DETERMINATION OF MAXIMUM POSSIBLE FUEL ECONOMY OF HEV FOR KNOWN DRIVE CYCLE: GA BASED APPROACH

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By

RANDOMBAGE SUDATH WIMALENDRA

Supervised by Dr. Lanka Udawatta

Department of Electrical Engineering

University of Moratuwa

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DECLARATION

I certify that this dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any University to the best of my knowledge and believe it does not contain any material previously published, written or orally communicated by another person or myself except where due reference is made in the text. I also hereby give consent for my dissertation if accepted, to be made available for photocopying and for interlibrary loans, and for the title and summary to be made available to outside organizations.

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Dr. Lanka Udawatta

Supervisor

Date : 31-01-200

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ABSTRACT

Hybrid electric vehicles (HEVs) have 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 using a combination of an internal combustion engine and Electric motor (EM) have the potential of improving fuel economy by operating Internal Combustion Engine (ICE) in the optimum operating range and by making use of regenerative braking during deceleration This paper described a methodological approach to find out the maximum fuel economy that can 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 consumption. The optimization process represents a constrained nonlinear and time-varying problem that is not easily solved. Here GA approach was used to find out optimum power split between two power sources over a 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 (HEV) 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. Variables are defined to find out optimum power contribution from EM and ICE. The objective function is defined to minimize weighted sum of the fuel economy and to keep the battery SOC within the desired range throughout the drive cycle. These results represent the maximum fuel economy any power management system of a Hybrid Electric Vehicle with the selected HEV configuration can ever achieve and does allow a benchmark to be set against which the fuel economy is measured. It is obvious that fuel economy varies with the driving cycle and hence the result obtained from this study is valid only for the selected drive cycle. The optimum fuel economy for the selected drive cycle is compared with that of conventional vehicle

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R.S.Wimalendra
Department of Electrical Engineering,
University of Moratuwa,
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Chapter 1

1.0 Introduction

The Oxford Dictionary explains the word "hybrid" as "the offspring of two plants or animals of different species or varieties" and as being "things composed of diverse elements." A Hybrid Electric Vehicle (HEV) can, thus, be seen as a mixture of an Internal Combustion Engine (ICE) powered automobile and an electric vehicle.

As 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 Vehicle has 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.

1.1. HEV Evolution

Two centuries ago, in 1881 the first electric vehicle (EV) was already in use by Gustave Trouvé, shortly after Nikolaus August Otto invented the four-stroke internal combustion engine (ICE) in 1876. In 1902, the first Gasoline Electric Hybrid "Mixte" was built up as a range extender principle. The first manufacturer to market HEVs in any great volume was Toyota by launching the Prius I in 1997. In 2010, HEV sales forecast is expected to be more than 800.000 units per year [1], nearly 40 times higher than today's figures.

1.2. Motivation for HEVs

Today's discussion about sustainable technologies concerning emission reduction, fuel saving potential and carbon dioxide reduction (CO2) respectively, treats often two subjects: alternative fueled ICEs, especially compressed natural gas (CNG), and hybrid electric vehicles, which besides the high fuel saving potential, bring further benefits for our society. Throughout the motored vehicle evolution, there have always been concept and prototype cars combining the advantages of two different propulsion systems, which include a second power source and energy storage device to supplement the fuel tank.

Because of pricing by the petroleum exporting countries, HEVs are under discussion concerning fuel consumption benefit and therefore lower running costs. But also higher manufacturing costs by HEV related components need to be considered. From the technical point of view, the combination of an ICE with an electric machine appears to make sense because of their different torque characteristics. Therefore the power assisting by the electric motor in forms of high low-end torque results in a win in comfort as well as increased "Fun-to-Drive" behavior, and in addition an improved noise-vibration-harshness behavior can be achieved [2]. Such an advanced technology could also make a contribution for a better public image.

1.3. Literature review:

Because of the importance and potential benefits of the hybrid technology, many of the research institutions and universities all over the world are actively involved in this research area.

HEV concept, impacts and benefits of HEVs are discussed and compared with those of conventional vehicles in [3] - [6]. Current status, design and selection of HEV components have been presented in [7] - [10]. A braking control strategy that is based on estimating the parameter for achieving the maximum braking force is presented in [11].

The control strategies of hybrid electric vehicles are in an area of high interest due to the complex nature of hybrid electric vehicles. 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 in [2], [12], [13], [14] & [15] and fuel economy improvement compared to conventional vehicle, achieved by these control systems are in the range from 8% to 13%. 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.

Researchers have explored different ways leading to an optimal control to minimize fuel consumption of parallel hybrid vehicles in general. A driving situation identification process which can subsequently used by the HEV power management system, based on fuzzy logic and Neural Network is discussed in [14] and the HEV control strategy based on above is presented in [15].

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. This information can be used by the HEV power management system to predict its future speed trend in order to decide optimum power split between the two sources more effectively. Several algorithms have been proposed to predict the future speed trends, with the use of preview information provided by the telematics. A methodology of combining two technologies, hybrid and telematics together to create "intelligent vehicle" which provides improved fuel economy with traffic preview is discussed in [16].

Traditional optimization techniques such as linear programming and nonlinear programming are not good at dealing with very high complex problems like HEV systems

[17]. Fortunately, the stochastic search techniques such as GA are particularly suitable for complex engineering design. For instance, such algorithms require little a .priori knowledge about the search space. Application of Genetic Algorithm to solve search and optimization problems are given in [17], [18]. An approach to generate on-line adaptive system based on GA was presented in [19], [20].

Though, many different kind of power management system to improve both fuel economy and emission of HEVs have been proposed, discussion about systematic approach to find the maximum possible fuel economy of HEV could not be found.

1.4. Objective

Many power controllers have been proposed in previous researches to improve the fuel economy of HEVs and the performance of these controllers are evaluated based on the improvement of fuel economy with respect to that of conventional vehicles. But it does not make sense about the level of improvement that can be achieved by them with respect to the maximum possible fuel economy. Though it is obvious that the HEVs have great potential of improving fuel economy, it is not very clear to what extent fuel economy can be improved with introduction of second power source to a vehicle.

The aim of this study is to develop a methodology to find out the maximum fuel economy that a Parallel HEV (PHEV) can achieve with any type of HEV energy management system for a known drive cycle [18]. Parallel configuration of HEV is selected for this study as it's flexibility of powertrain design. Here, genetic algorithm (GA) which will lead to find a global optimum has been used as the technique for optimization. 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

In this study, fuel consumption of the PHEV is formulated as an optimization problem. Since the optimization process represents a constrained and time-varying problem, which is highly complex and nonlinear, Genetic Algorithm is used to solve the optimization problem. Backward looking vehicle simulation model [1] is used with empirical engine model based on test data is used for calculation of fuel consumption through out the drive cycle.

The result from this study may be useful not only to evaluate the performance of any PHEV power management system but also to develop a more effective control strategy for HEV.

Chapter -2

2.0 Hybrid Electric Vehicles

A **hybrid vehicle** is a vehicle that uses two or more distinct power sources to propel the vehicle. A **hybrid electric vehicle** is a hybrid vehicle which combines a conventional propulsion system with a rechargeable energy storage system to achieve better fuel economy than a conventional vehicle.

The ICE in an HEV can be smaller, lighter, and more efficient than the one in a conventional vehicle, because the combustion engine can be sized for slightly above average power demand rather than peak power demand. The drive system in a vehicle is required to operate over a range of speed and power, but an ICE's highest efficiency is in a narrow range of operation, making conventional vehicles inefficient. On the contrary, in most HEV designs, the ICE operates closer to its range of highest efficiency more frequently [12]. The power curve of electric motors is better suited to variable speeds and can provide substantially greater torque at low speeds compared with internal-combustion engines [1]. The greater fuel economy of HEVs has implication for reduced petroleum consumption and vehicle air pollution emissions.

2.1. The Need of Hybrid Electric Vehicles

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 internal combustion engines, batteries, ultracapacitors, or hydrogen fuel cells. 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.

2.1.1. Environmental Concerns

The United Nations estimated that over 600 million people in urban area worldwide were exposed to traffic-generated air pollution [21]. Therefore, traffic related air pollution is drawing increasing concerns worldwide. Hybrid Electric Vehicles hold the potential to considerably reduce greenhouse gas 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.

2.1.2. Energy Consumption

Around the world, we are experiencing a strong upward trend in oil demand and tight supply. Maintaining a secure energy supply becomes an on-going concern and a high priority. It is important to note that over 15 million barrels of crude oil are being consumed; of which 69% are for the transportation sector [1]. The transport energy consumption worldwide are also continue to rise rapidly. In 2000 it was 25% higher than in 1990 and it is projected to grow by 90% between 2000 and 2030 as shown in Figure 2.1.

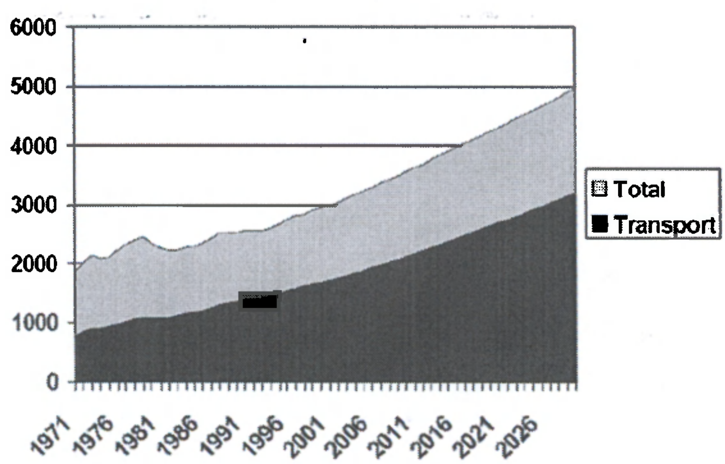


Figure 2.1 Globe Oil Consumption Perspectives [20]

Many HEV projects reported fuel economy improvement from 10% to 25% [12] - [16]. Therefore, HEV provides a promising solution to relieve the energy shortage.

2.2. Classification of HEV

The drivetrain of a vehicle is composed of the components that are responsible for transferring power to the drive wheels of the vehicle. With hybrids there are three possible setups for the drivetrain: the series drivetrain, the parallel drivetrain, and the series/parallel drivetrain.

2.2.1 Series Hybrid System

This is the simplest hybrid configuration. In a series hybrid, the electric motor is the only means of providing power to get your wheels turning. The motor receives electric power from either the battery pack or from a generator run by a gasoline engine. Figure 2.1 shows the series HEV configuration. A computer determines how much of the power comes from the battery or the engine/generator set. Both the engine/generator and regenerative braking recharge the battery pack. The engine is typically smaller in a series drivetrain because it only has to meet average driving power demands; the battery pack is generally more powerful than the one in parallel hybrids in order to provide remaining peak driving power needs. This larger battery and motor, along with the generator, add to the cost, making series hybrids more expensive than parallel hybrids.

The biggest advantage of the series HEV configuration is that the engine power output is buffered by the battery pack, which allows the engine to operate predominately at steady state in its most efficient mode to provide minimum fuel consumption. Because the engine can operate in its most efficient mode when running, emissions are significantly decreased. The efficiency of series HEVs is lowered as energy is converted two times when the vehicle is cruising [21].

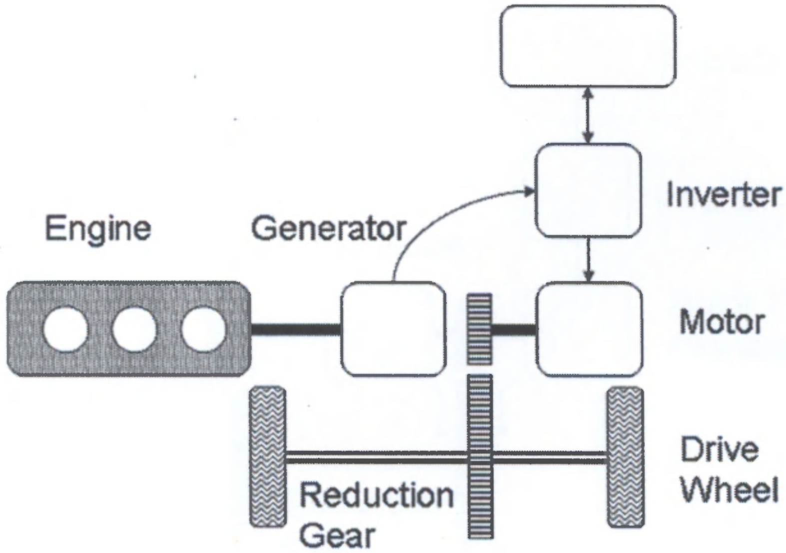


Fig 2.1: Series Hybrid Electric Vehicle

2.2.2 Parallel Hybrid System

In a parallel hybrid electric vehicle, the IC engine can deliver mechanical power directly to the powertrain. Figure 2.2 shows the parallel HEV configuration. With a parallel HEV, either the battery–electric system or the heat engine may be used to propel the vehicle, or they may be used simultaneously when maximum power is required [14]. The parallel hybrid needs two propulsion devices — the engine and the electrical motor. Another advantage over the series HEV is that a smaller engine and a smaller electric motor can be used to provide the maximum vehicle performance as long as the battery is not depleted.

Since, the engine is connected directly to the wheels in this setup, it eliminates the inefficiency of converting mechanical power to electricity and back, which makes these hybrids quite efficient on the highway. Yet the same direct connection between the engine and the wheels that increases highway efficiency compared to a series hybrid does reduce, but not eliminate, the city driving efficiency benefits (i.e. the engine operates inefficiently in stop-and-go driving because it is forced to meet the associated widely varying power demands)

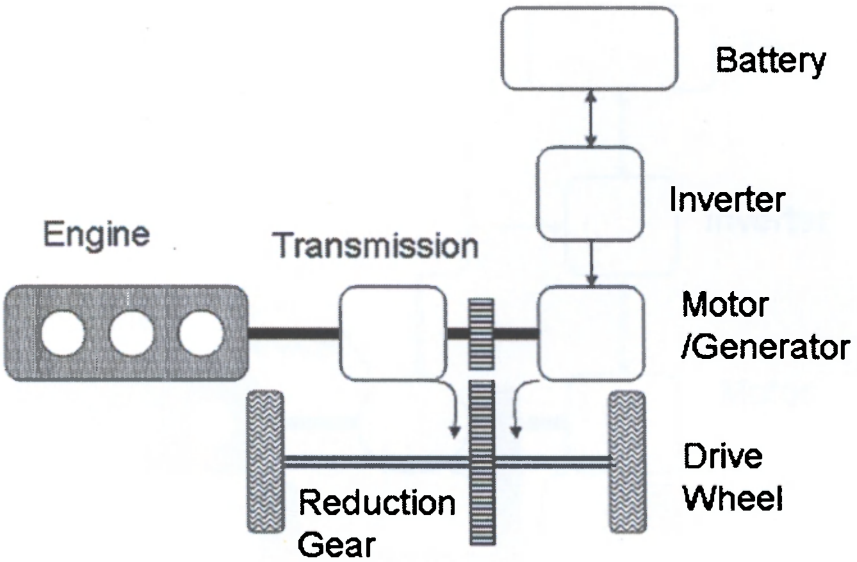


Fig 2.2: Parallel Hybrid Electric Vehicle

2.2.3 Series-Parallel Hybrid System

A series–parallel HEV configuration incorporates the features of both the series and parallel HEVs, but this technique involves an additional mechanical link as compared with the series hybrid and also an additional generator as compared with the parallel hybrid, as shown in Figure 2.3. As a result of this dual drivetrain, the engine operates at near optimum efficiency more often. At lower speeds it operates more as a series vehicle, while at high speeds, where the series drivetrain is less efficient, the engine takes over and energy loss is minimized. This system incurs higher costs than a pure parallel hybrid since it needs a generator, a larger battery pack, and more computing power to control the dual system. However, the series/parallel drivetrain has the potential to perform better than either of the systems alone. The Toyota Prius is a well known commercial example of split architecture HEV. Although it has the advantages of both series and parallel HEV operation, the series–parallel HEV is relatively more complicated.

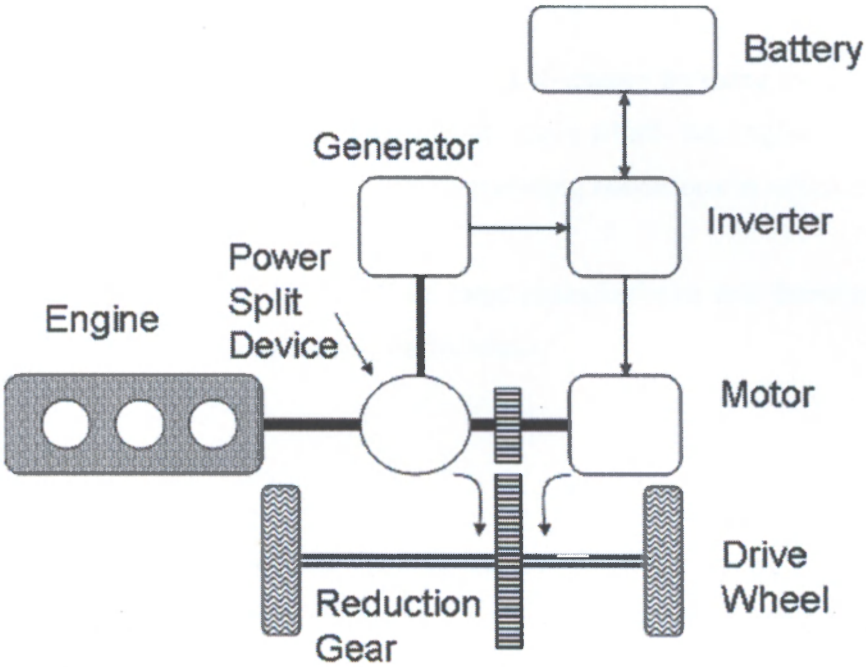


Figure 2.3: Series-Parallel Hybrid Electric Vehicle

2.3. Characteristics of Hybrid Systems

Hybrid systems possess the following four 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 be wasted 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.

The series/parallel hybrid system has all of these characteristics and therefore provides both superior fuel efficiency and driving performance.

2.4. HEV Components

Main components of HEV except the ICE are electric motor, energy storage system, transmission, etc. The following paragraphs documents the decisions and process for choosing or rejecting the specific components for the architecture.

2.4.1. Electric Motor

The electric propulsion system is one of the most important parts of a hybrid electric vehicle. The electric motor is the heart of the system. Recently, technological developments have pushed electric motors 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 DC motors, induction motors, permanent magnet (PM) motors, or switched reluctance motors. Induction motors and PM motors are the more promising for HEV applications [3].

Although a PM motor is desirable for a HEV, its high cost for large rare earth magnets is a deterrent [3].

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. Battery

The performance, life cycle, and safety of hybrid electric vehicles depend strongly on the vehicle's energy storage system. Based on modern technologies, chemical batteries predominate in HEVs as energy storage. Batteries offer mature technology, easy maintenance, high energy density and low cost [1]. 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 2.1 [3].

Table 2.1: Parameters of HEV Batteries

	Lead–Acid	***NiCd***	***NiMH***	***Li–ion***
Specific Energy (Wh/kg)	~30	40–60	60–70	90–130
Energy Density (Wh/dm^3)	~90	80–110	130–170	220–260
Specific Power (W/kg)	~200	150–350	150–300	250–450
Cycle Life[b] (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 ssociated with regenerative braking and are easier to package in the vehicle. Currently, Li–ion batteries are much 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 [3].

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. Transmission

The transmission and differential gear ratios greatly influence fuel economy and emissions because they determine operating speeds and loads on the engine. Gear shifting logic must be based on vehicle status information such as input shaft speed, current gear position, vehicle load and driver pedal command. Automatic transmissions, manual transmissions and continuously–variable transmissions are all available for use in HEVs.

2.5. Energy management systems of HEV

A power controller is needed to manage the flow of energy between all components, while taking into account the energy available in the battery. 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 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.

Chapter 3

3.0 Modeling & Simulation of HEV

Vehicle simulation is a method for fast and systematic investigations of different design options (fuel choice, battery, transmission, fuel reformer, etc.) in vehicle design and development. Simulation helps the designers understand the effects of powertrain design on overall vehicle system behavior analyze, component sizing, quantify benefits, and explore options.

A simple simulation model used in this study is based on the empirical data of ICE and Motor. It is important to note that the simulation used in this study essentially works in a reverse direction to what happens in the real scenario. The drive cycle is the input to the vehicle model. Power demand and speed and torque before gear box is calculated based on the drive cycle. Power management system then decide the power share from each source considering SOC of the battery and efficiencies of the ICE and the motor. The share of IEC power is then converted in to engine speed and torque requirements by taking the current gear ratio into account (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). Schematic diagram of the HEV model is shown in Figure 3.1.

3.1. Modeling of Drivetrain

The "power at the wheels" P_{wheel}, which is a sum of the total mechanical power demanded, is calculated according to vehicle speed and acceleration. The power at the wheels, calculated as the dot product of the vehicle velocity and the various forces acting upon the vehicle, considers the following determining factors as shown in Figure 3.2.

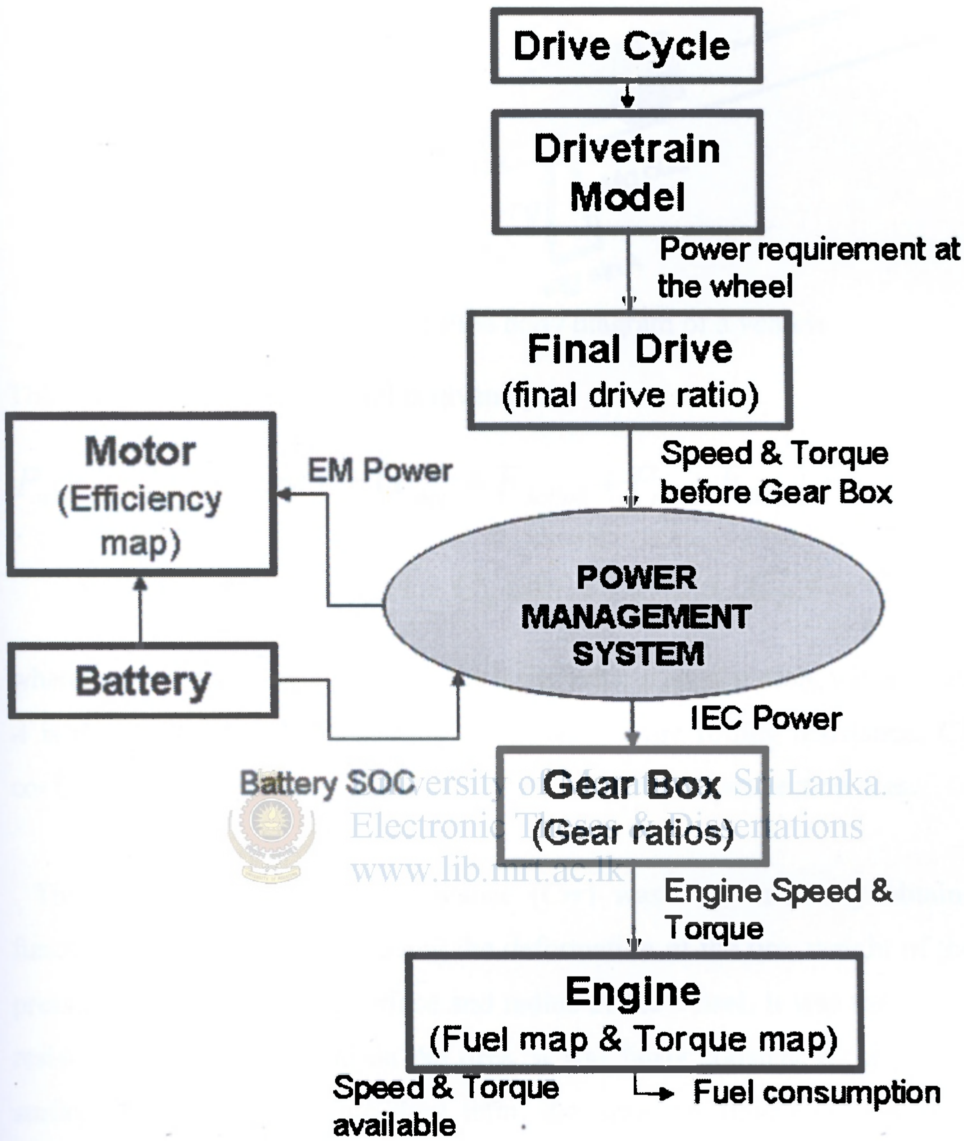


Figure 3.1 Schematic diagram of the HEV model

The four resistances a vehicle facing were force for acceleration, force to overcome gravity, rolling resistance of the wheels, aerodynamic resistance or drag.

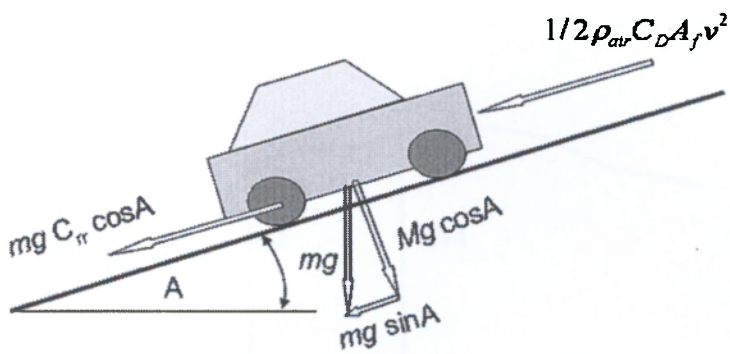


Figure 3.2 Free body diagram of a vehicle

The power at the wheels model is given by:

$$P_{wheel} = \sum force \times v = (F_{acc} + F_{incline} + F_{rr} + F_{drag}) \times v \qquad (3.1)$$

$$= (m \times a + mg \sin A + C_{rr} \cos A + 1/2\rho_{air} C_D A_f v^2) \times v \qquad (3.2)$$

where m is the total mass of vehicle, 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, CD is the drag coefficient, ρ is the density of air and AF is the frontal cross-section area.

The coefficient of rolling resistance (Crr) was experimentally obtained. It was 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 was 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 C_D was a dimensionless constant that attempted to capture the resistance caused by the relative motion of the vehicle and the air. The C_D 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 [1]. 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 with respect to velocity

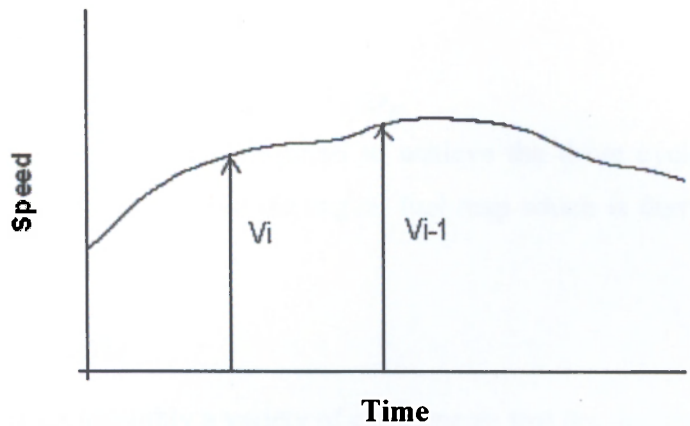


Figure 3.3: Sample Drive Cycle

If Vi and V_{i+1} is the vehicle speeds at two consecutive sampling instances, mean velocity V and acceleration of vehicle "a" can be calculated as follows.

$$V = (V_i + V_{i=1})/2 \qquad (3.3)$$

$$a = \left(V_{i=1} + V_i\right)/T \qquad (3.4)$$

T is the Sampling period of the drive cycle.

Having calculated the power demand at the wheels, Wheel speed (Vw) and the Wheel Torque (Tw) are calculated as follows.

$$V_w = V / R_w \qquad (3.5)$$

$$T_w = P_{wheel} / V_w \qquad (3.6)$$

Where, Rw is the wheel radius.

If the final drive ratio (R_{fd}) is known speed and torque before the final drive (V_{GB}, T_{GB}) can be calculated as follows.

$$V_{GB} = V_w * R_{fd} \qquad (3.7)$$

$$T_{GB} = T_w / R_{fd} \qquad (3.8)$$

Then, the engine speed and the engine torque (VE and TE) can be calculated if the gear ratio corresponding to the vehicle speed (GR_i) is known, as follows. Here I_E and ω_E are Moment of Inertia of the engine rotating mass and the engine angular velocity

$$V_E = V_{GB} * GR_i \tag{3.9}$$

$$T_E = T_{GB} / GR_i + I_E \dot{\omega}_E \tag{3.10}$$

Once the engine speed and torque required to achieve the drive cycle speed, the fuel consumption rate can be found from the engine fuel map which is derived based on test data.

3.2. Modeling of Engine

An ICE is a complex assembly a variety of components that are designed on the basis of aerodynamic laws. A mathematical engine model with individual components is complicated. Also, the engines designed by different manufacturers can be significant different in material and structure. Therefore, it is difficult to quantified modeling parameters which are also confidential. In the vehicle simulation, engine model was used to represent the accuracy of fuel consumption and emission calculation.

An empirical model based on test data of existing engine served as a choice for this particular need. The required torque and speed was calculated from externally as an input signal to this block. The engine model decided the torque and speed available to delivery and calculated fuel consumption accordingly.

Two look up maps, engine torque and fuel consumption are in this model. Engine torque map decides engine torque limit at each speed, while fuel consumption map (figure 3.6) decides fuel rate (g/s) of engine speed and torque.

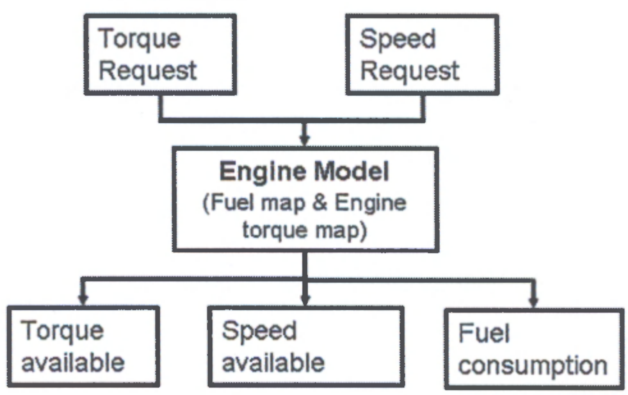


Figure 3.4 Engine Model Schematic Diagram

3.3. Modeling of Motors

The motor model mainly decides the torque and speed to be delivered at the output shaft. At the same time, the energy consumption (electricity) is calculated. The simplified explanation is shown in Figure 3.5. A motor model receives torque and speed request from final drive and decides torque and speed available to be delivered and hence the motor power. The experimental data was based on current demand indexed by motor torque and speed. Motor input power is calculated based on this empirical efficiency curves.

Motor Power required = (Speed at Final Drive) x ***(Torque to be produced by Motor)***

Motor Power required = (Motor Efficiency) x ***(Motor Input Power)***

Motor input power is the power drawn from the Battery.

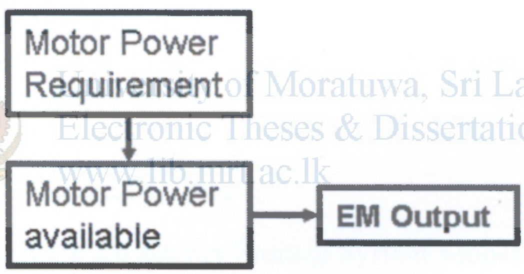


Figure 3.5 Motor Model Power Flow

Motor power available depends on both the battery state and the motor capacity. Even though the motor capacity is enough, if the Battery state of charge (SOC) is not sufficient the required power cannot be delivered by the motor. On the other hand if the battery is fully charged the motor cannot be run in generating mode even during breaking.

3.4. Modeling of Energy Storage System.

The selection of energy storage devices was largely based on the energy density, power density and costs of the device. In this study, battery is used as the energy storage system. Contribution from motor for total power requirement and the share of ICE power for charging the battery, operating the EM in generating mode is vastly depend on the Battery (SOC). The SOC variation at the end of sampling period is given by;

$$\Delta SOC = -\left(\frac{P_{EM} \times T}{\eta_{EM} \times \eta_B}\right) / Q_B \text{ ....For motoring mode} \tag{3.11}$$

$$\Delta SOC = \left(P_{EM} \times \eta_{EM} \times \eta_B \times T\right) / Q_B \text{ ...For Generating Mode} \tag{3.12}$$

Where ΔSOC is the change of SOC, P_{EM} is the EM power, T is the sampling period, Q_B is the maximum energy stored in the battery, η_B is the battery efficiency and η_{EM} is the EM efficiency.

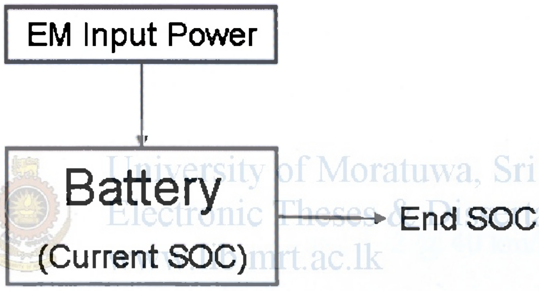


Figure 3.6 Energy Storage System Model

3.5. Specifications of the Selected Vehicle.

The baseline vehicle chosen for this study has been a 4 - l production family sedan a decision made since similar size vehicles are more popular and which has been used throughout the study

Specification of the components of the selected vehicle which are in specific Parallel Hybrid Electric Vehicle (PHEV) configuration are shown in following table,

Table 3.1: Vehicle model specifications

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 characteristics of the engine of the selected vehicle are represented by the following fuel consumption map and engine torque map which are derived based on the empirical data. Fuel consumption increases as engine power (torque x speed) increases and the shape of the fuel consumption map is more or less similar for any ICE. Engine torque map indicates the maximum torque that can be generated by the engine and the corresponding engine speeds

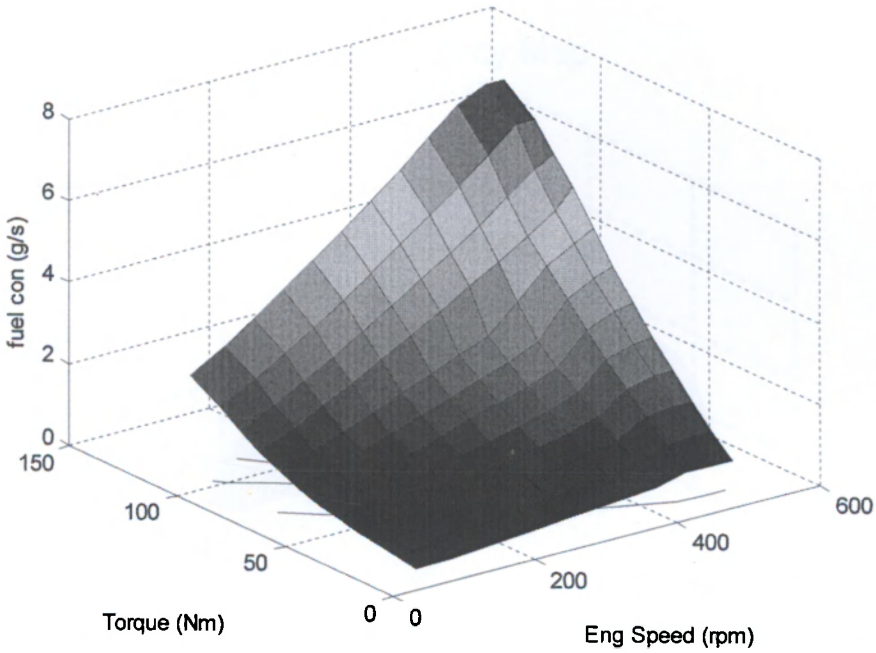


Figure 3.7: Fuel consumption map of the ICE of tested HEV

Table 3.2: Engine Torque map. This indicates the maximum engine torque for different engine speeds.

Engine Speed	1898	3452	4732	6015	7298	8581	9861	11144	12426	13709	14916	15730
Maximum Engine Torque	61.11	111.13	152.34	193.63	234.93	276.22	317.43	358.72	400.02	441.31	480.16	506.35

Figures 3.8 and 3.9 show the efficiency contours and Engine efficiency map of the tested vehicle. It can clearly be seen from these two figures that the maximum efficiency is achieved when the engine operates in the range of speed within 220 – 430 rad/sec and torque within 25-75 Nm.

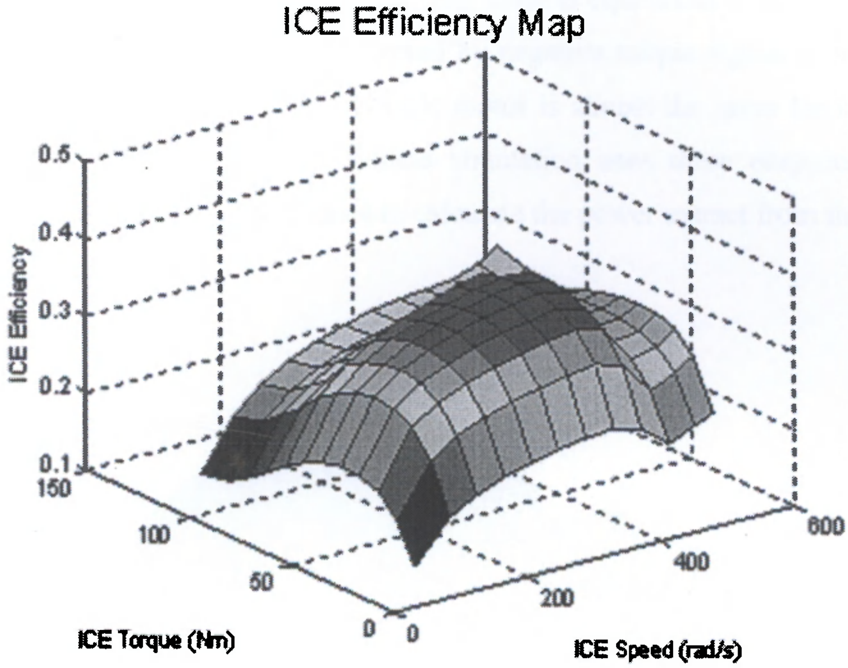


Figure 3.8: Engine fuel efficiency map

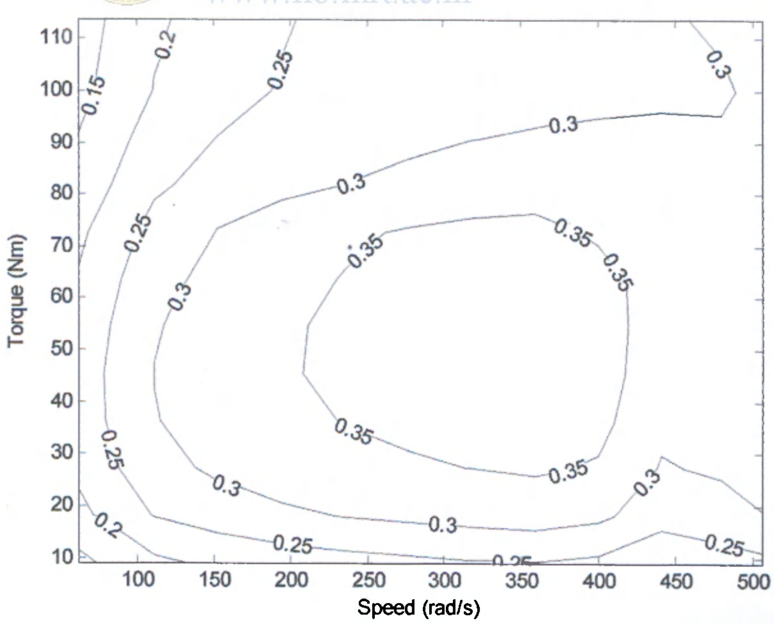


Figure 3.9: Engine fuel efficiency contours

Motor efficiency of the selected vehicle as a function of speed and torque is represented by the Figure 3.10. Efficiency map for motoring mode is equivalent to that for generating mode and the generating mode is represented by negative torque region of the graph. It can be seen that the efficiency of the electric motor is almost the same for speed above 100 rad/sec. Motor model in the vehicle simulation uses these empirical data for calculating motor input power and hence to calculate the power extract from the battery.

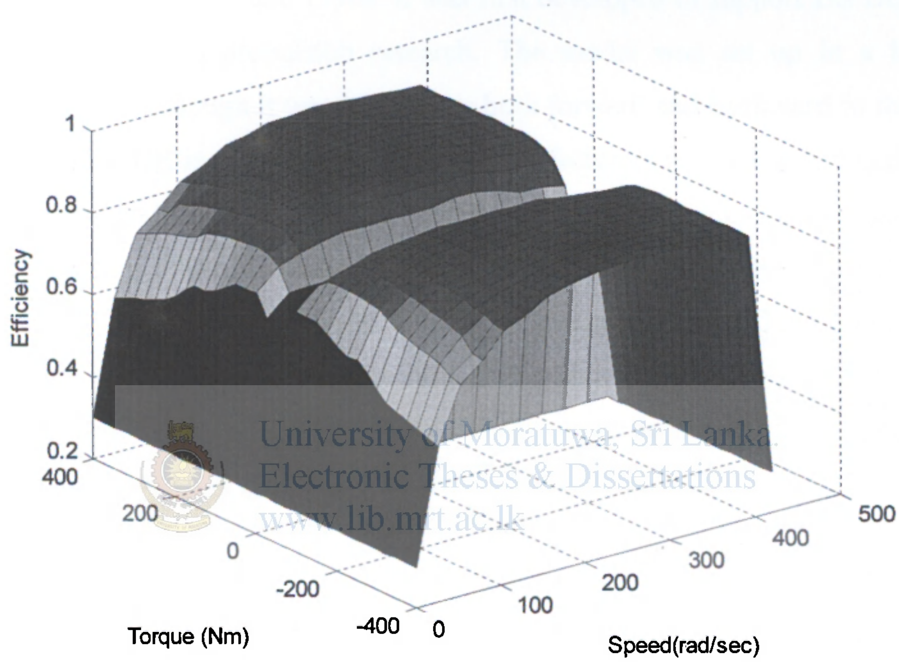


Figure 3.10: Motor Efficiency Map.

In this study, Battery efficiency during both charging and discharging is considered as constant and is taken as 85%.

3.6 Advanced Vehicle Simulation Tools

At present, several simulation tools based on different modeling platforms are available [1], [12]. 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. Among the most widely used vehicle modeling and analysis platforms are MatLab/Simulink and Modelica/Dymola. Following is the brief introduction of three vehicle simulation packages, ADVISOR, Dymola, and PSAT.

3.6.1 ADVISOR

ADvanced VehIcle SimulatOR (ADVISOR) was developed by the National Renewable Energy Laboratory of US in late 1990s. It was first developed to support US Department of Energy in the hybrid propulsion research. The model was set up in a backward modeling approach, although it was labelled as both forward and backward in the official documents. ADVISOR is widely used by auto manufacturers and university and institute researchers worldwide. Users also can contribute new components and data to the ADVISOR library. With a friendly user interface, ADVISOR was created in MatLab/Simulink which is a software module in MatLab for modeling, simulating and analyzing dynamic systems. It supports both linear and nonlinear systems, modeled in continuous time, sampled time, or a hybrid of the two. Systems can also be MultiMate [1], e.g. having different parts that are sampled or updated at different rates.

3.6.2 Dymola

Dymola is developed by Dynasim in Lund, Sweden, and the name is an abbreviation for Dynamic Modeling Laboratory. The tool is designed to generate efficient code and it can handle variable structure Modelica mode. (Modelica is a relatively new programming language, introduced in Europe to model a broad scope of physical systems.) It finds the different operating modes automatically and a user does not have to model each mode of operation separately. Dymola is based upon the use of Modelica models, which are saved as files. The tool contains a symbolic translator for the Modelica equations and a compiler that generates C-codes for simulation. When needed, the codes can also be exported to MatLab Simulink. The main features of Dymola are experimentation, plotting and animation.

3.6.3 PSAT

Powertrain System Analysis Toolkit (PSAT), developed by the Partnership for a New Generation of Vehicles (PNGV) [27] and maintained by Argonne National Laboratory, is a powerful modeling tool that allows users to realistically evaluate not only fuel consumption but also vehicle performance. PSAT operates within the Matlab/Simulink environment. It is a forward-looking model, which employs a virtual driver that compares the trace speed and the actual vehicle speed and controls the vehicle with a torque input. This method of modeling is closer to the operation of a real vehicle.

Chapter 4

4.0 Drive Cycles

A driving cycle is a standardized driving pattern. This pattern is described by means of a velocity-time table [1]. The track that is to be covered is divided in time-steps, mostly seconds. The acceleration during a time step is assumed to be constant. As a result the velocity during a time step is a linear function of time. Because velocity and acceleration are known for each point of time, the required mechanical power as a function of time can be determined with formulas, which was discussed in the previous chapter. This function integrated over the duration of the driving cycle produces the mechanical energy needed for that driving cycle.

Driving cycles are produced by different countries and organizations to assess the performance of vehicles in various ways, as for example fuel consumption and polluting emissions. The driving cycle of any country is the probable plot of the vehicle speed right from the start of the engine through its journey over a prescribed time.

This information is acquired by averaging the extensive data when the vehicle is driven under actual service conditions on designated urban routes or on highways where the traffic density and driving pattern is representative of the prevailing working day pattern of the country.

The data is available as a plot of vehicle speed km/h versus time and is called the urban or highway driving cycle of the country. This speed vs. time profile can be used to evaluate a vehicles behavior especially in the process of vehicle modeling and simulation for various aspects, such as energy efficiency, fuel consumption, stability certification testing etc.

There are many developed drive cycles to utilize in above purposes. Basically we can categorize drive cycles in to two main categories.

- Transient Drive cycle
- Model drive cycles

4.1 Transient drive cycles

Transient drive cycles are derived by collecting actual data in the real world [22]. 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.

4.2 Model drive cycles

Model drive cycles are the cycles which derived by mathematical modeling with the help of statistics [22]. 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 are belongs to this category

4.3 Drive cycles used in this study

In this optimization study, to evaluate the objective function of the GA, two driving cycles; New European drive Cycle (NEDC) and Colombo Drive Cycle (CDC) have been used.

4.3.1 NEDC

NEDC is the most commonly used drive cycle in Europe for regulatory work and for vehicle performance testing. This driving cycle belongs to the modal cycles. This means there are parts in these cycles where the speed is constant.

This is a combined cycle consisting of four ECE 15 cycles followed by an EUDC cycle. ECE 15 driving cycle represents urban driving. ECE15 and EUDC are two model drive cycled represent suburb and urban driving. ECE 15 is characterized by low vehicle speed (max. 50 km/h), low engine load and low exhaust gas temperature. EUDC cycle describes a suburban route. At the end of the cycle the vehicle accelerates to highway-speed. Both speed and acceleration are higher than the ECE 15 but it still is a modal cycle.

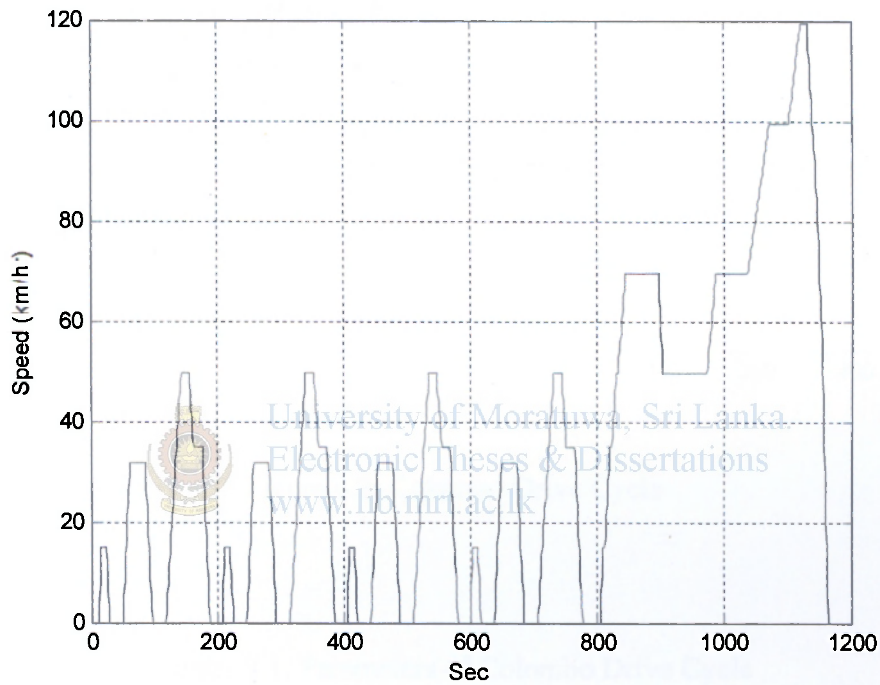


Figure 4.1: New European Drive Cycle

4.3.2 CDC

Colombo Drive Cycle (CDC) was formulated very recently, after extensive road tests by the Department of Electrical Engineering of University of Moratuwa as a part of a 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.

CDC involves too many transients because of haphazard traffic situations in Colombo. This drive cycle consists of mixture of driving modes including cruise, acceleration and deceleration. This belongs to the category of transient drive cycles. The Table 7.1 shows the parameters of the cycle.

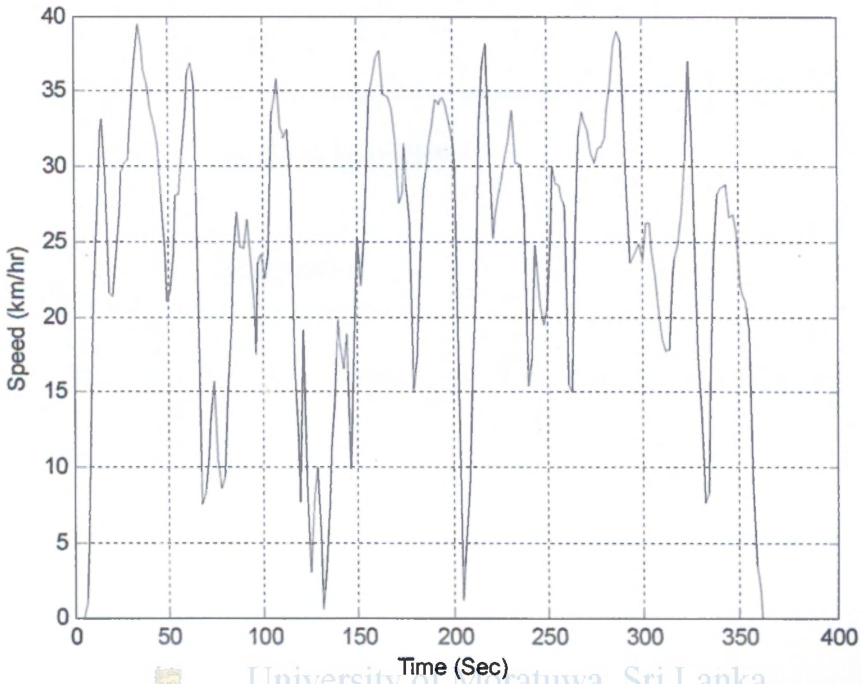


Figure 4.2: Colombo Drive Cycle

Table: 7.1: Parameters of Colombo Drive Cycle

Parameter	**Value**
Average Speed	23.9 km/hr
Maximum Speed	39.5 km/hr
Maximum Acceleration	2.06 m/sec^2
Minimum Acceleration	2.01m/sec^2
Total Duration	750 sec

Chapter 5

5.0 Overview Of Genetic Algorithm

5.1. Introduction and background

The Genetic Algorithm (GA) was invented by Prof. John Holland [23] at the University of Michigan in 1975, and subsequently it has been made widely popular by Prof. David Goldberg [24] at the University of Illinois. The original GA and its many variants, collectively known as genetic algorithms, are computational procedures that mimic the natural process of evolution

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 attempt to use a similar method of inheritance to solve various problems; such as those involving adaptive systems. GAs have also been applied to optimization problems. The objective of the GA is then to find an optimal solution to a problem. Of course, since GAs are heuristic procedures, they are not guaranteed to find the optimum, but experience has shown that they are able to find very good solutions for a wide range of problems.

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

5.2. Overview

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 the genetic algorithm, fitness is defined by: fi/fA where fi is the evaluation associated with string i and fA 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 the genetic algorithm 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 [23] 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.

5.3. Coding

Before a GA can be run, a suitable coding (or representation) for the problem must be devised. We also require a fitness function, which assigns a figure of merit to each coded solution. During the run, parents must be selected for reproduction, and recombined to generate offspring.

It is assumed that a potential solution to a problem may be represented as a set of parameters. These parameters (known as genes) are joined together to form a string of values (often referred to as a chromosome). For example, if our problem is to maximize a function of three variables, F(x; y; z), we might represent each variable by a 10-bit binary number (suitably scaled). Our chromosome would therefore contain three genes, and consist of 30 binary digits. The set of parameters represented by a particular chromosome is referred to as a genotype. The genotype contains the information required to construct an organism which is referred to as the phenotype.

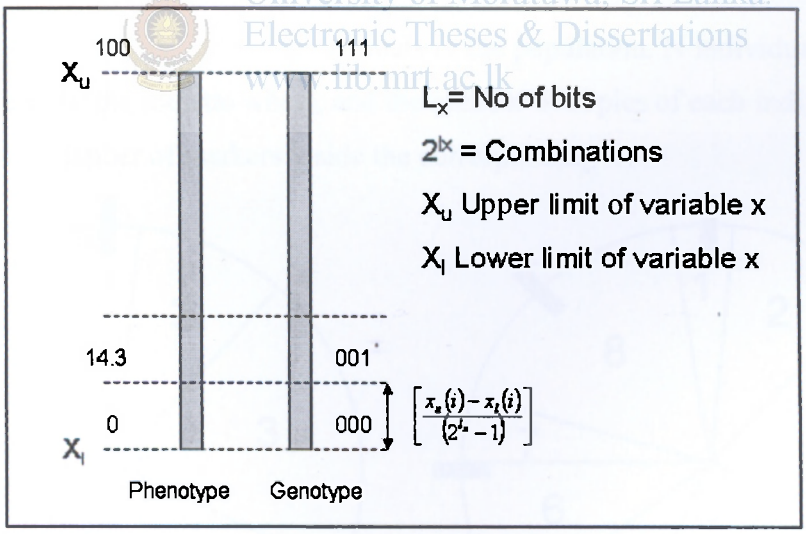


Figure 5.1: Segment decoding

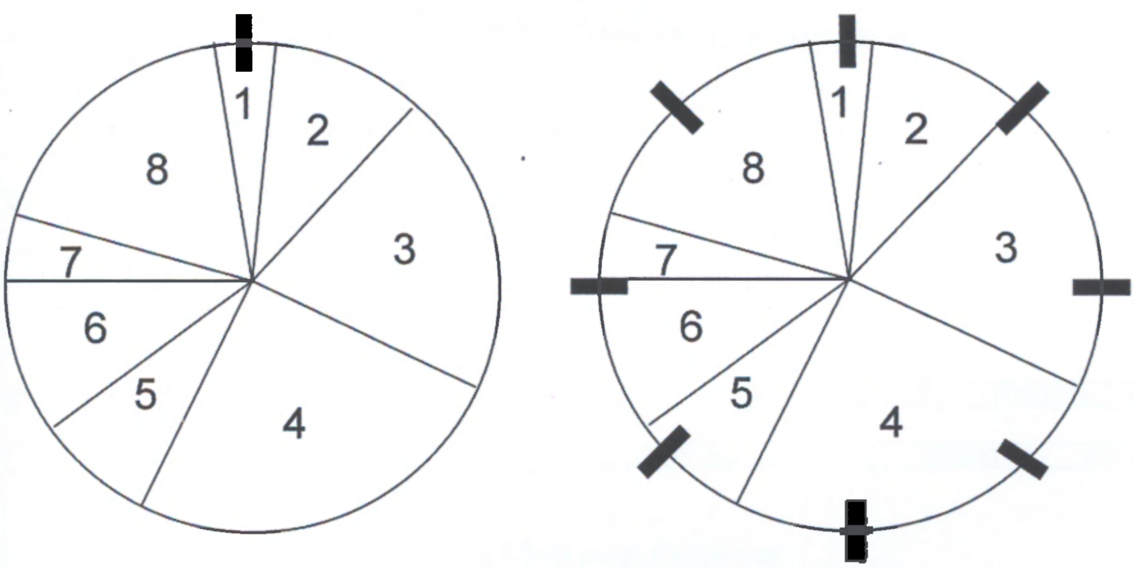
The fitness of an individual depends on the performance of the phenotype. This can be inferred from the genotype, i.e. it can be computed from the chromosome, using the fitness function. Assuming the interaction between parameters is nonlinear; the size of the search space is related to the number of bits used in the problem encoding. For a bit string encoding of length L; the size of the search space is 2^L.

5.4. Genetic Operators

5.4.1 Selection

Various selection schemes have been used, but we will focus on roulette wheel selection and stochastic universal selection [23], [24]. As illustrated in Fig. 5.1(a), roulette wheel selection is a proportionate selection scheme in which the slots of a roulette wheel are sized according to the fitness of each individual in the population. An individual is selected by spinning the roulette wheel and noting the position of the marker. The probability of selecting an individual is therefore proportional to its fitness.

As illustrated in Fig. 5.1(b), stochastic universal selection is a less noisy version of roulette wheel selection in which N equidistant markers are placed around the roulette wheel, where N is the number of individuals in the population. N individuals are selected in a single spin of the roulette wheel, and the number of copies of each individual selected is equal to the number of markers inside the corresponding slot.



(a) Roulette Wheel Selection (b) Stochastic Universal Selection

Figure 5.2: Proportionate Selection Schemes

5.4.2 Crossover

Once two chromosomes are selected, the crossover operator is used to generate two offspring. In one- and two-point crossover, one or two chromosome positions are randomly selected between one and (L−1), where L is the chromosome length and the two parents are crossed at those points. 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. 5.2. In uniform crossover, each chromosome position is crossed with some probability, typically one-half

Parent 1:	*110001011*	*110010100*
Parent 2:	**010010110**	**100011001**
Offspring 1:	*110001011*	**100011001**
Offspring 2:	**010010110**	*110010100*

`Figure 5.3: 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 Fig 5.3.

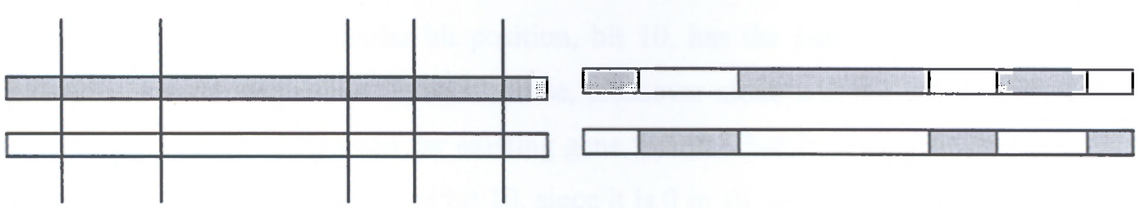


Figure 5.4: Multi point Crossover

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.

5.4.3 Mutation

As new individuals are generated, each character is mutated with a given probability. In a binary-coded GA, mutation may be done by flipping a bit, while in a non-binary-coded GA, mutation involves randomly generating a new character in a specified position. Mutation produces incremental random changes in the offspring generated through crossover, as shown in Figure 5.4. When used by itself, without any crossover, mutation is equivalent to random search, consisting of incremental random modification of the existing solution, and acceptance if there is improvement. However, when used in the GA, its behavior changes radically. 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:	**110100010011**
After Mutation:	**110000010011**

Figure 5.5: 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 mutation probability PM 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.

Chapter 6

6.0 Optimization Using GA

6.1 Power Split in HEV

Before going into detail of fuel economical operation of HEV, it is important to study the power flow in HEV. Figure 6.1 shows the power flow paths of HEV [12].

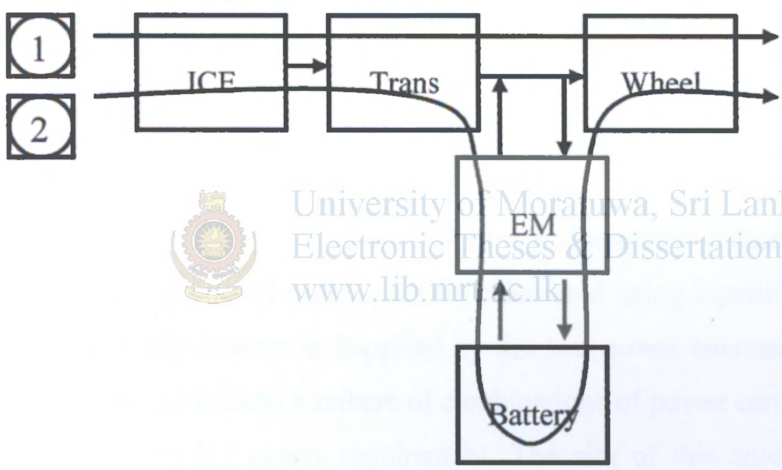


Figure 6.1: Block diagram of energy flow; 1- Mechanical path, 2- Electrical path

The difference between using the ICE or the EM to drive the wheels is explained in Figure 6.1. When the ICE is used (path 1), the energy flows directly from the ICE through the transmission to the wheels. When the EM is used (path 2), energy first flows from the ICE through the transmission to the EM, operated as a generator, for charging the battery; later the energy will flow from the battery to the EM, operated as motor, to the wheels.

In path 1 the mechanical power produced by the ICE will immediately be used to drive the wheels. In path 2 the same mechanical power will be converted to electrical, chemical, electrical, and back to mechanical. Inherent to these power conversions are losses. These additional losses considerably lower the efficiency of using the EM for driving the wheels. Therefore, using the EM (path 2) will only be efficient in a few (extreme) situations, when directly using the ICE (path 1) is very inefficient.

The minimum losses due to power conversions are determined by the efficiency of the EM, first used as a generator and then as a motor, and of the battery, first used to store and then to release energy. Therefore, it is only justified to use the EM (path 2), in the cases that the losses in path 1 (directly using the ICE) is at least more than the minimum losses when using the ICE in path 2 (for charging the battery).

For better fuel economy, the average ICE efficiency in path 2 (ICE used for charging the battery), will be close to the optimal ICE efficiency.

6.2 Optimization Problem Formulation.

Since this study is done for a known drive cycle, the power requirement of the vehicle to achieve the known speed profile can be calculated using equations (3.1) & (3.2). In HEV, this power requirement is supplied by the two power sources; ICE and EM. It is obvious that there are infinite numbers of combinations of power contributions from these two sources to meet the power requirement. The aim of this study is to find out the optimum power split between the two sources, which make the total fuel consumption a minimum during the period of the drive cycle.

6.2.1 Domain and Constraints

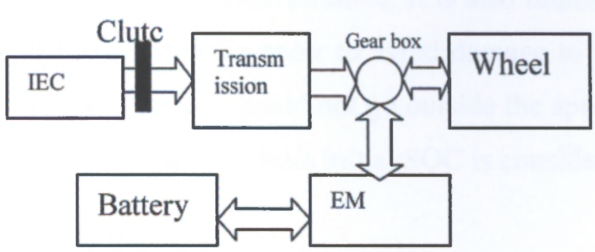


Figure 6.2: Block diagram of the parallel hybrid vehicle

Figure 6.2 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 (3.1), taking sampling period as one second. (Sampling period of the drive cycle is one second)

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 state of charge of the battery plays a major role of deciding the power split of the HEV. 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. At any time of operation, the battery SOC should not go outside the specified minimum and maximum limits (40% & 80%). In this analysis initial SOC is considered as 50%.

It is very important to keep the initial and end SOCs as close as possible to have a meaningful fuel consumption value in this study. If the SOC at the end of the cycle is lower than the initial value means that during the drive cycle the HEV has used some amount of energy which corresponds to the SOC difference, stored in the battery prior to start of the drive cycle. On the other hand, if the end SOC is higher than the initial, the HEV has not used some of the energy generated by the ICE during the drive cycle and that indirectly causes the fuel consumption to increase. In both cases, the difference in SOC represents the difference of energy consumed by the vehicle and energy generated by the ICE, during the drive cycle. If this difference is higher, the result obtain from such a situation is not fair. In order to have meaningful result (fuel economy), SOC at the end of the cycle should not vary much from the initial value.

Rate of change of ICE and EM power is another constrain to be considered in this optimization process. It is required to keep the rate of increase or decrease of power of both power sources within the allowable limit to have a meaningful result.

6.2.2 Population and Individuals

In this approach each individual represent the possible EM power trajectory which is a combination of EM share by the HEV at each sampling period. So that it is obvious that there are variables equivalent to the total number of samples of the drive cycle and each variable represents the power contribution from EM during the corresponding sampling period. The total population represents the total possible combinations of EM contribution through out the drive cycle. EM power can have any value between maximum motor power and maximum generator power (generation is represented by negative sign).

6.2.3 Chromosomes

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

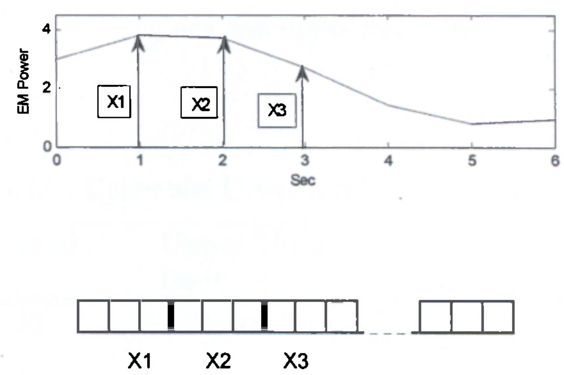


Figure 6.3: Example of EM contribution (Top), Chromosome (Bottom). This composes of string of binary numbers which represent EM power at each seconds of the drive cycle.

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 as its sampling period is one second and the total duration is 1200 seconds. Therefore if each variable is corded as 'n' bit binary number total chromosome length is nx2000 bits. On the other hand, total population contains 2^{nx1200} individuals. The larger the population the longer the time it takes for convergence. However 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. Since the peak power of the selected motor both in motor and generator mode is 40kW, the precision of the variable is at least $80/2x2^6$kW.

However, in this analysis, upper and lower limits of each variable are not taken as fixed values in order to avoid suggesting unrealistic values for EM power during the optimization process. Therefore the span of possible power demand is divided into several regions considering the efficiency of IEC and for each region deferent upper and lower limits for EM power have been defined.

It can be seen in the ICE efficiency map used in this study (figure 3.7) that the ICE efficiency is highest for engine speeds between 230 and 350 rad/s and the corresponding ICE power is between 20 and 35 kW. Therefore as we discussed earlier, the ICE should be operated within that region as much as possible to achieve higher fuel economy. Keeping this in mind, power regions and upper and lower limits for those regions have been selected as follows.

Table 6.1: Upper and Lower limits for decision variables.

Power Demand	Upper EM power limit	Lower EM power Limit
0 ~ 30	Power Demand	-30
30 <	40	10
0	0	0
0 ~ -40	0	Power demand*0.65 ++

++ The maximum Braking power recovered by the regenerative braking is 65%, because the regenerative breaking can only be used for the front wheel [13].

6.2.4 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 contribution for the power demand 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 contributions should be equal to the power demand. Here the power contribution is considered as the effective power which contributes to drive the wheels. In fact it is the effective power after losses.

For positive power demand;

ICE Contribution = Power Demand – EM contribution.

For negative or zero power demand;

ICE Contribution = 0, however the ICE is spinning at its idle speed and consumes certain amount of fuel to keep the engine running.

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. (Refer equations 3.1 to 3.8) 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 (Table 3.1) decides engine torque limit at each speed, while fuel consumption map (figure 3.7) decides fuel rate (g/s) at given engine speed and torque.

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

$$J(x) = \sum_{i=1}^{n} FCi + M^k W(N_B + N_P) \tag{6.1}$$

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 change of power exceed the limits within the drive cycle corresponding to a chromosome. Here, 10 and 1.2 have been used for 'W' and 'k' respectively. The Figure 6.4 indicates this process of calculation of fitness value for an individual.

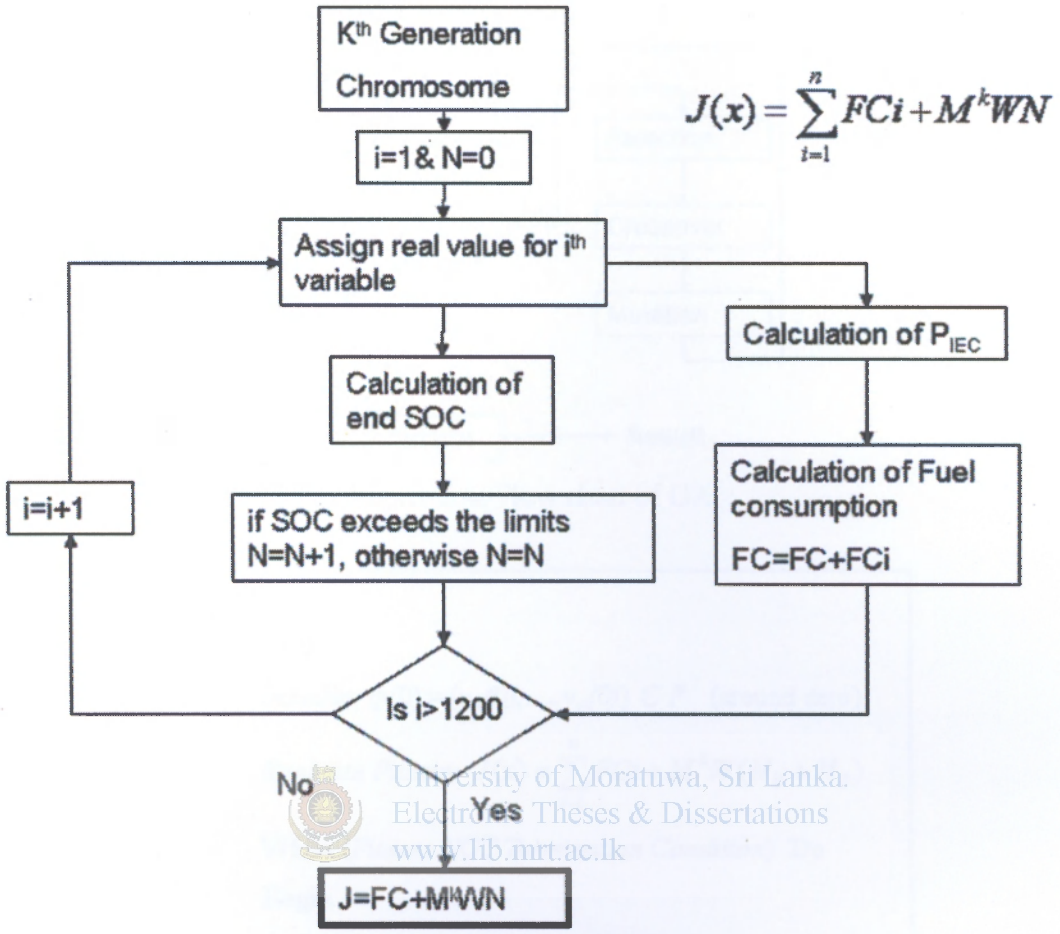


Figure 6.4: Flow chart of calculation of Fitness Value for an individual of k^{th} generation

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.

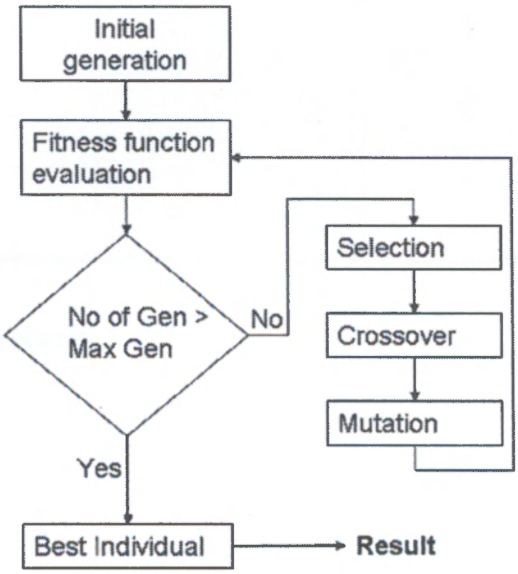


Figure 6.4: Flow chart of GA

Begin

$t = 0$;

Initialize $\phi(0) := \{v_1(0), \ldots v_\mu(0)\} \in I^\mu$ (around zero)

Evaluate Fitness: $J(x) = \sum_{i=1}^{n} FCi + M^k W(N_g + N_p)$

While (*Fitness NOT Termination Condition*) **Do**

Begin

Recombine $v'_k(t) := r(\phi(t))$

Mutate $v''_k(t) := m(v'_k(t))$

Evaluate $\phi'(t)$: $J(x(t)) \cup J(x'(t))$

Select $\phi(t+1)$ from $\phi(t)$:

If $(J(x(t)) > J(x'(t)))$

$x(t+1) = x'(t)$

else

$x(t+1) = x(t)$

$t = t+1$;

End

End

Figure 6.5: Evolutionary Algorithm

Chapter 7

7.0 Results & Analysis

Figures 7.1 and 7.2 show the optimization process histories for NEDC and CDC. The x and y axes of the graphs are number of generations and the fitness value which is the total fuel consumption for the drive cycle. As it could be seen in these figures, 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.

For NEDC, even after 1000 generations it has not completely converged to the optimum value but rate of convergence after 1000 generation is very low and it is almost 0.5mili liters per 10 generations. The trend of optimization process history shows that it likely to come to the global optimum within next 100 generations. Therefore the result may not change much and it will not affect to the percentage increase in fuel economy significantly at the end.

In general, optimum solution for a problem is not guaranteed by GA. However, the results from these GA optimizations can be considered as the global optimums as they produced the same results every time the GA programs were run.

The Power demand to achieve the given speed profile and the optimum contribution from the EM for both drive cycles are indicated in figures 7.2, 7.3, 7.6 and 7.7 below.

In Table II, the optimum fuel economy for the selected drive cycles are compared with that of a conventional vehicle. This indicates that a maximum of about 30% and 22% improvements can be achieved for NEDC and CDC respectively, 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 cycles. From the Figure 7.2 & 7.6, it can be seen that the vehicle operate within a lower power range for CDC than for NEDC and the breaking power involved in CDC that can be recovered by HEV is comparatively very low. However CDC has higher potential for fuel economy improvement than that of NEDC mainly due to its frequent speed transients.

Figure 7.4 & 7.8 show the battery SOC variation throughout the drive cycles. 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 7.1: Fuel Economies for conventional and optimized HEV

Drive Cycle		NEDC	CDC
Fuel Economy (L/100km)	Conventional Vehicle	7.69	8.6
	Parallel HEV	5.39	5.84
Improvement with HEV (%)		30	32

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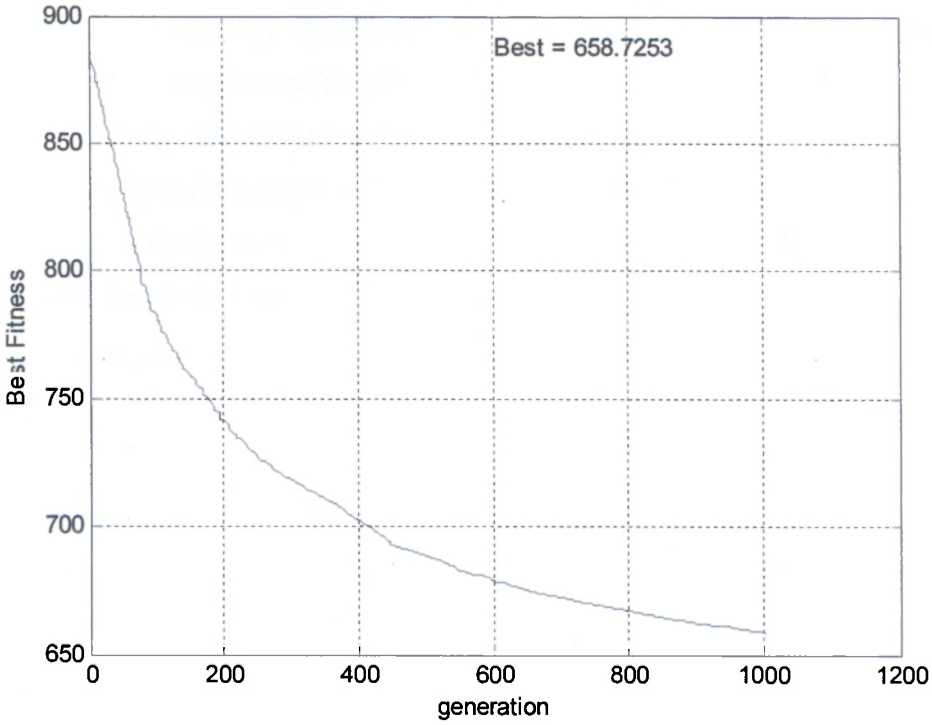

Figure 7.1: History of genetic algorithm optimization process for NEDC.

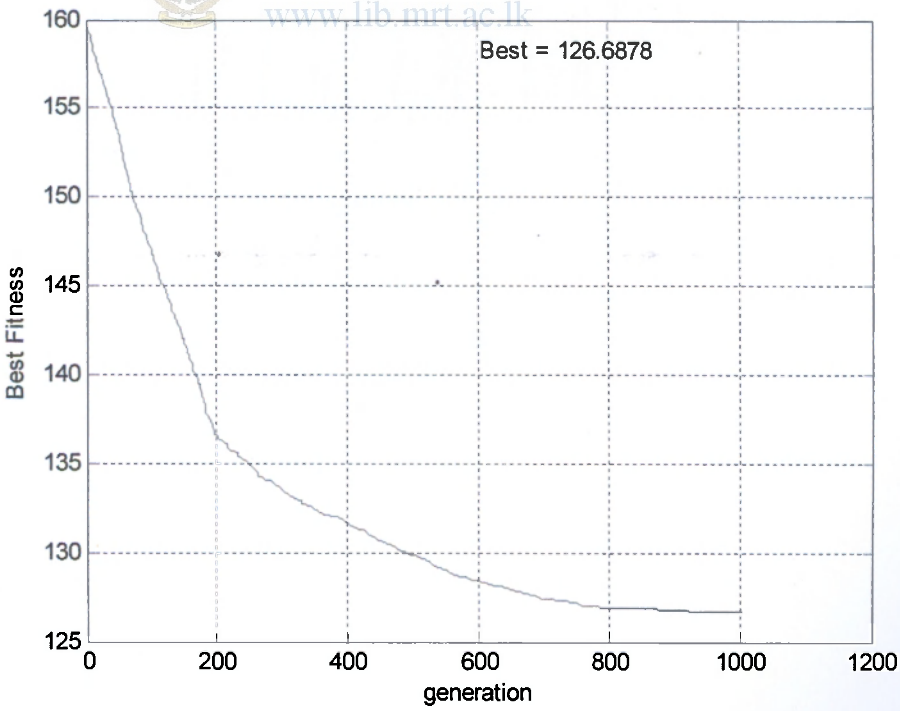

Figure 7.2: History of genetic algorithm optimization process for CDC.

The following two figures indicate the power demand by the vehicle to achieve the speed profile represented by the NEDC and CDC respectively. These are actually the outputs from the drivetrain module of the simulation model. Since the road is considered as flat for this study, hill climbing power is not included in the power demand. Since CDC represents typical urban driving which has no high accelerations and higher speeds, power involved in the drive cycle is comparatively low. But, for NEDC, it could be seen in the figure 7.4 that the vehicle requires more power to achieve the speed profile at the latter part of the cycle.

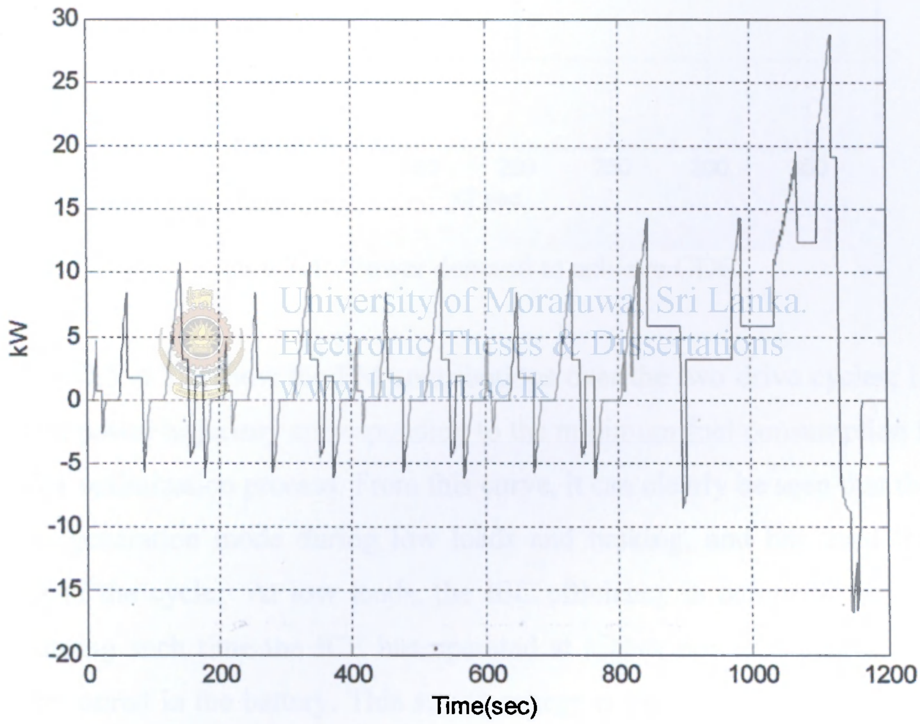

Figure 7.3: Power demand to achieve the NEDC speed profile.

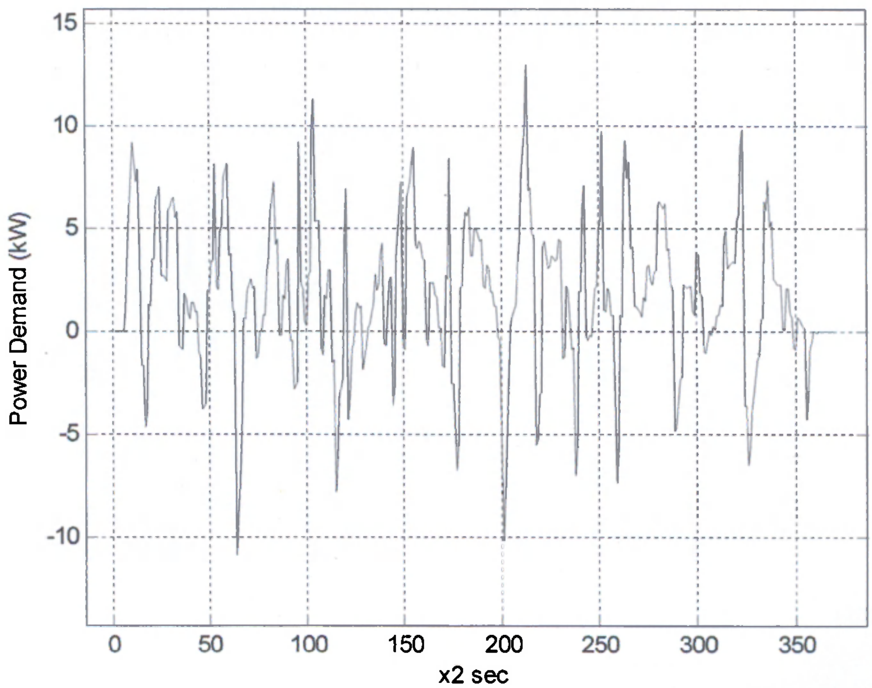

Figure 7.4: Power demand to achieve CDC.

The Figure 7.5 & 7.6 show the EM contributions over the two drive cycles; i.e. in fact the optimum power trajectory corresponding to the minimum fuel consumption found out from the GA optimization process. From this curve, it can clearly be seen that the EM has operated in generation mode during low loads and braking, and has used that energy during rest of the cycle. At low loads, the IEC efficiency is comparatively lower and therefore during such time the ICE has operated at higher power levels allowing extra power to be stored in the battery. This stored energy is used at the latter occasion when ICE operation is not so economical. Since, the limitations in rate of change of EM power has not considered in this study for NEDC, sudden increase in generation power can be seen in the corresponding optimum EM power curve.

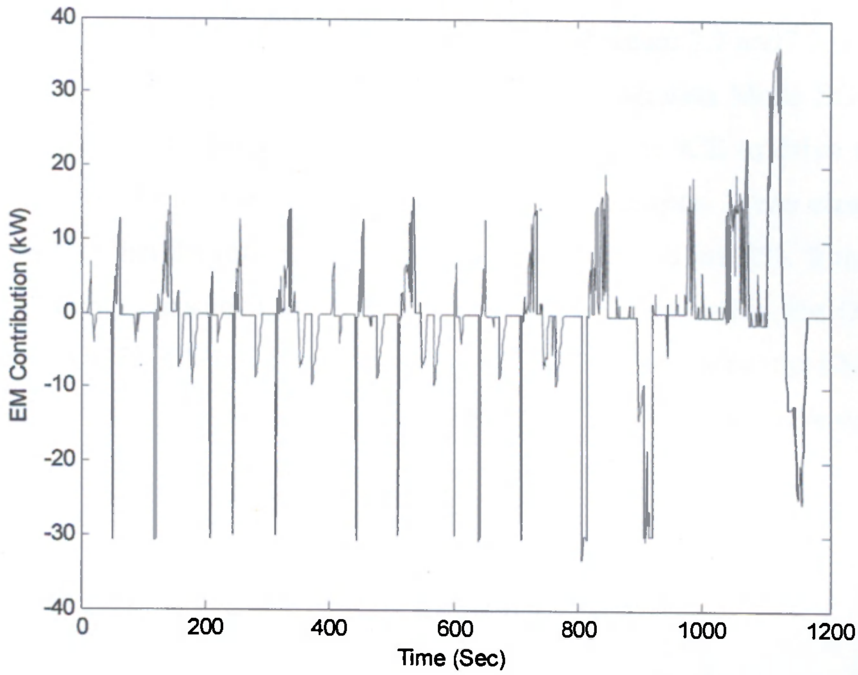

Figure 7.5: Contribution from EM over NEDC.

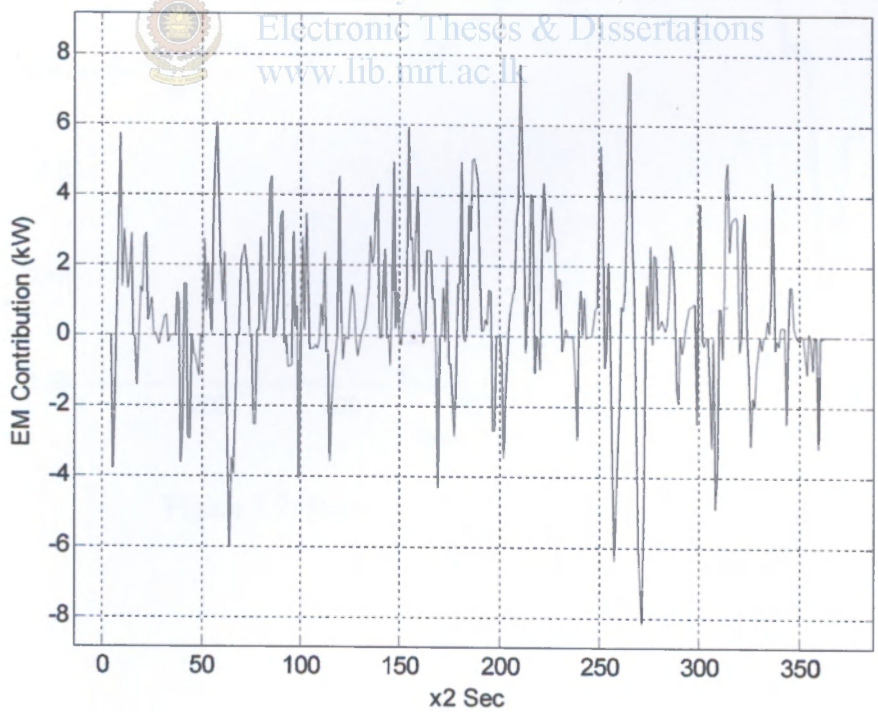

Figure 7.6: Contribution from EM over CDC

SOC variations for both NEDC and CDC are shown in figure 7.7 and7.8. Battery SOC depends on the EM power. When the EM operates in Generation Mode SOC increases and when EM supplies total power requirement or assist the ICE to drive the vehicle, SOC decreases as EM uses stored energy during those occasions. It can clearly be seen from these curves that the difference of staring and end SOC is just 2%. It indicates that almost total energy consumed by the EM has been generated within the Drive Cycle. Here, the end SOC is little bit lower than the starting SOC. That means the EM has used a small amount of energy that had been stored in the battery prior to this drive cycle.

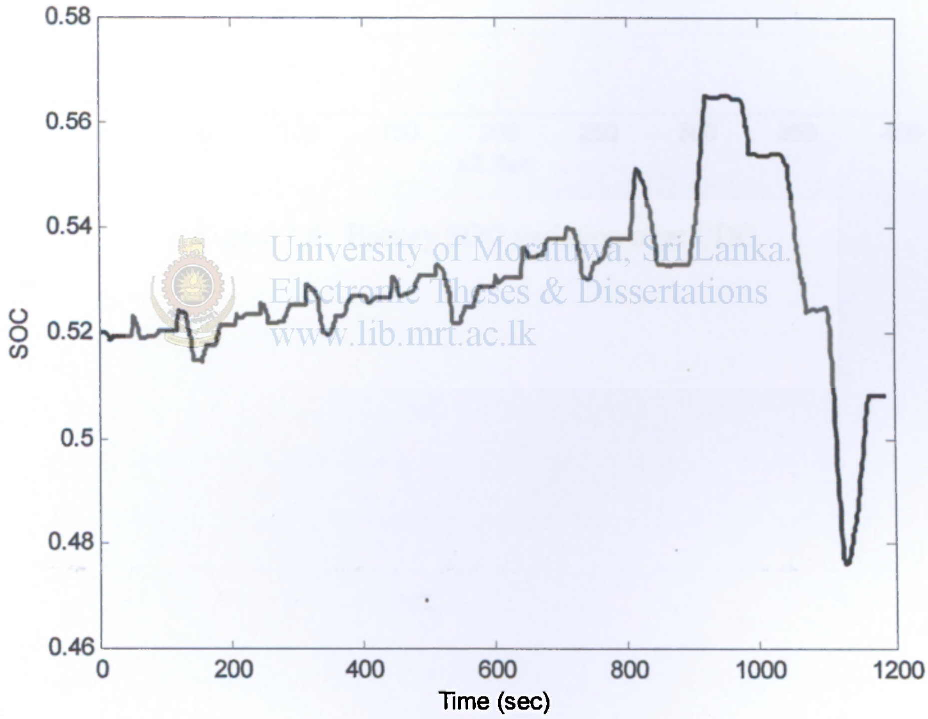

Figure 7.7: Battery SOC variation over NEDC.

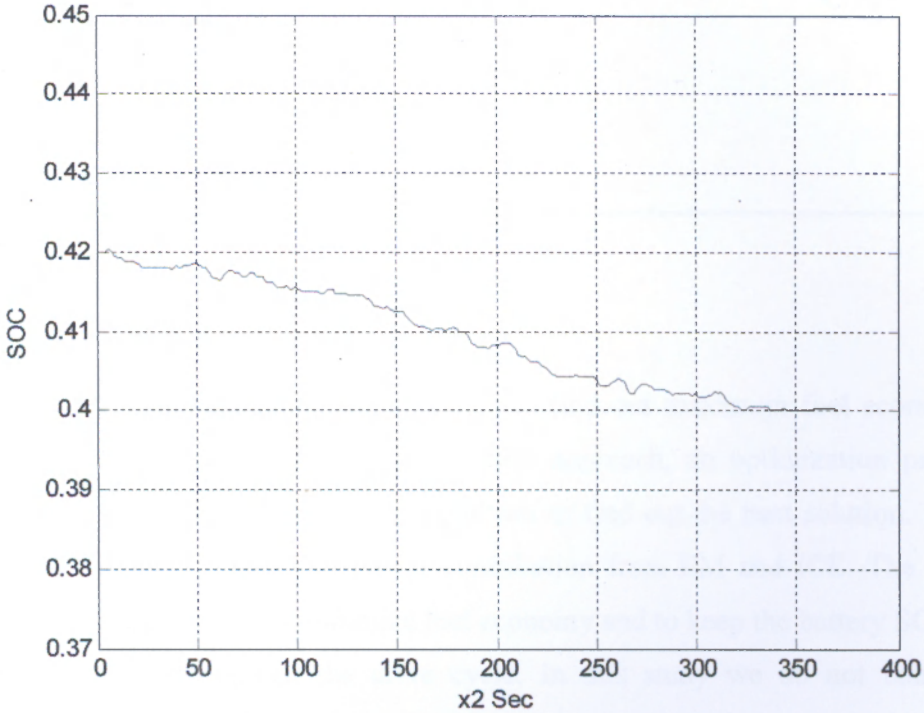

Figure 7.8: Battery SOC variation over CDC.

Chapter 8

8.0 Conclusion & Remarks

In this Study, 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 to find out 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. From the results of this study, it can be concluded that the currently proposed power management systems for PHEVs are capable of exploiting less than even 50% of the full potential, with regards to fuel economy.

With the simple simulation model used in this study, based on the empirical data, it was not possible to simulate the result in forward direction i.e. the optimum contributions from IEC and EM are the input to the vehicle model, and check whether the same speed profile could be obtained with the assumptions made in this study. If an advance vehicle simulation model mentioned in chapter-4 could be used, the results could have been validated and hence more accurate results could have been obtained.

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, possibility of employing real time genetic algorithm with less number of chromosomes and optimum code lengths will be investigated. 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 A

MathLab Programs

Following MathLab codes implement the main Genetic Algoritm which is used to optimize the fuel consumption of HEV.

```
-----------------------------------------------------------------------

function [PEM]=HEVGA(drive_cyc,SOC)

[DP,sped_beforeGearbox,torq_beforeGearbox]=driverdemand(drive_cyc);
[m,n]     = size(DP);
% This script implements the  GA

NIND = 1;            % Number of individuals per populations
MAXGEN =1500;        % maximum Number of generations
GGAP = .90;          % Generation gap, how many new individuals are
created
NVAR = m;            % Number of variables
PRECI = 6;           % Precision of binary representation

driverDemand=DP/1000;
LimitUpper = zeros(1,m);
LimitLower = zeros(1,m);

for i=1:m
    if driverDemand(i)>30
        LimitUpper(i)= driverDemand(i);
        LimitLower(i)= -10;
    elseif driverDemand(i)>0
        LimitUpper(i)= driverDemand(i);
        LimitLower(i)= -40;
    elseif driverDemand(i)==0
        LimitUpper(i)= 0;
        LimitLower(i)= 0;
    elseif driverDemand(i)<0
        LimitUpper(i)= 0;
        LimitLower(i)= driverDemand(i)*.8;
    end
end

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

```
%.......................................................................
%creation of initial population
 Zr= zeros(1,m);
   for i=1:m
   Zr(i)=round(2^PRECI*(LimitUpper(i)-0)/(LimitUpper(i)-
LimitLower(i)+0.000005));

   BinZr=dec2bin(Zr(i));
   ELMNT((i-1)*PRECI+1:i*PRECI)=Element(BinZr,PRECI);
   end

        Chrom = [crtbp(NIND, NVAR*PRECI);rep(ELMNT,[499,1])];
%.......................................................................

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

% Evaluate initial population
   ObjV =
objfun(bs2rv(Chrom,FieldD),SOC,sped_beforeGearbox,torq_beforeGearbox,gen
);
% xxx=bs2rv(Chrom,FieldD)
% Track best individual and display convergence
   Best(gen+1) = min(ObjV);
   plot((Best),'r.');xlabel('generation'); ylabel('Best Fitness');
   text(0.5,0.95,['Best = ',
num2str(round(Best(gen+1)))],'Units','normalized');
   drawnow;


% 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,0.0001);
     % Evaluate offspring, call objective function

       ObjVSel =
objfun(bs2rv(SelCh,FieldD),SOC,sped_beforeGearbox,torq_beforeGearbox,gen
);

     % Reinsert offspring into current population
```

```
        [Chrom ObjV]=reins(Chrom,SelCh,1,1,ObjV,ObjVSel);

     % Increment generational counter
        gen = gen+1;

     % Update display and record current best individual
        Best(gen+1) = min(ObjV);
        plot((Best)); xlabel('generation'); ylabel('Best Fitness');
        text(0.5,0.95,['Best = ',
num2str(Best(gen+1))],'Units','normalized');

        drawnow;
    end
% End of GA

OPTIMUM_VALUES = getopv(Chrom,ObjV,FieldD);
PEM=OPTIMUM_VALUES
Best = num2str(Best(gen+1))
```

Following MAthLab code implements the objective function to be optimized by the main GA program

```
---------------------------------------------------------------

function ObjVal =
objfun(CHROM,SOC,sped_beforeGearbox,torq_beforeGearbox,gen)


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

%creation of Motor Torque Metrix
for i=1:n
    for j=1:m
        if torq_beforeGearbox(j)>0;
          EngT(i,j)=torq_beforeGearbox(j)-
CHROM(i,j)*1000/sped_beforeGearbox(j);
        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
        Fuel(i,j)=fuelCon(EngT(i,j),sped_beforeGearbox(j));
    end
end

%Creation of Objective Function
```

```
SOC1=SOC;
k=charge(SOC1,CHROM);
ObjVal=zeros(n,1);
for i=1:n
    for j=1:m
        ObjVal(i)=ObjVal(i)+Fuel(i,j);
    end
end

% ObjVal=ObjVal.*k;
ObjVal=ObjVal+((gen+1)^1.2)*k;
```

Following codes implements the penalty function of the constrained optimization.

```
 function k=charge(SOC,CHROM)

% this function create the penelty metrix which is used in GA

[nn,mm] = size(CHROM);
EffB=.9;  %Battery efficiency
Qm=4*3600; %kWsec
k=zeros(nn,1)+1; %create metrix in which each element is 1

%Creation of k metrx,
for i=1:nn
    SOCE=SOC;
    N=0;
    for j= 2:mm
        if abs(CHROM(i,j)-CHROM(i,(j-1)))>5 %if rate of change of power
exceeds
            N=N+1;
        end
    end
    for j=1:mm
        if CHROM(i,j)>=0   % motor
            SOCE=SOCE-CHROM(i,j)/(EffB*Qm);
        else
            SOCE=SOCE-CHROM(i,j)*EffB/Qm;  % generating
        end
        % SOC upper and lower limits
        if SOCE>.8
            N=N+1;
        elseif SOCE>.4
            N=N;
        else
            N=N+1;
        end
    end
        k(i)=10*N;   % this defines the penetty for each individual

 end
```

Following MathLab program is used for obtaining the driver demand with respect to drive cycle.

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

% 1. vehicle model

veh_chars.base_mass = 1000;           % vehicle base mass
veh_chars.CdA       = 0.32*1.92;      % drag coeificient * area
0.366*2.45   %
veh_chars.Crr       = 0.015;          % rolling resistance
veh_chars.wheel_r   = 0.29;           % wheel radius
drive_chars.rho     = 1.22;           % air density [kg/m^3],
drive_chars.slope   = 0;              % road slope  [m/m],

MaxPlantPower       = 44000;          % engine capaciity 44kW
MaxStoreSize        = 2160000;        % battery capacity 2.16MW


plant_chars.mass          = 6 + (1/922+1/28440)*MaxPlantPower; % engine
mass
plant_chars.max_power     = MaxPlantPower;              % einge power
store_chars.mass          = MaxStoreSize/(60.5*3600);   % battery mass

m   = veh_chars.base_mass + plant_chars.mass + store_chars.mass; % total
mass
m=1642;
CdA = veh_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);
%     if abs(vdot(i))<0.000001   % eleminate very small accelerations
%         vdot(i)=0;
%     end

    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=[3.8,2.2,1.6,1.25,0.9];

% 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
```

This MAthLab program calculate the fuel consumption at given speed and torque

```
------------------------------------------------------------
function EngFuel=fuelCon(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=1.0*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>0
    T=1.0*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
if T<=0
    fuel = .1284;
else
fuel  = interp2(Speed_eng,Torque_eng,eng_fuel_con,W,T,'linear');
end

EngFuel=fuel;
```


Following two programs implement the fuel map of ICE and efficiency map of the motor

```
------------------------------------------------------------
% engine Map
% 1.5L Prius_jpn (Atkinson cycle)engine
% Maximum Power 43kW @4000rpm
% Peak Torque  75 lb-ft @ 4000 rpm.


fc_fuel_type='Gasoline';
fc_disp=1.5;  % (L), engine displacement
```

```
fc_emis=1; % boolean 0=no emis data; 1=emis data
fc_cold=0;      % boolean 0=no cold data; 1=cold data exists
fc_cap=40;
scalefac=1;%40/35;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% 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);
Eng_effic               =
(Speed_eng.*Torque_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


fc_fuel_den=0.749*1000; % (g/l), density of the fuel
fc_fuel_lhv=42.6*1000; % (J/g), lower heating value of the fuel
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% SPEED & TORQUE RANGES over which data is defined
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% (rad/s), speed range of the motor
mt_spd=[0 250 500 750 1000 1250 1500 1750 2000 2250 2500 2750 3000 3250
3500 3750 4000]*(2*pi/60);
% Note: the above conversion from RPM to rad/s was fixed 6/16/98

% (N*m), torque range of the motor
mc_map_trq=[0 25 50 75 100 125 150 175 200 225 250 275 300 325 350 375
400];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% EFFICIENCY AND INPUT POWER MAPS
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% (--), efficiency map indexed vertically by mc_map_spd and
% horizontally by mc_map_trq
mc_eff_map=[...
     0.3   0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3 0.3
0.3
     0.3   0.7   0.75  0.75  0.75  0.73  0.71  0.7   0.7   0.68  0.65
0.63 0.62  0.61  0.6   0.59  0.58
     0.3   0.75  0.8   0.82  0.824 0.823 0.82  0.815 0.81  0.8   0.78
0.77 0.76  0.755 0.745 0.73  0.72
     0.3   0.75  0.82  0.842 0.855 0.856 0.854 0.85  0.845 0.84  0.835
0.825 0.82 0.808 0.8   0.77  0.765
     0.3   0.75  0.83  0.86  0.871 0.875 0.877 0.873 0.871 0.869 0.862
0.859 0.85 0.842 0.836 0.825 0.82
     0.3   0.75  0.84  0.87  0.881 0.887 0.889 0.887 0.884 0.882 0.878
0.873 0.867 0.861 0.855 0.85 0.842
     0.3   0.75  0.84  0.873 0.89  0.895 0.897 0.896 0.894 0.893 0.89
0.887 0.881 0.876 0.876 0.876 0.876
     0.3   0.75  0.84  0.88  0.893 0.9   0.901 0.901 0.901 0.9   0.895
0.892 0.89 0.89  0.89  0.89  0.89
     0.3   0.75  0.84  0.88  0.895 0.901 0.904 0.905 0.904 0.903 0.902
0.902 0.902 0.902 0.902 0.902 0.902
```

```
        0.3    0.75   0.84   0.88   0.9    0.903 0.908 0.909 0.907 0.906 0.906
0.906 0.906 0.906 0.906 0.906 0.906
        0.3    0.75   0.85   0.88   0.9    0.905 0.91   0.915 0.91   0.91   0.91
0.91  0.91   0.91   0.91   0.91   0.91
        0.3    0.75   0.85   0.88   0.9    0.904 0.908 0.909 0.909 0.909 0.909
0.909 0.909 0.909 0.909 0.909 0.909
        0.3    0.75   0.84   0.875 0.89   0.9    0.904 0.904 0.904 0.904 0.904
0.904 0.904 0.904 0.904 0.904 0.904
        0.3    0.74   0.82   0.865 0.885 0.894 0.9    0.9    0.9    0.9    0.9
0.9   0.9    0.9    0.9    0.9    0.9
        0.3    0.7    0.82   0.86   0.88   0.89   0.895 0.895 0.895 0.895 0.895
0.895 0.895 0.895 0.895 0.895 0.895
        0.3    0.7    0.81   0.855 0.878 0.888 0.892 0.892 0.892 0.892 0.892
0.892 0.892 0.892 0.892 0.892 0.892
        0.3    0.3    0.3    0.3    0.3    0.3    0.3    0.3    0.3    0.3    0.3
0.3   0.3    0.3    0.3    0.3    0.3];
pos_trqs=find(mc_map_trq>0);
pos_spds=find(mt_spd>0);
mt_trq=[-fliplr(mc_map_trq(pos_trqs)) mc_map_trq]; % negative torques
are represented too
mt_eff=[fliplr(mc_eff_map(:,pos_trqs)) mc_eff_map]; % the new efficiency
map
[Mot_sp_nom,Mot_tr_nom]= meshgrid(mt_spd,mt_trq);


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% LIMITS
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% max torque curve of the motor indexed by mc_map_spd
mc_max_trq=[340 375 402 403 401 400 348 300 250 227 202 190 175 170 150
148 0]; % (N*m)

mc_max_gen_trq=-1*[340 375 402 403 401 400 348 300 250 227 202 190 175
170 150 148 0]; % (N*m), estimate
```