, average speeds provided by transportation model or traffic surveys are obtained. In the second step, these average speed values are used as inputs to calculate average fuel consumption with models such as developed by Santini et al (2000). However, several researchers have pointed out that, to fully capture the effects of innovative transportation control measures, such as Intelligent Transportation Systems, the use of fuel consumption models sensitive to instantaneous speed and acceleration values are required (Khan, 1993, Hassounah and Miller, 1994, Rakha et al, 2000). In order to show how the algorithm developed in the present thesis can be used in the transportation planning process at two different levels of detail, namely microscopic and macroscopic, three different sample applications are discussed below.

5.3 Sample Model Application: Micro and Macroscopic Fuel Consumption in Urban Arterial Traffic Conditions

Information collected from a 30-minute simulation created in CORSIM, was used to evaluate the fuel consumption values for both directions of Bronson Avenue for AM Peak hour traffic starting at its intersection with Albert St.

So as to take into account not only the different traffic conditions but also the effect of the SOC over the fuel consumption of advance technology vehicles, the trajectory presented in Figure 5-7 was created by simulating a vehicle that starts the drive cycle at Albert St. with a SOC value of 0.60 and ended again at Albert St. after driving approximately 25-minute.

Figure 5-7 Urban arterial (Bronson Avenue)

With the objective of comparing the results at micro and macroscopic levels, the number of links considered at the macroscopic level corresponds to the distance travelled by the simulated vehicle in the first and the last 5 minutes of travel.

5.3.1 Macroscopic Level

As a part of CORSIM's outputs, link average speed, link length, and vehicle-km per link are provided. Appendix F shows an example of the output file generated by CORSIM. From CORSIM's output file, link average speed values for a section at the beginning and the end of the simulated Bronson Avenue were extracted and translated from miles per hour (MPH) to kilometres per hour (KPH). It should be noted that for the beginning of the drive cycle (North to South section of Bronson Avenue), due to the un-congested traffic conditions, a distance of approximately 2.5 km was considered. For the last portion of the drive cycle (South to North section of Bronson Avenue), subjected to heavy traffic, the distance travelled was approximately 0.8 km (Figure 5-8 and Figure 5-9, respectively).

Figure 5-8 Link average speed Bronson Avenue (North to South)

Note: As compared to the South to North direction shown in Figure 5-9, the level of congestion is lower.

Figure 5-9 Link average speed Bronson Avenue (South to North)

Note: As compared to the North to South direction shown in Figure 5-8, the level of congestion is higher.

The use of this information in the developed algorithm to calculate average fuel consumption for conventional ICE (large and small) vehicles, a Hybrid ICE vehicle and a Hybrid Fuel Cell Battery vehicle did not encounter any problem:

- Once the link average speed values from CORSIM were adequately organized in an Excel spreadsheet, a “text” file was generated and used as input for the algorithm.
- The algorithm acknowledged the text file, and using the corresponding model, average fuel consumption was calculated for every vehicle, in litres per 100 km.
- An output file was created containing both the link average speed used as input and the predicted average fuel consumption for every link.

Average fuel consumption for every link, type of vehicle and traffic condition is presented in Table 5-3.

Table 5-3 Average Fuel Consumption values calculated by the algorithm

(A)	Average	FC	FC	FC	FC
LINK	Speed	Small ICE	Large ICE	Hybrid ICE	FC
	KPH	L/100 KM	L/100 KM	L/100 KM	Hybrid
					Fuel Cell Battery
					L/100 KM
200	16.57	25	34	13	4
201	18.18	22	24	12	4
202	14.64	25	31	13	4
203	25.10	12	15	10	3
204	14.16	25	29	13	5
205	38.29	7	8	4	3
206	16.57	25	34	13	4
207	38.78	7	8	4	3
208	45.21	7	7	5	3
209	14.00	24	28	13	5
210	21.72	14	14	10	5
211	37.01	7	9	5	3
212	44.25	7	7	5	3
213	43.28	7	7	5	2
214	10.30	24	31	12	10
215	14.96	25	32	13	4
216	35.88	8	9	4	3
217	41.51	7	7	4	2
218	19.79	18	16	11	5
219	34.59	8	9	3	3
220	11.58	23	27	12	8
221	39.74	7	8	3	3
222	41.99	7	7	4	2
223	41.83	7	7	4	2
224	41.51	7	7	4	2
225	16.25	25	35	13	4
226	39.74	7	8	3	3
227	30.09	9	11	6	2
228	42.16	7	7	4	2
7229	48.69	6	7	5	1
230	51.94	6	6	5	3

Table 5-3 Average Fuel Consumption values calculated by the algorithm

(B)	Average	FC	FC	FC	FC
LINK	Speed	Small ICE	Large ICE	Hybrid ICE	Hybrid
	KPH	L/100 KM	L/100 KM	L/100 KM	Fuel Cell Battery
		L/100 KM			L/100 KM
211	18.83	20	20	12	4
210	10.30	24	31	12	10
209	4.83	44	56	35	20
208	4.02	47	61	38	23
207	36.36	8	9	5	3
206	14.80	25	31	13	4
205	37.49	7	8	5	3
204	31.05	9	10	5	2
203	12.71	23	25	12	7
202	14.64	25	31	13	4
201	12.87	23	25	12	7

Note that section (a) of the table shows the values that correspond to North-South Bronson while section (b) presents the results for the South-North section of Bronson Ave.

Knowing the length and vehicles-km for every link, it was also possible to calculate the fuel consumed per link and total fuel consumed in both sections of Bronson Avenue (Tables 5-4 and 5-5).

In order to develop a baseline for comparing algorithm results, information from two types of vehicles (i.e., NETSIM vehicle type 5, a low performance passenger car, and NETSIM vehicle type 1, a high performance passenger car) was collected from CORSIM.

Table 5-4 Fuel consumed per link.

(A)	LINK	FC	FC	FC	FC
LINK	LENGTH	Small ICE	Large ICE	Hybrid ICE	FC
	100 KM	Litres	Litres	Litres	Hybrid Fuel Cell Battery
					Litres
200	0.000655	0.0164	0.0223	0.0085	0.0026
201	0.000863	0.0190	0.0207	0.0104	0.0035
202	0.000652	0.0163	0.0202	0.0085	0.0026
203	0.000622	0.0075	0.0093	0.0062	0.0019
204	0.000844	0.0211	0.0245	0.0110	0.0042
205	0.000829	0.0058	0.0066	0.0033	0.0025
206	0.000792	0.0198	0.0269	0.0103	0.0032
207	0.000741	0.0052	0.0059	0.0030	0.0022
208	0.000744	0.0052	0.0052	0.0037	0.0022
209	0.000789	0.0189	0.0221	0.0103	0.0039
210	0.001570	0.0220	0.0220	0.0157	0.0078
211	0.000640	0.0045	0.0058	0.0032	0.0019
212	0.000686	0.0048	0.0048	0.0034	0.0021
213	0.000747	0.0052	0.0052	0.0037	0.0015
214	0.000692	0.0166	0.0214	0.0083	0.0069
215	0.000863	0.0216	0.0276	0.0112	0.0035
216	0.000631	0.0050	0.0057	0.0025	0.0019
217	0.000884	0.0062	0.0062	0.0035	0.0018
218	0.000725	0.0131	0.0116	0.0080	0.0036
219	0.000780	0.0062	0.0070	0.0023	0.0023
220	0.000680	0.0156	0.0184	0.0082	0.0054
221	0.000923	0.0065	0.0074	0.0028	0.0028
222	0.000719	0.0050	0.0050	0.0029	0.0014
223	0.000686	0.0048	0.0048	0.0027	0.0014
224	0.000786	0.0055	0.0055	0.0031	0.0016
225	0.000716	0.0179	0.0251	0.0093	0.0029
226	0.000975	0.0068	0.0078	0.0029	0.0029
227	0.001042	0.0094	0.0115	0.0063	0.0021
228	0.000381	0.0027	0.0027	0.0015	0.0008
7229	0.000384	0.0023	0.0027	0.0019	0.0004
230	0.001445	0.0087	0.0087	0.0072	0.0043

Table 5-4 Fuel consumed per link

(B)	LINK	FC	FC	FC	FC
LINK	LENGTH	Small ICE	Large ICE	Hybrid ICE	FC
	100 KM	Litres	Litres	Litres	Hybrid Fuel Cell Battery
					Litres
211	0.001569643	0.0314	0.0314	0.0188	0.0063
210	0.000789393	0.0189	0.0245	0.0095	0.0079
209	0.000743676	0.0327	0.0416	0.0260	0.0149
208	0.000740628	0.0348	0.0452	0.0281	0.0170
207	0.000792441	0.0063	0.0071	0.0040	0.0024
206	0.000829016	0.0207	0.0257	0.0108	0.0033
205	0.000844255	0.0059	0.0068	0.0042	0.0025
204	0.000621762	0.0056	0.0062	0.0031	0.0012
203	0.00065224	0.0150	0.0163	0.0078	0.0046
202	0.000862542	0.0216	0.0267	0.0112	0.0035
201	0.000655288	0.0151	0.0164	0.0079	0.0046

Note that section (a) of the table shows the values that correspond to North-South Bronson while section (b) presents the results for the South-North section of Bronson Ave.

Table 5-5 Total fuel consumed per link

(A)		FC	FC	FC	FC
LINK	VEH-KM	Small ICE	Large ICE	Hybrid ICE	FC
		Litres	Litres	Litres	Hybrid Fuel Cell Battery
					Litres
211	95.060	19.012	19.012	11.407	3.802
210	47.916	11.500	14.854	5.750	4.792
209	45.583	20.057	25.526	15.954	9.117
208	45.470	21.371	27.737	17.279	10.458
207	43.974	3.518	3.958	2.199	1.319
206	41.609	10.402	12.899	5.409	1.664
205	43.974	3.078	3.518	2.199	1.319
204	32.389	2.915	3.239	1.619	0.648
203	35.141	8.082	8.785	4.217	2.460
202	24.183	6.046	7.497	3.144	0.967
201	22.864	5.259	5.716	2.744	1.600

Table 5-5 Total fuel consumed per link

(B)		FC	FC	FC	FC
LINK	VEH-KM	Small ICE	Large ICE	Hybrid ICE	Hybrid Fuel Cell Battery
		Litres	Litres	Litres	Litres
200	6.887	1.722	2.341	0.895	0.275
201	12.759	2.807	3.062	1.531	0.510
202	26.211	6.553	8.125	3.407	1.048
203	26.725	3.207	4.009	2.673	0.802
204	20.515	5.129	5.949	2.667	1.026
205	20.386	1.427	1.631	0.815	0.612
206	19.099	4.775	6.494	2.483	0.764
207	20.225	1.416	1.618	0.809	0.607
208	20.370	1.426	1.426	1.018	0.611
209	21.786	5.229	6.100	2.832	1.089
210	41.351	5.789	5.789	4.135	2.068
211	28.045	1.963	2.524	1.402	0.841
212	31.681	2.218	2.218	1.584	0.950
213	34.642	2.425	2.425	1.732	0.693
214	31.536	7.569	9.776	3.784	3.154
215	38.455	9.614	12.306	4.999	1.538
216	41.641	3.331	3.748	1.666	1.249
217	59.034	4.132	4.132	2.361	1.181
218	48.447	8.720	7.752	5.329	2.422
219	54.368	4.349	4.893	1.631	1.631
220	47.433	10.910	12.807	5.692	3.795
221	58.857	4.120	4.709	1.766	1.766
222	47.031	3.292	3.292	1.881	0.941
223	44.843	3.139	3.139	1.794	0.897
224	51.424	3.600	3.600	2.057	1.028
225	47.337	11.834	16.568	6.154	1.893
226	62.317	4.362	4.985	1.869	1.869
227	66.387	5.975	7.303	3.983	1.328
228	24.795	1.736	1.736	0.992	0.496
7229	28.479	1.709	1.994	1.424	0.285
230	93.805	5.628	5.628	4.690	2.814

Note that section (a) of the table shows the values that correspond to South-North Bronson while section (b) presents the results for the North-South section of Bronson Ave.

However, it was not possible to make a direct comparison between the average fuel consumption provided by CORSIM and results of the algorithm because CORSIM used the term “performance” only to identify the environmental look-up table that is used to calculate fuel consumption and emission values and it does not represent a specific type of vehicle in terms of weight or engine power. Average fuel consumption values provided by CORSIM were translated from miles per gallon (MPG) to litres per 100 km. These are presented in Appendix F. When the average fuel consumption for both NETSIM vehicles were compared qualitatively against the values provided by the algorithm (Appendix F) it was observed that the results of the algorithm followed the same fuel consumption trend as calculated by CORSIM for both type of traffic conditions. Similarly, if average fuel consumption for the simulated conventional ICE large vehicle is compared against the rest of the simulated vehicles, it is observed in Table 5-6 that although the average fuel consumption values are more than 100% higher in the South-North section of Bronson Avenue, the expected savings in fuel consumption remains remarkably constant.

Table 5-6 Average fuel consumption values (Lt/100 km)

Simulated Vehicles	Average Fuel Consumption (Lt/100 km)	
	Bronson Avenue North - South	Bronson Avenue South - North
ICE Large	13.77	27.76
ICE Small	11.90	23.26
ICE Hybrid	6.80	15.04
Fuel Cell Battery	3.41	7.97
Simulated Vehicles	Fuel savings in comparison with a conventional ICE Large vehicle	
ICE Large	1	1
ICE Small	1.15	1.17
ICE Hybrid	2.02	1.84
FC Battery	4.03	3.48

5.3.2 *Microscopic Level*

In order to observe not only the effects of the energy provided by the battery and the different control strategy implemented in the simulated advance technology for the fuel consumed in both sections of Bronson Avenue, but also to show the microscopic capabilities of the algorithm developed in the present thesis, the speed trace extracted from CORSIM, on a second-by-second basis, was used as input to the algorithm in the following way:

- Once the instantaneous speed from CORSIM was adequately organized in an Excel spreadsheet, a “text” file was generated and used as input for the algorithm. An initial SOC value of 0.60 is used by default.
- The algorithm acknowledged the text file, and using the corresponding neural network model, ESS values were calculated for every vehicle (Amperes per second) upgrading at the same time the SOC value,
- An output file was created containing: time, speed, acceleration, state of charge, and ESS values on a second-by-second basis. This output file was used for a second neural network model as explanatory variable to calculate instantaneous fuel consumption for every vehicle and traffic condition.

Although fuel consumption values for the entire drive cycle were calculated, only the first and last 5 minutes of driving were subjected to detailed examination (Figures 5-10 and 5-11).

Figure 5-10 Instantaneous Speed Trace – Bronson Avenue North-South (BNS)

Figure 5-11 Instantaneous Speed Trace – Bronson Avenue South-North (BSN)

Again, to have a base of comparison, the same speed trace was used as input to ADVISOR and instantaneous fuel consumption values for all the simulated vehicles were calculated.

Figures 5-12 to 5-21 present, in a qualitative manner, the comparison between the instantaneous fuel consumption predicted by the algorithm and the values calculated with ADVISOR. For all vehicles and traffic conditions, a good level of agreement was observed, except for fuel consumption values in congested conditions for the Hybrid Fuel Cell vehicles in which a higher variation is observed.

Figure 5-12 Instantaneous fuel consumption values. Large ICE vehicle (BNS)

Figure 5-13 Instantaneous fuel consumption values. Large ICE vehicle (BSN)

Figure 5-14 Instantaneous fuel consumption values. Small ICE vehicle (BNS)

Figure 5-15 Instantaneous fuel consumption values. Small ICE vehicle (BSN)

Figure 5-16 Instantaneous fuel consumption values. Hybrid ICE vehicle (BNS)

Figure 5-17 Instantaneous fuel consumption values. Hybrid ICE vehicle (BSN)

Figure 5-18 Instantaneous fuel consumption values. Fuel Cell Battery vehicle (BNS)

Figure 5-19 Instantaneous fuel consumption values. Fuel Cell Battery vehicle (BSN)

Figure 5-20 Instantaneous fuel consumption values. Fuel Cell Dominant (BNS)

Figure 5-21 Instantaneous fuel consumption values. Fuel Cell Dominant (BSN)

Table 5-7 summarized the coefficient of determination values for both sections of Bronson Avenue and all the simulated vehicles.

Table 5-7 Quantitative analysis for Bronson Avenue Example

Vehicles	Coefficient of Determination R^2	
	BNS	BSN
Large ICE	0.9585	0.9627
Small ICE	0.9761	0.9540
Hybrid ICE	0.8844	0.9243
Fuel Cell Battery	0.9033	0.6904
Fuel Cell Dominant	0.9644	0.4402

Note: Correlation Coefficient and Coefficient of Determination between algorithm results and ADVISOR estimates.

It is possible to observe a moderately strong relationship between the values predicted by the algorithm and the values calculated with ADVISOR for all the vehicles with exception of the Hybrid Fuel Cell Dominant in the South to North part of the cycle. An explanation of this particular behaviour may be found in the effects of the energy control strategy discussed in Section 4.1.1.3.2. That is, due to its low capacity, the battery of a

Hybrid Fuel Cell Dominant vehicle is charged more frequently and the use of a bigger fuel cell stack increases the complexity of the process expressed in Equation 3-5 for a hybrid fuel cell dominant vehicle. With the values of consumed fuel presented in Table 5-8 and the distance travelled in both sections of Bronson Avenue, it was possible to calculate average fuel consumption for all the simulated vehicles and compare it against the average fuel consumption previously calculated in a macroscopic way (Table 5-9).

Table 5-8 Total fuel consumed per section (in grams)

Facilities	Bronson North-South (BNS)		Bronson South-North (BSN)	
Vehicles	Algorithm	ADVISOR	Algorithm	ADVISOR
Large ICE	205.80	206.12	211.95	213.83
Small ICE	171.05	169.77	166.84	168.79
Hybrid ICE	67.39	69.96	112.54	124.27
Fuel Cell Battery	49.22	51.29	63.65	64.92
Fuel Cell Dominant	95.66	102.23	75.87	103.62

Table 5-9 Average fuel consumption values (Bronson Example)

Facilities	Bronson North-South (BNS)		Bronson South-North (BSN)	
Vehicles	Average Fuel Consumption (Lt/100 km) Macroscopic Model	Average Fuel Consumption (Lt/100 km) Microscopic Model	Average Fuel Consumption (Lt/100 km) Macroscopic Model	Average Fuel Consumption (Lt/100 km) Microscopic Model
Large ICE	13.77	11.38	27.76	34.37
Small ICE	11.90	9.46	23.26	27.05
Hybrid ICE	6.80	3.73	15.04	18.09
Fuel Cell Battery	3.41	2.72	7.97	10.33
Fuel Cell Dominant	-	5.30	-	12.31

As expected, the microscopic neural network model used by the algorithm was able to calculate the instantaneous fuel consumption for all the vehicles by taking into account

the variations in speed and acceleration caused by the differences in traffic conditions along the drive cycle. In the case of advance technology vehicles, the differences between the amount of energy provided by the battery system at the beginning and at the end of the drive cycle were also taken into account.

As a consequence the average fuel consumption in the North to South part of Bronson Avenue was smaller than the average fuel consumption observed at the South to North part of the cycle. Although the average fuel consumption values calculated by using micro and macroscopic information are different (specially at the end of the drive cycle) the estimated fuel savings derived from the use of advanced technology vehicles compared well, not only among them but also to the savings calculated using results from ADVISOR (Table 5-10).

Table 5-10 Fuel savings in comparison with a ICE Large vehicle (Bronson)

Facilities	Microscopic Bronson North-South (BNS)		Microscopic Bronson South-North (BSN)		Macroscopic	
	Algorithm	ADVISOR	Algorithm	ADVISOR	BNS	BSN
Vehicles						
ICE Large	1	1	1	1	1	1
ICE Small	1.203	1.214	1.270	1.266	1.15	1.17
ICE Hybrid	3.053	2.946	1.883	1.72	2.02	1.84
Fuel Cell Battery	4.181	4.018	3.329	3.293	4.03	3.48
Fuel Cell Dominant	2.151	2.016	2.793	2.063	-	-

Finally, average fuel consumption values for the entire drive cycle presented in Table 5-11, support the notion of integration between modelling levels discussed in Section 3.4.

Table 5-11 Total fuel savings in comparison with a ICE Large vehicle (Bronson)

	Average Fuel Consumption Bronson Avenue (lt/100 km)		
Vehicles	Microscopic	Macroscopic	ADVISOR
Large ICE	15.92	15.26	15.96
Small ICE	12.97	13.01	12.94
Hybrid ICE	8.32	8.74	8.55
Fuel Cell Battery	5.14	4.77	5.20
Fuel Cell Dominant	9.24	-	9.22
	Fuel Savings (against conventional ICE large vehicle)		
Vehicles	Microscopic	Macroscopic	ADVISOR
Large ICE	1	1	1
Small ICE	1.22	1.17	1.23
Hybrid ICE	1.91	1.74	1.86
Fuel Cell Battery	3.09	3.19	3.06
Fuel Cell Dominant	1.72	-	1.73

5.4 Sample Model Application: Microscopic Fuel Consumption in Freeway Traffic Conditions

In the previous section, the relationship between the results of the algorithm for advanced technology vehicles and ADVISOR's results was weaker at the end of the drive cycle than at the beginning. This means that the algorithm's performance was either affected by the complexity of the speed trace under congested traffic conditions (as was suggested in Section 4.1.1.3.2.) or by a possible miscalculation of state of charge along time. In an attempt to verify which assumption is correct, a second traffic scenario, one with a similar driving time but a more steady traffic condition, was used as input to the algorithm as well as ADVISOR.

This traffic scenario was based in a CORSIM simulation of the AM Peak hour traffic of Highway 417 from Terry Fox Dr. to Walkley Rd. (Figure 5-22). To take into account the depletion and/or charging of the battery system in the fuel consumption estimate at the end of the drive cycle, the entire speed trace was used, but only the last five minutes of data were examined in detail.

Figure 5-22 Urban freeway. Highway 417 from Terry Fox Dr. to Walkley Rd.

After extracting the speed trace on a second-by-second basis from CORSIM's outputs (Figure 5-23), the procedure described in Section 5.3.2, was used to present the data to the algorithm and to calculate instantaneous fuel consumption values for all the simulated vehicles.

Figures 5-24 to 5-28 shows a graphical comparison between the algorithm's results and the results provided by ADVISOR for the same speed trace.

Figure 5-23 Instantaneous speed trace of a section of HWY 417

Note: Highway 417 ending at its intersection with Walkley Rd.

Figure 5-24 Instantaneous fuel consumption values. Large ICE vehicle (HWY 417)

Conventional ICE Small vehicle - HWY 417 at Walkley Rd.

Figure 5-25 Instantaneous fuel consumption values.Small ICE vehicle (HWY 417)

Hybrid ICE vehicle - HWY 417 at Walkley Rd.

Figure 5-26 Instantaneous fuel consumption values. Hybrid ICE vehicle (HWY 417)

Figure 5-27 Instantaneous fuel consumption values. Fuel Cell battery (HWY 417)

Figure 5-28 Instantaneous fuel consumption values. FC dominant (HWY 417)

It is interesting to note that fuel consumption values presented in Figures 5-24 and 5-25 for the simulated large and small ICE vehicles respectively, suggest that a better performance in terms of fuel consumption could be expected for a large ICE vehicle than a small one under cruise traffic conditions over 100 km/h. This phenomena is a consequence of the higher efficiency in energy conversion achieved for the large engine in this particular traffic conditions (Forster H.J., 1982).

Aso, it is observed that instantaneous fuel consumption values predicted by the algorithm follow very well the ADVISOR's trend for all vehicles. In this respect, coefficient of determination values presented in Table 5-12 suggested a stronger relation between algorithm predicted and ADVISOR calculated fuel consumption values in this traffic conditions than those observed for stop-and-go traffic conditions in the final part of the Bronson Avenue's drive cycle.

Table 5-12 Quantitative analysis (Bronson – HWY 417 Example)

Vehicles	Coefficient of Determination	
	BSN	HWY 417
ICE Large	0.9627	0.9943
ICE Small	0.9540	0.9940
ICE Hybrid	0.9243	0.9483
Fuel Cell Battery	0.6904	0.9524
Fuel Cell Dominant	0.4402	0.7758

Furthermore, when the fuel consumed predicted by the algorithm for the entire section of Highway 417 ending at its intersection with Walkley Rd, and the South-North section of Bronson Avenue were compared against the values calculated by ADVISOR for both

type of facilities, a smaller error between them was observed in the highway section, especially for the Hybrid Fuel Cell Dominant vehicle (Table 5-13).

Table 5-13 Fuel consumed per section (Bronson – HWY 417 Example)

Facilities	Bronson South - North (BSN) (grams)		HWY 417 at Walkley Rd. (grams)	
	Algorithm	ADVISOR	Algorithm	ADVISOR
Vehicles				
ICE Large	211.95	213.83	441.33	440.22
ICE Small	166.84	168.79	505.07	505.06
ICE Hybrid	112.54	124.27	337.55	328.09
Fuel Cell Battery	63.65	64.92	279.78	276.43
Fuel Cell Dominant	75.87	103.62	286.40	291.58
	Ratio between algorithm and ADVISOR calculated fuel consumption values			
Vehicles	BSN		HWY 417 at Walkley Rd.	
ICE Large	0.9912		1.002	
ICE Small	0.9848		1	
ICE Hybrid	0.9056		1.0288	
Fuel Cell Battery	0.9804		1.0121	
Fuel Cell Dominant	0.7321		0.9822	

These results support the assumption made in Section 4.1.1.3.2 that the main factor responsible for the reduction in the algorithm's performance is the complexity of the fuel consumption behaviour in stop-and-go traffic conditions and, a possible error in the calculation of the state of charge over time can be discarded.

With the values of average fuel consumption for non-freeway (Table 5-11) and freeway traffic conditions (Table 5-14) predicted by the algorithm and the values calculated by ADVISOR, it was possible to calculate the average fuel consumption values for a

combined drive cycle (CAFE) with 55% Urban Traffic Conditions and 45% Highway Traffic Conditions, and the estimated fuel savings derived from the use of advanced technology vehicles against a conventional ICE large vehicle (Table 5-15).

Table 5-14 Average Fuel Consumption, Highway Traffic Conditions

Vehicles	Average Fuel Consumption Highway 417 (lt/100 km)		Fuel Savings (against conventional ICE large vehicle)	
	Algorithm	ADVISOR	Algorithm	ADVISOR
ICE Large	8.22	8.19	1	1
ICE Small	8.53	8.52	0.963	0.961
ICE Hybrid	5.94	5.92	1.383	1.383
FC Battery	3.80	3.76	2.163	2.178
FC Dominant	4.66	4.64	1.763	1.765

Table 5-15 Average fuel consumption, combined drive cycle

Vehicles	Average Fuel Consumption (Lt/100 km)		Fuel Savings (against conventional ICE large vehicle)	
	Algorithm	ADVISOR	Algorithm	ADVISOR
ICE Large	12.45	12.46	1	1
ICE Small	10.97	10.95	1.13	1.13
ICE Hybrid	7.24	7.36	1.71	1.69
FC Battery	4.53	4.55	2.74	2.73
FC Dominant	7.17	7.16	1.73	1.74

Note (55% urban and 45% highway)

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Based on the results of this research, the following conclusions can be drawn.

1. When the methodological framework discussed in Chapter 3 was implemented for three different traffic conditions and three types of vehicle technology, traffic volumes and average fuel consumption values for all the simulations complied with the selected validation criteria.
2. A single MLP neural network structure that uses speed and acceleration (on a second-by-second basis), as explanatory variables, was found to be suitable to achieve an accurate prediction of instantaneous fuel consumption of conventional ICE vehicles. However, in the case of advanced technology vehicles, a system of two MLP neural networks, and the inclusion of additional explanatory variables, (i.e. time, SOC, and the ESS's current), were required for the same purpose.
3. In the case of average fuel consumption, neural network models for conventional ICE vehicles and advanced technology vehicles shared a similar structure, with average speed as the only explanatory variable.
4. Use of excessive number of hidden units can enhance the prediction properties of a neural network model but it compromises the generalization capabilities of the model. This research indicates that the Bayesian evidence framework of learning

in neural networks was capable of generating models that not only reproduce the results of the training data sets not only with a small margin of error, but also that adequately responds to novel inputs.

5. For instantaneous fuel consumption of conventional ICE vehicles, coefficient of determination values of 0.96 to 0.99 indicates a strong relationship between the neural network outputs and the outputs included in the testing data sets.
6. Plotted values of speed and acceleration against the predicted instantaneous fuel consumption showed behaviour very similar to those observed for ADVISOR's results. In general, instantaneous fuel consumption of conventional ICE vehicles increased when acceleration increases for all speed levels and traffic conditions.
7. For advanced technology vehicles, the strength of the relationship between predicted and fuel consumption values provided by ADVISOR, was similar to the observed for conventional ICE vehicles with coefficient of determination values ranging from 0.96 to 0.99. However, their fuel consumption pattern was remarkably different.
8. The simulated hybrid ICE vehicle exhibited very close the trend described in the literature for "stop-and-go" urban traffic and highway traffic conditions meaning that under certain conditions (i.e., speeds lower than 45 km/h and low acceleration levels, or idle conditions), no fuel or minimum fuel was consumed. Only when the speed increased or more power was required to accelerate the vehicle or charge the battery system, an increase in the consumption of fuel was predicted by the neural network model.

9. Predicted fuel consumption values for hybrid fuel cell vehicles indicate that the trained neural network models were able to adequately reproduce the instantaneous fuel consumption behaviour in non-freeway as well as freeway operating environments. In this case, two of the most important aspects of a vehicle equipped with a fuel cell reformer were taken into account (i.e., the time required for the fuel processor to start the production of hydrogen, and the operation of the fuel cell system at a minimum power level in order to minimize losses and inefficiency).
10. Results of neural network models trained to reproduce average fuel consumption of conventional ICE and advanced technology vehicles using a single explanatory variable (namely link average speed), did show a moderate to moderately weak relationship with fuel consumption values included in the testing data sets.
11. For highway traffic conditions, coefficients of determination below 0.55 indicate that the use of link average speed as the only explanatory variable was not enough to adequately explain the fuel consumption behaviour of advanced technology vehicles under this particular traffic conditions.
12. Similarly, owing to the complexity of the fuel consumption behaviour of a hybrid vehicle with a fuel cell dominant system, the average speed-based fuel consumption models, showed coefficient of determination values that in most cases were lower than 0.5.
13. Integration of the neural network models into a mathematical algorithm, implemented in Visual Basic, reduced the amount of data required to calculate

instantaneous fuel consumption or average fuel consumption. Depending on the model type, the instantaneous speed or the link average speed is required. The algorithm internally calculates the rest of the explanatory variables.

14. For the three representative traffic conditions used in this thesis research, the algorithm results show a moderately strong relationship with results provided by ADVISOR.
15. With an initial State of Charge value of 0.60, results of the algorithm indicates that if advanced technology vehicles such as, Hybrid ICE and Hybrid Fuel Cell Battery vehicles are used instead of large conventional ICE vehicles; the conventional ICE vehicle would consume 1.71 to 2.74 times the fuel consumed by these advance technology vehicles.
16. In general, this thesis research provided a number of significant insights into the microscopic and macroscopic fuel consumption characteristics of advance technology vehicles in non-freeway and freeway traffic conditions. A significant contribution of this thesis is that it is the first attempt to model fuel consumption of advanced technology vehicles under real world traffic conditions using MLP neural networks. Furthermore, it is the first attempt to develop an algorithm that may be used as a stand alone tool or, as an add on, to micro and macroscopic traffic simulation model that takes into account the specific characteristics of advanced technology vehicles without requiring the use of dedicated programs such as MATLAB or ADVISOR.

6.2 Recommendations

Further research is recommended in support of the modelling framework developed in this thesis, and to improve the understanding of all the phenomena involved in fuel consumption behaviour of advanced technology vehicles.

1. A comparison of the performance of the Bayesian framework of learning in neural networks should be made with that of numerical methods for evaluating integrals, such as Monte Carlo methods combined with Markov Chain sampling could be explored.
2. Use of dedicated computer programs (i.e. GCTool Fuel Cell model) can be investigated in order to improve the confidence in the determination of the parameters for hybrid fuel cell vehicles specifically for highly congested traffic and depleted battery conditions.
3. The effects of additional electric loads, such as air conditioning and entertainment systems can be studied on the performance of advanced technology vehicles.

4. A drive cycle with high-speed operation and demanding accelerations can be incorporated for gaining more knowledge on the response of the battery system under aggressive driving conditions.
5. Implementation of this methodological framework to other types of advanced technology vehicles should be considered, specifically hybrid sport utility vehicles and hybrid fuel cell transit buses.

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APPENDIX A. Bayesian Regularization

The objective of non-linear regression analysis is to find the model for a variable Y on a set of possible explanatory variables $X_1, X_2, \dots, X_n$, that better explain the relationship between X and Y . However, if no constraints are included in the regression analysis, due to the fact that a very large number of possible functions exist that can fit a set of training data, this may lead to overfitting and bad predictive performance of the developed model (Lee, 1998).

Neural networks have become a popular tool for non-linear regression, as they are very flexible models that do not require a predetermined parametric form. However, as with all such models, the flexibility must be controlled to avoid overfitting and poor predictions. In such a situation, the two most common methods to avoid overfitting are early stopping and weight decay (Orr and Muller, 1996).

An early stopping procedure is included in MATLAB's Neural Network Toolbox. This procedure makes use of two different sets of data, the training set and the validation set, to monitor the error behaviour during the training process. When the network begins to overfit the data, the error on the validation set will typically begin to rise. If the rise in the error values is observed for a specified number of iterations, the training is stopped. Although this procedure may lead to shorten training times, the number of iterations required to stop the training process early has not been well defined. On the other hand,

weight decay can produce solutions that are significantly better than those produced with the early stopping method, making use of a modified objective function such as:

$$S(w) = E_D + \lambda E_w$$

Equation A-1 Modified objective function (weight decay method)

where E_D is the standard sum-of-square error function, E_w is the sum-of-square of the weights in the network and λ is a penalty factor named weight decay parameter. As a result, the training process using weight decay is a compromise between fitting the data and minimizing λ . However this procedure is very expensive in terms of time consumption because not only the calculation of derivatives of λ with respect to the network weights is required, but also a search of several values of λ and their correspondent performance estimate is necessary.

In this respect, Mackay (1994), proposed an approximate Bayesian framework for training neural networks, in which penalty factors α and β are added to the objective function, treated as hyper-parameters and found in an iterative search.

$$S(w) = \beta E_D + \alpha E_w$$

Equation A-2 Modified objective function (Source: Mackay, 1994)

Where E_D is the sum-of-square error, E_w is the sum-of-square of the network weights, and α and β are objective function parameters. According to this approach, before any data are collected, our knowledge of the weights can be represented as a prior probability

distribution $p(w)$. Once a data set D has been observed, the posterior probability distribution for the weights can be expressed according to Bayes' rule as follow:

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)}$$

Equation A-3 Posterior probability distribution for the weights (Source: Bishop, 1995)

In this equation, $p(D|w)$ is the likelihood function, which is the probability of the data occurring given the weights w , and $p(D)$ is a normalization factor which guarantees that the total probability is 1.

$$p(D) = \int p(D|w)p(w)dw$$

Equation A-4 Normalization factor $p(D)$ (Source: Bishop, 1995)

In this approach, a Gaussian distribution is assumed for the noise in the target variables included in the training data set and the prior distribution of the weights, making it possible to write the probability densities as:

$$p(D|w) = \frac{1}{Z_D(\beta)} \exp(-\beta E_D)$$

Equation A-5 Likelihood function $p(D|w)$ (Source: Bishop, 1995)

$$p(w) = \frac{1}{Z_w(\alpha)} \exp(-\alpha E_w)$$

Equation A-6 Prior distribution of the weights (Source: Bishop, 1995)

where Z is a normalization factor presented in Equation A-7, the parameter β defines the noise level on the target variables, $1/\sigma_t^2$, α represents the inverse variance of the prior

distribution of weights $1/\sigma_w^2$, N is the number of input vectors in the target data set and W is the number of parameters. (Mackay, 1994)

$$Z_D(\beta) = \left(\frac{2\pi}{\beta} \right)^{N/2}$$

$$Z_W(\alpha) = \left(\frac{2\pi}{\alpha} \right)^{W/2}$$

Equation A-7 Normalization factor Z (Source: Bishop, 1995)

Although for a very large database this Gaussian approximation is appropriate, the primary motivation for the Gaussian approximation is that it makes it possible to use analytical techniques instead of using techniques based on Markov chain Monte Carlo integration. Using the new expressions of $p(D|w)$, $p(w)$, and $p(D)$, the result of this Bayesian technique is a new expression for the posterior probability distribution of the weights:

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)}$$

From Equation A-5 and Equation A-6:

$$p(D|w) = \frac{1}{Z_D(\beta)} \exp(-\beta E_D) \text{ and } p(w) = \frac{1}{Z_W(\alpha)} \exp(-\alpha E_W)$$

$$p(D|w)p(w) = \frac{1}{Z_D(\beta)} \exp(-\beta E_D) * \frac{1}{Z_W(\alpha)} \exp(-\alpha E_W)$$

Due to the exponential's properties:

$$p(D|w)p(w) = \frac{1}{Z_D(\beta)} * \frac{1}{Z_W(\alpha)} \exp(-\beta E_D - \alpha E_W)$$

From Equation A-4:

$$p(D) = \int p(D|w)p(w)dw$$

Substituting the corresponding values:

$$p(D) = \int \frac{1}{Z_D(\beta)} * \frac{1}{Z_W(\alpha)} \exp(-\beta E_D - \alpha E_W) dw$$

$$p(D) = \frac{1}{Z_D(\beta)} * \frac{1}{Z_W(\alpha)} \int \exp(-\beta E_D - \alpha E_W) dw$$

$$\text{and } Z_S(\alpha, \beta) = \int \exp(-\beta E_D - \alpha E_W) dw$$

Eliminating similar elements and observing that $-S(w) = -\beta E_D - \alpha E_W$:

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)} = \frac{1}{Z_S(\alpha, \beta)} \exp(-S(w))$$

Equation A-8 Posterior probability distribution of the weights based in a Gaussian approximation (Source: Bishop, 1995)

This leads to the observation that maximizing the posterior probability is comparable to minimizing the modified objective function, expressed in Equation A-2. This expression satisfies the Bayesian framework, in which the optimal weights should maximize the posterior probability $P(w|D)$.

In order to find α and β , the posterior distribution of α and β has to be found. This is given by:

$$p(\alpha, \beta|D) = \frac{p(D|\alpha, \beta)p(\alpha, \beta)}{p(D)}$$

Equation A-9 Posterior distribution of α and β (Source: Bishop, 1995)

where the likelihood function $P(D|\alpha, \beta)$ can be expressed as:

$$p(D|\alpha, \beta) = \int p(D|w, \beta) p(w, \alpha) dw$$

Equation A-10 (Source: Bishop, 1995)

Substituting Equation A-2, Equation A-5, and Equation A-6 into Equation A-10

$$p(D|\alpha, \beta) = \frac{1}{Z_D(\beta)} * \frac{1}{Z_W(\alpha)} \int \exp(-S(w)) dw$$

And, given that $Z_S(\alpha, \beta) = \int \exp(-\beta E_D - \alpha E_W) dw$, then:

$$p(D|\alpha, \beta) = \frac{Z_S(\alpha, \beta)}{Z_D(\beta) Z_W(\alpha)}$$

Equation A-11 Modified expression for the posterior distribution of α and β (Source: Bishop, 1995)

in which the normalization factors Z_D and Z_W are given by Equation A-7, and the unknown factor $Z_S(\alpha, \beta)$ is obtained by Taylor expansion of $S(w)$ around a minimum point (MP) (Bishop, 1995):

$$Z_S(\alpha, \beta) = \exp(-S(w_{MP})) (2\pi)^{W/2} |A|^{-1/2}$$

Equation A-12 Factor $Z_S(\alpha, \beta)$ (Source: Bishop, 1995)

Substituting the corresponding values in Equation A-11:

$$p(D|\alpha, \beta) = \frac{Z_S(\alpha, \beta)}{Z_D(\beta) Z_W(\alpha)} = \frac{\exp(-\alpha E_{W_{MP}} - \beta E_{D_{MP}}) (2\pi)^{W/2} |A|^{-1/2}}{\left(\frac{2\pi}{\beta}\right)^{N/2} \left(\frac{2\pi}{\alpha}\right)^{W/2}}$$

$$\ln p(D|\alpha, \beta) = \ln \frac{\exp(-\alpha E_{w_{MP}} - \beta E_{w_{MP}})(2\pi)^{W/2} |A|^{-1/2}}{\left(\frac{2\pi}{\beta}\right)^{N/2} \left(\frac{2\pi}{\alpha}\right)^{W/2}}$$

$$\ln p(D|\alpha, \beta) = -\alpha E_w^{MP} - \beta E_D^{MP} - \frac{1}{2} \ln |A| + \frac{W}{2} \ln \alpha + \frac{N}{2} \ln \beta - \frac{N}{2} \ln(2\pi)$$

Equation A-13 (Source: Bishop, 1995)

Using the approximation of the partial derivative of the log of the matrix determinant $|A|$ with respect of α , presented in Equation A-14, it is possible to get the derivative of Equation A-13 with respect of α (Nabney, 2002).

$$\frac{\partial \ln |A|}{\partial \alpha} = \sum_{i=1}^W \frac{1}{\lambda_i + \alpha} = \text{tr}(A^{-1})$$

Equation A-14 (Source: Nabney, 2002)

$$-E_w^{MP} - \frac{1}{2} \sum_{i=1}^W \frac{1}{\lambda_i + \alpha} + \frac{W}{2\alpha}$$

Equation A-15 Derivative of Equation A-13 with respect of α (Source: Nabney, 2002)

where λ_i are the eigenvalues of the Hessian and $A = \text{Hessian} + \alpha I$.

Equating Equation A-15 to zero yields an implicit equation for α :

$$2(\alpha E_w)_{MP} = W - \sum_{i=1}^W \frac{\alpha}{\lambda_i + \alpha}$$

Equation A-16 Optimal value of α (Source: Nabney, 2002)

Defining a value γ such as:

$$\gamma = \sum_{i=1}^W \frac{\lambda_i}{\lambda_i + \alpha} = W - \sum_{i=1}^W \frac{\alpha}{\lambda_i + \alpha}$$

$$\alpha_{MP} = \frac{\gamma}{2E_W}$$

Equation A-17 Optimal value of α (Source: Nabney, 2002)

The value γ is a measure of the effective number of parameters, determined by the data rather than the prior, and W is the total number of parameters in the network. If a Gaussian distribution is a reasonable approximation to the posterior weight distribution, γ should be between 0 and W .

To optimize Equation A-13 with respect of β , the following approximation is required (Nabney, 2002):

$$\frac{\partial \ln|A|}{\partial \beta} = \frac{\partial}{\partial \beta} \sum_{i=1}^W \ln(\lambda_i + \alpha) = \frac{1}{\beta} \sum_{i=1}^W \frac{\lambda_i}{\lambda_i + \alpha}$$

Using this approximation, the optimal value of β is expressed as follow:

$$\beta_{MP} = \frac{N - \gamma}{2E_D}$$

Equation A-18 Optimal value of β (Source: Nabney, 2002)

Based on this framework, Foresee and Hagan (1997) implemented a Bayesian optimization of the regularization parameters with the Gauss-Newton approximation to Hessian matrix for MATLAB's Neural Network Toolbox function TRAINBR.

The following algorithm describes the steps followed by the MATLAB function TRAINBR for Bayesian learning:

1. Initial values for hyper-parameters α and β are selected and the weights of the network are initialized,
2. The neural network is trained using the Levenberg-Marquardt to minimize the objective function $S(w)$,
3. Once a local minimum is reached, the Gaussian approximation is used to compute the effective number of parameters γ , and the objective function parameters α and β are re-estimated,
4. Steps 2 and 3 are repeated until convergence is achieved.

It should be noted that the Bayesian evidence framework proposed by MacKay (1994) not only provides a methodology for the determination of optimal hyper-parameters but also allows the selection of the optimal model using only the training data contrary to other methods such as cross-validation in which the use of independent data is required. For a set of MLP neural network models H_i with a different number of hidden units, the posterior probability of each model can be expressed as:

$$p(H_i|D) = \frac{p(D|H_i)p(H_i)}{p(D)}$$

Equation A-19 Posterior probability of the model H_i (Source: Bishop, 1995)

Where $p(H_i)$ is the prior probability of every model H_i , and $p(D|H_i)$ is a quantity named as the evidence for H_i . Since $p(D)$ does not depend on the model it can be ignored for the purposes of model comparison. If there are no reasons to prefer one of the models over the others, then it is possible to assume that all the prior $p(H_i)$ have the same probability and the different models can be compared on the basis of $p(D|H_i)$. Once a network has been trained, it is possible to use Equation A-13 to calculate the (log)evidence for that network. The most probable model will be the one with the highest evidence (Penny and Roberts, 1999)

APPENDIX B. Simulation Models

The latest version of CORSIM included in TSIS 5.1, is assembled around a set of graphical user interfaces (GUI), that allows the user an easily manipulation of several simulation parameters (i.e., car-following logic, lane changing, and response to traffic control devices), in order to reproduce non-freeway and freeway traffic conditions in a stochastic manner (Figure B-1).

Figure B-1 Graphical User Interface CORSIM

This stochastic process depends on a variety of inputs and specifications that could be classified in two different types: direct inputs and default inputs (Sacks et al, 2000). Direct inputs include: (Figure B-2)

- Specification of the network via fixed inputs describing the geometry,
- Probability distributions of inter-arrival times governing the generation of vehicles at each entry node of the network (i.e., uniform, normal or Erlang distribution),
- Vehicle mix, auto or truck,
- Turning movements at intersections in the network and desired speeds,
- Traffic signal timing consisting of a specific cycle for every signal, green times for movements at each intersection, and offsets.

Figure B-2 Example of CORSIM's direct inputs

However, individual vehicle's information such as instantaneous speed of individual vehicles is stored in an output file "*.tsd" from which it is not possible to directly extract information. In order to extract instantaneous speed of individual vehicles from the CORSIM output file "*.tsd" an Excel add-in developed at the Georgia Institute of Technology by John D. Leonard II, named CORTOOLS (Leonard, 2000) could be used. The source code is presented as follow only for illustrative purposes.

```

Sub Macro1()
'
' Macro1 Macro
' Macro recorded 5/25/2000 by John D. Leonard II
Dim TSDReader As Object
Dim Time As Integer
Dim StartingColumn, StartingRow As Integer
Dim i, j As Integer
Dim tsdLink As Object
Dim LinkCount As Integer

Set TSDReader = CreateObject("cortools.tsdriver")
TSDReader.tsdFileName = ActiveWorkbook.ActiveSheet.Range("c1").Value

' Write status information to worksheet

ActiveWorkbook.ActiveSheet.Range("c2").Value = TSDReader.IsOpen
ActiveWorkbook.ActiveSheet.Range("c3").Value = TSDReader.tsdFileName
ActiveWorkbook.ActiveSheet.Range("c4").Value = TSDReader.gtCompileTime

StartingColumn = 67 ' ASCII code for "c"
StartingRow = 10 ' Starting Row Number
UpNode = ActiveWorkbook.ActiveSheet.Range("c8").Value
DnNode = ActiveWorkbook.ActiveSheet.Range("c9").Value

Count = 0
Do While TSDReader.tsdReadNext
Time = TSDReader.tsdTime
For i = 0 To TSDReader.tsdLinkCount - 1
Set tsdLink = TSDReader.tsdLinks(i)
up = tsdLink.linkid \ 10000
dn = tsdLink.linkid Mod 10000

```

```

        If ((up = UpNode) And (dn = DnNode)) Then
            For j = 0 To tsdLink.LinkVehCount - 1
                Count = Count + 1
                Set veh = tsdLink.linkVehicles(j)
                ActiveWorkbook.ActiveSheet.Range(Chr(StartingColumn + 0) +
CStr(StartingRow + Count)).Value = Time
                ActiveWorkbook.ActiveSheet.Range(Chr(StartingColumn + 1) +
CStr(StartingRow + Count)).Value = up
                ActiveWorkbook.ActiveSheet.Range(Chr(StartingColumn + 2) +
CStr(StartingRow + Count)).Value = dn
                For k = 1 To 18
                    ActiveWorkbook.ActiveSheet.Range(Chr(StartingColumn + 2 + k) +
CStr(StartingRow + Count)).Value = veh.vehFields(k)
                Next k
            Next j
        End If
    Next i
Loop
ActiveWorkbook.ActiveSheet.Range("c10").Value = TSDReader.tsdTime
'
End Sub

```

By using this approach, it is possible to collect information on individual vehicles to create speed traces for different types of traffic conditions and facilities. These speed traces can be exported to MATLAB, to be used as inputs for ADVISOR, as follows:

- From the information extracted by CORTOOLS, instantaneous speed (in feet per second) of individual vehicles is converted to miles per hour, and one Excel worksheet is created for every speed trace,
- Using MATLAB's Import Wizard, every speed trace contained in the aforementioned Excel file, is individually imported into MATLAB and a new MATLAB variable named "cyc_mph" is created containing the information for every speed trace (time and speed on a second-by-second basis),

- Finally, a set of two different MATLAB files, a “*.mat” file containing the speed trace information, and a “*.m” file containing instructions that allow the use of this information in ADVISOR, are created for every speed trace and added to ADVISOR’s data library.

Once again, the code included in the “*.m” file is presented only for illustrative purposes since that type of files is a part of ADVISOR’s data library and only small changes in the description and location of the file are required to create a new speed trace.

```
% ADVISOR data file: CYC_ARTERIAL.m
% FILE ID INFO

cyc_description='ARTERIAL Bronson Driving Schedule';
cyc_version=2002; % version of ADVISOR for which the file was generated
cyc_proprietary=0; % 0=> non-proprietary, 1=> proprietary, do not distribute
cyc_validation=0; % 0=> no validation, 1=> data agrees with source data,
% 2=> data matches source data and data collection methods have been verified
disp(['Data loaded: CYC_BRONSON_7 - ',cyc_description])

% SPEED AND KEY POSITION vs. time

%load variable 'cyc_mph', 2 column matrix with time in the first column
load CYC_BRONSON_7.mat
% keep key in 'on' position throughout cycle ('1' in the 2nd column => 'on')
vc_key_on=[cyc_mph(:,1) ones(size(cyc_mph,1),1)];

% OTHER DATA

% Size of 'window' used to filter the trace with centered-in-time averaging;
% higher numbers mean more smoothing and less rigorous following of the trace.
% Used when cyc_filter_bool=1
cyc_avg_time=3; % (s)
cyc_filter_bool=0; % 0=> no filtering, follow trace exactly; 1=> smooth trace
cyc_grade=0; %no grade associated with this cycle
cyc_elevation_init=0; %the initial elevation in meters.
if size(cyc_grade,1)<2
    % convert cyc_grade to a two column matrix, grade vs. dist
```

```

    cyc_grade=[0 cyc_grade; 1 cyc_grade]; % use this for a constant roadway grade
end

% A constant zero delta in cargo-mass:
% First column is distance (m) second column is mass (kg)
cyc_cargo_mass=[0 0
    1 0];
if size(cyc_cargo_mass,1)<2
    % convert cyc_grade to a two column matrix, grade vs. dist
    cyc_cargo_mass=[0 cyc_cargo_mass; 1 cyc_cargo_mass]; % use this for a
    constant roadway grade
end

if exist('cyc_coast_gb_shift_delay')
    gb_shift_delay=cyc_coast_gb_shift_delay; % restore the original
    gb_shift_delay which may have been changed by cyc_coast
end

```

Figure B-6 shows graphically the speed trace information (i.e. speed in kph against time on a second-by-second basis) that is added to ADVISOR's data library

Figure B-6 Example of a speed trace information used as input for ADVISOR

ADVISOR is a computer program that works in MATLAB/Simulink environment. The model uses as a basis for the estimates of the capabilities and efficiency of key components, tables or maps of efficiency or fuel use against output-torque and speed (for engines and motors) that can be selected for every simulated vehicle using the first of three primary graphical user interface (GUI) screens included in the latest version of ADVISOR (Figure B-7).

Figure B-7 ADVISOR vehicle input window (Source: NREL, 2002)

In this screen, named ADVISOR vehicle input window, the user selects a vehicle configuration and the components that compose the driveline. In this respect, ADVISOR 2002 incorporates many drivetrain types including conventional internal combustion engine, electric, series and parallel hybrid, and fuel cell hybrid models. This allows an

easy manipulation of data files that represent conventional or unique vehicle components. In the second GUI named ADVISOR simulation setup window, the user defines the event over which the desired vehicle is to be simulated specifying a speed trace (defined through second-by-second profiles of vehicle speed) and the initial conditions for the simulation. (Figure B-8)

Figure B-8 ADVISOR simulation setup window (Source: NREL, 2002)

This profile determines the second-by-second power requirement of the vehicle, which in conjunction with the vehicle's efficiency determines the vehicle operation regimes and vehicle's fuel economy. With the simulation parameters configured, is just required to click the "run" button to start the simulation. Once the simulated has been completed,

results of the simulation process are presented in a new GUI named ADVISOR results window (Figure B-9).

Figure B-9 ADVISOR results window (Source, NREL, 2002)

After a simulation has been completed, every variable of interest can be exported from ADVISOR to MATLAB's workspace to create a matrix containing all the variables of interest. This information can be saved as an "ascii" file, and exported to Excel for future use.

APPENDIX C. Microscopic Fuel Consumption Models

Figure C-1 Predicted vs ADVISOR values [FC]. Small ICE vehicle, CBD

Figure C-2 Predicted vs ADVISOR values [FC]. Small ICE vehicle, Bronson

Figure C-3 Predicted vs ADVISOR values [FC]. Small ICE vehicle, HWY 417

Figure C-4 Predicted vs ADVISOR values [FC]. Large ICE vehicle, CBD

Figure C-5 Predicted vs ADVISOR values [FC]. Large ICE vehicle, Bronson

Figure C-6 Predicted vs ADVISOR values [FC]. Large ICE vehicle, HWY 417

Figure C-7 Predicted vs ADVISOR values [ESS]. Hybrid ICE vehicle, CBD

Figure C-8 Predicted vs ADVISOR [FC]. Hybrid ICE vehicle, CBD

Figure C-9 Predicted vs ADVISOR values [ESS]. Hybrid ICE vehicle, Bronson

Figure C-10 Predicted vs ADVISOR values [FC]. Hybrid ICE vehicle, Bronson

Figure C-11 Predicted vs ADVISOR values [ESS]. Hybrid ICE vehicle, HWY 417

Figure C-12 Predicted vs ADVISOR values [FC]. Hybrid ICE vehicle, HWY 417

Figure C-13 Predicted vs ADVISOR values [ESS]. Fuel Cell Battery vehicle, CBD

Figure C-14 Predicted vs ADVISOR values [FC]. Fuel Cell Battery vehicle, CBD

Figure C-15 Predicted vs ADVISOR values [ESS]. Fuel Cell Battery vehicle, Bronson

Figure C-16 Predicted vs ADVISOR values [FC]. Fuel Cell Battery vehicle, Bronson

Figure C-17 Predicted vs ADVISOR values [ESS] Fuel Cell Battery HWY 417

Figure C-18 Predicted vs ADVISOR values [FC].Fuel Cell Battery, HWY 417

Figure C-19 Predicted vs ADVISOR values [ESS]. Fuel Cell Dominant vehicle, CBD

Figure C-20 Predicted vs ADVISOR values[FC]. Fuel Cell Dominant vehicle, CBD

Figure C-21 Predicted vs ADVISOR values [ESS] Fuel Cell Dominant, Bronson

Figure C-22 Predicted vs ADVISOR values [FC] Fuel Cell Dominant, Bronson

Figure C-23 Predicted vs ADVISOR values [ESS] Fuel Cell Dominant, HWY 417

Figure C-24 Predicted vs ADVISOR values [FC]. Fuel Cell Dominant, HWY 417

APPENDIX D. Coefficients of Neural Network Models

Table D-1 Microscopic FC Model – CBD – Small ICE

w1		w2	b1	b2		Min	Max
1.3365	1.8507	0.44975	-1.0012	-0.42097	Speed	0	65.24
5.3782	-10.368	-0.02618	3.7458		Accel	-27.394	17.814
37.574	-13.171	-0.19568	39.359				
-7.865	13.246	20.317	-9.7565		FC	0.27845	5.7583
-0.87755	-20.293	5.1717	3.3818				
9.4408	-15.012	7.2381	11.273				
-3.6061	0.27955	1.3805	-0.02888				
-0.85977	-23.017	-13.346	4.0327				
-3.5836	0.16849	-1.4065	-0.03442				
-6.3878	11.964	-18.754	-8.5022				
-5.4504	10.399	-8.5835	-7.4258				
0.16059	-3.3353	-3.7634	1.7823				
-0.37626	3.0716	-3.5765	-1.7622				
-0.9136	-33.37	2.1124	5.5297				
0.94127	25.038	-6.0918	-4.6213				
4.3306	-10.831	8.1996	7.11				
-1.2775	-4.6205	0.54421	1.7719				
0.57249	3.6733	1.2729	-0.40451				
-4.8593	10.644	22.581	-7.2491				
0.83361	3.7146	-1.14	-0.22122				

Table D-2 Microscopic FC Model – CBD – Large ICE

w1		w2	b1	b2		Min	Max
-3.3137	0.14613	1.7269	0.019448	2.3134	Speed	0	64.417
-0.82678	-11.557	0.98814	3.108		Accel	-27.348	13.53
-0.06443	8.9411	0.30773	-2.5971				
-0.15872	1.5359	1.0497	-1.3154		FC	0.38752	11.804
-1.9993	-2.2411	0.11208	-0.96049				
-3.2168	0.25299	-1.8039	-0.00704				
1.4167	-4.5433	-1.7433	2.8822				
-1.3819	3.9883	-2.0617	-2.6624				
1.1823	13.262	0.65597	-3.5048				
1.3662	2.6697	2.6955	-4.3047				

Table D-3 Microscopic FC Model – CBD – Hybrid ICE - ESS

	Min	Max
time	0	5499
speed	0	64.45034
accel	-28.4826	12.42433
SOC	0.458519	0.6
ESS	-66.9624	63.98074
FC	0	2.000262

w1				w2	b1	b2
0.12402	1.0312	-0.55928	-40.96	4.1258	-16.099	1.2165
-0.70091	5.3263	35.981	7.5757	0.086491	-13.971	
-7.8186	-3.3549	-0.83316	4.1858	-0.61193	1.1509	
-0.04129	-0.16256	2.7678	-0.01636	-10.242	-1.9495	
-2.1764	-3.7529	-35.043	-3.9461	2.7331	17.908	
8.9512	4.2688	5.8665	-0.85046	0.047548	0.33857	
-0.02856	-1.3696	-12.292	-0.31275	-0.5834	8.8756	
0.10056	-3.0336	2.9237	-1.1514	0.34541	0.2742	
0.033162	-0.09488	-1.8554	-0.01498	-6.9037	1.5717	
0.012889	2.0391	1.165	1.2018	2.7483	0.53654	
0.024032	-2.28	0.23728	-0.40673	0.56264	-1.0513	
0.02204	2.332	1.0444	1.5283	-2.2027	0.7278	
-2.0483	-3.541	-33.895	-3.9362	-2.8221	17.218	
-0.13757	-0.99041	0.11963	39.553	-4.5926	15.277	
-7.5109	-3.2256	-1.0384	3.8515	0.66233	1.041	
-0.31365	-8.8017	-24.672	-0.97104	-0.27351	10.704	
-0.09007	-10.568	11.387	7.0097	-0.05057	-2.3309	
0.052255	0.49994	-3.9009	0.080699	-4.1239	2.5875	
-0.12489	-0.97717	0.35679	39.261	8.778	15.291	
0.34365	8.7272	20.224	-1.2711	-0.29707	-10.427	

Table D-4 Microscopic FC Model – CBD – Hybrid ICE - FC

w1					w2	b1	b2
-0.0029	-0.13477	0.16885	-1.183	1.0754	3.4564	-0.97174	-0.73524
0.075839	-1.1243	15.341	0.49663	0.90486	-3.5422	-4.8573	
0.20881	-7.3444	-9.7954	8.393	3.8171	-3.1284	0.819	
-0.30726	10.11	15.147	-10.622	-8.9536	0.34534	-1.3655	
0.020469	0.089194	-1.5423	0.82819	-6.6021	-4.9671	0.74375	
-0.00201	-0.08445	0.36181	-1.3604	1.0443	-2.8963	-1.1357	
-0.07244	1.1383	-14.924	-0.48992	-0.49705	-3.7245	4.7856	
-0.92767	10.461	32.619	-3.1435	10.081	0.19361	-26.964	
-0.03676	0.52684	1.2736	-0.8872	7.0072	7.3571	-0.64893	
-0.10449	1.9848	-7.2175	-1.833	11.687	-0.14151	1.3582	
0.02894	-0.42328	-2.2212	0.77449	-6.1151	2.6905	0.46194	
-0.10535	-8.9142	-3.6708	-0.63821	0.3336	0.9677	-4.9812	
0.2033	11.218	5.131	0.55584	-2.3831	-4.5759	5.8785	
-0.08304	1.0921	7.129	-0.5063	0.44963	1.5025	-3.6798	
-0.109	1.2365	5.7528	-1.0426	4.9803	-1.5483	-2.9833	
0.21231	-7.464	-10.146	8.4321	4.1933	3.4954	0.84628	
-0.17052	0.64821	7.767	-0.83593	3.3184	-0.57361	-6.0069	
-0.03191	0.23027	1.2259	-0.94912	7.7014	-8.4961	-0.72708	
-0.18129	-10.586	-4.7843	-0.54718	2.0401	-5.5878	-5.5846	
0.00347	-0.51673	0.42856	-0.19728	0.34793	-1.2647	-0.8207	

Table D-5 Microscopic FC Model – CBD – Fuel Cell Battery – ESS

	Min	Max
Time	0	5498
Speed	0	65.8335
Accel	-26.3334	17.81512
SOC	0.485176	0.6
ESS	-20.5061	30.15147
FC	0	0.61648

w1					w2	b1	b2
0.000984	0.53259	-1.8655	0.009809		1.9083	1.8576	-13.3293
-0.19893	0.086783	3.1728	-1.8297		-0.01743	-1.5362	
0.040089	-26.32	9.0077	0.077601		14.48	-28.026	
1.3509	2.6647	1.3107	11.56		-0.01158	-0.25723	
-0.32263	-0.68295	19.091	-0.6823		-0.94198	-4.6396	
-0.0588	1.0253	-0.02759	-0.06254		1.1194	-0.11178	
5.705	-0.18458	-0.33011	-11.376		1.6599	7.4487	
3.8767	0.25658	-0.09904	16.689		2.1041	-0.48551	
1.0742	1.2913	0.51256	1.7305		0.051409	0.51918	
-0.0342	-1.1282	0.30563	-0.08744		-5.2604	1.3877	
0.3052	0.65654	-18.143	0.63014		-0.97846	4.4254	
-4.2114	-0.25718	0.10842	-17.16		2.0787	0.36775	
0.048367	0.79459	-0.6405	0.085383		-7.3593	-1.2113	
0.043439	-0.35479	-0.52521	0.049765		5.8968	0.83127	
5.6552	-0.20315	-0.34306	-11.839		-1.6817	7.5583	
-0.03032	25.999	-9.8337	-0.0625		17.119	28.573	
-0.05835	-0.31568	-4.7343	-0.21837		0.1713	0.76042	
0.04763	-27.672	8.9123	0.086342		-5.7765	-29.002	
-0.15707	0.79915	4.5172	-0.20721		0.59177	-3.7995	
0.04299	-0.11742	-1.6294	0.062499		-2.9264	0.93819	

Table D-6 Microscopic FC Model – CBD –Fuel Cell Battery - FC

w1					w2	b1	b2
-0.49197	0.90284	-1.4647	0.094561	-0.61522	0.88677	0.92027	-0.61825
0.50679	1.512	0.081558	0.057143	1.8339	4.979	2.1278	
-0.02087	0.003412	0.039796	-0.0269	-0.00396	-0.08799	0.014137	
-0.02484	0.05237	0.045127	-0.00622	-0.02668	-0.03417	0.020866	
0.088073	-0.07641	-0.07807	0.008392	0.004842	0.24952	-0.07455	
-0.04423	-0.00292	0.042722	-0.03892	0.023858	-0.11053	0.042589	
0.04244	-0.02852	-0.0719	0.0147	0.000552	0.1516	-0.03806	
-0.12096	0.022801	0.034678	-0.02129	0.055443	-0.221	0.081667	
0.17356	0.51781	-1.769	-0.04589	-1.0093	-1.6086	0.038789	
-1.6659	0.63397	0.24714	0.23686	-1.9878	-1.8445	-0.69498	
0.13546	0.52248	-0.08219	-0.22349	0.59136	-0.66449	-0.21478	
1.9999	0.81887	-0.84735	-0.31438	-0.08716	-0.97599	2.0613	

-0.06017	-0.02419	0.096517	-0.06478	0.32181	-0.37428	0.17148
0.050186	-0.10478	-0.12008	-0.02383	0.047071	0.32953	-0.18394
0.045111	-0.9067	-2.7536	0.023146	0.56845	-7.6615	1.7976
-0.00434	0.28852	-3.6209	0.040036	0.44517	5.1156	3.1025
-0.05543	0.019336	0.043607	-0.04898	-0.07054	-0.10913	0.074131
0.81301	1.2083	1.5107	0.12567	-2.1008	-0.93663	0.18784
0.1671	-0.04753	-0.01897	-0.04293	-0.07311	0.29133	-0.10437
0.051644	-0.01501	-0.06164	0.042828	-0.02746	0.13899	-0.04423
0.046318	-0.08505	-0.09694	0.05958	0.08237	0.1947	-0.11978
2.104	-0.51721	1.607	0.028735	0.15819	-0.26256	-0.00283
0.61991	2.8862	-0.28499	0.098993	0.98176	-2.0076	3.1023
-0.11432	0.020443	-0.00867	-0.02361	0.013555	-0.19237	0.09999
0.1372	0.042194	-0.09454	0.00899	-0.00053	0.047416	-0.08123
0.90609	-0.17173	-0.97183	-0.40359	1.0944	0.69968	-0.72866
1.4662	-1.1083	-1.1419	-0.28223	1.5093	2.0239	0.88555
1.7203	-1.1718	-1.5886	-0.35736	2.7009	-1.4963	1.4495
0.028946	-0.03323	-0.07917	0.025218	0.036148	0.13263	-0.04736
-0.04027	0.097972	-4.0951	0.015459	-2.1805	-2.4742	0.83513
-2.1644	-0.41408	0.68892	0.36511	-0.2429	-1.19	-2.1455
0.058682	0.16366	3.3691	0.011252	1.2681	-3.5852	-0.57634
-0.01057	-0.00435	0.038809	-0.04079	0.038868	-0.07317	0.023257
-0.03759	0.019219	0.058146	-0.02909	-0.00453	-0.12527	0.026382
0.003646	-1.3134	1.7773	0.060278	-0.17103	3.1516	0.98764
-0.0587	0.00915	0.043421	-0.07779	0.18523	-0.19983	0.12917
0.0516	-0.02466	-0.05728	0.020739	0.01015	0.14969	-0.049
-0.02023	0.011111	0.049217	-0.01586	-0.03538	-0.09072	0.0335
-0.67065	-0.03951	-1.7582	-0.03591	-2.3345	1.7778	-1.317
-0.12192	1.5934	-0.4358	-0.01614	-0.32595	-2.9929	0.059426
-0.1298	0.94079	1.3184	0.022048	-3.4777	2.3323	-0.86495
0.69982	0.67567	1.1936	-0.03777	2.3455	1.828	1.4663
-0.63907	-0.7135	-0.13297	-0.01404	-3.047	4.2689	-2.3412
-0.05843	0.033085	0.069951	-0.06439	0.068521	-0.17174	0.066967
0.00501	1.2429	-0.21927	0.054531	-1.5987	3.6393	0.83057
-0.11483	0.11241	0.15364	-0.0993	-0.23733	-0.35571	0.20162
0.024443	-1.5341	-1.6462	0.053815	0.33926	-1.6871	0.35895
-1.7376	1.0982	0.01898	0.27475	-1.6338	1.4052	-0.42617
0.020515	-2.0163	0.23838	-0.05417	0.29219	2.288	-1.4141
-0.04948	-0.02224	-0.0367	-0.00547	-0.04914	0.034596	-0.03101

Table D-7 Microscopic FC Model – CBD – Fuel Cell Dominant - ESS

	Min	Max
Time	0	5499
Speed	0	65.834
Accel	-27.387	17.815
SOC	0.51751	0.6
ESS	-61.612	63.812
FC	0	1.4252

w1				w2	b1	b2
0.007976	0.17984	-0.22518	-10.947	-0.15971	0.26887	-2.376
0.003172	1.2947	0.076423	0.062154	5.8307	1.4725	
-0.05356	-1.4213	0.37168	-0.20874	2.6144	-0.54799	
-0.04746	5.7294	-9.1148	20.926	-0.06214	6.0352	
-0.00844	-0.02052	1.7441	0.22064	6.1037	-1.1809	
0.027496	2.6352	0.02436	0.050943	-2.3604	2.3648	
-0.18601	-1.3855	0.58706	-0.69591	-0.89411	-0.7829	
0.1512	-1.5133	-0.17774	8.7818	-0.06643	-0.0144	
0.008494	0.31948	-1.7565	-0.26619	5.8834	1.2943	
0.023946	-6.2059	20.178	-1.4769	0.078178	-8.0393	

Table D-8 Microscopic FC Model – CBD – Fuel Cell Dominant - FC

w1					w2	b1	b2
0.010097	1.4985	2.9709	0.000751	0.32783	-4.814	-2.712	-3.8517
-0.00027	-0.79874	-3.8075	0.006331	2.3867	4.3265	-0.61851	
-0.00229	-1.2128	-0.36979	0.006532	0.48844	-4.9298	-0.20766	
0.001354	-1.1829	-1.5791	0.003935	0.61426	5.631	-0.72118	
0.005336	0.55019	-1.0677	-0.01959	-5.0042	4.0243	0.71101	
0.001435	-0.70324	0.99166	0.002392	-0.03847	-11.679	-0.89837	
0.007557	7.6911	-2.0343	-0.00878	10.083	-0.10976	8.3332	
-0.0029	8.545	2.3923	-0.00454	-1.3655	8.5628	9.955	
0.003954	-9.9119	-2.1673	-0.0036	0.2066	7.5031	-11.554	
0.004917	0.43352	-1.3589	-0.01639	-4.4811	-4.634	0.75782	
0.012164	1.491	3.7011	-0.00139	0.24017	4.7849	-3.0005	
0.001125	0.74481	3.4109	-0.00543	-1.6666	7.1338	0.67469	
0.016192	-10.429	-4.532	0.0199	18.36	3.9983	-11.919	
0.00323	0.6797	3.918	0.001697	-0.83149	7.313	-0.98221	
-0.00269	-0.88516	-4.318	-0.00302	0.71899	4.8786	0.96529	

0.00328	0.95822	-0.10838	-0.00232	0.073599	-5.5792	0.1267
0.002846	-1.541	-0.83893	0.019155	1.219	-6.0746	-0.89628
0.01864	-10.557	-4.4018	0.027375	18.758	-3.9212	-12.306
-0.00167	1.1817	-0.14983	-0.0141	-0.60351	-10.891	0.82833
-0.0099	0.11362	-2.3887	0.043013	4.3342	-0.26427	0.71443

Table D-9 Microscopic FC Model – Bronson – Large ICE

w1		w2	b1	b2		Min	Max
4.8781	16.009	0.79063	-15.058	0.54584	Speed	0	108.63
-13.649	-20.027	0.051235	11.557		Accel	-27.479	13.608
-1.2016	-25.056	-4.0255	7.5327		FC	0.38752	8.2813
-8.5251	7.0392	0.23814	-10.874				
1.7396	-3.7296	-10.874	2.8365				
1.2991	-3.1388	12.329	2.5228				
-9.5224	-21.378	0.096047	13.642				
21.728	-59.861	0.039406	40.784				
1.6686	0.6174	-4.0535	0.26372				
-2.9087	-3.1814	-0.08428	-0.98708				
0.35408	-2.9637	-4.7756	2.0655				
-0.45837	-22.715	3.5994	7.2928				
-0.64656	-21.899	-9.2832	6.9052				
2.4237	10.177	0.51475	-7.5506				
2.3092	0.56914	-1.9244	-0.09238				
1.8008	0.45567	5.7894	0.05738				
-2.0866	4.4773	-3.2202	-3.1589				
-0.94657	-22.904	9.7003	7.0174				
-0.90355	-2.0464	-0.2956	-0.76708				
-3.9219	-3.7008	0.15512	1.7407				

Table D-10 Microscopic FC Model – Bronson – Small ICE

w1		w2	b1	b2		Min	Max
-1.1841	8.1381	-10.755	-5.836	-0.53519			
90.854	-36.976	-0.06282	95.278		Speed	0	108.63
0.80436	4.1286	1.3399	-2.3129		Accel	-27.535	17.807
-0.63374	30.445	18.409	-6.6859		FC	0.27845	5.9093
6.3377	-47.428	-7.1959	13.368				
6.4206	-47.667	7.0705	13.444				

-0.35543	30.549	17.83	-6.7835
-1.5153	7.8644	25.619	-5.9402
1.6914	-7.5129	15.838	5.8929
-0.4965	30.25	-36.33	-6.682

Table D-11 Microscopic FC Model – Bronson – Hybrid ICE - ESS

	Min	Max				
Time	0	1519				
Speed	0	108.63				
Accel	-28.582	12.46				
SOC	0.44716	0.6				
ESS	-67.557	64.2				
FC	0	2.7501				
w1				w2	b1	b2
-0.06797	1.2479	8.9906	0.050938	-0.36265	-3.2214	8.2853
-0.37516	3.8754	6.2555	-17.326	-1.8391	-7.908	
0.11916	2.5158	1.2762	0.79556	-4.2388	0.83744	
-4.3241	4.8396	8.9826	0.25222	3.0573	-7.6089	
0.12545	2.6608	1.5568	0.90061	3.7711	0.85338	
-18.575	-23.47	1.0144	-33.669	-8.0593	3.2925	
-0.21275	2.4933	6.7128	-0.02898	2.3807	-2.8518	
-0.04656	-1.5874	-1.3816	0.67844	11.527	0.11165	
0.71608	1.7058	-20.535	-13.97	-0.08465	8.6011	
0.076188	1.6626	1.2476	-0.7151	5.7618	-0.37504	
0.38271	-3.944	-6.2175	17.734	-1.7824	8.0513	
-0.27363	3.2391	8.9561	-0.26807	-1.6708	-3.8898	
-0.99022	-0.73061	24.833	1.577	0.19326	-11.661	
-0.29042	-2.4582	2.9559	0.8647	0.3957	0.4037	
3.646	-6.1901	8.669	-8.73	0.10208	-3.2792	
5.2143	-5.5499	-10.116	-0.33646	2.886	8.6277	
1.0184	26.422	-20.419	-5.4053	0.15802	34.605	
-0.19815	-0.25782	0.14344	53.474	-3.2124	15.003	
0.041062	1.789	1.6474	-0.7315	6.1138	0.13597	
0.14178	0.27049	-0.20344	-51.038	-3.2858	-14.326	

Table D-12 Microscopic FC Model – Bronson – Hybrid ICE - FC

w1					w2	b1	b2
0.090399	0.15319	-5.2692	-0.18935	1.1945	0.3087	0.80344	0.063122
0.015049	-4.0337	0.38002	-0.96779	9.6139	2.6357	-3.7305	
0.024006	1.4136	-2.7471	0.39416	-4.5439	-4.8371	3.4955	
0.068945	-1.9823	1.5879	-0.01936	0.51764	-4.0078	-2.8292	
0.14457	5.1089	1.9358	-0.95063	1.0811	-0.07893	-0.24386	
-0.01005	3.5127	-0.23426	0.83882	-8.5397	3.3764	3.3062	
-0.07034	0.93403	9.3303	0.024059	0.29602	-0.80532	-3.336	
0.062298	-1.2771	-12.927	-0.22112	2.4276	-0.63226	4.9052	
-0.07951	2.3605	-1.4529	0.001969	-0.59746	-3.0376	2.9043	
-0.02834	-0.50468	-6.9411	0.13284	-0.39051	-5.8618	3.9063	
0.031837	0.97635	-3.6053	0.34633	-3.8631	4.7347	3.6761	
-0.06516	0.61282	2.2642	0.48166	-3.8666	-0.57286	1.959	
0.032823	0.32077	7.6057	-0.09988	0.18544	-4.8199	-4.3486	
0.040809	-2.1305	-3.1416	0.37369	0.11859	0.38491	2.4511	
-0.03471	-1.1501	-5.5486	-0.20452	3.8994	0.7374	2.341	
0.55632	-2.9495	-8.8947	3.5831	4.4662	1.8895	-1.4565	
0.083166	-1.1095	3.2077	0.16468	3.3443	-1.0195	6.2756	
-0.00217	-0.82252	-3.3979	-0.05936	1.7092	-1.4204	1.2845	
-0.05477	-2.426	2.0639	-0.78811	5.9412	0.266	-1.762	
0.55903	-3.036	-8.6755	3.5089	4.2283	-1.9301	-1.5606	

Table D-13 Microscopic FC Model – Bronson – Fuel Cell Battery - ESS

	Min	Max
Time	0	1519
Speed	0	106.43
Accel	-27.497	17.809
SOC	0.52624	0.6
ESS	-37.826	63.86
FC	0	1.1184

w1				w2	b1	b2
-0.27083	1.0738	-0.45395	0.21408	0.56818	-0.36143	-2.9842
0.40312	7.5074	-15.939	0.13886	-0.01626	9.5998	
-0.18854	-0.1477	20.354	0.019011	-1.5098	-4.7547	
-2.0418	-1.1135	-0.78854	1.4652	0.023334	-2.6348	
0.54923	0.01127	-0.26389	-0.48673	-1.6946	0.057515	

-1.7061	5.8925	15.015	-2.9504	2.7431	-13.118
-0.44263	-0.01574	0.24843	0.38552	-2.8422	-0.09743
-3.9127	1.9064	-0.76606	11.744	1.8428	-9.7527
-0.07014	-3.2853	38.665	0.036711	1.7198	-10.268
0.062153	0.88757	2.9072	0.081988	0.31984	-1.3169
-0.30267	3.7422	8.7745	-1.3832	-9.1438	-8.4143
3.9803	-1.909	0.74214	-11.886	2.7444	10.032
0.035835	0.08028	-0.41698	-0.00495	-4.6491	0.20171
-0.19145	-0.17898	20.795	0.025161	1.5482	-4.8951
-4.7711	2.129	-0.80846	14.103	0.91498	-12.3
0.070953	-1.0413	0.68175	-0.04968	-1.3968	-0.97351
-0.00245	0.32625	0.033575	-0.02396	-6.5219	0.75938
-0.07554	-3.2023	38.763	0.042691	-1.7606	-10.276
-0.01623	2.39	5.6509	-0.33844	2.9584	-5.2705
0.05892	-0.64982	0.98367	-0.02803	-3.5803	-2.2627

Table D-14 Microscopic FC Model – Bronson – Fuel Cell Battery - FC

w1					w2	b1	b2
0.11848	1.766	0.72407	0.12062	1.6788	2.11	1.9493	-0.48191
-0.11857	0.77025	0.22349	-1.1559	0.23366	-1.2116	0.92033	
0.24138	-1.0412	1.7848	-0.07541	-1.4083	2.6033	0.11869	
0.16835	1.4385	-1.2055	0.25784	-1.1851	-1.0311	0.21347	
-0.40839	1.0198	0.22258	-2.6798	0.80132	-0.56574	2.7982	
-0.15656	-0.10957	0.24303	-0.18647	0.15981	-0.43905	-0.20462	
-0.19757	-0.42573	-0.16743	-0.01547	-0.75498	0.95976	-0.83794	
-0.5395	-0.85961	-0.53435	-0.11807	-1.1273	1.5001	-2.0181	
-0.02172	-0.72365	-0.00683	0.4834	0.2842	2.8223	0.42665	
0.046287	-2.6242	0.36222	0.12016	1.7421	-6.7143	-2.707	
0.027578	-0.69711	-0.5705	-0.35877	-0.03452	0.8385	-0.60457	
-0.09542	0.56085	2.3421	-0.07816	4.0516	1.7989	0.67054	
-0.11715	0.68968	-0.51149	-0.17652	1.9893	-2.0217	-0.14428	
-0.01376	-0.05819	0.067239	0.096866	0.12072	-0.08468	0.00328	
0.077675	0.9485	-1.0341	0.032895	-1.9391	-2.8883	-1.2917	
0.001326	-1.9645	1.7744	0.005114	3.9041	-4.4039	-3.2403	
-0.21108	0.005846	2.1412	-0.22902	-2.2494	3.4392	-0.92981	
0.24437	1.3356	-0.21972	0.22425	1.6072	1.7875	0.76726	
0.29356	-1.1086	-3.0113	0.29107	5.8929	1.8413	0.71495	
0.40661	-1.4653	-0.91859	-0.20514	-0.123	-1.6951	1.5699	
-0.18711	1.2467	2.5845	-0.14567	0.32285	3.2652	0.78082	

0.4509	-0.18615	0.51305	-0.38338	0.79154	1.1354	-0.06491
-0.1696	-0.18666	0.37734	-0.09618	0.24568	-0.58456	-0.1186
-0.37977	-0.66404	-0.02472	-3.1287	-0.03288	-0.82265	1.3881
-0.24286	0.63198	1.0971	-0.19553	-4.9096	2.38	0.14782
0.055857	0.11321	-0.11797	0.075253	-0.07223	0.21047	0.008831
-0.02653	0.40892	6.8105	0.053124	2.9969	3.2688	-0.5262
0.33094	-1.9019	-1.8136	0.327	2.9456	-2.4672	-0.33213
0.006294	0.32108	0.20903	0.14395	1.3335	-1.3496	1.2893
-0.08969	-0.92044	-1.3048	-0.03496	-0.9049	-7.9018	1.0974
0.41704	2.1159	0.55631	0.17143	-1.0536	1.8996	2.1983
-0.02298	-0.34668	-0.18766	-0.1396	-1.3156	1.3652	-1.2959
-0.66781	0.075661	-0.49847	0.20248	-1.5581	0.698	-0.11206
0.23913	-2.2172	-3.3931	0.22317	3.6046	1.406	-0.36066
0.040957	-0.60844	-6.3178	-0.04404	-3.5498	4.9305	0.037263
-0.00096	-2.9247	-0.09652	0.071358	4.2818	6.9602	-2.0553
0.14159	4.0545	0.092845	0.095301	-1.3132	-1.4278	3.2984
-0.25426	-0.15968	0.43608	-0.01881	0.28604	-0.55393	-0.01387
0.034228	3.8767	-0.53236	-0.04054	-4.7683	1.9235	2.3839
-0.37623	0.91275	1.2599	-0.6188	0.67544	-0.87959	0.38153
0.082391	-0.11743	-1.8894	0.043376	-3.8598	2.8194	-0.76909
-0.01733	0.1146	0.26369	0.063434	0.82014	-0.90874	0.74079
0.099311	-0.76227	0.096412	0.18394	1.0853	-1.3094	0.1399
0.036515	-1.155	1.9889	0.061115	2.9011	-0.9598	1.9172
0.22014	-1.8028	-2.4585	0.17699	-0.27787	3.1362	-0.90789
-0.10037	1.3792	-1.7414	0.11214	0.78031	1.7236	0.3764
0.10425	-0.5143	-0.44398	-0.19816	-1.6495	1.5162	-1.6177
0.067561	-0.78409	-5.0873	-0.03494	-5.4257	-2.0097	-0.98978
-0.20221	-0.71216	0.030435	-0.90577	-0.51848	0.84174	-0.356
-0.26868	-0.60186	-0.08348	-2.5501	0.15759	1.6466	1.3889

Table D-15 Microscopic FC Model – Bronson – Fuel Cell Dominant – ESS

	Min	Max				
Time	0	1518				
Speed	0	103.14				
Accel	-27.497	17.37				
SOC	0.52923	0.7028				
ESS	-65.083	64.708				
FC	0	2.13412				

w1				w2	b1	b2
7.9733	6.071	3.41	1.7337	0.7395	0.89283	4.993
1.0833	-1.4592	-0.47028	0.026896	-2.5188	0.71808	
-1.3984	1.5345	-1.8007	6.0214	0.096713	-0.18379	
-2.6018	3.6011	-0.52776	-1.6905	-0.0918	-1.5972	
1.7367	-1.1825	-0.50998	-0.11445	1.4632	1.3174	
-0.19573	-0.63333	-0.96493	-5.6107	-4.0684	5.0424	
-0.13155	-0.54062	-1.1159	-7.173	1.8432	6.2939	
8.3417	6.5616	3.6231	2.0391	-0.71101	0.86972	
0.15912	-1.5085	3.4341	0.30441	-1.404	-3.904	
-0.30228	-0.26421	-2.6382	-0.05489	-1.7892	1.9243	
-9.9735	-0.07437	0.31902	-1.9227	1.9783	-11.506	
0.66371	-0.6273	-1.7372	-0.39458	0.72071	-0.34963	
-0.20114	0.80531	-1.3027	0.083524	-2.631	-0.31345	
-0.66713	0.59566	-1.4904	2.0007	0.6356	1.5932	
-0.34503	-0.95455	-0.78623	-4.499	2.2054	4.1032	
0.059236	-0.58556	-1.0867	-0.26991	2.8053	-1.6626	
0.24913	-0.98289	0.10311	-0.51036	-4.5056	-0.05596	
0.50486	-1.1094	-1.3819	-0.00734	2.4463	0.47473	
0.074538	-1.4692	0.053748	-0.82655	1.6418	-0.33314	
-0.04121	0.12378	1.2026	-0.42242	3.6146	-0.79145	

Table D-16 Microscopic FC Model – Bronson – Fuel Cell Dominant – FC

w1					w2	b1	b2
0.22348	-1.5078	0.562	0.20632	-0.22584	1.2485	2.1637	2.5206
-0.79514	3.1509	-3.039	0.65264	2.0532	1.7417	-1.0667	
0.050416	0.18952	-3.414	0.11027	-2.2802	1.1566	-4.3957	
-0.17011	0.48729	-4.4685	0.20911	1.5284	1.9922	-0.07697	
0.012578	0.8352	3.8572	-0.01002	-1.8086	0.94666	-0.21949	
-0.03423	0.37328	0.81331	0.026109	-2.9329	-1.9248	1.5482	
0.27991	0.22624	1.4621	-0.38118	-0.55736	-0.91189	0.26818	
-0.01405	1.6531	1.1557	0.030409	0.38832	-1.9788	1.0092	
-0.14481	0.89237	-0.77384	0.65052	-0.00891	1.2374	-0.17779	
0.014705	-4.3303	0.66148	-0.01152	-0.49672	0.74643	-3.6035	
-0.0791	-0.19842	0.054936	0.047809	-1.7411	-3.0553	2.1307	
-0.01986	0.42247	-1.1164	0.006909	-2.0066	-0.94199	0.13464	
0.26565	1.222	0.5101	-0.10537	-0.14905	-1.0853	-0.60395	
-0.404	2.3797	-0.65462	1.4934	0.0642	0.29293	-1.3777	
-0.02075	-0.55104	-3.6857	0.03515	-2.0232	-4.6068	1.2198	
0.24653	3.0619	-2.0774	0.13828	-0.43237	2.2628	-2.0583	
-0.00236	-0.45919	-1.3854	0.01255	-1.5211	5.6568	0.65412	
0.003072	-1.4676	-0.35079	-0.01773	6.8246	-6.0763	-1.3955	
-0.08241	-0.43499	1.3994	0.023909	-0.38004	-2.6119	-0.18059	
0.1192	-0.03564	0.060406	-0.09657	0.17414	0.23393	0.020491	
0.006944	-0.10913	-0.12919	0.003608	-2.3398	-4.8266	0.40081	
-0.12349	0.51625	-0.77765	0.52646	-0.21281	-1.6376	-0.43846	
-0.75898	3.1703	-3.1655	0.65795	1.9823	-1.7602	-1.0434	
0.041759	-2.8908	-0.84412	-0.22374	1.8341	2.5386	2.3048	
-0.04817	0.20857	-0.0081	0.030237	-0.19656	-0.47077	-0.25505	
0.049253	-0.0317	4.2488	-0.05109	2.753	1.6384	-1.2406	
-0.02829	1.9767	-0.95665	0.051752	-7.496	2.5251	1.9323	
-0.0132	-0.70405	-1.9656	0.00021	2.6382	-3.0626	-1.1404	
-0.01762	-0.34139	-0.03969	0.045523	0.21298	0.7954	0.53909	
0.047389	3.2909	-3.8814	0.11792	-0.29366	-1.8929	-1.6268	
0.015015	-0.35258	1.8219	-0.03838	5.3314	-6.8737	-1.7008	
0.080205	-3.2978	0.5367	-0.18334	1.7227	-2.4613	2.1741	
0.013505	0.8305	-1.2757	-0.04008	-1.0414	-1.7961	-0.749	
-0.03435	-1.3462	-2.0964	0.036114	2.4017	-1.3076	0.87239	
-0.03503	-0.65876	-2.4323	0.021145	3.1023	-1.7348	0.000453	
-0.0129	2.0267	-0.11661	0.030874	-7.4999	-4.2999	1.6946	
-0.35714	-0.23648	-0.30511	0.25311	0.39456	0.62692	-0.22663	

1.0659	-0.65614	0.81004	-1.0716	-0.49914	-1.1188	0.77273
-1.0008	0.55379	-0.63184	0.92816	0.26515	-1.1139	-0.81612
0.098814	-0.10079	1.6025	0.004472	-0.9953	-2.1153	0.05863
0.1468	-0.53334	4.19	-0.16982	-1.6613	2.7728	-0.05708
0.44323	-0.95976	0.33879	-0.78017	-0.42625	1.1213	0.78481
0.14915	-0.14659	-0.15321	-0.05405	0.33802	0.69934	0.22782
0.028782	0.28591	3.4856	-0.04034	2.7323	-4.4294	-1.0152
-0.01117	2.7443	-0.67275	0.01249	0.26249	5.0829	2.9055
0.11903	-0.04838	0.051051	-0.10632	0.26343	0.39079	0.13126
0.013354	-0.76908	0.85739	-0.03263	5.9249	10.536	-1.5441
-0.02447	3.9179	0.098421	0.024537	-0.05957	-2.8864	3.9752
-0.0083	0.96181	3.0507	0.017979	-1.8861	3.3147	-2.0056
0.061122	1.2775	6.2551	-0.05804	-0.14963	0.52953	-2.8697

Table D-17 Microscopic FC Model – HWY 417 – Large ICE

w1		w2	b1	b2		Min	Max
0.12586	1.6039	-0.50201	-3.2515	-0.30948			
1.377	2.0352	0.39529	-3.4207		Speed	0	117.4
0.26744	3.1432	-0.85251	-1.4971		Accel	-28.208	13.594
0.5411	8.1438	5.3453	-4.348		FC	0.38752	11.882
0.67494	7.4754	-4.4261	-4.7466				
1.0236	12.944	-2.8252	-6.9454				
3.4466	2.8769	-2.1966	-4.9652				
4.3039	-1.0556	1.7569	-1.5636				
-1.4881	2.1854	-1.1932	1.8743				
1.3197	8.3077	2.6731	-5.63				
-4.2589	-1.3253	-1.5838	5.0698				
-2.8352	1.1825	1.7701	3.0548				
3.8797	-1.9696	-1.7233	-1.3409				
1.0582	-2.4129	0.096248	-0.67731				
-1.3945	-2.822	-1.7535	2.3887				
1.8732	-5.6758	-3.4712	2.2621				
-0.95675	-12.676	3.5093	5.3146				
4.6393	-0.56631	-0.91314	-1.7521				
-1.9554	4.6034	-2.292	-1.4912				
-1.0479	-7.0988	-3.0832	3.7816				
-1.8606	-1.2127	-0.809	2.8327				
1.4886	5.3656	-2.0253	-3.3304				

4.2329	-2.9192	0.59993	-1.4018
1.2229	4.7577	-0.08028	-2.4165
3.3979	2.0346	-0.9286	-0.48898
2.5709	2.2231	0.89389	-0.21252
-5.5953	-0.53162	-1.507	-0.8821
-2.4478	-0.93774	-0.80668	-0.51145
3.0665	-15.202	1.8884	5.16
-5.4727	-0.722	1.6932	-0.83858
1.1243	15.576	1.9231	-6.3352
-2.6048	10.135	-3.2782	-3.6384
3.4656	-3.8268	-2.082	2.6645
2.6025	1.3386	1.448	0.23488
-3.5264	-2.3354	0.84334	-0.26096
3.2012	-2.5866	2.511	2.2896
2.3254	-4.0603	-1.4699	1.3005
3.3827	1.1223	-0.89267	1.1478
4.1102	-1.3456	-1.3589	3.2051
-2.179	5.269	-1.8552	-2.6853
-1.1097	-2.0824	0.31521	-1.7142
2.8607	-12.998	-4.0553	4.494
1.8938	0.92227	-0.84703	2.597
2.3864	1.814	0.86079	2.3661
3.9415	-3.1279	-2.8302	3.7246
0.42238	2.369	-0.13999	-2.0291
1.5501	1.9519	-0.83371	2.0113
0.040438	-3.0533	-0.74608	-2.0091
-4.2182	2.519	-3.2297	-3.7248
0.44441	2.3931	0.25706	2.3215

Table D-18 Microscopic FC Model – HWY 417 – Small ICE

w1		w2	b1	b2	Min	Max
-2.3778	-1.2436	1.7473	2.7306	0.008861		
0.077635	-13.919	2.1469	5.74		Speed	0 117.4
-1.1212	2.2126	0.31663	1.9586		Accel	-28.573 13.167
1.6511	-8.4284	-3.5278	6.5029		FC	0.27845 6.6521
-3.2656	-5.9809	-2.0052	4.7447			
-1.1008	2.1213	0.31258	1.7976			
-0.13985	9.9482	4.4527	-4.1602			
1.58	-1.3613	-0.03756	-1.8023			
-1.5311	-13.376	-2.1684	5.4145			
-1.3822	1.994	-0.64344	0.96722			

0.23235	-6.7697	2.4096	2.2916
0.13824	2.3315	-1.3176	2.0065
-4.1154	2.3068	-1.0055	1.6172
1.6496	19.541	1.7943	-7.6306
1.926	-2.2269	-0.81696	-0.7821
-3.8123	-4.4576	1.9437	2.838
-1.6714	-15.889	-2.4386	5.6962
2.848	6.3883	-1.8388	-4.6813
3.2231	3.2677	1.866	-4.6308
3.6239	3.3853	1.3958	-2.4875
-1.412	-13.788	7.0086	5.2656
1.1559	2.0208	-0.44637	-2.1798
-3.0079	-5.9754	0.54831	3.0129
4.8679	-2.0227	-0.74842	-2.0814
6.3086	-3.4755	1.2081	-0.52337
-3.2211	-4.8273	-2.001	2.7613
-5.9115	2.7195	2.7326	0.55423
-0.46003	-8.0952	1.9156	4.3705
4.7732	0.3891	1.5189	-0.87301
0.20065	-6.3421	-2.3205	1.9078
0.39764	2.6895	1.8128	-1.3999
0.14722	-2.6772	-0.57888	0.30753
-5.6084	1.5479	-3.1026	0.64794
-0.43273	-4.7326	1.5709	1.1716
-1.8409	1.9051	0.57934	-1.7756
-0.59069	5.2622	-6.3031	-3.4728
5.0432	-0.421	-3.3185	-0.75996
2.7577	2.4461	-0.49565	0.60305
2.7322	-7.4712	-0.143	3.9205
0.50532	-8.4323	-3.4672	5.0533
-2.1187	-1.8294	-1.1372	-0.33645
0.47514	3.1776	-0.68321	0.22581
2.4585	-8.2956	2.811	6.901
1.7735	-1.2366	0.69087	1.4964
-0.04714	2.302	-0.84522	-2.6186
1.7336	-4.6215	-3.032	4.2199
2.2189	-0.55636	0.2733	0.88028
2.359	-1.8857	-0.49498	1.2415
1.4552	1.5163	0.25006	2.267
-1.6342	1.8696	-0.80315	-2.5798

Table D-19 Microscopic FC Model – HWY 417 – Hybrid ICE - ESS

	Min	Max
Time	0	1521
Speed	0	117.4031
Accel	-29.2703	12.48514
SOC	0.443683	0.701964
ESS	-77.2186	80.09715
FC	0	2.7501

w1				w2	b1	b2
0.26461	-0.4959	5.6585	0.038252	-3.0127	-0.16281	0.07164
0.037061	1.8451	9.7932	-0.00692	11.368	-5.3233	
0.2314	-0.56932	5.6195	0.025733	3.3866	-0.21128	
-4.1648	-0.67679	1.2784	-0.83571	-1.2936	-0.47712	
-0.04935	-1.1462	-9.7592	-0.00391	-8.0534	5.4776	
-7.3574	3.2444	4.7212	2.5819	0.021461	-9.3297	
-0.02741	-2.1697	-22.27	-0.0435	-13.68	11.732	
0.29415	-14.652	-91.087	0.032747	0.40973	52.643	
3.1447	-3.1029	1.4784	0.026883	1.7783	-1.9857	
-1.1907	-1.9314	6.7776	0.12262	-0.14283	-4.7522	
0.28575	4.7337	15.419	-0.00146	-0.28582	-8.2664	
5.5472	-2.0242	17.455	-0.04816	-0.14019	-15.108	
0.029596	1.6674	10.477	-0.00509	-22.848	-5.7601	
-0.02892	-2.5339	-26.947	-0.07884	6.8816	14.144	
3.3507	-2.9226	1.743	-0.02999	-2.8079	-2.1384	
0.55727	4.485	-37.015	0.41901	-0.12587	18.014	
-4.1283	-0.69608	1.2859	-0.80278	1.3229	-0.46882	
-3.7945	2.7829	-2.0651	0.095503	-1.0599	2.4708	
-0.0108	1.8925	13.715	-0.0204	7.9715	-7.7016	
0.015481	1.6705	16.572	0.004131	-10.011	-8.9619	

Table D-20 Microscopic FC Model – HWY 417 – Hybrid ICE - FC

w1					w2	b1	b2
0.053252	1.3698	18.685	-0.172	-0.26568	0.82771	-9.1003	0.13402
-0.00224	-0.75908	5.55	-0.08488	0.56463	4.0512	-1.775	
0.004746	-0.58564	4.185	-0.09074	0.95761	-6.0945	-1.5767	
0.009927	-0.98667	7.4141	-0.30241	2.7656	1.2352	-3.3331	
0.018278	0.32859	-1.1628	-0.07164	1.8376	1.0318	-0.49183	

Table D-21 Microscopic FC Model – HWY 417 –Fuel Cell Battery - ESS

	Min	Max
Time	0	1521
Speed	0	117.4031
Accel	-28.4626	13.1667
SOC	0.344601	0.6
ESS	-53.1174	64.00828
FC	0	1.300509

w1				w2	b1	b2
-0.19909	0.60619	0.017201	-0.14146	2.3213	-0.64688	-0.3758
-0.00025	0.98934	-1.2619	-0.07037	-1.8288	-0.57911	
-0.28585	-0.83551	0.78636	0.16993	2.5729	2.0983	
-0.04385	1.8815	4.3046	-0.11678	0.3437	-4.1142	
17.821	-1.8206	0.68615	-19.674	-0.01469	-0.13391	
0.70931	0.62524	0.21351	0.26509	0.78397	-1.0647	
0.042478	0.24333	-0.98789	-0.05664	2.4818	-0.17944	
-0.80893	-2.8456	40.861	0.22177	-0.02122	-11.571	
6.305	1.4027	-0.93416	4.3973	0.035429	-0.33997	
0.1093	0.69724	-1.4047	-0.04025	-1.2684	0.6525	

Table D-22 Microscopic FC Model – HWY 417 –Fuel Cell Battery – FC

w1					w2	b1	b2
0.070236	0.7353	0.58244	0.022267	2.1958	4.6379	-0.38366	4.9315
-0.02409	1.7405	-1.1213	-0.00149	-1.3612	3.7453	0.72577	
0.030292	1.923	7.6922	-0.01906	-3.2728	5.5298	-5.2115	
0.007975	0.089225	-8.5768	-0.04879	2.5594	-0.99536	2.5748	
-0.11565	-0.55585	-2.7815	0.008786	2.5282	-1.6825	0.22721	
0.033506	1.1704	-0.86493	-0.01599	-1.493	-3.0782	-1.5351	
0.05319	0.97434	1.9697	-0.02677	-0.00633	-2.431	0.73873	
-0.01629	-0.21801	-5.8065	-0.02523	0.59515	-7.7374	2.747	
0.023768	0.38186	3.7188	0.021793	0.35381	-10.773	-1.7398	
-0.00441	-0.6021	-6.9842	-0.01818	2.5882	-4.6926	4.2988	
-0.03026	0.29623	-2.7696	-0.01409	0.93698	-4.7252	0.52939	
-0.06829	-0.32036	-1.3855	-0.00013	3.1517	-3.7964	2.1956	
0.0138	-0.81155	2.1246	0.035649	-1.4575	-5.7926	-0.96285	
0.070915	0.3495	27.256	0.052836	-1.9035	0.1474	-10.067	
0.003994	-1.9493	1.6385	0.041163	-1.7522	-9.1266	1.8673	
-0.01406	-0.41745	2.8904	0.006862	-1.4451	-7.723	-2.1823	
0.010924	3.3935	-0.44128	-0.06159	1.5437	-2.9206	-3.4548	

0.0499	1.8528	6.51	-0.01502	-1.779	-4.3937	-4.3132
-0.02314	1.6838	-1.1413	-0.01028	-0.80941	-4.6631	0.77737
0.060343	0.75844	-0.78521	-0.0084	2.4027	-5.5935	0.49278

Table D-23 Microscopic FC Model – HWY 417 –Fuel Cell Dominant – ESS

	Min	Max				
Time	0	1520				
Speed	0	117.4031				
Accel	-28.1326	13.1667				
SOC	0.285574	0.6				
ESS	-70.7977	63.82879				
FC	0	3.177517				

w1				w2	b1	b2
-1.0157	1.4377	-1.6285	-0.25522	0.79019	-0.21794	0.11539
-1.003	8.6459	30.722	-1.922	0.094278	-19.265	
-0.48652	0.96182	-2.0638	-0.08104	-2.2289	-0.10301	
-0.8795	0.032642	-1.2885	0.055549	7.6364	-0.16081	
-0.1325	-1.0101	137.19	-0.65083	0.11452	-64.386	
-0.53567	-8.3596	9.1705	-1.0423	-0.14741	-12.247	
-1.0024	-0.01779	-1.2211	0.054399	-6.1802	-0.19429	
1.9936	-0.71651	-0.88957	0.014751	0.25475	-0.13102	
0.33474	4.9907	-0.94567	-1.1479	0.11861	-2.0738	
0.021299	-0.59246	-3.7124	-0.05992	-0.65332	1.574	

Table D-24 Microscopic FC Model – HWY 417 –Fuel Cell Dominant – FC

w1					w2	b1	b2
0.017326	0.6402	-1.3365	-0.03837	0.48635	3.1062	1.4169	1.4561
-1.109	2.5334	-2.4997	0.27942	-10.959	-4.1091	-12.657	
-1.027	2.1167	-2.485	0.42182	-10.753	9.3643	-12.502	
-0.12536	-0.83811	2.1792	-0.0242	-0.72608	-6.5081	0.70876	
0.063616	-1.0221	-0.97999	0.091957	-0.2816	2.7003	-0.33513	
0.23187	0.79527	7.5523	0.16517	0.63985	-0.21082	-2.1013	
-0.00012	-0.59689	-1.5195	0.033552	0.063751	-5.778	0.30111	
0.19206	-2.0308	-0.92501	0.085412	0.032198	-2.5595	1.9319	
0.21486	-1.7906	0.39439	0.11444	-0.23684	3.4781	1.3432	
0.058729	0.00545	0.067009	0.12614	-1.1388	1.1786	0.66856	
0.028642	-0.12094	-1.3458	0.036724	-0.32272	5.4066	0.062481	

-0.2555	-0.62806	-4.3533	-0.06661	-0.02704	-1.9235	1.4198
0.25723	-1.7172	5.3453	0.22037	-1.4592	-0.54186	-0.26684
0.020083	8.3956	15.364	-0.60773	-7.8218	2.7097	-1.0512
-0.21509	-0.6054	-3.8752	-0.01841	0.099185	2.3563	1.2756
-0.07278	-0.27197	1.5353	-0.05271	0.090167	5.1628	-0.49243
-0.07706	2.5946	7.0527	-0.00338	-0.86491	3.4746	-6.7988
-0.16942	-1.206	3.8786	-0.03956	-0.91753	3.0762	0.21036
1.2314	-1.6089	2.4193	-0.78493	11.424	8.5423	13.714
0.026205	8.4091	15.725	-0.59056	-8.0288	-2.701	-1.148

Table D-25 Macroscopic FC Model – CBD – Small ICE

w1	w2	b1	b2		Max	Min
-2.0544	3.0457	2.0807	-0.63404	Speed	61.445	4.3501
-4.5547	-1.6642	3.8979		FC	40.642	5.0042
-0.77055	1.4185	-0.03059				
3.5686	2.4146	-1.0823				
9.5496	-5.9591	-2.3044				
14.168	2.9425	-3.7712				
7.9478	6.5843	-0.8512				
-13.404	3.2375	1.0346				
-1.969	2.4351	-0.87454				
6.4151	2.9842	2.3746				
1.969	-2.4351	0.87454				
-7.4226	-4.8369	-5.5664				
-0.77055	1.4185	-0.03059				
-10.918	2.7508	-8.4315				
1.969	-2.4351	0.87453				

Table D-26 Macroscopic FC Model – CBD – Large ICE

w1	w2	b1	b2		Max	Min
-0.55927	0.43813	0.21238	1.0923	Speed	62.039	3.4952
-2.941	0.92462	-0.71408		FC	69.651	4.0058
-1.6179	-1.4532	-0.89823				
-0.02349	0.38908	0.37043				
-3.0689	2.574	-3.3754				

Table D-27 Macroscopic FC Model – CBD– Hybrid ICE

w1	w2	b1	b2		Max	Min
1.19E-07	-3.53E-06	-3.53E-06	0.59548	Speed	61.445	3.1537
1.2447	-1.5006	-1.5049		FC	37.88	1.632
1.2133	1.2481	0.17965				
3.2647	-0.92086	-1.0771				
-1.2133	-1.2481	-0.17965				
4.326	-1.2109	0.18838				
-1.2133	-1.2481	-0.17965				
3.7873	-1.3213	1.7654				
1.2133	1.2481	0.17965				
-3.1775	2.7812	-3.4613				

Table D-28 Macroscopic FC Model – CBD – Fuel Cell Battery

w1	w2	b1	b2		Max	Min
-0.1698	-1.2415	-0.86837	1.6624	Speed	62.542	4.0479
-0.95548	-1.1046	0.03296		FC	21.936	0
2.1457	-0.71511	-1.2693				
-0.9557	-1.1048	0.033003				
-2.83	0.48575	0.13211				
-3.0183	1.299	-1.5911				
-11.099	2.7235	-7.1724				
-7.3199	-8.4524	-5.3657				
-13.049	4.0742	-10.032				
4.9538	-4.3314	5.1013				

Table D-29 Macroscopic FC Model – Bronson – Small ICE

w1	w2	b1	b2		Max	Min
-0.29549	-0.45602	-0.1443	0.7974	Speed	106.07	3.0531
0.76783	0.93284	-0.58184		FC	57.26	3.0443
1.7977	-0.69443	-0.85087				
-2.4847	-1.3618	-0.848				
-3.4712	0.88403	-0.67721				
-0.29549	-0.45602	-0.1443				
-11.477	2.5442	-8.1997				
-8.0813	-5.0968	-5.9604				
-0.29549	-0.45602	-0.1443				
3.9141	-4.8761	3.1535				

Table D-30 Macroscopic FC Model – Bronson – Large ICE

w1	w2	b1	b2		Max	Min
3.2646	5.3253	-2.7318	4.0091	Speed	105.33	3.0733
-9.2776	3.9155	8.2218		FC	76.756	2.5301
3.2646	5.3253	-2.7318				
-8.3421	2.5984	5.7264				
4.5931	-3.7429	-1.4729				
9.0669	1.8821	-3.0142				
7.3178	1.6153	-1.1974				
-3.4958	2.2166	0.81748				
-2.8504	-3.0547	-0.81383				
-5.044	1.1672	-1.3318				
-2.6961	2.7652	-2.3277				
-10.055	-8.4136	-7.7796				
17.04	-2.751	12.305				
13.804	-3.7938	11.148				
-2.6961	2.7653	-2.3278				

Table D-31 Macroscopic FC Model – Bronson – Hybrid ICE

w1	w2	b1	b2		Max	Min
0.7786	1.3849	-0.17419	-0.53428	Speed	106.91	2.906
3.0259	-1.4521	-2.3006		FC	47.967	0
0.7786	1.3849	-0.17419				
0.7786	1.3849	-0.17419				
0.7786	1.3849	-0.17419				
4.1394	-0.98774	-1.2496				
-0.7786	-1.3849	0.17419				
4.7443	-1.4135	0.36537				
-9.7505	1.9136	-1.9878				
6.9214	4.3587	1.7582				
13.658	2.3717	5.2058				
-9.0782	5.1843	-3.3335				
-6.6987	2.4588	-4.9782				
10.07	-3.7309	9.4704				
4.5565	5.8991	4.1736				

Table D-32 Macroscopic FC Model – Bronson – Fuel Cell Battery

w1	w2	b1	b2		Max	Min
6.9682	-3.685	0.98542	4.0029	Speed	106.07	3.0988
1.2639	0.097783	-1.6972		FC	29.128	0
4.6397	1.6373	0.834				
11.679	4.6401	1.39				
-19.64	5.2197	-2.1063				
-25.806	-2.7609	-2.6469				
7.5005	5.0456	5.6836				
-7.5978	2.3011	-5.1895				
10.859	-2.6716	8.5795				
7.637	-4.8694	8.3303				

APPENDIX E. Visual Basic Source Code (Computer Program to Calculate Neural Network Results)

Figure E-1 Algorithm's vehicle and type of facility input window

Figure E-2 Algorithm's results window

```

***** standard model: *****
*** globa data declare
*** procedures define ***
*** algorithm designed by jaime garcia ***
*** code by xiaotao shu ***
*****

```

Option Explicit

```

Public folder_name As String
Public input_type As Integer, output_type As Integer ' 1--LM 2--NB
Public number_input As Integer, number_output As Integer, number_vector As Integer
Public number_hidden_units As Integer 'weight and bias
Public b2() As Double, w2() As Double 'weight and bias

'declare input parameter array
Public input_min() As Double, input_max() As Double
Public input_avg() As Double, input_stdev() As Double

'declare output parameter array
Public output_min() As Double, output_max() As Double
Public output_avg() As Double, output_stdev() As Double

'declare output standard zero value
Public output_standardzero As Double

'declare the time of collection input data
Public system_time As Integer
Public inputcount As Integer

Public b1() As Double, w1() As Double 'weight and bias parameter
Public a1() As Double, z() As Double ' for calculating
Public a2() As Double ' for calculating
Public formula() As String 'store input formula for calculating
Public formula_display() As String 'input formula for display
Public initial_input_value() As Double 'for calculated value

Public iscalculate() As Integer '0 -false, 1-true
Public inputstyle As String 'style of input : manual, file or sensor
Public inputfile As String 'inputdata location
Public isfirstvector As Boolean

```

Public inputdata() As Double

ATTENTION: The following code has been modified in order to show the SOC approximation (*italic letters*)

'This module calculates microscopic and macroscopic fuel consumption of conventional ICE vehicles and advanced technology vehicles

Function calculate_output()

Dim i As Integer, j As Integer

Dim index_vector As Integer, index_output As Integer

Dim k As Integer, h As Integer

Dim tp() As Double

ReDim tp(1 To number_input) As Double

'initial calculate explanatory variables

ReDim a1(1 To number_input, 1 To number_hidden_units) As Double

ReDim a2(1 To number_hidden_units) As Double

ReDim z(1 To number_hidden_units) As Double

ReDim outputdata(1 To number_output) As Double

For index_output = 1 To number_output

 'calculate the input data

 For j = 1 To number_input

 'calculation are required?

 If iscalculate(j) Then

 'If isfirstvector = True Then 'initial value

 'inputdata(1, j) = initial_input_value(j)

 ' Else

 inputdata(1, j) = P_calculate(j)

 'End If

 End If

 inputdata(0, j) = inputdata(1, j)

Next j

'calculate the tp(i,j)_ Input/Output normalization

For j = 1 To number_input

 If input_type = 1 Then 'LM model

 tp(j) = 2 * (inputdata(1, j) - input_min(j)) / (input_max(j) - input_min(j)) - 1

 Else 'NB model

 tp(j) = (inputdata(1, j) - input_avg(j)) / input_stdev(j)

 End If

Next j

'Neural network algorithm

```

'compute aij(i,j)
For i = 1 To number_input
    For j = 1 To number_hidden_units
        a1(i, j) = w1(i, j) * tp(i)
    Next j
Next i

'computer Z(j)
For j = 1 To number_hidden_units
    a2(j) = 0
    For i = 1 To number_input
        a2(j) = a2(j) + a1(i, j)
    Next i
    a2(j) = a2(j) + b1(j)
    z(j) = tanh(a2(j))
Next j

'compute fuel consumption
For j = 1 To number_hidden_units
    outputdata(index_output) = outputdata(index_output) + w2(j) * z(j)
Next j

outputdata(index_output) = outputdata(index_output) + b2(index_output) 'result

'calculate the to(i)_Normalization of Neural Network Output
If output_type = 1 Then 'LM model
    outputdata(index_output) = 0.5 * (outputdata(index_output) + 1) *
(output_max(index_output) - output_min(index_output)) + output_min(index_output)
Else 'NB model
    outputdata(index_output) = outputdata(index_output) *
output_stdev(index_output) + output_avg(index_output)
End If

'standard the output if output<=standard zero the it standardize to zero
If outputdata(index_output) <= output_standardzero Then
    outputdata(index_output) = 0
End If
Next index_output
calculate_output = outputdata 'this is array

End Function
Sub p_setparameter()
    Dim i As Integer, j As Integer
    Dim response As Integer

```


On Error Resume Next

'This module calculates ESS and SOC values for advanced technology vehicles

```

Function calculate_output()
    Dim i As Integer, j As Integer
    Dim index_vector As Integer, index_output As Integer
    Dim k As Integer, h As Integer
    Dim tp() As Double
    ReDim tp(1 To number_input) As Double

    'initial calculate data
    ReDim a1(1 To number_input, 1 To number_hidden_units) As Double
    ReDim a2(1 To number_hidden_units) As Double
    ReDim z(1 To number_hidden_units) As Double
    ReDim outputdata(1 To number_output) As Double

    For index_output = 1 To number_output
        'calculate explanatory variables. Initial value of SOC = 0.6
        For j = 1 To number_input
            If inputdata(1, 1) = 1 Then inputdata(1, 4) = 0.6
            'calculation are required?
            If iscalculate(j) Then
                'If isfirstvector = True Then 'initial value
                'inputdata(1, j) = initial_input_value(j)
                ' Else
                inputdata(1, j) = P_calculate(j)
                'End If
            End If
            inputdata(0, j) = inputdata(1, j)
        Next j

        'calculate the tp(i,j)
        For j = 1 To number_input
            If input_type = 1 Then 'LM model
                tp(j) = 2 * (inputdata(1, j) - input_min(j)) / (input_max(j) - input_min(j)) - 1
            Else 'NB model
                tp(j) = (inputdata(1, j) - input_avg(j)) / input_stdev(j)
            End If
        Next j

        'Neural network algorithm
    
```

```

'compute  $a_{ij}(i,j)$ 
For i = 1 To number_input
    For j = 1 To number_hidden_units
         $a1(i, j) = w1(i, j) * tp(i)$ 
    Next j
Next i

'computer  $Z(j)$ 
For j = 1 To number_hidden_units
     $a2(j) = 0$ 
    For i = 1 To number_input
         $a2(j) = a2(j) + a1(i, j)$ 
    Next i
     $a2(j) = a2(j) + b1(j)$ 
     $z(j) = \tanh(a2(j))$ 
Next j

'compute ESS
For j = 1 To number_hidden_units
     $outputdata(index\_output) = outputdata(index\_output) + w2(j) * z(j)$ 
Next j

 $outputdata(index\_output) = outputdata(index\_output) + b2(index\_output)$  'result

'calculate the  $to(i)$ 
If output_type = 1 Then 'LM model
     $outputdata(index\_output) = 0.5 * (outputdata(index\_output) + 1) * (output\_max(index\_output) - output\_min(index\_output)) + output\_min(index\_output)$ 
Else 'NB model
     $outputdata(index\_output) = outputdata(index\_output) * output\_stdev(index\_output) + output\_avg(index\_output)$ 
End If

'standard the output if  $output \leq standard\ zero$  the it standardize to zero
If  $outputdata(index\_output) \leq output\_standardzero$  Then
     $outputdata(index\_output) = 0$ 
End If

'Approximation of SOC values using the internal resistance battery model (Rint)
If  $outputdata(index\_output) \leq 0$  Then
     $inputdata(1, 4) = inputdata(1, 4) - outputdata(index\_output) / 23400$ 
Else
     $inputdata(1, 4) = inputdata(1, 4) - (outputdata(index\_output) * 0.905) / 23400$ 
End If

```

Next index_output
calculate_output = outputdata 'this is array

End Function

'This module creates the array of neural network coefficients

```
'get parameters from the system parameter form
'input algorithm type LM=1 BN=2
If systemform.Option1.value = True Then
    input_type = 1
Else
    input_type = 2
End If

'output algorithm type
If systemform.Option3.value = True Then
    output_type = 1
Else
    output_type = 2
End If

number_input = systemform.num_input_text.Text
number_output = systemform.num_output_text.Text
number_hidden_units = systemform.num_hidden_text.Text
output_standardzero = systemform.zero_text.Text

'define the range of all array
ReDim input_min(1 To number_input) As Double
ReDim input_max(1 To number_input) As Double
ReDim input_avg(1 To number_input) As Double
ReDim input_stdev(1 To number_input) As Double

ReDim output_min(1 To number_output) As Double
ReDim output_max(1 To number_output) As Double
ReDim output_avg(1 To number_output) As Double
ReDim output_stdev(1 To number_output) As Double

ReDim w1(1 To number_input, 1 To number_hidden_units) As Double
ReDim b1(1 To number_hidden_units) As Double
ReDim w2(1 To number_hidden_units) As Double
ReDim b2(1 To number_output) As Double

For i = 1 To number_input
```

```

systemform.LMinputGrid.Row = i
systemform.LMinputGrid.Col = 1
input_min(i) = systemform.LMinputGrid.Text
systemform.LMinputGrid.Col = 2
input_max(i) = systemform.LMinputGrid.Text

systemform.NBinputGrid.Row = i
systemform.NBinputGrid.Col = 1
input_avg(i) = CDb1(systemform.NBinputGrid.Text)
systemform.NBinputGrid.Col = 2
input_stdev(i) = CDb1(systemform.NBinputGrid.Text)
Next i

For i = 1 To number_output
    systemform.LMoutputGrid.Row = i
    systemform.LMoutputGrid.Col = 1
    output_min(i) = CDb1(systemform.LMoutputGrid.Text)
    systemform.LMoutputGrid.Col = 2
    output_max(i) = CDb1(systemform.LMoutputGrid.Text)

    systemform.NBoutputGrid.Row = i
    systemform.NBoutputGrid.Col = 1
    output_avg(i) = CDb1(systemform.NBoutputGrid.Text)
    systemform.NBoutputGrid.Col = 2
    output_stdev(i) = CDb1(systemform.NBoutputGrid.Text)
Next i

systemform.w2Grid.Row = 1 'b1
systemform.b1Grid.Row = 1 'b1
For j = 1 To number_hidden_units
    systemform.w2Grid.Col = j 'b1
    systemform.w1Grid.Col = j 'w1
    systemform.b1Grid.Col = j 'b1

    b1(j) = CDb1(systemform.b1Grid.Text) 'b1
    w2(j) = CDb1(systemform.w2Grid.Text) 'w2

    For i = 1 To number_input
        systemform.w1Grid.Row = i 'w1
        w1(i, j) = CDb1(systemform.w1Grid.Text)
    Next i
Next j

systemform.b2Grid.Row = 1 'b2

```

```

For j = 1 To number_output
    systemform.b2Grid.Col = j 'b2
    b2(j) = CDbl(systemform.b2Grid.Text) 'b2
Next j

End Sub

Sub p_initialsystemform()
    Dim i As Integer, j As Integer
    Dim response As Integer

    On Error Resume Next

    'initialized table title
    systemform.LMinputGrid.Row = 0
    systemform.LMinputGrid.Col = 1
    systemform.LMinputGrid.Text = "min"
    systemform.LMinputGrid.Col = 2
    systemform.LMinputGrid.Text = "max"

    systemform.NBinputGrid.Row = 0
    systemform.NBinputGrid.Col = 1
    systemform.NBinputGrid.Text = "average"
    systemform.NBinputGrid.Col = 2
    systemform.NBinputGrid.Text = "stdev"

    systemform.LMoutputGrid.Row = 0
    systemform.LMoutputGrid.Col = 1
    systemform.LMoutputGrid.Text = "min"
    systemform.LMoutputGrid.Col = 2
    systemform.LMoutputGrid.Text = "max"

    systemform.NBoutputGrid.Row = 0
    systemform.NBoutputGrid.Col = 1
    systemform.NBoutputGrid.Text = "average"
    systemform.NBoutputGrid.Col = 2
    systemform.NBoutputGrid.Text = "stdev"

    systemform.w2Grid.Row = 0
    systemform.w2Grid.Col = 0
    systemform.w2Grid.Text = "W2 table"
    systemform.w1Grid.Row = 0
    systemform.w1Grid.Col = 0
    systemform.w1Grid.Text = "W1 table"

```

```

systemform.b1Grid.Row = 0
systemform.b1Grid.Col = 0
systemform.b1Grid.Text = "b1 table"

systemform.b2Grid.Row = 0
systemform.b2Grid.Col = 0
systemform.b2Grid.Text = "b2:"

'get parameters from the system parameter form
'input algorithm type  LM=1 BN=2
systemform.Option1.value = (input_type = 1)
systemform.Option2.value = (input_type = 2)

'output algorithm type
systemform.Option3.value = (output_type = 1)
systemform.Option4.value = (output_type = 2)

systemform.num_input_text.Text = number_input
systemform.num_output_text.Text = number_output
systemform.num_hidden_text.Text = number_hidden_units

systemform.zero_text.Text = output_standardzero

For i = 1 To number_input
    systemform.LMinputGrid.Row = i
    systemform.LMinputGrid.Col = 1
    systemform.LMinputGrid.Text = input_min(i)
    systemform.LMinputGrid.Col = 2
    systemform.LMinputGrid.Text = input_max(i)

    systemform.NBinputGrid.Row = i
    systemform.NBinputGrid.Col = 1
    systemform.NBinputGrid.Text = input_avg(i)
    systemform.NBinputGrid.Col = 2
    systemform.NBinputGrid.Text = input_stdev(i)
Next i

For i = 1 To number_output
    systemform.LMoutputGrid.Row = i
    systemform.LMoutputGrid.Col = 0
    systemform.LMoutputGrid.Text = " output " & i

    systemform.LMoutputGrid.Col = 1
    systemform.LMoutputGrid.Text = output_min(i)

```

```

systemform.LMoutputGrid.Col = 2
systemform.LMoutputGrid.Text = output_max(i)

systemform.NBoutputGrid.Row = i
systemform.NBoutputGrid.Col = 1
systemform.NBoutputGrid.Text = output_avg(i)
systemform.NBoutputGrid.Col = 2
systemform.NBoutputGrid.Text = output_stdev(i)

'b2
systemform.b2Grid.Col = i
systemform.b2Grid.Row = 0
systemform.b2Grid.Text = "output 1"
systemform.b2Grid.Row = 1
systemform.b2Grid.Text = b2(i)

Next i

systemform.w2Grid.Row = 1 'w2
systemform.b1Grid.Row = 1 'b1
For j = 1 To number_hidden_units
    systemform.w2Grid.Col = j 'w2
    systemform.w1Grid.Col = j 'w1
    systemform.b1Grid.Col = j 'b1

    systemform.w2Grid.Text = w2(j) 'w2
    systemform.b1Grid.Text = b1(j) 'b1

    For i = 1 To number_input
        systemform.w1Grid.Row = i 'w1
        systemform.w1Grid.Text = w1(i, j)
    Next i
Next j

End Sub

Sub p_openfolder(folder)
    On Error GoTo errorhandle 'Resume Next
    Dim fso, f, ts
    Dim temp As String, variablename As String
    Dim i As Integer, j As Integer
    Dim index As Integer
    Dim fileopened As Boolean
    Dim line As Integer 'for read a line data

```

```

fileopenned = False
If (folder = "") Then
    'open the common dialog
    mainform.CMDialog1.filename = folder_name
    mainform.CMDialog1.filename = "c:\FC Micro 1\data\*.fold"
    mainform.CMDialog1.Filter = "*.fold"
    mainform.CMDialog1.ShowOpen
    folder_name = mainform.CMDialog1.filename
    folder = folder_name
End If
'open the file as textstream
Set fso = CreateObject("Scripting.FileSystemObject")
Set f = fso.GetFile(folder)
Set ts = f.OpenAsTextStream(1, -2) 'ForReading, TristateUseDefault)
fileopenned = True

'read preprocessing data
temp = ts.readline 'read #input
index = InStr(temp, "number_input=")
If index Then
    number_input = Mid(temp, 14)
End If
temp = ts.readline 'read type of algorithm of input
index = InStr(temp, "input_type=")
If index Then
    input_type = Mid(temp, 12)
End If

'read weights and bias data
temp = ts.readline 'read #hidden units
index = InStr(temp, "number_hidden_units=")
If index Then
    number_hidden_units = Mid(temp, 21)
End If

temp = ts.readline 'read #output
index = InStr(temp, "number_output=")
If index Then
    number_output = Mid(temp, 15)
End If
temp = ts.readline 'read type of algorithm of output
index = InStr(temp, "output_type=")
If index Then

```



```

    output_type = Mid(temp, 13)
End If

ReDim input_min(1 To number_input) As Double
ReDim input_max(1 To number_input) As Double
ReDim input_avg(1 To number_input) As Double
ReDim input_stdev(1 To number_input) As Double
ReDim output_min(1 To number_output) As Double
ReDim output_max(1 To number_output) As Double
ReDim output_avg(1 To number_output) As Double
ReDim output_stdev(1 To number_output) As Double
ReDim b1(1 To number_hidden_units) As Double
ReDim w2(1 To number_hidden_units) As Double
ReDim w1(1 To number_input, 1 To number_hidden_units) As Double
ReDim b2(1 To number_output) As Double

Do While ts.AtEndOfStream <> True
    temp = ts.readline

    'input_min(i)
    index = InStr(temp, "input_min(")
    If index = 1 Then
        temp = Mid(temp, index + 10)
        index = InStr(temp, ")")
        i = CInt(Left(temp, index - 1))
        input_min(i) = Mid(temp, index + 2)
        GoTo whileloop
    End If

    'input_max(i)
    index = InStr(temp, "input_max(")
    If index = 1 Then
        temp = Mid(temp, index + 10)
        index = InStr(temp, ")")
        i = CInt(Left(temp, index - 1))
        input_max(i) = Mid(temp, index + 2)
        GoTo whileloop
    End If

    'input_avg(i)
    index = InStr(temp, "input_avg(")
    If index = 1 Then
        temp = Mid(temp, index + 10)
        index = InStr(temp, ")")

```

```

    i = CInt(Left(temp, index - 1))
    input_avg(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

'input_stdev(i)
index = InStr(temp, "input_stdev(")
If index = 1 Then
    temp = Mid(temp, index + 12)
    index = InStr(temp, "(")
    i = CInt(Left(temp, index - 1))
    input_stdev(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

'line read b2
index = InStr(temp, "b2(")
If index = 1 Then
    temp = Mid(temp, index + 3)
    index = InStr(temp, "(")
    i = CInt(Left(temp, index - 1))
    b2(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

'read b1(j)
index = InStr(temp, "b1(")
If index = 1 Then
    temp = Mid(temp, index + 3)
    index = InStr(temp, "(")
    i = CInt(Left(temp, index - 1))
    b1(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

index = InStr(temp, "w2(") 'w2(j)
If index = 1 Then
    temp = Mid(temp, index + 3)
    index = InStr(temp, "(")
    i = CInt(Left(temp, index - 1))
    w2(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

```

```

index = InStr(temp, "w1(")
If index = 1 Then
    temp = Mid(temp, index + 3)
    index = InStr(temp, ",")
    i = CInt(Left(temp, index - 1))
    temp = Mid(temp, index + 1)
    index = InStr(temp, ")")
    j = CInt(Left(temp, index - 1))
    w1(i, j) = Mid(temp, index + 2)
    GoTo whileloop
End If
    'output_min(i)
index = InStr(temp, "output_min(")
If index = 1 Then
    temp = Mid(temp, index + 11)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    output_min(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

    'output_max(i)
index = InStr(temp, "output_max(")
If index = 1 Then
    temp = Mid(temp, index + 11)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    output_max(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

    'output_avg(i)
index = InStr(temp, "output_avg(")
If index = 1 Then
    temp = Mid(temp, index + 11)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    output_avg(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

    'output_stdev(i)
index = InStr(temp, "output_stdev(")
If index = 1 Then

```

```

temp = Mid(temp, index + 13)
index = InStr(temp, ")")
i = CInt(Left(temp, index - 1))
output_stdev(i) = Mid(temp, index + 2)
GoTo whileloop
End If

'iscalculate(i)
index = InStr(temp, "iscalculate(")
If index = 1 Then
    temp = Mid(temp, index + 12)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    iscalculate(i) = CInt(Mid(temp, index + 2))
    GoTo whileloop
End If

'formula(i)
index = InStr(temp, "formula(")
If index = 1 Then
    temp = Mid(temp, index + 8)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    formula(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

'formula_display(i)
index = InStr(temp, "formula_display(")
If index = 1 Then
    temp = Mid(temp, index + 16)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    formula_display(i) = Mid(temp, index + 2)
    GoTo whileloop
End If

'initial input value
index = InStr(temp, "initial_input_value(")
If index = 1 Then
    temp = Mid(temp, index + 20)
    index = InStr(temp, ")")
    i = CInt(Left(temp, index - 1))
    initial_input_value(i) = Mid(temp, index + 2)

```

```

    'GoTo whileloop
'End If

'inputstyle
index = InStr(temp, "inputstyle")
If index = 1 Then
    inputstyle = Mid(temp, 12)
    GoTo whileloop
End If

'inputfile
index = InStr(temp, "inputfile")
If index = 1 Then
    inputfile = Mid(temp, 11)
    GoTo whileloop
End If

'system_time
index = InStr(temp, "systemtime")
If index = 1 Then
    system_time = CInt(Mid(temp, 12))
    GoTo whileloop
End If

whileloop:
    Loop

errorhandle:
    If fileopenned Then
        ts.Close
    End If
End Sub

Sub p_savefolder(folder)
    Dim fso, f, ts
    Dim temp As String, variablename As String
    Dim i As Integer, j As Integer
    Dim index As Integer
    Dim fileopenned As Boolean

    fileopenned = False
    If Not (folder = "c:\FC Micro 1\data\current.fold") Then
        'open the common dialog

```

```

    mainform.CMDialog1.filename = folder_name
    mainform.CMDialog1.filename = "c:\FC Micro 1\data\*.fold"
    mainform.CMDialog1.Filter = "*.fold"
    mainform.CMDialog1.ShowSave
    folder_name = mainform.CMDialog1.filename
    folder = folder_name
End If
On Error GoTo errorhandle 'Resume Next
'open the file as textstream
Set fso = CreateObject("Scripting.FileSystemObject")
fso.CreateTextFile folder          'create a file
Set f = fso.GetFile(folder)
Set ts = f.OpenAsTextStream(2, -2) '(ForWriting, TristateUseDefault)
fileopened = True

'write file
ts.Writeline "number_input=" & number_input
ts.Writeline "input_type=" & input_type
ts.Writeline "number_hidden_units=" & number_hidden_units
ts.Writeline "number_output=" & number_output
ts.Writeline "output_type=" & output_type

'save input_min(i)
For i = 1 To number_input
    ts.Writeline "input_min(" & i & ")=" & input_min(i)
Next i
'save input_max
For i = 1 To number_input
    ts.Writeline "input_max(" & i & ")=" & input_max(i)
Next i
'save input_avg
For i = 1 To number_input
    ts.Writeline "input_avg(" & i & ")=" & input_avg(i)
Next i
'save input_stdev
For i = 1 To number_input
    ts.Writeline "input_stdev(" & i & ")=" & input_stdev(i)
Next i

'save b2
For i = 1 To number_output
    ts.Writeline "b2(" & i & ")=" & b2(i)
Next i

```

```

'save b1
For i = 1 To number_hidden_units
    ts.Writeline "b1(" & i & ")=" & b1(i)
Next i
'save w2
For i = 1 To number_hidden_units
    ts.Writeline "w2(" & i & ")=" & w2(i)
Next i

'save w1(i,j)
For i = 1 To number_input
    For j = 1 To number_hidden_units
        ts.Writeline "w1(" & i & "," & j & ")=" & w1(i, j)
    Next j
Next i

'save output_min(i)
For i = 1 To number_output
    ts.Writeline "output_min(" & i & ")=" & output_min(i)
Next i
'save input_max
For i = 1 To number_output
    ts.Writeline "output_max(" & i & ")=" & output_max(i)
Next i
'save input_avg
For i = 1 To number_output
    ts.Writeline "output_avg(" & i & ")=" & output_avg(i)
Next i
'save input_stdev
For i = 1 To number_output
    ts.Writeline "output_stdev(" & i & ")=" & output_stdev(i)
Next i

'save iscalculate(i)
For i = 1 To number_input
    ts.Writeline "iscalculate(" & i & ")=" & iscalculate(i)
Next i

'save formula for input calculate
For i = 1 To number_input
    ts.Writeline "formula(" & i & ")=" & formula(i)
Next i
'save display formula
For i = 1 To number_input

```

```

        ts.Writeline "formula_display(" & i & ")=" & formula_display(i)
    Next i

    'save initial input value
    'For i = 1 To number_input
        ' ts.Writeline "initial_input_value(" & i & ")=" & initial_input_value(i)
    'Next i

    ts.Writeline "inputstyle=" & inputstyle
    ts.Writeline "inputfile=" & inputfile
    ts.Writeline "systemtime=" & system_time

errorhandle:
    If fileopenned Then
        ts.Close
    End If
End Sub

'new a folder :clear all data in memory
Sub p_newfolder()
    Dim response As Integer
    If Not (number_input = 0 And number_output = 0 And number_hidden_units = 0)
    Then
        response = MsgBox("Do you want to save your folder?", 4, "Conform ")
        If response = 6 Then ' 4-YesNo, 7-No
            p_savefolder ("")
        End If
    End If

    'initial all globa variables in program
    p_initialvariable

    'initial all components of systemform
    p_initialsystemform
End Sub

Sub p_initialvariable()
    Dim i As Integer

    folder_name = ""
    input_type = 1      'LM or BN for input
    output_type = 1     'LM or BN for input
    number_input = 0

```



```

number_output = 0
number_hidden_units = 0 'weight and bias

ReDim b1(0 To 0) As Double
ReDim b2(0 To 0) As Double
ReDim w1(0 To 0) As Double

ReDim w2(0 To 0) As Double
ReDim input_min(0 To 0) As Double, input_max(0 To 0) As Double
ReDim input_avg(0 To 0) As Double, input_stdev(0 To 0) As Double

w2(0) = 0

'declare output parameter array
ReDim output_min(0 To 0) As Double, output_max(0 To 0) As Double
ReDim output_avg(0 To 0) As Double, output_stdev(0 To 0) As Double
ReDim formula(0 To 20) As String
ReDim formula_display(0 To 20) As String
'ReDim initial_input_value(0 To 20) As Double
ReDim iscalculate(0 To 20) As Integer '0-false 1-true

For i = 1 To 20
    iscalculate(i) = False
Next i

inputstyle = "manual" 'manual, file or sensor
inputfile = "" 'input data file loaction

End Sub

Function P_calculate(index_input)
    Dim k As Integer, h As Integer, index As Integer
    Dim tempindex As Integer

    Dim temp As String, term1 As String
    Dim result As Double

    temp = formula(index_input)
    index = InStr(temp, ",")
    result = 0
    Do While index > 0
        term1 = Left(temp, index - 1)
        temp = Mid(temp, index + 1)
        Select Case Left(term1, 2)

```

```

Case "+n":
    result = result + CDbI(Mid(term1, 3))
Case "-n":
    result = result - CDbI(Mid(term1, 3))
Case "*n":
    result = result * CDbI(Mid(term1, 3))
Case "/n":
    result = result / CDbI(Mid(term1, 3))
Case "+p":
    tempindex = InStr(term1, " ")
    k = 1
    h = 0
    k = CInt(Mid(term1, 3, tempindex - 3))
    h = CInt(Mid(term1, tempindex + 1))
    If k < 0 Then
        result = result + inputdata(0, h)
    Else
        result = result + inputdata(1, h)
    End If
Case "-p":
    tempindex = InStr(term1, " ")
    k = 1
    h = 0
    k = CInt(Mid(term1, 3, tempindex - 3))
    h = CInt(Mid(term1, tempindex + 1))
    If k < 0 Then
        result = result - inputdata(0, h)
    Else
        result = result - inputdata(1, h)
    End If
Case "*p":
    tempindex = InStr(term1, " ")
    k = 1
    h = 0
    k = CInt(Mid(term1, 3, tempindex - 3))
    h = CInt(Mid(term1, tempindex + 1))
    If k < 0 Then
        result = result * inputdata(0, h)
    Else
        result = result * inputdata(1, h)
    End If
Case "/p":
    tempindex = InStr(term1, " ")
    k = 1

```

```

        h = 0
        k = CInt(Mid(term1, 3, tempindex - 3))
        h = CInt(Mid(term1, tempindex + 1))
        If k < 0 Then
            result = result / inputdata(0, h)
        Else
            result = result / inputdata(1, h)
        End If
    End Select
    index = InStr(temp, ",")
Loop
P_calculate = result
End Function

```

```

Sub calculate(inputdatafile)
    On Error GoTo errorhandle 'Resume Next

    Dim i As Integer, j As Integer, num_vector As Integer
    Dim index As Integer
    Dim file1 As String
    Dim output() As Double
    Dim fileopened As Boolean
    Dim fso, f, ts
    ReDim output(1 To number_output) As Double

    file1 = inputdatafile
    Open file1$ For Input As #1
    ReDim inputdata(0 To 1, 1 To number_input) As Double

    fileopened = False
    'open the file as textstream
    Set fso = CreateObject("Scripting.FileSystemObject")
    fso.CreateTextFile "c:\FC Micro 1\data\output.txt" 'create a file
    Set f = fso.GetFile("c:\FC Micro 1\data\output.txt")
    Set ts = f.OpenAsTextStream(2, -2) '(ForWriting, TristateUseDefault)
    ts.WriteLine "Speed" & Chr(9) & Chr(9) & Chr(9) & Chr(9) & "Accel" & Chr(9) &
Chr(9) & "Fuel Consumption"
    ts.WriteLine "kph" & Chr(9) & Chr(9) & Chr(9) & Chr(9) & "kph/sec" & Chr(9) &
Chr(9) & "g/sec" & Chr(9) & Chr(9)

    isfirstvector = True

```

```

Do While Not EOF(1)
    For j = 1 To number_input
        Input #1, inputdata(1, j)
    Next j
    output = calculate_output()
    isfirstvector = False
    'write output into a file
    For j = 1 To number_input
        ts.Write inputdata(1, j) & Chr(9) & Chr(9)
    Next j
    ts.WriteLine myformat(output(1), 12, 5)
Loop
ts.Close
Close (1)
Exit Sub
errorhandle:
    Close (1)
    If fileopenned Then
        ts.Close
    End If
End Sub

```

```

Function myformat(number, length, del)
    Dim temp As String, str As String
    Dim i As Integer
    Dim j As Integer

```

```

    If number = 0 Then
        temp = "0"
        For i = 2 To length
            temp = temp + " "
        Next i
        myformat = temp
        Exit Function
    End If

```

```

    If del > 0 Then
        temp = "."
        For i = 1 To del
            temp = temp & "0"
        Next i
        j = length - del - 1
    Else

```

```

    j = length
End If

For i = 1 To j
    temp = "#" & temp
Next i

str = Format(number, temp)
If Len(str) < length Then
    j = (length - Len(str)) * 2
    str = str & String(j, " ")
End If

myformat = str
End Function

Function tanh(X)
    Dim temp As Double, temp1 As Double
    On Error GoTo handleerror
    temp = Exp(X) - Exp(-X)
    temp1 = Exp(X) + Exp(-X)
    temp = temp / temp1
    tanh = temp
Exit Function
handleerror:
    If X > 0 Then
        tanh = 1
    Else
        tanh = -1
    End If
End Function

Sub load_inputdata(filename)
    On Error GoTo errorhandle 'Resume Next
    Dim fso, f, ts
    Dim temp As String

    Dim i As Integer, j As Integer, num_vector As Integer
    Dim index As Integer

```

```

Dim fileopenned As Boolean
Dim file2 As String
Dim value As Double
    fileopenned = False
    'open the file as textstream
Set fso = CreateObject("Scripting.FileSystemObject")
Set f = fso.GetFile(filename)
Set ts = f.OpenAsTextStream(1, -2) 'ForReading, TristateUseDefault)
fileopenned = True
num_vector = 0
Do While ts.AtEndOfStream <> True
    num_vector = num_vector + 1
    temp = ts.readline()
Loop
ts.Close
fileopenned = False
    If (num_vector < 1) Or (num_vector > 500) Then
        MsgBox (" the number of the input vector is too big")
        Exit Sub
    End If
    file2 = filename
    Open file2$ For Input As #1
    datainputform.Text4.Text = num_vector
    datainputform.inputgrid.Rows = num_vector + 1
    datainputform.inputgrid.Cols = number_input + 1
    For i = 1 To num_vector
        datainputform.inputgrid.Row = i
        For j = 1 To number_input
            datainputform.inputgrid.Col = j
            Input #1, value
            datainputform.inputgrid.Text = value
            If EOF(1) Then
                Exit For
            End If
        Next j
    Next i
    Close (1)
    Exit Sub
errorhandle:
    If fileopenned Then
        ts.Close
    End If
    Close (1)
End Sub

```

APPENDIX F. Macroscopic Fuel Consumption Models

Table F-1 Example of an output file from CORSIM (A)

		VEHICLE MINUTES		RATIO		MINUTES/MILE			
		VEHICLE	VEHICLE	MOVE	DELAY	TOTAL	MOVE/	TOTAL	DELAY
LINK		MILES	TRIPS	TIME	TIME	TIME	TOTAL	TIME	TIME
(200, 201)		4.28	105	8.6	16.5	25	0.34	5.85	3.85
(201, 202)		7.93	148	15.9	26.3	42.1	0.38	5.31	3.31
(202, 203)		16.29	402	32.6	75.2	107.8	0.3	6.61	4.61
(203, 204)		16.61	430	33.2	30.8	64	0.52	3.85	1.85
(204, 205)		12.75	243	25.5	61.9	87.4	0.29	6.86	4.86
(205, 206)		12.67	246	25.3	6.6	32	0.79	2.52	0.52
(206, 207)		11.87	241	23.7	45.6	69.3	0.34	5.84	3.84
(207, 208)		12.57	275	25.1	6.1	31.2	0.8	2.48	0.48
(208, 209)		12.66	274	25.3	1.7	27	0.94	2.13	0.13
(209, 210)		13.54	276	27.1	66.8	93.8	0.29	6.93	4.93
(210, 211)		25.7	264	51.4	62.8	114.2	0.45	4.44	2.44
(211, 212)		17.43	462	34.9	10.5	45.4	0.77	2.6	0.6
(212, 213)		19.69	462	39.4	3.6	43	0.92	2.18	0.18
(213, 214)		21.53	464	43.1	5	48.1	0.9	2.23	0.23
(214, 215)		19.6	456	39.2	144.9	184.1	0.21	9.39	7.39
(215, 216)		23.9	446	47.8	106.5	154.4	0.31	6.46	4.46
(216, 217)		25.88	660	51.8	17.9	69.6	0.74	2.69	0.69
(217, 218)		36.69	668	73.4	12.1	85.4	0.86	2.33	0.33
(218, 219)		30.11	668	60.2	87.1	147.3	0.41	4.89	2.89
(219, 220)		33.79	697	67.6	26.9	94.5	0.72	2.8	0.8
(220, 221)		29.48	698	59	187.3	246.2	0.24	8.35	6.35
(221, 222)		36.58	654	73.2	15.6	88.8	0.82	2.43	0.43
(222, 223)		29.23	654	58.5	8.7	67.1	0.87	2.3	0.3
(223, 224)		27.87	654	55.7	8.5	64.3	0.87	2.31	0.31
(224, 225)		31.96	654	63.9	10.3	74.2	0.86	2.32	0.32
(225, 226)		29.42	661	58.8	115.9	174.7	0.34	5.94	3.94
(226, 227)		38.73	639	77.5	16.5	93.9	0.82	2.43	0.43
(227, 228)		41.26	637	82.5	49.9	132.4	0.62	3.21	1.21
(228, 7229)		15.41	651	26.6	8.6	35.2	0.75	2.29	0.56

Table F-2 Example of an output file from CORSIM (B)

		SECONDS/VEHICLE				AVERAGE VALUES	
		TOTAL DELAY		CONTROL QUEUE		STOP*	SPEED
LINK		TIME	TIME	DELAY	DELAY	TIME	MPH
(200, 201)		14.4	9.5	6.6	6.6	6.5	10.3
(201, 202)		17.1	10.7	8.3	7.8	7.6	11.3
(202, 203)		16	11.2	7.4	6.3	5.5	9.1
(203, 204)		8.9	4.3	1.1	0.6	0.3	15.6
(204, 205)		21.6	15.3	13.2	12.2	11.7	8.8
(205, 206)		7.8	1.6	0	0.1	0	23.8
(206, 207)		17.4	11.5	10.3	9.6	9.3	10.3
(207, 208)		6.8	1.3	0	0	0	24.1
(208, 209)		5.9	0.4	0	0	0	28.1
(209, 210)		20.5	14.6	12.8	11.6	11.1	8.7
(210, 211)		26	14.3	11.6	10.9	10.6	13.5
(211, 212)		5.9	1.4	0	0.1	0.1	23
(212, 213)		5.6	0.5	0.1	0	0	27.5
(213, 214)		6.2	0.6	0.1	0	0	26.9
(214, 215)		24.1	18.9	16.2	14.4	13.4	6.4
(215, 216)		20.7	14.2	11.1	9.8	9.1	9.3
(216, 217)		6.3	1.6	0	0.1	0.1	22.3
(217, 218)		7.7	1.1	0.2	0	0	25.8
(218, 219)		13.2	7.8	5.6	4.8	4.3	12.3
(219, 220)		8.1	2.3	0.7	0.5	0.5	21.5
(220, 221)		20.9	15.9	13.4	12.4	11.6	7.2
(221, 222)		8.1	1.4	0	0.1	0	24.7
(222, 223)		6.1	0.8	0	0	0	26.1
(223, 224)		5.9	0.8	0	0	0	26
(224, 225)		6.8	0.9	0.1	0	0	25.8
(225, 226)		15.8	10.5	8.7	7.7	7.2	10.1
(226, 227)		8.8	1.5	0	0	0	24.7
(227, 228)		12.4	4.7	3.5	3.1	3.1	18.7
(228, 7229)		3.2	0.8	0	0	0	26.2

Table F-3 Example of an output file from CORSIM (C)

NETSIM CUMMULATIVE VALUES OF FUEL CONSUMPTION								
LINK		M.P.G.						
VEHICLE TYPE		5	1	2	6	7	8	4
(200	201)	5.11	7.27	0.00	0.00	0.00	0.00	0.00
(201	202)	6.72	10.54	0.00	0.00	0.00	0.00	0.00
(202	203)	4.84	7.49	0.00	0.00	0.00	0.00	0.00
(203	204)	5.87	9.15	0.00	0.00	0.00	0.00	0.00
(204	205)	8.06	11.60	0.00	0.00	0.00	0.00	0.00
(205	206)	7.11	13.36	0.00	0.00	0.00	0.00	0.00
(206	207)	11.42	15.54	0.00	0.00	0.00	0.00	0.00
(207	208)	6.50	11.32	0.00	0.00	0.00	0.00	0.00
(208	209)	20.47	34.59	0.00	0.00	0.00	0.00	0.00
(209	210)	10.47	13.35	0.00	0.00	0.00	0.00	0.00
(210	211)	8.27	12.93	0.00	0.00	0.00	0.00	0.00
(211	212)	4.84	8.71	0.00	0.00	0.00	0.00	0.00
(212	213)	14.84	30.96	0.00	0.00	0.00	0.00	0.00
(213	214)	20.24	32.32	0.00	0.00	0.00	0.00	0.00
(214	215)	6.52	8.75	0.00	0.00	0.00	0.00	0.00
(215	216)	5.15	7.32	0.00	0.00	0.00	0.00	0.00
(216	217)	5.45	9.24	0.00	0.00	0.00	0.00	0.00
(217	218)	16.33	27.11	0.00	0.00	0.00	0.00	0.00
(218	219)	10.07	14.02	0.00	0.00	0.00	0.00	0.00
(219	220)	8.20	13.59	0.00	0.00	0.00	0.00	0.00
(220	221)	6.73	8.73	0.00	0.00	0.00	0.00	0.00
(221	222)	8.66	13.74	0.00	0.00	0.00	0.00	0.00
(222	223)	20.08	32.47	0.00	0.00	0.00	0.00	0.00
(223	224)	19.45	31.66	0.00	0.00	0.00	0.00	0.00
(224	225)	19.81	29.16	0.00	0.00	0.00	0.00	0.00
(225	226)	9.20	13.06	0.00	0.00	0.00	0.00	0.00
(226	227)	9.78	18.63	0.00	0.00	0.00	0.00	0.00
(227	228)	15.57	22.98	0.00	0.00	0.00	0.00	0.00
(228	7229)	6.81	11.05	0.00	0.00	0.00	0.00	0.00

Figure F-1 Link average fuel consumption of NETSIM vehicle type 5. (BNS)

Figure F-2 Link average fuel consumption of NETSIM vehicle type 1. (BNS)

Figure F-3 Link average fuel consumption of NETSIM vehicle type 5. (BSN)

Figure F-4 Link average fuel consumption of NETSIM vehicle type 5. (BSN)

Figure F-5 Predicted link average fuel consumption. Large ICE vehicle. (BNS)

Figure F-6 Predicted link average fuel consumption. Small ICE vehicle. (BNS)

Figure F-7 Predicted link average fuel consumption. Hybrid ICE vehicle. (BNS)

Figure F-8 Predicted link average fuel consumption. Fuel cell battery vehicle. (BNS)

Figure F-9 Predicted link average fuel consumption. Large ICE vehicle. (BSN)

Figure F-10 Predicted link average fuel consumption. Small ICE vehicle. (BSN)

Figure F-11 Predicted link average fuel consumption. Hybrid ICE vehicle. (BSN)

Figure F-12 Predicted link average fuel consumption. Fuel cell battery vehicle.(BSN)