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Development of Energy Management Techniques for Hybrid Electric Vehicle (HEV): Three Wheeler Rickshaw

by

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Development of Energy Management Techniques for Hybrid Electric Vehicle (HEV): Three Wheeler Rickshaw

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To the people who care about me, and look after me.

To the people who admire me, and look up to me.

To the people who loved me, and now look at me from the sky.
To my family.

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Abstract

Environmental challenges and reduction of global crude oil reserves gained the attention of researchers and automobile manufacturers for exploration of novel vehicle technologies. Hybrid Electric Vehicles (HEVs) established a thought for minimizing the fuel consumption and greenhouse gases (GHG) emissions. Transportation sector consumes about 66% of total oil consumption in the world and 50% of that is utilized by small passenger cars and trucks.

The main challenge for the designing of Hybrid Electric Vehicles is the coordination of onboard energy sources and optimal power flow control for both the electrical and the mechanical paths. This requires the utilization of an appropriate control strategy or energy management strategy. Energy management technique is employed, ensuring optimal power sharing between two energy sources (engine and motor) while keeping the battery state of charge in the charge-sustaining mode.

On the basis of research, conducted by the industry and the academia, different energy management strategies have been proposed. These strategies can be categorized into non-implementable and implementable energy management strategies, relying on the data required for real time implementation. Normally, the non-implementable strategies formulate the energy management problem as an optimal control problem of minimizing a performance index over a finite time interval under components operational constraints. These strategies are considered as bench mark strategies providing global optimal solution. The implementable strategies have been developed for implementation in real vehicles and provide near optimal solution.

The main emphasis of this research is to develop the energy management strategy of HEV (Three Wheeler Auto Rickshaw), as the energy management strategy has a key role in fuel economy and reduction of emissions. By introducing the Dynamic Programming for the evaluation of fuel economy for a particular vehicle provides a bench-mark fuel economy for other energy management strategies. The main contribution of the dissertation is to evaluate the bench-mark fuel economy for parallel hybrid electric rickshaw through dynamic programming. DP is used as a feasible technique for powertrain benchmark analysis. A parallel hybrid electric three-wheeler vehicle is modeled in Matlab/Simulink through forward facing simulator. The DP technique is employed through the backward facing simulator,

ensuring optimal power-sharing between two energy sources (engine and motor) while keeping the battery state of charge in the charge-sustaining mode. The extracted rules from DP forming near-optimal control strategies is playing a vital role in deciding overall fuel consumption. Unlike the DP control actions, these extracted rules are implementable through the forward facing simulator.

From the simulation results, it can be concluded that a substantial improvement of fuel economy up to 27% through DP is achieved for HEV (33 Km/liter) in comparison with conventional vehicle (24 Km/liter) and is taken as reference value for other strategies. Equivalent Consumption Minimization Strategy is also implemented, which shows fuel economy of 31.35 Km/liter showing 5% more fuel consumption than DP. Results also indicate that there is an improvement of about 9% in fuel economy, in comparison with the heuristics based strategy (not conforming to DP rules). The rule-based strategy (rules extracted from DP) is then compared with non-optimal rules based heuristics controller. It is shown that non-optimal rule based controller has 18% more fuel consumption than DP results. The dissertation also narrates a comprehensive comparison of the different proposed energy management strategies.

Additionally, an attempt is made to devise and demonstrate Energy Management Strategy (EMS) by giving full consideration to the powertrain using Atkinson cycle engine. A novel energy management strategy based on the vehicle speed for Atkinson cycle engine for HEV is proposed. The proposed EMS with Atkinson cycle engine control framework exhibits the significant improvement in the fuel economy around 12.30% for standard Manhattan driving cycle at part load conditions and 7.22% for the modified Federal Urban Driving Schedule (FUDS) driving cycle in comparison with the Otto cycle engine.

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Abbreviations

Acronym	**W**hat (it) **S**tands **F**or
ADVISOR	ADVanced VehIcle SimulatOR
BSFC	Brake Specific Fuel Consumption
CV	Conventional Vehicle
DP	Dynamic Programming
DoH	Degree of Hybridization
EMS	Energy Management Strategy
ESS	Energy Storage System
ECMS	Equivalent Consumption Minimization Strategy
FCV	Fuel Cell Vehicle
FLC	Fuzzy logic Controller
GPS	Global Positioning System
GHG	Green House Gases
HC	Hydrocarbons
HEV	Hybrid Electric Vehicle
HVAC	Heating Ventilation and Air Conditioning
ICE	Internal Combustion Engine
MEP	Mean Effective Pressure
mpg	Miles per gallon
PBS	Power Balancing Strategy
PMS	Power Management Strategy
PHEV	Plug-in Hybrid Electric Vehicle
PNGV	Partnership for a New Generation of Vehicles
PSAT	Powertrain System Analysis Toolkit

SFC	Specific Fuel Consumption

Symbols

α	Acceleration command [-]
β	Brake pedal command [-]
$\dot{m}_f$	Fuel consumption rate of engine [g/s]
$\dot{S}OC(t)$	Battery state of charge dynamics [-]
η_m	Efficiency of the electric motor/generator [-]
η_e	Efficiency of the internal combustion engine [-]
η_{chg}	Average recharging efficiency of the electric system [-]
η_{dis}	Average discharging efficiency of the electric system [-]
η_{ele}	Average efficiency of the electric system [-]
W_m	Output speed of the electric motor generator [rad/s]
W_e	Output speed of the engine [rad/s
W_{gb}	Gearbox rotational speed [rad/s]
CO	Carbon Monoxide [-]
CO_2	Carbon Dioxide [-]
λ_{dis}	Equivalent factor of discharged battery energy [-]
λ_{chg}	Equivalent factor of recharged battery energy [-]
C_{rr}	Coefficient of rolling resistance [-]
F_{trac}	Traction Force [N]
I_{batt}	Battery current [A]
K_I	Integral gain [-]
K_P	Proportional gain [-]
K_D	Differential gain [-]
P_{dem}	Vehicle power demand [W]

P_{ele}	Power contribution of the electric system to the total power demand [W]
P_e	Power output of the engine [W]
P_{batt}	Battery power [W]
P_{gb}	Gearbox power [W]
Q_{LHV}	Lower heating calorific value of diesel [kJ/kg]
Q_{max}	Battery charge capacity(maximum) [Ah]
$T_{m,max}$	Electric machine torque (maximum)[Nm]
$T_{m,min}$	Electric machine torque (minimum)[Nm]
T_{gb}	Gearbox torque [Nm]
T_e	Engine torque [Nm]
V_{oc}	Battery open-circuit voltage [V]
ρ_a	Density of air [kg/m3]
C_d	Drag coefficient [-]
A_f	Projected frontal area of vehicle [m2]
V	Vehicle velocity [m/s]
t	Variable for time [s]
M	Total mass of the vehicle [kg]
g	Gravitational force [kg/ms2]
a	Acceleration of the vehicle [m/s2]
α	Angle of the road with the horizontal [rad]
η_t	Transmission efficiency [-]
η_e	Engine efficiency [-]

Chapter 1

Introduction

Recently hybrid electric vehicles (HEVs) have picked up consideration because of the expanded concern about fuel economy and emissions. Worldwide environmental change has turned it into an issue of essential concern. The regularly exhausting characteristic assets of oil and geopolitical issues identified with oil providers have made individuals to think about the elective ways of transportation. In spite of the fact that HEV don't totally discount the use of fossil fuel, they diminish its use to a significant extent. This chapter provides a brief overview of HEVs, its motivation and problem statement, the concept of energy management strategies, and introduction of vehicle (Three wheeler Rickshaw) has been narrated along with the contribution of the thesis.

1.1 Introduction to Hybrid Electric Vehicles

A brief overview focusing on the energy flow characteristics of hybrid electric vehicles is presented in this section. A complete introduction about hybrid electric vehicles can be found in text books [6, 7] and lecture notes [8]. Some other theses and dissertations [9–12] also encounter with the problem and give details about aspects that are not considered in this work, such as mechanical design and driveability issues.

To give an idea, why hybrid electric vehicles are useful from the efficiency perspective, it is compulsory to keep in mind the way in which fuel/energy is used in a vehicle. To start with, think about a conventional vehicle in which chemical energy is converted to mechanical energy, providing the whole energy required during a journey. The mechanical energy obtained from the engine is utilized for the drive line components and all auxiliary devices (power steering, air conditioning) and, for the propulsion of the vehicle.

From the pedal position (acceleration and brake commands) and driving pattern (speed, accelerator, grade), the mechanical power from the engine is determined. While in an HEV, the total power required is provided from the coupling of the engine power and the electric power (batteries, super capacitor) in torque assist mode. The share of two energy sources can be chosen freely and constitutes a degree of freedom that makes the changing of operating conditions of the engine with respect to counter part (i,e conventional vehicle), thus providing the potential to enhance its average efficiency.

The useful aspect of hybrid electric vehicles is that the electric motor driving the wheels is reversible in operation and can provide kinetic energy recuperated through regenerative braking. In this way, generating electrical energy for charging the batteries. The regenerative braking can recover energy that is generally dissipated in the mechanical brakes as the form of heat. In practice, only a fraction of kinetic energy can be regenerated, thus providing a significant improvement in the overall vehicle efficiency. The storage devices can be of any kind: electrical (batteries, capacitors), mechanical (flywheels, springs) and hydraulic (pressure accumulators).

There are other benefits of hybrid electric vehicles, like ON/OFF the engine when it is not required (at very low speed or at a stop) and also the fuel economy through the downsizing of the engine.

1.2 Motivation of Hybrid Electric Vehicle and Problem Statement

Now-a-days awareness about energy savings and environment protection has gained attention because of the global warming and greenhouse gas (GHG) emissions. Regulations have been formed for the environmental protection in the developed countries and day by day , they are getting more strict in view of the upcoming challenges. Transportation sector and industries are the main cause of environmental pollution. An international agreement (Kyoto protocol) has been signed by different countries to reduce the emissions of the pollutant gases up to 5.2% by 2012 [13]. It was concluded that the energy conversion efficiency for the conventional vehicle is only upto 20%. Thus, due to the increasing energy demands, depleting sources of fuel, and regulations regarding emissions , the researchers and automotive industry are searching energy efficient propulsion systems.

The need of automobile has emerged in modern society. In automobile sector,the development of Internal combustion engine has a great contribution. But the green house gases in the form of Carbon dioxide(CO_2), Carbon Mono oxide(CO), Hydrocarbons(HC), and oxides of Nitrogen(NO_x) create pollution problems and are a danger for Ozone layer. So in addition to Internal Combustion Engine(ICE), other parallel energy source in the form of batteries/electric motor has been adopted. Hybridization can lessen fuel utilization to a substantial percentages and can likewise help to reduce GHG emissions.

Using this concept, new types of vehicles such as Electric Vehicles(EVs), Hybrid Electric Vehicles(HEVs), and Plug-in-Hybrid Electric Vehicles(PHEVs) have emerged in transportation sector which are fuel efficient and help in reducing toxic emissions. Undeniably, hybrid electric vehicles give some advantages in comparison to conventional vehicles, despite additional components, with increased cost.

Gustave Trouve built a first Electric Vehicle in 1881 [3]. In this electric vehicle, a D.C motor of 0.1hp installed which was powered by Lead-Acid batteries. Due to limited range of operation, electric vehicle did not gain too much attention.

In HEVs, batteries play a supportive role of propulsion power, hence diminishing the need of fossil fuels and reduce toxic emissions. In 1901 Ferdinand Porsche built the Lohner-Porsche Mixte Hybrid, the premier gasoline Hybrid electric vehicle [3]. Charging of batteries is done either by ICE or by regenerative braking in HEVs. However, HEVs have been ignored because of the evolution of the engines technologies and the supply of fossil fuel at a reasonable price. Now-a-days, with rapidly declining in the fuel and the legislation about emissions control, the scenario is changing continuously.

Plug-in-Hybrid electric vehicles provide a medium solution of fuel economy in which batteries are charged through the grid. By using the cheaper grid electricity, PHEVs are replacing liquid fuels by storing the electrical energy in the batteries. The size of batteries used in the PHEVs is larger compared to HEVs. In contrast to HEVs, batteries are used as primary energy source and ICE as secondary energy source. Recharging infrastructure for these vehicles can be provided at different places and also at home in garages.

Electric cars are still not competitive due to small energy density of batteries. It is expected that energy density of batteries will always trail that of fossil fuels. Table.1.1 shows the energy densities of different energy sources. This motivates Hybrid electric vehicles.

If we had better batteries, we would not need hybrids at all. Energy Management strategies play a vital role for the improvement of fuel economy and reduction in greenhouse gases for HEVs.

Parallel hybrid rickshaw has been proposed along with minimization of fuel consumption, because already battery operated rickshaw was introduced. There were problems of limited range of distance. Solution was given by replacing the batteries at different filling station but that facility was not available in remote areas, so its better solution is proposed by giving the idea of Hybrid electric Rickshaw. There are two technical reasons to convert a Rickshaw into HEV. First one is its low speed and the 2nd is frequent braking. As the nature of traffic has high stop/Km

Table 1.1: Energy and Power Needs[3]

Sr	Storage Technology	Energy Density
1	Lead-Acid batteries	100 KJ/Kg
2	Nickle-Metal Hydride batteries	250 KJ/Kg
3	Lithium-ion batteries	600 KJ/Kg
4	Conventional capacitors	0.20 KJ/Kg
5	Ultra capacitors	20 KJ/Kg
6	Fly-Wheels	100 KJ/Kg
7	Gasoline	43000 KJ/Kg

and long idling duration at low speed. So these factors are helpful for achieving good fuel economy. Frequent braking provides the opportunity of recovering inertial power through regenerative braking.

Hybrid electric vehicles provide the advantage of partitioning the total torque demand between the engine and the motor and this fact needs some challenges from the control point of view. Minimum fuel consumption through optimal power split between the two energy sources is discussed throughout this dissertation. Optimization of fuel consumption is achieved under system dynamics, instantaneous (local) and integral (global) constraints on the state and control variables. Here the state of the system is the state of charge of the battery and the control variable is the torque split between the engine and the motor. The problem constraints are formulated by the maximum and minimum power, torque and speed requirements of the engine, transmission, the electric motor and the battery.

Dynamic programming is used to optimize the fuel consumption and the constraints are handled through exclusion of infeasible solutions. Implementation of a backward facing model under the assumption of correctly following a driving cycle can produce many infeasible solutions where particular components or operating states cannot meet the imposed load. As DP can not be implemented online due to large computation time, the rules are extracted from DP implementation. The extracted rules from DP forming near-optimal control strategies is playing a vital role in deciding overall fuel consumption. Unlike the DP control actions, these extracted rules are implementable through the forward facing simulator.

1.3 Energy Management Strategies

A lot of energy management strategies have been devised for the efficient control of the different driving modes and the optimal power sharing between the ICE and the electric motor for the Hybrid Electric Vehicles. The main purpose of energy management strategy is to reduce the fuel consumption by managing the power demand among different energy sources in the HEVs. For hybrid electric vehicles, energy management controller takes the series of control action in the form of instantaneous power split between different energy sources; the overall impact is the fuel consumption over a specified driving cycle, or the total pollution emission, or any other criterion, whose minimization is the objective of optimization.

Fig.1.1 shows the role of energy management for an HEV. The outcome of an energy management strategy is the regulation of speed and maintaining of SOC of the battery. The driver model is usually represented by a PID controller. The strategy decides the partitioning of the power/torque between the energy sources like an ICE and the motor. The difference of the desired speed and the actual speed is given to the driver model and it regulates the speed according to the desired speed.

The research concerned with energy management area has been a hot issue for the last decade. Numerous computation methods have been used to devise the energy management techniques (optimal/non-optimal), e.g Rule Based control, Fuzzy logic based control, Adaptive control,Dynamic Programming, Quadratic programming and Model Predictive Control. These techniques have their own

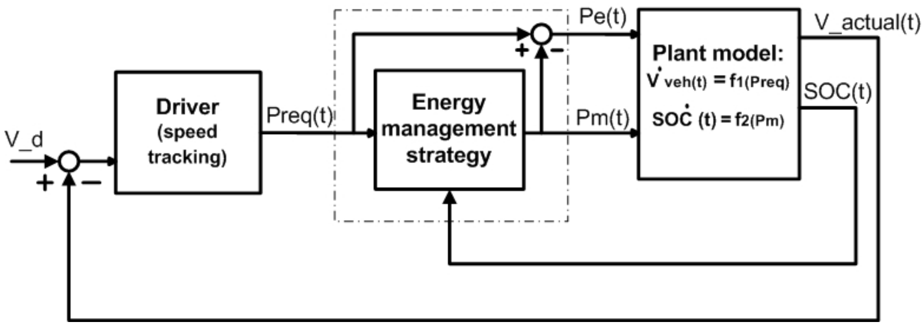

FIGURE 1.1: Energy Management Scheme

advantages and disadvantages. From the available global optimization methods, DP was chosen as the method for the benchmarking analysis, as it not only provides dramatically reduced computation time as compared to other graph search methods [14], but also offers implicit exclusion of infeasible solution paths.

Until now, the dynamic programming has been used for every type of vehicle, but for the Three Wheeler Auto Rickshaw has not been explored so far. There are two reasons to ignore this vehicle, The first one is that it exists in the developing countries and the second one is its small size. Due to its small size, there is less space available for hybridization. The solution is proposed by us to occupy the space available under the rear seats.

1.4 Three Wheeler Rickshaw

The three-wheeler auto-rickshaw with a two or four-stroke engine is a petite, highly maneuverable vehicle and is suitable for the heavily-congested roads. It is an affordable means of transportation in south Asian countries shown in Fig. 1.2. Engine capacities are ranging from 150 to 175 cm^3 for air cooled and 200 to 250 cm^3 for forced air and water cooled. Peak engine power varies from 6.3 to 8.5 h.p. Table.1.2 shows the physical dimensions of retrofitted Rickshaw. The specifications of Rickshaw conforms to Pakistan Standard specification for Three wheeler Auto Vehicles (I.C.S.No.43.080.99). In rickshaw, manual transmission is used, whereas

Table 1.2: Physical Dimensions of prototype Rickshaw[4]

Sr	**Parameter**	**Value**
1	Length	2680 mm
2	Width	1295 mm
3	Height	1700 mm
4	Clearance	180 mm
5	Frontal Area	$2.10m^2$
6	Coefficient of Drag	0.50
7	Vehicle Mass center	400 mm
8	Wheel Base	2000 mm
9	Kerb Weight	280 Kg
10	Distance Driven daily	60-120 Km

Figure 1.2: Conventional Auto Rickshaw

cars and other types of vehicles use continuously variable transmissions (CVTs). Manual transmissions have a fixed set of gear ratios, but CVTs continuously change their gear ratios for maximum fuel efficiency. Manual transmissions provides a driver a little more control over how hard the engine works. By using a manual transmissions, the fuel economy is somewhat compromised. If we use continuously variable transmissions (CVTs), then another control variable would be considered which represents the gear shift schedule vector, because non-optimized gear shift schedule can compromise the fuel economy. As we are optimizing the torque split ratio, we have to make state variable as $X = [SOC,\mu], where\mu$ represents torque split ratio. The control variable now becomes the gear shift ratio.

1.5 Financial Assessment of Conventional and Hybrid Electric Rickshaw

1. Conventional Rickshaw

Average consumption of conventional Rickshaw = 24 Km/liter

Cost of 1 liter petrol = 120 Rs

cost of 1 Km = 120/24 = 05 Rs/Km

2. Hybrid Electric Rickshaw

Average consumption of Hybrid electric Rickshaw = 30 Km/liter

Cost of 1 liter petrol = 120 Rs

cost of 1 Km = 120/30 = 04 Rs/Km

Daily distance driven = 100 Km

Daily saving = $100 * 1$ Km = 100 Rs

Annual saving = $100 * 365 = 36500$ Rs

Saving for 10 years = $36500 * 10 = 365000$ Rs

Cost of Battery and motor = 300000 Rs

Net savings for 10 years = 365000- 300000= 65000 Rs

1.6 Structure of the Thesis

The thesis report is structured as follows:

Chapter 2 focuses on literature review, which is organized in two parts: In the first part, different types of HEVs are introduced. In the second part, different energy management strategies are introduced, which can be sub-divided into optimization-based strategies and Ruled-based strategies. Merits and demerits of different control strategies are discussed later on. Charge-sustaining and charge depleting modes are also discussed in this chapter. Summary and future direction is also the part of this chapter.

Chapter 3 comprises of the mathematical modeling of the hybrid electric vehicle. At the beginning of this chapter, simulation methods are discussed. Simulation methods are further categorized as Forward-face simulation, Backward-face simulation. Merits and demerits of these simulation methods are also the part of this discussion. Definition of vehicle modes in mathematical form is also the part of this chapter. Models of different components of Hybrid electric vehicles such as Engine, clutch, transmission, brakes, differential, motor and battery models are presented with detailed discussion.

Chapter 4 emphasizes on the Energy Management Techniques for HEVs.

Chapter 5 describes the Comparative Analysis of Energy Management Strategies.

Chapter 6 outlines the conclusion and the future research direction.

1.6.1 Research Objectives and Contribution of the Thesis

The main objective of this research is to design an optimal control strategy (minimization of fuel consumption) for the quasi-static model of the vehicle (Rickshaw) which serves as the benchmark solution for other control strategies. DP was chosen as the method for the benchmarking analysis, as it not only provides dramatically reduced computation time as compared to other graph search methods [14], but also offers implicit exclusion of infeasible solution paths. Research objectives are subdivided into different tasks and these are the major contributions of this dissertation regarding the energy management strategies for HEV (Rickshaw) as follows.

1. Design and development of a stable and optimal energy management strategies for a pre-transmission parallel HEV (Rickshaw).

2. Implementation of DP for pre-transmission parallel HEV and deduction of implementable rules.

3. Implementation of extracted rules (optimized values of the engine and the motor torques) in rule-based (RB) controller.

4. Another heuristic-based strategy (rules not conforming to the DP strategy) based on the equal sharing of torque an ICE and the motor (parallel mode) is analyzed.

5. Optimal rules versus non optimal rules extraction is an useful work done in this research .

6. Performance evaluation and comparison of different energy management strategy (ECMS) against the global optimal solution such as DP.

7. Exploring the fuel benefits of an Atkinson cycle engine based HEV at part loading conditions.

Chapter 2

Literature Review

2.1 Introduction

Generally, an hybrid electric vehicle(HEV) consists of an ICE and the electric motor with a battery pack. Depending on the vehicle architecture and degree of hybridization an HEV has at least five features that can be incorporated for fuel economy and reduction in toxic emissions.

IDLE-OFF CAPABILITY. Whenever the vehicle is stopped (engine idling), the engine can be switched off. By avoiding idle speed operation, benefit of fuel consumption reduction along with the emissions reduction can be attained. For example at a traffic signal, if the vehicle is stopped, the engine can be turned off and for the accessory load all-electric propulsion of the HEV may be used.

REGENERATIVE BRAKING. In a conventional vehicle, the inertial forces stored in the vehicle while accelerating is wasted as heating during braking events. These inertial forces can be regenerated using the electric motor and stored in the batteries. This phenomenon can be accomplished because of an electric machine as a generator for charging of batteries. In this way, energy can be utilized for the propulsion of electric motor and therefore regenerative braking is used in all types of HEVs.

POWER ASSIST. The power requested by the driver can be assisted by electric motor in addition to the ICE depending on the HEV architecture.

ENGINE DOWNSIZING. Designing of engine capacity is also beneficial for fuel economy. In the presence of an electric machine and a storage battery in HEV, the total power supplied to the vehicle will increase significantly. The engine is designed according to the reduced power, in this way it will operate on its maximum efficiency and the additional power will be supplied by the motor.

ELECTRIC-ONLY DRIVE CAPABILITY. Based on the HEV architecture and the degree of hybridization, the engine can be shut-off and vehicle can be driven in electric mode only. Later on, engine can be run on its full efficiency and extra power can be used for recharging of batteries.

These additional capabilities of HEVs in comparison to the conventional vehicles will increase the fuel efficiency and helps in reducing emissions. The main purpose of energy management strategy lies within optimal torque/power sharing between the engine and the secondary power sources along with the minimization of a prescribed objective function during a whole driving trip. The objective functions may be fuel consumption, total emissions reduction, battery aging, or a combination of all with different weighting constants, satisfying different constraints. Energy management strategy plays a vital role in utilizing the different capabilities of the HEV. The design, development and utilization of the energy management strategy has been the part and parcel of the research in the industry and academia. After the first Hybrid Electric Vehicle, several prototypes were developed by different companies. Toyota Motor Company developed and produced commercially the most successful HEV called Toyota Prius. This was commercially available by 2000 and it was a big success. Renowned vehicle manufacturers started producing HEVs with different topologies. Charging of batteries is done either by ICE or by regenerative braking [15] in HEVs. Plug-in-Hybrid electric vehicles provide a medium term solution in which batteries are charged through the grid. By using the cheaper grid electricity, PHEVs are replacing liquid fuels by storing the electrical energy in the batteries. The size of batteries used in the

PHEVs is larger compared to HEVs. In contrast to HEVs, batteries are used as major power source and ICE as minor power source. Recharging infrastructure are provided at different places and also at home in garages. We are focusing our research on the Energy Management of Three Wheeler Auto Rickshaw.

There are two reasons for the focusing on Rickshaw

1) It is found in Asian/developing countries. Transportation in developing countries is different from developed countries. Major cities in developing countries are facing various transportation problems, one of them is congestion and as a result increasing travel time. Restricting personal car use and promoting small vehicles could be the possible solution for relieving traffic congestion and diminishing costs of transportation in developing cities.

2) It is the vehicle of masses. Utilization of vehicle in its most efficient way and cost effectiveness is achieved through hybridization of Rickshaw. Rickshaws serve as a feeder services to bus rapid transit (BRT) system.

So, if we save some fuel by Energy Management Technique, that will be beneficial for poor owner of the vehicle. In the past, research has been done on Hybrid Electric Vehicle and Plug-in Hybrid Electric Vehicles. Research on Three Wheeler Auto Rickshaw was also done by different researchers. Priscilla et al [16], worked on Three Wheeler auto Rickshaw, its charging technique, development of Indian Driving Cycle, recharging infra-structure and fuel economy. Research on the Energy Autonomous Solar/ battery Auto Rickshaw was carried out, with the trickle charging done with the help of solar panel installed on the roof of a Rickshaw. In [17] Micro Hybrid System was developed for a Three Wheeler Rickshaw and its performance was observed. In [18] Fuel cell auto Rickshaw with Urban Drive Cycle was studied using PSAT software. In [19], Advantages and disadvantages of Battery driven Easy Bike and CNG driven Auto Rickshaw in Bangladesh was studied and comparison of daily income of owners having different topology based Rickshaws was done. **None of them considered the bench-mark fuel economy of three wheeler Auto Rickshaw and its comparison with other control strategies. So, bench-mark fuel economy is the focal point of**

our research on Three wheeler Auto Rickshaw, because by attaining Bench-mark fuel economy, we can compare other strategies behavior in the sense of fuel economy. Dynamic Programming is the optimal Energy Management Technique that gives the Bench-mark fuel economy. We have also developed rule based (rules extracted from DP) energy management technique and its comparison with Dynamic Programming technique. Development of another heuristic based controller (rules not conforming to DP) and its comparison with DP is also the contribution of the thesis.

2.1.1 Architecture of Hybrid Electric Vehicles

The main categories of HEVs are as follows:

1) parallel hybrid

2) series hybrid

3) parallel-series hybrid

In parallel framework, an ICE and the electric motor are mechanically coupled and can share the propulsion power or provision of power individually. Parallel configuration is more complicated and expensive but serves for greater efficiency and performance. Honda's Insight, Accord, Chevrolet and Saturn VAU used parallel arrangement. Fig. 2.1 depicts the parallel framework.

In series configuration (Fig. 2.2), an ICE and the electric motor have no mechanical connection between them. They are electrically connected and a motor drives the wheels. Two diverse energy conversion operations are needed for all distinct operations in series hybrid electric vehicles. Energy conversion operations include fuel to electricity and electric to mechanical operation (motor) for driving of wheels. Renault Kangoo, Fisher Karma, Coaster light duty bus and Opel Flexetreme use series configuration.

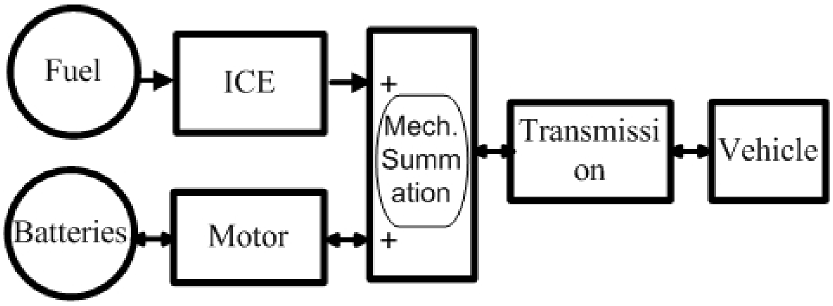

FIGURE 2.1: Parallel Hybrid Electric Vehicle

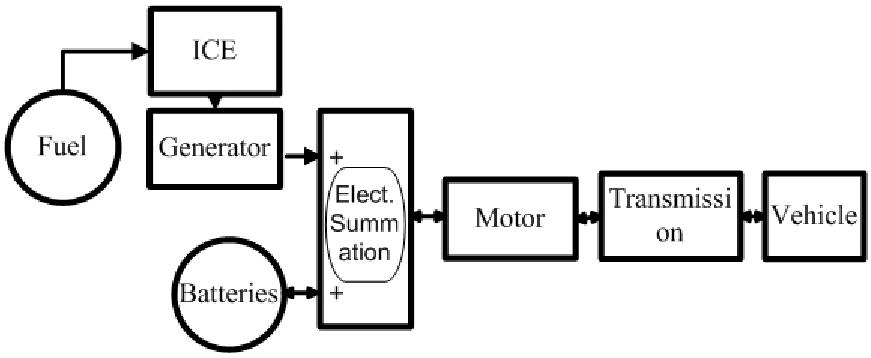

FIGURE 2.2: Series Hybrid Electric Vehicle

In a power split or series parallel hybrid (Fig. 2.3), the combination of both parallel and series configuration exist in a single framework. Generally, it enhances the All Electric Range of Hybrid electric vehicle.

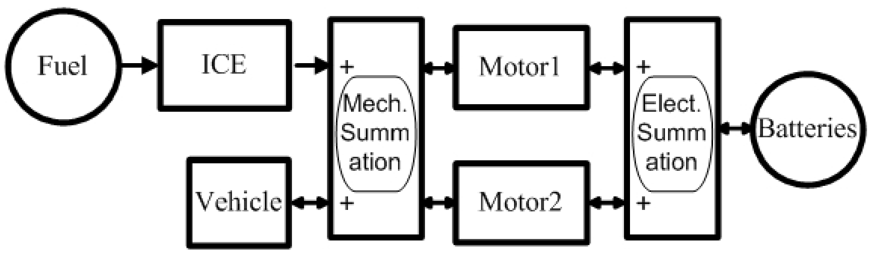

FIGURE 2.3: Parallel Series Hybrid Electric Vehicle .

All the configurations of HEVs can be implemented in PHEVs. There are two modes of battery usages. In HEVs, if the state of charge (SOC) at the starting and the ending of the trip remains same, it is called charge sustaining mode. In PHEVs, the charging of batteries is done through grid supply, so it depletes to an appropriate minimum acceptable level at the termination of the trip. Such a mode is called charge depleting mode.

The designing of a control strategy is somewhat tedious job. The main purpose of the control strategy is to meet the driver's power request with lowest fuel consumption and reduction of green house gases along with the satisfaction of vehicle performance/drivability. Fuel efficiency and emission reduction are clashing objectives. So in a control strategy, there is a trade off between two objectives.

2.2 Overview of Different Optimal/Non-optimal Control Strategies

An optimal control is the branch of control theory that encompasses the problem of finding a control law for a specified system along with the satisfaction of optimality criterion, the system is usually defined as an objective function over a certain time frame. In true sense, it is a set of mathematical techniques for calculating a series of control actions in such a way that their integral behavior is approached to a desired value.

Several categories of energy management strategies have been described in literature, with different characteristics and different possible implementations. Guzzella and Sciarreta [20] suggested the following subdivision:

1. Numerical optimization strategies, the entire drive cycle information is taken and the global optimization is searched numerically. Dynamic programming, stochastic dynamic programming, model predictive and numerical search methods come into this category.

2. Analytical optimization strategies, also accounts for the whole drive cycle, but an analytical optimization problem is formulated and is used to search the solution in analytical form that makes the numerical solution fast. Pontryagin's minimum principal and Hamilton-Jacobi-Bellman equation lie in this category.

3. Equivalent consumption minimization strategies, deals with the minimization at every step of the optimization horizon, of a reasonably defined instantaneous cost function, resulting to the minimization of the global cost function, if the instantaneous cost function is appropriately defined.

The energy management methods for HEVs are categorized keeping in view multiple criteria. On the basis of the amount of information used and the optimization method, three categories are found in literature. Global optimization strategies, local optimization strategies and heuristic methods:

1. Global optimization strategies (numerical or analytical), at each instant of the optimization horizon, knowledge about past, present and future driving conditions is supposed to be known. Dynamic programming and Pontryagin's minimum principle lie in this category.

2. Local optimization strategies, which transform the global optimal problem to a sequence of local optimal problem. Stochastic dynamic programming, ECMS and model predictive control come into this category.

3. Heuristic strategies, depending on the mode of operation, Rule-based control strategies are fundamental control strategies. Mathematical models, human intelligence, heuristics are the criteria used for making rules, without prior information of a drive cycle. Static behavior is found in these types of controllers.

A comprehensive detail of different control strategies along with their pros and cons is narrated here.

Comparison is done by keeping in view solution type (Global or Local), computation time, structural complexity and prior knowledge of driving pattern among the strategies. Structural complexity involves complexity class, relationship between complexity classes and the internal structure of complexity classes. The length of time needed for the computation of process is called computation time. A controller shows robustness, if it behaves well under a set of assumptions designed for a particular set of parameters. Under the presence of uncertainty, robust controllers are designed with certain parameters set or disturbance set. Optimization problem dealing with local optimal point (either maximal or minimal) gives a solution within a neighboring set of solutions. Contrary to local solution, a global optimal solution is amongst all feasible solutions of an optimization problem.

2.2.1 Dynamic Programming

In 1940, Richard Bellman introduced Dynamic Programming (DP). Dynamic programming suggests to simplify a complicated problem by splitting to a simpler sub problems in a recursive manner. The advantage of dynamic programming is that it is applicable for linear as well as non-linear system with constrained and unconstrained problems. It has the disadvantage of intensive computation time, so it is not applicable for complicated systems. This is an offline optimization technique because it requires a priori of driving cycle which is not available in real time application [21]. For known driving cycle, power management optimization can be performed off line using deterministic DP. Optimal sharing between ICE and motor for a series HEV was done using DP and a rule-based approach [22]. To overcome the disadvantage of computational efficiency, they proposed the discrete state formulation technique of DP. The authors considered a parallel hybrid electric truck, depending on a DP based optimal control technique, fuel efficiency was improved in [23] . Sundstrom et al [24] proposed a degree of hybridization for two types of parallel hybrid electric vehicle, namely (1) full hybrid and, 2) Torque assist. With different hybridization ratio, they achieved the fuel consumption improvement by using the DP optimal solution. The results showed that fuel consumption is less in case of full hybrid. DP was used in case of medium duty hybrid electric truck for the optimization of power and fuel economy. In [23], it was observed that 45% more fuel economy than conventional truck is achieved using Dyanamic Programming. Koot et al [25], devised an Energy management technique for HEVs and verification was done by Quadratic Programming, DP and modified DP strategies. With the increase of drive cycle (DC) length, computation cost increases. To overcome this problem, Quadratic Programming was used which also ensures global solution. In modified DP, the entire DC is subdivided into various segments and then DP is implemented in parts for the entire Driving Cycle. Improved Dynamic Programming has the advantage over DP and quadratic programming in the sense that it is also applicable for the non-convex cost function. DP was performed on PHEVs to get an optimal power split solution [26]. They suggested that electric vehicle for urban driving cycle giving improved fuel economy over others. Gong et al [27] executed a DP for power optimization technique for PHEVs in charge depleting mode. They concluded that 37% reduction is achieved in fuel consumption.

Sundstrom and Guzzela [24] used a Bellman's DP technique by proposing a generic DP function to find the solution of discrete time optimal control problem. In [28], there were DP and Equivalent Consumption Minimization Strategy (ECMS) for charge depletion mode. They showed similarity in the sense of fuel economy and SOC profile between DP and ECMS for large batteries and for long distances. Shen and Chaoying [29] used a forward search algorithm by using improved DP in solving the optimal control problem and to reduce computation time. Kum et al [30] suggested a new idea of Energy to distance ratio (EDR) by estimating the battery SOC and using the remaining distance. They proposed an adaptive supervisory power-train controller for the minimization of fuel and emissions using the extracted results from EDR. Ravey et al [31] proposed an algorithm for the sizing or dimensioning of drive-train components using the genetic algorithm initially and then they used the DP for the optimal power management control and found the better fuel efficiency. Shams-Zahraei et al [32] implemented an optimal energy management by adding the temperature noise factors. They concluded that temperature has a great impact on fuel economy and emissions for same driving cycle and conditions. The disadvantage of this technique is that, it is an off-line technique, so it is not applicable in a real vehicle, due to following two reasons.

1. the solution is obtained through backward calculation with the knowledge of complete driving cycle and

2. computationally intensive.

Irrespective of these shortcomings, dynamic programming furnishes the optimal solution, thus serving as a benchmark for other control strategies.

2.2.2 Stochastic Dynamic Programming

Optimization methods that involve random variables for the formulation of an optimization problem is called stochastic optimization. In DP, if state or decision is in the form of probability function, it is termed as stochastic dynamic programming (SDP). A brief introduction of the stochastic dynamic programming strategy is found in [33]. Several research papers [34–38] have discussed its application to hybrid electric vehicles energy management. Contrary to dynamic programming, in which the length of the optimization horizon is well defined, in stochastic DP, there is no actual driving cycle. For this reason, it is the need of defining an infinite horizon problem, which composed of finding an optimal control policy. In [23], authors proposed an infinite-horizon SDP in which random Markov process is used for the estimation of power request of drive-train. The control law derived can be used for real time implementation. In shortest path SDP power management strategy, the low SOC and high SOC from a reference SOC are allowed to vary to obtain a trade-off between fuel economy and emissions. The shortest path SDP controller is comparatively better than SDP in the sense of better SOC regulation and tuning of few parameters [39]. In [40], an optimal control technique for a combined power was formulated using Engine-in-loop (EIL) set up and showed the effect on engine emissions by including the transients conditions. Tate et al [39] implemented the SP-SDP on HEV to estimate the trade-off between fuel consumption and tail-pipe emissions. Moura [41] used an optimization strategy for PHEVs. In [42], they proposed a controller for energy management strategy which was real-time in nature. The efficiency of this controller was found to be more than

11% compared to the industrial base line controller. Opila et al [42], developed an energy management strategy based on short path dynamic programming and was successfully implemented for a prototype HEV.

It is worth noting that normally prediction of driving pattern is done through a Markovian process, but this prediction may not be applicable to real driving due to the other outside features like traffic lights and traffic flow dynamics that are beyond the scope of Markov process.

2.2.3 Model Predictive Control (MPC)

For a dynamic system, model predictive control is a best choice and it is implemented through system identification. MPC is implemented through the principle of optimization of current time slot keeping in view the future time slot. MPC is used for the prediction of upcoming events and actions are taken according to prediction. West et al [43] proposed MPC for vehicle driving range, enhancement of battery lifetime, reduction of drive-train oscillations and reduction of emissions for HEVs and EVs. In [44] real time application on parallel hybrid electric vehicle was done by using MPC without the future knowledge of driving pattern. In [45], they used a technique of mixed integer linear programming for the best achievement of control policy. They concluded that by using MPC, fuel economy improvement was greater than that of instantaneous optimization techniques. In conventional model predictive control, an online optimization is required at each step to solve it. MPC with improved speed is implemented in [46]. Kermani et al [47] implemented global optimization algorithm using MPC with Lagrange formula. In [48], authors used MPC based energy management strategy for an HEV (series configuration). They also used Quadratic Programming in-addition to MPC and Matlab /Simulink based quasi-static simulator was developed for the implementation of MPC. The length and type of predictions was also investigated by them. Borhan et al [49] proposed a non-linear MPC for HEVs and found on-line power split between energy sources. In [50], they proposed a stochastic-model predictive control based energy management for an HEV (series configuration). Markov Chain rule was used for the modeling of power request from driver. Optimization algorithm predicts upcoming power demand keeping in view the present power demand at each instant.

Borhan et al [49] used MPC based strategy to find the minimum fuel consumption through a power-split among the energy sources. Two levels of energy management strategy are narrated, future control sequences are calculated in the first level by MPC that minimizes an objective function and in the second level, it is applied to the first element of the calculated control sequence of the hybrid vehicle model. In [51], they suggested an MPC based torque-split strategy for a parallel hybrid electric vehicle that takes into account the transient behavior of the diesel engine. They concluded that MPC methods are helpful for the improvement of fuel economy for HEVs.

2.2.4 Pontryagin's Minimum Principle

In 1956, The Russian mathematician LEV Semenovich formulated Pontryagin's minimum Principle (PMP) which is a best controller for a dynamic system between two states with constraints for input control. PMP strategy is a particular case of calculus of variations using Euler-Lagrange equation. For an optimal solution, PMP gives necessary and sufficient condition that are then satisfied by Hamilton-Jacobi Bellman equation. In PMP strategy, the solution of non-linear second order differential equations could be a local optimal, away from the global optimal solution. This solution can be made global optimal under certain assumptions. Geering [52] proposed the solution of PMP for the transformation of a global energy optimization problem into a local energy optimization problem. Rizzoni and Serrao [53] proposed an optimal control strategy by using PMP to find the optimal solution. An instantaneous optimization problem was obtained by converting a global optimization problem. Kim et al [54] implemented PMP on PHEVs for obtaining a control law using instantaneous optimization. The literature on PMP suggests that by appropriate selection of state constraints, instantaneous optimization strategy gives a solution close to optimal solution as given by DP. Stockar et al [55] implemented PMP for the formulation of an optimal supervisory controller by converting a global optimization problem into a local optimization problem. The strategy is less computational expensive and provides the liberty to find the solution of continuous time domain problem. By using PMP, an optimal control is found through the instantaneous minimization of the Hamiltonian function. Trajectory derived from PMP may not give a global optimal solution, therefore PMP based controller may be treated as inferior to DP for the reason of trajectories derived from PMP may not give a global optimal solution. DP is considered as more computational expensive than PMP for the reason of providing solutions to all control variables to fill the whole region optimal field. Computational time of DP is same as HJB equation because DP is a numerical representation of Hamiltonian-Jacobi-Bellman equation through the solution of a partial differential equation. PMP strategy is mainly applicable for the solution of nonlinear second-order differential equations. In short, the solution of a two-point boundary value problem through analytical method is the out-come of PMP.

2.2.5 Equivalent Consumption Minimization Strategy

Paganelli et al [56] introduced the idea of Equivalent Consumption Minimization strategy for the energy management of HEV. It transforms a global optimization problem into an instantaneous minimization problem and giving solution at every instant. The instantaneous minimization problem is computationally less demanding than the global problem solved with dynamic programming or a convex optimization problem. It is a real time optimization strategy and there is no need of advance information of driving cycle. ECMS is formulated by calculating total fuel used as a sum of actual fuel consumed by an ICE and energy used by the motor (equivalent fuel). Some of the control parameters are required to be tuned without future prediction. These control parameters differ from one topology of HEVs to another topology as a function of driving patterns. Absence of assurance for charge-sustaining of the vehicle is one of disadvantage of the strategy. Jalil et al [57] used a simple strategy of thermostatic control (Engine ON/OFF), but did not find the optimal solution rather a near-optimal solution. Paganelli et al [58] used ECMS in a sports vehicle using charge-sustaining mode for the improvement of fuel economy and reduction of GHG emissions. In [57], authors also used ECMS for power splitting between two energy sources like the engine and the electric motor for the minimization of fuel consumption and concluded a result of fuel economy improvement by 17.5% as compared to the conventional vehicle. Supina and Awad [59] proposed a thermostatic strategy in another way, by seeing the conditions of SOC and according to status of SOC, decision about the engine ON/OFF is taken and showed 1.6% to 5% fuel economy over the conventional thermostat strategy. In [59] a real time strategy was implemented without the future knowledge of driving conditions for parallel HEVs and showed improved fuel economy with cost function using instantaneous optimization based ECMS. Won et al [60] devised an energy management strategy for torque splitting between the engine and the motor, satisfying the charge sustaining condition by using ECMS. In the implementation of afore-mentioned strategy, multi objective torque partitioning strategy is devised primarily and then it is converted into single objective linear optimization problem. An adaptive-ECMS was implemented [61, 62] for real time energy management strategy. It continuously updates the control parameters according to driving pattern giving a quasi-static solution in comparison with rule based and ECMS strategies. Wang et al [46] proposed a technique for hybrid electric vehicles (series configuration) with less computational time. Sciaretta and Guzzela [44] used the ECMS for PHEV and found better results of fuel economy. In [63], authors used ECMS for different energy sources like Fuel cell, the engine, and the battery for buses having different topology. In [64], they proposed real time energy management strategy with advance prediction of driving cycle and found optimal solution for fuel economy and GHG emissions reduction. Tulpule et al [28] suggested a control strategy using ECMS which requires the knowledge of total distance trip for the evaluation of fuel economy. Marano et al [65] elaborated a comparison between DP and ECMS based on the optimal performance of PHEVs. Cui et al [66] proposed an energy management strategy consisting of two strategies 1) Global parametric estimation by DP, 2) ECMS as instantaneous optimization technique.

Generally ECMS faces the difficulty of sensitivity of parameter called equivalence factors; thus, the technique needs proper tuning of equivalence factor for each drive cycle. Knowledge of the efficiencies of the converting devices is used for the estimation of equivalent fuel used. In short, this method is causal inherently and needs high memory for implementation.

2.3 Rule-based Control Strategies

Depending on the mode of operation, Rule-based control strategies are fundamental control strategies. Mathematical models, human intelligence, and heuristics are the criteria used for making rules, without advance information of a drive cycle. Shaohua et al [67] implemented the energy management method for the Belt Driven Starter Generator (BSG), keeping in view the road load. Improvement in fuel economy was accomplished while implementing this strategy. Other aspects like dynamic performance and drivability were also improved as well. Online energy management between two energy sources with extended range and improved battery life was done by Travao et al [68]. With the help of rule tables or flowcharts, the operating points of an ICE, the Traction motor, and the generator are chosen such that the driver request and other components' energy requirements accomplished in an efficient way. Instantaneous inputs are the only criteria for the decision of rules. There are two sub-categories of rule-based strategy namely, Deterministic rule-based control strategy and fuzzy rule-based strategy.

2.3.1 Deterministic Rule-based Control Strategy

Fuel maps or emissions data, drive-train power flow, ICE operating maps and driving experience are the criteria for designing the rules. Rules are made and executed through look up tables by sharing the power demand among the energy sources like an ICE and the motor. Deterministic rule based control strategy has certain operation modes such as " Thermostat mode", "Pure Electric mode", " Electric Assist mode", and Regenerative mode, under each of which the control strategy is exclusive. The transition between different modes is decided by transition conditions, which are definitely deterministic rules. However, the performance in terms of fuel economy is limited by the finite number of modes and transition conditions. Generally, a fixed threshold value based on the parameters of the vehicle for mode transition may lead to mode fluctuation, particularly if the signals from the sensors have significant noise.

Thermostat control strategy employs only turning ON/OFF the ICE while maintaining the SOC low and high level. This is simple strategy, saving fuel consumption during idling of engine. In Electric Assist control strategy, an ICE plays a role of main source of energy supply and the role of an electric motor is to supply additional power according to the demand of driver.

2.3.2 Fuzzy Rule-based Strategy

The term fuzzy logic and mathematics of fuzzy set theory was introduced by L.A.Zadeh [69]. Fuzzy logic system has specialty in handling linguistic knowledge and numerical data simultaneously. Instead of a true / false type membership, it uses partially true type membership function, known as fuzzy sets. Fuzzy sets are presented as fast, slow, low, medium, and high. For the fuzzy logic, the truth-ness of any statement depends upon its degree. The expertise of the designer is used in making rules. In fuzzy logic, with the help of fuzzy set theory, we derive the multi-valued logic that are approximated rather than precise. Using the fuzzy logic as a tool, an intelligent control system can be developed. The expert knowledge is transformed in the shape of rules that help in decision making. Tuning and adaptation is the main advantage of fuzzy logic , in this way it enhances the degree of freedom of control. In short, fuzzy logic technique is an extended version of many rule-based techniques (based on look-up tables). Uncertainties measurement of noises and disturbances can be easily handled in Fuzzy Logic controller. Fuzzy logic control strategy implemented on a parallel HEV is discussed in [70]. By selecting inputs (M) and fuzzy sets (N) for each input, there could be maximum N^M rules, while increasing inputs (M) and fuzzy sets (N), one can improve the performance of a fuzzy controller, but a faster micro controller with extended memory is needed to store and processing of large number of rules.

2.3.3 Traditional Fuzzy Control Strategy

With the adoption of input, output and rule-based technique, one can decide the efficiency of a controller. The inputs can be desired torque from an ICE and the state of charge (SOC) of the battery. By selecting the inputs and mode, the operating region of an ICE is set. The demand of power from an electric motor is selected by subtracting the power demand of an ICE from the total power demand. It is desired that ICE operation should be close to the torque region for the reason of maximum efficiency at a particular speed region. Maintaining SOC of the battery, the motor is used to assist the ICE, so that minimum fuel consumption is achieved. By avoiding the frequent charging and discharging of Electrical Storage System (ESS) and to meet power demand, load balancing is necessary between the energy sources. By attaining the operating region of an ICE close to peak efficiency near torque region and recharging of batteries through extra torque generation, it is possible that ICE generates more torque than required and thus increasing fuel consumption. For strategy implementation, Lee et al [71] introduced FLC for the fuel economy of Hybrid Electric Vehicle. Fu et al [72] implemented energy management strategy based on FLC using ADVISOR software and proved improvement in fuel economy with reduction in GHG emissions.

2.3.4 Adaptive Fuzzy Control Strategy

For the optimization of both fuel efficiency and emissions simultaneously, adaptive fuzzy control strategy is also used. Since there is trade-off between fuel economy and emissions, so achieving an optimal solution through the satisfaction of all the objectives is not possible. A weighted sum technique is adopted for different objectives. Appropriate selection of weights helps in achieving optimal solution. The conflicting objectives may be fuel economy, CO, NO_x (oxides of Nitrate) and HC (Hydrocarbon) emissions. ICE data map can be used for finding the near optimal solution of fuel economy and emissions at particular ICE speed. Weight selection is done on the importance of each conflicting objective. Anyone of the objectives can be controlled in this control strategy by the choice of relative weights. Vehicle emissions reductions can be achieved with a small compromise with fuel economy. Brahma et al [22] designed a modeling tool using FLC for the evaluation of fuel economy which is universal for any model. Syed [73] designed a FLC for the controlling of engine power at a particular speed adopted for an HEV.

2.3.5 Predictive Fuzzy Control Strategy

The advantage of Predictive fuzzy control strategy is that it is implemented for real time application and with the help of GPS (Global Positioning System) identification of the obstacles like steep grade and heavy traffic can be predicted. It is advisable that when the vehicle is running on a highway and it is entering into the city, the battery should be recharged fully so that it can be used in the city traffic. For the vehicle motion history and variation in prediction, the optimal torque is determined that is helpful for attaining the fuel economy of the vehicle. The GPS signal is normally in the form of $(-1,+1)$ obtained through Predictive FLC and this information is given to master controller for charging and discharging of batteries and storing energy for future operational modes. Won and Langari [60] designed the FLC strategy for torque distribution between the energy sources. Fuzzy sets to design driver command, motor/generator speed, and battery SOC were implemented in FLC for parallel HEVs.

Bathaee et al [60] worked on optimal energy management strategy using torque control for parallel HEVs. Zhang et al [74] proposed a supervisory control which is fast and compact with double input, single input. Transient and steady state behavior of a vehicle was seen in the dynamic model of HEV using different driving conditions. Poursamad and Montazeri [75] tuned FLC using Genetic Algorithm for the minimization of fuel consumption and GHG emissions while improving the driving performance of the parallel HEVs. Liu et al [40] proposed a FLC for series HEV, keeping battery SOC within limits. In the proposed strategy, the engine operates in its high efficiency region. Zhou et al [76] used Particle Swarm Optimization (PSO) for tuning of parameters for energy management in parallel HEV taking battery SOC and torque demand (as inputs) and torque required (as output). Lu et al [77] used FLC in PHEV for the partitioning of torque between the energy sources like the engine and the motor. Using Advisor software for different driving cycles, they developed a controller and showed improvement in fuel economy. The designing process of fuzzy logic based controllers comprise of many parameters that are responsible for the entire performance of the controller. For best results, these parameters should be properly tuned. Presence of large number of rules and their inter-dependency bring a difficulty of tuning them properly. The problem can be resolved by blending the FLC with some optimization algorithm. A tuned rule-based controller performs well to the specified drive cycles and need to be re-tuned for other drive cycle. Optimization of the instantaneous operation is the basis of majority of controllers, due to this SOC may not be controlled for the reason of sudden increase/decrease of future demands such as upgrading a steep or down steep.

The main disadvantage of rule based strategies is the lack of optimality, also the absence of standard methodology for synthesizing the rules due to different rules for different case studies. Additionally, the rules decided are not appropriate for a wide variety of driving conditions.

Table 2.1 shows the different control strategies implemented for Rickshaw. Research gap has been demonstrated in the discussion Research gap and Motivation subsequently.

Table 2.1: Different control strategies used in Rickshaw

Electric Rickshaw	Hybrid electric Rickshaw
Rule based controller for analysis of battery electric Rickshaw [Priscilla :2009]	Rule based controller for a parallel hybrid Rickshaw electric range Rickshaw [Sagar Tatipamula :2013]
Rule based controller for Photo- voltaic battery powered electric Rickshaw [Y.Gurkayank :2009]	Rule based study of Hybridization of Hybrid Electric Rickshaw[M.Asghar:2015]
Rule based controller for all electric range Rickshaw [Priscilla :2010]	Benchmark Fuel Economy for a Parallel Hybrid Electric Three-Wheeler Vehicle (Rickshaw)[This work]
Rule based controller for Hybrid energy assisted electric Rickshaw [Necolus Shah :2013]	

2.4 Research Gap and Motivation

From the literature review, the following shortcomings in the Hybrid Electric Vehicles literature motivates the main contributions of the dissertation.

1. All the optimal strategies were implemented on each type of vehicle, but these strategies were not implemented for Three Wheeler auto Rickshaw(Table.2.1). The solution was restricted to use the battery operated Rickshaw, in which trickle charging of batteries was done by solar system installed at the roof of the vehicle or swapping of batteries at different stations. So there was not requirement of optimal control strategies. Only rule based strategies were implemented for Three Wheeler auto Rickshaw. Parallel hybrid rickshaw has been proposed along with minimization of fuel consumption, because already battery operated rickshaw was introduced.

There are two technical reasons to convert a Rickshaw into HEV. First one is its low speed and the 2nd is frequent braking. As the nature of traffic has high stop/Km and long idling duration at low speed. So these factors are helpful for achieving good fuel economy. Frequent braking provides the opportunity of recovering inertial power through regenerative braking.

2. As we can not apply optimal strategies straightforwardly for the reason of intensive computation time, rules are extracted from Dynamic Programming, which are implementable online. The rules extraction (optimized values of the motor and the engine torques) from DP was done for Rickshaw parameters and is implemented through a rule-based (RB) strategy. The purpose of rules extraction from DP is to investigate the fuel economy close to the ultimate fuel saving. The strategy based on these rules (rule-based strategy) is computationally efficient and can be effectively executed.

2.4.1 Summary

The energy management strategy has a prominent role in controlling the fuel economy and emissions. A detailed review of all control strategies to optimize the power sharing between ICE and motor in HEVs and PHEVs has been done and comparison was done among these control strategies. Control strategies starting from advanced optimal control strategies to rule-based are included in the literature review. Ruled- based controller are easy to implement, but they do not give the optimal solution. For the optimal solution, a prior knowledge of driving pattern is required for the whole trip. As the optimization based strategies are unable to be used directly for the real time scenario, so rules extracted from these strategies enable us to implement for real time scenario. The strategy that is less computational expensive, providing global optimal solution, and can be fitted to desired simulation environment would be the right choice.

In the next chapter, Dynamics of the Vehicle are discussed. Any Energy Management Technique can not be accomplished without the dynamics of the system.

Chapter 3

Mathematical Modeling of Hybrid Electric Vehicle

3.1 Introduction

This chapter presents a comprehensive detail of vehicle's model and various simulation approaches. It then gives detail about the parallel HEV model developed in Matlab/Simulink environment. The conventional vehicle's model is also presented and is considered as a benchmark vehicle.

3.2 Simulation Techniques

From the perspective of power flow direction, the simulation techniques are divided into two categories; forward-facing simulation and backward-facing simulation.

3.2.1 Forward-facing Simulation

As for as the forward-facing simulation technique is concerned, the calculations of power flow is done in the direction of tractive energy flow. Main simulink block diagram is shown in the Fig.3.1. There are three main blocks, Driver, HEV power train and vehicle dynamics blocks and the outcome of this main block is the actual velocity from the vehicle.

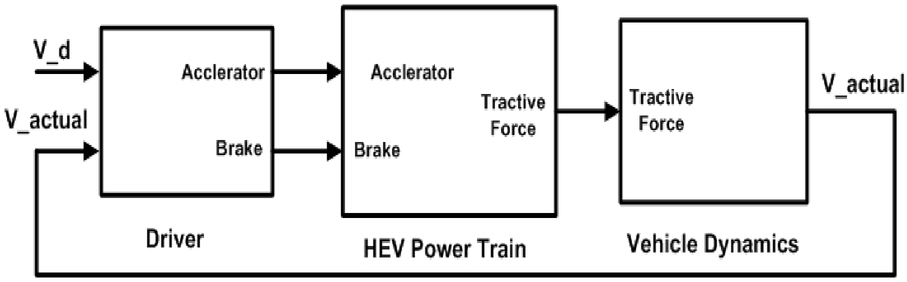

FIGURE 3.1: Main simulink block diagram

The information flow in a generic forward vehicle simulator is shown in Fig.3.2. This approach is close to real driving scenario through which the vehicle is driven according to drivers pedal position and braking commands. The driver's acceleration and brake commands are set to meet the desired speed and braking. According to desired speed and actual speed, the throttle command is converted into actual power/torque demand. The main purpose of energy management controller (HEV controller) is to split the torque between the ICE and the motor. Vehicle speed is achieved through tractive torques with the help of transmission and dynamics of vehicle. The main advantage of Forward-facing approach is that quantities are measurable at each step in a physical drive-train like torques and command signals. In this way, energy management strategies can be directly transferred to hardware. The variables used in the Forward simulator are explained below.

- V_d: Vehicle's velocity (desired) [m/s]
- V_actual: Vehicle's velocity (actual) [m/s]
- Te_req: Engine Torque request [Nm]
- Tm_req: Motor Torque request [Nm]

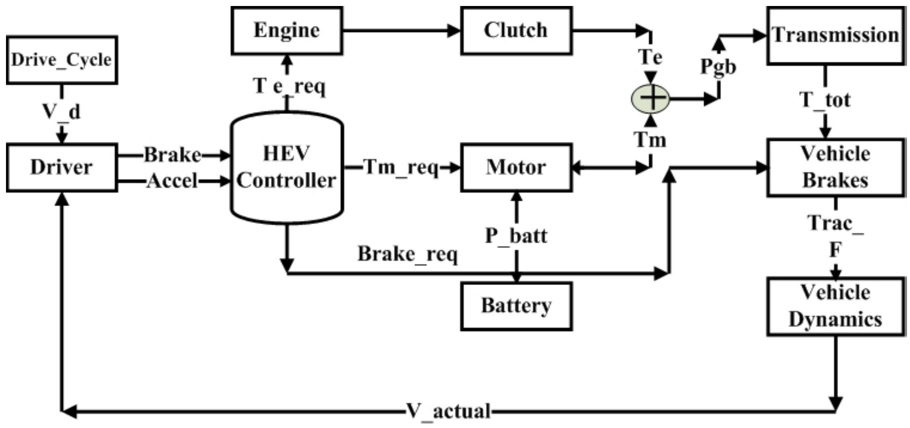

Figure 3.2: The forward simulator diagram

- *Brake_req*: Brake request [Nm]
- *P_batt*: Battery Power [W]
- *Te*: Engine Torque outcome [Nm]
- *Tm*: Motor Torque outcome [Nm]
- P_{gb}: Power before gear box [W]
- *T_tot*: Total Torque [Nm]
- *Trac_F*: Traction Force [N]

This simulator can be used to perform the following tasks

1. Comportment of vehicle system over specified driving cycles.

2. Evaluation of instantaneous and cumulative fuel consumption and estimation of SOC of the battery.

The major drawback of this simulation technique is its slow simulation speed. The detail of main components of a forward vehicle simulator are mentioned with the corresponding input and output signals.

3.2.2 Driver Model

Driver model represents a PID controller shown in the Fig.3.3 and is used in the forward vehicle simulator and takes the actual and desired vehicle velocity (driving cycle) as inputs. From the error in velocity, it estimates the accelerator and brake pedal commands. The function of the driver block is to enable the simulator to follow the desired drive cycle. For the given simulator, the driver block is a feedback controller that employs proportional, integral and derivative(PID) controller. The main objective of PID controller is to minimize the difference between the current vehicle's velocity and that of the desired driving cycle velocity. Simulink driver model is shown in the Fig. 3.4.

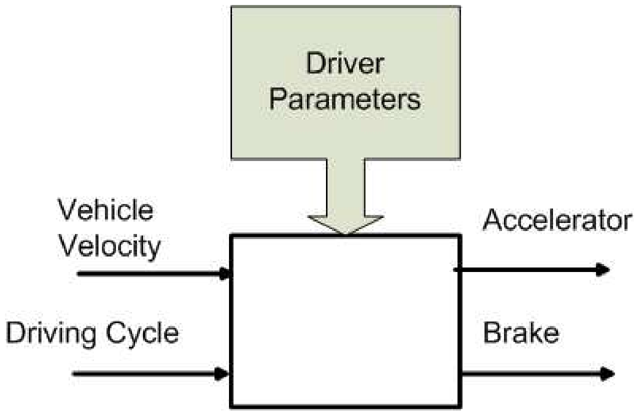

FIGURE 3.3: Driver model

The equations related to the driver model are narrated as follows

$$e(t) = V\_d(t) - V\_actual(t) \quad (3.1)$$

$$y(t) = K_p e(t) + K_I \int e(t)dt + K_D \frac{de(t)}{dt} \quad (3.2)$$

$$\alpha(t) = y(t) \qquad \forall y(t) > 0 \quad (3.3)$$

$$\beta(t) = y(t) \qquad \forall y(t) \leq 0 \quad (3.4)$$

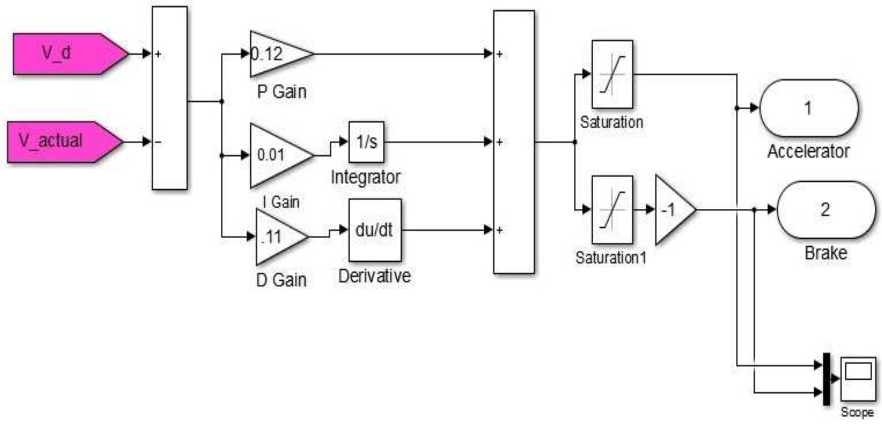

FIGURE 3.4: Simulink model of Driver model

- $V\_d(t)$: Vehicle velocity (desired) [m/s]
- $V\_actual(t)$: Vehicle velocity (actual) [m/s]
- $y(t)$: Output of PID controller [-]
- K_p: Proportional constant [-]
- K_I: Integral constant [-]
- K_D: Derivative constant [-]
- $e(t)$: Difference of actual and desired velocity [m/s]
- $\alpha(t)$: Acceleration command
- $\beta(t)$: Brake pedal command

The values of K_p, K_I and K_D are shown in table 3.1 and these values are tuned by trial and error method.

3.2.3 Vehicle Dynamics Block

The main objective of the Vehicle dynamics block lies with the calculation of the vehicle velocity. From net tractive force (difference of vehicle loads and force

TABLE 3.1: Physical values of K_p, K_I and K_D parameters

Parameter	Value
K_p	0.12
K_I	0.01
K_D	0.11

provided by the powertrain), vehicle velocity is calculated. This block consists of Vehicle Load calculation block and the vehicle speed calculation block as shown in the Fig.3.5

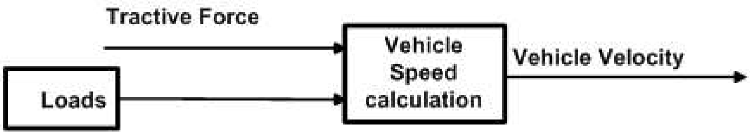

FIGURE 3.5: Vehicle Speed Calculation block diagram

The vehicle loads is the sum of Grade force, Aerodynamic Drag and Roll force as shown in the Fig.3.6 and their description are narrated in the vehicle dynamics section. Vehicle speed calculation block is shown in the next section.

3.2.3.1 Vehicle Speed Calculation Block

By using Newton's second law of motion, vehicle velocity is calculated as shown in the equation 3.5. Simulink model of the vehicle speed calculation is shown in Fig.3.7

$$\begin{aligned} V(t) &= T_{rac}\_F - F_{total} \\ V\_actual &= \int \frac{V(t)dt}{M} \end{aligned} \tag{3.5}$$

- $V(t)$: difference of tractive force and load force [N]

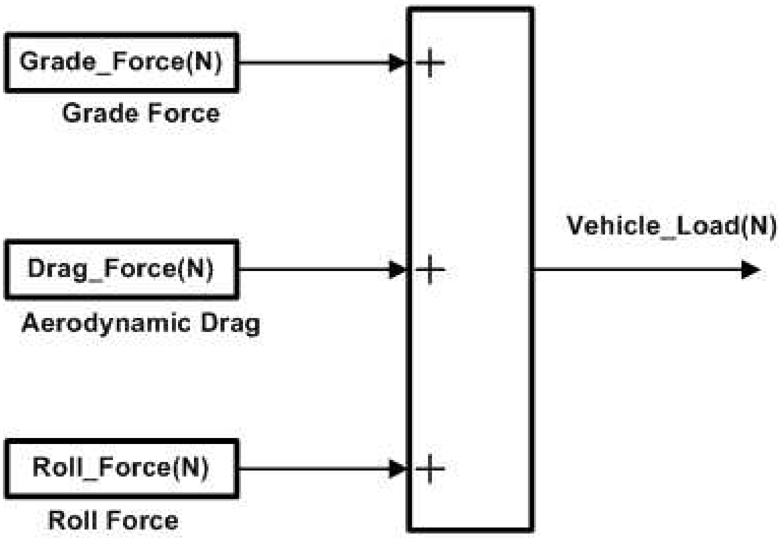

Figure 3.6: The vehicle load diagram

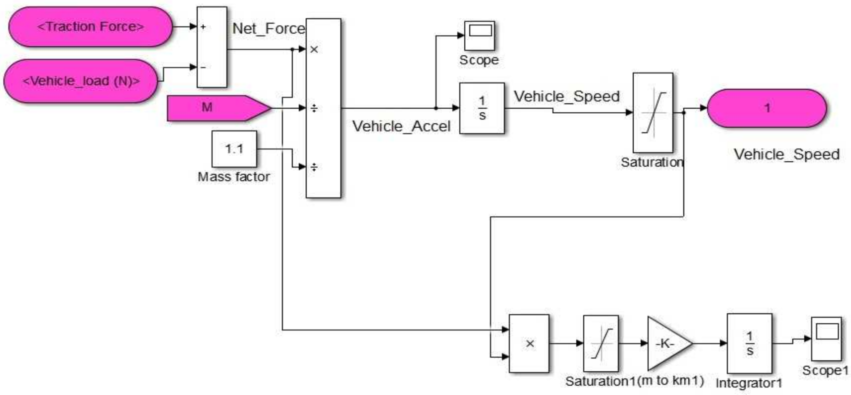

Figure 3.7: Simulink model of vehicle speed calculation

- V_actual: Vehicle velocity (actual) [m/s]
- T_{rac}_F: Tractive Force [N]
- F_{total}: Total resistive Force [N]
- M: Vehicles total mass [kg]

3.2.4 Backward-facing Simulation

For the backward-facing simulation technique, the calculation of power flow is done backward. So this simulation technique is opposite to what happens in real driving situation. It depends on the hypothesis that if the vehicle follows the drive cycle, then how each component should perform accordingly. So, there is no need of driver model in this type of simulation technique. In this technique, desired or calculated quantities at the wheels are converted to the quantities at the output of the power sources accordingly. The task of controller is to divide the power/torque request between the energy sources like an ICE and the EM. The drawback of this technique is the absence of measurement of physical quantities of each component in the power-train. In this way, backward simulation technique is not appropriate for designing and validation of controllers. The advantage of this approach lies within its simplicity and also it provides fast computation. So this technique is widely used in HEV simulations. The information flow in backward simulator is shown in Fig.3.8. This simulator can be used to perform the following tasks.

Evaluation of instantaneous and cumulative fuel consumption and estimation of SOC of the battery;. DP uses this type of simulation in Hybrid Electric Vehicles and its detailed discussion is mentioned during implementation of DP. Various components of a backward vehicle simulator are mentioned in Fig.3.8 with the corresponding input and output signals. The variables used in the backward simulator are explained below. The outcome of this simulator is the total fuel consumption along with the SOC pattern of the battery.

- V_veh: Vehicle velocity [m/s]
- SOC: State of charge [-]
- W_wh: Speed at wheel [rad/s]
- T_{gb}: Torque before gear box [Nm]
- W_{gb}: Speed before gear box [rad/s]
- T_{rac}_F: Traction Force [N]

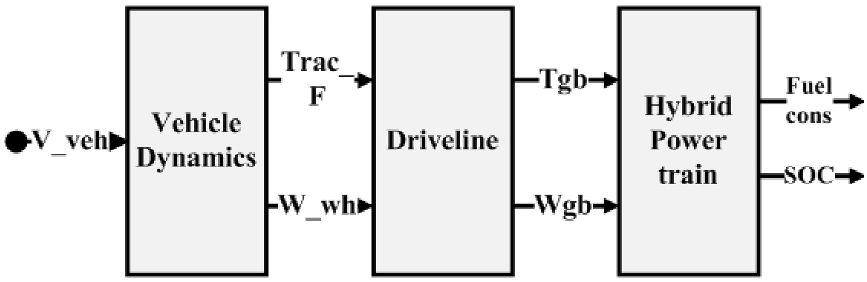

FIGURE 3.8: Backward Simulator model

3.3 Mathematical Modeling of Parallel Hybrid Electric Vehicle

This section deals with the detailed description of Mathematical modeling of parallel Hybrid Electric Vehicle. Main components of HEV includes vehicle dynamics, the ICE, transmission dynamics, the electric motor/generator and the battery. Summary of different concepts related to model are presented here. Backward-facing simulations with simplified vehicle dynamics are represented in the model. Interpolation of components is done to achieve the components of required sizes. It is assumed that at standstill, there is no power consumption from energy sources.

3.4 Vehicle Dynamics

Tractive force provided by the power sources are mainly used to overcome the sum of resistive force acting on the wheel. Total resistive force can be divided into following components.

- Aerodynamic drag
- Rolling resistance
- Grading resistance

- Inertial resistance

3.4.1 Aerodynamic Drag

Aerodynamic drag resistance is the force exerted by the air on the vehicle in motion. Equation (3.6) represents the aerodynamic force which is directly proportional to the air drag coefficientC_d, frontal area A_f of the vehicle and the square of the speed of the vehicle V_{veh}. A vehicle with larger frontal area and higher vehicle speed definitely has greater aerodynamic resistance [78].

$$F_a = [\frac{1}{2}\rho_a A_f C_d {V_{veh}}^2] \tag{3.6}$$

- F_a: Aerodynamic drag force [N]
- ρ_a: Density of air [kg/m3]
- A_f: Vehicle's frontal area [m2]
- C_d: Air drag coefficient [-]
- V_{veh}: vehicle speed [m/s]

3.4.2 Rolling Resistance

The vehicle running over the surface of road comes across with a rolling resistance due to the deformation of tire material and the surface of the road. On a hard surface, uneven distribution of pressure occurs at the contact surface between the tire and the road way which is shifted towards the direction of vehicle movement from the wheel axle providing a retarding torque. The rolling resistance can be represented as follows [79].

$$F_r = [Mgcos(\alpha)C_{rr}] \tag{3.7}$$

- M: Mass of the vehicle [kg]

- g: Gravitational acceleration [kg/ms2]
- C_{rr}: Coefficient of rolling resistance [-]
- F_r: Rolling resistance force [N]

3.4.3 Grading Resistance

For the road terrains (mountainous, hilly) are environmental factors that are beyond to control, but have a direct impact on fuel consumption. These dynamics are neglected, and if they are added then the load torque will increase and we have to increase the propulsion power.

A weight component produced by road inclination is always acting in the downward direction. Thus, while in the uphill motion, the grade resistance retards the motion and in downhill motion, the grade resistance supports the motion. The following equation gives the relationship of grade resistance.

$$F_g = [Mgsin(\alpha)] \tag{3.8}$$

3.4.4 Inertial Resistance

The vehicle's acceleration and spinning components like ICE produces rotational inertia resistance. From the Newton's second law , the inertial resistance can be written as follows [44, 80].

$$\begin{aligned} F_{total} &= [\frac{1}{2}\rho_a A_f C_d {V_{veh}}^2] + [Mgcos(\alpha)C_{rr}] + [Mgsin(\alpha)] \qquad (3.9) \\ Ma &= M\frac{dV}{dt} \\ &= F_{trac}(t) - F_{total}(t) \end{aligned}$$

- F_{total}: Total resistive force [N]

- $F_{trac}(t)$: Traction force [N]
- a: acceleration [m/s2]

3.5 Degree of Hybridization

It is worth noting that the electric power may be changed within the total power capacity of the power train. A parameter named as "Degree of Hybridization" (DoH) is incorporated to find the level of electric power. It is defined as the ratio of electric power to the total power of an ICE and the electric system.

$$HF = \frac{P_m}{P_m + P_e} \tag{3.10}$$

Where

- P_m: Maximum Power of motor [W]
- P_e: Maximum Power of engine [W]
- HF: Hybridization factor [-]

HF is

- 0: for Conventional vehicle
- 1: for an all electric vehicle

The main categories of hybridization are mild hybrids and full hybrids

3.5.1 Mild Hybrids

In mild hybrid system, the contribution of electric system is much smaller as compared to the ICE power. Therefore, only assistance to the engine power is done in Mild hybridization. Energy saving of mild hybrids is only about 20% to 30% in city driving [81]. Commercially available examples of mild hybridization are Honda Insight and Honda Civic.

3.5.2 Full Hybrids

In full hybrids, the share of electric system is more than the mild hybrids. Additionally, in full hybrids, the fuel saving is achieved also by regenerative braking. Therefore, higher fuel saving capacity(30% to 50%) is achieved in full hybrids provided that appropriate power flow control was achieved.

3.6 Degree of Hybridization and Control Strategy

The efficiency characteristics of the power components that are responsible for most of the driving, plays a pivoting role in overall efficiency of the power-train system. The power management strategy of an Hybrid system should optimize the dominant power source. In mild hybrid system, the ICE is the dominant power source, therefore, optimization of ICE power delivery is done in mild hybridization. While in full hybrid system, both ICE and EMG have equal share and should be optimized equally. For the charge sustaining of SOC, a small electric system with a larger recharging system can easily sustain the charge. But a large electrical system with a small recharging system has difficulty in charge sustaining of battery. Due to the above mentioned criteria, full hybrid system experiences more difficulty in charge sustaining than in mild hybrid system. The optimization of fuel economy in full hybrid needs more attention than mild hybridization.

3.7 Definition of Vehicle Modes

From the positive power demand, different power flow paths can be generated within parallel HEV power-train. Numerically, we can define the power split ratio μ, which is the ratio of the motor torque T_m at any instant to the total torque T_{tot} at same instant as

$$\mu = \frac{T_{m(t)}}{T_{tot(t)}} \tag{3.11}$$

Where

- $T_{m(t)}$: Torque of Electric machine [Nm]
- $T_{tot(t)}$: Total torque demand [Nm]

Each mode can be defined as follows:

- 0: Pure Thermal (Engine) mode
- 1: Pure Electric mode
- $0 \leq \mu \leq 1$: Hybrid mode (Parallel mode)
- $\mu \leq 0$: Recharging mode (through engine or regenerative braking)

When it is required that an ICE operates in the highest peak efficiency region, the engine mode is the first preference. The electric mode is preferred in low speed requirements. In hybrid mode, both the ICE and the Electric Motor share the total power demand. This mode of operation is preferred when high power demands are required beyond the power capacity of ICE or to prohibit the low efficiency of the Engine operation at high torque. When the SOC of the battery is low, the ICE produces extra energy for the recharging of the battery. It is the intelligence of the power management strategy to find the best split ratio μ for the hybrid mode.

3.8 End-Charge Controlling

According to the state of battery charging, there are two modes of vehicle operation: Charge sustaining mode and charge depleting mode. In charge sustaining mode, the charge of battery at the start of journey and at the end of journey remains almost same, while in charge depleting mode, the state of charge at the termination of journey drops as compared to the starting SOC of the battery [27]. Since the vehicle can not sustain the SOC on its own, its All Electric Range is limited and needs charging from an ICE power source during the journey. The example of charge depleting hybrids is Plug-in Hybrid Electric Vehicle. The disadvantages of Plug-in Hybrid Electric Vehicle are the limited range of driving and requires large battery pack. While, the HEVs with Charge sustaining have the ability to maintain its SOC continuously, therefore, the problem of driving range does not exist in such types of HEVs. This type of HEVs need a smaller battery and the SOC of battery is maintained either through charging by the engine or by regenerative braking.

3.9 Model for the Internal Combustion Engine

For the assessment of fuel economy, two types of ICEs are used. The first one is the SI engine and the second one is Atkinson cycle engine. The model of SI engine is the quasi-static model, while dynamic model of an Atkinson cycle engine is used(Appendix A). Table 3.2 represents the physical parameters of the engine. The MT is configured with four ratios; 0.18, 0.32, 0.50 and 0.85. The total weight of the vehicle is 600 Kg, the tire radius is 0.205 m, and the final drive-ratio is 0.22.

The Internal Combustion Engine and electric motor are mechanically coupled to the input shaft of Manual Transmission (MT). This mechanical coupling gives automatically same shaft speed. The output shaft of MT is directly connected to the clutch. The torque is transmitted to the wheel via the final drive.

The quasi static representation of ICE is represented in Fig.3.9. In this model, the inputs are requested speed and torque from engine and the output is the power provided through the engine. The simulink model of the engine is shown in Fig.3.10.

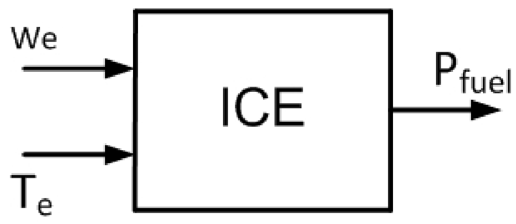

FIGURE 3.9: The quasi static representation of the ICE

Brake Specific Fuel Consumption represents the fuel consumption in g/Kwh. The mass fuel rate and fuel power are calculated in the relations below. Due to unavailability of efficiency and Brake Specific Fuel Consumption maps for 07KW engine, an interpolation [82] was done for the selection of engine BSFC maps used for the parallel HEV (Rickshaw). These maps are derived from SI engine rated 43KW.

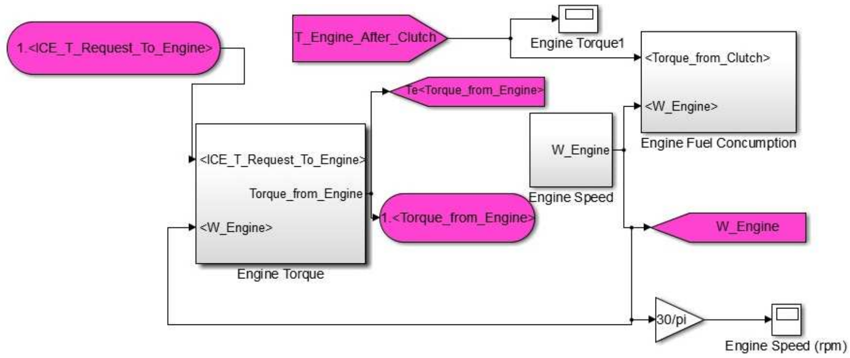

FIGURE 3.10: Simulink model of the engine

Table 3.2: Physical parameters of the engine of rickshaw

Parameter	Value
Class	Four Stroke,SI,Air Cooled
Weight	30.5 Kg
Displacement	275cc
Max. Power	7kw @ 4400 rpm
Max. Torque	19 Nm @ 2800 rpm
Payload	320 Kg

$$P_e = T_e W_e \tag{3.12}$$

$$\dot{m} = \frac{P_e.BSFC}{3600.1000} \tag{3.13}$$

$$P_{fuel} = \dot{m}.\Delta H \tag{3.14}$$

$$\eta(T_e, W_e) = \frac{P_e}{P_{fuel}} \tag{3.15}$$

$$= \frac{3600.1000}{BSFC.\Delta H} \tag{3.16}$$

- P_e: Engine Power [W]
- T_e: Engine Torque [Nm]
- W_{ice}: Engine speed [rad/s]
- $\dot{m}$: mass fuel rate [kg/s]
- $BSFC$: Brake Specific Fuel Consumption
- ΔH: Lower Heating value of fuel [KJ/Kg]
- P_{fuel}: Fuel Power [W]

3.10 Clutch

Clutch is used to engage and disengage the engine shaft from the output shaft. So there are two positions of clutch.

- 0: Clutch is disengaged
- 1: Clutch is engaged

The function of clutch is performed by using a simple switch with a delay. In the clutch block shown in Fig.3.11, a switch block is used to manipulate the torque to the drivetrain by switching between the engine torque and zero torque based on the clutch position issued by the powertrain controller.

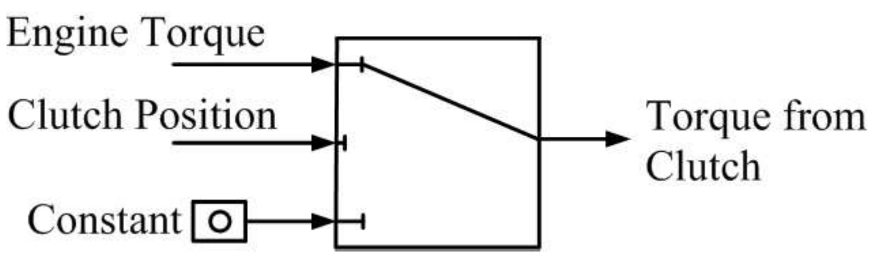

FIGURE 3.11: Clutch block Simulink model

3.11 Model for the Electric Motor/Generator

The electric motor/generator represents the electromechanical conversion of energy and the electric machine is operated in both modes that is from electrical energy to mechanical energy and vice versa. The shaft speed and torque are the mechanical characteristics of electric motor, while on electric side (generator), there are terminal voltage and current. During the energy conversion, some of the energy is wasted due to presence of copper losses and iron losses. These losses are due to copper resistance and the core of rotor. The efficiency of EMG at any point is given as the ratio of output power to the input power. Unlike other applications, Electric Vehicles and HEVs require the frequent starts and stops of electric motor. Sudden increase/decrease of acceleration, need of high/low torque along with low/high speed when starting and hill climbing are also the application of motor in above said requirements. While cruising, a low torque with high speed is required and a wide range of speed operation [83]. Also the electric drives of HEVs must fulfill the requirements for the regenerative braking. No doubt, this is a challenging task for the designers of motors. For traction application, DC motor drives have been used successfully a couple of decades ago. However due to bulky construction, low efficiency, the need of commutator and maintenance compel the designers for advanced candidates[84]. So they thought of permanent magnet motor, induction motor, and switched reluctance motors. Generally, the characteristics of motor torque speed are in such a way that at low speed, constant torque is obtained and at high speed, constant power is obtained. These are the requirements of HEV application because for acceleration and hill climbing, high torque is required with a low speed. A Permanent Magnet motor of 10 kW rating is used for the propulsion of the vehicle as indicated in Table 3.3. The vehicle is capable of running in electric mode as the motor can fulfill the total torque demand. For electric motor, the quasi static model is given as in Fig.3.12, where output is the power requested from battery according to requested torque and speed of the motor and the efficiency of electric motor can be calculated as follows. Simulink model of the motor is shown in Fig.3.13.

$$\eta_m = \frac{P_{batt}}{W_m . T_m} \tag{3.17}$$

- η_m: Efficiency of the electric motor [-]
- P_{batt}: Battery Power [W]
- W_m: Electric motor speed [rad/s]
- T_m: Electric motor Torque [Nm]

The motor power in motoring and generating mode is given as follows in the equation

$$P_m(k) = \eta P_{elec}(k) \qquad motoring \tag{3.18}$$
$$P_m(k) = \frac{1}{\eta} P_{elec}(k) \qquad generating \tag{3.19}$$

- $P_m(k)$: Motor/Generator Power [W]

Table 3.3: The motor and the battery used in the proposed vehicle

Component	Parameter	Type
Motor	10 kw	Permanent Magnet Motor
Battery	4.8 kWh	Li-ion

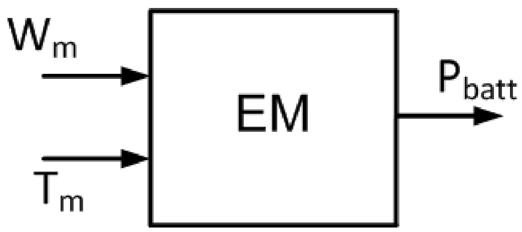

Figure 3.12: The quasi static representation of the motor

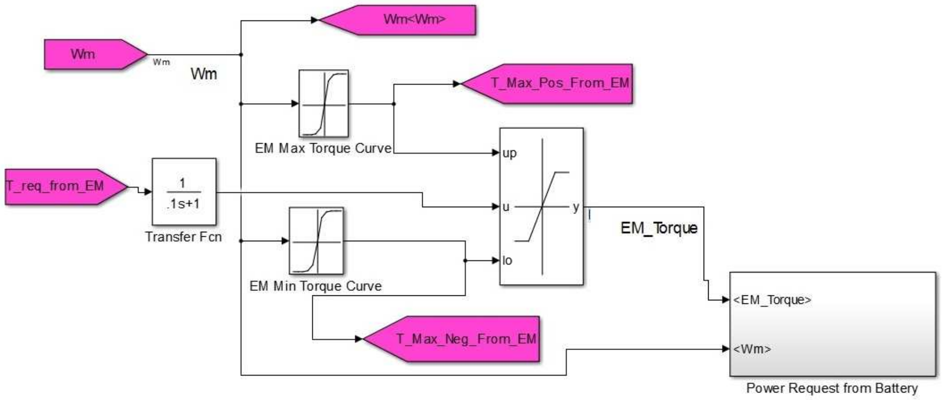

FIGURE 3.13: Simulink model of the motor

3.12 Model for the Transmission

The model of the transmission comprises of a stationary gear ratio map to find the torque and speed at the output of the gear terminals. The quasi static representation of Transmission alongwith inputs and outputs is represented in Fig.3.14.

$$T_{gb,out} = \eta_{tras} * R * T_{gb,in} \tag{3.20}$$

$$W_{gb,out} = W_{gb,in} * R \tag{3.21}$$

- $T_{gb,out}$: Gear box output torque [Nm]
- $T_{gb,in}$: Gear box input torque [Nm]
- R: Gear ratio [-]
- η_{tras}: Transmission efficiency [-]
- $W_{gb,out}$: Gear box output speed [rad/s]
- $W_{gb,in}$: Gear box input speed [rad/s]

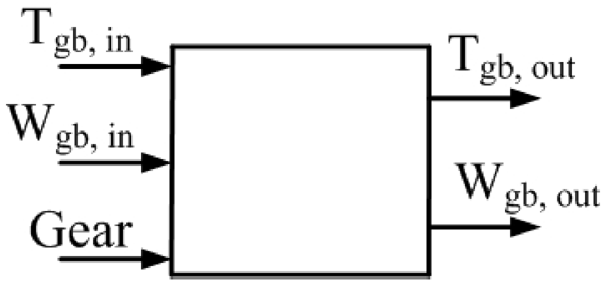

FIGURE 3.14: The quasi static representation of the Transmission

Table 3.4 shows the gear ratio of different gears.

TABLE 3.4: Gear ratio of different gears

Gear number	**1st**	**2nd**	**3rd**	**4th**
Gear ratio	0.18	0.32	0.50	0.85

3.13 Model for the Vehicle Brakes

The purpose of this block is to determine the braking torque according to the brake command issued by the driving block. The vehicle brakes block has traction torque and brake torque as inputs. The output is the torque available at the wheels that is the difference of the traction and braking torque shown in the equation below. The brake signal is used to compute the braking torque. The vehicle brakes block is shown in the Fig.3.15.

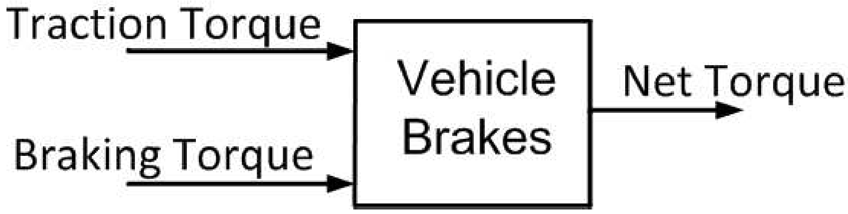

Figure 3.15: The quasi static representation of the Vehicle Brakes

$$
\begin{aligned}
T_{net} &= T_{trac} - T_{brak} \qquad (3.22)\\
T_{trac} &= F_{trac}.R_w\\
T_{brak} &= T_{fb} + R_w[\frac{1}{2}\rho_a A_f C_d {V_{veh}}^2] + [Mgcos(\alpha)C_{rr]+[Mgsin(\alpha)]}
\end{aligned}
$$

where,

- T_{net}: Net Torque [Nm]
- T_{trac}: Traction Torque [Nm]
- T_{brak}: Braking Torque (Torque from the opposing forces) [Nm]
- F_{trac}: Traction force [N]
- R_w: Radius of wheel [m]
- T_{fb}: Torque from the friction brakes [Nm]

3.14 Final Drive (Differential)

A differential is used to control the applied torque and rotational speed of the wheels. It is a device which controls a pair of wheels to rotate at different speeds without slipping while turning around a corner. The power from the engine or the motor is supplied to the differential and is distributed to both wheels in different amounts according to the rotational speeds [85]. In our research work, the differential gear ratio is 0.22. Final drive torque is expressed as functions of the efficiency, final drive ratio and total torque shown in the following equation.

$$T_{fd} = \eta_{fd} * r_{fd} * T_{tot} \tag{3.23}$$

- T_{fd}: Final drive torque [Nm]
- η_{fd}: Final drive efficiency [-]
- r_{fd}: Final drive ratio [-]
- T_{tot}: Total torque [Nm]

3.15 Model for the Battery

The battery model represents the electrochemical energy conversion and the losses of energy storage devices. Some important terminologies related to battery are discussed here before the presentation of battery model. The key terminologies related to battery are the cycle life, specific power, specific energy density, and the cost of manufacturing. The number of charging and discharging cycles determine the battery life before the ability of battery to hold a useful charge. With the increasing no. of charging and discharging cycles and at high temperature decreases the Ah (Q_{max})rating of the battery. In particular, Life cycle is dependent on the depth of charge used. Prolonged running of battery at high temperature will shorten the life of the battery. Batteries deteriorate in operation due to structural changes caused by charge-discharge cycling. It is required that battery retains as

80% of their original power and energy over the life of the vehicle. Nominal life of the vehicle is considered as 10 years to set battery life cycle requirements. The upper and lower limits of battery are selected between $40-80\%$ and is selected according to the rating of the battery [86]. The voltage remains nearly constant between this region due to nearly constant behavior of charging and discharging resistances. Energy density is the amount of energy stored per unit mass and the power density represents the maximum amount of power that is provided per unit mass. A device having a high energy density will have a lower power density and vice versa. In order to run the vehicle successfully, one should meet the energy and power demands of the load. A battery pack consists of multiple modules, in which there is a combination of cells in parallel and series connections. This whole arrangement is taken as a voltage source with a series resistance. The battery model is given in Fig.3.16.

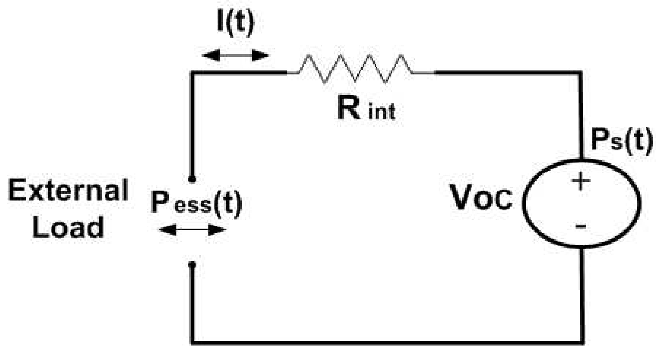

FIGURE 3.16: Battery Model for Hybrid Electric Vehicle

The battery power $P_s(t)$ with current $I(t)$ is given in the following relation below. The terminal power is also calculated after subtracting the losses of the battery.

$$\begin{aligned} P_s(t) &= V_{oc}(t, SOC).I(t) \qquad (3.24) \\ P_{ess}(t) &= P_s(t) - P_{loss}(t) \\ &= V_{oc}(t, SOC).I(t) - I(t)^2.R_{int}(t, SOC) \end{aligned}$$

- $P_{ess}(t)$: Terminal power (instantaneous) [W]

- R_{int}: Internal resistance [ohm]
- v_{oc}: Open circuit voltage [V]

The state of charge of a battery is the scalar state variable of the energy management problem and is expressed as in equation 3.25

$$\dot{SOC}(t) = -\frac{I(t)}{(Q_{max})} \tag{3.25}$$

- $\dot{SOC}(t)$: Derivative of state of charge [1/s]
- $I(t)$: In/Out current flow of the battery [A]
- Q_{max}: Charge capacity of the battery (max) [Ah]

From the Quadratic equation 3.24, the battery current $I(t)$ is represented in the following equation 3.26

$$I(t) = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4(P_{ess}).(R_{int})}}{2 * (R_{int})} \tag{3.26}$$

This result can be substituted in the equation 3.25, resulting the nonlinear mapping as

$$\dot{SOC}(t) = -\frac{1}{(Q_{max})}\frac{V_{oc} - \sqrt{V_{oc}^2 - 4(P_{ess}).(R_{int})}}{2 * (R_{int})} \tag{3.27}$$

The next state of charge is calculated as follows [87, 88].

$$\begin{aligned} SOC(k+1) &= \\ SOC(k) &- \frac{V_{oc} - \sqrt{V_{oc}^2 - 4(R_{int}).T_m.W_m.\eta_m^{-sgn(T_m)}}}{2 * (R_{int}).Q_{max}} \end{aligned} \tag{3.28}$$

In parallel HEVs, a battery with a high specific power is required to meet the peak power demand of the large motor. Due to dependability of electric system on battery, the battery power should be more than the calculated power to meet the other driving cycles also. The advantage of excessive energy storage gives the liberty to operate the battery within narrow SOC range (about5% - 10% at most) which in turns enhances the battery cycle and its calendar life. In automotive applications, three types of batteries exist to meet the energy requirements of electric system: Lead acid, Lithium ion and nickle metal hydride.

Normally, Lead acid batteries possess low energy density and, therefore, their application to HEVs is limited. Today, most of the auto manufacturing companies utilize Nickel metal hydride batteries for the reason of their superior energy density capacity. Emerging vehicles are using Lithium ion batteries due to their superior characteristics in terms of energy density over 100 wh/kg. The battery used for the proposed vehicle is Li-ion type of rating 4.8 KWh shown in Table 3.3. The battery has been selected in such a way that the Rickshaw can be run on battery only. Relationship between battery energy, motor power and running time is given as

Battery energy = motor power *running time

So, If the battery is discharged at $2C$ rate, then the vehicle can be run on full electric mode for half an hour depending on the load on motor.

3.16 Summary

The pre-transmission parallel HEV explained in this chapter is the vehicle architecture over which different energy management strategies are tested. Dynamic programming technique is implemented through backward simulator (Benchmark strategy) and the rules obtained from DP are implemented through forward vehicle simulator. Modeling of different components of parallel HEV(Rickshaw) has been described in this chapter. The energy management techniques implemented are discussed in Chapter 4.

Chapter 4

Energy Management Techniques for HEVs

Energy management in hybrid vehicles consists in deciding the amount of power delivered at each instant by the energy sources present in the vehicle. Sometimes, it is termed as supervisory controller, in contrast to low level or component-based control strategies, which are used to command individual components so that their comportment is according to driver demand. However, the concept of energy management and supervisory controller are not synonyms. While the energy management is used for the partition of power demand between the energy sources. The role of supervisory controller is to decide at what instant that power split action should be applied and other special behavior should be imposed according to driving situation.

In a non-hybrid (conventional) vehicle, the concept of energy management is absent, the driver is the only operator for speed and power delivery using the accelerator and brake pedals and, in manual transmission vehicles, gear is engaged according to speed requirement at each instant. The driver's demands are transformed into action by component-level controllers. For instant, the engine control unit (ECU) decides the injection of fuel quantity given by the accelerator command and gear shifting takes place according to vehicle speed.

In contrast to conventional vehicle, hybrid electric vehicle needs a controller that decides, how much power is transferred from each of the energy sources available onboard. In principle, this could be the responsibility of the driver (for instance, provision of two individual commands); but it is more convenient, if a computer takes care of it, giving the driver only the decision that how much quantity of power is needed. That is why all hybrid electric vehicles consist of an energy management controller, which could be as an additional layer between the driver and the component controllers.

This chapter represents the designing of an optimal control problem for a pre-transmission parallel HEV and development of various energy management strategies. In order to compare the different energy management strategies, the solution obtained from Dynamic Programming (DP) is used, which is considered as the bench mark solution. A Matlab based open source code [5] is used, which is implemented through backward simulator. The rules extracted from DP are used in forward simulator, which is called the rule based technique. Another heuristic based energy management strategy has been designed, in which equal sharing of the motor and the engine has been proposed and its results are compared with DP and the rules extracted from DP.

4.1 Objective of the Energy Management Strategies

4.1.1 Definition of the Optimal Control Problem for HEV

An optimal control is the branch of control theory that encompasses the problem of finding a control law for a specified system along with the satisfaction of optimality criterion. The control problem is defined through some objective function over a specified time frame (length of a drive cycle). In true sense, it is a set of mathematical techniques for calculating a series of control actions in such a way that their integral behavior is approached to a desired value. For hybrid electric vehicles, energy management controller takes the series of control action in the form of instantaneous power split between different energy sources; the overall impact is the fuel consumption for a specified driving cycle, or the total pollution emission, or any other criterion, whose minimization is the objective of optimization.

The classic optimal control techniques can be employed only with mathematical models of the system and the assumption is made that the knowledge of the entire optimization horizon is known. As these conditions are not available in real conditions, optimal control implementation in a physical dynamic system without the information of future is necessarily sub-optimal.

For a generic HEV, irrespective of the architecture of vehicle, there are two energy sources onboard that can provide power/torque demand by the driver. The ultimate objective of the energy management strategy is to search the optimal power/torque split between two energy sources like an ICE and the motor, while minimizing a given objective function for a specified driving cycle. Generic form of minimization problem can be formulated with respect to several objectives, such as fuel consumption, emissions and performance or a combination of these objectives. For all strategies, we consider the problem of minimizing the total mass of fuel (m_f) during a driving cycle, so minimizing the following objective function

$$J = \int_{t_0}^{t_f} \dot{m}_f(x(t), (u(t))dt \tag{4.1}$$

- $\dot{m}_f$: Fuel consumption (instantaneous) expressed in [g/s]
- $u(t)$: Control input (Torque split ratio between engine and motor)[-]
- $x(t)$: State of the system (State of charge of the battery) [-]
- $t_0 - t_f$: Time frame of the driving cycle [s]

The energy management problem is a constrained optimization problem, where the objective function (4.1) is minimized under system dynamics, instantaneous (local) and integral (global) constraints on the state and control variables as mentioned in the following

1. Integral constraint (global): For a charge sustaining HEV, the overall energy provided by the battery $E_{batt}(t)$ is zero for a specified driving cycle. In other words, the final SOC is the same as the initial SOC. Mathematically, this can be described as follows

$$E_{batt}(t)|_{t_0}^{t_f} = \int_{t_0}^{t_f} P_{batt}(t)dt = 0 \tag{4.2}$$

2. Instantaneous constraints (local): Like the integral constraint (4.2) on the SOC of battery, there are instantaneous constraints imposed on the state and control variables. The constraints are mostly concerned with the operation range of the system components. These constraints are given in the following

$$\begin{aligned}
W_{e\,min} &\leq W_e \leq W_{e\,max} \\
W_{m\,min} &\leq W_m \leq W_{m\,max} \\
0 &\leq T_e \leq T_{e\,max} \\
T_{m\,min} &\leq T_m \leq T_{m\,max} \\
P_{m\,min} &\leq P_m \leq P_{m\,max} \\
0 &\leq P_e \leq P_{e\,max} \\
-1 &\leq \mu \leq 1 \\
SOC_{min} &\leq SOC \leq SOC_{max} \\
W_e &= W_m
\end{aligned} \tag{4.3}$$

where

- $W_{e\,min}$: Minimum speed of the engine [rad/s]
- $W_{e\,max}$: Maximum speed of the engine [rad/s]
- $W_{m\,min}$: Minimum speed of the electric motor [rad/s]
- $W_{m\,max}$: Maximum speed of the electric motor [rad/s]
- T_e: Torque of ICE [Nm]

- T_m: Torque of Electric Motor [Nm]
- P_e: Power of ICE [W]
- P_m: Power of Electric Motor [W]
- μ: Torque split ratio [-]
- SOC: State of Charge of Battery [-]
- SOC_{min}: Minimum State of Charge of Battery [-]
- SOC_{max}: Maximum State of Charge of Battery [-]

The problem constraints are formulated by the maximum and minimum power, torque and speed requirements of the engine, transmission, the electric motor and the battery. In a parallel HEV, an ICE and the Electric Motor are both connected to the input of the Manual Transmission (MT) through the same shaft, ensuring that the same shaft speed for both the ICE and the Electric Motor (EM). The value of state of charge (SOC) is kept between minimum and maximum value for charge-sustaining purposes. In dynamic programming, these constraints are met by excluding of infeasible solution paths. Implementation of a backward facing model under the assumption of correctly following a driving cycle can produce many infeasible solutions where particular components or operating states cannot meet the imposed load.

As we are extracting rules from the DP, where all these constraints are met, so there is no need to handle these constraints in forward facing simulation model.

4.2 Dynamic Programming

4.2.1 General Concepts

Dynamic programming [89] is a numerical technique for the solution of multistage decision making problems. It serves as the optimal control technique, providing the optimal solution to problems of any complexity level. It is a non causal (requirement of complete driving cycle knowledge) and therefore is applicable to off-line environment. Based on Bellman's principle of optimality [90], it is expressed as follows:

An optimal control policy has the property that no matter what the previous decision (controls) have been, the remaining decisions must constitute an optimal policy with regard to the state resulting from those previous decisions [91].

This means that the optimal path from any of its intermediate steps to the end corresponds to the terminal part of the entire optimal solution.

Definition. **(Principle of Optimality)**, From any point on an optimal trajectory, the remaining trajectory is optimal for the corresponding problem initiated at that point cycle. The principle states that for the trajectory from x(0) to x(p) to be optimal, a small trajectory from x(k) to x(k + 1) has to be optimal also, as shown in Fig. 4.1. The principle has the application, while calculating the cost-to-go matrix, which contains all optimal costs to come from state x(k) to state x(k + 1).

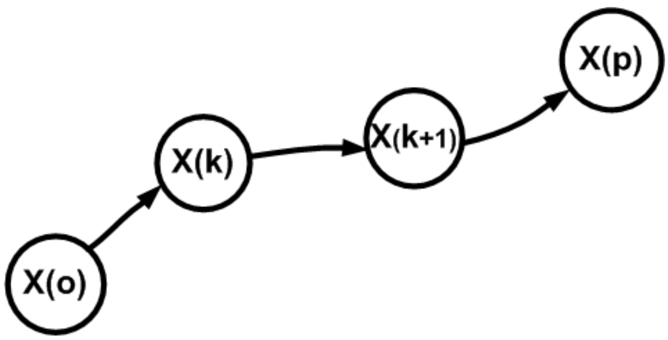

FIGURE 4.1: Optimal Trajectory

A discrete-time dynamic system [78, 92] is described by

$$x_{k+1} = f(x_k, u_k) \tag{4.4}$$

where the state x_k lies in the space S_k and the control variable u_k lies in the space C_k. The control variable is constrained to take values in a given non-empty subset $U_{x_k} \in\ C_k$ depending on the current state x$_k$

$U_k \in\ U_k(x_k) \qquad \forall X_k \subset\ S_k$

in such a way that the coming new state $x(k+1)$ lies in the the state space S_k. The main objective of optimization problem is to search a control variables set

$$\pi \quad = \quad u_0, ..., u_{N-1} \tag{4.5}$$

in bringing the system from state $x(0) = 0$ to $x(N) = x_N$ and minimizing the cost function J

$$J_\pi(x_0) \quad = \quad L_N(x_N) + \sum_{k=0}^{N-1}(L_k(x(k), u(k))) \tag{4.6}$$

where $L_N(x_N)$ is the terminal cost and L_k is the instantaneous cost function.

The optimal cost function is the one that minimizes the total cost

$$J^*(x_0) \quad = \quad {}^{min}_{\pi} J_\pi(x_0) \tag{4.7}$$

and the optimal policy

$$\pi^* \quad = \quad u_0^*, ..., u_{N-1}^* \tag{4.8}$$

is such that

$$J_{\pi^*}(x_0) \quad = \quad J^*(x_0) \tag{4.9}$$

These are the optimal cost associated with a optimal control decision at a given time step and the state of the system and is shown in the Fig.4.2.

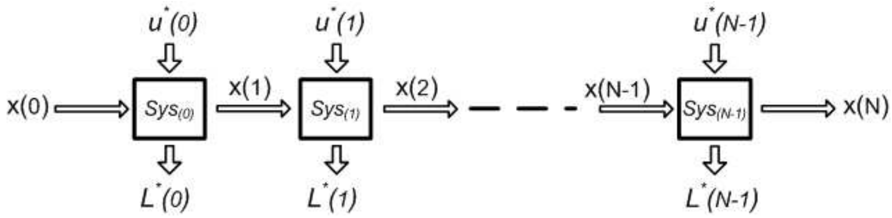

FIGURE 4.2: Implementation of DP.

The Energy Management problem can be summarized as an optimization problem in which the cost function *J(x)* is described by L, which is the cumulative fuel consumption in $[g/s]$ over the entire drive cycle. The cost function is minimized with respect to equal and non-equal constraints as follows

$$\begin{aligned} \min_{x} J(k) \quad Subject \quad & to \\ h(x) &= 0 \\ g(x) &\leq 0 \end{aligned}$$

Where the state of charge of the battery is represented by state variable x and the torque split between two energy sources like the engine and the motor is represented by control variable u. So, by utilizing these variables, the cost function [93] can now be represented as follows.

$$J(x) = \int_{t_0}^{t_f} \dot{m}(x(k), u(k))dt \tag{4.10}$$

$$J(x) = \int_{t_0}^{t_f} \dot{m}(SOC, \mu)dt \tag{4.11}$$

- SOC: State of Charge [-]

- μ: Torque split ratio [-]
- t_0: Initial time of driving cycle [s]
- t_f: Final time of driving cycle [s]
- $\dot{m}$: Fuel mass rate [g/s]

4.2.2 Optimality and Stability

The proof of optimality of dynamic programming is fundamentally derived from the sufficient conditions of optimality given by the Hamilton-Jacobi-Bellman equation [94].

Definition. An energy management strategy for a charge-sustaining HEV is called charge-sustaining if the system origin ($e < \epsilon$) is asymptotically stable, while minimizing the fuel consumption over the driving cycle

$$\begin{aligned} e &= SOC(t_f) - SOC_{ref} \\ \dot{e} &= \lambda \frac{V_{oc} - \sqrt{V_{oc}^2 - 4(R_{int}).P_{batt})}}{2 * (R_{int}).Q_{max}} \\ P_{batt} &= 0 \\ \dot{e} &= 0 \end{aligned} \tag{4.12}$$

The asymptotic stability guarantees that battery SOC is close to reference value of SOC at the end of driving cycle. where λ represents the difference between initial and final values of SOC (if any). Dynamic programming guarantees optimal solution through an exhaustive search of all Control and state grid and excluding all infeasible solution paths through exhaustive search.

4.2.2.1 Basic Algorithm

Let $\pi = [\mu_0, \mu_1, ..., \mu_{N-1}]$ be a control policy. The state of the system is the state of charge (SOC) of the battery. Now the discretized cost of generic form of cost function using the control policy along with the initial state $x(0) = x_0$ would be

$$\begin{aligned} J_\pi(x_0) &= g_N(x_N) + \phi_N(x_N)........ \\ &+ \sum_{k=0}^{N-1} h_k(x(k), u_k(x_k)) + \phi_k(x_k) \end{aligned} \tag{4.13}$$

where $g_N(x_N) + \phi_N(x_N)$ represents the final cost. The term $g_N(x_N)$ indicates the final cost in equation 4.13, and the term $\phi_N(x_N)$ represents the additional penalty function, forcing a partially bound final state. The function $h_k(x(k), u_k(x_k))$ is the cost of applying the control $u_k(x_k)$ at $x_(k)$. The state constraints mentioned in 4.3 are enforced by the penalty function $\phi_k(x_k)$ for $k = 0, 1, ..., N-1$. The optimal control policy minimizes J_π

$$J^o(x_0) = {}^{min}_{\pi\epsilon\Pi} J_{(\pi)}(x_0) \tag{4.14}$$

where, Π represents the set of all permissible policies. Keeping in view the optimality criterion, DP strategy calculates the optimal cost-to-go function $J_{(k)}(x^i)$ at each node in the discretized state-time space by actioning backward in time:

1. End cost computation step

$$J_N(x^i) = g_N(x^i) + \phi_N(x^i) \tag{4.15}$$

2. Intermediate calculation step for $k = N-1$ to 0

$$\begin{aligned} J_k(x^i) = & {}^{min}_{u_k\epsilon\mu_k} g_k(x^i, u_k) \\ & + J_{k+1}(f_k(x^i, u_k)) \end{aligned} \tag{4.16}$$

The optimal torque split factor is given by the argument that minimizes the right hand side of equation 4.16 for each x_k and k.

In the next section, we will discuss how Dynamic Programming is implemented practically.

4.3 Dynamic Programming Code Description

This section describes an open-source MATLAB based DP function used for the solution of the energy management problem in a charge-sustaining HEV, along with the method of implementation and the simulation results for a variety of driving cycles.

4.3.1 Overview

4.3.2 DP as Energy Management Strategy for HEVs

Based on the explanation of DP presented in the previous section, DP is used to solve the energy management problem in the pre-transmission parallel HEV. The state variable, control input, instantaneous and integral constraints and the performance objective of the energy management problem in a charge sustaining HEV were stated in Section 4.1. The next battery SOC dynamics in the discrete-time version are expressed as

$$SOC_{k+1} \quad = \quad F_{SOC}(SOC(k), \mu(k)), k = 0; 1; ...; N-1 \tag{4.17}$$

where $SOC(k)$; $\mu(k)$ represent the battery SOC and power/torque split ratio in discrete time, F_{SOC} denotes the nonlinear mapping expressed in discrete time and $N$is the number of intervals considered over the length of the driving cycle $(t_0 - t_f)$

.

4.3.3 Implementation of DP Algorithm

For the implementation of DP algorithm to solve the energy management problem for charge-sustaining HEVs (Section 4.1), a generic DP code in MATLAB environment [5] is used. This function solves the discrete-time optimal control problem using Bellmans principle of optimality [90]. The Dynamic Programming Matrix (DPM) MATLAB function is used in conjunction with a backward vehicle dynamics and powertrain model as shown in Fig. 3.8.This section shows the commands and syntax for solving the energy management problem. For the purpose of implementation, the DPM function has parameters such as options; prb; grd and par listed in Table 4.1.

When solving an optimal control problem, the dpm function is called using the syntax

$$[res; dyn] \quad = \quad dpm(model; options; prb; grd; par) \tag{4.18}$$

The DPM function accepts the variables prb; grd and par as inputs which has information about the vehicle velocity, length of the optimization interval, number of state and control input grids, vehicle characteristics, etc., as shown in Table 4.2. input grids and constraints.

For each combination of the state variable and control input variable, the function calls the backward vehicle model for the solution of the problem. For each state transition, the arc cost is calculated and then it is used by the Dynamic Programming. With the use of input and output variable, the HEV backward vehicle model is implemented in the manner [95].

$$Function[X; C; I; signals] \quad = \quad model(inp; par) \tag{4.19}$$

where X;C; I; signals are listed in Table 4.2.

Table 4.1: Parameters of DPM function[5]

Sr	Parameters	Description
1	dpm	DP algorithm function handle
2	model	HEV backward model function handle
3	options	Options structure for DPM function (e.g., Maximum number of iterations, Tolerance allowed)
4	prb	Problem structure: External inputs to DPM function (e.g., Time step, Number of time steps in the problem, Vehicle velocity)
5	grd	Grid Structure (e.g., Number of state grid points, control input grid points, limits)
6	par	User defined parameter structure (e.g., Vehicle characteristics, component maps)
7	res	Results using optimal control sequence
8	dyn	Dynamic structure used by the DPM function (e.g., Optimal cost-to-go function, optimal control input map)

In short, the DP algorithm estimates the optimal sequence of engine torque, machine torque, engine status and clutch status such that battery SOC constraints are not violated, while ensuring the minimum consumption of fuel over the whole driving cycle. The global optimal solution is ensured to the energy management problem with the help of different modes of operation and the torque split choice between the devices. Optimized parameters of DP has been mentioned in table 4.3.

TABLE 4.2: Parameters of HEV backward model[5]

Sr	Parameters	Description
1	inp	X: State variable at the current time step (State of charge (SOC) of the battery) U: Control input variables at the current time step(Torque split ratio) W: External input variables(vehicle velocity, vehicle acceleration and gear ratio)
2	X	Resulting state variables after applying control input U
3	C	Resulting cost after applying control input U
4	I	Infeasible combinations
5	signals	User defined output variables

4.4 Detail of Implementation of DP Strategy

The following steps are adopted in implementation of DP strategy. Temperature effect and road conditions are neglected. Energy losses due to waiting by stopping are also ignored.

1) Selection of Driving Cycle.

Manhattan driving cycle is chosen and following three parameters are found from driving cycle.

- W_1: Speed of the driving cycle [m/s]
- W_2: Acceleration of the driving cycle $[m/s^2]$
- W_3: Gear no. according to speed [-]

Table 4.3: Optimized Parameters of DP

Sr	Parameters	Value	Description
1	time step	1 (sec)	appropriate value
2	time steps in the problem	1088*(1/time step)+1	driving cycle time
3	maximum number of iterations	61	appropriate no. leading to a faster and good enough solution. Larger value leads to better accuracy, but higher computation time.
4	minimum tolerance	1e-8	allowable limit
5	upper boundary of the state grid	0.8	preset value for maximum utilization of the battery based on the battery specification
6	lower boundary of the state grid	0.4	preset value for maximum utilization of the battery based on the battery specification
7	initial state	0.550	own choice
8	final state upper constraint	0.551	tolerance between final value
9	final state lower constraint	0.550	tolerance between final value

These three parameters(W_1, W_2 and W_3) are used to compute the following quantities.

$$
\begin{aligned}
W_{wh} &= \frac{W_1}{R_{wh}} \\
\Delta W_{wh} &= \frac{W_2}{R_{wh}} \\
T_{wh} &= F_{total} * R_{wh}
\end{aligned}
$$

- W_{wh}: Wheel rotational speed
- ΔW_{wh}: Wheel rotational acceleration
- T_{wh}: Wheel Torque
- R_{wh}: Radius of the wheel
- F_{total}: Aerodynamic, rolling and inertial forces

From the wheel rotational speed (W_{wh}), Wheel rotational acceleration (ΔW_{wh}) and Wheel Torque (T_{wh}), the following three quantities are found

$$
\begin{aligned}
W_{gb} &= W_{wh} * \gamma \\
\Delta W_{gb} &= \Delta W_{wh} * \gamma \\
T_{gb} &= \frac{T_{wh}}{\gamma * \eta_{gb}}
\end{aligned}
$$

- W_{gb}: Crankshaft rotational speed [rad/s]
- ΔW_{wh}: Crankshaft rotational acceleration [rad/s*2]
- T_{gb}: Torque at gearbox [Nm]
- γ: Gear ratio [-]

The gear ratio is given in the Table 3.4. The T_{tot} is obtained by adding the engine and motor drag torque.

By defining the Torque split ratio as

$$\mu = \frac{T_m}{T_{tot}}$$

we found the torque provided by the motor

$$T_m = \mu * T_{tot}$$

and the torque provided by the engine is given as

$$T_e = (1 - \mu) * T_{tot}$$

These are the dynamics of Hybrid electric vehicle and is called by dpm function (Eq.4.18) and decides the partitioning of total torque between the engine and the motor.

4.4.1 Data used for Different Components

For the engine used, its Torque and speed profiles are added in the code along with efficiency maps. For the motor used, its torque and speed profiles are included in the code along with efficiency maps. For the battery used, its charging and discharging resistances along with the open circuit voltage data is included in the code. In order to apply DP, ($SOC_{min} - SOC_{max}$) is discretized. The no. of discretization levels (N_x) in SOC is important and it determines the accuracy and computation requirement of DP solution. The torque split ratio is also discretized (N_u) , so arc cost (fuel consumption) is calculated in the backward direction. The minimum cost to go (fuel consumption) is found. In a way, DP provides the closest approximation on the optimal solution of the energy management problem.

While implementing the dynamic programming strategy, the input control space $C = [-1 \quad 1]$ and state space $S = [0.4 \quad 0.8]$ must be limited and discretized. Dynamic programming is implemented through backward simulation. As shown in Fig. 3.8, the vehicle speed derived from the driving cycle is utilized for the calculation of the propulsion force. Using the drive line model, the demanded torque before the transmission is calculated. At the end, through the power train model, the fuel consumption is computed with the charge-sustaining of the battery.

For electric mode, $W_{gb} < 104$, condition is applied along with $T_{gb} > 0$, where 104 is the speed in rad/sec.

For parallel mode, $W_{gb} > 104$, condition is applied along with $T_{gb} > 0$ and

For charging or regenerative mode, $W_{gb} > 0$, condition is applied along with $T_{gb} < 0$

Energy recovery can be formulated as

$$E = \eta_{batt} * \eta_m * ((\frac{m * W_{wh}^2}{2}) - (T_{wh} * W_{wh} * t))$$

- E: Energy recovery
- η_{batt}: Efficiency of the battery
- η_m: Efficiency of the motor/generator
- m: Mass of the Vehicle
- t: time

This is the energy obtained after subtracting the load energy(aerodynamic and resistive load)from the kinetic energy.

Dynamic programming is a powerful tool to solve optimization problems and it is proved that it gives bench-mark solution through the exclusion of infeasible solution paths. As we are using Quasi-Static model in which experimental maps and real data of components is used, giving simulation results close to real results.

4.5 Rule-based (extracted rules from the DP) Strategy

A rule-based (RB) strategy is easy to implement in a computationally efficient way, but resulting in a solution quite far from the optimal solution. Contrary to this, DP gives the optimal result on each driving cycle ,therefore, by analyzing the control actions of DP, useful rules can be extracted and by using these rules, a near-optimal solution can be achieved. For establishing RB strategy from DP, extensive simulations are produced through which an appropriate optimal driving pattern is searched for the specified driving cycle, encompassing both urban and sub-urban driving patterns. A deep analysis of the results enables us to search for common decisions of the algorithm that is then reproduced by suitable rules [96]. The input variables like the gear-box power P_{gb}, speed W_{gb}, and the battery SOC are required for the extraction of useful rules. As described in the literature[96, 97], the power-train controller consists of the supervisory controller (which determines the appropriate operation modes) and the energy management controller (which determines the optimal power split between the energy sources), while satisfying the total power demand[98]. The rules extracted from these two controllers are expressed as follows. For further understanding the control strategy effects in powertrain for fuel efficiency, the comparison was done of global optimization method (DP) with the rule-based (non-optimal method) derived from DP.

4.5.1 Supervisory Control

For understanding the comportment of the supervisory control, the operating mode decided by DP was plotted between the gear-box input power P_{gb} and gear-box speed W_{gb} as depicted by the Fig. 4.3. The plot is split into three main regions as shown in Fig. 4.3.

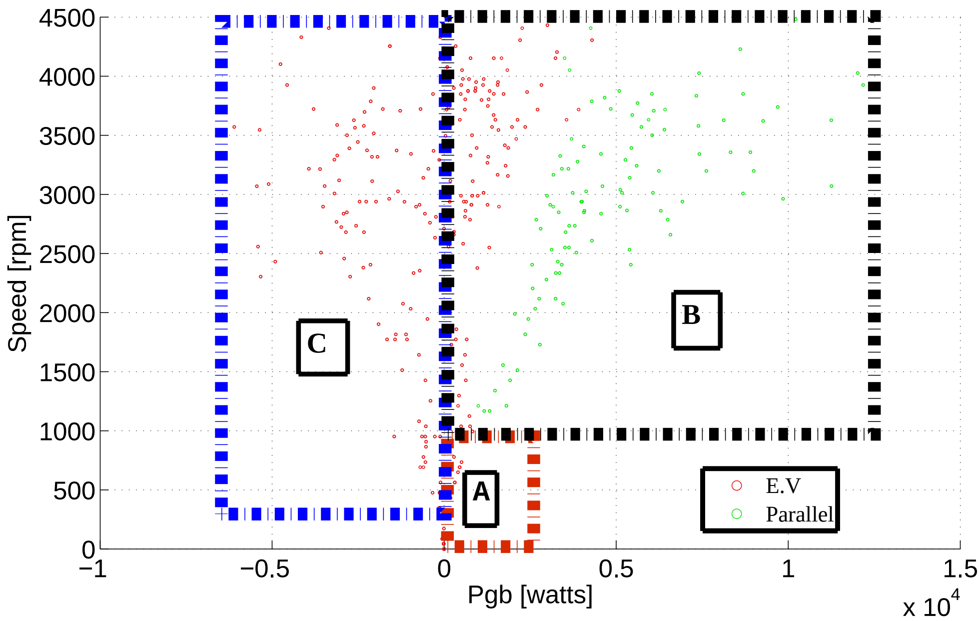

FIGURE 4.3: Speed versus total power required for the propulsion of the vehicle (results obtained from the DP).

TABLE 4.4: Supervisory control strategy parameters

Mode	Torque	Speed
Electric launch	$T_{gb} \geq 0$	$W_{gb} \leq W_{idle}$
Parallel	$T_{gb} \geq 0$	$W_{gb} \geq W_{idle}$
Regenerative	$T_{gb} < 0$	$0 \leq W_{gb} \leq W_{gb}(max)$

1. With low torque and speed (region A), the power-train operates in electric vehicle (EV) mode: with the clutch in open position and the Internal Combustion Engine is off.

2. The area (region B) is above ICE idle speed and positive gear-box torque. By carefully analyzing this area, the conclusion is made that the parallel configuration exists in this region.

3. The area (region C) exhibits each point with a negative torque, the supervisory controller switched off the engine during regenerative process, as long as the decelerating mode of vehicle is in progress. From the above discussion about the three regions, the supervisory control rules are executed as shown in Table 4.4.

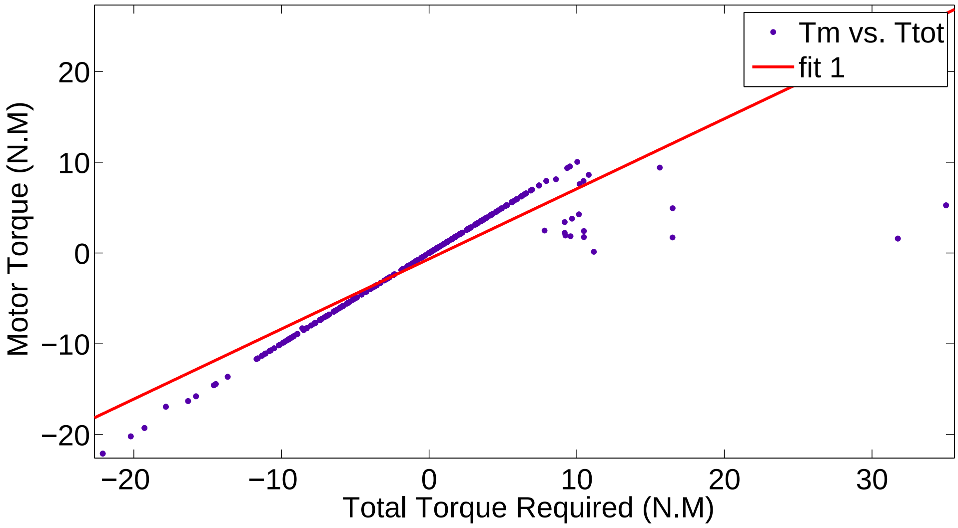

FIGURE 4.4: Motor torque versus total torque required (results obtained from the DP).

4.5.2 Energy Management

After having the mode selection through supervisory controller, power sharing among the ICE and the motor is done in parallel mode.

4.5.2.1 Parallel Mode

All the energy sources are coupled to the gear-box input shaft to cater for the resistive torque offered by the vehicle. The energy management controller has to decide what share of torque should be provided by the motor and an ICE. The motor torque against total torque is represented in Fig. 4.4 and fit1 represents the linear fit, and is given by the linear function as in the following equation.

$$T_m = mT_{tot} + k \tag{4.20}$$

- m: Slope of the line
- k: off-set value

The engine torque is provided after deducting motor torque from the total torque demand as shown in the following equation.

$$T_e \quad = \quad T_{tot} - T_m \tag{4.21}$$

By carefully analyzing the Fig. 4.4, it does not predict any reliance upon SOC of the battery. Also, the mode selection through supervisory controller does not indicate any clear correlation between the mode selection and the state of charge of the battery. To cater this problem, rules are modified and is explained in the following section.

4.5.3 State of Charge Control Problem

Supervisory control and the energy management technique are strongly dependent on SOC of the battery. Nevertheless, the rules extracted from DP, do not exhibit the presence of the effect of SOC, discussed in the previous section, therefore, these rules should be modified to attain charge sustainability. The starting point of doing so involves the shifting up or down shifting of the linear laws that calculate the electric loads. To accomplish this goal, a correction factor p(SOC) is introduced in the linear correlations which multiply the regression line's intercept as shown in the following equation.

$$T_m \quad = \quad mT_{tot} + kp \tag{4.22}$$

It is a challenge to select the appropriate form of correction function p(SOC). For a small divergence from the SOC_{ref} (reference SOC), the correction should be minor and increases smoothly for a stronger correction. For better results, a cubic polynomial function is chosen. The correction function [96] is outlined as follows;

$$p(SOC) = -\delta.x_{SOC}^3 + 1 \tag{4.23}$$

$$x_{SOC} = \frac{SOC - (SOC_{ref})}{\frac{(SOC_{max})+(SOC_{min})}{2}}$$

where the divergence of SOC from the reference SOC value is given by the x_{SOC} [96] and the amount of correction defined in equation 4.23 by a parameter δ represents the charge-sustaining condition. The mode choice of RB strategy is shown in Fig. 4.5. The supervisory control (responsible for mode selection of the vehicle) is well replicated in the Fig. 4.5, showing each mode of operation.

Fig 4.5 shows the operating modes of the vehicle. The vehicle always starts from the electric mode (blue region). In this mode, motor operates in its most efficient region. As soon as, the vehicle crosses this region (above idle speed), it enters into the parallel mode (green region). In parallel mode, both the engine and the motor share the demanded torque. This optimal sharing has been extracted from the DP results. No doubt, fully optimal sharing of two sources can not be achieved, linear fit approximation approach has been adopted for the motor torque (Fig. 4.4) and the engine torque is obtained from subtraction of the motor torque from total torque demand.

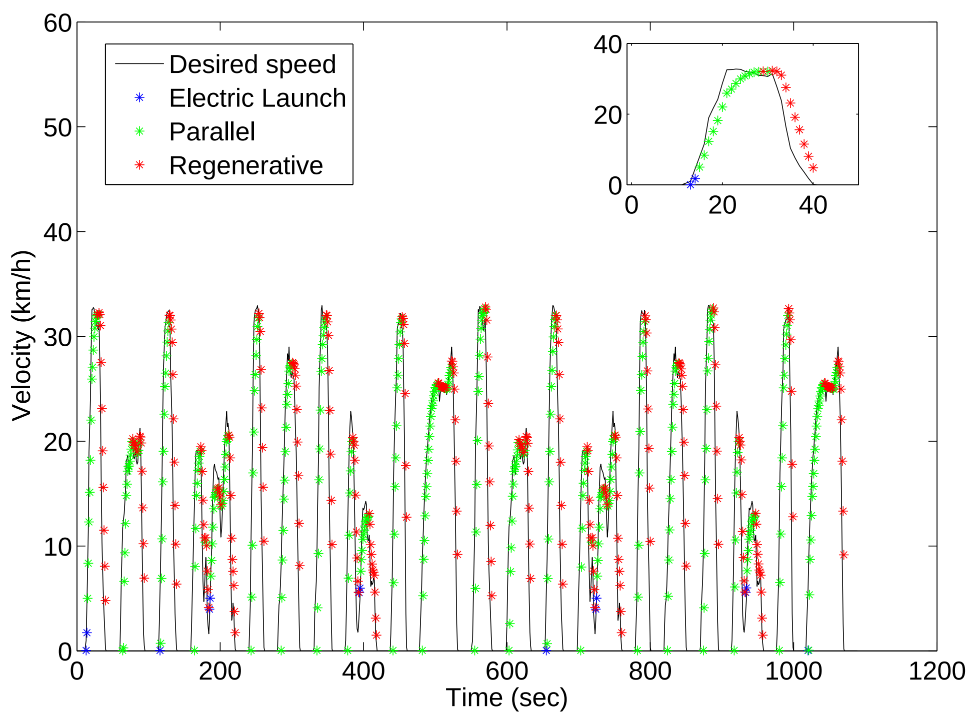

FIGURE 4.5: Mode choice of RB strategy.

Table 4.5: Overview of discussed strategies

DP	RB
+globally optimal	-sub-optimal
- apparently unstructured result	-tuning of many parameters
- high computation time	+fairly simple, engineering intuition
- offline strategy	+ online strategy
+ managing nonlinear constraints	-specific rules rely strongly on the drive-train choice

As soon as the vehicle decelerates, it enters into regenerative braking mode (red region). In this mode, kinetic energy of the vehicle is recovered through regenerative braking.

Finally, the merits and demerits of these two strategies (DP and RB) are summarized in Table 4.5.

In next section, we will describe the effect on fuel economy, when we choose equal sharing of the load demand by the engine and the motor in parallel operating mode. This heuristic based RB control strategy will reveal us how much fuel economy is compromised when non-optimized rules are adopted (equal sharing of demanded torque between the engine and the motor).

4.5.4 Heuristic-based RB Control Strategy(not conforming to DP rules)

The rule-based energy management strategy, not conforming to DP rules is developed based on engineering intuition and heuristics. Using this torque demand, the task of this controller is split into three control modes and the following control strategy is used. At starting, vehicle goes at State-1 where both the engine and the motor have zero torque request.

1. If the vehicle speed at gear box W_{gb} is less than idling speed W_{idle} and SOC of the battery is greater than its minimum limit ($SOC > 0.4$) then the vehicle will be driven by the motor in EV mode.

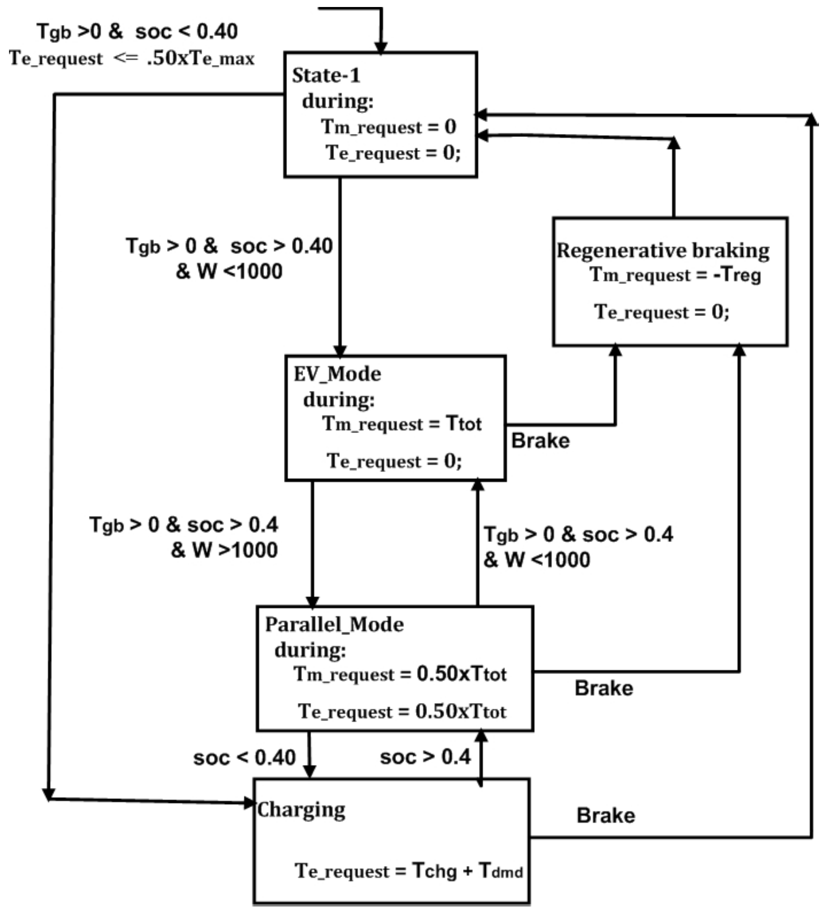

Figure 4.6: Stateflow chart of Heuristic based RB control strategy

2. If the vehicle speed at gear box W_{gb} is above the idling speed W_{idle} and the battery SOC is greater than its minimum limit ($SOC > 0.4$) then the total torque will be equally shared by the engine and the motor in parallel mode.

3. At the point, when the power demand of the vehicle goes negative, the whole negative energy is used for the charging of the battery by means of regenerative braking or charging through engine (conditions are mentioned on the state flow diagram).

This whole process is shown in Fig.4.6

4.6 Equivalent Consumption Minimization Strategy (ECMS)

The Equivalent Consumption Minimization Strategy (ECMS) was initially proposed by Paganelli [56] as a strategy for the global optimization minimization problem to an instantaneous minimization problem being solved at every instant without the advance knowledge of driving cycle. This method is relying on the notion that in charge-sustaining mode of HEV, the battery serves only as an energy cushion, and the whole energy is provided by the fuel and regenerative braking. Thus, the battery may be considered of fuel tank which is not refilled by any energy from outside sources of the vehicle. For maintaining the charge-sustaining, the energy utilized by the discharge process must be refilled using the fuel energy of engine directly or through the process of regenerative braking. Equivalent Consumption Minimization Strategy deals with the splitting of global optimization problem into a local optimization problem providing solution at each instant. The idea behind this strategy is that the usage of the electric power can be transformed into an equivalent fuel utilization. The fuel consumed by the engine and motor can be added up to have the instantaneous equivalent fuel consumption as follows,

$$\dot{m}_{eq} = \dot{m}_f + \dot{m}_{batt} = \dot{m}_f + S.[\frac{P_{batt}}{Q_{lhv}}] \tag{4.24}$$

- $\dot{m}_f$: Fuel mass rate of the engine
- $\dot{m}_{batt}$: Equivalent Fuel consumption from battery

- P_{batt}: Battery power
- Q_{lhv}: The fuel lower heating value (energy density)
- S: Equivalence factor

Using the expression for P_{batt} as a function of V_{batt} and I_{batt}, the equivalent fuel consumption rate can be re-formulated as

$$P_{batt} = V_{batt}.I_{batt}$$

$$\dot{m}_{eq} = \dot{m}_f + S(t).[\frac{V_{batt}.I_{batt}}{Q_{lhv}}]$$

Battery virtual fuel used is shown in Fig. 4.7. The SOC penalty is represented by the correction function $p(soc)$.

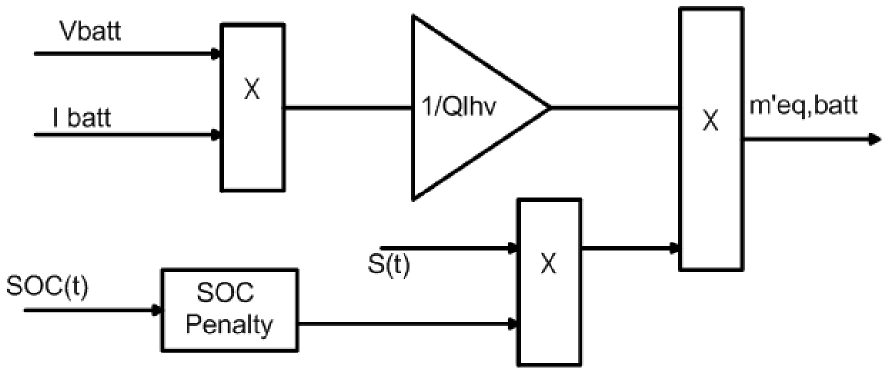

FIGURE 4.7: Battery virtual fuel used

The state of charge (SOC) is not a part of the above equations. However, its status must be taken into account, since we have to consider the SOC within a predetermined range to ensure safe vehicle operation and the life of the battery. For considering the current value of SOC, a feedback controller is often applied to the equivalent factor given in the following equations below

$$S = S(t).K_p.K_i$$

where S_t is the initial guess of the equivalence factor and K_p and K_i represents the gains, whose values are found from the equations below.

$$\begin{aligned} K_p &= 1 - x_1^3 \\ x_1(t) &= \frac{SOC(t) - SOC_{ref}/2}{\Delta SOC/2} \\ x_2(t) &= 0.01.(SOC_{ref} - SOC(t)) + 0.99.x_2(t - \delta(t)) \\ K_i &= 1 + tanh(12.x_2) \end{aligned} \tag{4.25}$$

where $SOC(t)$ is the instantaneous value of SOC, SOC_{ref} is the reference value of SOC and ΔSOC is the variation around SOC_{ref}. The term K_p represents a proportional correction term and the term K_i is an integral correction term. $\delta(t)$ represents sampling time used for updating the ECMS, the product of gains represents the correction function as shown below

$$p(soc) = K_p.K_i$$

defined in this way multiplies the initialS_t equivalence factor and artificially enhances or reduces the value of equivalence factor near the boundaries of the desired SOC.

4.7 Summary

Problem formulation along with its integral and instantaneous constraints is the part of this chapter. Dynamic programming code description including control inputs, state of the system and system external inputs are described here. Rules extraction from the DP and their implementation for different modes is also discussed. At the end, another heuristic based RB control strategy (equal sharing of torque between the engine and the motor) is narrated in this chapter. This control strategy is compared with RB (extracted rules from DP), so that we can see the difference between optimized rules and non-optimized rules.

The next chapter reveals the comparison between different control strategies.

Chapter 5

Comparative Analysis of Energy Management Strategies

Different energy management strategies proposed in the previous chapters are compared and evaluated in this chapter. Categorization of energy management strategies is done on the basis of feasible implementation in a real vehicle. These can be classified into implementable and non-implementable strategies.

1. **Non-implementable Strategies**. A non-implementable strategy is that which needs a complete advance knowledge of the driving cycle for the solution of the energy management problem and hence not implementable in a real vehicle. The strategies like DP and ECMS lie in this category. Dynamic Programming discussed in the previous chapter gives the solution of energy management problem through backward simulation, using the advance knowledge of complete driving cycle and is unable to be implemented in a real vehicle.

2. **Implementable Strategies**. An implementable strategy does not need the advance knowledge of the driving cycle for the solution of energy management problem and has the ability to be implemented in a real vehicle. Heuristic strategies lie in this category.

For the comparison and the evaluation of performance of the strategies, two performance metrics such as SOC variation and equivalent fuel consumption are considered. The depart of the battery SOC from its base value and finally its value should be the same as of initial value. The amount of fuel used at the termination of driving cycle is estimated for different control strategies. The comparative analysis is performed over driving cycle such as Manhattan drive cycle.

5.1 Evaluation of Non-implementable Energy Management Strategies

This part of the chapter narrates the battery SOC variation and equivalent fuel consumed for the non-implementable energy management strategies such as DP.

5.1.1 Equivalent Fuel Consumption and SOC Variation

For the HEV in charge-sustaining mode, the initial assumption is that, the whole energy for the propulsion of vehicle, is provided by the fuel (primary energy source). The energy used from battery at the termination of driving cycle should ideally be same as the energy at the start of driving cycle. For the comparison of any energy management strategy, the following two standard criterion are used;i,e equivalent fuel consumption and charge-sustainability. They are defined as

$$\Delta SOC = \frac{SOC(t_f) - SOC_{ref}}{SOC_{ref}}.100 \tag{5.1}$$

$$FC_{equ} = \int_{t_0}^{t_f} \dot{m}_f + \frac{\Delta SOC E_{max}}{\eta_{path} Q_{LHV}} \tag{5.2}$$

- $SOC(t_f)$: State of charge at the termination of drive cycle [-]
- SOC_{ref}: Reference (base value) state of charge [-]
- ΔSOC: Variation in the state of charge [-]
- η_{path}: Efficiency of the drivetrain [-]

- FC_{equ}: Equivalent fuel consumption [grams]
- $\dot{m}_f$: Fuel mass rate [g/s]
- E_{max}: Maximum energy of battery [KJ]
- Q_{LHV}: Lower heating value of fuel(Energy density of the battery)[KJ/Kg]

The equivalent fuel consumption is represented as the fuel consumed plus a correction for the net change in battery SOC. If there is depletion of battery at the termination of driving cycle, obviously the amount of fuel used will be less. Thus, the equivalent fuel consumed will add an equivalent quantity of fuel proportional to the battery energy consumption. For the case of positive ΔSOC, this implies that $SOC(t_f) > SOC_{ref}$ and the excessive battery SOC is used later for the propulsion of the vehicle. Contrary to this, if ΔSOC is negative, it means that some fuel is needed for charging of the battery to bring SOC to the reference (base) value. From above discussion, it is clear that a strategy with minimum ΔSOC and minimum FC_{equ} is considered as best strategy. The state of charge (SOC) are related to ΔSOC. Thus, for the optimal control problem of HEV, the SOC trajectory is determined by the discretization resolution of the state variable SOC, whereas the optimality of fuel consumption is primarily on the discretization resolution of the state variable and the discretization resolution of the control variables. Thus, for $SOC(t_f) = SOC(t_0)$ ensures the convergence of the system.

While optimizing fuel economy in this research, the constraints on SOC (initial and final) of the battery are chosen to be 0.55. Simulation outcomes of the vehicle specified under the DP policy and Rule Based (RB) strategies are demonstrated in Table 5.1. The graph of fuel used in the rule-based (extracted rules) and DP strategy is shown in Fig. 5.1. From Fig. 5.4, state of charge pattern of the battery demonstrated in DP and RB (Rules extracted from DP) strategies do not exactly match, but the charge sustaining is attained. As the SOC is well maintained during the whole cycle, the fuel economy improvements is directly comparable with RB (Rules extracted from DP) strategy without the fuel correction. The pattern of SOC of two strategies shows the similarity in power-sharing between the two energy sources (with a minute difference). The fuel consumption through DP for HEV (Rickshaw) is about $33Km/liter$ taken as a benchmark fuel consumption. This fuel economy is achieved through optimal torque sharing between the engine and the motor and recuperation of kinetic energy, while the modified RB strategy on the basis of rules extraction from DP (optimal sharing of the engine and the motor torque) has about 9% more fuel consumption than DP showing the near-optimal solution. This more fuel consumption is due to the fact that DP results can not be fully exploited in rule based strategy. Heuristic based RB controller (not conforming to DP rules) with equal sharing of the engine and the motor torque shows about 18% more fuel consumption than DP. Heuristic based rules can be made on past experience and engineering intuition. Another Equivalent Consumption Minimization Strategy has been implemented, which shows 5% more fuel consumption than DP.

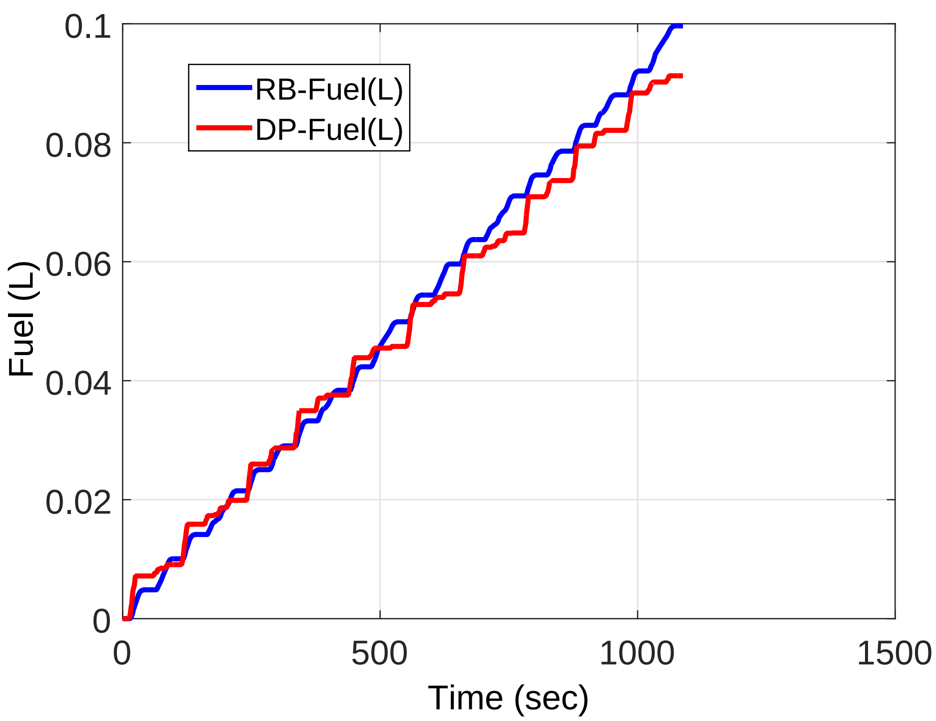

FIGURE 5.1: Comparison of fuel used in the RB (rules extracted from the DP) and DP strategies.

Fig. 5.2 shows the fuel comparison of DP strategy and ECMS strategy, indicating more fuel consumption for ECMS strategy.

TABLE 5.1: Fuel economy comparison

Strategy	**Fuel consumption**	**Comparison**	**Remarks**
Dynamic Programming	33 Km/liter	-	Reference value
Equivalent Consumption Minimization Strategy	31.35 Km/liter	05% more fuel consumption	near optimal solution
RB controller (optimized sharing of torque based on DP results)	30.03 Km/liter	9% more fuel consumption	DP rules can't be fully exploited, so near-optimal solution
Heuristic based RB controller (equal sharing of torque between motor and engine)	27 Km/liter	18% more fuel consumption	Non optimal rules

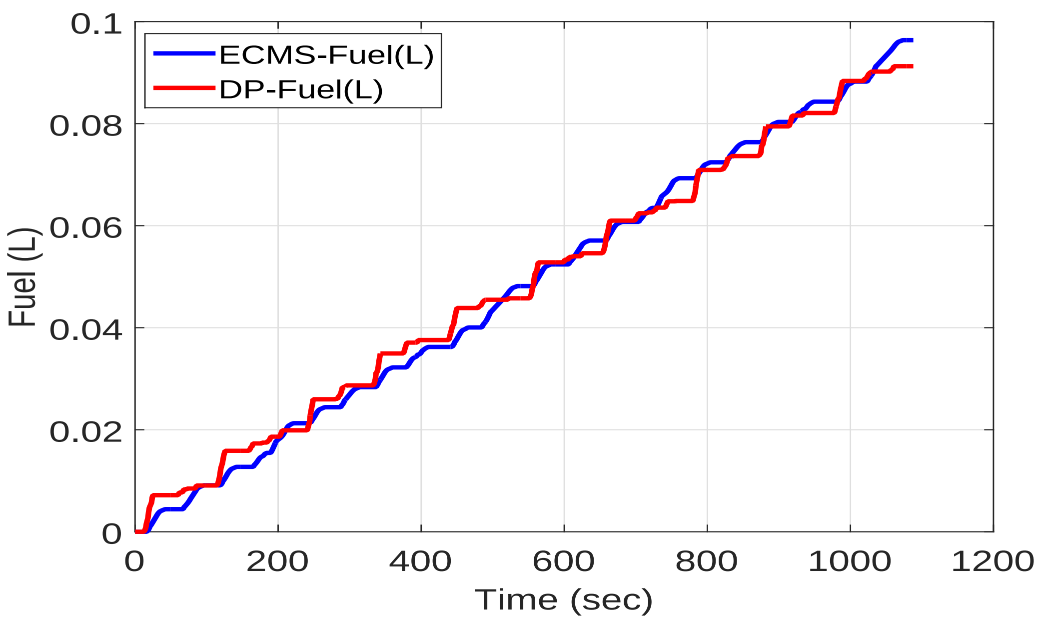

FIGURE 5.2: Comparison of fuel used in DP and ECMS strategies.

Fig. 5.3 shows the comparison of SOC for DP and ECMS strategy.

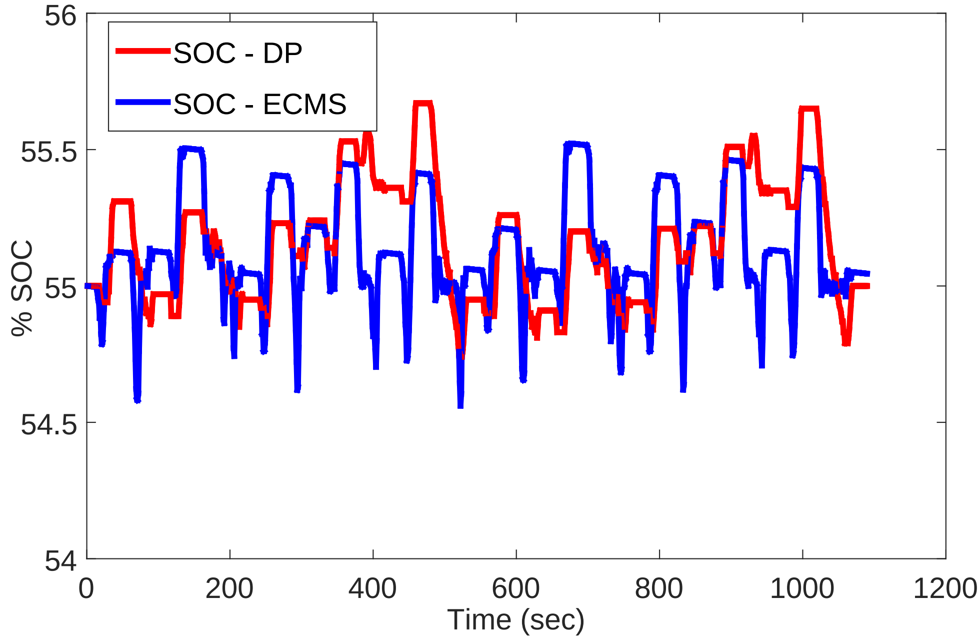

FIGURE 5.3: Comparison of SOC for DP and ECMS strategies.

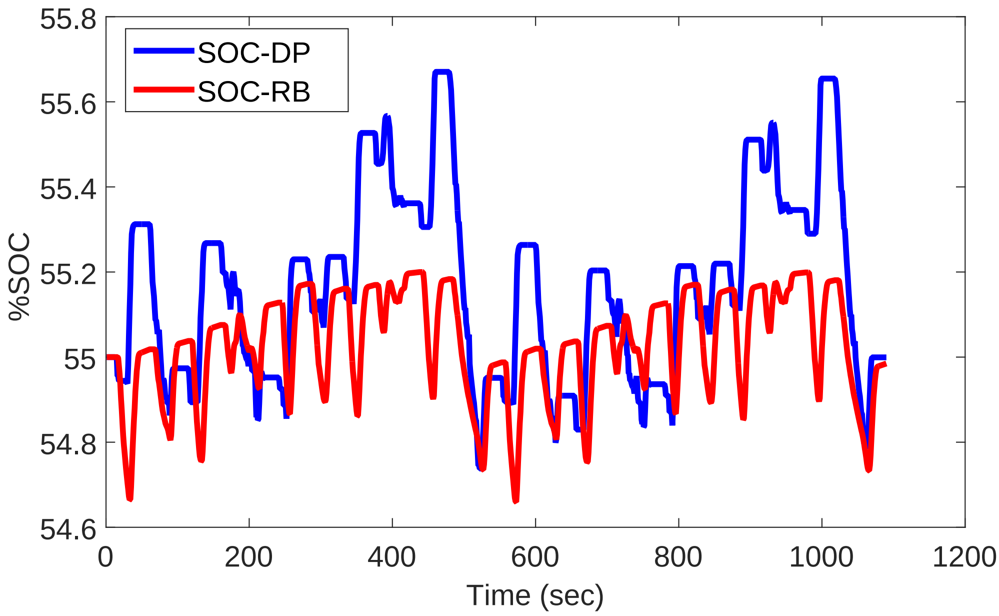

FIGURE 5.4: Comparison of SOC for DP and RB (extracted rules from DP) strategies.

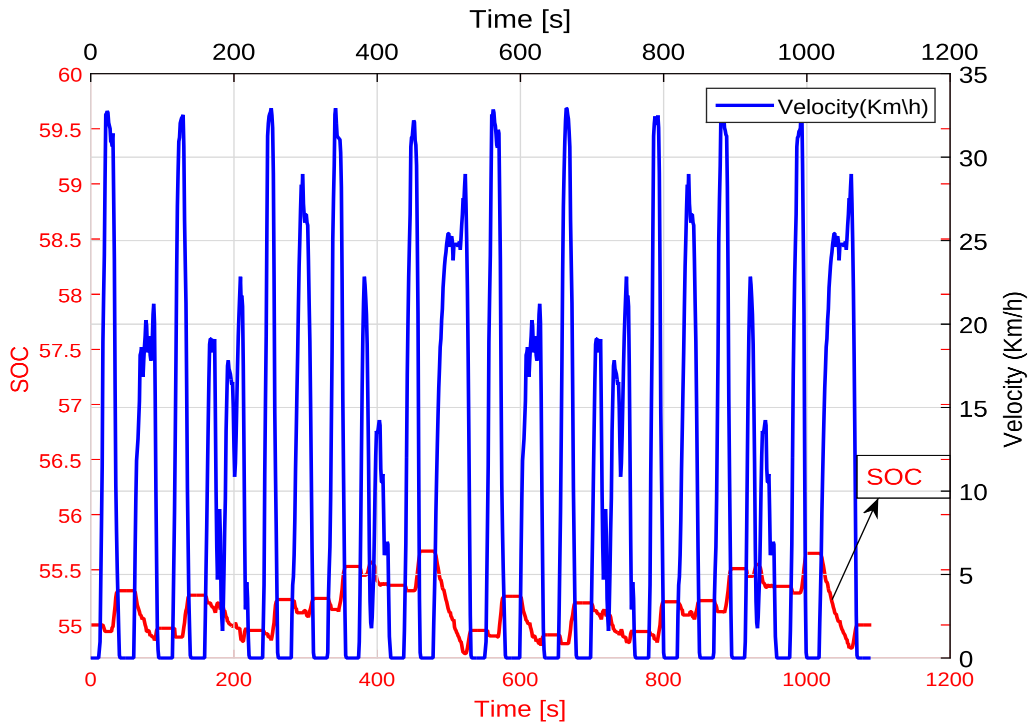

FIGURE 5.5: Driving cycle and SOC variation of DP strategy

Fig. 5.5 demonstrates the behavior of the state of charge of the battery. One can see that the final constraint of SOC is met and it is clear from the pattern that during electric vehicle and parallel mode, battery is depleting and during regenerative or charging, SOC of battery is increasing.

Fig. 5.6 shows the driving cycle with the torque split ratio. This graph shows different torque split ratio during the implementation of DP strategy. As indicated by the torque split ratio, we are going towards charge sustaining criteria, so less Battery is used and remaining torque demand is fulfilled by the engine. In implementation of DP, it always calculates average value of SOC and if it deviates more from the reference value of SOC, the decision goes towards utilization of engine instead of alone motor torque.

Fig. 5.7 shows that with positive torque split ratio, the SOC of battery is available and this is used to drive the motor fully, while the negative torque split ratio is for charging of battery and the battery is charged through engine or regenerative breaking.

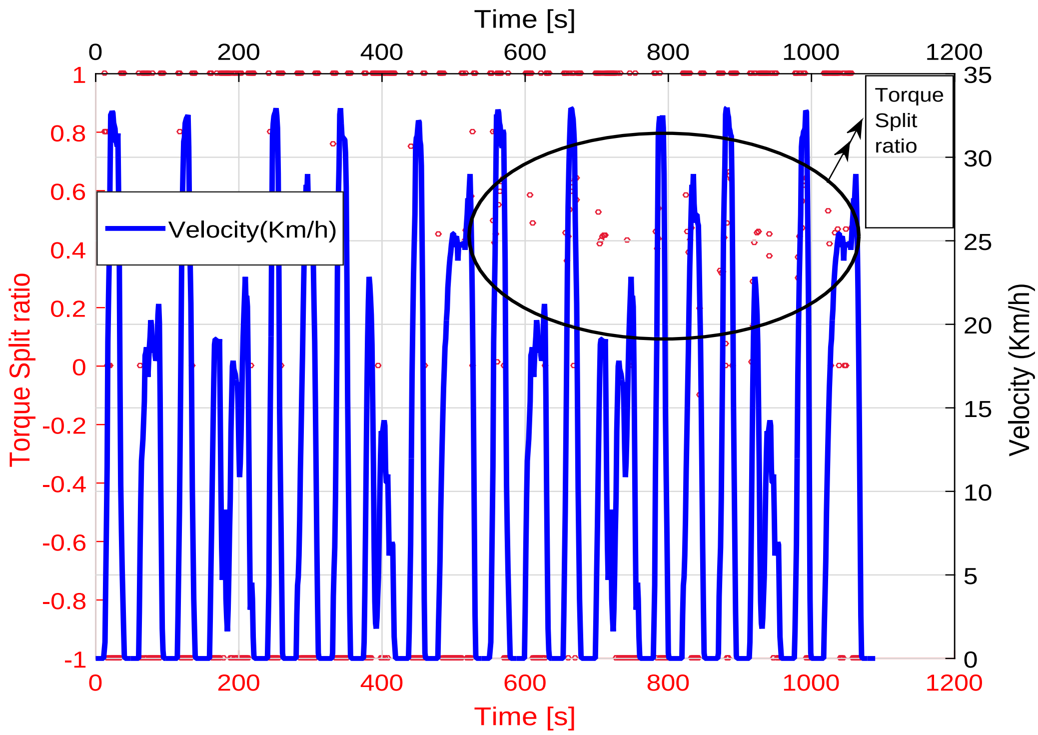

FIGURE 5.6: Driving cycle and torque split ratio of DP strategy

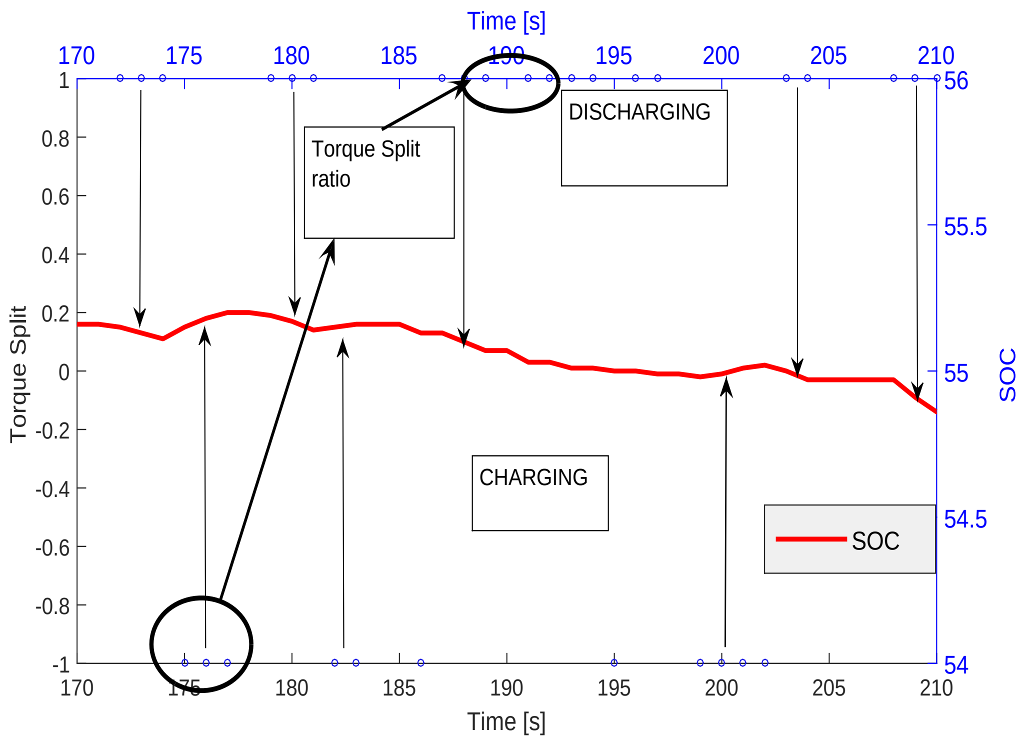

FIGURE 5.7: Torque split ratio associated with charging and discharging of battery

So, it is evident from graph that whenever enough battery energy is available, DP tries to run the vehicle in electric mode and available kinetic energy or through engine is fully used to charge the battery. For analysis purpose, a small portion of graph is taken to show the variation of charging and discharging of the battery.

5.1.2 Comparison of Torque Split Ratio with Another Driving Cycle

Another driving cycle (CBDTRUCK) is tested on dynamic programming to see how the torque split behaves. For this purpose, driving cycle is selected, whose speed is low. Fig. 5.8 shows that there is similar pattern of torque split ratio as the driving cycle has similar pattern of speed.

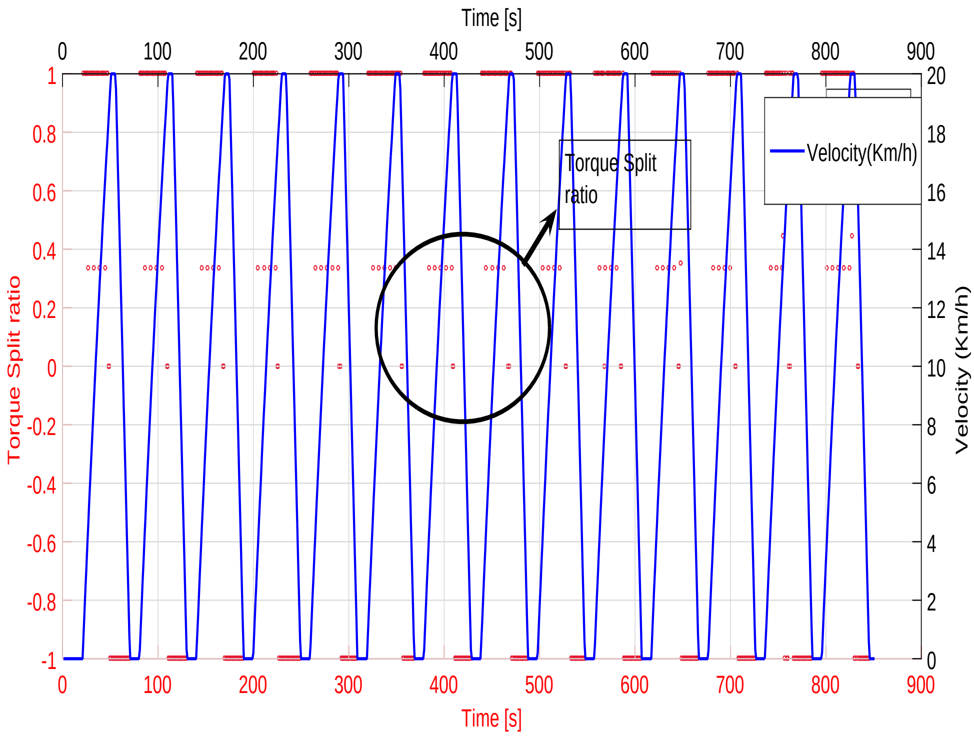

FIGURE 5.8: Torque split ratio of driving cycle CBDTRUCK

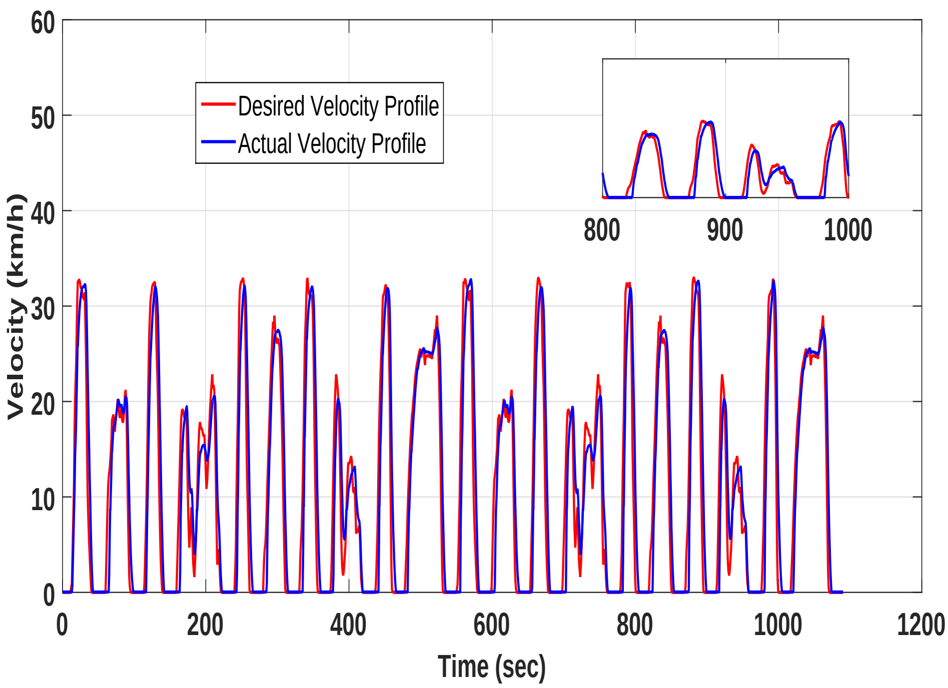

FIGURE 5.9: Actual and desired velocity profile of Manhattan drive cycle.

Fig. 5.9 shows the velocity profile of Manhattan drive cycle, demonstrating that with the proposed drive train components, it is possible to meet the desired speed of the drive cycle. The percentage difference between the desired and actual speed is about 2%, which is admissible.

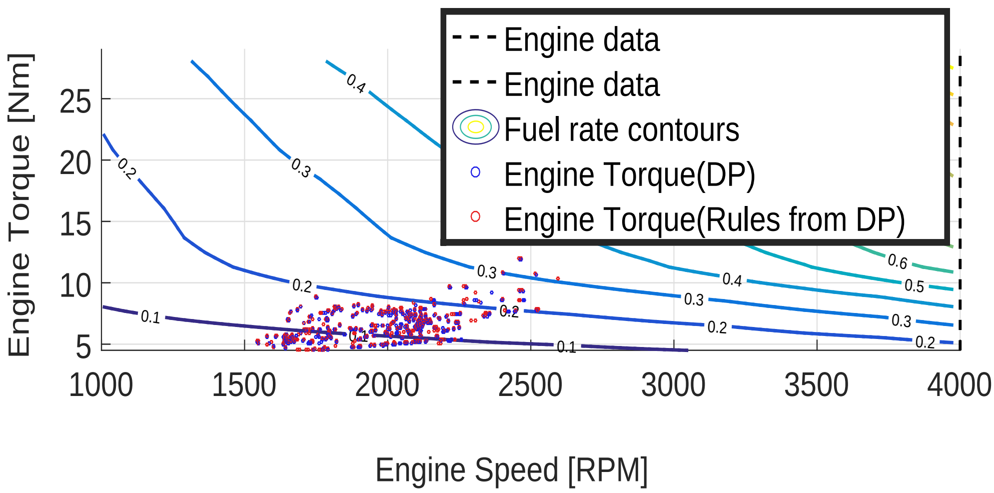

FIGURE 5.10: Fuel maps and operating points of the engine for the DP and rules extracted from DP control strategies.

The fuel consumption map of Internal combustion engine along its operating points for the DP and rules extracted from DP control strategies is shown in Fig. 5.10.

The operating points of electric motor for the DP and rules extracted from DP control strategies drawn on the efficiency maps are shown in Fig. 5.11.

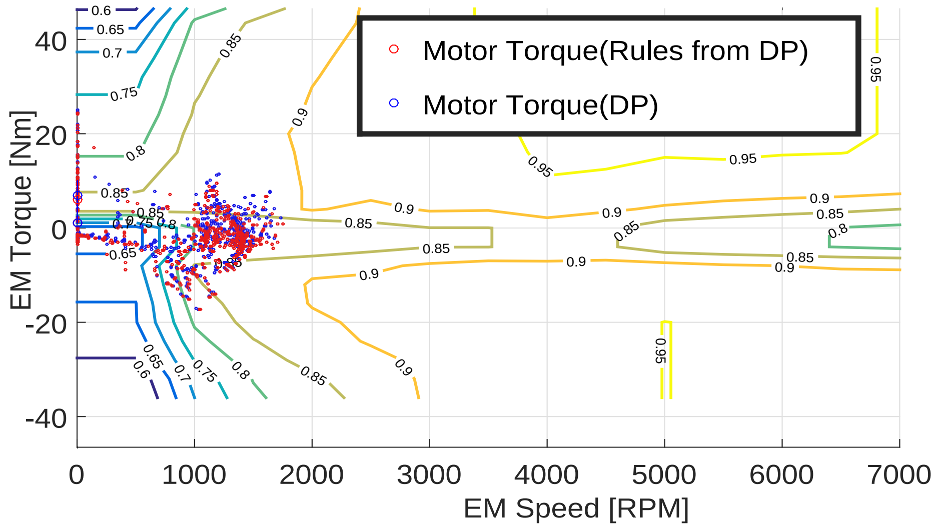

FIGURE 5.11: Efficiency maps and operating points of the electric motor for the DP and rules extracted from DP control strategies.

5.2 Evaluation of Implementable Energy Management Strategies

In this section, variation of battery SOC and equivalent fuel consumption for the implementable energy management technique, such as rule-based technique has been discussed.

5.2.1 Rule-based Controller Design for the Proposed HEV Powertrain

The implementation of rule-based technique used for the energy management strategy is narrated in this section. Rule-based controller operates on a set of predefined rules for actual operation of the proposed powertrain. The controller utilizes the state machine models (Matlab/Stateflow) to reflect various operating modes. The transition between the modes is determined by predefined rules based on current operating conditions (instantaneous inputs for the decision making process). The three modes of operation with respect to the instantaneous parameters are narrated as.

1. Electric vehicle mode: At the starting of vehicle, the whole torque demand is provided by the motor with the selection of Positive torque demand and the speed limit of 1000 RPM of the vehicle, the power-train operates in electric vehicle (EV) mode with the clutch in open position and the Internal Combustion Engine is off.

2. parallel mode: As the speed crosses over the limit of 1000 RPM and the torque demand is positive, the vehicle goes into parallel mode. Here the optimized motor torque from DP results is provided by the motor and the remaining torque is provided by the engine.

3.Charging or Regenerative mode: As soon as the vehicle decelerates with a negative torque, the supervisory controller charging the battery either through engine or regenerative braking, as long as the vehicle is in decelerating mode. The transition between these modes is accomplished, when the values of instantaneous parameters change according to the operating conditions of the vehicle.

5.2.2 Significance of Heuristic-based RB Control Strategy (not conforming to DP rules)

Heuristic based RB control strategy (not conforming to DP rules) narrates the effect on fuel economy when equal sharing of the torque demanded by the engine and the motor in parallel mode is considered. Fuel economy is compromised when these non-optimized rules are adopted (Table 5.1). These rules are selected on engineering intuition that depict that how optimized and non-optimized rules reflect on the fuel economy.

5.3 Driving Cycle, its Torque and Power Profile

Previous discussion shows that advantages of Hybrid Electric Vehicles rely on how the vehicle is used. If the engine is run on constant efficiency and the vehicle run at constant speed on a smooth road, the hybrid electric vehicle gives no advantage. A driving cycle narrates the way the vehicle is driven during a trip, and the road properties. In a simplest way, it is defined as a sequence of vehicle speed, acceleration and road grade. The road load is actually the sum of several terms (aerodynamic drag, rolling resistance and inertia). It is worth mentioning that each road load term is a function of driving cycle (speed, acceleration and grade) and the vehicle parameters (frontal area, mass, rolling resistance and aerodynamic coefficient). All the attributes related to vehicle are constant, so fuel consumption is mainly dependent on the driving cycle and hence there is different fuel economy for each driving cycle for the same vehicle.

Manhattan Drive Cycle has been selected for simulation purpose shown in Fig.5.12. The simulation is done in Matlab/Simulink environment. Torque and Power required are calculated from the following equations. We assume that the road is smooth and there is no angle of inclination.

$$F_{total} = [\frac{1}{2}\rho_a A_f C_d {V_{veh}}^2] + [MgC_{rr}] \tag{5.3}$$

and the Torque required is calculated as follows

$$W_{veh} = [\frac{V_{veh}}{R_{wh}}] \tag{5.4}$$

$$T_{total} = [\frac{1}{2}\rho_a A_f C_d {R_{wh}}^3 {W_{veh}}^2] + [MgC_{rr}R_{wh}] \tag{5.5}$$

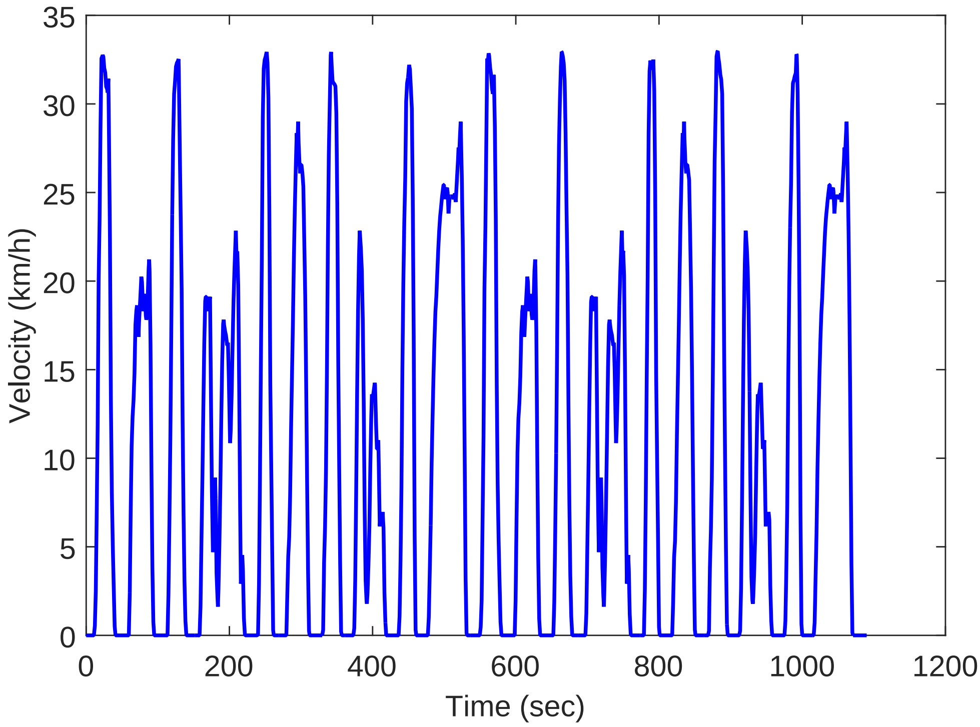

Figure 5.12: Velocity profile of Manhattan drive cycle used for the evaluation of the designed control strategies.

and the Power required is calculated as follows

$$P_{total} = [T_{total} * W_{veh}] \tag{5.6}$$

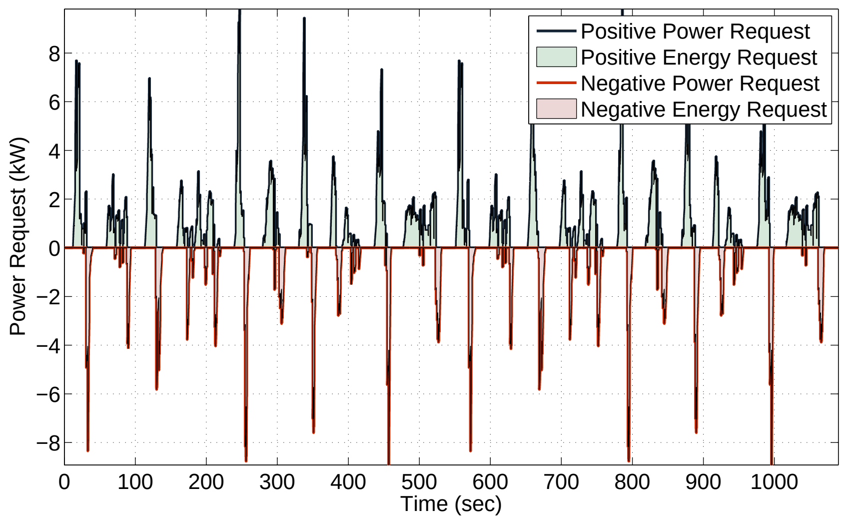

Figure 5.13: Power profiles of Manhattan drive cycle.

Power profiles of Manhattan drive cycle has been shown in Fig.5.13.

5.4 Case Study

A different research was carried out to demonstrate the fuel economy improvement for an Atkinson cycle engine based HEV(Rickshaw) at part load conditions, and its comparison was done with the conventional Otto cycle engine based HEV(Rickshaw). Typical spark ignition (SI) engines are designed to achieve optimal efficiency by taking into account the full load, while, the automotive engines operate at part loads most of the times and the load is controlled with the conventional throttle that results in more engine part load losses. Correspondingly, the thermal efficiency of the conventional SI gasoline degrades considerably at engine light loads, on account of fixed compression ratios varying from 8 to 12 as well as limitations of fuel quality and engine knocking. In this work, an Atkinson engine model is a dynamic model, while the electric machine and battery model are quasi-static models. The dynamic model of Atkinson cycle engine is given in Appendix A. As the engine used is of 3.5 Kw rating, so the total weight of the vehicle is reduced from 600 Kg to 450 Kg to cater for the power rating of the engine. Permanent Magnet motor of 07 kW rating is used as a secondary power source as indicated in Table 5.2. The motor is capable of providing the total torque demanded, so the vehicle can be run in pure electric mode also. The battery used is Li-ion type of 4.8 KWh rating indicated in Table 5.2.

The drive cycle used are Manhattan and modified FUDS. The controller used is simple rule-based that decides the mode of vehicle operation on the basis of speed and torque demand of the vehicle. In the Atkinson cycle engine model, late Intake Valve closing Timing (IVT) load control scheme is employed, whereas conventional throttle is kept wide open. However in the parallel HEV model, the Atkinson engine block calculates the torque produced by the engine and is provided to the vehicle according to HEV controller scheme as shown in the Fig. 5.14. The simulation model comprised of the drive cycle input to the driver control module,

Table 5.2: Physical specifications of the motor and the battery for Atkinson engine based Rickshaw

Component	**Parameter**	**Type**
Motor	07 kw	Permanent Magnet Motor
Battery	4.8 kWh	Li-ion

Table 5.3: Physical values of K_p, K_I and K_D parameters

Parameter	Value
K_p	0.25
K_I	0.01
K_D	0.05

the energy management strategy module and the plant module (vehicle module). First, the reference vehicle speed (desired) V_d for time t is given to the driving cycle module. On the basis of this speed V_d, the acceleration and brake signals are calculated in the driver model through PID controller. Physical values of K_p, K_I and K_D parameters are shown in the Table 5.3 and these values are tuned by trial and error method.. These signals are given to the HEV controller, in which the selection of Electric machine and Engine mode is accomplished on the basis of speed and torque demand.

- V_d: Vehicle's velocity (desired) [m/s]
- V_actual: Vehicle's velocity (actual) [m/s]
- ON/OFF: Engine ON/OFF request [-]
- T_m_req: Electric motor Torque request [Nm]
- T_{Atk}: Atkinson engine Torque outcome [Nm]

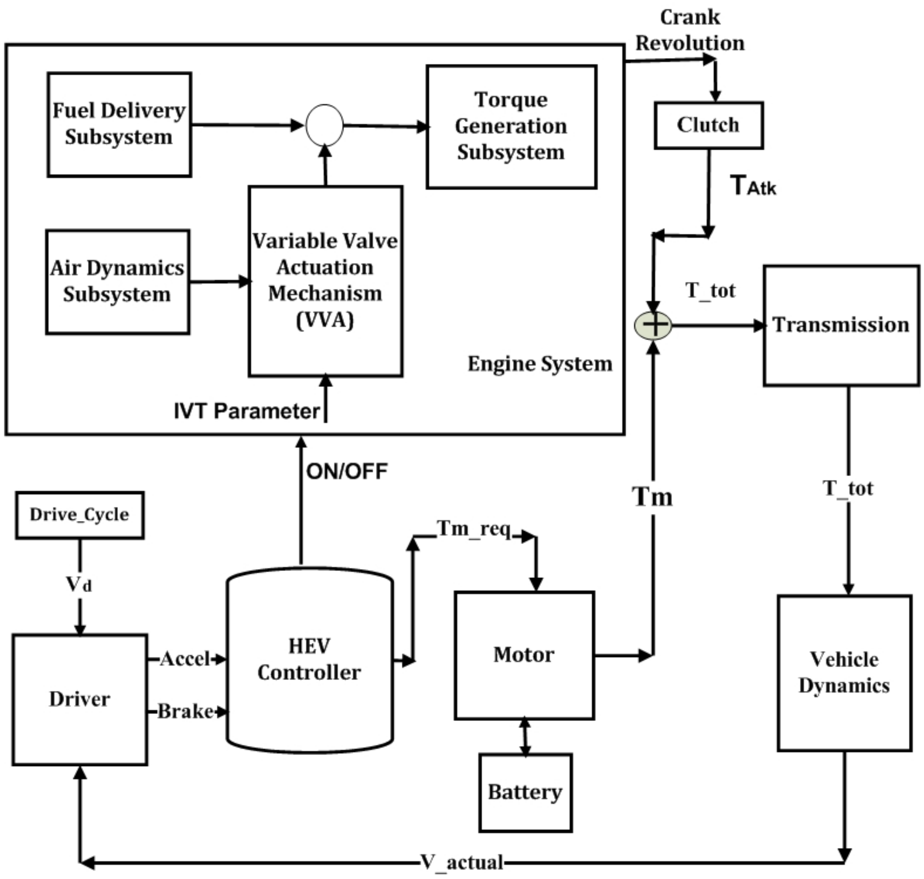

Figure 5.14: Simulation model of Atkinson cycle engine based HEV.

- T_m: Motor Torque outcome [Nm]
- T_tot: Total Torque [Nm]

5.5 Proposed Energy Management Strategy

The power-train controller consists of a supervisory controller (decision of the appropriate operating mode) and the energy management controller (which decides the torque sharing among the energy sources), while satisfying the overall torque demand of the driver. The thresholds and rules for each of these two controller levels are narrated in the following subsections.

5.5.1 Supervisory Control

As far as the supervisory control is concerned, the following rules are implemented.

1. At low speed, positive torque: the power-train works in pure electric vehicle (EV) mode, keeping engine in off state. This is presented by region A as shown in Fig.5.15.

2. At high speed, positive torque: the power-train works in thermal (engine) mode. This is presented by region B as shown in Fig.5.15.

3. While operation with a negative torque, the supervisory controller shut off the engine for fuel saving. Since the vehicle is in decelerating mode, the power-train works in regenerative mode. This is presented by region C as shown in Fig.5.15.

For all above operating modes, the supervisory control rules implemented are summarized in Table 5.4;

TABLE 5.4: Supervisory control strategy parameters

Mode	**Torque**	**Speed**
Electric vehicle mode	$T_{demand} \geq 0$	$W \leq W_{sel}$
Engine mode	$T_{demand} \geq 0$	$W \geq W_{sel}$
Regenerative mode	$T_{demand} < 0$	$0 \leq W \leq W_{max}$

- T_{demand}: Varies according to drive cycle [Nm]
- W: Current speed of the Vehicle [RPM]
- W_{sel}: Selected speed of the Vehicle [1600 RPM]
- W_{max}: Maximum speed of the Vehicle [3500RPM]

W_{sel} is the selected speed for electric mode which is selected from the running experience of Rickshaw. This is the boundary line between the electric mode and the engine mode, whereas 3500RPM is the maximum speed of the Atkinson cycle engine.

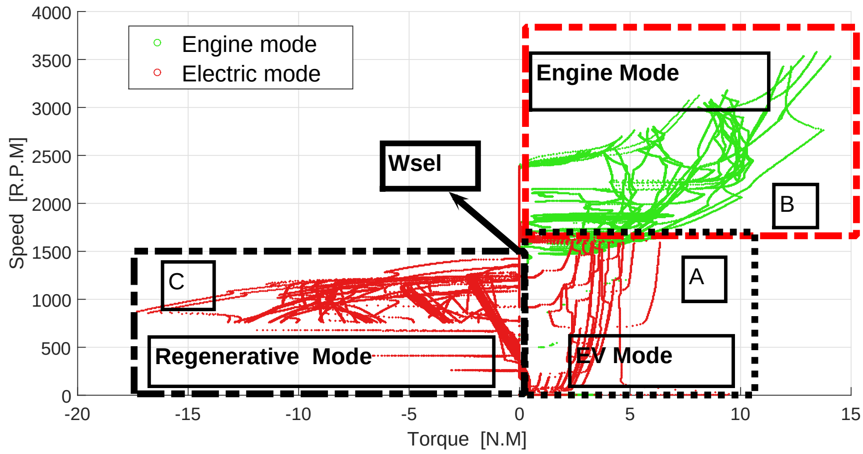

FIGURE 5.15: Operating points of engine and motor in different modes

5.5.2 Energy Management

After the decision of mode selection by the supervisory controller, the torque sharing among the engine and the electric machine is decided as follows in the Fig. 5.16. Three modes of operation of the vehicle have been discussed, namely Electric vehicle mode, Engine mode, and Regenerative mode. At starting, vehicle goes at State-1 where both the engine and the motor have zero torque request.

Electric Vehicle (EV) Mode: When $SOC > 0.4$, the vehicle system is in electric vehicle mode only, in this mode battery does not need charging and speed of the vehicle is less than the threshold selected W_{sel}, while the torque demand is provided by the motor only.

Engine Mode: When $SOC > 0.4$, the vehicle system is in engine mode only, in this mode battery does not need charging and speed of the vehicle is more than the threshold selected W_{sel}, while the torque demand is met by the engine only.

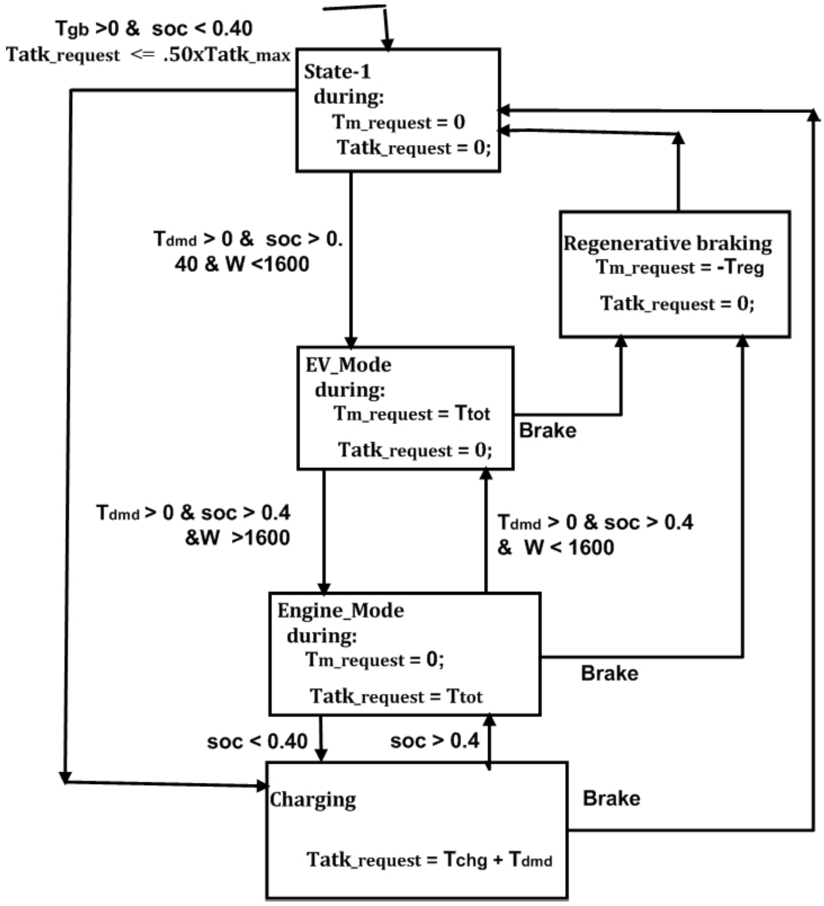

FIGURE 5.16: Stateflow chart of energy management strategy

Regenerative mode: When the brake is applied, the vehicle system is in regenerative mode only, in this mode battery need charging and it is charged either through recuperation of kinetic energy or through engine (conditions are mentioned on the state flow diagram). These three modes are well depicted in Fig.5.15. The threshold of speed selected W_{sel} is the boundary line between regions A and B. To optimize fuel economy, the initial and final constraints chosen for SOC is 0.55, which is met in the SOC profile of Otto and Atkinson cycle for Manhattan drive cycle shown in Fig 5.17. The proposed EMS regulates the engine ON/OFF status according to the SOC values.

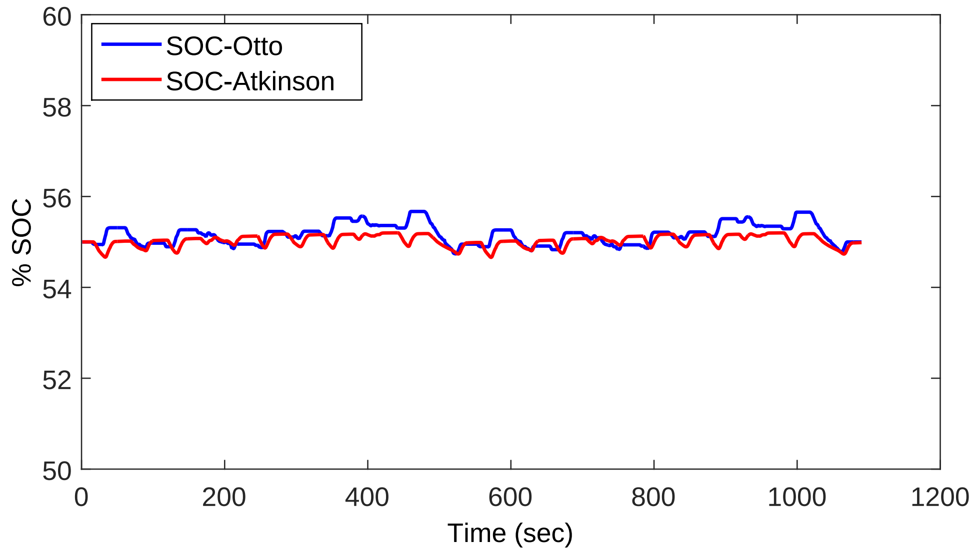

FIGURE 5.17: SOC profile of Otto cycle engine and Atkinson cycle engine for Manhattan drive cycle

To evaluate the substantial benefits of the proposed strategy, the Atkinson cycle engine along with variable LIVC load handling strategy instead of the conventional throttle is utilized. The control strategy proposed for the assessment of fuel economy is explained for Manhattan drive cycle, while the same approach is also adapted for modified FUDS drive cycle. For the simulation purposes, Manhattan and modified FUDS drive cycles are considered due to their frequent stop/start driving pattern, which in turns represents the driving pattern of congested cities. The motor drive is facilitated by kinetic energy recuperation related to the frequent stop/start behavior experienced within these drive cycles. The supervisory control (which decides the mode selection) is well replicated in the Fig. 5.15, showing each mode of operation. The comparison of torque provided by Atkinson cycle engine and the electric motor is exhibited through Fig. 5.18. For the proposed EMS, engine is turned off during the regenerative mode and motor behaves like a generator, providing kinetic energy for charging purposes. The pre-transmission parallel HEV is modeled in the Matlab/Simulink environment by using the forward simulator for the comparison of the performance of proposed EMS. The flexible LIVC load control strategy has been employed in the EMVEM modeling approach of Atkinson cycle engine instead of the conventional throttle.

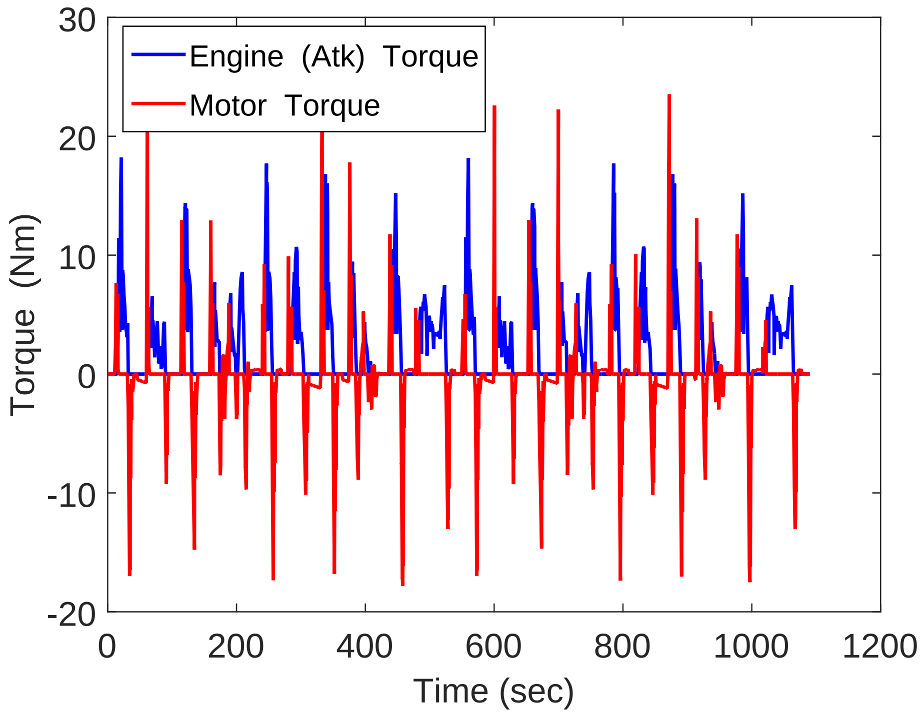

FIGURE 5.18: Torque profile of motor and engine for Manhattan drive cycle

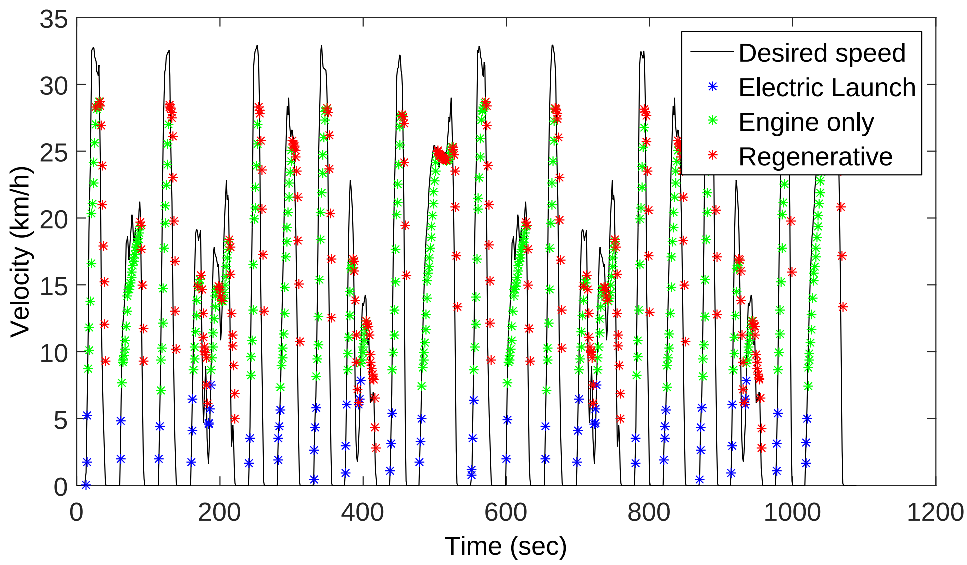

FIGURE 5.19: Mode choice for Manhattan drive cycle exhibited for energy management strategy.

The mode choice of proposed energy management strategy is depicted by Fig. 5.19, showing Electric launch, Engine only and Regenerative modes. The vehicle always starts in Electric mode and when the speed crosses over the selected threshold, it goes in the Engine mode and while decelerating, receives the kinetic energy. The kinetic energy recuperated is used to charge the battery, thus saving fuel energy.

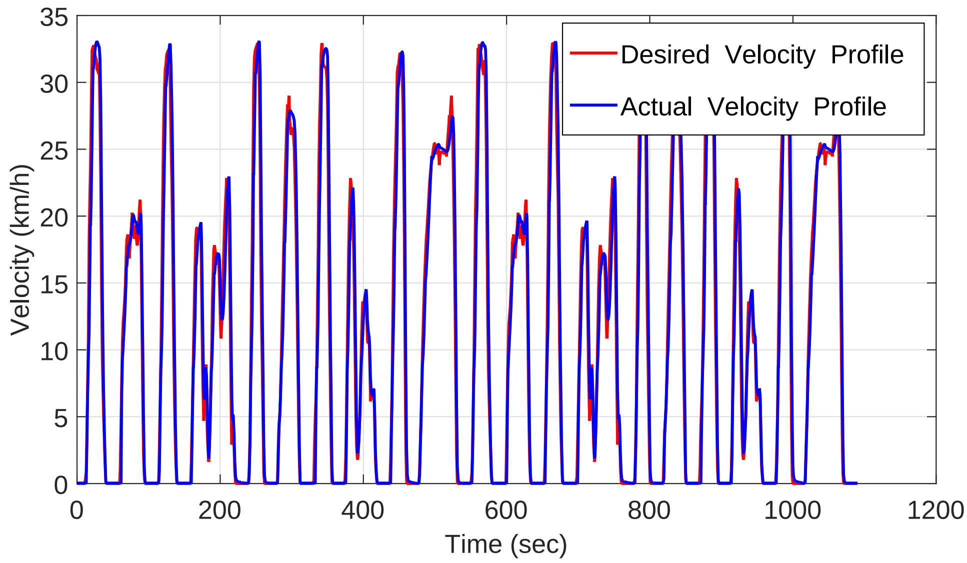

FIGURE 5.20: Actual and desired velocity profile of Manhattan drive cycle

Fig. 5.20 depicts the tracking velocity profile of the proposed strategy for Manhattan drive cycle. The result also shows that the HEV components' sizing fulfills the performance requirements during the driving cycle.

The fuel consumption comparison attained with proposed EMS along with Atkinson cycle engine over the conventional Otto cycle engine with the variable loading condition during the standard Manhattan and modified FUDS drive cycles, is depicted in Fig. 5.21. The standard FUDS drive cycle is modified due to its high-speed profile. The improvement in fuel consumption is achieved about 12.30% for the variable loading conditions during the Manhattan drive cycle, whereas about 7.22% during the modified FUDS driving cycles for the proposed EMS. Simulation results of the fuel economy for a parallel hybrid electric vehicle for the proposed EMS is shown in Table 5.5. The torque load is dependant on the speed and the mass of the vehicle of the vehicle as shown in equation (1). As the mass of the vehicle is constant, so by lowering the threshold of speed, the torque load on the engine can be reduced, resulting in more fuel economy.

TABLE 5.5: Simulation results of fuel economy of Atkinson cycle engine in comparison with Otto cycle engine at part load

Driving cycle	**Improvement of fuel economy of Atkinson cycle engine at part load**
Manhattan	12.30%
modified FUDS	7.22%

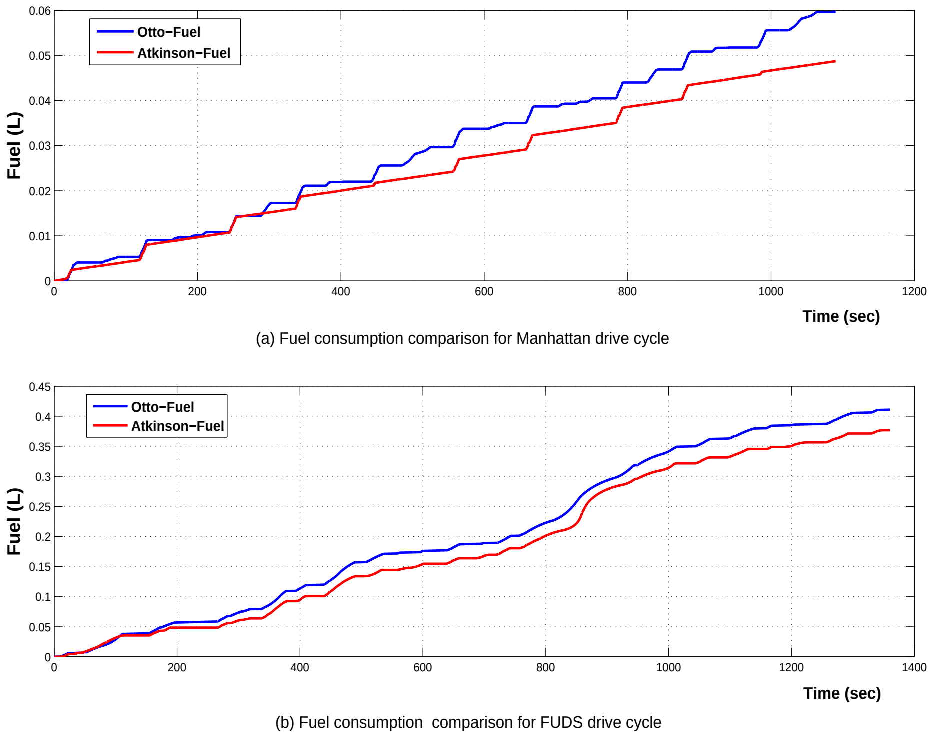

FIGURE 5.21: Comparison of fuel economy for Manhattan and modified FUDS drive cycles

The improvement in fuel consumption during the Manhattan drive cycle is more than that of modified FUDS driving cycle as Manhattan drive cycle is inclined more towards the engine part loads as compared to modified FUDS driving cycle. Even though the proposed EMS shows very promising results, there is room for further improvement in the fuel economy and the performance of a parallel HEV.

Further improvement can be achieved through some optimal control strategy, but the algorithm of proposed EMS in this research is computationally efficient due to the simple rules based on the Heuristic methods.

5.6 Summary

The optimal control strategy (Dynamic Programming) is implemented using a backward facing simulator in this dissertation. Rules were extracted from DP and these extracted rules were implemented through forward facing simulator. Important performance metrics are defined and the energy management strategies are assessed using defined metrics. Keeping in view, the implementation criteria in a real vehicle, the techniques are categorized into two groups, namely, non implementable and implementable techniques. Dynamic Programming (DP) and Equivalent Consumption Minimization strategy (ECMS) lie in the category of non implementable techniques, while rule based technique falls in the category of implementable strategies. Dynamic Programming is considered as a benchmark strategy and rule based technique is compared with DP. The rule-based energy management strategy, not conforming to DP rules is developed based on engineering intuition and heuristics. In this strategy, equal sharing of motor and the engine is proposed in parallel mode and it was concluded that there is about 9.00% more fuel consumption for this control strategy. A different research was carried out to demonstrate the fuel economy improvement for an Atkinson cycle engine based HEV(Rickshaw) at part load conditions, and its comparison was done with the conventional Otto cycle engine based HEV(Rickshaw).

Chapter 6

Conclusion and Future Work

6.1 Conclusion

In this dissertation, two major areas of energy management strategies implemented for HEV's are discussed: design of energy management strategies,their implementation, and comparison of various non-implementable and implementable energy management strategies. The purpose of the dissertation is to design above mentioned strategies for a parallel HEV (Rickshaw). In chapter 2, dependence of fuel economy and GHG emissions on different features has been discussed along with the literature review of different optimal and non-optimal control strategies. Research gap analysis is the contribution of this chapter. Mathematical modeling of parallel HEV (Rickshaw) is the part of of chapter 3. Different simulation techniques have been discussed along with their merits and demerits.

The vehicle architecture and simulation setup for the implementation of the strategies are developed in chapter 4 and utilized throughout the dissertation for the comparison of the strategies. The forward and backward facing simulators are used for different strategies. The major contribution of chapter 4 involves the development and implementation of different energy management strategies such as DP, and Rule-based for a pre-transmission parallel HEV. Energy management problem is designed keeping in view the charge sustaining criteria and other constraints of the system. As DP provides the global optimal solution through the backward simulation process based on the sufficient conditions of the optimality, it is considered as the Bench mark solution for the rest of strategies. The DP algorithm gives the optimal power/torque partitioning between an ICE and the motor by selecting an appropriate mode of operation. The mode selection process used by DP is analyzed and appropriate rules are extracted to select the mode of operation.

The implementation of DP algorithm for a pre-transmission parallel HEV (Rickshaw) is an important contribution of the dissertation. The extraction of rules from DP for mode selection and optimal torque/power split analysis is another contribution of the dissertation. With these rules extracted, a Rule based controller implementation is another task performed in this research. The energy management strategies developed are compared while considering the certain performance metrics in chapter 5. Dynamic Programming based energy management technique has been introduced for the Hybrid Electric Vehicle(Three wheeler auto Rickshaw). Manhattan Driving Cycle(Urban) has been chosen for this vehicle because it is specially designed for stop and go behavior in the cities. The proposed technique can be used as bench-mark for other energy management techniques because its optimality appears throughout the trajectory.

The proposed technique has been implemented using the parameters of Rickshaw as depicted in Table (1.2). The battery power has been selected according to the power requirement of the driving cycle, also the advantage of enhanced degree of hybridization has been achieved through bigger size of battery and motor. Dynamic Programming technique algorithm is used almost for every vehicle, because it provides an insight of fuel economy limitations. Due to unavailability of efficiency and Brake Specific Fuel Consumption maps, an interpolation was done for the selection of engine BSFC maps used for the parallel HEV (Rickshaw).

Both DP and RB strategies proposed in the dissertation have been derived from the literature and tailored according to requirement, while the implementation of the strategies for a parallel HEV (Hybrid electric Rickshaw) is an important contribution. The optimality of the control strategy guarantees the minimum fuel consumption and stability ensures the convergence of battery SOC to SOC_{ref}. Different energy management strategies proposed in the dissertation have been implemented using a forward vehicle simulator in chapter 5. Before comparing the different energy management strategies, some performance metrics are defined and on the basis of those metrics, the comparison between the strategies is evaluated. The performance metrics of the implementable strategies is evaluated over Manhattan driving cycle to simulate real world driving conditions. The results show that the proposed EMS is able to give considerable improvements of fuel economy for a parallel HEV. Due to significant fuel saving, it is a viable option to operate a hybrid three wheeler auto Rickshaw in the densely busy roads of Asian cities. The DP strategy exhibits the optimal energy management technique for the HEV and provides a benchmark solution for the assessment of minimum fuel consumption. This optimization technique yields 27% higher fuel efficiency for HEV (33 Km/liter) than conventional vehicle(24 Km/liter) fuel efficiency and is taken as reference value for other strategies. Equivalent Consumption Minimization Strategy is also implemented, which shows fuel economy of 31.35 Km/liter showing 5% more fuel consumption than DP. Proposed approach (DP) is then exhibited through rules extraction and implemented in RB controller, showing 9% improvement in fuel efficiency than heuristic based strategy (not conforming to DP rules). The rule-based strategy (rules extracted from DP) is then compared with non-optimal rules based heuristics controller. It is shown that non-optimal rule based controller has 18% more fuel consumption than DP results.The RB controller is calibrated in such a way to obtain the charge-sustaining requirements.

As we are focusing on the fuel economy of Hybrid electric Rickshaw, it will play an important factor in reducing fuel consumption of automobiles. In this research, fuel economy is achieved through different optimized modes of operation of vehicle, which are described in the following discussion.

By running the vehicle at starting with motor, saves fuel consumption and contributes to emissions reductions. The vehicle in parallel mode with optimal torque sharing also contributes towards fuel economy. The inertial energy is lost due to friction brakes. By regenerative braking, some percentage of the inertial energy can be recovered and is used for charging of batteries that will be used for the propulsion of the vehicle.

A different research was carried out to demonstrate the fuel economy improvement for an Atkinson cycle engine based HEV(Rickshaw) at part load conditions, and its comparison was done with the conventional Otto cycle engine based HEV(Rickshaw). Typical spark ignition (SI) engines are designed to achieve optimal efficiency by taking into account the full load, while, the automotive engines operate at part loads most of the times and the load is controlled with the conventional throttle that results in more engine part load losses. In the Atkinson cycle engine model, late Intake Valve closing Timing (IVT) load control scheme is employed, whereas conventional throttle is kept wide open. The improvement in fuel consumption is achieved about 12.30% for the variable loading conditions during the Manhattan drive cycle, whereas about 7.22% during the modified FUDS driving cycles for the proposed EMS. The significance of this research is to see the effect on fuel economy at part load conditions. This fuel economy is achieved through the application of Atkinson cycle engine istead of Otto cycle engine.

6.2 Future Works

Future work based on the foundation developed by the dissertation is described in this section.

1. In this dissertation, Rule-based (rules extracted from DP) strategy was developed. This strategy must be evaluated using a hardware-in-loop setup. The strategy should also be implemented in a real vehicle (Rickshaw) using chassis dynanometer and its results may be compared with other strategies.

2. Another strategy like DP can be implemented. The results of this strategy should be compared to the results of DP.

3. Minimization of Engine Emissions and Battery Aging. Evaluation of GHG emissions from the vehicle and the battery aging factor can also be included in the objective function as shown below.

$$J(x) \quad = \quad \int_{t_0}^{t_f} \alpha_1 \dot{m}(W_e, T_{e)} + \alpha_2 \dot{m}(W_e, T_e) + \alpha_3 \dot{m}_{eqv,age} dt \tag{6.1}$$

where, α_1, α_2, and α_3 are the weighting factors corresponding to the different objectives. The objective function $\dot{m}_{eqv,age}$ is the equivalent amount of fuel consumption related to the aging of the battery and is modeled through a severity factor of the battery. The severity factor (σ) may be modeled as a function of SOC of the battery, its temperature, and C-rate. The variation of C-rate depends upon the type of the vehicle (HEV or PHEV). This is due to the fact that in charge-sustaining HEV, a smaller range of operation (0.5 to 0.8) of battery is used while in charge-depleting mode (PHEV), a larger range of operation (0.2 to 0.9) is used. From the above discussion, it is quite obvious that the effect of battery C-rate on aging is minimum for PHEV. To cater for the temperature effect on battery life, thermal dynamics must be incorporated in the battery model. The main difference between the PHEV and HEV is due to the range of SOC of the battery used. As mentioned earlier PHEV uses a much larger range of battery SOC due to replenishment of battery using the grid energy.

4. Implementation of strategies to Plug-in HEVs.

The strategies discussed in the dissertation are implemented for a pre-transmission parallel HEV. The same strategies may be implemented for PHEV and the batteries used may be charged through grid-connection.

Appendix A

Modeling of Atkinson Cycle Engine

A.1 Model for the Internal Combustion Engine

For the assessment of fuel economy, two types of ICEs are used. The first one is the SI engine and the second one is Atkinson cycle engine. Modeling of Atkinson cycle engine is described here. The model of SI engine is the quasi-static model, while dynamic model of an Atkinson cycle engine is used. Specification of VVT engine and gear ratios are depicted in Table A.1. The Internal Combustion Engine and electric motor are mechanically coupled to the input shaft of Manual Transmission (MT). This mechanical coupling gives automatically same shaft speed. The output shaft of MT is directly connected to the clutch. The torque is transmitted to the wheel via the final drive.

A.1.1 Atkinson Cycle Engine Model Description

The precision of the spark ignition engine model with variable innovative technology as well as model-based robust control strategies play a vital role in the improvement of the engine performance [2, 99–101]. In this perspective, Murtaza

Table A.1: VVT engine characteristics

Symbol	Description	Value/Units
	No. of cylinders	1
B	Engine Bore	70 mm
S	Engine Stoke	55 mm
V_d	Displaced volume	0.21166 dm^3
P	Maximum power	3.5kW @ 3500rpm
T_{max}	Maximum torque	18N-m @ 2500rpm
g_k	1^{st} gear ratio	5.55
	2^{nd} gear ratio	3.12
	3^{rd} gear ratio	2.00
	4^{th} gear ratio	1.16
G	Final drive ratio	4.54
C_{tre}	Transmission efficiency coef.	0.9

et al. [1] have developed a physically provoked control-oriented EMVEM Atkinson cycle engine model, in which the modern technologies as flexible valve timing, over-expansion, VCR and Atkinson cycles realization have been incorporated, and is described in the ensuing subsection.

A.1.1.1 Control-Oriented Atkinson Cycle Engine EMVEM Model

A physically motivated Atkinson cycle engine's control-oriented EMVEM dynamics consisting of the modeling processes like air dynamics which includes intake manifold pressure dynamics with Variable Valve Actuation (VVA) incorporated for the realization of the Atkinson cycle, throttle body, air mass suction system, the rotational dynamics with an alternate Late Intake Valve Closing (LIVC) control strategy [1, 102] and then the fuel dynamics [103], based on

- Fluid Dynamics and Thermodynamics Principles
- Atkinson cycle for the in-cylinder dynamics analysis
- Inertial laws

is given as

$$
\begin{aligned}
&\dot{P}_m = \Psi_1\chi(p) - (2-\lambda)\Psi_2 P_m\omega_e\alpha(P_m,\omega_e)\\
&\dot{\omega}_e = \frac{1}{J_e}\left(T_{ind}(\lambda) - T_{pump} - T_{fric} - T_{load}\right)\\
&where,\\
&\Psi_1 = \frac{T_m R}{V_m}C_D A_e P_a \gamma_c\\
&\Psi_2 = \frac{V_{ivc}}{4\pi V_m}\\
&\chi(p) = 1 - \exp\left(9\frac{P_m}{P_a} - 9\right)\\
&A_e = \pi\frac{D^2}{4}(1-\cos(\frac{\phi+\phi_{cl}}{\phi_{cl}}))\\
&\gamma_c = \sqrt{\frac{1}{RT_a}}\sqrt{\gamma(\frac{2}{\gamma+1})^{\frac{\gamma+1}{\gamma-1}}}
\end{aligned}
\tag{A.1}
$$

A theoretical Atkinson cycle engine torque termed as indicated torque, generated as a process of air to fuel mixture burning is described as

$$T_{ind} = \frac{V_d}{4\pi}\eta_{atk}\ mep$$

$$
\begin{aligned}
&while\\
&mep = \frac{r_c}{(\gamma-1)(r_e-1)}[\frac{\zeta(r_c^{\gamma-1}-\lambda)}{r_e^{\gamma-1}} + (\lambda-1)(\gamma-2)]P_m\\
&\eta_{atk} = 1 - \frac{1}{r_e^{\gamma-1}} - \frac{[(\gamma-1)\lambda^{\gamma} - \gamma\lambda^{\gamma-1} + 1]}{\zeta\lambda^{\gamma-1}}\\
&where\\
&\zeta = \frac{Q_{LHV}\eta_c}{T_m C_v(AFR+1)}\\
&\eta_c = \eta_{cmax}\left(-1.6082 + 4.6509\sigma - 2.0764\sigma^2\right)
\end{aligned}
$$

where, η_c is the combustion efficiency with $0.75 < \sigma < 1.2$ [104] and η_{cmax} is the maximum η_c typically considered as 90 to 95 % for a SI engines [2, 99]. The Pumping torque essential to carry out pumping action and engine frictional torque mathematically is given as [99]

$$T_{pump} = \frac{V_d}{4\pi}(Pa - Pm)$$
$$T_{fric} = \frac{V_d}{4\pi}[(0.97 + 0.15\frac{N}{10^3} + 0.05\frac{N^2}{10^6})10^5]$$

Furthermore, to explore the fuel economy of an Atkinson cycle engine, the stable fuel dynamics subsystem [103] is utilized.

A.1.1.2 Intake Valve Timing Parameter (λ)

To incorporate VVA phenomenon in the conventional SI engine for the Atkinson cycle realization, a novel intake valve timing (IVT) parameter λ is introduced [1]. It has prodigious importance to summarize the physical dynamics of the Atkinson cycle engine, besides the accomplishment of the advantages of the overexpansion and VCR characteristics. Mathematically, it can be expressed as

$$\lambda = \frac{r_e}{r_c}, \qquad 1 \leq \lambda \leq 1.60 \tag{A.2}$$
$$where,$$
$$r_e = \frac{V_c + V_d}{V_c}$$
$$r_c = \frac{V_c + V_{ivc}}{V_c}$$

where V_c is the clearance volume and the combustion cylinder's displaced volume in accordance with the intake valve closing time (IVC) is specified by $V_{ivc} = V_1$ is depicted in Fig. A.1 and is described in the following.

$$V_{ivc} = \frac{\pi B^2}{4}\left[r + a - \left\{acos\theta + \sqrt{r^2 - a^2sin^2\theta}\right\}\right] \tag{A.3}$$

and the engine displaced volume V_d is described as

$$V_d = \frac{\pi}{4} B^2 S \tag{A.4}$$

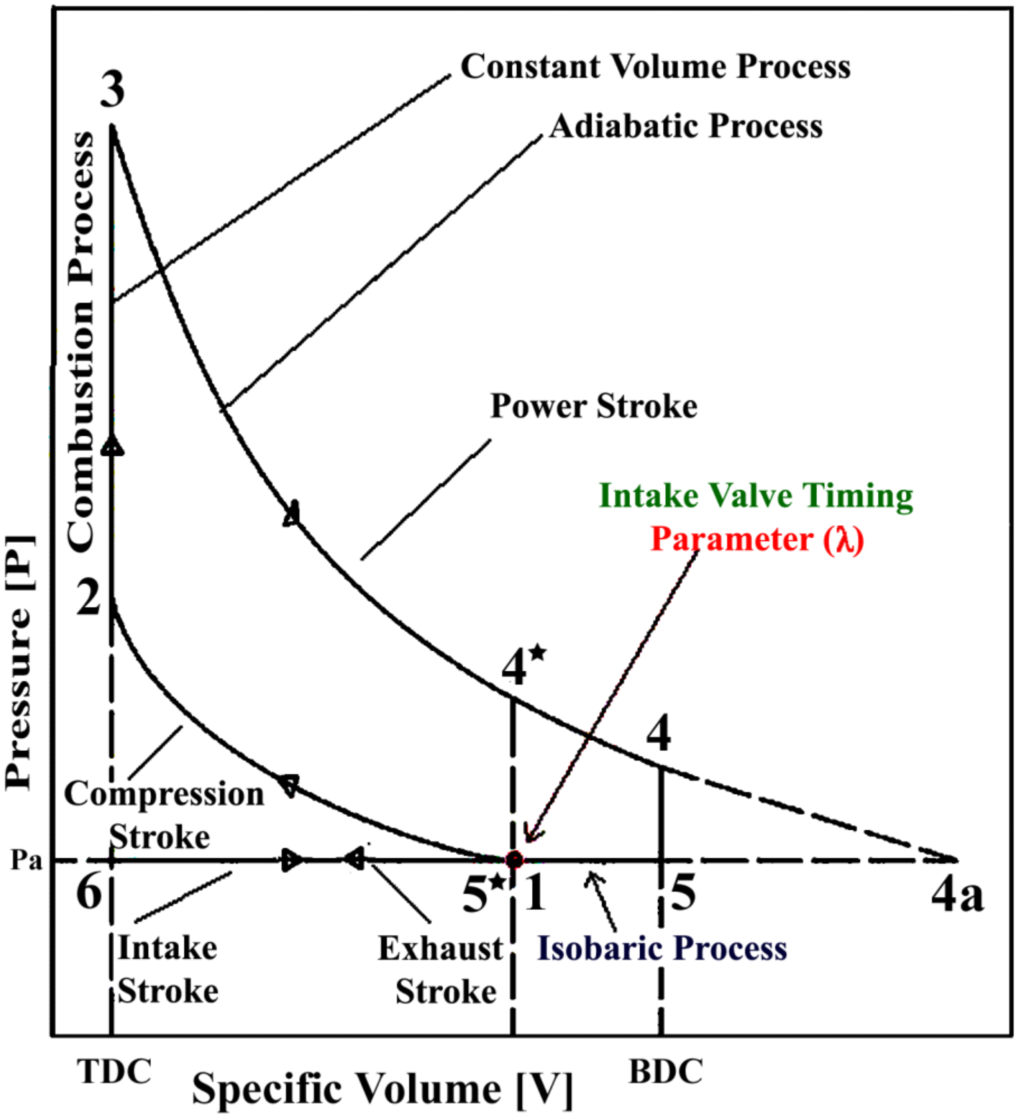

FIGURE A.1: Theoretical PV representation of an ideal Atkinson cycle engine [1, 2]

The EMVEM model parameters, their comprehensive description and values are as depicted in Table A.2.

The primary source of energy in HEV (Rickshaw) is the Internal Combustion Engine. The ICE used has maximum power of 3.5 Kw at 3000 rpm and the torque capacity is 18 Nm at 2500 rpm.

Table A.2: EMVEM parameters description and nominal values

Symbol	Description	Value/Units
AFR	Air to fuel ratio	14.7
ω_e	Angular speed	rad/s
N	Angular speed	RPM
P_a	Ambient pressure	101325 $Pascal$
T_a	Ambient temperature	298 K
η_{atk}	Atkinson cycle engine's thermal efficiency	
η_c	Combustion efficiency	0.9
r_c	Compression ratio	
T_{fric}	Engine frictional torque	N-m
J_e	Engine inertia	0.20 $kg.m^2$
T_{ind}	Engine indicated torque	N-m
T_l	Engine load torque	N-m
T_{pump}	Engine pumping torque	N-m
r_e	Expansion ratio	11.5
C_v	Heat capacity at specific volume	717 J/Km^3
Q_{LHV}	Heat value of fuel	44 MJ/Kg
D	Inlet diameter	19 mm
P_m	Manifold pressure	$Pascal$
T_m	Manifold temperature	325 K
V_m	Manifold volume	dm^3
mep	Mean effective pressure	$Pascal$
β	Pressure ratio	
γ	Ratio of heat capacities	1.4
R	Specific gas constant	287 $J/Kg.K$
ϕ_{cl}	Throttle angle at closed position	9.8 deg
C_D	Throttle discharge coefficient	0.345
A_e	Throttle effective area	
$\alpha(P_m, \omega_e)$	Volumetric efficiency	

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