FUEL ECONOMY OF A HYBRID ELECTRIC VEHICLE WITH SHORT TERM VELOCITY PREDICTIONS : GA BASED APPROACH

A dissertation submitted to the

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degree of Master of Science

by

E.M.C.P. EDIRISINGHE

Supervised by : Dr. Lanka Udawatta

Department of Electrical Engineering

University of Moratuwa, Sri Lanka

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DECLARATION

The work submitted in this dissertation is the result of my own investigation, except where otherwise stated.

It has not already been accepted for any degree, and is also not being concurrently submitted for any other degree.

UOM Verified Signature

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E.M.C.P. Edirisinghe.

Date : 30th January 2009.

I endorse the declaration by the candidate.

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Dr. Lanka Udawatta.

CONTENTS

Abstract

The increasing of fuel price and environmental concerns, researches were pushed to think about more fuel-efficient and less emission vehicles. As a result of this great enthusiasm, researchers were able to introduce Hybrid technology to the field of automobile. In hybrid electric power trains, an internal combustion engine (ICE) together with an electric motor (EM) is used as two energy sources. Use of an electrical motor in place of the ICE during different stages of driving results a definite saving in fuel usage.

Researches did not satisfy with this saving and these endless efforts gave the birth to the concept of intelligent vehicles or telematics – enabled Hybrid Electric Vehicles (HEV). These vehicles may use a sensor network to obtain the information about the degree of traffic flow in the environment which they are operating, and subsequently adjust their drive cycle to get the better improvement in fuel economy based on these information.

In this thesis, a conventional vehicle and a HEV with different amount of traffic flow information are compared in terms of fuel economy over two different drive cycles. First simulation results for conventional vehicle was compared with simulation results for an HEV without traffic flow information and HEV with available of traffic flow information for 4 seconds & 8 seconds ahead of current time, over New European Drive Cycle (NEDC). Thus estimated the same for a Sri Lankan Drive Cycle named Colombo Drive Cycle (CDC) .

Results show that with increase of traffic flow information, the fuel economy of the HEV is increased. Finally two drive cycles were compared and the comparison shows that the improvement in fuel saving is very significant for CDC.

Dedication

I dedicate this dissertation to my loving parents.

Acknowledgement

First I would like to thank Dr. Lanka Udawatta for guiding me successfully in completing this research within the time frame. As the research supervisor, he directed me to find all necessary literature and to do the research work up to the standards.

I would like to extend my heart gratitude to Prof. Saman Halgamuge and Mr.Sunil Adikari, School of Engineering, University of Melbourne, Australia for providing the necessary research materials and information of HEVs for this study.

I should convey my gratitude to all the lectures of Electrical & Mechanical Engineering Departments of University of Moratuwa, who participated for the progress review presentations. Their valuable and fruitful comments helped me a lot to achieve the goals of this work.

Then I would like to convey my sincere thanks to my three colleagues Miss. Thusharie Mundigala, Mr. Sudath Wimalendra & Mr. Sudarshana Karunarathne. They encouraged me in making this task a success from the very beginning second to the very last moment.

My thanks are also due to Mrs. Hiranya Walpola for her kind support and patient in proof reading.

Finally, I would like to thank everyone who supported me even in a single word to complete this research work successfully.

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List of Abbreviations

ADVISOR	ADvanced VehIcle SimulatOR
CDC	Colombo Drive Cycle
DOE	Department of Energy – United States of America
EM	Electric Motor
ESS	Energy Storage System
FC	Fuel Cells
GA	Genetic Algorithm
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IEEE	Institute of Electronic and Electrical Engineers
IGBT	Insulated Gate Bipolar Transistors
NEDC	New European Drive Cycle
NREL	National Renewable Energy Laboratory
SCRAM	Signal Coordination in Regional Areas of Melbourne
SOC	State of Charge (of the battery)
SUS	Stochastic Universal Sampling
UN	United Nations
w.r.t	With Respect To

Chapter 1

Introduction

1.1 Literature Surveyor of Previous Work

Massive number of research papers based on HEV power control strategy and its researches and developments, can be found from the research institutions and the highly recognized web libraries like IEEE online library. Most of the papers that found in my literature surveyor, describe instantaneous splitting of demand power between ICE and EM.

The significance of my literature surveyor is most of the researchers used Fuzzy Logic for power management system of HEV. It is a good method for realizing an optimal tradeoff between the efficiencies of all components of the parallel HEV. Fuzzy logic control is tolerant to imprecise measurements and to component variability. It also gives a systematic methodology for the development of a rule-based energy management strategy [1]-[3].

Neural networks were also used to develop intelligent energy management systems for HEVs [4],[5]. In this, researchers were able to build an intelligent energy management system for the HEV.

But most of the researchers used only the driver demand rather than using traffic flow information for few seconds ahead of current time, to get the optimized power splitting command from their controller. But intelligent vehicle concept can be used to improve the fuel economy [6]. In this concept, HEV energy controller can get the traffic flow information through on board sensors and communication equipment which contact with the road infrastructure.

In my literature surveyor, it was too hard to find a single paper on GA for energy optimization of HEV. But for theoretical studies some researchers used GA for component optimization of HEV's for designing purposes [7],[8]. In general GA takes long time for its optimization process. Therefore it is not practicable to use real – time results needed problems. But this can be tackled using on – line GA [9],[10].

To do the computer simulations, most of them used ADvanced VehIcle SimulatOR (ADVISOR) software package [11}. Simulation based analysis on vehicle performance is crucial to the development of hybrid powertrain since design validation using costly prototype is impractical. Due to the inconvenience of the many separated modeling methods, integrated modeling tools are required to speed up the modeling process and to improve the accuracy. Vehicle simulation is a method for fast and systematic investigations of different design options (fuel choice, battery, transmission, fuel cell, fuel reformer, etc.) in vehicle design and development. At present, several simulation tools based on different modeling platforms are available, although none of them is sufficient to model all design options. These tools always focus on a specific application with focused concerns. After years of continuing improvements, a fast, accurate and flexible simulation tool is still under development. Compared to the available vehicle performance simulation tools, ADVISOR is one of the most user friendly and accurate tool for all kind of researchers.

Commercially available HEVs, some reports related to HEV emissions and performance [11]-[16] were also added into my literature surveyor. In 1970s, many auto makers such as GM, Ford and Toyota started to develop electric vehicles powered by batteries due to the oil shortage. However, these electric vehicles powered solely by battery power did not go far enough. The interest in hydrogen fuel cell cars has arisen as a result to address the range problem associated with battery power cars. However, with more than 15 years of intensive development, still there are no any fuel cell hybrid cars on market mainly due to the high manufacturing cost. In the meantime, other automotive manufacturers have moved in another direction of ICE based HEV. In 1997, Toyota introduced the Prius (Figure 1-2), the first ICE based HEV to the Japanese market. Ever since, an increasing number of HEV have become available. The sales of HEV are growing rapidly. An estimated 187,000 hybrids were sold in the first six months of 2007 in US, accounting for 2.3 percent of all new vehicle sales according to J.D. Power. J.D. Power also forecasted a total sale of 345,000 hybrids for 2007, a 35% increase from 2006 [11].

Genetic algorithm tool box user's guide of MATLAB [17] is a very good tool even for a beginner to learn GA. This was the foundation literature to build all genetic algorithms of this research work. GA assignment given in semester – I, was helped to understand the way that GA used in real world applications.

Finally, my literature surveyor was extended to cover the drive cycles too [19]. These speed – time sequences are used to standardize the evaluation of vehicles fuel economy and emissions. The maximum, minimum and average speeds are considered as the cycle characteristics.

This collection of literatures put forward the basement for this research work.

1.2 Objectives of the Research

As well as the technology changes internal to the vehicle, the telematics revolution of the past decade has generated the possibility for a vehicle to communicate with the road infrastructure and other vehicles to obtain greater information about the traffic environment in which it is operating [6]. Local traffic information can be provided completely on-board the vehicle itself through the use of radar and laser technologies.

To obtain even greater information to the vehicle over a longer look ahead distance it is most likely that some form of communication between the infrastructure and the vehicle is required. Presently, systems such as Signal Coordination in Regional Areas of Melbourne (SCRAM) in Australia obtain information about traffic flows in urban environments automatically to use in scheduling traffic signals, hence it is conceivable that this information could be made available to a suitably equipped vehicle [6].

In this study, my objective is to find out the behavior of the fuel economy when the traffic flow information is available for an HEV. Obviously we cannot get the traffic flow information of the whole drive cycle to the vehicle. Vehicle can get to know about the velocity predictions for few seconds ahead of the operating time. To get the velocity predictions for more and more seconds ahead of the operating time, more sophisticated sensors should be used. This is expensive. Therefore optimum number of prediction should be selected.

The second objective is to observe the variation of the fuel economy with the increasing of number of velocity information for the seconds ahead of the operating time.

Fuel consumption of a conventional vehicle in urban environments is up to 50% higher than during highway driving [6]. It is obvious that the fuel consumption will depend on driving style, road condition, weather conditions..etc. The third and final objective of this research, is to study the variation of the fuel economy of the HEV with those velocity predictions for driving on two deferent drive cycles, NEDC and CDC. Driving on the NEDC can be considered as driving on a road with lesser number of traffic interruptions. But CDC consists of real velocity data captured in traffic time on “Base – Line” road of Sri Lanka.

These studies may be useful for the researchers who are going to develop traffic situation awareness based energy management systems for HEVs. This will guide them to make decisions on selection of the length of predictions. They can measure the value of their research with the project cost against the theoretical saving of fuel usage.

1.3 Hybrid Electric Vehicles

In the past two decades the interest in HEV has increased all over the world mainly due to the environmental concerns and skyrocketing price of oil. Representing a revolutionary change in vehicle design philosophy, hybrid vehicles surfaced in many different ways. However, they share the hybrid powertrain that combines multiple power sources of different nature, including conventional ICE, batteries, ultracapacitors, or hydrogen fuel cells (FC).

These vehicles with onboard energy storage devices and electric drives allows braking power to be recovered and ensures the ICE to operate only in the most efficient mode, thus improving fuel economy and reducing pollutants [11].

Resent surveys of the United Nations (UN) show, over 600 million people in urban area worldwide were exposed to traffic-generated air pollution [11]. Therefore, traffic related air pollution is a vast problem anywhere in the globe. Hybrid electric vehicles hold the potential to considerably reduce greenhouse gas (GHG) emission and other gas pollution.

ICE based hybrids, can improve the fuel economy and reduce tailpipe emission by more efficient engine operation. The improvements come from regenerative braking, shutting down the ICE while stationary and allowing a smaller, more efficient engine which is not required to follow the power at the wheel as closely as the engine in a conventional vehicle must [11].

In an emission effect comparison of the Toyota Prius (HEV) and Toyota Corolla, it was reported that the Prius only produced 71% of CO_2, 4% of CO and 0.5% of NO_x compared with the Toyota Corolla. The Corolla is one of most efficient conventional vehicles on the market [11].

1.4 Intelligent Vehicles

The development in automobile and telematics industry will enable the power management systems to be more intelligent. Hybrid technology and telematics are combined together to create "intelligent vehicle" to make more accurate prediction about the possible speed trend ahead of current time and hence to make more effective decisions about the power split of the two power sources in order to bring the overall fuel economy of the vehicle close to its maximum point.

Telematics - enabled vehicles may use a relatively cheap sensor network to develop information about the traffic environment in which they are operating [6]. Local traffic information can be provided completely on-board the vehicle itself through the use of radar and laser technologies.

To obtain even greater information to the vehicle over a longer look ahead distance it is most likely that some form of communication between the infrastructure and the vehicle is required. Presently, systems such as Signal Coordination in Regional Areas of Melbourne (SCRAM) in Australia obtain information about traffic flows in urban environments automatically to use in scheduling traffic signals, hence it is conceivable that this information could be made available to a suitably equipped vehicle [6].

1.5 ADVISOR Software

The U.S. Department of Energy (DOE) and the National Renewable Energy Laboratory (NREL) have worked with industry partners to develop a sophisticated systems analysis tool that can answer crucial questions about specific component and vehicle designs. ADVISOR is a model written in the widely used MATLAB/Simulink software environment. It can be used to simulate and analyze conventional, advanced, light and heavy vehicles, HEVs and fuel cell vehicles [20].

ADVISOR tests the effect of changes in vehicle components (such as motors, batteries, catalytic converters, climate control systems, and alternative fuels) or other modifications that might affect fuel economy, performance, or emissions. The user can alter simulation results by selecting vehicle component types, sizes, and parameters.

ADVISOR uses basic physics calculations and measured component performance to model conceptual vehicles. The user defines a vehicle using overall vehicle data and prescribes a speed-versus-time trace, along with road grade, that the vehicle must follow. ADVISOR then puts the vehicle through its paces, making sure it meets the cycle to the best of its ability. It calculates predicted torque, speed, voltage, current, and power passed from one component to another.

Chapter 2

HEV Classifications

There are many ways to classify HEVs. One of the most common ways to classify HEV is based on configuration of the vehicle drivetrain. Based on this, three major hybrid vehicle architectures introduced are parallel, series and series-parallel (Dual) HEVs.

2.1 Parallel HEVs

In parallel configurations, both the engine and the motor provide traction power to the wheels, which means that the hybrid power is summed at a mechanical node to power the vehicle. As a result, both the engine and the motors can be downsized, making the parallel architecture more viable with lower costs and higher efficiency [11],[12].

The parallel HEVs usually use the same gearboxes of the counterpart conventional vehicles, either in automatic or manual transmissions. Based on where the gearbox is introduced in the powertrain, there are two typical parallel HEV architectures, named pre-transmission parallel and post-transmission parallel, as shown in Figure 2.1 and Figure 2.2, respectively.

In a pre-transmission parallel HEV, the gearbox is located on the main drive shaft after the torque coupler. Hence, gear speed ratios apply on both the engine and the electric motor. The power flow is summed at the gearbox.

On the other hand, in a post-transmission parallel hybrid, the gearbox is located on the engine shaft prior to the torque coupler. The gearbox speed ratios only apply on the engine.

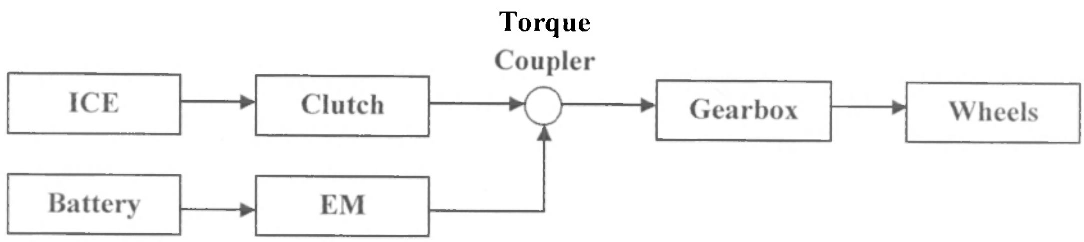


Figure 2.1 : Block Diagram of Pre – Transmission Parallel HEV

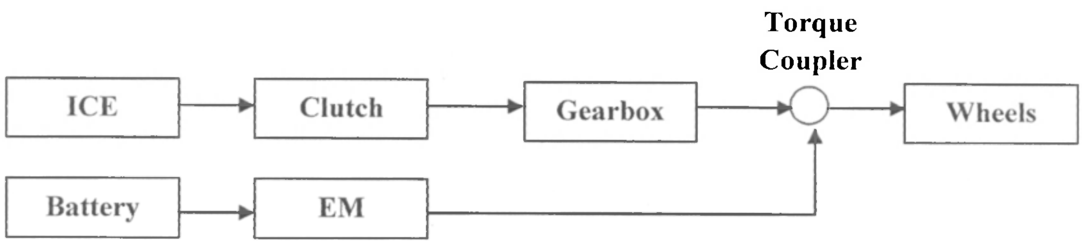


Figure 2.2 : Block Diagram of Post – Transmission Parallel HEV

In a pre-transmission configuration, torque from the motor is added to the torque from the engine at the input shaft of the gearbox. In a post-transmission, the torque from the motor is added to the torque from the engine delivered on the output shaft of the gearbox. A disconnect device such as a clutch is used to disengage the gearbox while running the motor independently.

There are attempts from different perspectives to improve the operation of a parallel HEV. One possibility is to run the vehicle on electric machine alone in city driving while running engine power alone on highways. Most contemporary parallel vehicles use a complex control system and special algorithms to optimize both vehicle performance and range.

One unique implementation of the parallel hybrid technology is on an all wheel drive vehicle as shown in Figure 2.3. The design is most beneficial if the ICE powers the rear wheels while the electric motor powers the front wheels. The more weight borne by the front wheels during braking will result in more power captured during regenerative braking. The design is also effective on slippery surfaces by providing vehicle longitudinal stability control that is not as easy with other types of hybrid designs. The power to each axle is manipulated by a single controller, although this requires a fast data communication.

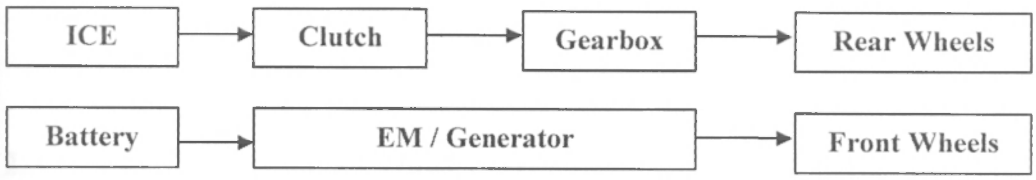


Figure 2.3 : Block Diagram of all wheel drive Parallel HEV

The flexibility in powertrain design, in addition to the elimination of the need for a large motor, of parallel hybrids has attracted more interest in HEV development than the series hybrids.

2.2 Series HEVs

One of the basic types of HEVs is series hybrid. In this configuration, as shown in Figure 2.4, the ICE is used to generate electricity in a generator. Electric power produced by the generator goes to either the motor or Battery. The hybrid power is summed at an electrical node, the motor [11],[12].

Despite the early research and prototypes, the possibility for series hybrids to be commonly used in vehicular applications seems to be remote. The series hybrid configuration tends to have a high efficiency at its engine operation. However, the summed electrical mode has tied up the size of every component. The weight and cost of the vehicle is increased due to the large size of the engine and the two electric machines needed. The size of the power electronic unit is also excessive.

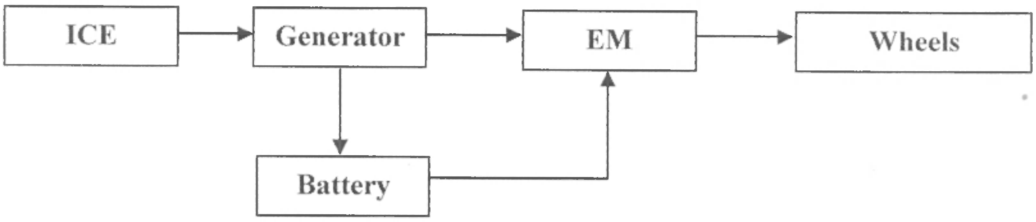


Figure 2.4 : Block Diagram Series HEV

2.3 Parallel - Series (Dual) HEVs

This system combines the series hybrid system with the parallel hybrid system in order to maximize the benefits of both systems [11],[12]. In the series-parallel configurations, the vehicle can be operated as a series hybrid, a parallel hybrid, or a combination of both. This design depends on the presence of two motors/generators and the connections between them, which can be both electrical and mechanical. One advantage of a series-parallel configuration is that the engine speed can be decoupled from the vehicle speed. This advantage is partially offset by the additional losses in the conversion between mechanical power from engine and electrical energy.

Table 2.1 : Comparison of Hybrid Systems (Toyota Hybrid System – THS II ,[12]).

Hybrid System Comparison						
	Fuel Economy Improvement				Driving Performance	
	Idling Stop	Energy Recovery	High – Efficiency Operation Control	Total Efficiency	Acceleration	Continues High Output
Series	Δ	★	Δ	Δ	⌖	⌖
Parallel	Δ	Δ	⌖	Δ	Δ	⌖
Dual	★	★	★	★	Δ	Δ

★ - Excellent Δ - Superior ⌖ - Somewhat unfavorable

2.4 Basic HEV Components

Following additional components w.r.t conventional vehicals, can be found in HEVs.

2.4.1 Electric Motor

The heart of a Hybrid system can be considered as the Electric propulsion system. Recently, technological developments have pushed EMs to a new era, leading to advantages of higher efficiency, higher power density, lower operating cost, more reliability, and lower maintenance. Motors for HEVs can be induction motors, permanent magnet (PM) motors, or switched reluctance motors. Induction motors and PM motors are the most prominent for HEV applications [25].

Although a PM motor is desirable for a HEV, its high cost for large rare earth magnets is a deterrent [25].

The advanced technology IGBT (Insulated Gate Bipolar Transistors) based motor controller is actually a bidirectional converter/inverter, which means it is multifunction — during normal operation it provides AC power to the motor from the batteries DC voltage, while during regenerative braking it acts as charge converter to convert AC to DC, so that the batteries can be recharged.

2.4.2 Energy Storage System (ESS)

The performance, life cycle, and safety of HEVs strongly depend on the vehicle's ESS. Based on modern technologies, chemical batteries predominate in HEVs as energy storage. Ultracapacitors and flywheel systems have not replaced batteries because batteries offer mature technology, easy maintenance, high energy density and low cost [26]. Commercial batteries in the market for the HEV include Lead–Acid, NiCd, NiMH, and Li–ion types. Some of their important parameters are compared in Table 2.2 [26].

Table 2.2 : Comparison of Batteries

	Lead–Acid	NiCd	NiMH	Li–ion
Specific Energy (Wh/kg)	~30	40–60	60–70	90–130
Energy Density (Wh/dm3)	~90	80–110	130–170	220–260
Specific Power (W/kg)	~200	150–350	150–300	250–450
Cycle Lifeb (Cycles)	~200	600–1200	600–1200	800–1200
Toxic Materials	Yes	Yes	No	No
Maintenance	Yes	Yes	No	No
Individual Cell Voltage (V)	2	1.25	1.25	3.6
Self Discharge (per month)	NA	20%	30%	10%

On the basis of the above comparison, the nickel metal hybrid (NiMH) or lithium ion (Li–ion) batteries are preferred to traditional lead–acid and nickel cadmium (NiCd) batteries for reasons of energy density, power density, and power output at low state of charge. NiMH and Li–ion batteries are able to accept the high peak power levels associated with regenerative braking and are easier to package in the vehicle. Currently, Li–ion batteries are more expensive than NiMH batteries. In addition, NiMH batteries are more desirable from the standpoint of their inherent internal charge balancing and low temperature performance [26].

In sizing the battery for an HEV, the required peak power of the battery is of great concern. It must be able to handle regenerative braking and peak power demands from the traction motor. A higher voltage battery pack can lower the power consumption of wires, connectors and loads due to the lower current required.

2.4.3 Power Splitter

A power controller is needed to manage the flow of energy between all components, while taking the energy available in the battery into account. The power controller adds the capability for the components to work together in harmony, while at the same time optimizes the operating points of the individual components. This is clearly an added complexity which is not found in conventional vehicles.

In particular, management of energy and distribution of torque (power) are two of the key issues in the development of hybrid electric vehicles. These issues can be summarily stated as follows.

- How to meet the driver's torque demand while achieving satisfactory fuel consumption and emissions.

- How to maintain the battery state of charge (SOC) at a satisfactory level to enable effective delivery of torque to the vehicle over a wide range of driving situations.

In order to achieve these goals, it is very important to optimize the architecture and components of the hybrid vehicle, but as important is the energy management strategy that is used to control the complete system. The energy management strategy is implemented by a power controller. It controls the energy flow between all components, and optimizes power generation and conversion in the individual components.

2.5 Characteristics of Hybrid Systems

Hybrid systems possess the following characteristics:

i. **Energy Loss Reduction**

   The system automatically stops the idling of the engine (idling stop), thus reducing the energy that would normally be wasted.

ii. **Energy Recovery and Reuse**

The energy that would normally wastes as heat during deceleration and braking is recovered as electrical energy, which is then used to power the starter and the electric motor.

iii. **Motor Assist**

The electric motor assists the engine during acceleration.

iv. **High efficiency operation control**

The system maximizes the vehicle's overall efficiency by using the electric motor to run the vehicle under operating conditions in which the engine's efficiency is low and by generating electricity under operating conditions in which the engine's efficiency is high.

2.6 Advantages & Disadvantages of HEVs

Following advantages can be identified for HEVs,

- Decreasing of fuel consumption and of exhaust emissions
- Possibility of braking energy regeneration
- Possibility of using ICE in the hybrid vehicles with decreased volume preserving dynamic characteristics
- Possibility of simple organization of all wheels drive using hub motors

The disadvantages of hybrid drive are:

- Rise in the cost of vehicle
- Complexity of recovered energy estimation

Chapter 3

Drive Cycles

Drive cycles are defined as the test cycles used to standardize the evaluation of vehicles fuel economy and emissions. Driving cycles are speed-time sequences that represent the traffic conditions and driving behaviour in a specific area. Driving patterns may vary from city to city and from area to area. Therefore the use of available driving cycles obtained for certain cities or countries are not necessarily applicable for other cities [8].

A driving cycle consists of a mixture of driving modes including idling, cruise, acceleration and deceleration. The maximum, minimum and average speeds are also considered as the cycle characteristics.

There are many developed drive cycles to utilize in above purposes. Basically two major categories of drive cycles can be identified. They are,

- Transient Drive cycles and
- Model drive cycles

Transient drive cycles

Test drive cycles are derived by collecting actual data in the real world. Those are very realistic and taken using a real vehicle in actual conditions and data recorded in a live environment with actual disturbances. Those drive cycles are considered as very effective when using for simulation of certification activities. Most of the US based drive cycles are transient drive cycles.

Model drive cycles

Model drive cycles are the cycles which derived by mathematical modeling with the help of statistics. In those drive cycles they have included some conditions where it is difficult to achieve in real world such as maximum speed and operate in a constant speed over time duration. Most of the European standard drive cycles and Japanese drive cycles belong to this category.

3.1 New European Drive Cycle (NEDC)

This is a model drive cycle shown in figure 3.1. it's X – axis represents the time in seconds and Y – axis represents the velocity of the vehicle in meters per second. From 0^{th} second to the 800^{th} second represents urban drive and the remain is extra urban drive.

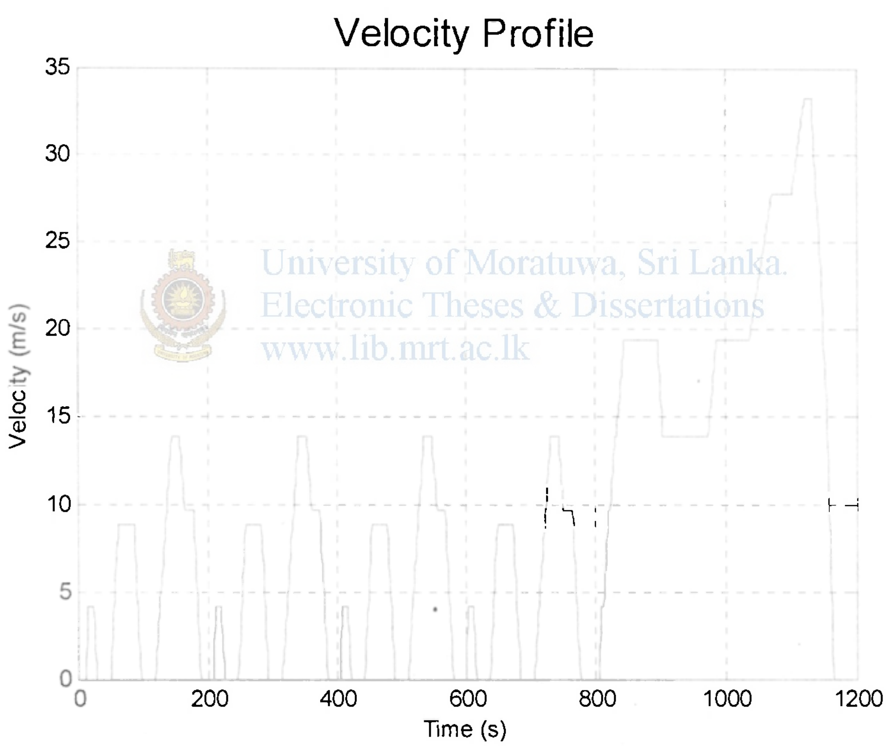


Figure 3.1 : NEDC

The NEDC is the basis for the homologation of cars. As for the EcoTest one specific car is measured the results of the NEDC measurement are compared with the homologation values to ensure the indisputable condition of the vehicle [24].

3.2 Colombo Drive Cycle (CDC)

A recent drive cycle is also developed for the city of Colombo based on the experimental data collected from the real traffic conditions on Base – Line road of'Sri Lanka. This drive cycle is named as CDC and is shown in Figure 3.2. it's axis are same as in the figure 3.1.

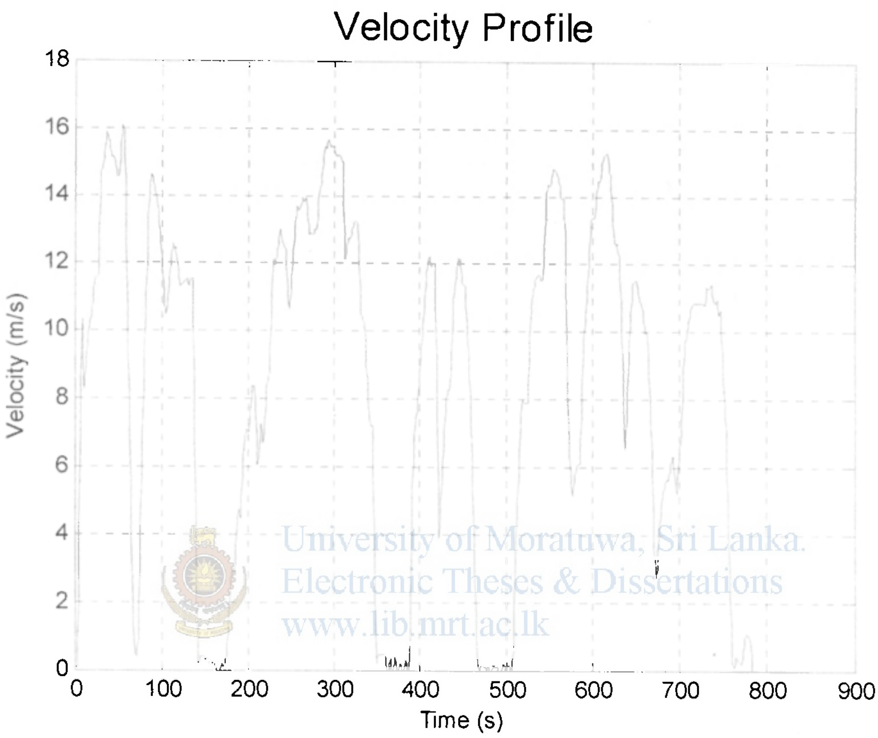


Figure 3.2 : CDC

There are lots of breakings and accelerations in this drive cycle. This shows the real traffic image of roads in Sri Lanka's capital, Colombo.

This Drive Cycle was formulated very recently, after extensive road tests by the Department of Electrical Engineering, University of Moratuwa, as a part of this post graduate research project on HEV. This in fact fulfilled the need of drive cycle to represent the total effects of the road infrastructure, traffic pattern and driving culture in Sri Lanka.

Chapter 4

HEV Model used for Simulations

4.1 Specifications of the Selected HEV

Table 4.1 : Specifications of the selected HEV

Parameter	Value
Total weight	1642 kg
Chassis weight	1000 kg
Frontal area	1.92 m^2
Coefficient of Drag	0.32
Vehicle length	5.00 m
Transmission	Manual, 5 speed
Transmission efficiency	95% (constant throughout all gears)
Gear ratios	3.5:2.14:1.39:1:0.78
Final drive ratio	3.98
Gear changes	1 → 2 and 2 → 1 @ 24 km/h
	2 → 3 and 3 → 2 @ 40 km/h
	3 → 4 and 4 → 3 @ 64 km/h
	4 → 5 and 5 → 4 @ 75 km/h
Motor/Generator	Permanent Magnet Motor, 20kW continuous, 40kW peak
Battery	Advanced Battery, 40kW, 4kWh, 100V

The coefficient of rolling resistance is experimentally obtained. It is a function of many factors including the deformation of the tire, weight of the vehicle, tire pressure, roughness of the surface and radius of the wheel. It is the ratio of the rolling resistance force to the load on the tires. It was fairly constant for a given tire and road surface.

In the aerodynamic drag term, the drag coefficient is a dimensionless constant that attempted to capture the resistance caused by the relative motion of the vehicle and the air. This can vary from as high as 1.2 for a bicycle with an erect rider to 0.7 for a truck, and to 0.20 for a very aerodynamically styled sport car. Although the equation used to determine the drag power was a simplification, it avoided complex airflow simulation while preserved the general behaviors of the drag force w.r.t velocity

4.2 Calculation of required power

Aerodynamic equations are used to calculate the instantaneous power demand, Symbolic format of the calculations is presented below [11].

Let,	m	= Total mass of the vehicle (kg)
	C_d	= Drag coefficient
	A	= Frontal Area (m^2)
	C_{rr}	= Coefficient of rolling resistance
	g	= Acceleration of Gravity (ms^{-2})
	ρ	= Air density (kgm^{-3})
	θ	= Horizontal slop of the road
	V	= Mean velocity of the vehicle (ms^{-1})
	a	= Acceleration of the vehicle (ms^{-2})

Calculation of V & a from the velocity input is carried out as follows,

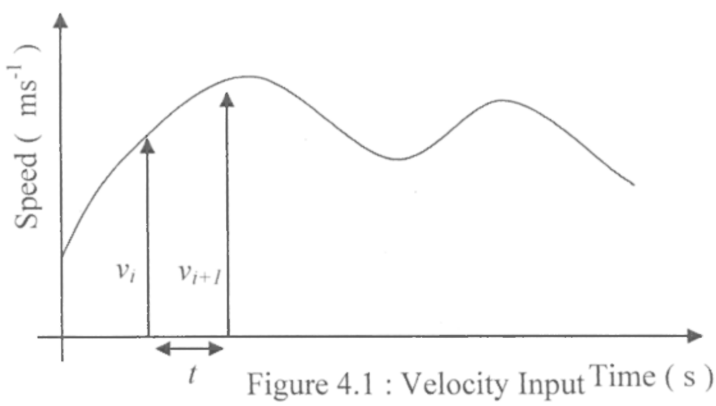


Figure 4.1 : Velocity Input

Where, t is the sample time and this is taken as 1 second for my simulations.

$$V = (v_{i+1} + v_i) / 2 \qquad (4.1)$$

$$a = (v_{i+1} - v_i) / t \qquad (4.2)$$

But $t = 1$,

Therefore, $a = (v_{i+1} - v_i)$ $\qquad (4.3)$

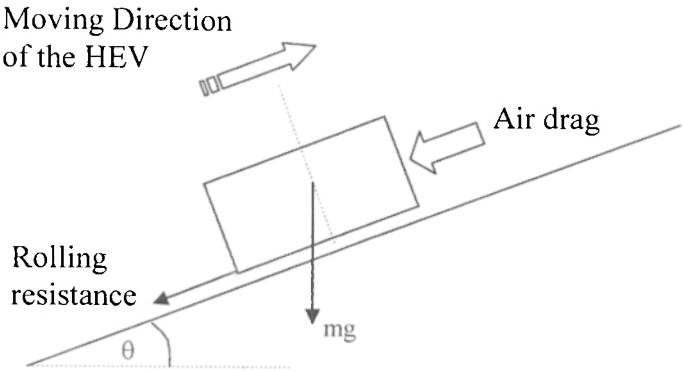


Figure 4.2 : HEV on the Road

Power demand against Air Drag,

$$\text{airDragP} = \tfrac{1}{2} (\rho . C_d . A . V^3) \qquad (4.4)$$

Power demand against Rolling resistance,

$$\text{rollDragP} = C_{rr} . m . g . \text{Cos}(\theta) . V \qquad (4.5)$$

Power demand against Acceleration,

$$\text{accelP} = m . a . V \qquad (4.6)$$

Power demand against weight due to road slope,

$$\text{hillP} = m . g . \text{Sin} (\theta) . V \qquad (4.7)$$

Total Instantaneous Power Demand at Wheels,

$$P_d = \text{airDragP} + \text{rollDragP} + \text{accelP} + \text{hillP} \qquad (4.8)$$

This research carried out simulations for a flat road. Therefore $\theta = 0$.

So, hillP = 0 and

$rollDragP \quad = C_{rr} . m . g. V$

This is the basic equation used to calculate the power demand for each second. Velocity is the input variable for the equation & output is the power demand.
This power demand is supplied by the combination of ICE and EM.

Let, P_{GB} = Power demand at Gearbox

P_{ICE} = Power contribution from ICE

P_{EM} = Power contribution from EM

η_{GB} = Efficiency of the Gearbox

$$P_{GB} = P_d / \eta_{GB} \quad (4.9)$$

$$P_{GB} = P_{ICE} + P_{EM} \quad (4.10)$$

When EM acts as a generator, the power contribution of EM is considered as $-P_{EM}$.

When calculated the power demand at the wheels, Wheel speed, ω_w (in rad/s) and the Wheel Torque (T_w) can be calculated as follows.

$$\omega_w = V / R_w \quad (4.11)$$

$$T_w = Pd / \omega_w \quad (4.12)$$

Where, R_w is the wheel radius.
If the final drive ratio is R_{fd}, speed and torque before the final drive (ω_{GB}, T_{GB}) can be calculated as follows.

$$\omega_{GB} = \omega_w \times R_{fd} \quad (4.13)$$

$$T_{GB} = T_w / R_{fd} \quad (4.14)$$

Speed before gearbox and torque before gearbox (ω and T) can be calculated by taking the gear ratio corresponding to the vehicle speed as GR_i, as follows.

$$\omega = \omega_{GB} \times GR_i \quad (4.15)$$

$$T = T_{GB} / GR_i \quad (4.16)$$

4.3 Engine Model

In my ICE model, real data of commercially available 1500 cc engine was used. To find out the fuel rate, set of fuel rates available for selected engine speeds & engine torques.

$$[\text{ Engine Speed }] = [\ \omega_1\ \ \omega_2\ \ \omega_3\ \ \omega_4 \ldots\ldots\ \omega_i \ldots\ldots\ \omega_n\ ] \qquad ; \text{in rad/s}$$

$$[\text{ Engine Torque }] = [\ T_1\ \ T_2\ \ T_3\ \ T_4 \ldots\ldots T_j \ldots\ldots T_n\ ] \qquad ; \text{in Nm}$$

$$[\text{ Fuel Rate }] = \begin{pmatrix} F_{11} & F_{12} & F_{13} & F_{14} \ldots\ldots\ldots\ldots\ldots & F_{1n} \\ F_{21} & F_{22} & F_{23} & F_{24} \ldots\ldots\ldots\ldots\ldots & F_{2n} \\ \ldots & \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots\ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots\ldots & \ldots \\ F_{i1} & F_{i2} & F_{i3} & F_{i4} \ldots\ldots\ F_{ij} \ldots\ldots & F_{in} \\ \ldots & \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots\ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots\ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots\ldots\ldots\ldots\ldots\ldots & \ldots \\ F_{n1} & F_{n2} & F_{n3} & F_{n4} \ldots\ldots\ldots\ldots\ldots & F_{nn} \end{pmatrix} \qquad ; \text{in ml/s}$$

Where, F_{ij} = Fuel rate at Speed ω_i and Torque T_j.

To find out fuel rates for any speed and torque, 2 – Dimensional (2-D) interpolation (table lookup) method of MATLAB was used.
Based on the fuel rate, engine efficiency was calculated for each operating second.

Let , P_{in-ij} = Input power to the engine (W) at Speed ω_i and Torque T_j.

P_{out-ij} = Output power from the engine (W) at Speed ω_i and Torque T_j.

η_{ij} = Engine efficiency at Speed ω_i and Torque T_j.

ρ = Density of the fuel (g/ml)

H = Calorific value of the fuel (J/g)

$$P_{in-ij} = F_{ij} \cdot \rho \cdot H \qquad (4.17)$$

$$P_{out-ij} = T_j \cdot \omega_i \qquad (4.18)$$

$$\eta_{ij} = eq^{\underline{n}}\, 4.18 \div eq^{\underline{n}}\, 4.17$$

$$\eta_{ij} = \frac{\mathbf{T_j \cdot \omega_i}}{\mathbf{F_{ij} \cdot \rho \cdot H}} \qquad (4.19)$$

Figure 4.3 shows the fuel rate variation of the ICE with engine torque and engine speed. it's X – axis is the speed in radians per seconds. Y – axis is the engine torque in newton meters. Z – axis is the fuel rate in grams per seconds. Region bounded by speed 200 rad/s to 400 rad/s and torque 20 Nm to 80 Nm, shows lower fuel rate. As this is the maximum efficient region of the ICE.

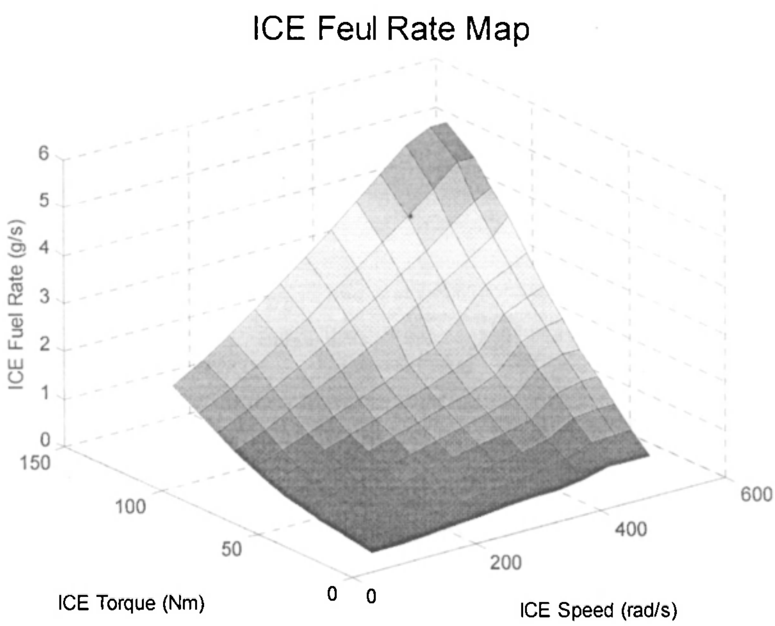


Figure 4.3 : Engine Fuel Rate Map

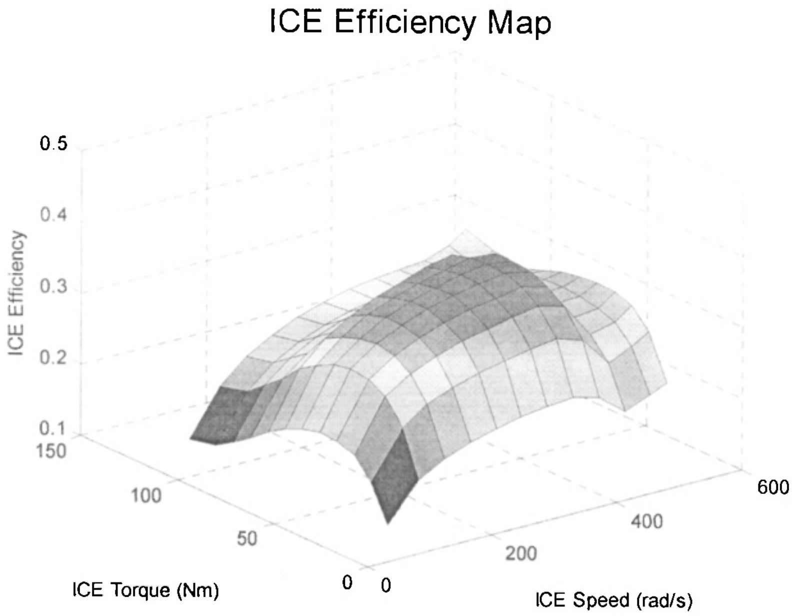


Figure 4.4 : Engine Efficiency Map

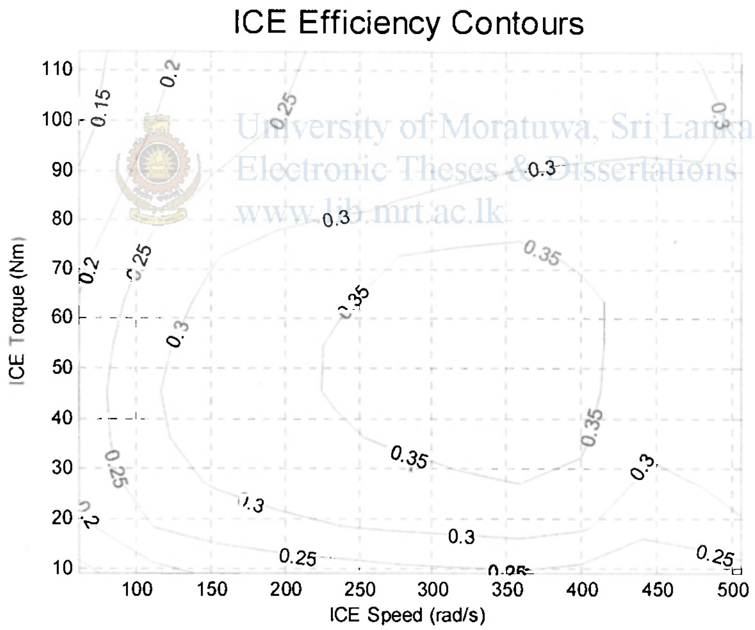


Figure 4.5 : Engine Efficiency Contours

Figure 4.4 and Figure 4.5 illustrate the efficiency variation of the ICE with torque and speed. Figure 4.4 is the 3 – dimensional (3D) map and the Figure 4.5 is the contour mode or 2 – dimensional (2D) map. As a typical petrol engine, the maximum efficiency is about 36%. This can be achieved in the speed range of 250 rad/s to 425 rad/s while the torque is in the rage of 25 Nm to 75 Nm.

4.3.1 Operating Regions

In this research, three major regions of ICE operations were identified. Following figure illustrates the operation modes.

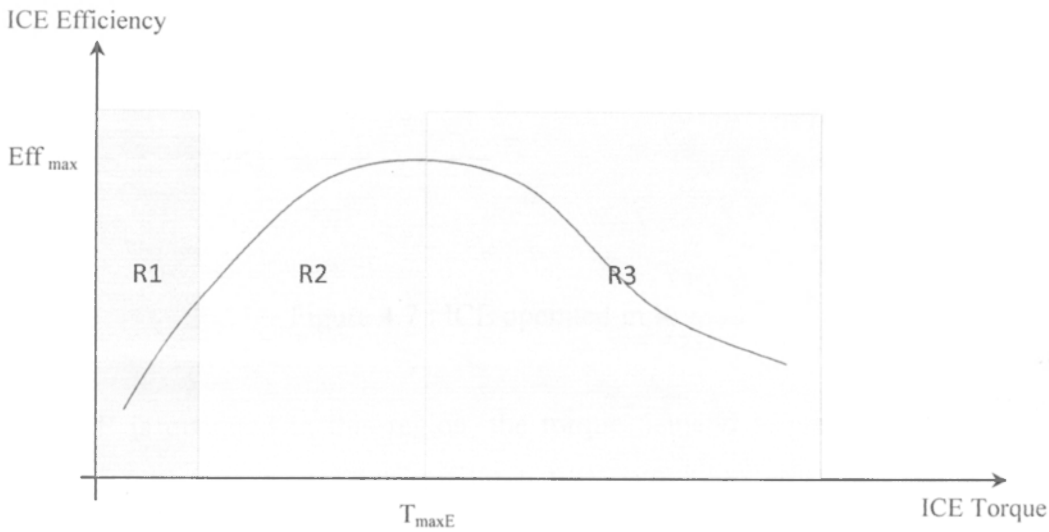


Figure 4.6 : Shape of the efficiency variation curve with torque for any speed

Let , Eff_{max} = Maximum efficiency

T_{maxE} = Torque at maximum efficiency

T_d = Torque demand

Region 1 (R1) :

This is the most inefficient region of ICE. In my ICE this belongs to 6 kW power demand operations and when the engine is operated in this region, the efficiency is around 20%. The most economical way is, the use of EM as much as possible while the ICE is at rest.

Region 3 (R3) : $T_d > T_{maxE}$

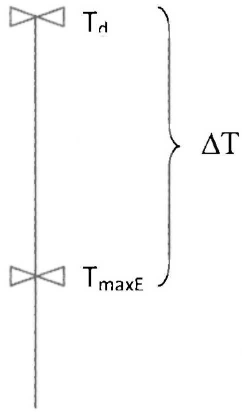


Figure 4.7 : ICE operated in Region 3

When ICE is operated in this region, the torque demand is greater than T_{maxE}. To operate the ICE at its most efficient point, balance ΔT can be given by the EM.

Region 2 (R2) : $T_d < T_{maxE}$

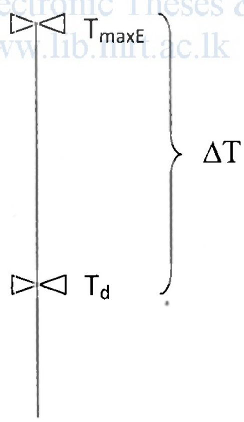


Figure 4.8 : ICE operated in Region 2

This is the most significant operating region of an HEV. In this region, the torque demand is less than T_{maxE}. Several combinations of ICE and EM can be employed in this region. The most important combination is, ICE operates at T_{maxE} and excess ΔT can be used to charge the batteries. But to do that, additional amount of fuel should be burnt. This additional fuel usage should be recovered with a profit, during the journey.

Therefore this decision is the most critical decision which an HEV control system should make.

4.4 Battery Model

In this research, the charging and discharging efficiency of the battery is considered as 90% and constant throughout the operation. To secure the battery life time, range for state of charge (SOC) of the battery should be 30% to 90% [1].

Let, ΔSOC = change of SOC

P_{EM} = EM power in kW

Q_B = Battery capacity in kJ or kWs

η_B = Battery efficiency

η_{EM} = EM efficiency.

SOC_B = SOC at the beginning of the sample time

SOC_E = SOC at the end of the sample time

The SOC variation at the end of sampling period is given by;

For motoring mode,

$$\Delta SOC = \left(\frac{P_{EM}}{\eta_{EM} \times \eta_B} \right) / Q_B \qquad (4.20)$$

For generator mode,

$$\Delta SOC = \left(P_{EM} \times \eta_{EM} \times \eta_B \right) / Q_E \qquad (4.21)$$

In this mode $P_{EM} < 0$,

For both modes,

$$SOC_E = SOC_B - \Delta SOC \qquad (4.22)$$

Chapter 5

Genetic Algorithms

5.1 Basics of GA

The GA, first formulated by Prof. John Holland at the University of Michigan in 1975 [8] and is a stochastic global search method that mimics the metaphor of natural biological evolution. GA usually operates offline in the sense that they can be seen as building a simulated application environment in which they evolve and select the best solution among all the generations, under the well known Darwinian principle of "survival of the fittest" [9].

Much has been learned about genetics since the time of Charles Darwin. All information required for the creation of appearance and behavioral features of a living organism is contained in its chromosomes. Reproduction generally involves two parents, and the chromosomes of the offspring are generated from portions of chromosomes taken from the parents. In this way, the offspring inherit a combination of characteristics from their parents.

GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation [17].

GAs work with a population of "individuals"; each representing a possible solution to a given problem. Each individual is assigned a "fitness value" according to how good a solution to the problem is. The highly-fit individuals are given opportunities to "reproduce", by "cross breeding" with other individuals in the population. This produces new individuals as "offspring", which share some features taken from each "parent". The least fit members of the population are less likely to get selected for reproduction, and so "die out". A whole new population of possible solutions is thus produced by selecting the best individuals from the current "generation", and mating them to produce a new set of individuals. This new generation contains a higher proportion of the characteristics possessed by the good members of the previous generation. In this way, over many generations, good characteristics are spread throughout the population. By favoring the mating of the more fit individuals, the most promising areas of the search space are explored. If the GA has been designed well, the population will converge to an optimal solution to the problem

The evaluation function, or objective function, provides a measure of performance with respect to a particular set of parameters. The fitness function transforms that measure of performance into an allocation of reproductive opportunities. The evaluation of a string representing a set of parameters is independent of the evaluation of any other string. The fitness of that string, however, is always defined with respect to other members of the current population. In GA, fitness is defined by, f_i/f_{Avg} where f_i is the evaluation associated with string i and f_{Avg} is the average evaluation of all the strings in the population.

Fitness can also be assigned based on a string's rank in the population or by sampling methods. The execution of GA is a two-stage process. It starts with the current population. Selection is applied to the current population to create an intermediate population. Then recombination and mutation are applied to the intermediate population to create the next population. The process of going from the current population to the next population constitutes one generation in the execution of a genetic algorithm.

The structure of a GA is composed by an iterative procedure through the following five main steps:

- creating an initial population P_0
- evaluation of the performance of each individual p_i of the population, by means of a fitness function
- selection of individuals and reproduction of a new population
- application of genetic operators: crossover and mutation and
- iteration of steps 2–4 until a termination criterion is fulfilled.

Above steps can be illustrated by the following flow chart.

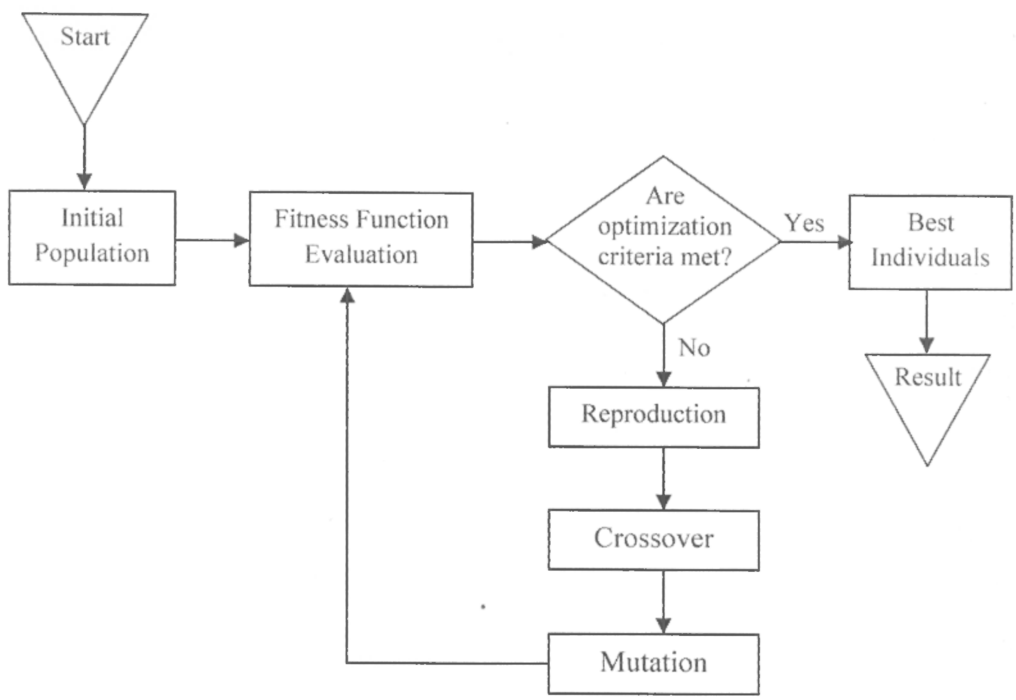


Figure 5.1 : Evolutionary algorithm mechanism

5.1.1 Individuals

Individuals, or current approximations, are encoded as strings, chromosomes, composed over some alphabet(s), so that the genotypes (chromosome values) are uniquely mapped onto the decision variable (phenotypic) domain. The most commonly used representation in GAs is the binary alphabet {0, 1} although other representations can be used, e.g. ternary, integer, real-valued etc.

5.1.2 Population

GAs operate on a number of potential solutions, called a population, consisting of some encoding of the parameter set simultaneously. Typically, a population is composed of between 30 and 100 individuals, although, a variant called the micro GA uses very small populations, ~10 individuals, with a restrictive reproduction and replacement strategy in an attempt to reach real-time execution.

5.1.3 Objective and Fitness Functions

The objective function is used to provide a measure of how individuals have performed in the problem domain. In the case of a minimization problem, the most fit individuals will have the lowest numerical value of the associated objective function. This raw measure of fitness is usually only used as an intermediate stage in determining the relative performance of individuals in a GA. Another function, the fitness function, is normally used to transform the objective function value into a measure of relative fitness.

5.1.4 Selection

Selection is the process of determining the number of times, or trials, a particular individual is chosen for reproduction and, thus, the number of offspring that an individual will produce.

There are two major methods of selection. They are, Roulette Wheel Selection Method and Stochastic Universal Sampling.

5.1.4.1 Roulette Wheel Selection

Many selection techniques employ a "roulette wheel" mechanism to probabilistically select individuals based on some measure of their performance. A real-valued interval, *Sum*, is determined as either the sum of the individuals' expected selection probabilities or the sum of the raw fitness values over all the individuals in the current population. Individuals are then mapped one-to-one into contiguous intervals in the range [0, *Sum*]. The size of each individual interval corresponds to the fitness value of the associated individual. For example, in Figure 5.2, the circumference of the roulette wheel is the sum of all six individual's fitness values. Individual 5 is the most fit individual and occupies the largest interval, whereas individuals 6 and 4 are the least fit and have correspondingly smaller intervals within the roulette wheel. To select an individual, a random number is generated in the interval [0, *Sum*] and the individual whose segment spans the random number is selected. This process is repeated until the desired number of individuals have been selected.

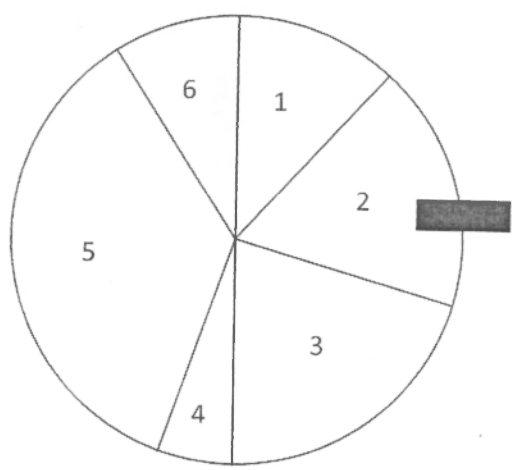


Figure 5.2 : Roulette Wheel Selection

5.1.4.2 Stochastic Universal Sampling

Stochastic universal sampling (SUS) is a single-phase sampling algorithm with minimum spread and zero bias. Instead of the single selection pointer employed in roulette wheel methods, SUS uses N equally spaced pointers, where N is the number of selections required (See Figure 5.3).

The population is shuffled randomly and a single random number in the range [0 Sum/N] is generated, *ptr*. The N individuals are then chosen by generating the N pointers spaced by 1, [*ptr*, *ptr*+1, ..., *ptr*+N-1], and selecting the individuals whose fitnesses span the positions of the pointers. As individuals are selected entirely on their position in the population, SUS has zero bias.

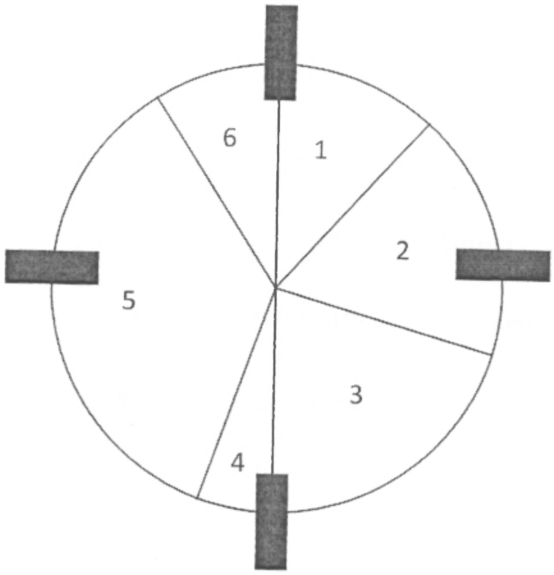


Figure 5.3 : Stochastic Universal Sampling

5.1.5 Crossover (Recombination)

The basic operator for producing new chromosomes in the GA is that of crossover. Like its counterpart in nature, crossover produces new individuals that have some parts of both parent's genetic material.

Once two chromosomes are selected, the crossover operator is used to generate two offspring. In one - point crossover, one chromosome positions are randomly selected between one and (L−1), where L is the chromosome length and the two parents are crossed at this point.

For example, in one-point crossover, the first child is identical to the first parent up to the crossing point and identical to the second parent after the crossing point. An example of one-point crossover is shown in Fig. 5.4. In uniform crossover, each chromosome position is crossed with some probability, typically one-half

Crossover point

Parent 1: ***110001011*** ¦ ***110010100***

Parent 2: **010010110** ¦ **100011001**

Offspring 1: ***110001011*** ¦ **100011001**

Offspring 2: **010010110** ¦ ***110010100***

Figure 5.4 : One-point crossover

For multi-point crossover, m crossover positions, , where $k_i \in \{1,2,....l-1\}$ are the crossover points and l is the length of the chromosome, are chosen at random with no duplicates and sorted into ascending order. Then, the bits between successive crossover points are exchanged between the two parents to produce two new offspring. The section between the first allele position and the first crossover point is not exchanged between individuals. This process is illustrated in Figure 5.5.

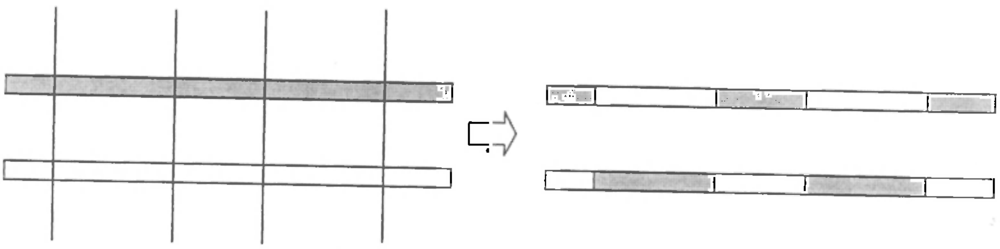


Figure 5.5: Multi-point crossover, m=4

The amount of crossover is controlled by the crossover probability, which is defined as the ratio of the number of offspring produced in each generation to the population size. A higher crossover probability allows exploration of more of the solution space and reduces the chances of settling for a false optimum. A lower crossover probability enables exploitation of existing individuals in the population that have relatively high fitness.

5.1.6 Mutation

In natural evolution, mutation is a random process where one allele of a gene is replaced by another to produce a new genetic structure. In GAs, mutation is randomly applied with low probability, typically in the range 0.001 and 0.01, and modifies elements in the chromosomes.

Usually considered as a background operator, the role of mutation is often seen as providing a guarantee that the probability of searching any given string will never be zero and acting as a safety net to recover good genetic material that may be lost through the action of selection and crossover.

In the GA, mutation serves the crucial role of replacing the gene values lost from the population during the selection process so that they can be tried in a new context, or of providing the gene values that were not present in the initial population.

Before Mutation: $1\ 1\ 0\ \boxed{1}\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1$

After Mutation: $1\ 1\ 0\ \boxed{0}\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1$

Figure 5.6 : Mutation Operator

For example, say a particular bit position, bit 10, has the same value, say 0, for all individuals in the population. In such a case, crossover alone will not help, because it is only an inheritance mechanism for existing gene values. That is, crossover cannot create an individual with a value of 1 for bit 10, since it is 0 in all parents. If a value of 0 for bit 10 turns out to be suboptimal, then, without the mutation operator, the algorithm will have no chance of finding the best solution. The mutation operator, by producing random changes, provides a small probability that a 1 will be reintroduced in bit 10 of some chromosome. If this results in an improvement in fitness, then the selection algorithm will multiply this chromosome, and the crossover operator will distribute the 1 to other offspring. Thus, mutation makes the entire search space reachable, despite a finite population size. Although the crossover operator is the most efficient search mechanism, by itself, it does not guarantee the reachability of the entire search space with a finite population size. Mutation fills in this gap.

The probability of mutation is defined as the probability of mutating each gene. It controls the rate at which new gene values are introduced into the population. If it is too low, many gene values that would have been useful are never tried out. If it is too high, too much random perturbation will occur, and the offspring will lose their resemblance to the parents. The ability of the algorithm to learn from the history of the search will therefore be lost.

5.1.7 Termination of the GA

Thus the GA is a stochastic search method, it is difficult to specify convergence criteria formally. As the fitness of a population may remain static for a number of generations before a superior individual is found, the application of conventional termination criteria becomes problematic. A common practice is to terminate the GA after a pre-specified number of generations and then test the quality of the best members of the population against the problem definition. If no acceptable solutions are found, the GA may be restarted or a fresh search should be initiated.

5.2 Inherent features of GA

The four most significant differences are:

- GAs search a population of points in parallel, not a single point.
- GAs do not require derivative information or other auxiliary knowledge;
- only the objective function and corresponding fitness levels influence the directions of search.
- GAs use probabilistic transition rules, not deterministic ones.
- GAs work on an encoding of the parameter set rather than the parameter set itself (except in where real-valued individuals are used).

Chapter 6

GA Based Approach

6.1 Problem mapped in GA Domain

6.1.1 Objective Function

Objective function is defined in order to minimize the fuel consumption.

Objective function $J(x)$,

$$J(x) = \sum_{i=1}^{n} FC_{ij} \qquad (6.1)$$

Where FC_{ij} is fuel consumption at i^{th} second of j^{th} time slot and n is the number of seconds of the time slot

Fitness of the individuals is found to Minimize $J(x)$.

6.1.2 Chromosome

In this problem, the variable is EM power in kW.

Following figure describes the time slot.

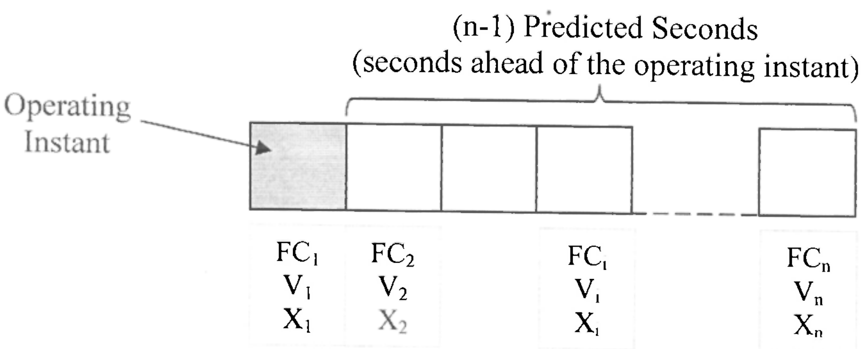


Figure 6.1: n second Time Slot

Where FC_i is the fuel consumption of i^{th} second; V_i is the velocity of i^{th} second and X_i is the EM power of i^{th} second.

When variables mapped in chromosome, length of a variable is selected as 5 bit binary number.

Therefore the word length = 5n

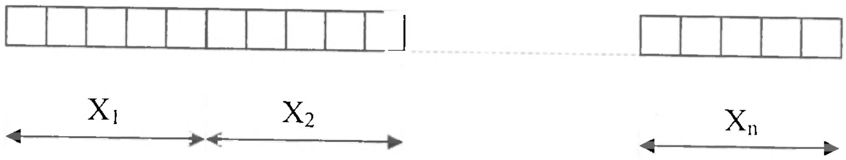


Figure 6.2 : Chromosome

6.2 GA Parameters

- No of individuals per generation = 20
- No of Generations = 50
- No of variables = No of predictions + 1
- Length of one variable = 5 bits
- Selection method = Roulette Wheel

Limits of selection of chromosomes are based on the ICE operating regions explained in section 4.3.1.

Let, T_d = Torque Demand at i^{th} second,

T_d in Region 1,

Lower limit of X_i = 0

Upper limit of X_i = 6

T_d in Region 2,

Lower limit of X_i = -10

Upper limit of X_i = 20

T_d in Region 3,

Lower limit of X_i = 0

Upper limit of X_i = 20

When $T_d = 0$,

Lower limit of X_i = 0

Upper limit of X_i = 0

When $T_d < 0$

Lower limit of X_i = -15

Upper limit of X_i = 0

6.3 Optimization Process

Let consider n second time slot. GA will do the optimization for this time slot based on the fitness function defined in the section 5.2.1. From this process EM power contribution values (${}^{i}EM_i$) can be obtained for each second in the time slot.

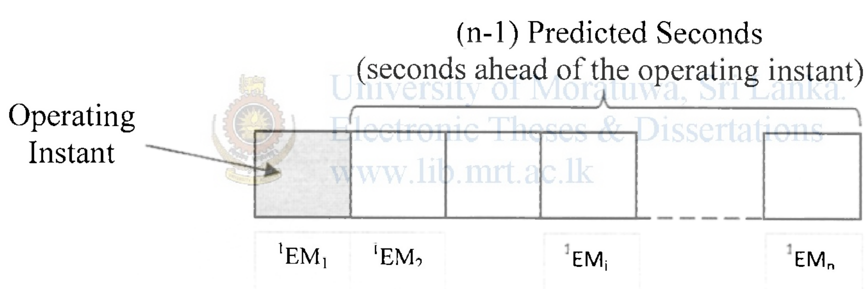


Figure 6.3 : Optimized EM Power contribution for n second Time Slot

Then for the operating instant, power contribution of the EM is ${}^{1}EM_1$.

Let, ${}^{1}P_d$ = Power demand for the operating instant

Therefore, ICE power contribution = ${}^{1}P_d - {}^{1}EM_1$

Then next second becomes the operating instant. One more velocity prediction is added to the end by the sensor system. Again there is an n second time slot is formed. As explained earlier, do the optimization process again. This process is illustrated by the Figure 6.4.

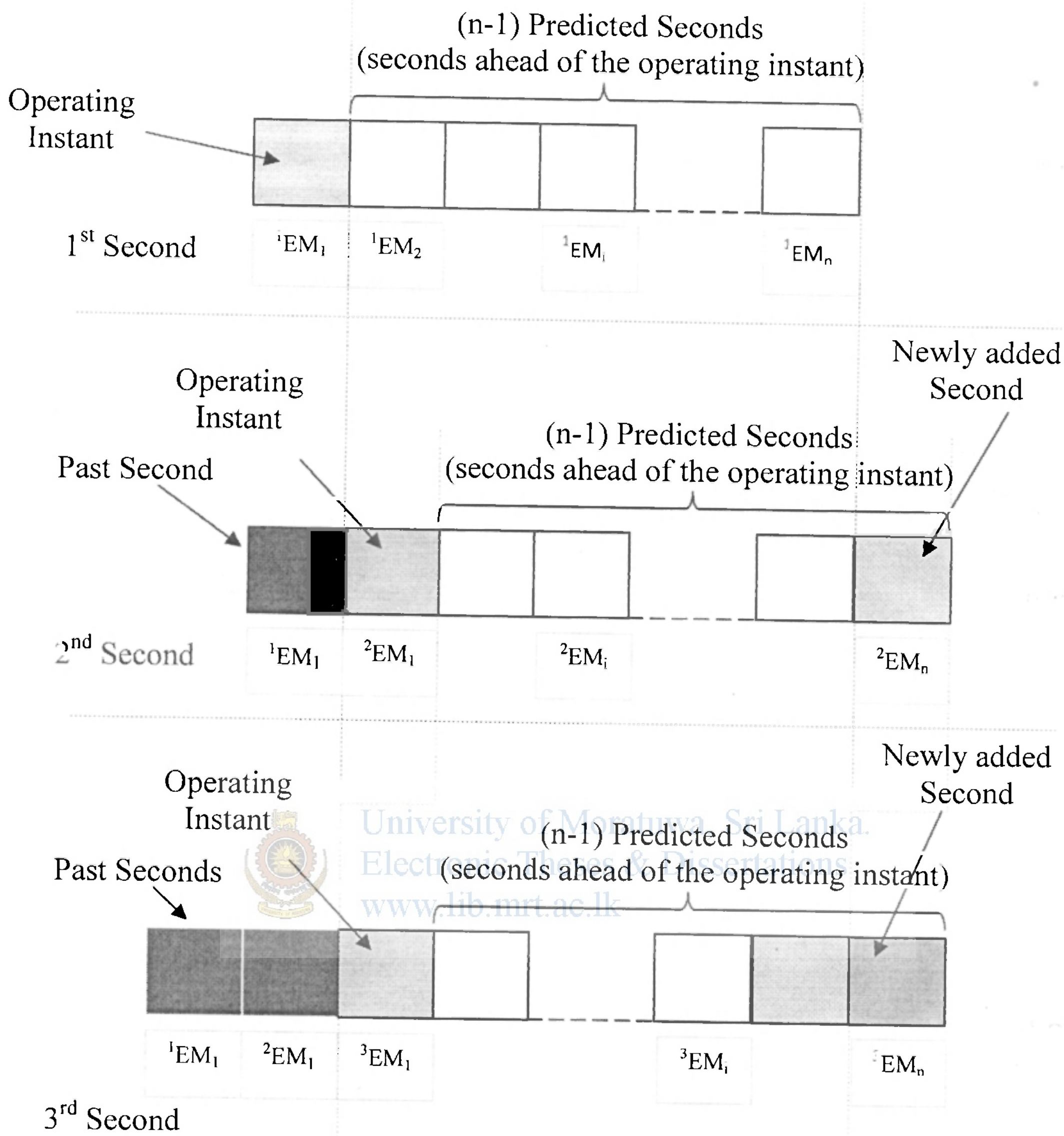


Figure 6.4 : Optimization Process

From the optimization for the 2^{nd} second, EM power contribution for the operating instant is $^2EM_1$.

Let, ^2P_d = Power demand for the operating instant

Therefore, ICE power contribution = $^2P_d - {}^2EM_1$

Similar process is employed for the third second and so on.

From the optimization for the 3^{rd} second, EM power contribution for the operating instant is $^3EM_1$.

Let. ${}^{3}P_d$ = Power demand for the operating instant

Therefore, ICE power contribution = ${}^{3}P_d - {}^{3}EM_1$

From the optimization for the ith second, EM power contribution for the operating instant is ${}^{i}EM_1$.

Let, ${}^{i}P_d$ = Power demand for the operating instant

Therefore, ICE power contribution = ${}^{i}P_d - {}^{i}EM_1$

Chapter 7

Results and Analysis

7.1 Results for NEDC

7.1.1 Velocity profile and relevant power demand

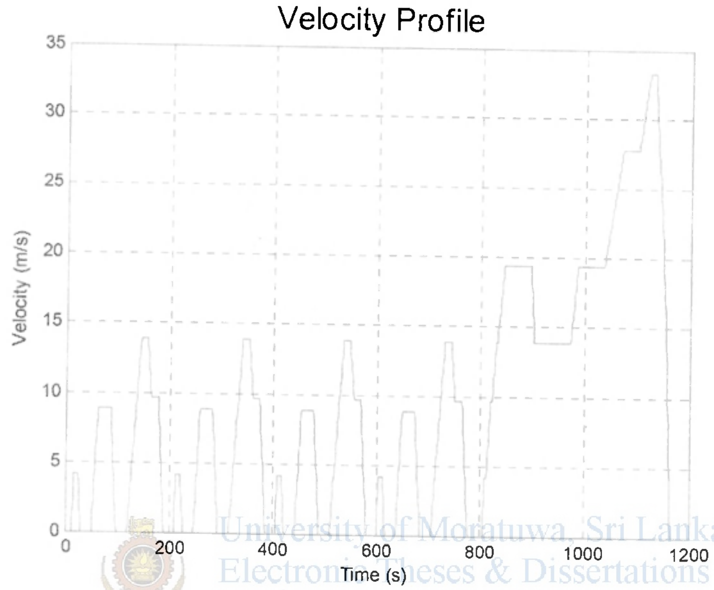


Figure 7.1: NEDC

This is the same plot explained in section 3.1 of chapter 3.

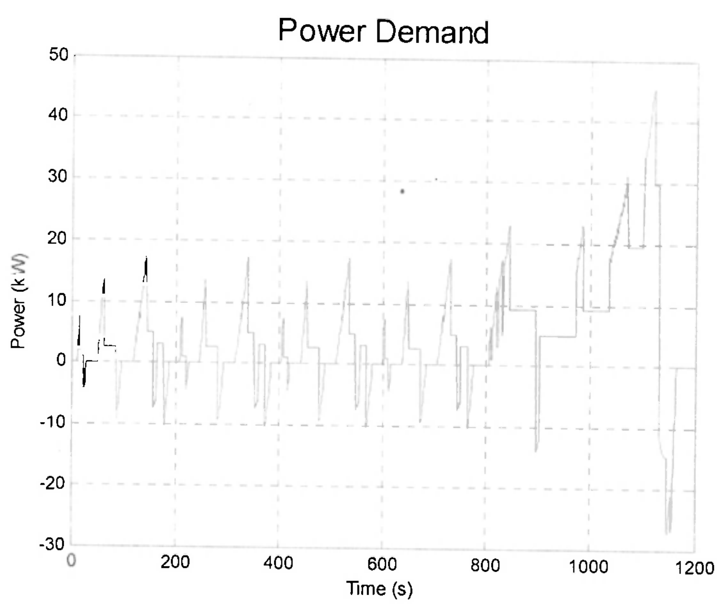


Figure 7.2 : Power demand for NEDC

This is the plot of power demand in kilo watt against the time in seconds in order to achieve the velocity at the wheels shown in Figure 7.1.

7.1.2 Operating points of ICE

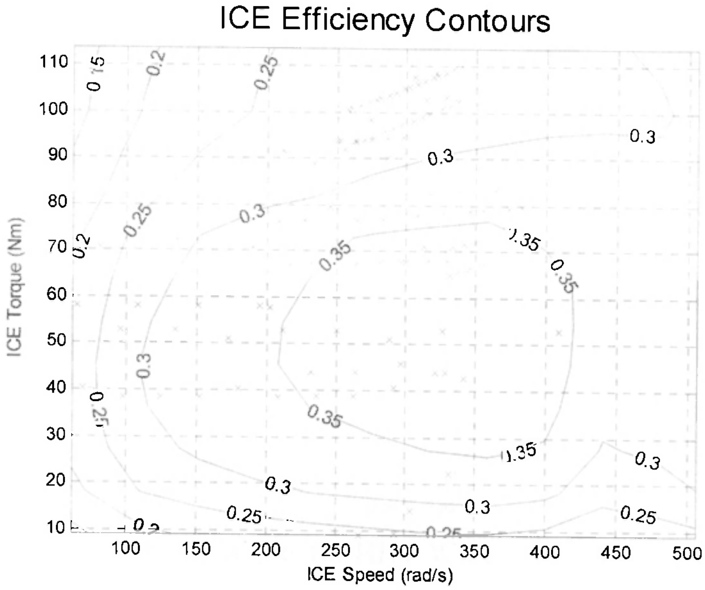


Figure 7.3 : ICE Operating points for Conventional Vehicle - NEDC

This is the plot of engine operating points on the ICE contour map explained in section 4.3 of chapter 4. In conventional vehicle, there is no EM to assist the engine. Therefore all the points laid on the contour map as the power demand. They did not concentrate on to more efficient regions. Because ICE should provide the whole power demand to achieve the velocity. It is clear that points in the efficiency region between 0.25 and 0.3 are high torque and hence ICE gives high power to the wheel at high fuel rate according to the map explained in Figure 4.3 of chapter 4.

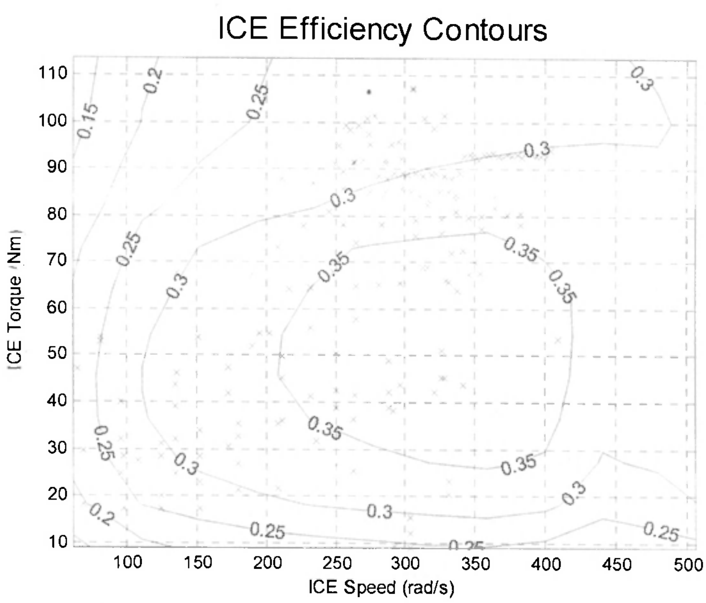


Figure 7.4 : ICE Operating points for HEV Without Predictions - NEDC

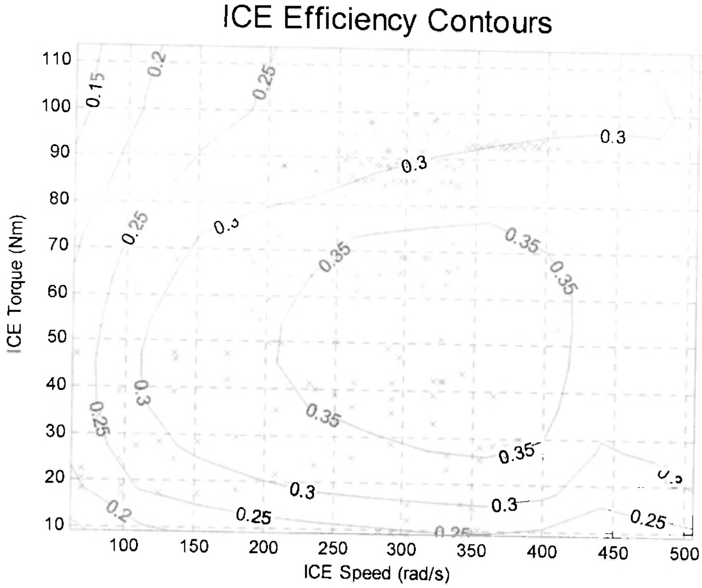


Figure 7.5 : ICE Operating points for HEV With 4 Seconds Predictions - NEDC

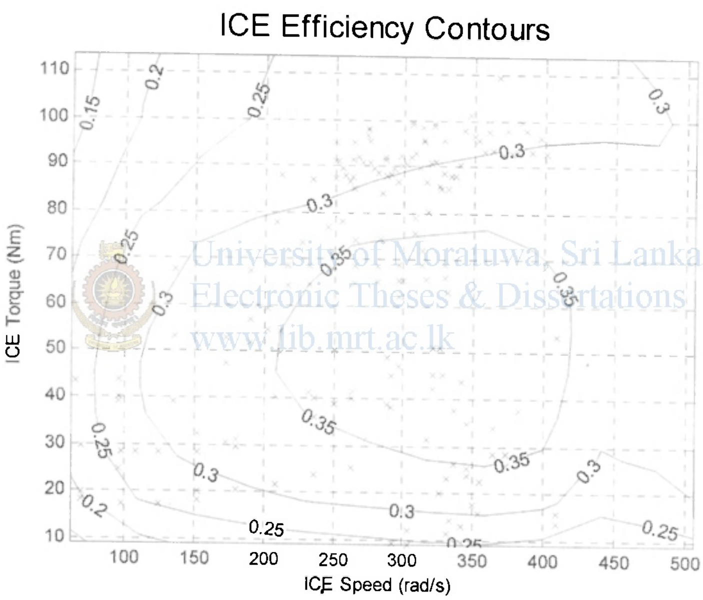


Figure 7.6 : ICE Operating points for HEV With 8 Seconds Predictions - NEDC

Figure 7.4, 7.5 and 7.6 are the same plot of Figure 7.3 but for HEV without velocity predictions, 4 second predictions and 8 second predictions respectively. In these cases EM comes to assist the ICE to achieve the power demand. Hence ICE can be operated in more efficient and relatively low power region. With the velocity predictions, HEV controller can manage battery SOC in very economical manner and Figure 7.5 and Figure 7.6 show most of the points come in to 0.3 ~ 0.35 efficiency region. Points in low efficiency regions represent low power demand. This also one of strategies to reduce fuel consumption.

7.1.3 EM Contribution

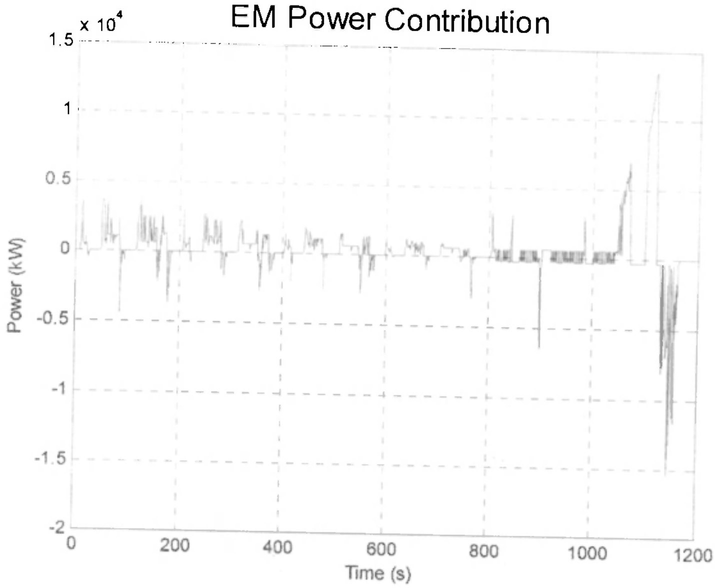


Figure 7.7 : EM Contribution for HEV Without Predictions - NEDC

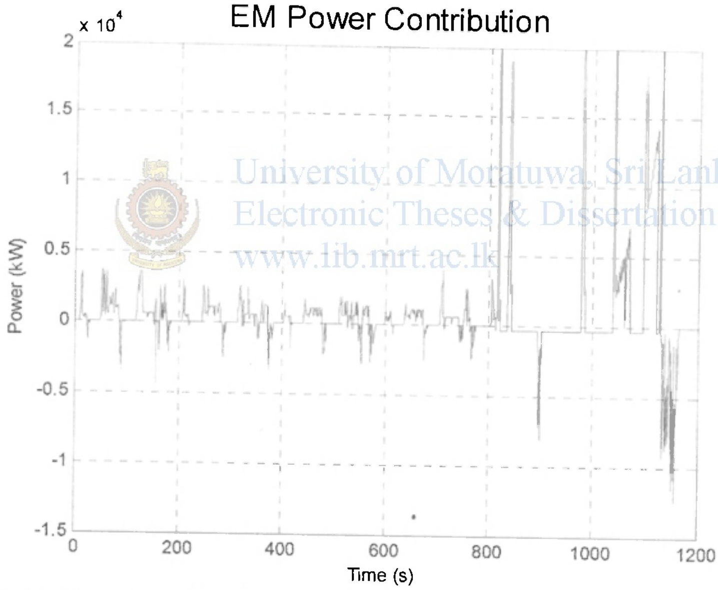


Figure 7.8 : EM Contribution for HEV With 4 Seconds Predictions - NEDC

Figure 7.7, 7.8 and 7.9 show the EM power contribution of HEV without predictions, HEV with 4 second predictions and HEV with 8 second predictions respectively. The X – axis of the graph is time in seconds and the Y – axis is EM power contribution in watts. With predictions, controller used EM to supply higher power demands to get down the ICE operating points in to the more efficient and economical region.

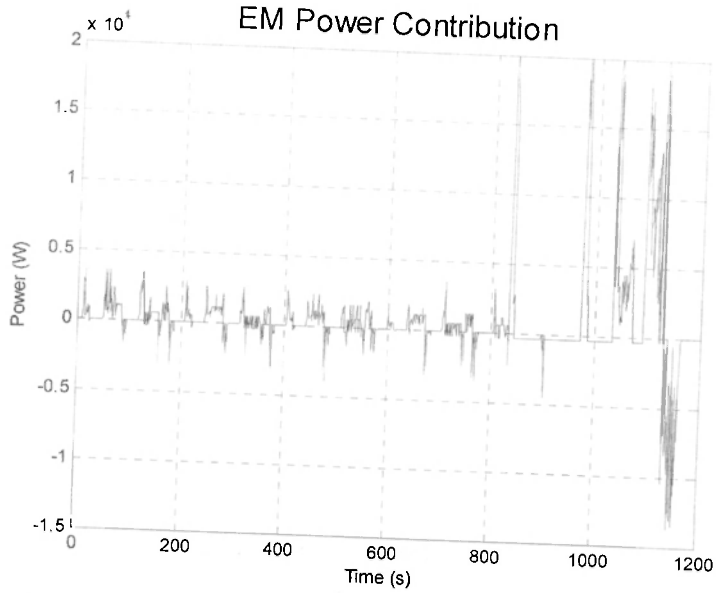


Figure 7.9 : EM Contribution for HEV With 8 Seconds Predictions - NEDC

7.1.4 SOC Variation

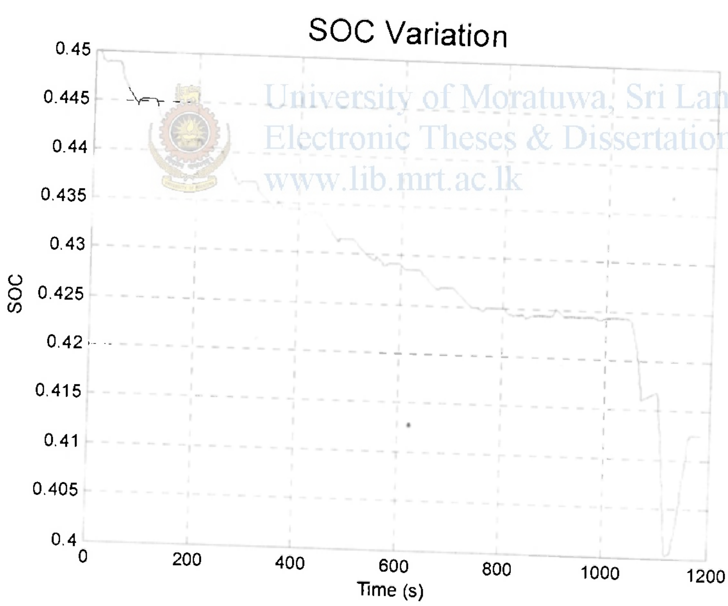


Figure 7.10 : SOC Variation for HEV Without Predictions - NEDC

SOC is the deciding factor for switching between ICE and EM. Figure 7.10. 7.11 and 7.12 represent the SOC variation of the battery through the journey. The independent axis of the graph is time in seconds and the dependant axis is the SOC as a fraction of full charge state taken as 1.

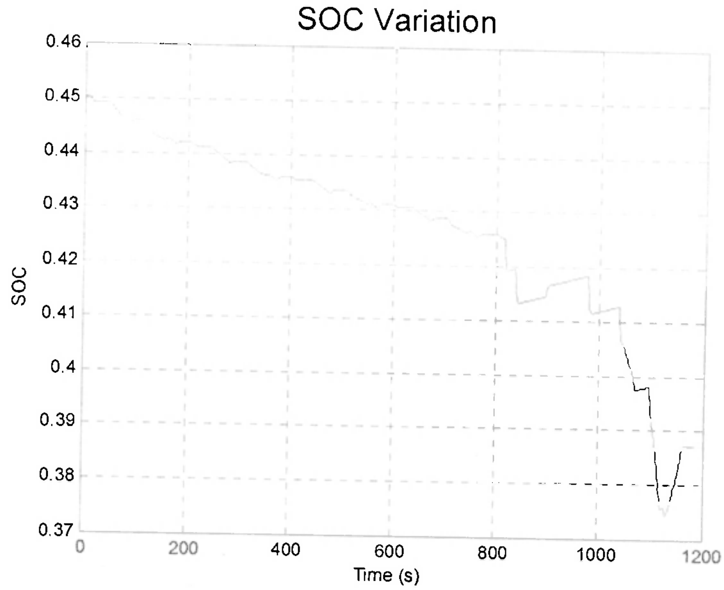


Figure 7.11 : SOC Variation for HEV With 4 Seconds Predictions - NEDC

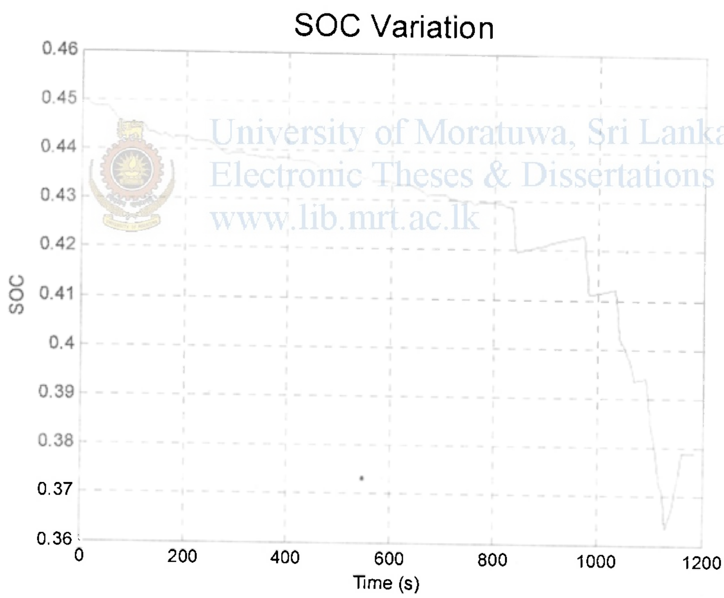


Figure 7.12 : SOC Variation for HEV With 8 Seconds Predictions - NEDC

In these simulations, simple controlling method was used. Therefore the charging of the battery is not sufficient and controller should be modified to overcome this problem. With increasing number of predictions, battery was used in its allowable full range.

7.2 Results for CDC

7.2.1 Velocity profile and relevant power demand

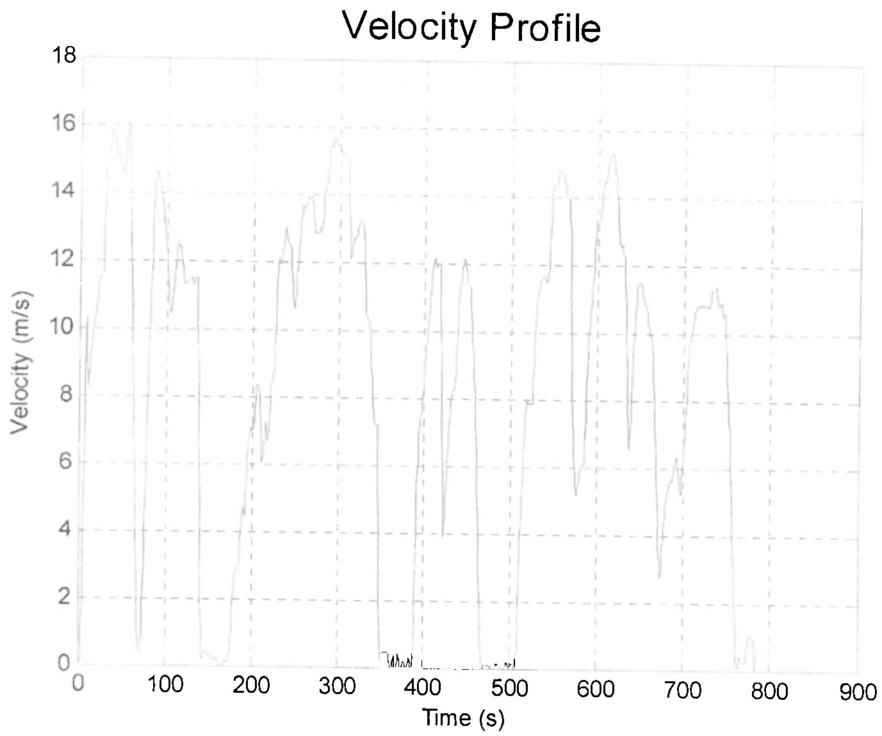


Figure 7.13 : CDC

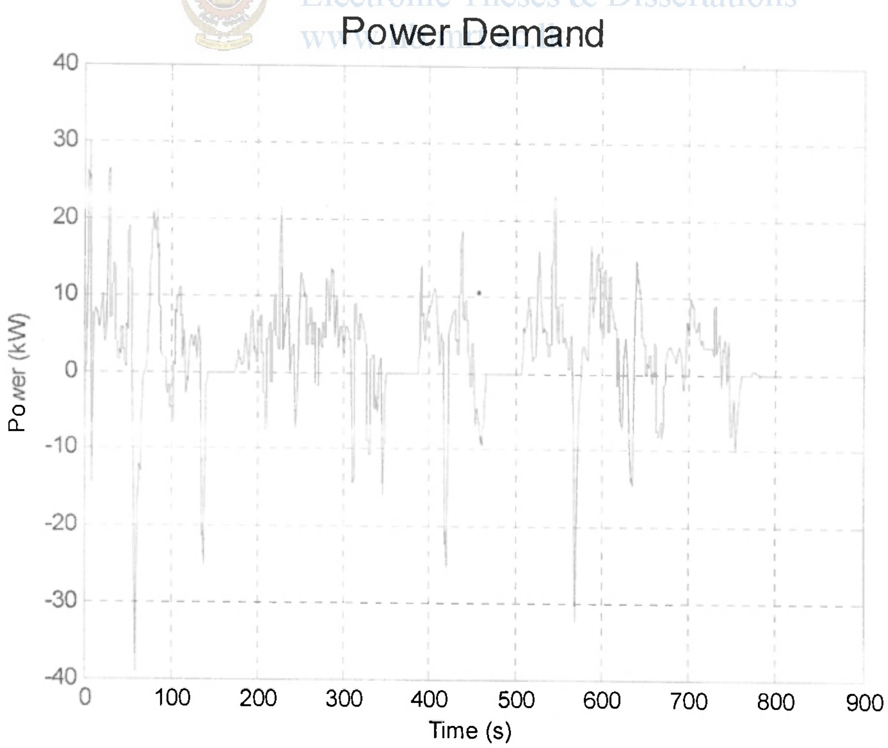


Figure 7.14 : Power demand for CDC

7.2.2 Operating points of ICE

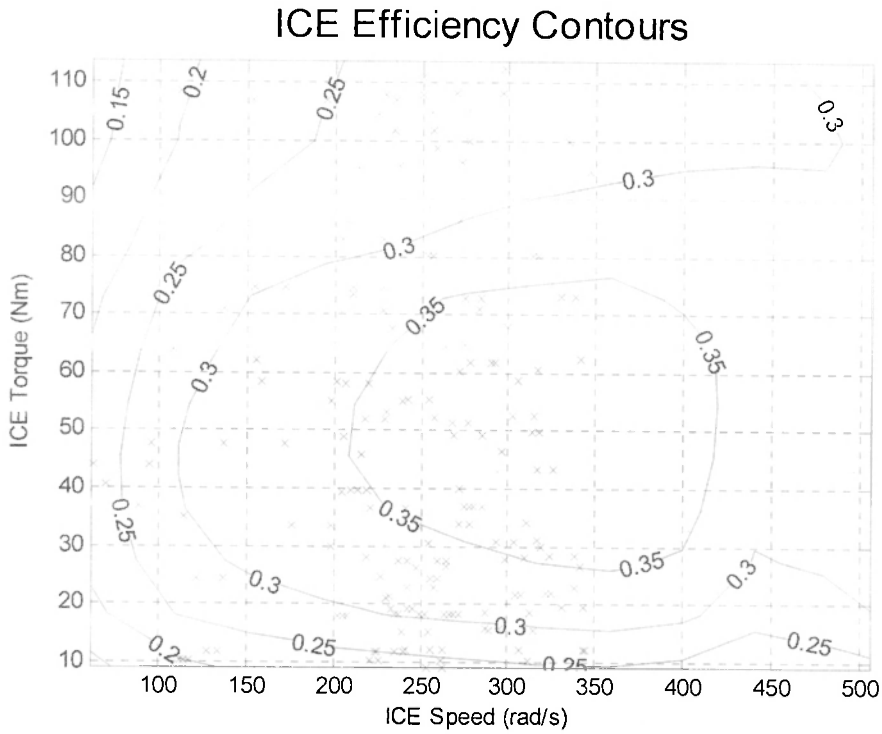


Figure 7.15 : ICE Operating points for Conventional Vehicle - CDC

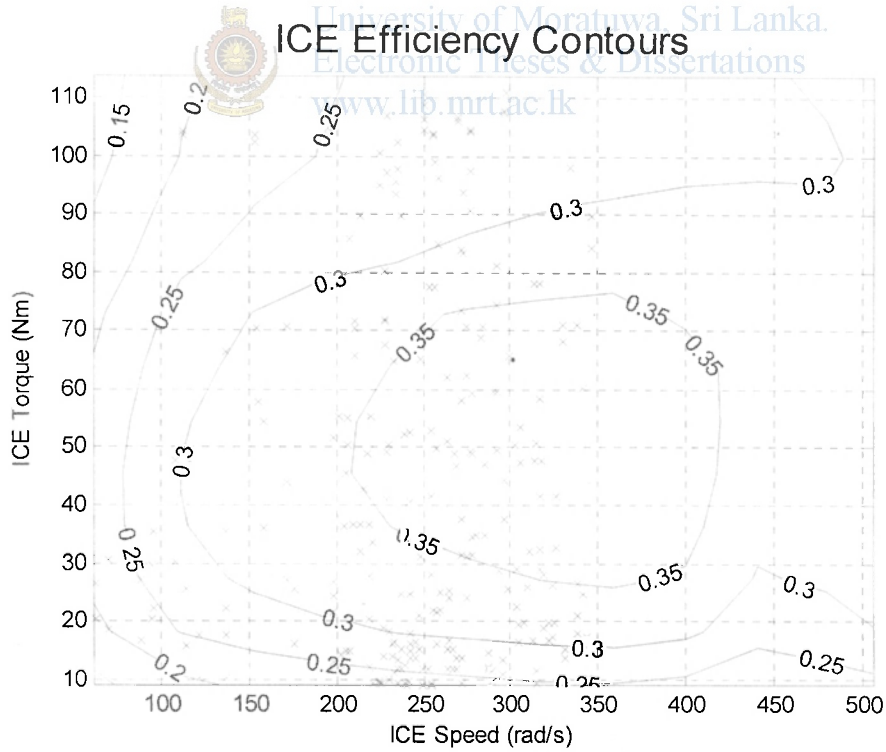


Figure 7.16 : ICE Operating points for HEV Without Predictions – CDC

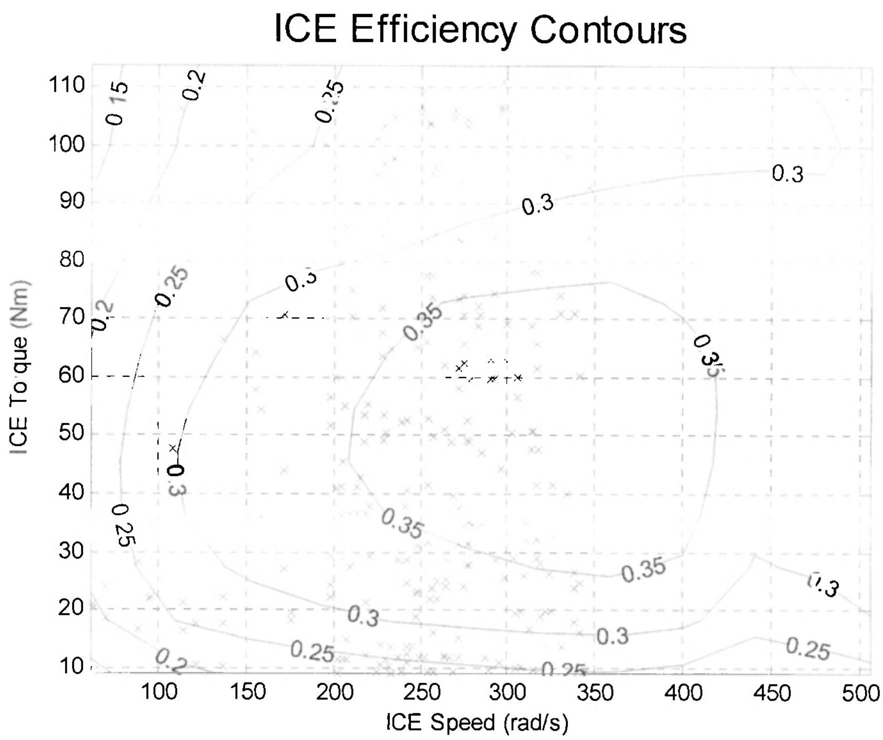


Figure 7.17 : ICE Operating points for HEV With 4 Seconds Predictions – CDC

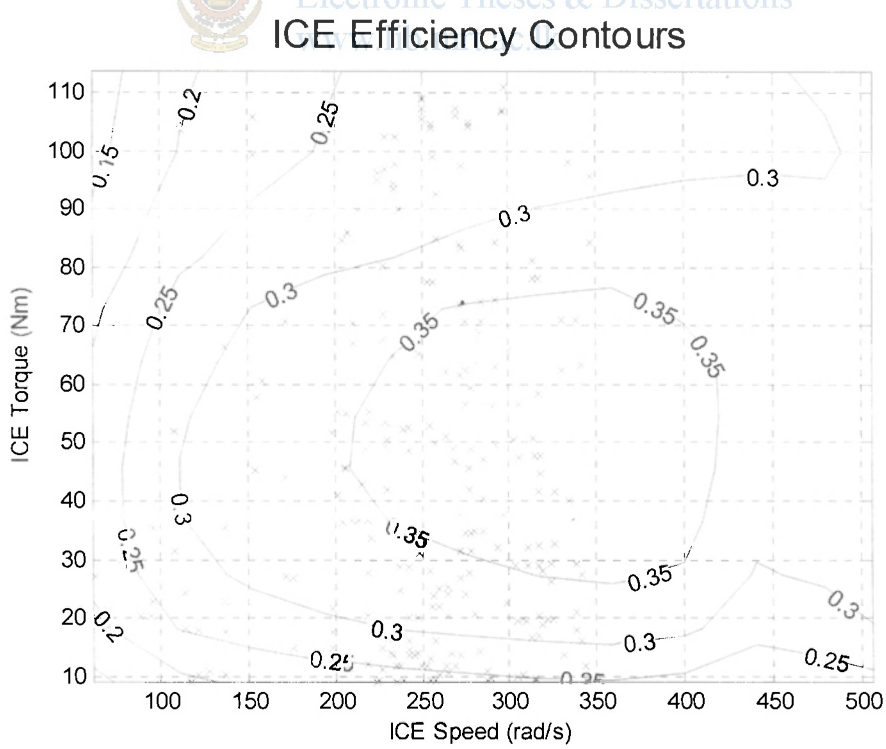


Figure 7.18 : ICE Operating points for HEV With 8 Seconds Predictions - CDC

7.2.3 EM Contribution

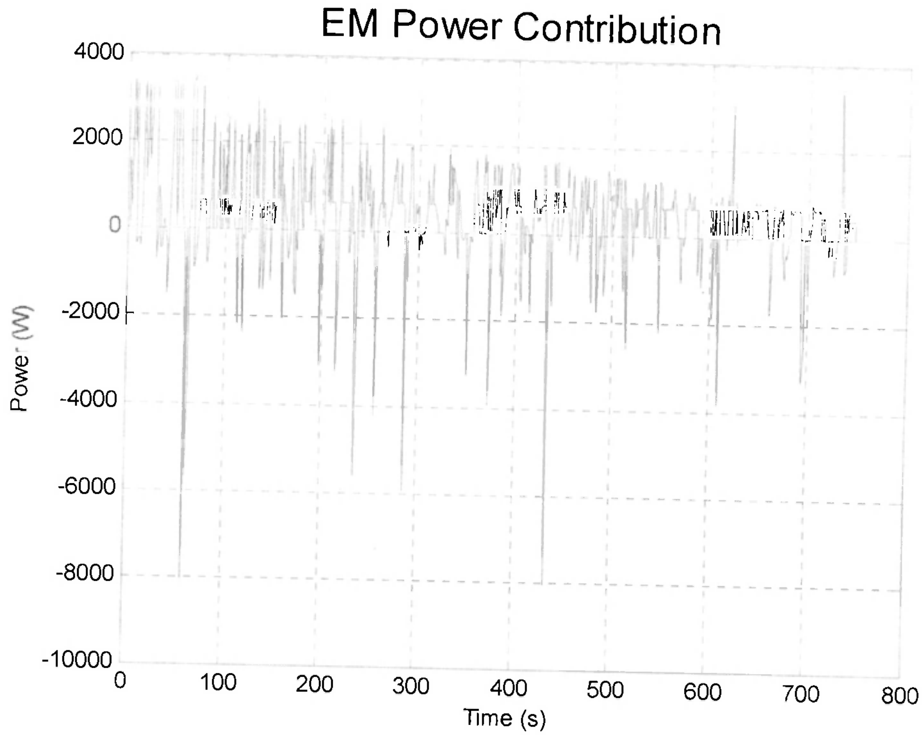


Figure 7.19 : EM Contribution for HEV Without Predictions - CDC

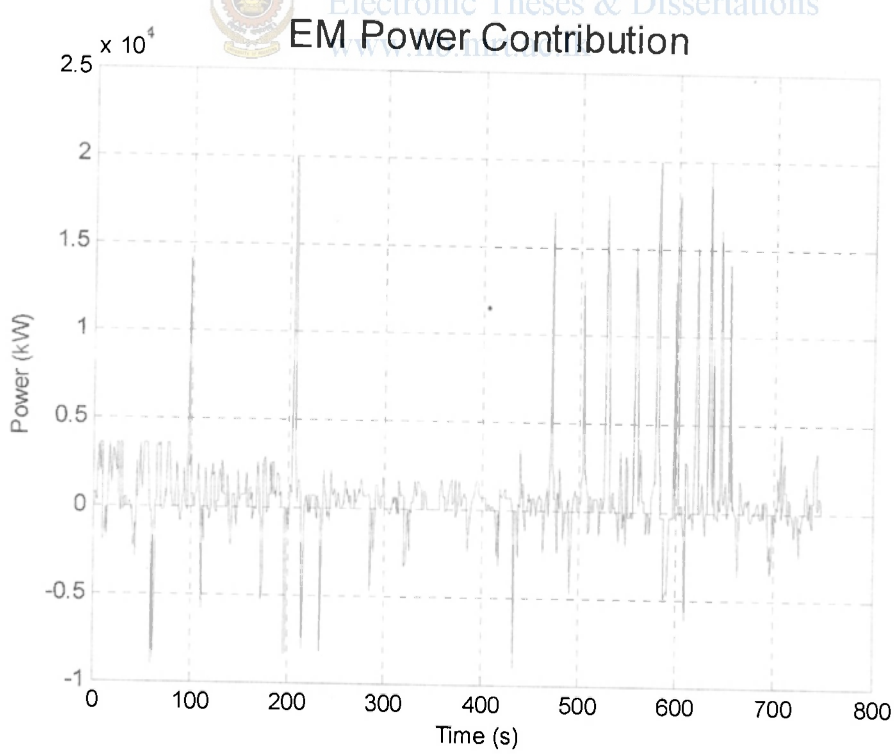


Figure 7.20 : EM Contribution for HEV With 4 Seconds Predictions - CDC

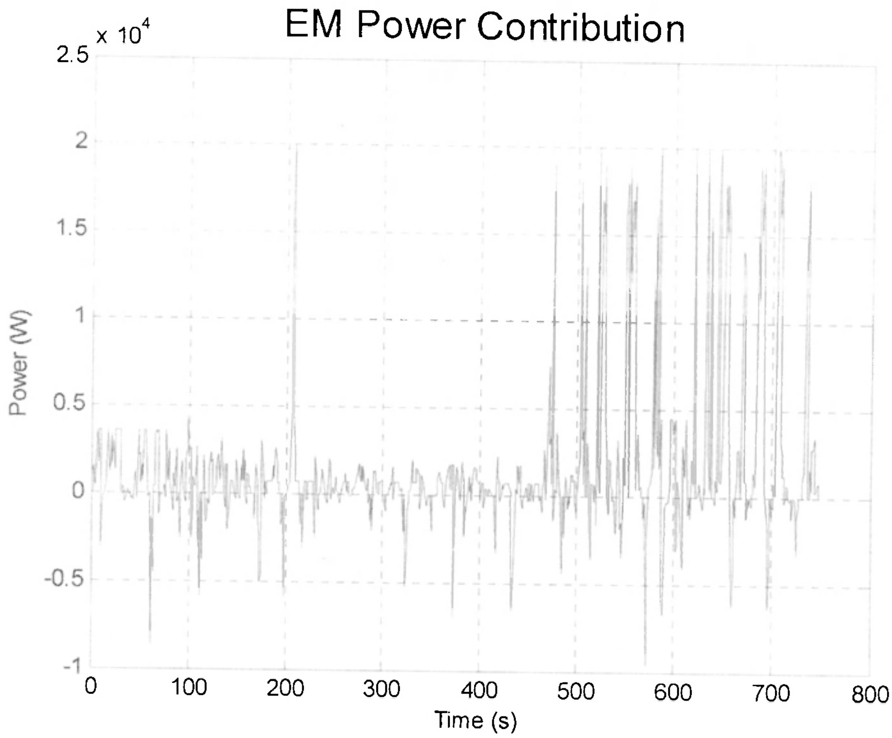


Figure 7.21 : EM Contribution for HEV With 8 Seconds Predictions - CDC

7.2.4 SOC Variation

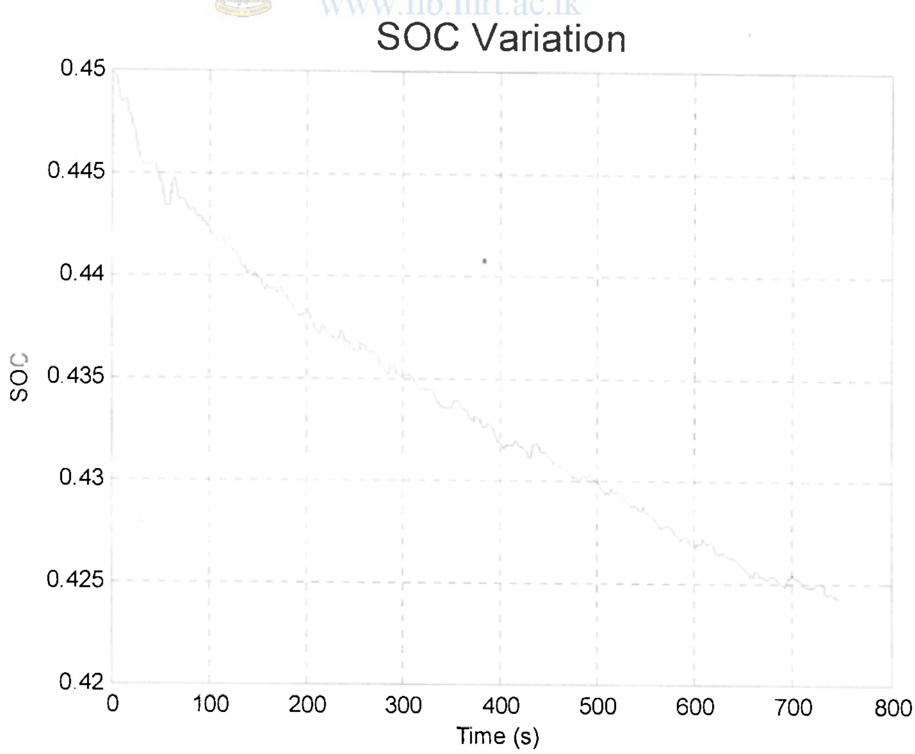


Figure 7.22 : SOC Variation for HEV Without Predictions - CDC

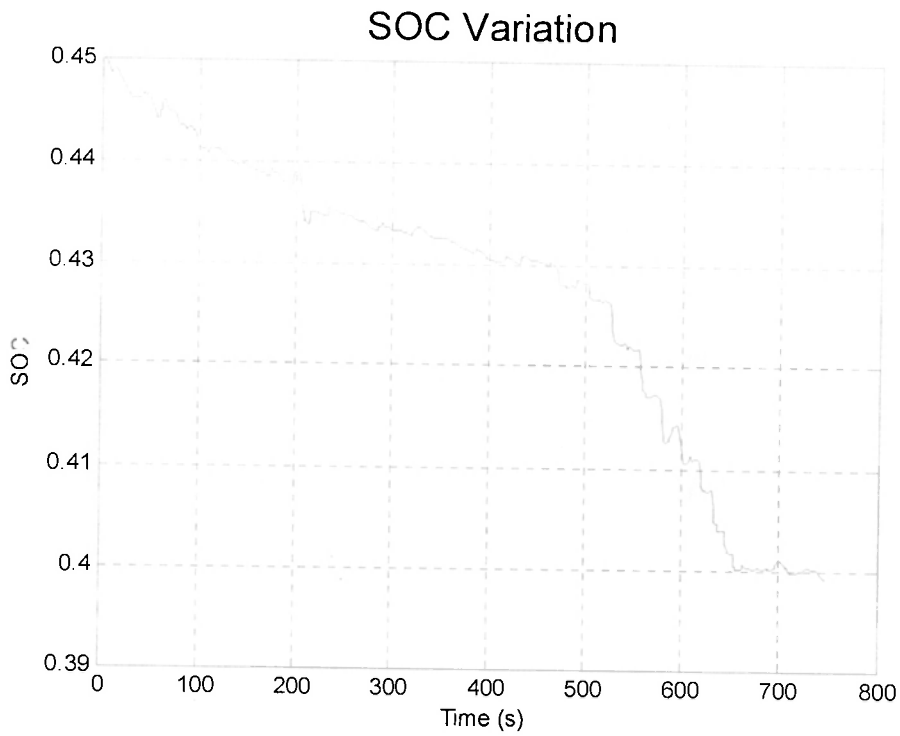


Figure 7.23 : SOC Variation for HEV With 4 Seconds Predictions - CDC

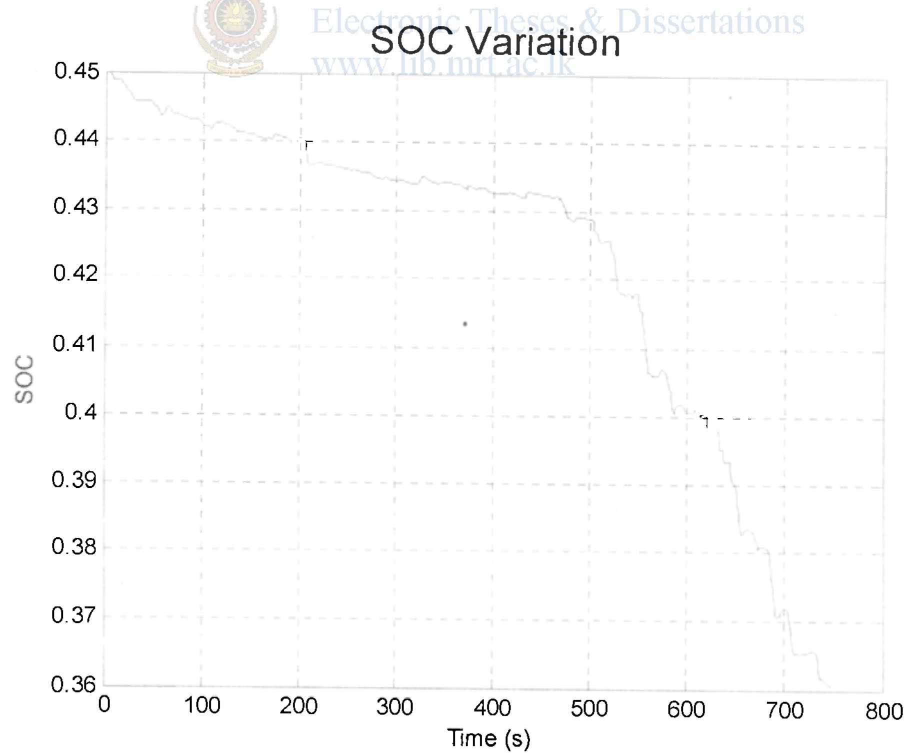


Figure 7.24 : SOC Variation for HEV With 8 Seconds Predictions - CDC

7.3 Analysis of Results

Table 7.1 : Comparison of Fuel Usage

Vehicle Type	NEDC *(1200 Sec.)* Fuel Usage (ml)	NEDC *(1200 Sec.)* Saving w.r.t conventional vehicle (%)	CDC *(800 Sec.)* Fuel Usage (ml)	CDC *(800 Sec.)* Saving w.r.t conventional vehicle (%)
Conventional Vehicle	835.95		516.70	
HEV without Predictions	780.47	6.61	475.83	7.91
HEV with 4 Seconds Predictions	747.76	10.53	449.06	13.09
HEV with 8 Seconds Predictions	734.77	12.08	375.56	27.32

It is very clear that the availability of velocity predictions for few seconds ahead of the operating instant of HEV, is a key factor to improve the fuel economy or the fuel saving of the vehicle. The other observed important factor is, increasing of predictions cause more improvements in fuel economy.

It is estimated the same for two drive cycles, NEDC and CDC. Even HEV itself shows more effective for CDC than NEDC. With more predictions CDC shows huge positive gradient for improvement of fuel economy (Figure 7.25).

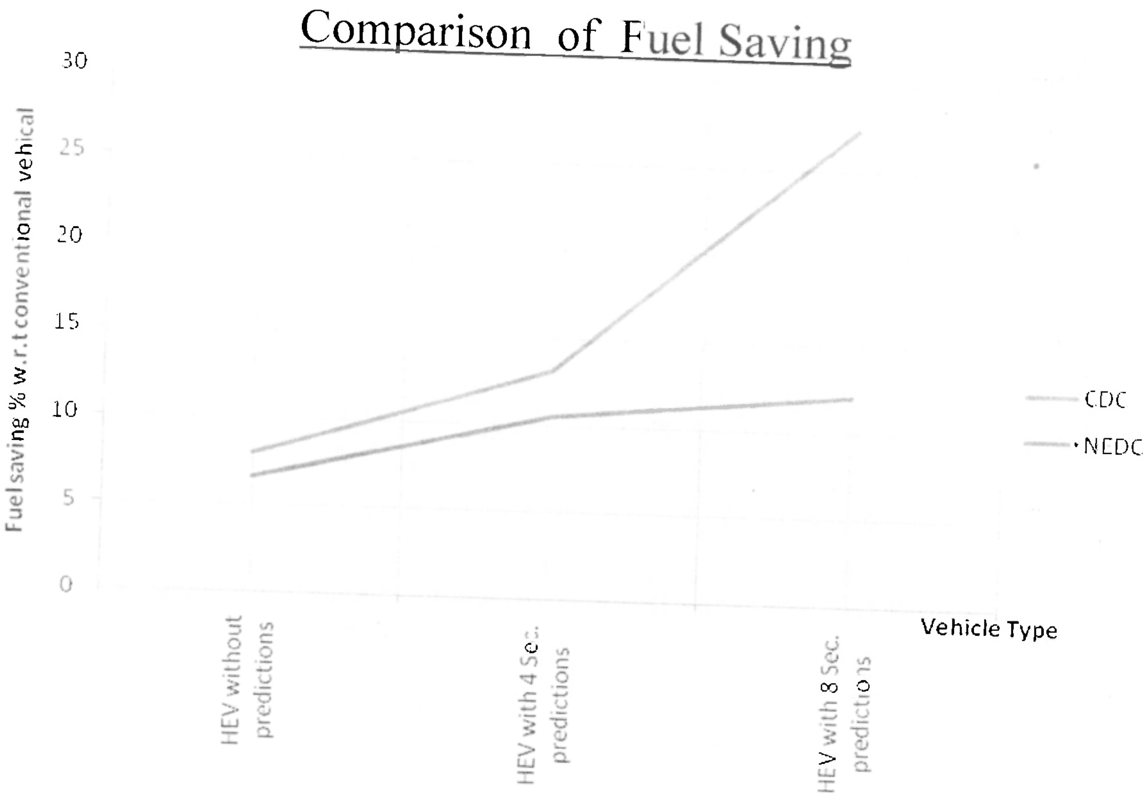
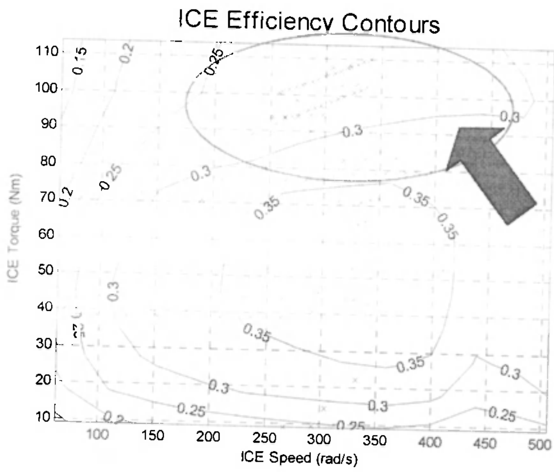


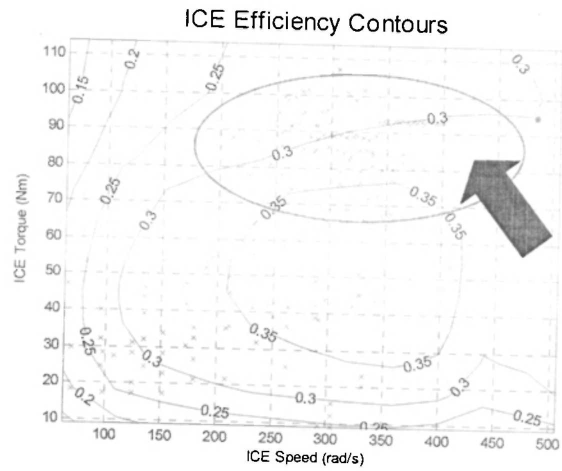
Figure 7.25 : Comparison of Fuel Usage

Figure 7.25 shows that huge fuel saving for the HEV with 8 second predictions. With more predictions, controller keeps battery SOC to release in more economical way. This saving is more significant for CDC. The reasons for the above saving are analyzed below.

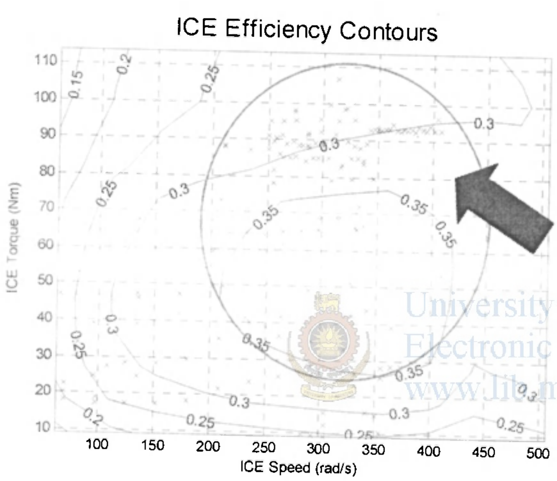
Let compare the operating points of ICE for NEDC.
Below comparisons clearly show that higher torques concentrated on to the 0.3 & 0.35 efficiency contours with the increase of number of velocity predictions. More number of predictions force the ICE to operate inside the 0.35 contour ring. That means ICE is operated in its maximum efficiency range with saving of.



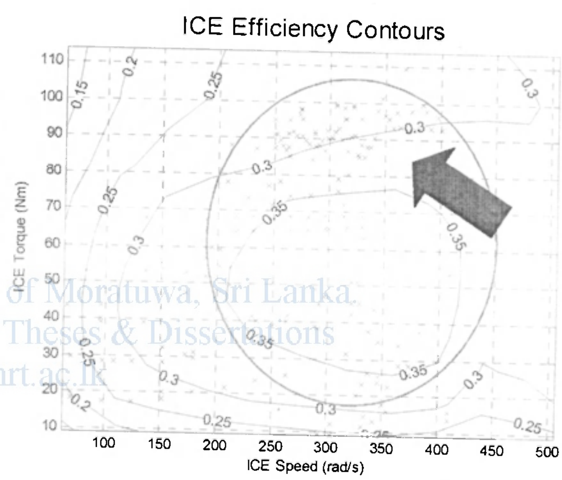
Conventional Vehicle



HEV without Predictions



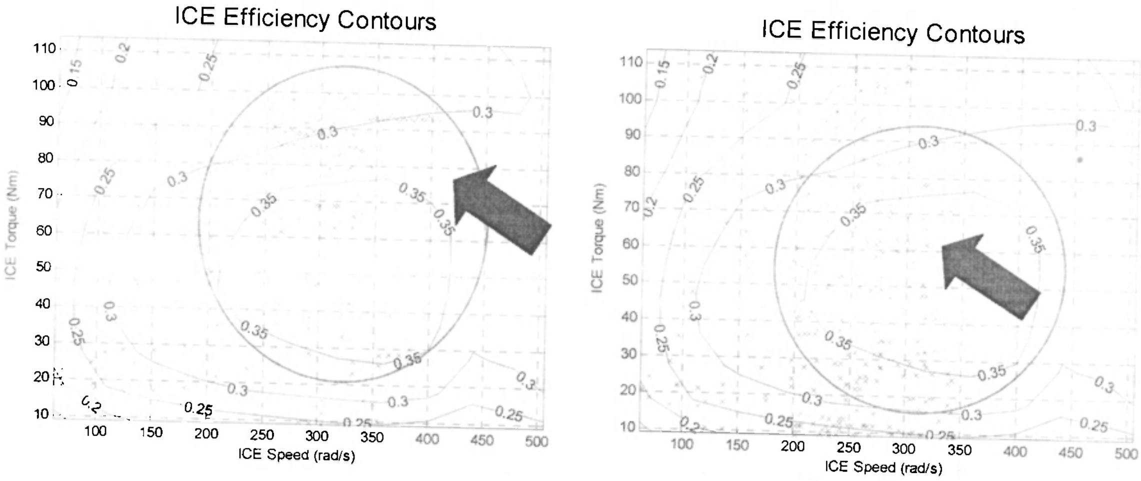
HEV with 4 Sec. Predictions



HEV with 8 Sec. Predictions

Figure 7.26 : Comparison of ICE Operating points for NEDC

Similar comparison can be done for the CDC. Same scenario can be observed but higher number of operating points laid in the maximum efficiency region than drive in NEDC. That is one reason for more fuel saving resulted in CDC than NEDC.



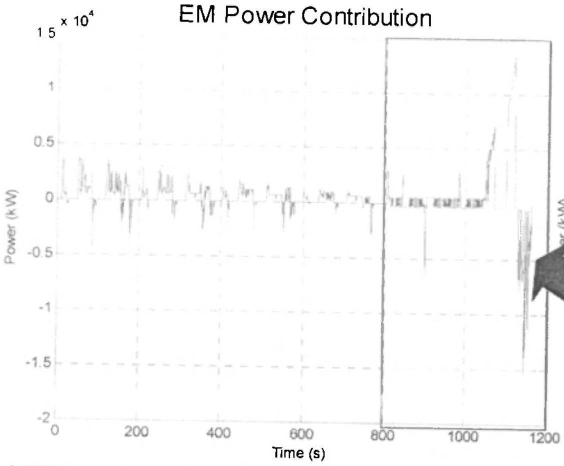
HEV with 4 Sec. Predictions-NEDC *HEV with 4 Sec. Predictions- CDC*

Figure 7.27 : Comparison of ICE Operating points for NEDC with CDC

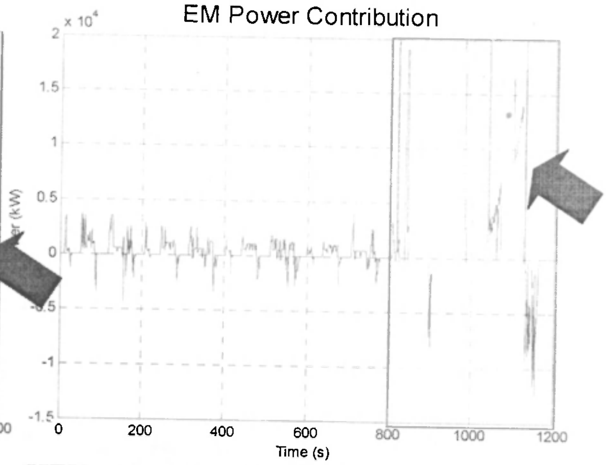
One reason for laying more points of CDC in maximum efficiency region than NEDC is, compared to NEDC, CDC is a low power demand drive cycle. The maximum velocity of CDC is 11 ms^{-1} ($\approx$ 40 km/h) and power demand for that is 25 kW. But for the NEDC, maximum velocity is 34 ms^{-1} ($\approx$ 122 km/h) and power demand for that is 45 kW. Therefore by giving lesser amount of motor torque, ICE can be operated at its maximum efficiency range when the HEV drives on CDC. This is the one of major facts that HEV more effective on CDC than NEDC.

Let consider the EM contribution and the SOC variation.

First analysis can be done for NEDC.
Significant variation of EM contribution with increase of velocity predictions can be observed for extra urban drive part of NEDC than urban part. In the extra urban region, it is very clear that with increasing number of velocity predictions, EM released big power slots at once instead of releasing small - small power contributions.



HEV without Predictions



HEV with 4 Sec. Predictions

Figure 7.28 : Comparison of EM Power Contributions of NEDC

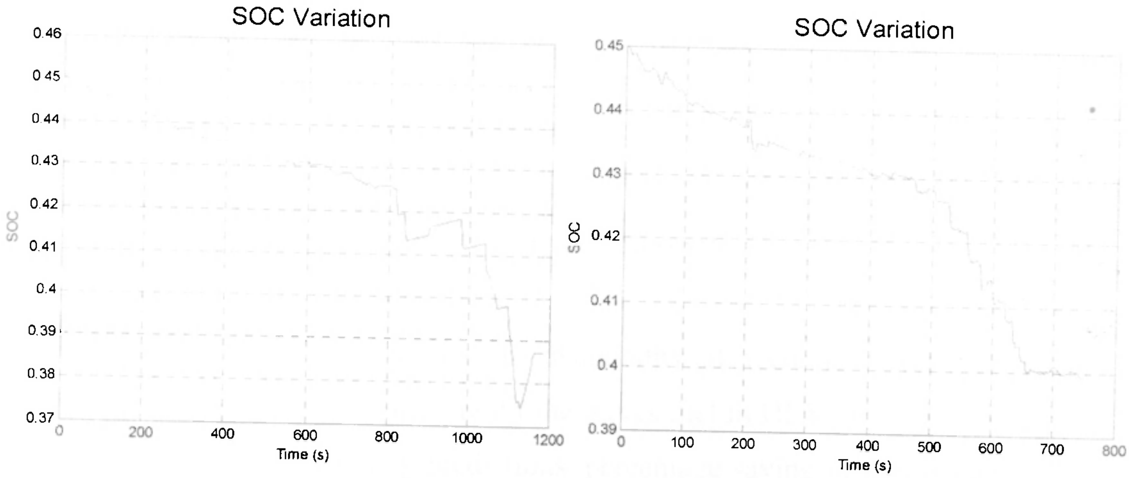
This scenario can be explained as a pro-active behavior of the EM. It saves battery energy to release at the most efficient moment rather spending energy continually. This is the major reason for improving of fuel economy of HEV with increasing number of velocity predictions.

For the CDC, same can be observed but motor contribution is very high due to CDC is a low power demand drive cycle.

SOC variation for NEDC with CDC can be compared as follows.

There are lots of charging areas can be observed in CDC than NEDC. This is because, CDC having lot of traffic conjunctions and therefore it has lot of breakings and decelerations. These regenerative breakings cause the above observation and save more fuel.

There are lesser number of breakings and decelerations available in NEDC. But still it allows battery to get charged while ICE operated in the operation region 3.



HEV with 4 Sec. Predictions-NEDC *HEV with 4 Sec. Predictions- CDC*

Figure 7.29 : Comparison of SOC Variation for NEDC with CDC

It is very clear, for all operations, battery keeps it SOC level between 0.35 and 0.85 for its safety and long life.

Chapter 8

Conclusions

8.1 Conclusions, Remarks and Discussion

The Table 7.1, clearly shows that the availability of accurate predictions about the possible speed trend ahead of current time, saves fuel in HEVs significantly. With the increasing number of velocity predictions, percentage saving in fuel is increased. But the getable number of velocity predictions cannot be increased infinitely due to the available limitations in technology and increase of cost for sensors with the increase of predictions.

HEV with 4 second predictions and 8 second predictions were simulated in this research. The results show even HEV with 4 second predictions can save fuel up to 10.53 % and 13.09 % with respect to the conventional vehicle for NEDC and CDC respectively. Therefore the availability of those predictions is worthy and money spent for this kind of prediction systems, is highly valuable.

This research results show that the HEVs driven on road conditions of countries like Sri Lanka is more effective. HEV even without velocity predictions, simulation results for CDC, shows more than 1% saving in fuel than NEDC. With prediction the saving of fuel is dramatically high for Sri Lankan roads than smooth drives like NEDC. That means HEVs with or without velocity predictions, are more effective and suitable for roads of countries like Sri Lanka.

Almost all simulations are done for drive cycles of developed countries. As they need to find out suitable vehicle and driving conditions for their own countries. The importance of doing simulations for the local drive cycles like CDC is highlighted in this research. It is true that still Sri Lanka is in the early stages of manufacturing of automobiles, but this kind of simulations and research results can be used to find out suitable vehicles to be imported.

8.2 Recommendations for Future Research

This research was done using GA. As a future research, it is better to carry out a research for the same, based on Fuzzy – logic. Because there are lot of researches can be found for HEV energy management systems using Fuzzy – logic. Then the results can be compared with GA results. That will be a great opportunity for everybody to develop a more reliable and efficient "driving situation awareness" - based energy management system for HEV.

These results show the predictions to save fuel successfully. Therefore the money spent for a project to develop a sensor network or even an on-board sensor system for HEVs to get speed trends, can be more rewarded.

In this research, the thermal effects on the efficiency of the ICE and the switching limitations of the EM were not taken into account in formulation of the models. Therefore this research can be further developed. With ADVISOR software more accurate simulations can be done and the above mentioned simulation difficulties can be overcome. I would like to forward my suggestion to the University of Moratuwa, to have an advanced simulation software like ADVISOR, as it will be a great help for researchers who are going to do their researches on vehicle simulations.

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Appendix - A

Published Research Papers

Determination of Maximum Possible Fuel Economy of HEV for Known Drive Cycle: Genetic Algorithm Based Approach

R. Sudath Wimalendra*, Lanka Udawatta+, E. M. C. P. Edirisinghe and Sudarshana Karunarathna
Department of Electrical Engineering, Faculty of Engineering
University of Moratuwa, Sri Lanka

*Emails: rs_wimalendra@yahoo.com.
+Email: lanka@ieee.org

Abstract— **This paper describes a methodological approach to investigate the maximum fuel economy that could be achieved by a hybrid vehicle with parallel configuration for a known drive cycle. A backward looking hybrid vehicle model is used for computation of fuel economies. The optimization process represents a constrained, multi-domain and time-varying problem, which is highly nonlinear. Here, genetic algorithm (GA) based approach was used to find out optimum power split between two power sources over their driving cycles that make maximum possible overall fuel economy for the given drive cycle by the vehicle. In this approach using Parallel Hybrid Electric Vehicle (PHEV) configuration, optimization problem is formulated so as to minimize the overall fuel consumption. The whole set of electric motor power contribution along the drive cycle is then coded as the chromosomes. These results represent the maximum fuel economy that could be ever achieved by any power management system of a Hybrid Electric Vehicle, with the tested HEV configuration and shall allow setting a benchmark against which the fuel economy is measured.**

Keywords— **Hybrid Electric Vehicles, Optimization, Genetic Algorithm**

I. INTRODUCTION

As a result of the endless interest of the society for improved fuel economy & reduced emission without sacrificing vehicle performance, safety, reliability, cost of ownership and other conventional vehicle attributes, Hybrid Technology came in to the world of automobiles, leaving lot of research topics to the researchers living all over the globe. The pressing environmental concerns and skyrocketing price of fuel oils are highly responsible factors for the rapid development of this technology within the past two decades.

Hybrid Electric Vehicles (HEV) have a great potential as new alternative means of transportation. The specific benefits of HEVs, compared to conventional vehicles, include improved fuel economy and reduced emissions.

Hybrid systems involving a combination of an Internal Combustion Engine (ICE) and electric motors (EM) have the potential of improving fuel economy, by operating the Internal Combustion Engine in the optimum operating range while making use of regenerative braking during deceleration.

An extensive set of studies have been conducted over the past two decades. In particular, several *logic*-based control strategies and fuzzy logic-based energy management strategies for distributing power demand have been suggested [1], [2] & [3]. These approaches have been adopted mainly due to their effectiveness in dealing with the problems appear in the complexity of hybrid drive train via both heuristics (human expertise) and mathematical models.

Recent changes in the technology of modern vehicles and revolutionary development in telematics industry have created the possibility for a vehicle to gather online information about the road infrastructure and the traffic environment in which it is in operation. Several algorithms have been proposed to predict the future speed trends, with the use of preview information provided by the telematics. Two technologies, hybrid and telematics are combined together to create "intelligent vehicle" which provides improved fuel economy with traffic preview [4].

The aim of this study is to find out the maximum fuel economy that a PHEV can achieve with any type of HEV energy management system. Here, genetic algorithm (GA) has been used as the technique for optimization which will lead to find a global optimum. In fact, though it is needed to find the maximum possible theoretical best, in actual practice it might not be reachable. However, knowing the maximum possible best fuel economy, it can be used as a benchmark value which might be useful in setting the standards of HEV.

Rest of the paper has been organized as follows; In Section II, it explains the vehicle model used in this study and briefly describes the driving cycle used. Evolutionary computational algorithm to find out the maximum fuel economy has been presented in Section III, followed by the analysis of the results of this study in Section IV. Finally, the Conclusion is presented in Section V.

II. VEHICLE MODEL AND DRIVE CYCLE

A. Modeling the hybrid vehicle

A parallel hybrid configuration has been taken in Fig. 1 to account for modeling the hybrid electric vehicle in this study. This configuration consists of an electric motor and internal combustion engine that can simultaneously or individually drive the transmission (and subsequently propel the vehicle). The split is determined by the vehicle's hybrid control strategy [subject to constraints on the battery state of charge (SOC)]. Normally, the EM is used to assists the engine for peak acceleration, hill climbing, and extremely fast highway driving conditions. Furthermore, the EM can act in reverse mode to become a generator during regenerative braking and consequently used to recharge the batteries.

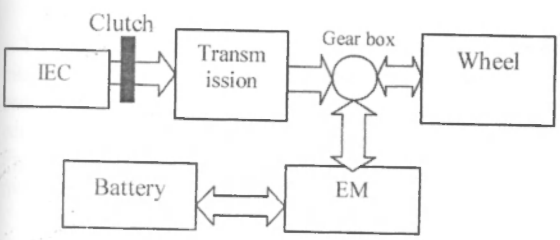


Fig. 1 Block diagram of the parallel hybrid vehicle

The city driving test standard starts from ambient initial conditions (known as "cold starts"). However, in this analysis, the engine has been assumed to be warm.

Another constraint during the optimization process is the change in state of battery charge at the beginning and end of the cycle in order to prevent misleading fuel economy results, arising from excessive use of the electric motor (this would result increased fuel usage during the next vehicle run, for battery replenishment).

The baseline vehicle chosen for this study has been a 4 - 1 production family sedan with a specific Parallel Hybrid Electric Vehicle (PHEV) configuration, which has been used throughout the study. Following table gives details of its' specifications;

TABLE I
VEHICLE MODEL SPECIFICATIONS

Parameter	Value
Total weight	1642 kg
Chassis weight	1000 kg
Frontal area	1.92 m2
Coefficient of Drag	0.32
Vehicle length	5.00 m
Transmission	Manual, 5 speed
Transmission efficiency	95% (all gears)
Gear ratios	3.5:2.14:1.39:1:0.78
Final drive ratio	3.98
Gear changes	1- 2 and 2 -1 @ 24 km/h 2- 3 and 3 -2 @ 40 km/h 3- 4 and 4 -3 @ 64 km/h 4- 5 and 5 -4 @ 75 km/h

(Permanent Magnet Motor 20kW continuous, 40kW peak, Advanced Battery 40kW, 4kWh, 100V)

It is important to note that the simulation essentially works in a reverse direction to what happens in the real scenario – i.e. the drive cycle is the input to the vehicle model, and the required changes to the vehicle speed are calculated based on the drive cycle. This change in vehicle speed is then converted in to engine speed and torque requirements by taking into account the current gear ratio (a shifting map is given for the model) and the efficiencies of the transmission. The fuel consumed is then calculated from a look-up table of fuel rate against engine operating point (defined by engine speed and torque). The fuel usage map as a function of operating point has been evolved from steady state maps and is illustrated in Fig. 2.

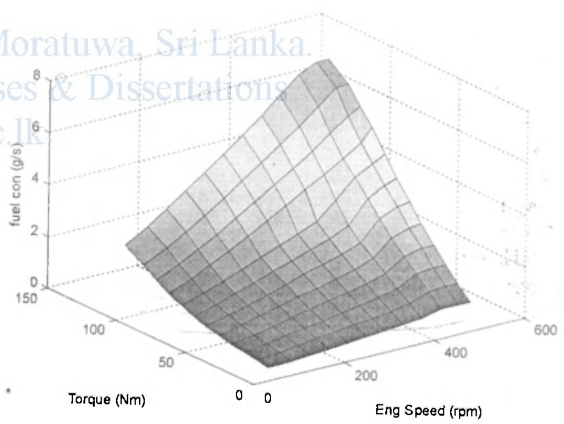


Fig. 2. Fuel consumption map of the ICE of tested HEV

B. Drive cycles

Driving cycles are defined as the test cycle used to standardize the evaluation of vehicle fuel economy and emissions. Driving cycles are speed time sequences that represent the traffic conditions and driving behavior in a specific area.

In this optimization study, New European Driving Cycle (NEDC), which is commonly used in regulatory work has been used and is shown in Fig-3.

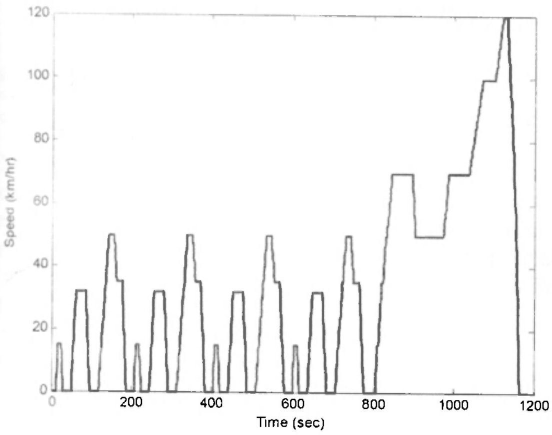


Fig. 3 New European Drive Cycle

The optimization process now represents a constrained multi-dimensional problem that could not be easily solved. In order to find a solution to the problem and to optimize fuel economy of the Parallel HEV configuration indicated in Figure 1. the Genetic Algorithm approach could be employed over the above drive cycle as mentioned below;

III. OPTIMISATION USING GA

In this section an Evolutionary Computational algorithm has been developed to find out the optimum fuel trajectory for a known drive cycle using Genetic Algorithm (GA). The GA is a stochastic global search method that mimics the metaphor of natural biological evolution. GAs operate on a population of potential solutions, applying the principle of survival of the fittest to produce (hopefully) better and better approximations to a solution [5]. In the following sub-section, the architecture of GA applied to the fuel economical operation of PHEV is presented.

A. Domain and Constraints

Fig. 1 presents a block diagram of a PHV with an EM and an ICE. For this particular configuration the ICE and EM power are combined downstream of the transmission. Alternatively the power could also be combined upstream of the transmission. There are five different ways to operate the system depending on the flow of energy: 1) provides power to the wheel with only ICE, 2) provides power to the wheel with only EM or, 3) provides power to the wheel with both ICE and EM simultaneously, 4) charges the battery, using part of the ICE power and generated power by EM running as a generator 5) slow down the vehicle by letting the wheel to drive the EM as a generator.

In this analysis, since the drive cycle is known, corresponding power demand to achieve the speed trajectory is calculated using dynamic equations [6], taking sampling period as one second.

The power at the wheel is given by,

$$P_{wheel} = \sum force \times v = (F_{acc} + F_{incline} + F_{rr} + F_{drag}) \times v$$
$$= (m \times a + mg \sin C_{rr} \cos A + 1/2 \rho_{air} C_D A_f v^2) \times v$$

where m is the total mass, a is the vehicle acceleration, v is the vehicle velocity, A is the angle of slope, C_{rr} is the coefficient of tire rolling resistance, C_D is the drag coefficient, ρ is the density of air and A_f is the frontal cross section area of the vehicle.

Power demand corresponding to each sampling period is split between two power sources. Here, it is also assumed that the ICE is in continuous operation throughout the drive cycle, even when the motor is providing the total power requirement for moving of the vehicle and also when the vehicle is at stand still.

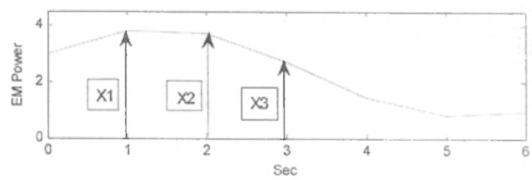
The SOC of the battery pack decides whether the required power contribution of the EM is possible or not. If the batteries are completely charged EM cannot be allowed to operate as a generator and on the other hand if the batteries are completely discharged, positive power contribution from EM is not possible. It is also required to keep the SOC within a certain upper and lower limit in order to avoid damage to the battery pack. In this analysis initial SOC is considered as 50%. In order to have meaningful result (fuel economy), SOC at the end of the cycle should not vary much from the initial value and at any time of operation, the battery SOC should not go outside the specified minimum and maximum limits (40% & 80%).

B. Population and Individuals

There are variables equivalent to the total number of operating seconds of the drive cycle and each variable represents the power contribution from EM during the corresponding sampling period. The individuals which composes the population of the current generation consists of contribution from EM at each second. EM power can have any value between maximum motor power and maximum generator power (generation is represented by negative sign).

C. Chromosomes

Chromosome composes of string of binary numbers corresponding to EM power at each second.



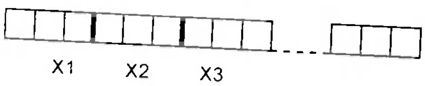


Fig. 4. Example of EM contribution (Top), Chromosome (Bottom). This composes of string of binary numbers which represent EM power at each seconds of the drive cycle.

X1, X2 ....are the binary representation of EM power at each second. In this approach, for New European Drive Cycle, there are 1200 variables to be optimized. The precision of variables depend on the size of binary coding of the variables. In this study, each variable has been represented by a binary value of 06 (six) bits.

D. Fitness Function

The fitness function calculates the total fuel consumption with respect to ICE power trajectory. Here, the EM power at each second is taken as the decision variable. Since the power demand is known the ICE power can be calculated. For negative power request (braking), the ICE power is considered zero and the sum of motor and mechanical braking power would be taken as equal to power demand. However for positive power demand, the sum of ICE and EM power should be equal to the power demand.

Once the ICE power is known, the corresponding engine torque and speed can be calculated taking gear ratios and efficiencies of transmission in to account. Then empirical model based on test data is used for fuel consumption calculation. Two look up maps are in this model, engine torque and fuel consumption. Engine torque map decides engine torque limit at each speed, while fuel consumption map (Fig. 2) decides fuel rate (g/s) of engine speed and torque

In this study, the objective function is defined as follows:

$$J(x) = \sum_{i=1}^{n} FCi + M^{k}W(N_B + N_P)$$

Where, FCi is the fuel consumption during i^{th} second and $J(x)$ is the total fuel consumption plus the penalty.
M is the number of generation and W is the weighting coefficient. N_B and N_P quantify magnitudes of constraints.

Some of the chromosomes which represent the EM power trajectory in the problem space are invalid, as the battery SOC and the rate of change of power at some instants may exceed the limits. To represent the poorness of the chromosome in such a situation, a penalty is introduced in to the objective function $J(x)$, similar to that used in constrained optimizations treated under penalty function concept in evolutionary computational techniques. Here, N_B and N_P are the number of instants that the battery SOC and the rate of charge of power exceed the limits within the drive cycle corresponding to a chromoscme. Here, 10 and 1.2 have been used for 'W' and 'k' respectively.

E. Selection

Once the individuals have been assigned a fitness value, they could be chosen from the population, with a probability according to their relative fitness, and could be recombined to produce the next generation. Selection is the mechanism for selecting the individuals with greater fitness over the low fitted ones to produce new individuals for the next population. In this study, individuals have been selected from the population using roulette wheel selection, in which the probability to chose a certain individual is proportional to its fitness.

F. Crossover

Crossover is the method of merging the genetic information of two individuals to produce new individuals. Here, multi point crossover which performs multiple-point crossover between pairs of individuals contained in the current population have been used, according to the crossover probability and return of a new population after mating.

G. Mutation

In natural evolution, mutation is a random process where one allele of a gene is replaced by another to produce a new genetic structure. In GAs, mutation is randomly applied with low probability, and modifies elements in the chromosomes. In this study, we have used mutation probability as 0.0001. The positive effect of mutation is the preservation of genetic diversity such that the local maxima can be avoided.

In this study, the population of GA has been initialized with 500 randomly selected individuals around zero (i.e. no contribution from EM throughout the drive cycle) and maximum number of generations have been set to 1000. Further improvement of the accuracy of the variables and the convergence rate can be achieved by increasing the size of the binary coding of variables and the number of individuals in a generation with the penalty of simulation run. The extreme expansion of the individual numbers would tend to a direct search method.

IV. RESULTS AND ANALYSIS

Fig. 5 shows the optimization process history for the driving cycle. As it could be seen in this figure, the rate of convergence is faster for the first 100 generations and then the convergence rate is slower. It has taken almost 1000 generations to converge to the optimum value. This is justified by the fact that this optimization process consists of 1200 variables as EM contributions at each second which is considered as decision variable and each variable has 2^6 different values. Since the battery SOC at any instant should be kept within the desired range, for every individual (i.e. EM power trajectory) the battery SOC at every second is calculated and if the SOC falls outside the limits at any instant, a penalty which represents the amount by which the constraints are violated by the chromosome is added to the fitness value, in order to reduce the probability of selecting it to form the next generation. Therefore, considerable amount of chromosomes in each generation will subject to this constraint and it will also be one of the reasons for slowing down of convergence. As each generation composes of 500 individuals, evaluation of fitness function including the objective function and constraints for one generation may take an average of about 20 minutes for a 3.0 GHz Pentium computer.

In Table II, the optimum fuel economy for the selected drive cycle is compared with that of a conventional vehicle. This indicates that a maximum of about 30% improvement can be achieved by a Parallel HEV, compared to a conventional vehicle. It is obvious that fuel economy varies with the driving cycle and hence the results obtained through this study are valid only for the selected drive cycle.

The Power demand to achieve the given speed profile and the optimum contribution from the EM are indicated in figures 6 and 7 below.

Fig. 8 shows the battery SOC variation throughout the drive cycle. It could be observed that, the SOC at any instant is within the upper and lower limits and the SOC difference at the beginning and the end of the cycle is just 2%.

TABLE II
FUEL ECONOMIES FOR CONVENTIONAL AND OPTIMISED HYBRID VEHICLE

Drive Cycle	NEDC	
Fuel Economy (L/100km)	Conventional Vehicle	10.3
	Parallel HEV	7.23
Improvement with HEV (%)	30	

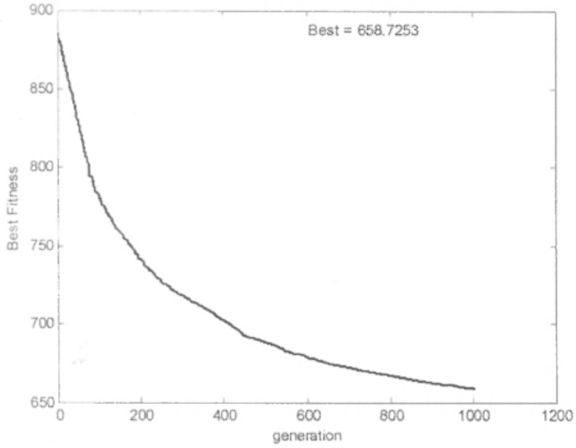


Fig 5. History of genetic algorithm optimization process.

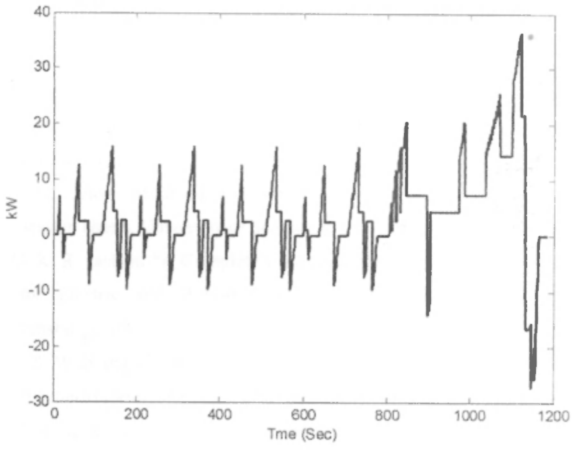


Fig. 6. Power demand to achieve the speed profile.

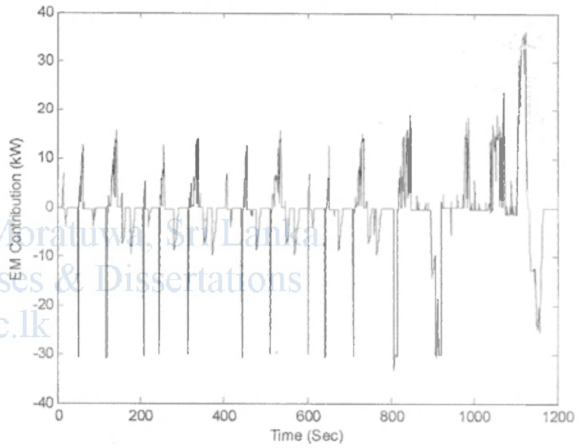


Fig. 7. Contribution from EM over the drive cycle.

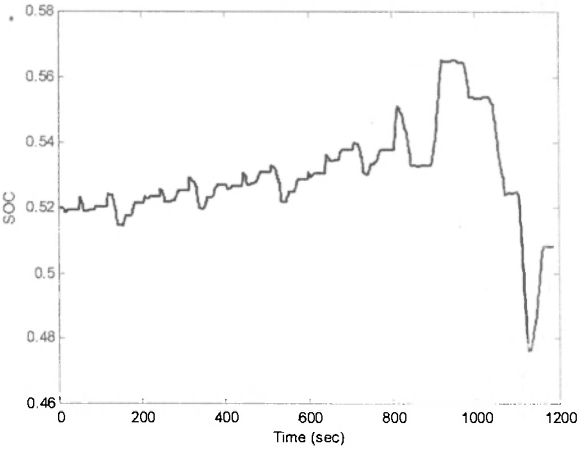


Fig. 8. Battery SOC variation over the drive cycle.

V. CONCLUSIONS AND REMARKS

In this paper, the methodological approach to find out maximum fuel economy of a PHEV for a known cycle is presented. In this approach, an optimization problem is formulated in order to employ genetic algorithm for the best solution. Variables are defined to find out optimum power contribution from EM and ICE. The objective function is defined in order to minimize fuel economy and to keep the battery SOC within the desired range throughout the drive cycle. In this study we do not consider the limitations in switching of electric motor between motor mode and generator mode. The result from the GA optimization is the maximum fuel economy that can be achieved by an HEV with selected configuration for the selected drive cycle.

The results of this GA optimization are useful to measure the effectiveness of a power management system of an HEV.

The development in automobile and telematics industry has enabled the power management systems to be more intelligent. Hybrid technology and telematics have combined together to create "intelligent vehicle" to make more accurate predictions about the possible speed trends well ahead of the current times, enabling more effective decisions on the power split of the two power sources, in order to bring the overall fuel economy of the vehicle close to its' maximum point.

In future, authors wish to research and investigate the possibility of employing real time genetic algorithm with less number of chromosomes and optimum code lengths. This will enable applications to optimize such situations online, to achieve the theoretical maximum possible fuel economy through optimally employed telematics.

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Appendix - B

Codlings of MATLAB Programs

```
% Data input program
% V - Drive Cycle, SOCE - Initial SOC, S - 1 + Number of predictions

function[WM,TMM,TEM,SOCnM,TDM]=cycle(V,SOCE,S)

% calculate the power demand, P and the Torque, Td

[P,W,Td] = driverdemand(V);

[n,m]=size(V);

% Results matrixes, TMM - Motor Torque, TEM - Engine Torque
% SOCnM - SOC

TMM = zeros(n,1);
TEM = zeros(n,1);
SOCnM = zeros(n,1);

for i=1:n

    if i < (n+2-S)

        INOP = zeros(S,1);
        INOW = zeros(S,1);
        INOTd = zeros(S,1);


    for j=1:S
        INOP (j) = P(i+j-1);
        INOW (j) = W(i+j-1);
        INOTd (j) = Td(i+j-1);
    end


    PMO=GA(INOP,INOW,INOTd,SOCE);% Call GA inputs P,W,T

    PMM=PMO';
    if W(i)==0
        TMM(i)=0;
    else
        TMM(i)=PMM(1)*1000/W(i);
    end
    if Td(i)>0
        TEM(i)=Td(i)-TMM(i);
        if TEM(i)>0
        TEM(i)= TEM(i);
        else
            TEM(i)=0;
        end
    else
        TEM(i)=0;
    end

        SOCE=soc(SOCE,PMM(1));
        SOCnM(i)=SOCE;

    else
```

```
        if W(i)==0
            TMM(i)=0;
        else
            TMM(i)=PMM(S-n+i)*1000/W(i);
        end


        if Td(i)>0
            TEM(i)=Td(i)-TMM(i);
            if TEM(i)>0
                TEM(i)=TEM(i);
            else
                TEM(i)=0;
            end
        else
            TEM(i)=0;
        end
        SOCE=soc(SOCE,PMM(S-n+i));
        SOCnM(i)=SOCE;
    end

end

 WM=W;
 TDM=Td ;
```

```
% This script implements the Simple Genetic Algorithm

function [PMot]=GA(DP,Win,Tin,SOCin)

driverDemand=DP/1000;
% kW
[m,n]     = size(DP);

LimitUpper = zeros(1,m);
LimitLower = zeros(1,m);



NIND = 20;            % Number of individuals per populations
MAXGEN =50;           % maximum Number of generations
GGAP = .90;           % Generation gap, how many new individuals created
NVAR = m;             % Number of variables
PRECI = 5;            % Precision of binary representation

% Limit selection
for i=1:m

    if Win(i)>500
         TOP=44;
    elseif Win(i)> 60
        TOP=Top(Win(i));
    else
        TOP=44;
    end

   if driverDemand(i)>0
       if driverDemand(i)< 6
        LimitUpper(i)= driverDemand(i);
        LimitLower(i)= 0;
       else
           if driverDemand(i)> TOP*Win(i)/1000
                LimitUpper(i)= driverDemand(i)- TOP*Win(i)/1000;
                LimitLower(i)= 0;
           else

               if driverDemand(i)> (TOP*Win(i)/1000)*.75

                    LimitUpper(i)= 0;
                    LimitLower(i)= -10;

               else

                LimitUpper(i)= 20;
                LimitLower(i)= 0;

               end
           end
       end
   end

   if driverDemand(i)==0
```

```
            LimitUpper(i)= 0;
            LimitLower(i)= 0;
    end

    if driverDemand(i)<0
            LimitUpper(i)= 0;
            LimitLower(i)= -15;
    end
end
% Limit selection end

% LimitUpper
% LimitLower
% Build field descriptor
  FieldD = [rep([PRECI],[1,NVAR]);
  LimitUpper;LimitLower;rep([0;0;1;1], [1, NVAR])];

%Initialise population
 Chrom = crtbp(NIND, NVAR*PRECI);

% Reset counters
   Best = NaN*ones(MAXGEN,1);    % best in current population
   gen = 0;           % generational counter

% Evaluate initial population
   ObjV = objfun(bs2rv(Chrom,FieldD),SOCin,Win,Tin);


% Generational loop
   while gen < MAXGEN,

    % Assign fitness-value to entire population
       FitnV = ranking(ObjV);

    % Select individuals for breeding
       SelCh = select('rws', Chrom, FitnV, GGAP);

    % Recombine selected individuals (crossover)
       SelCh = recombin('xovsp',SelCh,0.7);

    % Perform mutation on offspring
       SelCh = mut(SelCh,0.06);

    % Evaluate offspring, call objective function
       ObjVSel = objfun(bs2rv(SelCh,FieldD),SOCin,Win,Tin);

    % Reinsert offspring into current population
       [Chrom ObjV]=reins(Chrom,SelCh,1,1,ObjV,ObjVSel);

    % Increment generational counter
       gen = gen+1;

   end
% End of GA
OPTIMUM_VALUES=getopv(Chrom,ObjV,FieldD);

PMot = OPTIMUM_VALUES;
```

```
% Objective function

 function ObjVal = objfun(Chrom,SOCin,Win,Tin)


EngT=zeros(size(Chrom));
[n,m]=size(Chrom);

%creation of Motor Torque Metrix

for i=1:n
    for j=1:m
        if Tin(j)>0;
            if Tin(j)-Chrom(i,j)*1000/Win(j)>0
                EngT(i,j)=Tin(j)-Chrom(i,j)*1000/Win(j);
            else
               EngT(i,j)=0;
            end



        else
            EngT(i,j)=0;
        end
    end
end

%Creation of Fuel Consumption metrix

Fuel = zeros(size(Chrom));

for i=1:n
    for j=1:m

        [TE,WE,EF,engEff]=fuelConE(EngT(i,j),Win(j));

         Fuel(i,j)=EF;

    end
end

%Creation of Objective Function

SOC1=SOCin;
[Kk] = charge(SOC1,Chrom,Win);
ObjVal=zeros(n,1);
for i=1:n
    for j=1:m
        ObjVal(i)=ObjVal(i)+Fuel(i,j);
    end
end

ObjVal=ObjVal.*Kk;
```

```
%SOC Check program

function [k]=charge(SOC1,Chrom,W)

[nn,mm] = size(Chrom);

EffB=.9;  %Battery efficiency

Qm=4*3600; %kWsec

k=zeros(nn,1); %create metrix in which each element is 0

for i=1:nn
    SOCE=SOC1;


    p=zeros(mm,1);

        for j=1:mm

         SOCE=SOCE-Chrom(i,j)/(EffB*Qm);

          if SOCE>.8
             p(j)=10000;
             elseif SOCE>.4
                 p(j)=p(j);
             else
             p(j)=10000;
            end

         end

        k(i)= (p'*p)+1;

end
```

```
% Power Demand calculator

function
[PD,sped_beforeGearbox,torq_beforeGearbox]=driverdemand(drive_cyc)

% 1. vehicle model

% total mass
m=1642;
CdA = ven_chars.CdA;                                              %
drag coeificient * area
Crr = veh_chars.Crr;                                              %
rolling resistance
g   = 9.8;                                                        %
gravity [m/sec^2]
rho = drive_chars.rho;                                            %
air density
h   = drive_chars.slope;                                          %
slop of the road


% 2. drive cycle and energy variation

%melb_peak_cyc;                    %load the drive cycle
%ftp_75;                          % federal transpotation procedure
%NEDC;                             % new european drive cycle
v=drive_cyc;
v- v*1000/3600;                   % convert to m/s
T=length(v);                      % length of the drive cycle


%              v3
%             ____
%            |    |
%      _v2_|      |
%     |           |
%     |
%  __v1_|
%   1     2   3


% kinetic energy change
%   m*v2^2/2-m*v1^2/2
% = m(v2-v1)*(v2+v1)/2
% = mass* accleration* mean velocity

%calculate the acceleration and mean velocity
vdot    = zeros(size(v));        % acceleration
vmean   = zeros(size(v));        % mean velocity

for i=1:(T-1)
    vdot(i)        = v(i+1)-v(i);

    vmean (i)      = (v(i+1)+v(i))/2;
end

airDragP  = 0.5.*rho.*CdA.*vmean.^3;          % air drag power
```

```
rollDragP = m*g*Crr*vmean;                              % rolling resistance
accelP    = m*vdot.*vmean;                              % acceleration power
required
hillP     = m*g*h*vmean;                                % hill climbing power

% total drive power
driverDemand = airDragP + rollDragP  + hillP + accelP;
PD=driverDemand;



Eps=0.5;                                                % small value instead of
0
wheel_radius = 0.29;

wheelSpeed  = vmean/wheel_radius;                        % convert to
rotational speed [rad/sec]
wheelTorq   = zeros(size(driverDemand));               % initialze the wheel
torque
for i=1:length(driverDemand)-1
    if vmean(i)>Eps
        wheelTorq(i)= driverDemand(i)/wheelSpeed(i)+145*vdot(i)/0.29;
% add engine inertia also
    end
end


%%%% torque & speed before the final drive
Rr=3.98;                                        % final drive ratio
for i=1:length(v)
    fin_Dri.T(i)=wheelTorq(i)/Rr;               % torque before final drive.
    fin_Dri.W(i)=wheelSpeed(i)*Rr ;             % speed before final drive.
end


% VMax          = max(fin_Dri.W);
% scale         = 300/VMax*0.6/1.2;

% use the speed dependent gear shifts
torq_beforeGearbox=zeros(length(v),1);
sped_beforeGearbox=zeros(length(v),1);
% gearNo=[3.8,2.14,1.25,0.9,0.64];%*scale;      %%%%gear ratio
gearNo=[3.8,2.2,1.6,1.25,0.9];
%  gearNo=[3.8,1.81,1.21,0.86,0.64];

% the velocity at which the gear positions are changed
gear_1_speed    = 24*1000/3600/wheel_radius*Rr;
gear_2_speed    = 40*1000/3600/wheel_radius*Rr;
gear_3_speed    = 64*1000/3600/wheel_radius*Rr;
gear_4_speed    = 75*1000/3600/wheel_radius*Rr;



gearRa=zeros(size(v));
gearNNO=zeros(size(v));
for i=1:length(v)-1
    if fin_Dri.T(i)>=eps
```

```
        if fin_Dri.W(i)< gear_1_speed
            gearRa(i)          = gearNo(1);     gearNNO(i)=1;
        elseif fin_Dri.W(i)< gear_2_speed
            gearRa(i)          = gearNo(2);     gearNNO(i)=2;
        elseif fin_Dri.W(i)< gear_3_speed
            gearRa(i)          = gearNo(3);     gearNNO(i)=3;
        elseif fin_Dri.W(i)<gear_4_speed
            gearRa(i)          = gearNo(4);     gearNNO(i)=4;
        else
            gearRa(i)          = gearNo(5);     gearNNO(i)=5;
        end
    else
         if fin_Dri.W(i) >=gear_4_speed
            gearRa(i)          = gearNo(5);     gearNNO(i)=5;
        elseif fin_Dri.W(i)>= gear_3_speed
            gearRa(i)           = gearNo(4);     gearNNO(i)=4;
        elseif fin_Dri.W(i)>= gear_2_speed
            gearRa(i)          = gearNo(3);     gearNNO(i)=3;
        elseif fin_Dri.W(i)>=gear_1_speed
            gearRa(i)          = gearNo(2);     gearNNO(i)=2;
        else
            gearRa(i)          = gearNo(1);     gearNNO(i)=1;
        end
    end

    torq_beforeGearbox(i)= fin_Dri.T(i)/gearRa(i); % torque after
gear box
    sped_beforeGearbox(i)= fin_Dri.W(i)*gearRa(i); % speed after gear
box

end
```

```
% Engine Program


% engine Map
% 1.5L Prius_jpn (Atkinson cycle)engine



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% SPEED & TORQUE RANGES over which data is defined
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% (rad/s), speed range of the engine
eng_spd=[700 1273 1745 2218 2691 3164 3636 4109 4582 5055 5500
5800]*2*pi/60/1.2;
lbft2Nm=1.356; %conversion from lbft to Nm
% (N*m), torque range of the engine
eng_trq=[5.6 11.2 16.8 22.3 27.9 33.5 39.1 44.7 50.3 55.8 61.4
70.0]*lbft2Nm/scalefac*1.2;

clear lbft2Nm



% (g/s), fuel use map indexed vertically by fc_map spd and
% horizontally by fc_map_trq
% fuel use from Feng An's model calibrated with actual data for
Prius_jpn (Atkinson cycle) engine
eng_fuel_con = [
 0.0962  0.1269  0.1576  0.1883  0.2191  0.2498  0.2805  0.3112
0.3610  0.4566  0.4641  0.4641
 0.1420  0.1909  0.2398  0.2887  0.3375  0.3864  0.4353  0.4842
0.5584  0.7129  0.7383  0.7383
 0.1871  0.2541  0.3212  0.3882  0.4552  0.5223  0.5893  0.6563
0.7533  0.9683  1.0215  1.0215
 0.2371  0.3223  0.4075  0.4927  0.5779  0.6630  0.7482  0.8334
0.9524  1.2297  1.3207  1.3207
 0.2953  0.3987  0.5020  0.6053  0.7087  0.8120  0.9154  1.0187
1.1591  1.5012  1.6278  1.6399
 0.3656  0.4871  0.6086  0.7301  0.8516  0.9731  1.0946  1.2160
1.3777  1.7875  1.9363  1.9839
 0.4521  0.5918  0.7314  0.8711  1.0107  1.1504  1.2900  1.4297
1.6124  2.0936  2.2647  2.3577
 0.5591  0.7169  0.8747  1.0325  1.1903  1.3481  1.5059  1.6637
2.0304  2.4249  2.6182  2.7666
 0.7038  0.8993  1.1014  1.3102  1.5255  1.7475  1.9760  2.2112
2.4530  2.7014  2.9563  3.2156
 0.8680  1.0863  1.3123  1.5458  1.7869  2.0356  2.2919  2.5558
2.8272  3.1063  3.3930  3.5433
 1.0663  1.3087  1.5596  1.8193  2.0877  2.3647  2.6504  2.9448
3.2479  3.5596  3.8801  3.8830
 1.3032  1.5709  1.8484  2.1357  2.4330  2.7402  3.0572  3.3841
3.7208  4.0675  4.2459  4.2459 ]/0.749/scalefac;

[Speed_eng,Torque_eng]  = meshgrid(eng_spd,eng_trq);
en_pow                  = Torque_eng.*Speed_eng/1000;
en_fuel_con_gpkWh       = eng_fuel_con*0.749./en_pow*3600;
Eng_effic               =
(Torque_eng.*Speed_eng)./(eng_fuel_con*0.749*42*1000);
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% LIMITS
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

lbft2Nm=1.356; %conversion from lbft to Nm

eng_max_trq=[56.9 58.2 59.5 60.7 62.0 63.2 64.5 65.7 67.0 64.3 61.5
58.6]*lbft2Nm/scalefac*1.2; % N-m

clear lbft2Nm

function [TE,WE,EF,engEff]=fuelConE(T,W)
%FUELCON computes the fuel consumption at engine torque T
%and engine speed W
engine_map_ins;

% if the speed is less than the minimum engine speed
if W<min(eng_spd)
    W=1.01*min(eng_spd);
elseif W>max(eng_spd)
    W=0.99*max(eng_spd);
end

% if the torque is less than minimum torque or greater than max
torque
if T<min(eng_trq)
    T=1.01*min(eng_trq);
elseif T>max(eng_trq)
    T=0.99*max(eng_trq);
end

% check the torque exceed the maximum torque
Tmax=interp1(eng_spd,eng_max_trq,W);

if T>Tmax
    T=0.99*Tmax;
end

%then find the fuel consumption at (W,T) point
fuel  = interp2(Speed_eng,Torque_eng,eng_fuel_con,W,T,'linear');
engTor  =T;
engSpe  =W;

WE=engSpe;
TE=engTor;
EF=fuel;
engEff=(engTor*engSpe)/(fuel*0.749*42*1000);
```