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Fuzzy Logic Controller for Parallel Plug-in Hybrid Vehicle

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FUZZY LOGIC CONTROLLER FOR PARALLEL PLUG-IN HYBRID VEHICLE

by

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ABSTRACT

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By

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The University of Wisconsin-Milwaukee, 2012

Under the supervision of Dr. Anoop K. Dhingra

Hybrid electric vehicles combine two methods for propelling a vehicle. In a parallel hybrid vehicle, the two propulsion methods work in parallel to meet the total power demand. Among different combination of power sources, internal combustion engine and electric motor drive system are the most popular because of their availability and controllability. Plug-in hybrid vehicle is the latest version in hybrid vehicle family. In plug-in hybrid vehicle, battery is directly recharged from the electrical power grid and it can be used for a long distance with higher efficiency. Most of the hybrid vehicles on the road are parallel in nature and battery is recharged directly by the engine. If it is possible to convert existing hybrid vehicle into plug-in hybrid vehicle, it will lead to significant improvements in fuel economy and emissions.

In this thesis, two fuzzy logic controllers have been developed for the energy management system of the hybrid vehicle. For the first controller, it is assumed that the vehicle will work like a plug-in hybrid vehicle. For the second controller it is assumed that the battery will always recharged by the engine. It is found that with the help of developed fuzzy logic controller, the plug-in hybrid vehicle can run up to 200 miles with high efficiency. Both controllers are developed and their performance is tested on the highly reliable vehicle modeling and simulation software AUTONOMIE. The main objective of developing the controllers is increasing the fuel economy of the vehicle. The results from the both developed controllers are compared with the default controller in AUTONOMIE in order to show performance improvements.

Dedicated

with all my love to my parents

and

my respected teacher

Dr. Mozasser Rahman

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Chapter 1

Introduction

An ever increasing demand for energy combined with a limited supply of sources of energy has led to an increased awareness for the efficient use of energy. According to the US Department of Energy annual report of 2010 (Figure 1.1), the transportation sector consumes around 28 percent of the total energy produced in the United States, which is more than the residential and commercial power consumption, and only two percent less than industrial power consumption. The data given by the US energy administration for sector wise energy consumption (Figure 1.2) over the last sixty years depicts that energy consumption rate in transportation sector is increasing at a higher rate compared to the other three sectors. As most of the total energy in transportation sector is consumed by ground vehicles, a significant amount of attention is being given to the field of efficient energy management in ground vehicle systems.

Electric vehicle is one of the most energy efficient solutions for a ground vehicle as the electrical motor drive system has a higher efficiency compared to the mechanical internal combustion engine. But due to a lack of development in infrastructure and technical advancement of electric vehicles, electric vehicles can’t be used as a complete replacement for conventional IC engine based vehicles.

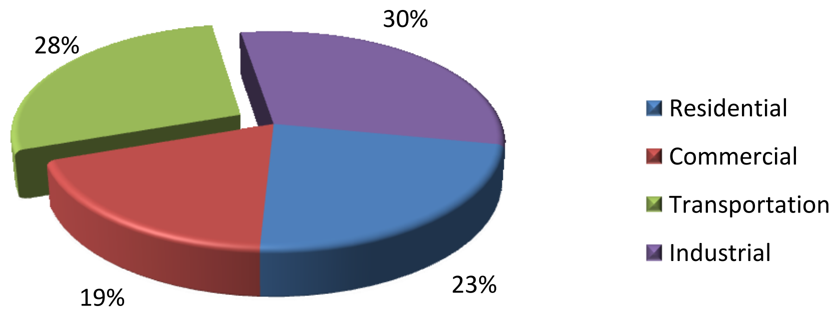

Figure 1.1 Total fuel consumption by sector in year 2010.

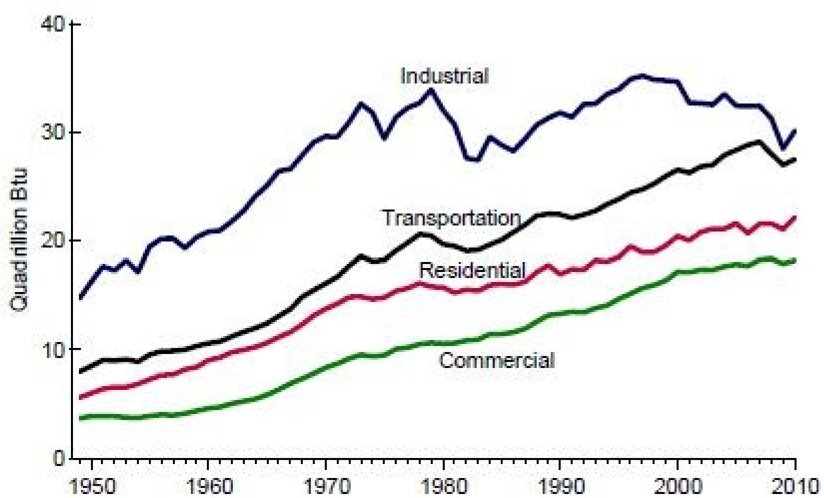

Figure 1.2 Total fuel consumption by sector from year 1949 to 2010.

Electric cars are comfortable, quiet, and clean compared to the conventional vehicles. Their main drawback is the travel distance (range) is limited. The total travel distance for these vehicles depends on the energy storage capacity of the battery; after a certain distance, the battery needs to be recharged. Recharging the battery takes long time

(upwards of several hours). Also, there is a significant relationship between the state of charge (SOC) of the battery and the battery life; repeated deep discharges reduce the battery life whereas to achieve maximum range, deep discharge is required. The two conflicting requirements of long battery life and maximum range before recharging are at odds with each other. So, we still need to rely on conventional vehicles to meet a large portion of our transportation needs.

The limitations of a conventional vehicle are its efficiency; the international combustion engine (ICE) has a low efficiency (only around 33%); emissions such as hydrocarbons, CO, NOx, particulate matters are high; the energy flow is one directional (from engine to the wheel); and engine failure, knocking and vibrations. In spite of these drawbacks, viable large scale alternatives to conventional vehicles do not exist.

Recently, engineers have discovered one possible solution to all the above mentioned problems is hybrid vehicle technology where all the positive features of an ICE are combined with the electric motor drive propulsion system. The main objectives accomplished by the hybrid system are that its efficiency is much higher than the conventional vehicle, emissions are controllable, the engine can operate in a narrow region (higher efficiency region) and its comparatively smaller component size, so a light weight system results. It is also possible to maintain a desired SOC on the battery which is essential to keeping the battery life longer. A significant amount of energy can also be recovered by using the regenerative braking system.

1.1 Hybrid vehicles

A hybrid vehicle combines two methods for propulsion for a vehicle; possible combinations include diesel/ gasoline, battery /flywheel and fuel cell /electric. Typically one source is storage and another source works as conversion of fuel to energy. Among these combinations, the combination of gasoline/electric and fuel cell/battery are easily controllable with faster response. Demirdoven and Deutch (2004) showed a comparison between different combinations of power sources in Figure 1.3. Although diesel/electric combination is little bit less efficient than the fuel cell/battery, the fuel cell/battery combination is still not a feasible solution as the production cost of hydrogen is very high and the amount of hydrogen in the atmosphere is limited. For this reason, most of the research work currently focuses on gasoline and electric combination.

Based on their power train configuration, there are three types of hybrid electric vehicles (HEV):

1. Parallel hybrid vehicle
2. Series hybrid vehicle
3. Power split or series-parallel hybrid vehicle

1.1.1 Parallel Hybrid vehicle

Among the three types of HEV, parallel hybrid vehicle is the most common. Both the internal combustion engine and the battery driven motor contribute in parallel to fulfill the driver’s torque demand. Depending on the driver’s torque demand, state of charge

of the battery and speed, one or more power source(s) contributes in supplying power. Parallel hybrid vehicle can operate in three modes: electric only mode, engine only mode, and combination of these two modes. The batteries are recharged by regenerative braking or by loading the electrically driven wheels during cruise.

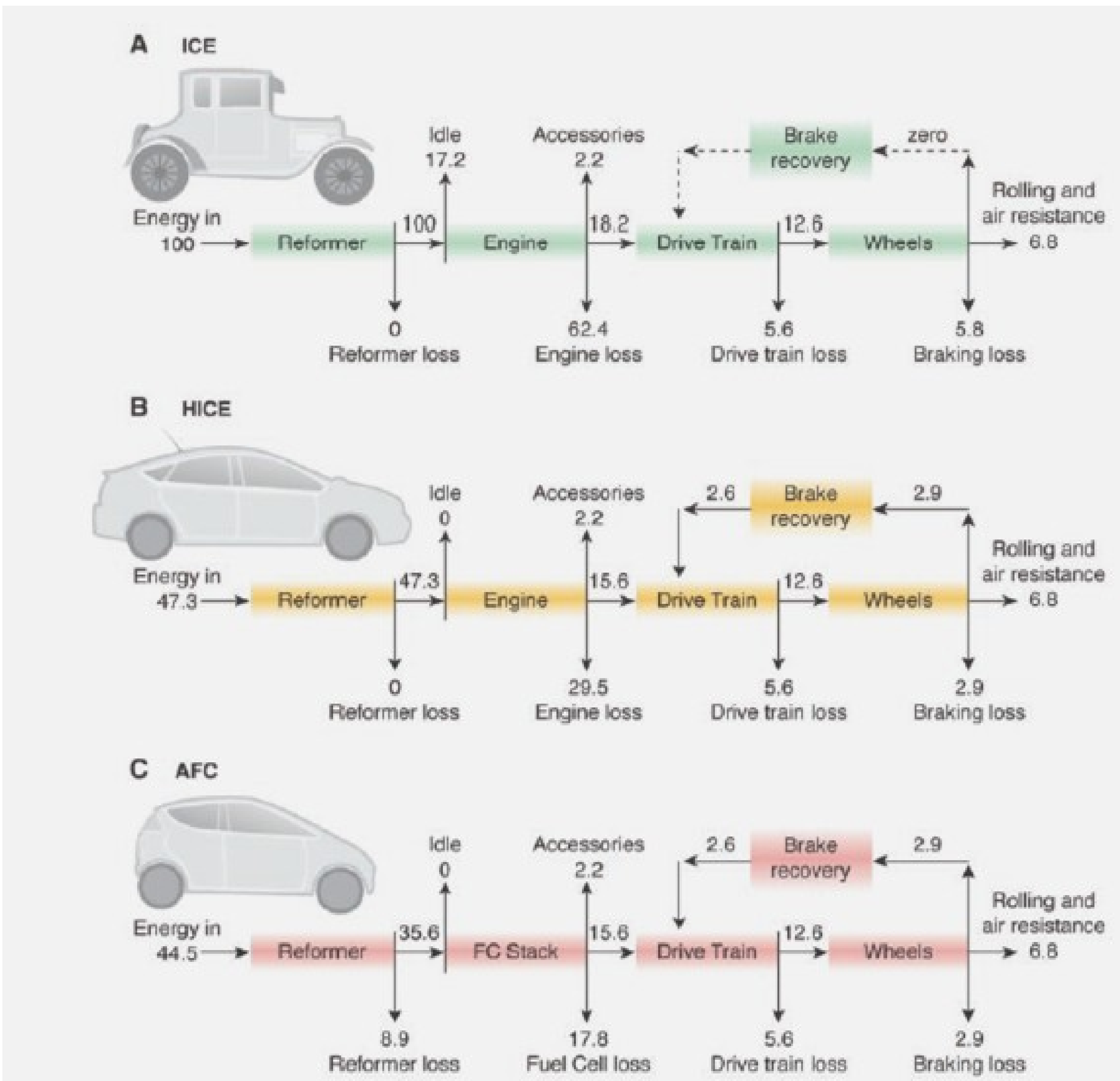

Figure 1.3 Comparison between different type of vehicle configurations, (a) Internal combustion engine drive vehicle, (b) Hybrid vehicle with parallel drive train and regenerative braking system, (c) Fuel cell vehicle with parallel drive train

Parallel hybrid vehicles are most efficient in highway driving compared to the urban stop and go conditions or city driving. Common examples of parallel hybrid vehicles are Honda's Insight, Civic and Accord. General motor's Parallel hybrid truck (PHT) and BAS Hybrids such as the Saturn VUE and Aura Greenline and Chevrolet Malibu hybrids follow the parallel architecture.

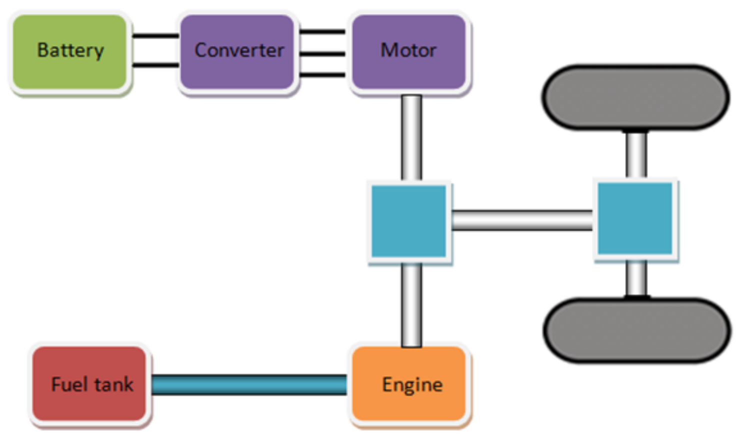

Figure 1.4 Power flow architecture of parallel hybrid vehicle.

1.1.2 Series Hybrid vehicle

The series hybrid vehicle may be considered as a pure electric vehicle where all the propulsion power comes from a battery operated electric motor. An internal combustion engine operated generator is used to recharge the battery. The internal combustion engine can be operated in a narrow bandwidth (higher speed and torque) high efficiency region. Since the efficiency of the electrical system (motor drive) is higher than the mechanical system (internal combustion engine) and the engine operates in high efficiency region, the overall efficiency of a series hybrid vehicle is higher than a parallel hybrid vehicle. The motor is capable of providing high torque over a wide speed

range and an additional gear box or CVT (continuous variable transmission) is not required. Further, this system doesn't face any type of cranking problem. Regenerative braking system is also used in series hybrid vehicle.

The main disadvantages of this configuration are that since the motor supplies total propulsion power in all situations, the motor as well the battery should comparatively large in size. An additional generator is needed to recharge the battery. Finally, the total power weight ratio is low for these vehicles. A significant amount of power is consumed in carrying the vehicle itself.

Some common examples of series hybrid vehicles include Toyota series hybrid bus (launched in Japan), city buses by Designline International of Ashburton, New Zealand which produces buses with a micro turbine powered series-hybrid system.

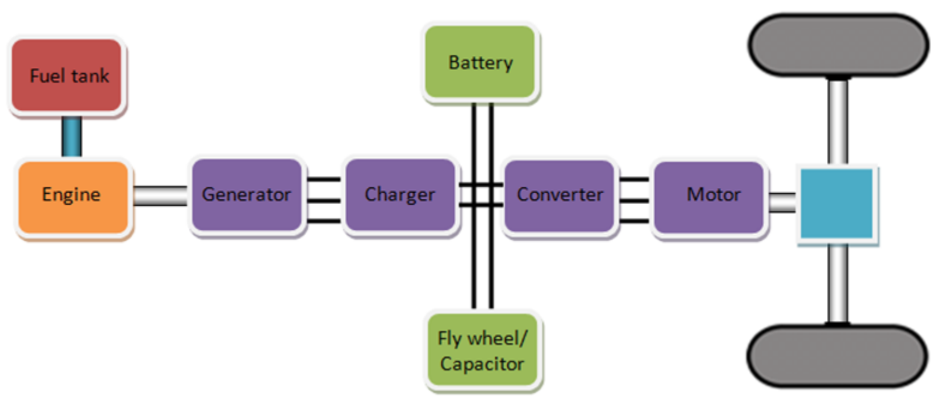

Figure 1.5 Power flow architecture of series hybrid vehicle.

1.1.3 Power split hybrid electric vehicle

Power split hybrid electric vehicle is a combination of series parallel hybrid propulsion configuration where both parallel and series propulsion systems can run individually. It can run in pure electric mode where the power goes directly from the electric motor to the wheel, parallel mode where both the engine and electric motor contribute in parallel, and the charging mode when the engine runs both the wheel as well the generator to recharge the battery. The most common driving configuration is the parallel mode.

In the parallel hybrid electric vehicle, the battery is charged through the engine. During braking the motor works like a generator and recharges the battery as well which is called regenerative braking. During braking, the regenerative braking system recovers energy from the vehicle and uses it to recharge the battery.

Some common examples of split hybrid vehicles are Toyota Prius, General Motors Two-Mode Hybrid full-size trucks and SUVs, the BMW X6 Active Hybrid, Chevrolet Tahoe Hybrid and the Mercedes ML 450 hybrid.

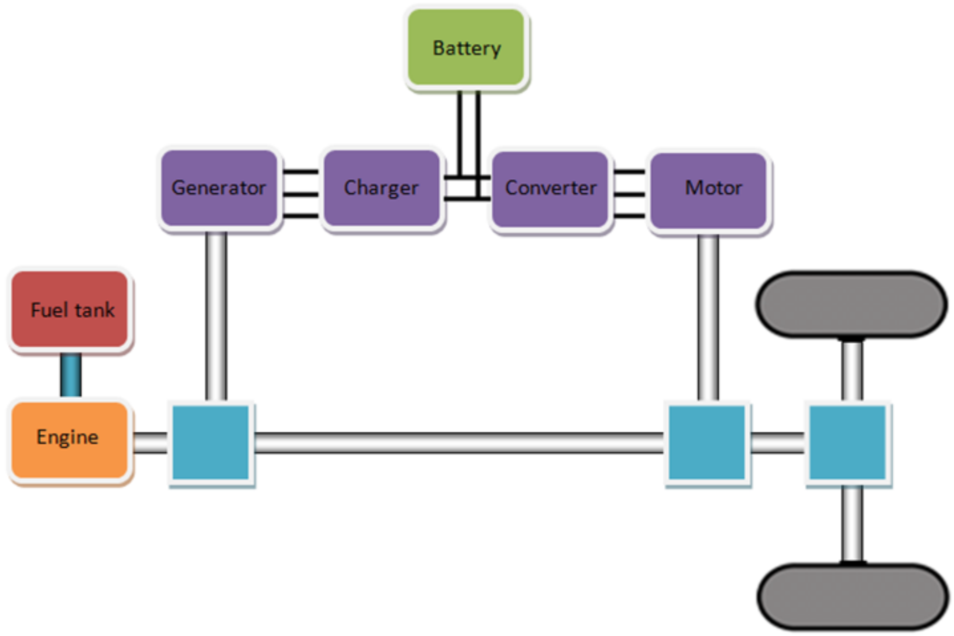

Figure 1.6 Power flow architecture of power split hybrid vehicle.

From the previous definition of the parallel hybrid electric vehicle, it is known that driver's demand power is met from two sources, the internal combustion engine and the electric motor. The most challenging part is to distribute the driver's total power demand between the internal combustion engine and the electric motor. Researchers are working continuously to find out the optimal solution by considering the total driver's total power demand, SOC of the battery, and the vehicle speed. The overall objective function is to minimize the total amount of fuel consumption and vehicle emissions.

1.2 Literature Review

In the last couple of years, a lot of research has been done on the development of energy management systems for parallel hybrid vehicles. The research has focused on

different types of optimization procedures to determine how much power should be supplied by the ICE and how much power is supplied by the electrical system.

Naderi et al. (2008) used a fuzzy logic algorithm for a parallel hybrid vehicle and evaluated its performance by forward simulation. A seven degree of freedom model was developed to simulate the dynamic behavior of the vehicle. A model for the engine gear box, clutch, and differential electric machine was also developed and a comparison was made between the authors' results and those obtained using one degree of freedom model in ADVISOR vehicle simulation software. However, it should be kept in mind that the real plant often exhibits a behavior different than the analytical model.

Mohebbi and Farrokhi (2007) used a neural network based adaptive control method for parallel hybrid electric vehicle. The controller can maximize the output torque of the engine and minimize the fuel consumption. The input variables to the controller are SOC of the battery and driver torque demand and the output variable is the throttle angle. For vehicle simulation, the ADVISOR vehicle simulation software was used and showed better performance than the default controller. However, more input and output variables can be added to the model for better description of the plant and efficient control.

Kessels et al. (2008) used the online energy management strategy for hybrid electric vehicles. An online optimal solution is almost impossible to obtain as it needs high computational power and knowledge about future power demand. A new methodology has been applied that concentrates more on immediately revealing physical phenomena

of the vehicle rather than any type of priori information about the input variables. Fuzzy logic, neural network, dynamic programming all needs prior information about different driving conditions and the required action. The authors showed that the fuel economy from proposed approach is nearly the same as that obtained using dynamic programming.

Xia and Langlois (2010) used optimized fuzzy logic controller to minimize the fuel consumption and emissions. For training of the fuzzy rules, a neuro-fuzzy approach has been used. The SOC of the battery and driver torque demand are considered as the input variables to the fuzzy logic controller. Data for training the fuzzy inference system and fuzzy membership functions are collected from the ADVISOR software. Modified data is used for the training the adaptive neural-fuzzy inference system (ANFIS).

Bin et al. (2009) applied spatial domain dynamic programming (DP) to get the optimum solution for a given drive cycle. The traffic data and the route information were used for predicting the driver torque demand. The proposed controller gives a solution near the optimum solution. Precise vehicle model is essential for using dynamic programming as well it will work efficiently on the predefined drive cycle only.

Borhan et al. (2009) used the model predictive control approach for energy management of power split hybrid electric vehicle which is adaptive in nature, as the modeling of the power split hybrid vehicle is very complex and the performance of the nonlinear optimization problem is a function of the model. They formulate optimization

problem with nonlinear objective function and constraints. Both the objective function and constraints are linearized in each sample time to obtain the optimum solution.

Bahar et al. (2009) developed a fuzzy logic based control strategy for a parallel hybrid vehicle. The difference between the vehicle speed and engine speed, battery SOC has been used as the input to the fuzzy logic controller. They developed their own vehicle model. The model specifications, however, are not given. They did not also mention the resulting fuel economy of the vehicle.

Majdi et al. (2009) developed a control strategy based on fuzzy logic control and used an analytical model for simulation. They considered the SOC of the battery, vehicle velocity and acceleration as the input variables and the engine power and motor power as the output variables of the fuzzy logic controller. They did not include the driver power demand or torque demand into the fuzzy logic controller. Analytical model based controller often gives better results during simulation, but exhibits different behavior in real cases.

Nejhad and Asaei (2010) developed genetic algorithm tuned fuzzy membership function based fuzzy logic controller. The solution approach involved converting the whole problem as an optimization problem. Next, the fuzzy logic controller was used to solve the optimization problem. The SOC of the battery and the required torque are considered as the input to the fuzzy logic controller, the engine torque is the output variable. Fuzzy membership functions are kept constant and the rule base was tuned for individual standard driving cycles with the help of genetic algorithm.

Ngo et al. (2010) developed an optimal control algorithm for hybrid electric vehicle by using appropriate information (speed limit, traffic condition) from the global positioning system and geographical information data. A combination of dynamic programming and classical optimal theory is used to solve the optimization problem. The route length, target time for travelling the distance as well as maximum and minimum speed for the specific route is considered as known, the controller will determine the appropriate speed of the vehicle so that the fuel consumption is minimized. Their solution modified the driving profile (speed profile) in order to get the optimum solution, which destroys the drivability of the vehicle.

Boyali and Guvenc (2010) designed a neuro-dynamic programming based real time controller for a parallel hybrid electric vehicle. Dynamic programming cannot be used in real time application because it needs apriori information and higher computational time. For this purpose, an artificial neural network was developed and trained by using the data from the dynamic program’s output. A significant improvement in fuel economy was shown.

Xu et al. (2010) proposed a control strategy based on fuzzy logic for controlling parallel hybrid electric vehicle. Driver torque demand, battery SOC is considered as the input to the fuzzy logic controller where engine torque and motor torque are considered as the output of the fuzzy logic controller. For simulation, the ADVISOR software was used.

Li et al. (2011) used HES-NSGA-II (a modified version of genetic algorithm) for solving a multi objective problem for parallel hybrid electric vehicles where the objective is to

reduce the fuel consumption and emissions. The constraints are SOC balance and the automobile dynamic quantities that include acceleration time. Acceleration time is typically used to measure the performance of an automobile. A better fuel economy was achieved without sacrificing the performance of the vehicle.

Zhu and Yang (2012) developed a fuzzy logic based control strategy for parallel hybrid vehicle by targeting minimum fuel consumption and minimum emissions. The main function of the fuzzy logic controller is to distribute the total power demand between the internal combustion engine and the electric motor by considering the wheel torque demand and the SOC of the battery. The main limitation of this work is the use of a simplistic model with body chassis wheel considered as a rigid body. There are no details provided on braking action, especially regenerative braking. No details are given on the components like the motor and the engine, except their description. The results show maximum motor torque demand is as high as 500 Nm. For supplying this amount of torque, the motor should be very big and it will reduce the power weight ratio below that of a conventional hybrid vehicle. Altogether, the whole model is too far from reality.

Kim et al. (2011) proposed a real-time optimal control strategy for power split hybrid electric vehicle based on Pontryagin’s minimum principle. In static simulation, the result was found to be very close to that obtained using dynamic programming. The Pontryagin’s minimum principle based solution was developed by targeting the analytical model of the vehicle. In real case, model parameters change with the road

conditions, number of passengers, weather, etc. For such real world situations, the model based controller often showed different behavior than the simulation.

A review of the above mentioned literature has revealed the following:

Most of the research has been done by considering the analytical models of the vehicle. Algorithms or controllers developed using analytical models often show different behavior in real cases. Some researchers have used dynamic programming method for solving the optimization problem in real time. For using dynamic programming method, prior knowledge about the trip is required. If dynamic programming solution is developed by considering a specific route, then the algorithm will work efficiently on that target route only. Some research work has been done by combining the geographical information and global positioning system data with dynamic programming. However, geographical information data is not available for all areas. Also, processing with dynamic programming takes a long time which makes a real time implementation quite challenging. Some researchers used SOC of the battery, driver torque demand as the input variable, some used vehicle speed, SOC as input variables; often two variables among three quantities is not enough to describe the state of the vehicle. The engine speed, which has not been considered as input variable in any work, may play an important role compared the vehicle speed. Neuro fuzzy and genetic fuzzy approaches have been used by some researchers for solving the optimization problem. Training the fuzzy rules using neural network requires a huge amount of data in order to work efficiently for all conditions.

To overcome these shortcomings, this thesis addresses the modeling problem by using highly reliable and accurate models provided by the Argonne National Laboratory in the AUTONOMIE software. All the models are based on look up table created by using data from real vehicles. In order to make the system efficient in all situations, expert knowledge has been gathered and transferred into the controller. Since a vehicle expert can make decision based on input output, if we can transfer expert's knowledge, the vehicle should be able to mimic the expert's behavior. This process of transferring human knowledge to machine knowledge is called artificial intelligence. Fuzzy logic algorithm is a popular approach for designing intelligent systems. For developing a fuzzy logic based system, one does not need huge amounts of data for training the system, all that is needed is capturing the expert's knowledge. Two fuzzy logic controllers have been developed in this work. The first one is for a plug in hybrid vehicle wherein the battery will able to recharge directly from the electrical power grid. The second controller is developed by considering that the battery will never recharge from the electrical power grid, instead the engine will recharge the battery. The engine speed, SOC of the battery and the driver's demand torque have used as the input variables for the controller and engine torque demand, motor torque demand are the output variables of the controller. The expert's knowledge has been gathered and converted into the fuzzy rule base. As the results will show later, in both cases, the developed controller shows better performance and fuel economy compared to the default controller available in the AUTONOMIE software. By using the fuzzy logic controller, the engine operated in more efficient region of the engine efficiency curve and the battery

maintained a better SOC. Finally the proposed controller yields a better fuel economy than the default controller.

1.3 Thesis organization

The remaining chapters of the thesis discuss the development of a fuzzy logic controller for better fuel economy and improved overall performance. Chapter 2 discusses the modeling of hybrid vehicles. An accurate and reliable model is a prerequisite for the development of a high performance controller. All the components of the vehicle are interconnected and have an effect on the fuel economy. The environment also has a significant impact on the overall performance of the vehicle. So, all problem aspects should be considered in the modeling.

Chapter 3 includes details about the fuzzy logic controller. For the development of fuzzy controller or fuzzy expert system, detailed knowledge about the structure of the fuzzy logic system, selection of fuzzy input output variables, fuzzy sets, fuzzification, fuzzy inference system, defuzzification are essential. A step by step development of the fuzzy logic controller is discussed in this chapter. Two fuzzy logic controllers have been developed; one by considering the vehicle as plug in parallel hybrid vehicle and another one by considering the vehicle as normal parallel hybrid vehicle.

Chapter four discusses the simulation of the overall system and presents numerical results. Simulation parameters such as the step size of the integration, method of integration etc. are included in this chapter. The influence of model vehicle parameters such as the weight of the vehicle, air temperature, humidity, pressure is discussed.

Finally, the simulation results are also presented in this chapter. The results from two different designs are compared. The results show that for both controllers, the system gives better fuel economy and a better overall performance.

Lastly, chapter five presents main findings of this research and scope for further improvements in this work.

Chapter 2

VEHICLE MODELING

In a parallel hybrid electric vehicle, the driving power comes from both the internal combustion engine (ICE) and the battery operated electric motor. The engine and the battery work together as a power source; the power flows through the clutch, gear box, wheel drive and finally to the sink, the driven wheel (see Fig. 2.1). The efficiency of the parallel configuration is solely a function of the distribution of the total power demand between the ICE and the battery driven motor. In order to develop a new controller and to evaluate its performance, an accurate and reliable model of the vehicle is required. For implementing and testing of the fuzzy logic based controller proposed herein, a realistic model of the parallel hybrid vehicle is needed. The model is selected using the AUTONOMIE software. AUTONOMIE is vehicle simulation software developed by the Argonne National Laboratory. Its key features are given below:

1. The software is plug and play.
2. It allows for model data customization.
3. It also allows for power train configuration customization.
4. It has an easy to use graphical user interface.

AUTONOMIE software has recently been used for

1. Evaluating fuel consumption
2. Fuel economy, emissions, and vehicle drivability
3. Simulation of a single component

4. Simulation of a component in loop
5. Software in loop, and
6. Hardware in loop.

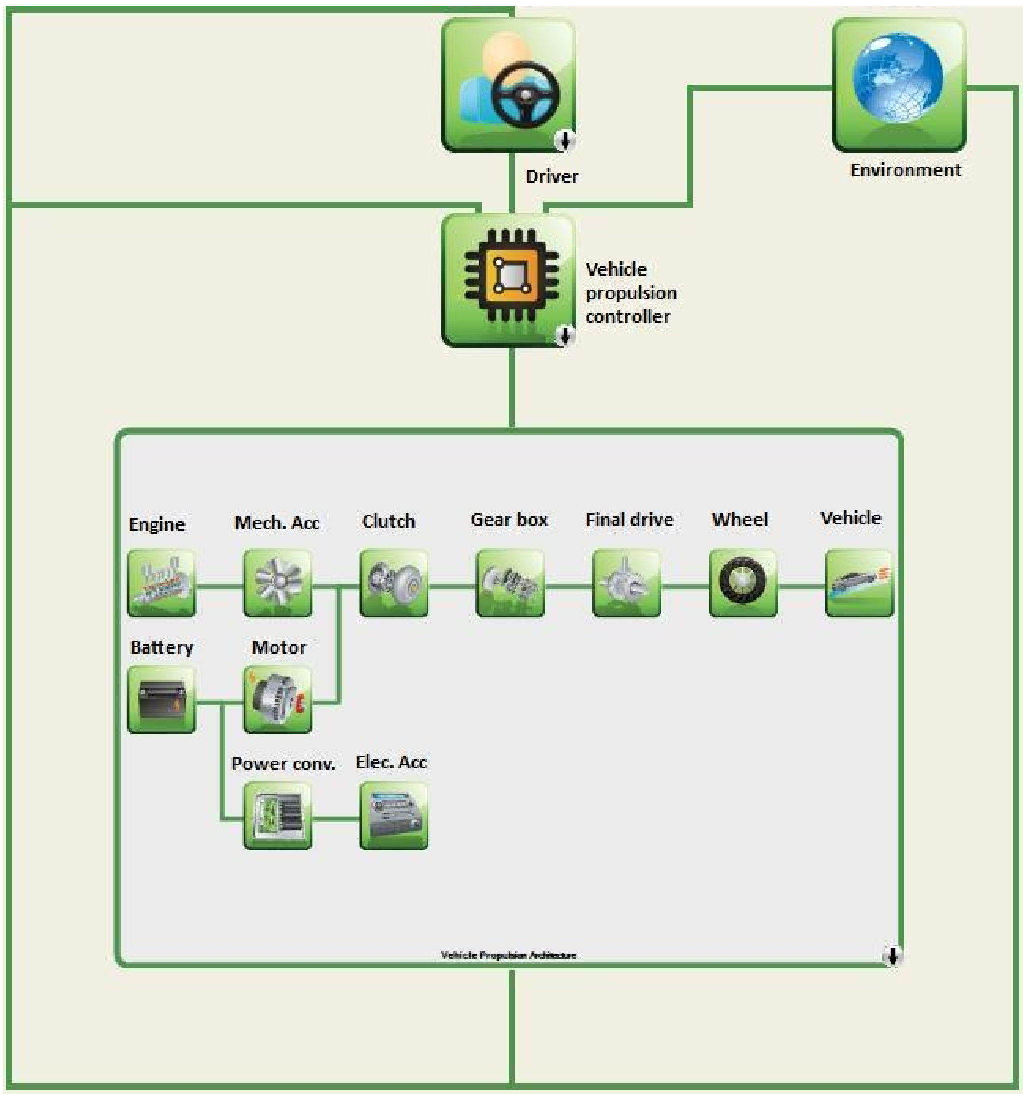

Figure 2.1 Parallel hybrid vehicle's energy flow diagram.

A detailed description of the components of the selected base vehicle is given next. These were used in a mathematical model for the whole vehicle.

2.1 Engine

The engine can be defined using a mathematical model or as a lookup table that provides the requested torque from the vehicle propulsion controller. The main function of engine is to produce mechanical energy from chemical energy stored in the fuel. Other outputs associated with the engine are fuel consumption rate and emissions, engine temperature.

Figure 2.2 ECOTECH GM family II engine.

Environmental factors (effect of air temperature, humidity) as well the engine losses (thermal loss and friction losses) are also included in the engine model. For controlling the engine, a separate engine controller has been used in the AUTONOMIE vehicle model; it maintains the desired torque and speed. For this simulation, the engine model is based on real data based look up table; all the data is collected from the ECOTECH GM family II engine (see Fig. 2.2). Both engine hot maps and cold maps are used. Some key features of the selected engine are given below:

1. SIDI (Spark Ignition Direct Injection)
2. Cylinder volume: 2200 cc
3. Number of cylinders: 4
4. Maximum power: 110 KWatt
5. Minimum speed for starting: 10 rad/sec

The torque-speed-efficiency map of the engine is given in Fig. 2.3 below.

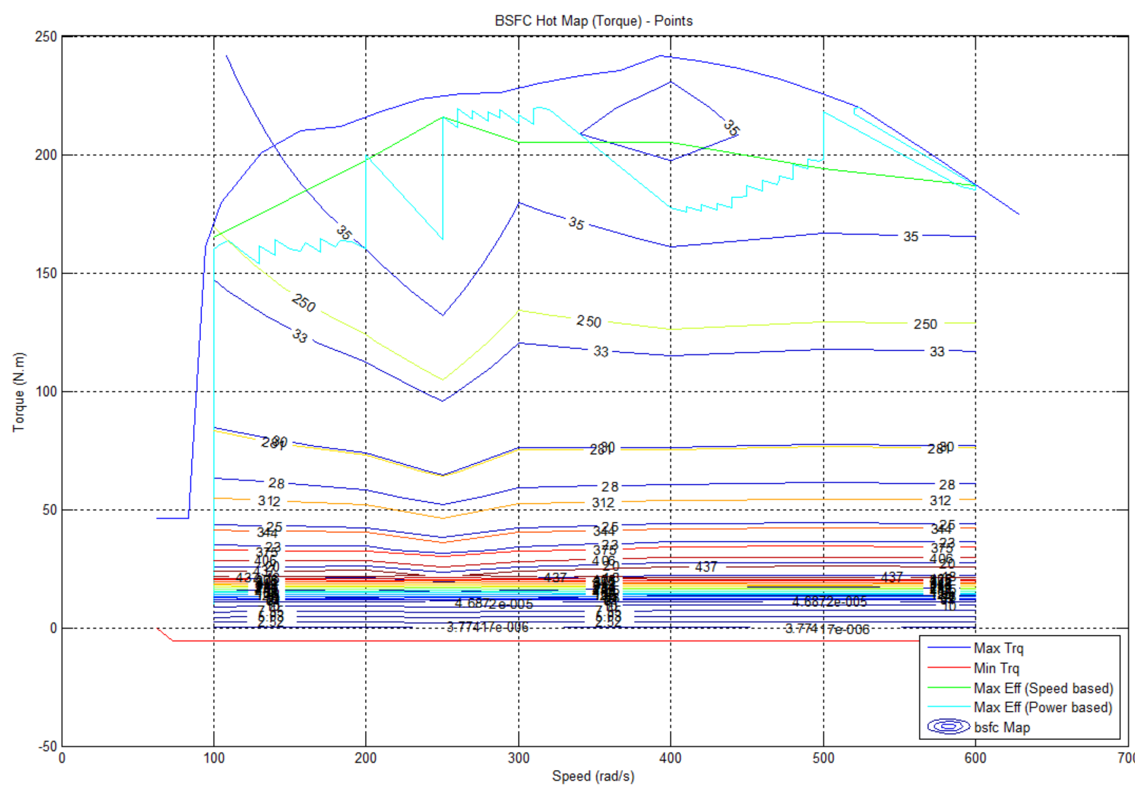

Figure 2.3 Engine efficiency map.

2.2 Mechanical accessories

The mechanical accessories help bring the mechanical losses under consideration. The energy losses due to a mechanical component are subtracted from the power stream. In the base model vehicle, some mechanical accessories are considered present between the engine and the automatic clutch. The mass of the mechanical accessories is 35 kg.

2.3 Battery model

A battery is a device that converts stored chemical energy into electrical energy. It consists of single or multiple electrochemical cells. There are two types of battery: primary battery (disposable) and secondary battery (rechargeable). The battery model is based on the look up table created from the real battery manufactured by the Saftbatteries. It is a Li-ion technology battery with following specifications: Total number of cell in the battery is 75, Maximum cell voltage is 3.6 volts, minimum cell voltage is 3.2 volts, and nominal cell voltage is 3.4 volts. The number of cell in series is 75, with total capacity of the battery of 555 Amp-hr and Open circuit output voltage of 255 volts.

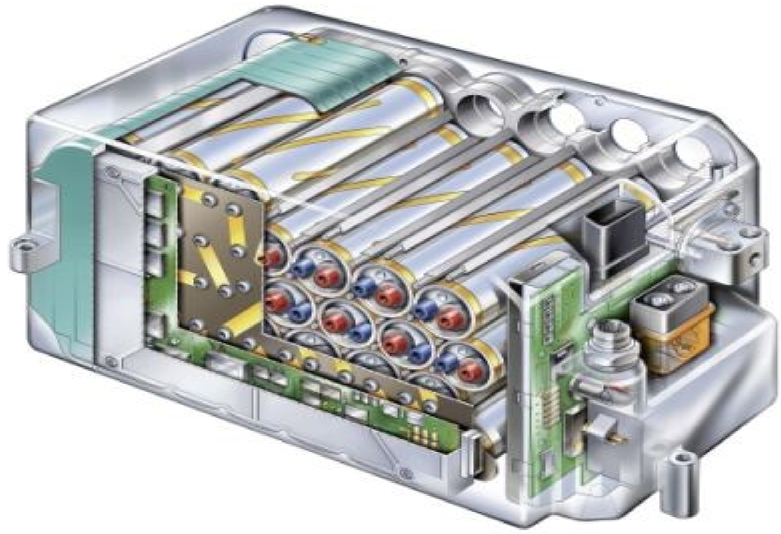

Figure 2.4 Internal architecture of the battery

2.4 Automatic Clutch

The model of an automatic clutch or a centrifugal clutch is defined as a system that transmits power from the input side to the output side based on the input torque and input-output speed difference. The transmitted amount may be zero, a partial value or the full amount. If the produced torque and the speed from the input side are higher than a threshold value, then the clutch is automatically engaged with the output side. However, if the torque and speed values fall below the threshold, the output is disengaged from the input.

In the model vehicle used, the clutch's maximum capacity is 150 Nm. The required speed difference between two shafts for locking is 40 rad/sec. The mass of the system is 25 kg. A lookup table is used to determine the percent of engagement based on the turbine speed, impeller speed, and the output torque.

2.5 Gear box model

The gear box may be defined as an assembly of parts that is capable of multiplication of torque or division of speed based on the command from the vehicle propulsion controller. The gear box controlling command may be manual (control commands from the driver) or automatic. The gear box model simulates these behaviors.

In the base vehicle, a model of five speed automatic gear box has been used. All the real data are collected from the five speed automatic transmission of Honda Accord. With the help of this data lookup, tables are made to simulate the real gear box and its efficiency. The total mass of the gear box is 75 kg. The gear shifting time is 0.6 second and the five gear ratios are 2.563, 1.552, 1.022, 0.727 and 0.52. An additional controller is used to control the gear box.

2.6 The final drive

The final wheel drive or the differential is used to connect the gear box with the wheels. In the final drive, three shafts work together where one is input and other two are output. The differential allows two output shafts to rotate at two different speeds which are essential for turning a vehicle. The mathematical model of the differential or the final drive is

$$\boldsymbol{a} = (\boldsymbol{p} * \boldsymbol{b} + \boldsymbol{q} * \boldsymbol{c}) \tag{2.1}$$

where, a, b, c are the angular velocity of three individual shafts. *a* is the input shaft and *b*, *c* are the angular velocity of the output shafts. Most often the value for p and q are same.

In the model vehicle, the final drive gear ratio is 4.438 and its mass is 25 kg. A lookup table has been used to calculate the efficiency of the final drive. The data for building the look up table is collected from the Honda Accord's final drive.

2.7 Wheel

The wheel is the final output component of the drive train. It converts rotational motion into linear motion. When a torque is applied, it rotates with a certain speed in order to advance the vehicle. The output speed and torque are determined by the vehicle's propulsion controller based on the driver power demand. The outer layer of the wheel is made of rubber. The rolling friction coefficient plays an important role in the wheel performance. The driving torque and the braking torque work individually on the wheels.

The wheel model in the base vehicle is based on the data collected from the real wheel of Honda Accord DX. The initial inertia per wheel is 1kg-m^2. The theoretical wheel radius is 0.317 m. Using a radius correction factor 0.95, the actual radius comes to 0.30115 m. The wheel mass is 30 kg and the maximum allowable braking torque is 2000 N-m. The rolling resistance is calculated by using a second order polynomial of speed. The three individual coefficients that have been used include:

Figure 2.4 Wheel

Coefficient of rolling

$$C_{r1} = 0.008,$$

$$C_{r2} = 0.00012$$

$$C_{r3} = 0.00$$

Rolling resistance

$$f_{rl} = C_{r1} + C_{r2} * W + C_{r3} * W^2 \quad (2.2)$$

2.8 Chassis

Vehicle body as well the internal structure for supporting the body is considered as chassis of the vehicle. In the model vehicle, the chassis mass is 990 kg. The chassis coefficient of drag C_D is considered 0.3. The vehicle's center of gravity is at a height 0.5

m. The front wheel weight ratio is 0.64, the cargo mass is 136 kg and the frontal area is 2.250 m^2.

2.9 Vehicle model

The vehicle model can be defined as a system where the summations of all acting forces are equal to zero. Aerodynamic resistance, rolling resistance, and grade resistance are included among these forces.

$$F = \left(m * a + R_a + R_{rl} + R_g\right) = 0 \tag{2.3}$$

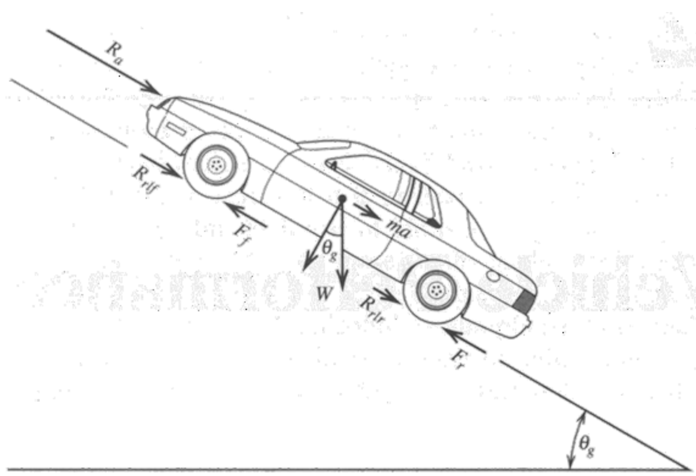

Figure 2.5 free body diagram of the vehicle

Resistance forces may be defined as the forces that impede the motion of the vehicle.

Aerodynamic resistance (R_a) includes turbulent air flow around the vehicle, friction of air over the vehicle body, and vehicle component resistance like the radiators and air vent.

$$R_a = \frac{\rho}{2} C_D A_f V^2 \tag{2.4}$$

where,

C_D Coefficient of drag

A_f Flow reference area (frontal area).

V vehicle speed.

The resistance from the tire is known as rolling resistance. The tire deformation, tire penetration into the surface, slippage affects the rolling resistance R_{rl}.

The rolling resistance can be simply approximated as:

$$R_{rl} = W * f_{rl} \tag{2.5}$$

$$f_{rl} = 0.01 * \left(1 + \frac{V}{147}\right) \tag{2.6}$$

Grade resistance R_g is the gravitational force acting on the vehicle.

$$R_g = W * sin\theta_g \tag{2.7}$$

For small angles, $\sin\theta \approx \tan\theta$

$$R_g = W * tan\theta_g \tag{2.8}$$

$$tan\theta_g = Grade \tag{2.9}$$

In Eq. (2.3), m is the mass of the total vehicle and a is the resulting acceleration of the vehicle.

2.10 Model of the Electric motor

The electric motor may be defined as a system that provides demand torque requested by the power train controller. Different types of losses are taken into account while defining the model. Two dimensional lookup tables have been used to calculate the losses and the output. The data is collected from the permanent magnet DC motor widely used in Honda Accord. Some specifications of the motor are given below:

1. Motor type: Permanent magnet DC motor
2. Continuous power: 7 kw
3. Peak power: 14.2 kw
4. Response time: 0.05 sec
5. Maximum torque: 140 Nm
6. Coefficient of regeneration: 1
7. Motor mass: 14.68 kg

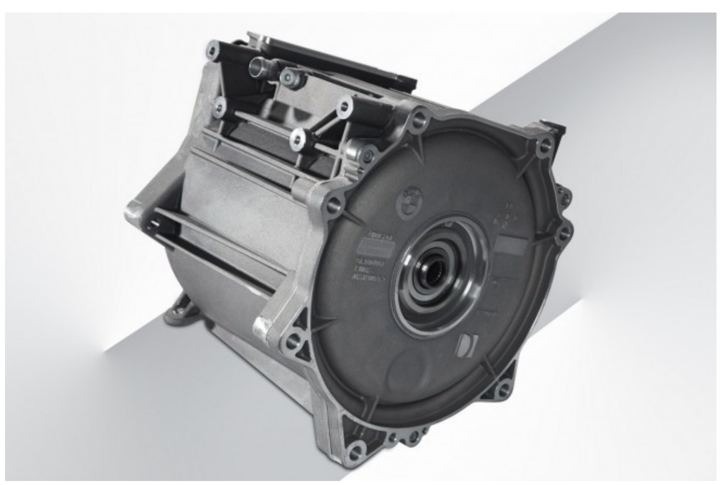

Figure 2.6 Permanent magnet DC motor.

The motor torque speed efficiency map is given in Fig. 2.7 below.

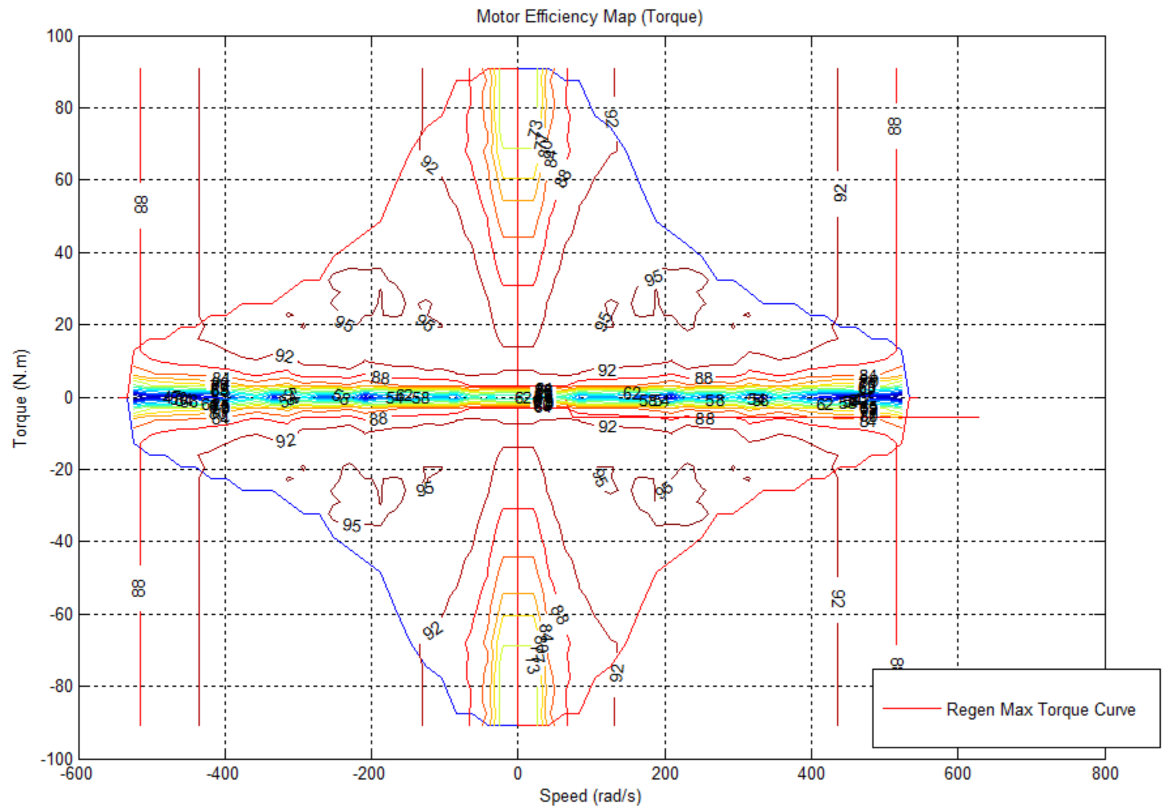

Figure 2.7 Motor efficiency map

2.11 Driver Block

The main function of the driver block is to simulate the driver's action over the driving cycle. For this simulation, since the selected vehicle is automatic in nature, it is assumed that the driver is driving an automatic vehicle. The driver block consists of a PI controller with proportional gain of 0.5 and the integral gain of 1000. The control variable is the speed of the vehicle. The response time of the driver is 0.2 seconds.

2.12 Environment Block

Environmental factors play an important role in engine performance. Ambient air temperature, air pressure, relative humidity, air density are related with the thermodynamic process occurring in the engine. For this simulation, the ambient air temperature is considered 20° C, the atmospheric air pressure is 1 bar. C_p of the air is 1009 J/kg K. Ambient air density 1.23 kg/m^3. Boltzman's constant 1.38×10^{-23} J/K. molecular weight of air is 28.97 g/mol.

2.13 Driving cycle

The driving cycle is a collection of data for representing the velocity profile versus time of a certain route. The velocity profile depends on several factors such as the traffic on the road, environmental factors like snow, wind speed, rain, road grade, road surface conditions etc. It has a strong relationship with the geographical location. As the velocity profile varies with the location, certain standards need to be followed for each area.

Driving cycle is used to determine the fuel consumption rate and emission of a vehicle with the help of dynamometer. Another important use of driving cycle is in vehicle modeling and simulation software for determining the fuel efficiency and emission, performance of the battery, transmission, performance of the fuel cell etc. Some standard driving cycles are EPA Federal test: Urban Dynamometer Driving Schedule (UDDS) drive cycle; FTP 72/75 (1978)/ SFTP US06/SC03 (2008) are used for representing the American Driving cycle. NEDC: ECE R15 (1970)/EUDC (1990) is widely used for simulating the European driving cycle.

UDDS cycle was introduced by the EPA for simulating the traffic in roads and highways in US urban areas. It is widely used for evaluating the performance of the vehicle on dynamometer testing. The velocity profile of the UDDS cycle is given in figure 2.8.

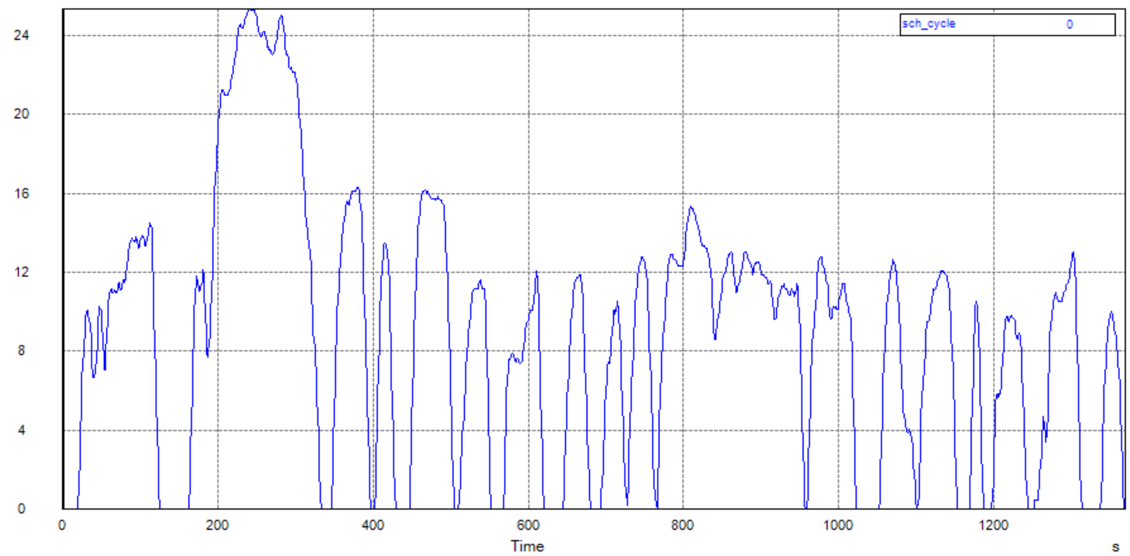

Figure 2.8 UDDS driving cycle.

The specifications for the UDDS cycle are given below:

Total duration: 8219 seconds

Total distance travelled: 44.27 miles

Maximum speed: 56.7 mph

Average speed: 19.58 mph

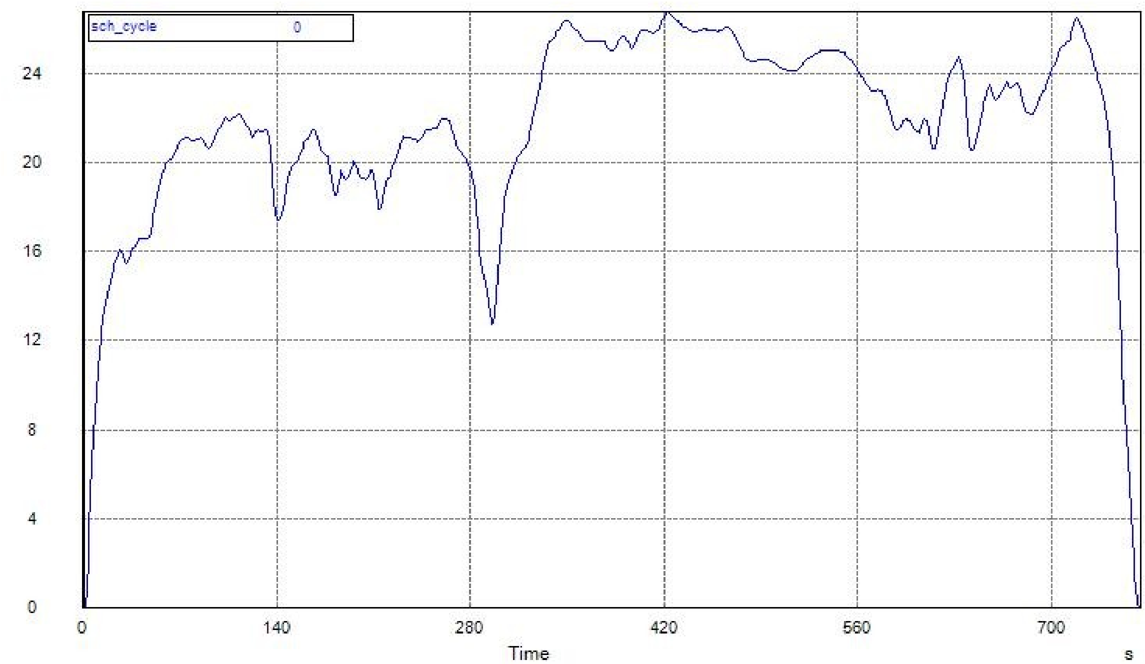

Figure 2.9 HWFET Cycle

FTP 75 (Federal test procedure) was established by the US Environmental Protection Agency to measure the fuel economy and emissions of passenger cars on US roads and highways. It was last modified in 2008; the modified version is known as HWFET (Highway Fuel Economy test). It consists of starting of a cold engine, a total 23 stops, and test duration of 31 minutes. The average speed is 32 km/hr. and the maximum speed is 90 km/hr. It consists of two phases; first phase is the “cold start” phase spans a total of 505 seconds over a distance 5.78 km with an average speed of 41.2 km/hr. The second phase, known as the “transient phase”, has duration of 864 seconds. The two phases are separated by a ten minutes stop.

The specifications of HWFET driving cycle is given below:

Starting condition: Warmed engine

Total duration: 765 seconds

Total travelled distance: 10.26 miles (16.451 km)

Average speed: 48.3 mile/hr (77.7 km/hr)

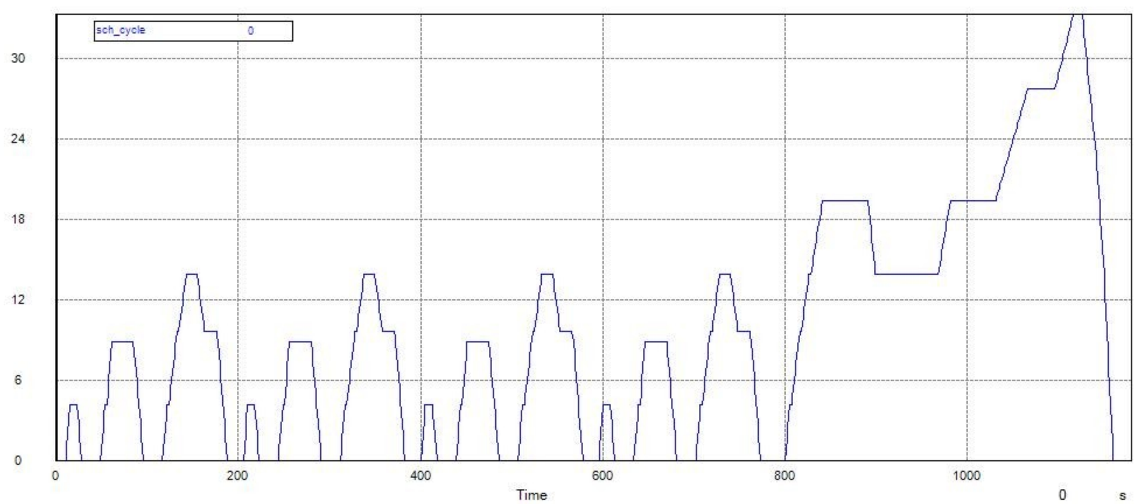

Figure 2.10 NEDC cycle

New European Driving cycle:

The New European Driving Cycle (NEDC) was first introduced by the Economic Commission of Europe. The main use of NEDC is to assess the fuel economy, emission of the passenger cars on European city roads and highways. It is also used for simulating the European drive cycle in vehicle simulation software. One modified version of NEDC cycle is EUDC (Extra Urban Driving Cycle) represents high speed driving condition. For the low power vehicle the speed is limited to as high as 90 km/hr. Four repeated urban driving cycles and one extra urban driving cycle make up the NEDC. The total length of

the cycle is 11023 meters and the total travel duration 1188 seconds. The average vehicle speed is 33.6 km/hr.

For simulation purposes in this thesis, the UDDS cycle is used to assess the controller performance.

Chapter 3

Fuzzy logic based controller

The conventional approaches for controller design and control algorithms is that they can be expressed in terms of some mathematical expressions and designed for controlling a mathematical model which mimics the behavior of the real plant. All the controller parameters are based on the physical requirements of the system. The whole procedure is called design of a model based control system. This approach provides excellent performance in simulation but a replication of this performance is not guaranteed on a real system. Most often, the model system performance is different from the actual requirements. It is very difficult and challenging to get an accurate analytical model of the plant as the plant parameters often vary with time and conditions. So, the controller cannot provide satisfactory results in real-life situations. It is proven that for medium and low speed systems (the system within the human control capacity limit), experienced human operator can control the system accurately and can handle all unfamiliar situations. This process is called man machine control system. The limitations of man machine control system are a human operator’s performance depends on several factors like health, mental condition, working time, fatigue etc. Often human can’t response quickly although solution is known. If it is possible to transfer human knowledge for controlling machine the above mentioned problem can be solved. The process of transferring human intelligence to machine intelligence is called artificial intelligence. There are several ways to give artificial intelligence to a

machine. Fuzzy logic is one popular method for imparting artificial intelligence to a machine.

Fuzzy set theory was first proposed by Zadeh (1965) in his seminal work "analysis of system based on the theory of fuzzy sets." Fuzzy logic, based on fuzzy sets, is a well-defined mathematical procedure to convert approximate human reasoning capabilities to a knowledge based system which is very precise and capable of responding quickly. For its functionality and high performance, nowadays, fuzzy logic is one of the well-established techniques for prediction, modeling and control.

Fuzzy logic based system are mostly suitable where the human operator or expert's well documented knowledge is available, the plant model is complex or unknown, system nonlinear , noisy sensor output, generic decision making problem in the presence of imprecise information.

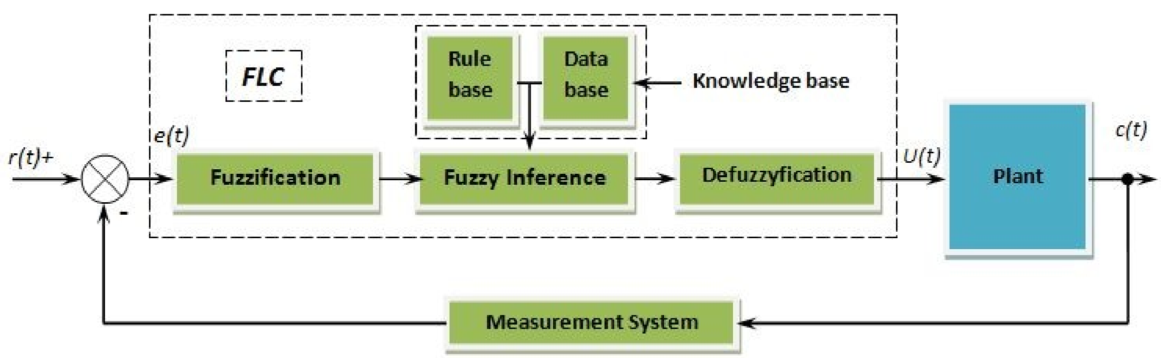

Figure 3.1 Block diagram of Fuzzy Logic Control System.

3.1 Fuzzy sets

A fuzzy set is a collection of objects with grade of membership. The first step in developing fuzzy system (fuzzy logic controller or fuzzy expert system) is to define fuzzy variables which will be represented using fuzzy sets. A fuzzy set is a collection of set of values related to fuzzy input. Each element in the fuzzy set has a degree of membership within the set. The membership value has limit between 0 to 100%. In comparison with the crisp set which has only two possible outcomes (0 or 1), the fuzzy set gives a degree of membership between 0 to 100%. Some of the most commonly used membership functions for fuzzy sets are symmetrical triangle, trapezoidal, Gaussians bell shaped curves, etc. Symmetrical triangular shape fuzzy sets are popular because they provide good results and computations using these shapes are simpler.

Two fuzzy logic controllers have been developed in this thesis. Each controller contains three input variables and two output variables. The first controller is developed by considering that the battery is able to recharge directly from the electrical power grid only. For the second controller, it is assumed that the engine will recharge the battery.

The input variables for the first fuzzy controller are given below:

1. Speed of the vehicle
2. Wheel torque demand
3. State of charge of the battery (SOC)

The input variables for the second fuzzy controller are:

1. Speed of the engine

2. Wheel torque demand

3. State of charge of the battery (SOC)

The output variables are common for both controllers and are given below

1. Motor torque demand (torque provided by the motor)

2. Engine torque demand (torque provided by the engine)

Individual membership functions based on the expert's knowledge have been defined for each input variable. Each membership function consists of some fuzzy sets. For example, according to the battery expert, if the state of charge of the battery is less than 40%, then it is considered to have a low SOC value. Low SOC is a fuzzy set, and low, medium and high SOC together represent the membership function for the battery state of charge. The battery SOC membership function is given in Fig. 3.2 below.

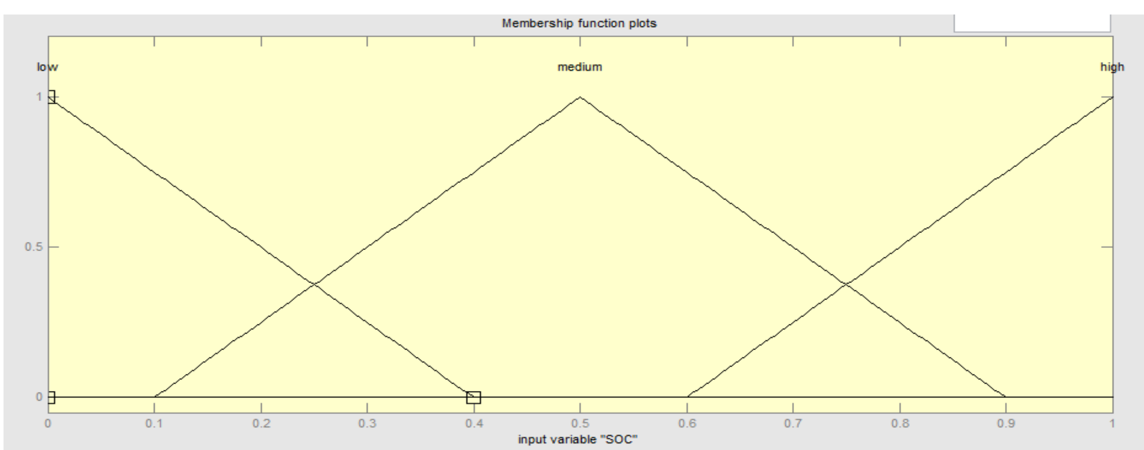

Figure 3.2 Membership function of Battery SOC.

The figures below depict the membership functions and fuzzy sets for input variables, namely, wheel equivalent torque demand (Fig. 3.3), vehicle speed (Fig. 3.4), and engine speed (Fig. 3.5).

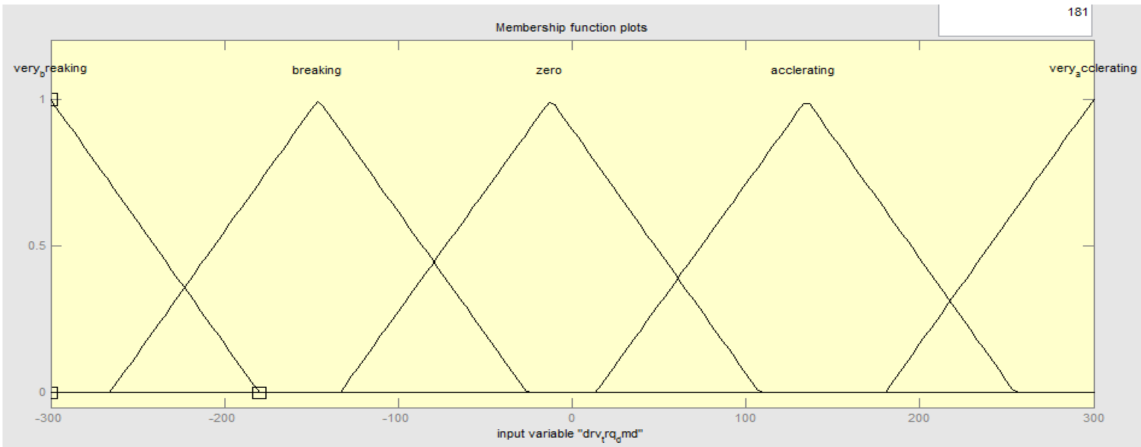

Figure 3.3 Membership functions of wheel equivalent torque demand.

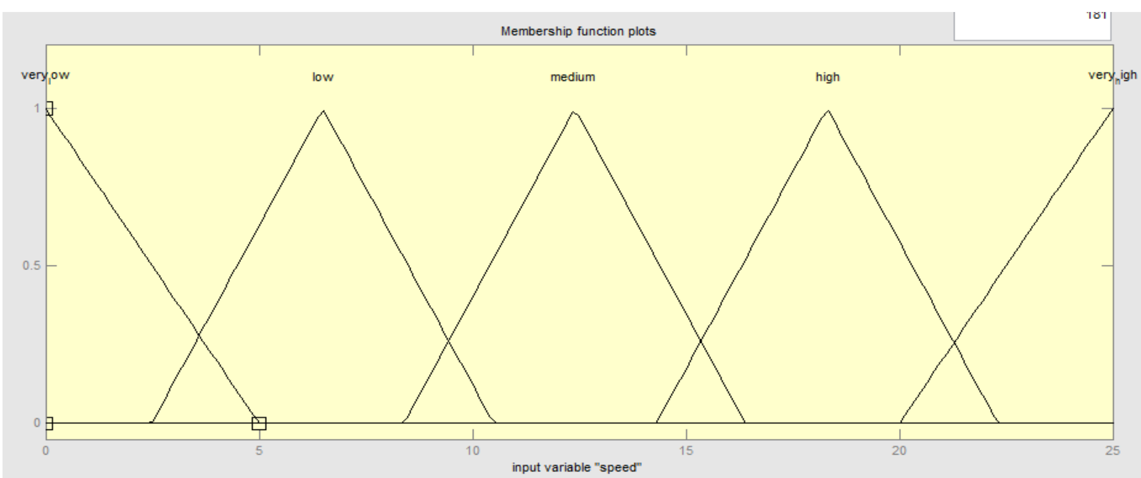

Figure 3.4 Membership functions of vehicle speed.

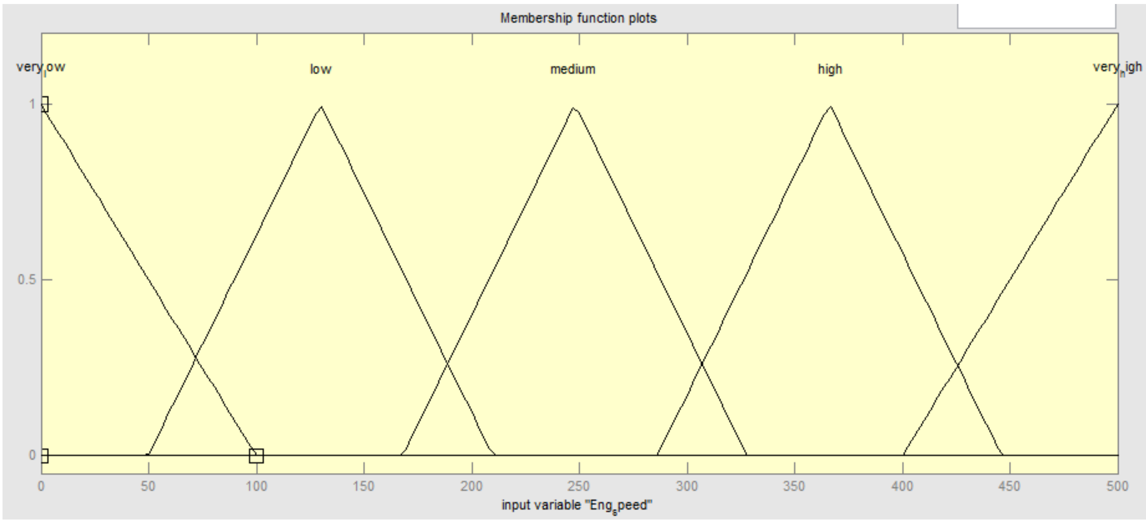

Figure 3.5 Membership functions of engine speed.

Output membership functions are necessary to convert the fuzzy output to crisp output. The membership functions of the two output variables, engine torque demand and motor torque demand, are given below.

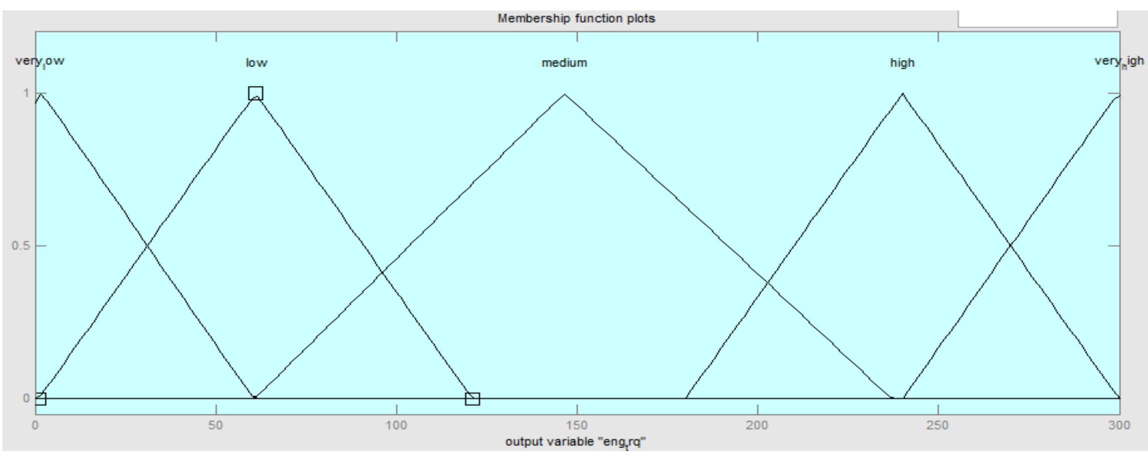

Figure 3.5 Membership functions of engine torque demand.

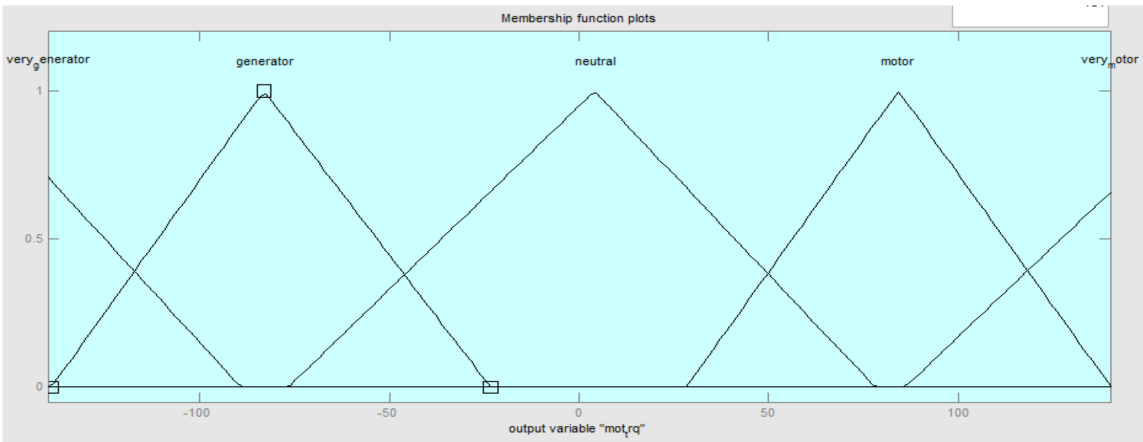

Figure 3.6 Membership functions of motor torque demand.

After defining the fuzzy sets, the next step is the fuzzification of the variables. Fuzzification is the process of mapping the input variables on the fuzzy membership function in order to determining the membership value for the specific input. For example, if at a particular instant the battery SOC is 0.33, then the membership value in low SOC values is μ_l=0.2 (Fig. 3.7) and in the set of medium SOC values, the membership value is μ_m=0.56.

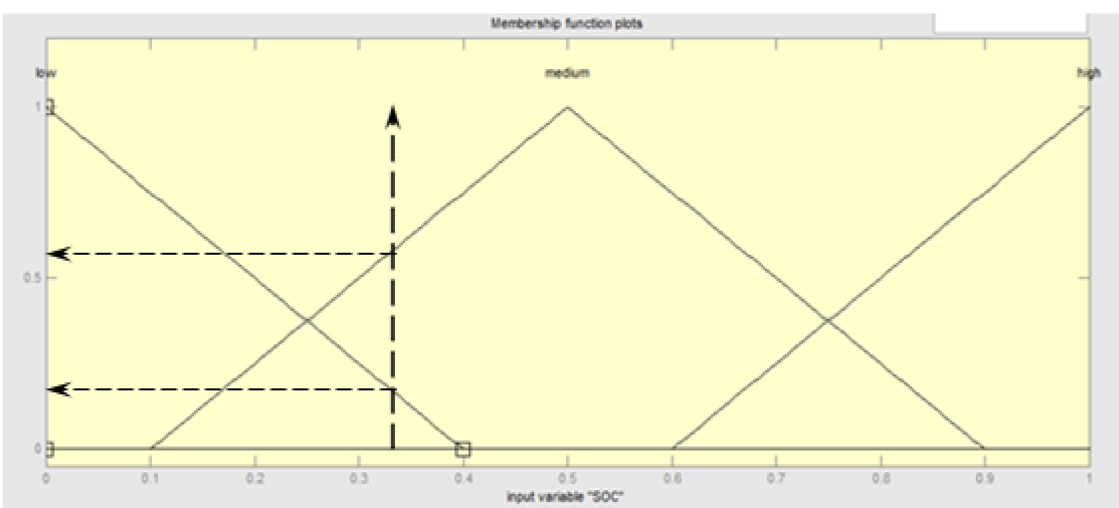

Figure 3.7 Fuzzification of battery SOC.

Similarly, let the equivalent wheel torque demand be -195 Nm. The membership value of this torque in sets "very braking" and "braking" are $\mu_{very\_braking}$ =0.22 and $\mu_{braking}$=0.5 (Fig. 3.8).

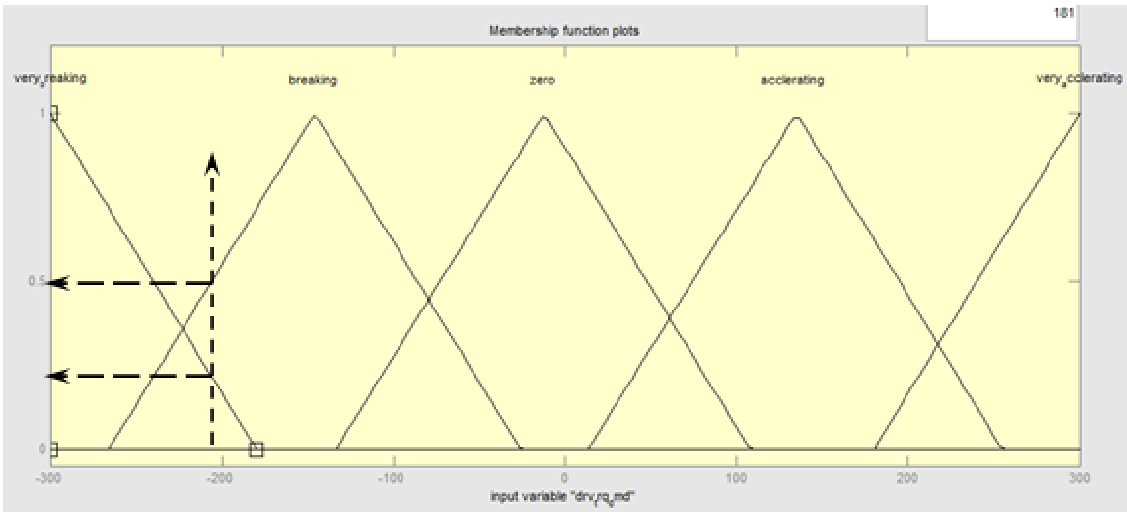

Figure 3.8 Fuzzification of equivalent wheel torque demand.

For example, when the input speed value is 10 m/s, the membership value in sets "medium" speed and "low" speed are μ_{medium}=0.45 and μ_{low}=0.05 (Fig. 3.9).

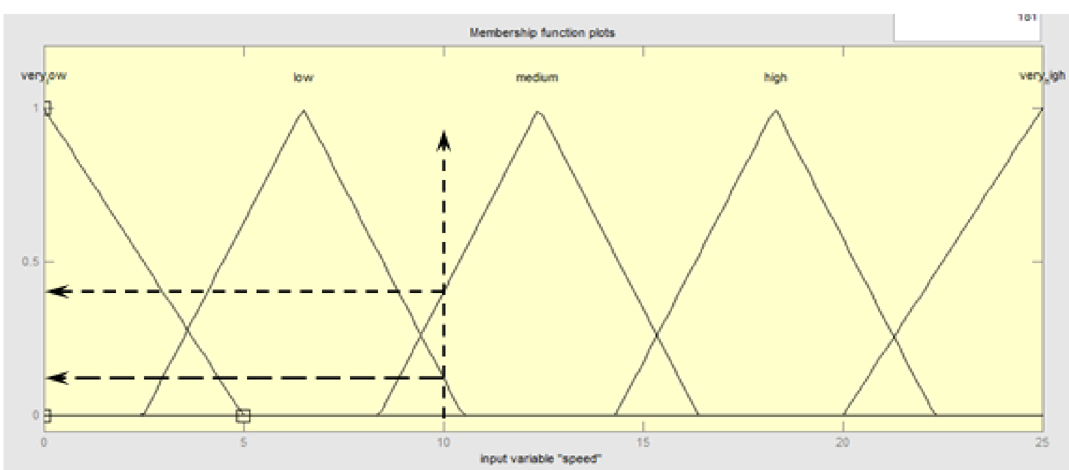

Figure: 3.9 Fuzzification of equivalent vehicle speed.

3.2 Fuzzy inference rule base

Fuzzy inference rule base consists of a set of antecedent-consequent linguistic rules relating system inputs and outputs using fuzzy sets. For example, a rule may be stated as

Rule 3: IF **SOC** *is* **HIGH** *and* **WHEEL TORQUE DEMAND** *is* **ACCELERATING** *and* **VEHICLE SPEED** *is* **LOW** *then* **MOTOR TORQUE** *is* **VERY HIGH** *and* **ENGINE TORQUE** *is* **HIGH.**

Rule 4: IF **SOC** *is* **LOW** *and* **WHEEL TORQUE DEMAND** *is* **ACCELERATING** *and* **ENGINE SPEED** *is* **LOW** *then* **MOTOR TORQUE** *is* **GENERATOR** *and* **ENGINE TORQUE** *is* **VERY HIGH.**

For the proposed fuzzy logic based controllers, 75 rules have been defined for each controller and are given in appendix B.

3.2.1 Determining the firing strength

After defining the rule base, the next step is to determine the firing strength of each rule. After fuzzification process, every input comes with certain membership of the fuzzy set. Suppose for controller 1, the value for the value of SOC of the battery is 33%, driver torque demand -195 Nm and the vehicle speed is 10 m/s. For this input values the corresponding memberships are given below.

Table 3.1 Input variables with fuzzy degree membership function

Input variables	**Membership function**
SOC of the battery 33%	$\mu_{low\ batt.} = 0.20$
	$\mu_{medium\ batt.} = 0.56$
Vehicle speed 10 m/s	$\mu_{low\ speed} = 0.20$
	$\mu_{medium\ speed} = 0.45$
Driver torque demand -195 Nm	$\mu_{braking} = 0.50$
	$\mu_{very\ braking} = 0.22$

From the fuzzy rule base it is defined that

IF **SOC** *is* **LOW** *and* **WHEEL TORQUE DEMAND** *is* **BRAKING** *and* **VEHICLE SPEED** *is* **LOW** *then* **MOTOR TORQUE** *is* **GENERATOR** *and* **ENGINE TORQUE** *is* **MEDIUM**

As the "and" operation is equivalent to the minimum of all membership so,

$$\boldsymbol{\mu_{low\ batt.}\ and\ \mu_{low\ speed}\ and\ \mu_{braking.} = min\left(\mu_{low\ batt.}, \mu_{low\ speed}, \mu_{braking.}\right)}$$

$$= \boldsymbol{min(0.20, 0.20, 0.50)}$$

So, the firing strength of the rule is 0.2

IF **SOC** *is* **MEDIUM** *and* **WHEEL TORQUE DEMAND** *is* **VERY BRAKING** *and* **VEHICLE SPEED** *is* **MEDIUM** *then* **MOTOR TORQUE** *is* **VERY GENERATOR** *and* **ENGINE TORQUE** *is* **LOW**

$$\boldsymbol{\mu_{medium\ batt.}\ and\ \mu_{medium\ speed}\ and\ \mu_{very\ braking.}}$$

$$= \boldsymbol{min}\left(\boldsymbol{\mu_{medium\ batt.}, \mu_{medium\ speed}, \mu_{very\ braking.}}\right)$$

$$= \boldsymbol{min(0.56, 0.45, 0.22)}$$

So, the firing strength of the rule 2 is 0.22

The combined strength of $\mu_{low\ batt.}\ and\ \mu_{low\ speed}\ and\ \mu_{braking.} = 0.20$

and

$\mu_{medium\ batt.}\ and\ \mu_{medium\ speed}\ and\ \mu_{very\ braking.} = 0.22$ will be used for the defuzzification process.

3.2.2 Defuzzification

Defuzzification is the process of mapping a set of inferred fuzzy input values on the fuzzy output membership function in order to get crisp output value. Some common methods of defuzzification are COG (center of gravity), FM (fuzzy mean), FOM (first of maximum), LOM (last of maximum), MEOM (mean of maxima), MOM (middle of maximum)

Among different methods, the center of area method is one of the popular defuzzification methods because of its performance and simplicity in calculation.

$$\text{Crisp control signal} = \frac{Sum\ of\ first\ moments\ of\ area}{Sum\ of\ areas}$$

$$Z_{COA} = \frac{\int_Z \mu_A(Z) Z dZ}{\int_Z \mu_A(Z) dZ}$$

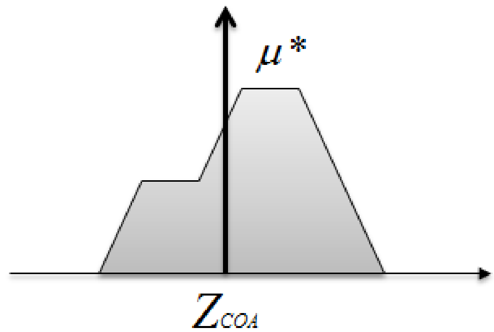

Figure 3.10 Center of area defuzzification method

Smallest of Maxima defuzzification method has been used for both controllers.

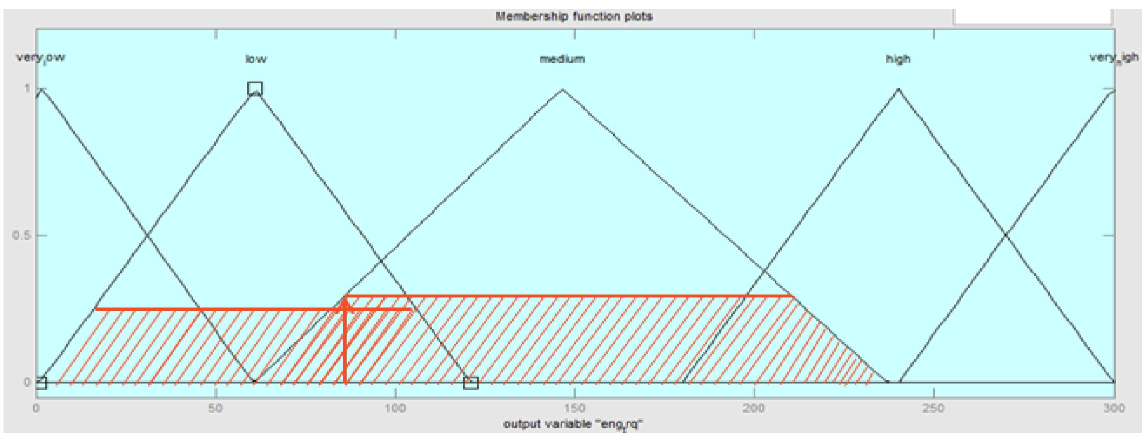

Figure 3.11 Smallest of maxima defuzzification method for engine output torque

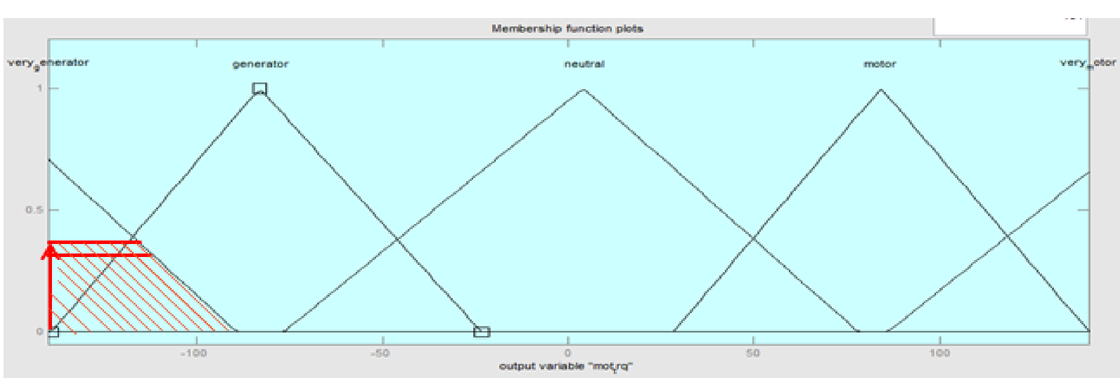

Figure 3.12 Smallest of maxima defuzzification method for motor output torque

Suppose from the rule base two rules fired, 1st engine speed low 0.33 and engine speed medium 0.84, then according to the SOM defuzzification method the output crisp value will μ^{*}

The resultant engine torque and motor torque for both controllers under different conditions are given below.

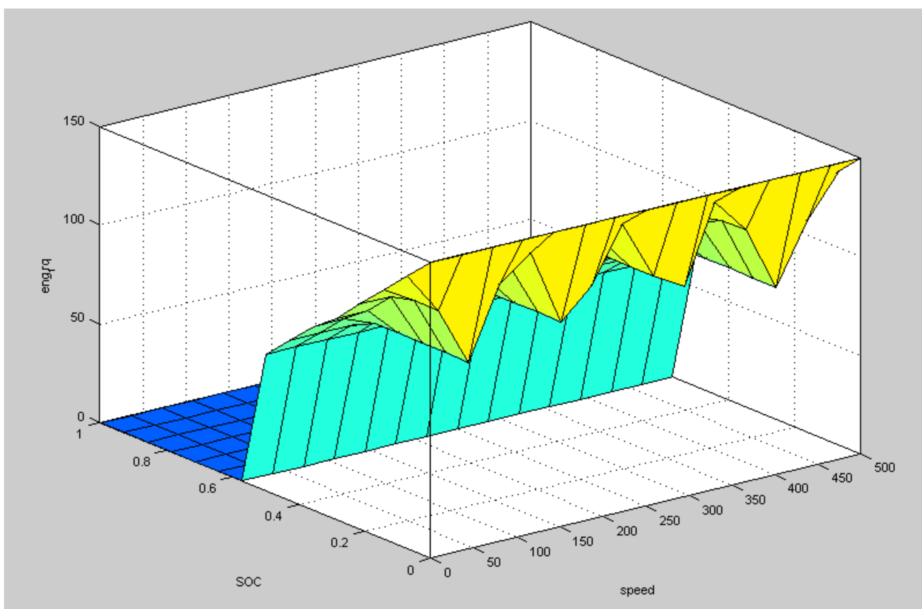

Figure 3.13 SOC, speed versus engine torque (Controller 1)

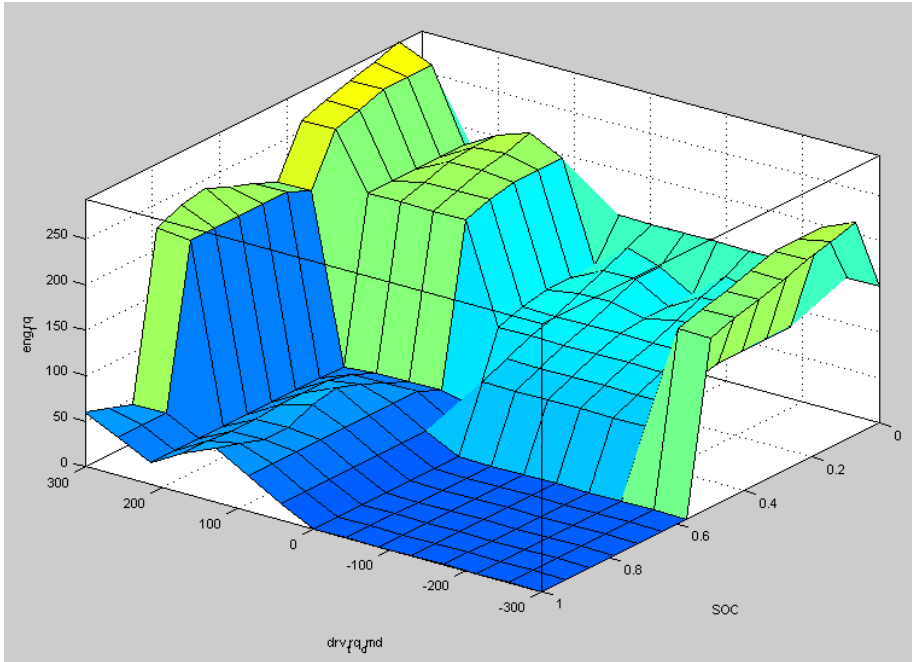

Figure 3.14 SOC, driver torque demand versus engine torque (Controller 1)

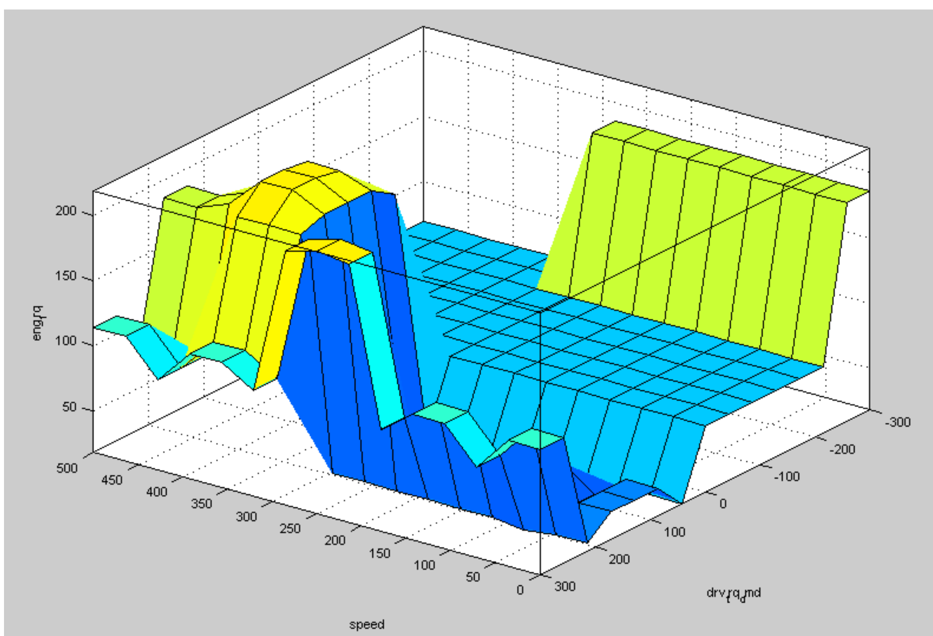

Figure 3.15 speed, driver torque demand versus engine torque (Controller 1)

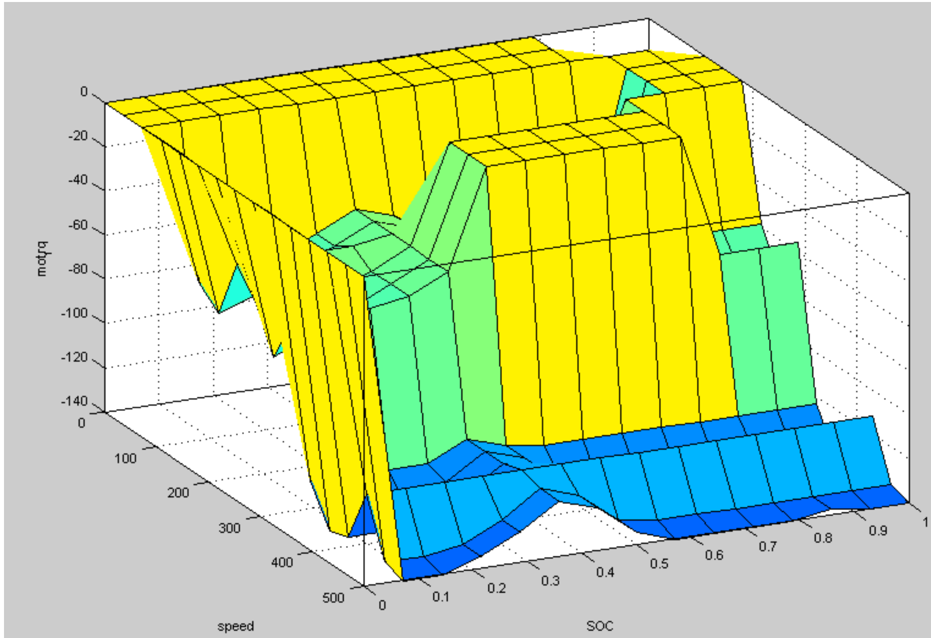

Figure 3.16 SOC, speed versus motor torque (Controller 1)

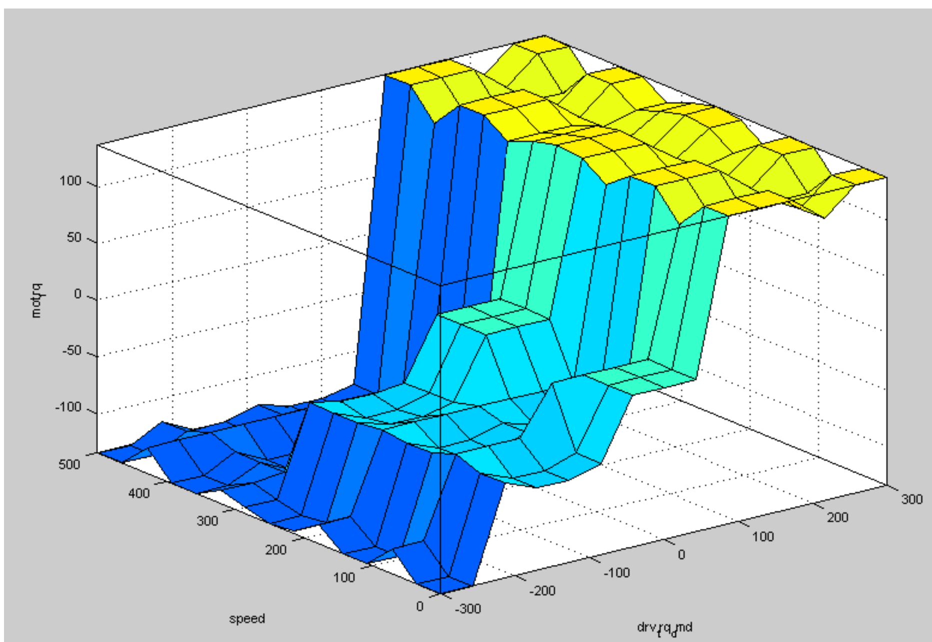

Figure 3.17 speed driver torque demand versus motor torque (Controller 1)

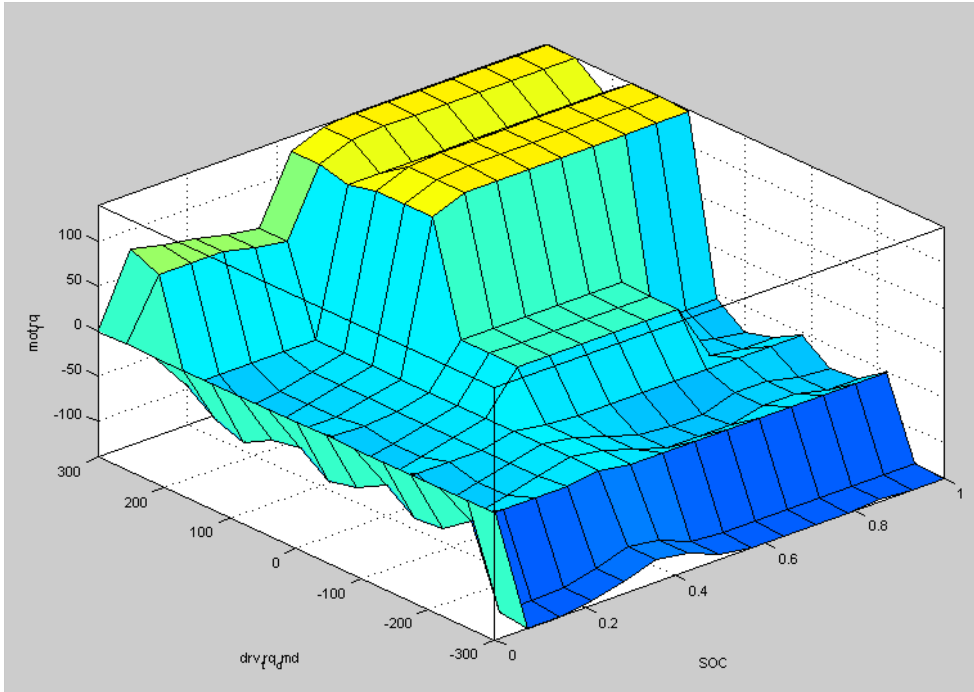

Figure 3.18 SOC, driver torque demand versus motor torque (Controller 1)

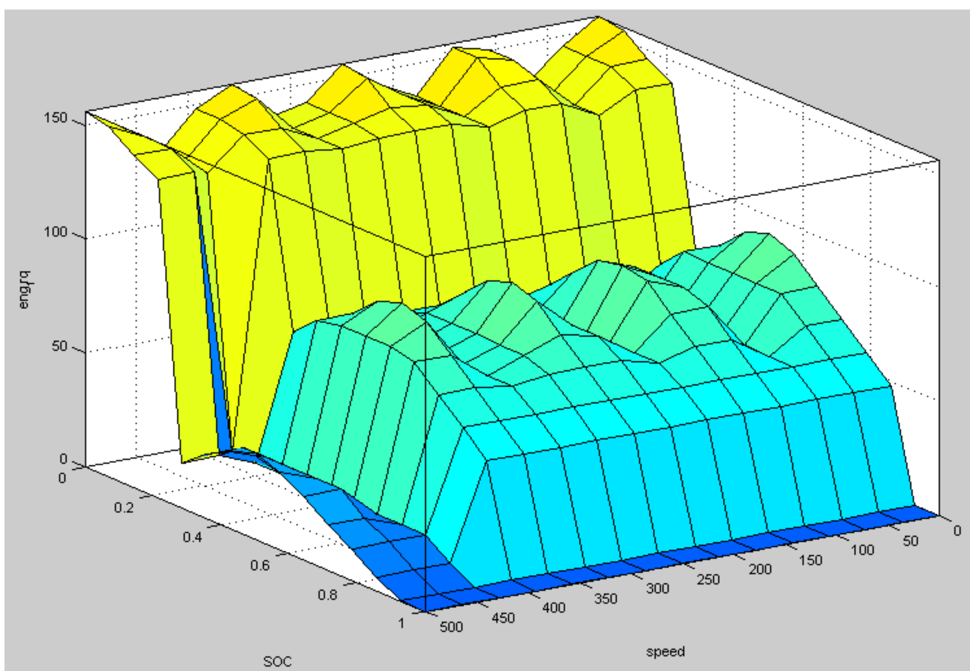

Figure 3.19 SOC, speed versus motor torque (Controller 1)

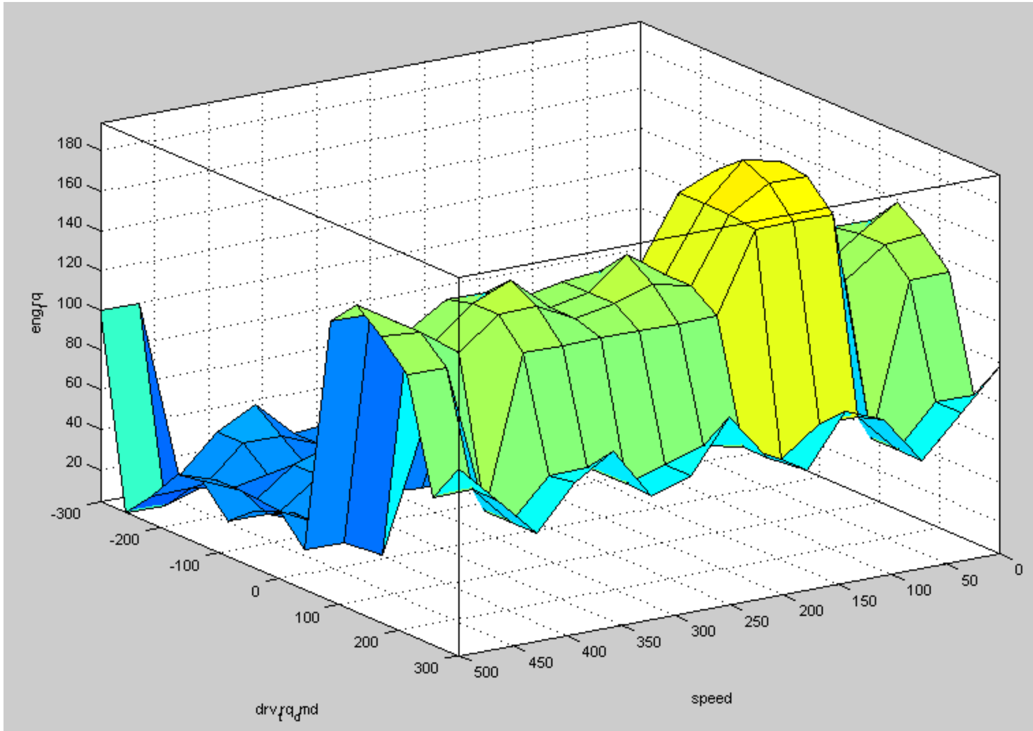

Figure 3.20 Speed, driver torque demand versus engine torque (Controller 2)

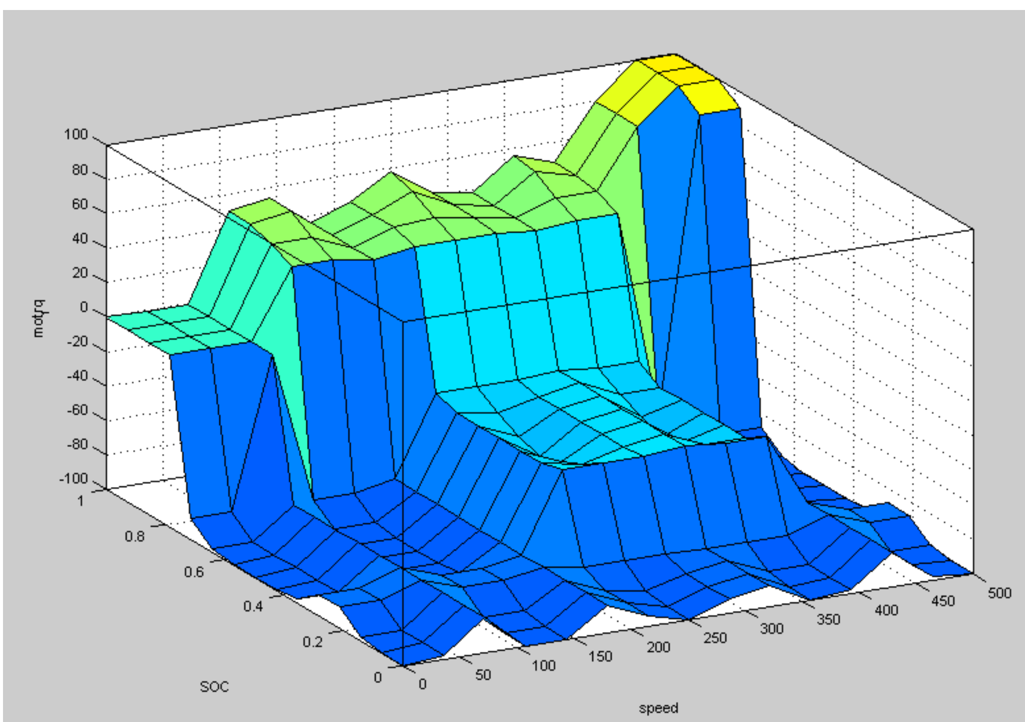

Figure 3.21 Speed, SOC versus motor torque (Controller 2)

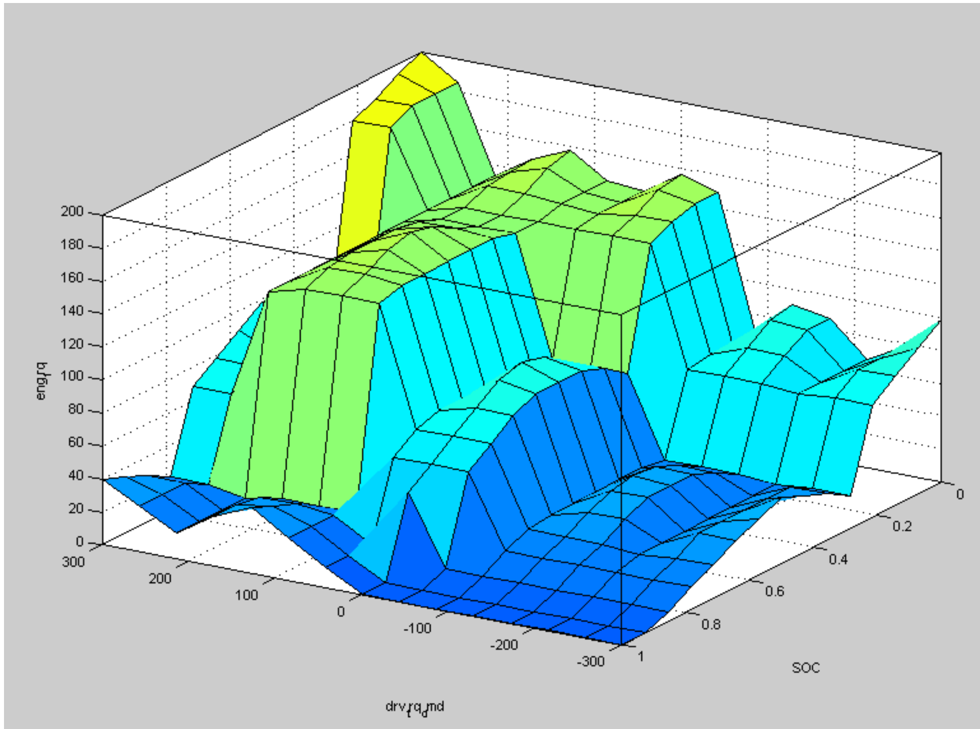

Figure 3.22 SOC, driver torque demand versus engine torque (Controller 2)

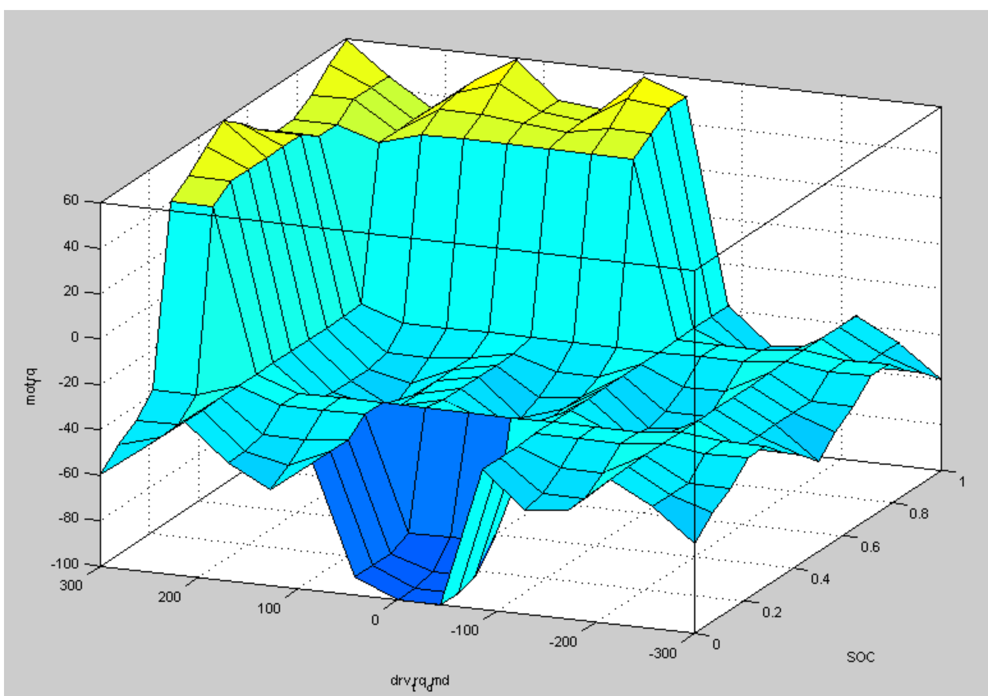

Figure 3.23 SOC, driver torque demand versus motor torque (Controller 2)

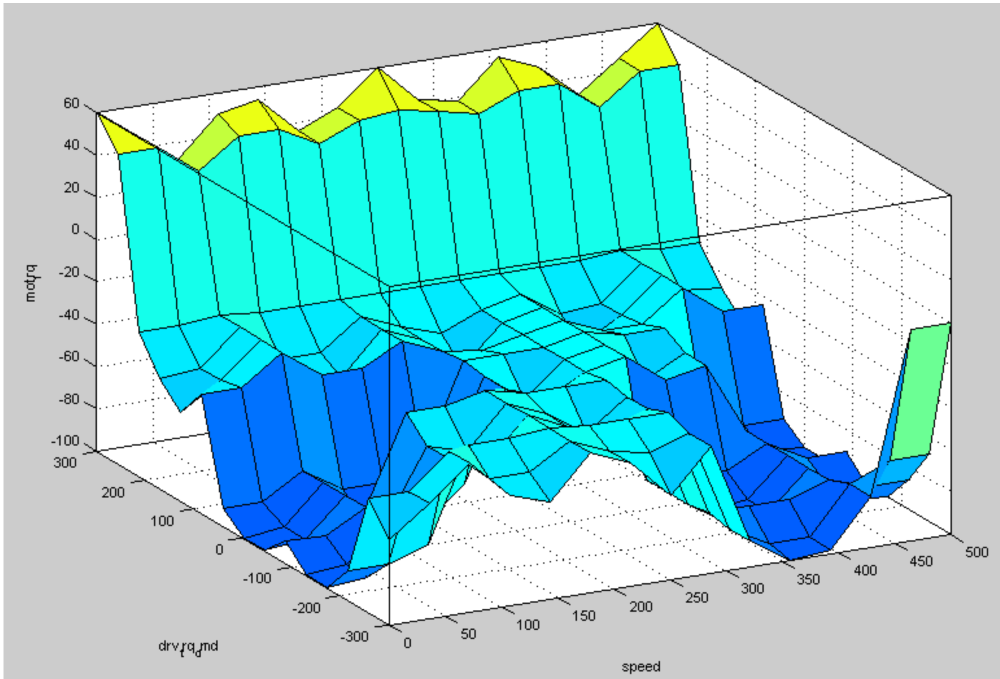

Figure 3.24 Speed, driver torque demand versus motor torque (Controller 2)

Chapter 4

Simulation Results and Analysis

Two fuzzy logic controllers are implemented in AUTONOMIE version 1210 vehicle simulation software developed by Argonne national laboratories to simulate vehicle performance. An interface with the software is developed in this thesis using the Matlab/Simulink environment. AUTONOMIE is frequently used to measure the performance of conventional, electric, hybrid vehicles or individual component of the vehicle in standard driving cycles. Different vehicle models are available in the software which are based on the collected data from real vehicles. All the environmental parameters are also included into this software.

4.1 Simulation setup

For developing the fuzzy logic controller, a mid-size hybrid vehicle with parallel integrated starter generator has been selected. In order to implement the fuzzy control system and for measuring the performance of the controller, the default controller of the vehicle has been replaced by the developed fuzzy logic controller and then the vehicle runs through the standard cycle. All the important data are collected and then processed to measure the performance of the vehicle with fuzzy logic controller. Some measured quantities are then plotted to evaluate the performance of the individual components of the vehicle. The vehicle model parameters used for the simulation are given below.

Table 4.1 Simulation parameters

Mass of the body of the vehicle	990 kg
Total mass (cargo+body+component+fuel)	1630 kg
Distance of center of gravity from the ground	0.50 m
Coefficient of drag	0.30
Vehicle frontal area	2.25 m^2
Height of the vehicle	1.45 m
Electrical accessories mass	0 kg
Mass of the Battery for electrical accessories	18 kg
Power consumed by the Electrical accessories	0.20 kW
Mass of the mechanical accessories	35 kg
Power consumed by the Mechanical accessories	0 kW
Clutch response time	1 sec
Mass of the clutch	25 kg
Threshold input , output speed difference value for locking of the clutch	40 rad/sec
Number of cells in the battery	75
Maximum cell voltage	3.6 volts
Minimum cell voltage	3.2 volts
Nominal cell voltage	3.4 volts

Number of cell per module	3
Number of cell in series	75
Nominal battery voltage	255 volts
Individual cell capacity	7.4 Ah
Total battery capacity	555 Ah
Mass of Final drive	25 kg
Gear box ratio (engine speed/wheel speed)	2.563,1.552, 1.022, 0.727, 0.52
Motor mass	14.68 kg
Motor inertia	$8.45e^{-3}$ $kg.m^2$
Mass per wheel	30 kg
Number of wheels	4
Wheel Radius	0.30 m
Wheel Radius correction factor	0.95
Air molecular weight	28.97 gm/mol
Boltzmann constant	$1.38e^{-23}$ J/K
Air density	1.23 kg/liter
Gravitational constant	9.81 m/s^2
Percentage of ambient humidity	20 %
Ambient pressure	1 bar
Ambient temperature	20 ˚C
Type of the engine	SIDI

Total engine cylinder volume	2200 cc
No of cylinders	4
Maximum engine power	110 kilo watt
Minimum speed for starting the engine	10 rad/sec

4.2 Simulation and result analysis of developed fuzzy logic controller based vehicle in UDDS cycle

Urban Dynamometer Driving Schedule (UDDS) simulates the traffic and environmental effects in busy American cities roads and highways. It is widely used to measure the fuel economy and emissions of the passenger car in an American urban driving cycle. The simulation results for UDDS cycle are given below.

The simulation is done using both fuzzy logic controllers. The first controller is developed by considering the vehicle is a plug in hybrid vehicle, and the second controller is developed by considering the vehicle will operate as a parallel hybrid vehicle where the battery will recharged by the engine only. During simulation through the UDDS cycle, the default controller in AUTONOMIE has been replaced by the developed fuzzy logic controllers. All the data are collected to measure the performance of the controller. The speed profile for the UDDS cycle is given in Fig. 4.1 below. The generated speed profiles when controllers 1 and 2 are used are given in Figs. 4.2 and 4.3 respectively.

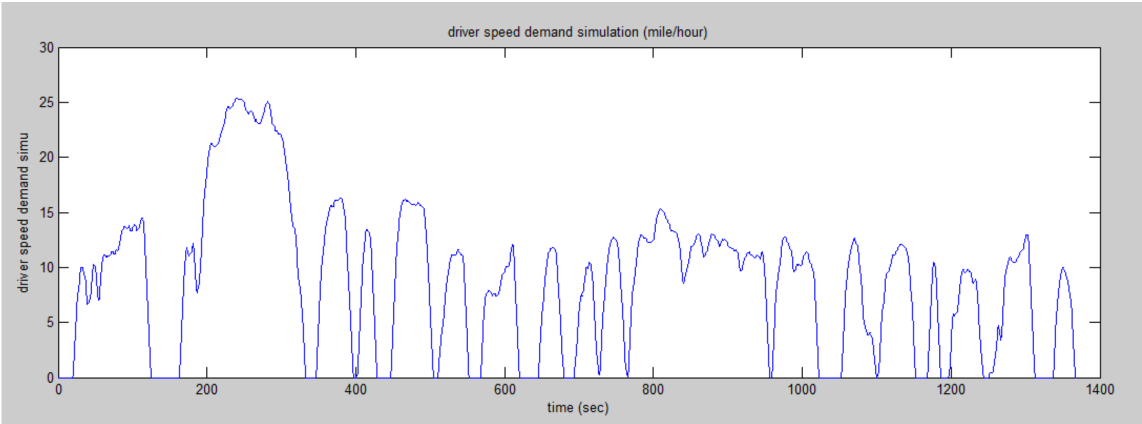

Figure 4.1 UDDS driving cycle.

Figure 4.2 Output vehicle speed using controller 1.

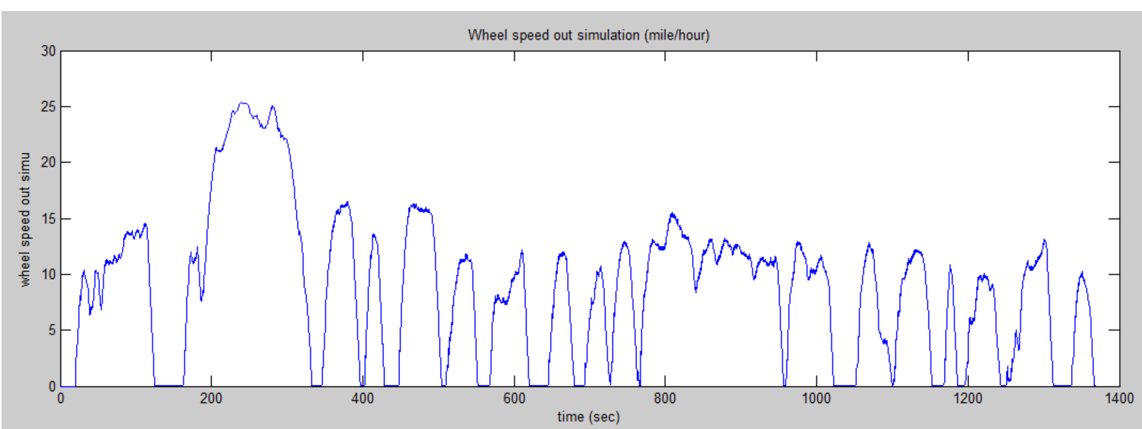

Figure 4.3 Output vehicle speed using controller 2.

For both simulation runs, the initial state of charge, driving cycle, and all other parameters remain the same. By comparing Figures 4.2 and 4.3 with Figure 4.1, it is seen that the output speed of the vehicle is similar to the speed profile of the UDDS drive cycle. This means that the controller is able to satisfy vehicle drivability requirements.

Figures 4.4 and 4.5 depict the initial state of charge and the final state of charge of the battery using both the controllers. The fuzzy logic controller for plug-in hybrid vehicle is developed by considering that if the SOC of the battery is high, then motor will contribute more in supplying the propulsion power where as if the SOC of the battery is low then engine will contribute more. Since the efficiency of the motor drive system is much higher than the internal combustion engine, total efficiency will be higher when the SOC will high; with decreasing battery SOC, the efficiency of the vehicle will decrease. Another function accomplished by the first fuzzy logic controller is that it will always maintain the SOC of the battery more than 35%, which is essential to protect the battery’s life. The second controller is developed in such a way that the engine will recharge the battery and always maintain the battery SOC more than 70%. The final goal of both controllers is to minimizing the fuel consumption of the vehicle over the complete drive cycle.

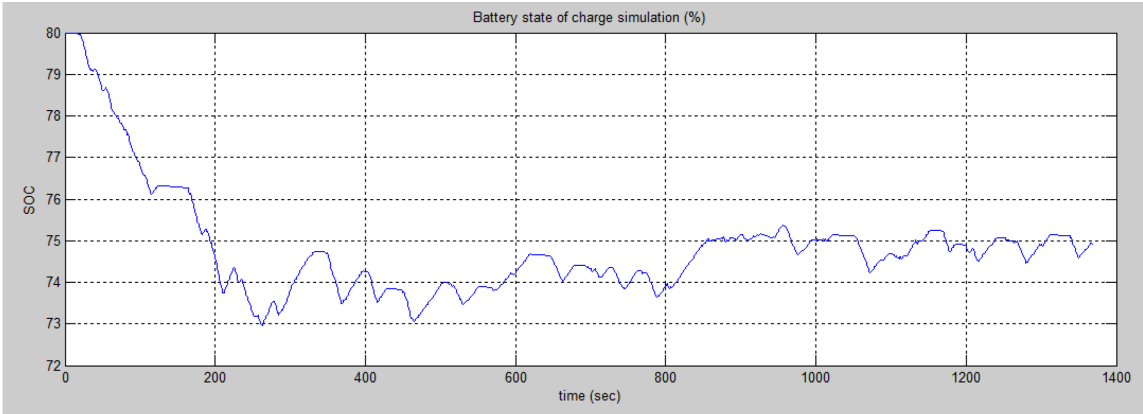

Figure 4.4 Battery SOC using controller 1.

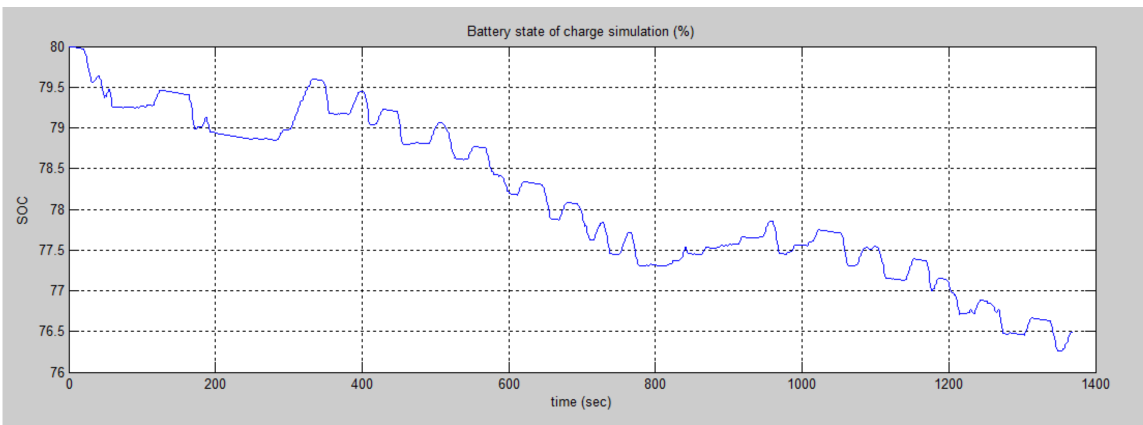

Figure 4.5 Battery SOC using controller 2.

From Figures 4.4 and 4.5, it is clearly visible that while completing the UDDS cycle, the first controller consumes more energy from the battery and as a result the state of charge dropped more over the whole cycle. While running through the UDDS cycle, both engine and motor work in parallel to meet the total torque demand for the vehicle. The engine supplied torque and motor supplied torque for both the controllers are given below.

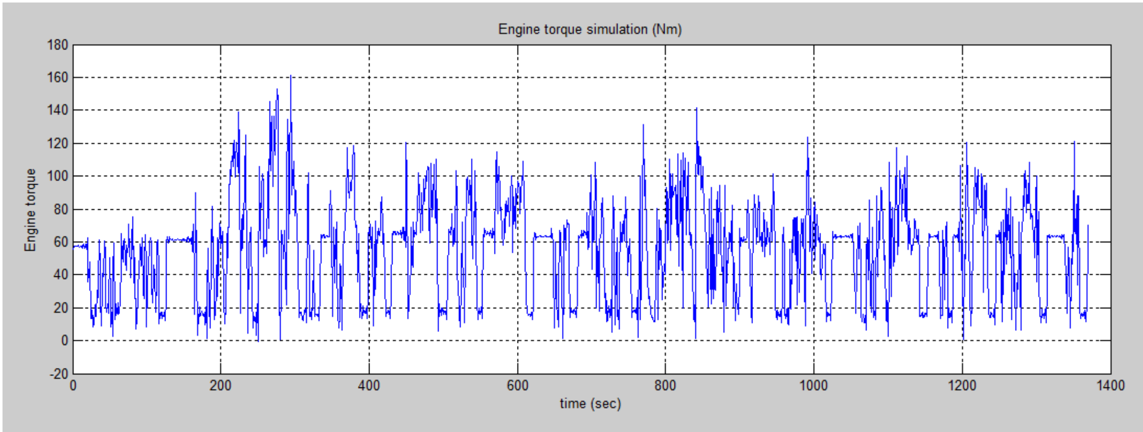

Figure 4.6 Engine output torque using controller 1.

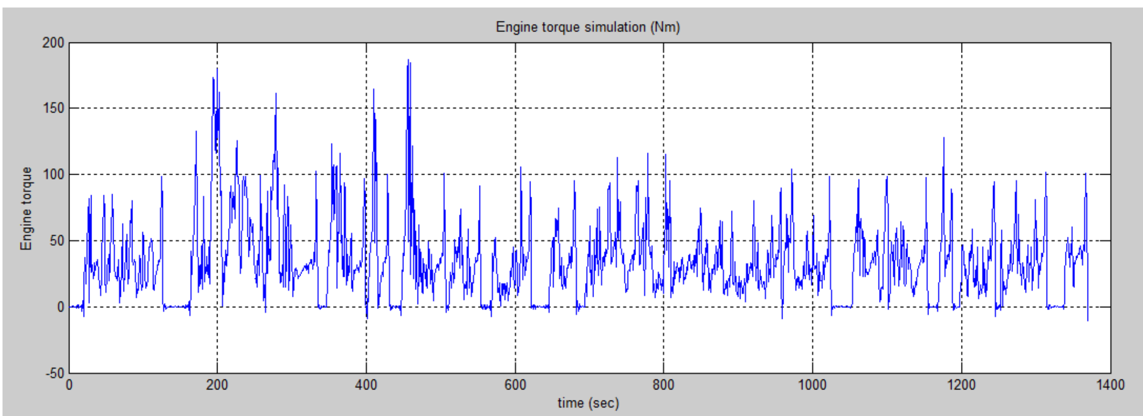

Figure 4.7 Engine output torque using controller 2.

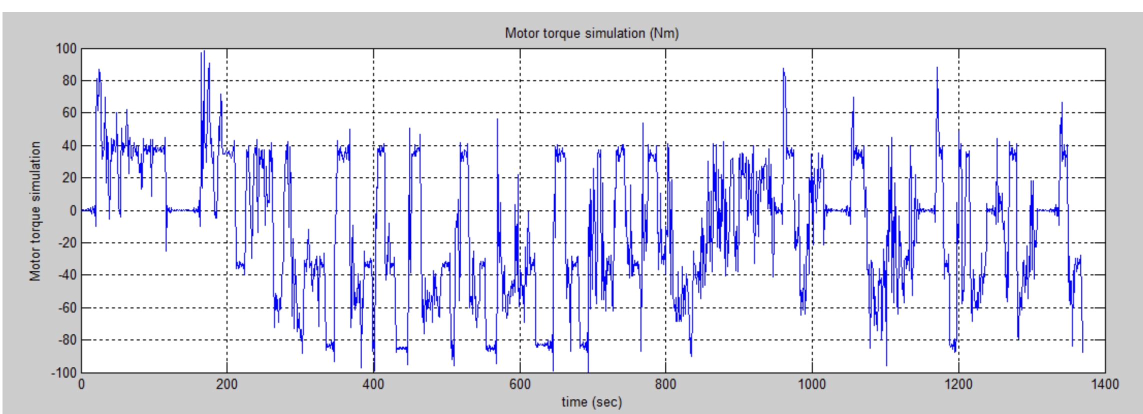

Figure 4.8 Motor output torque using controller 1.

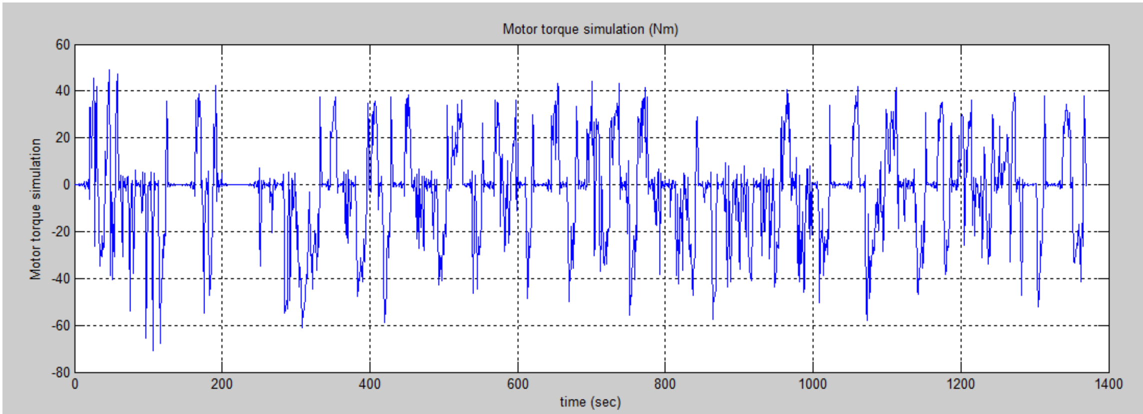

Figure 4.9 Motor output torque using controller 2.

Figures 4.8 and 4.9 show the torque supplied by the motor during the drive cycle. When comparing both the figures, it is clear that when using controller 1 the motor provides more torque than the engine. The negative part of the motor output torque represents generator input torque; the energy produced by the generator is used to recharge the battery. As the efficiency of the electrical system is better than the mechanical system, the overall performance will be better when comparatively more power comes from the motor instead of the engine.

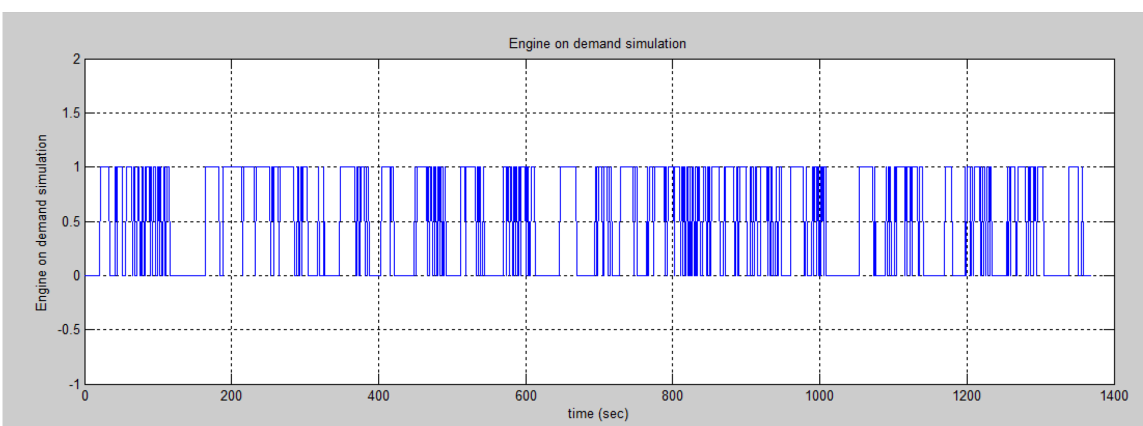

Figure 4.10 Engine ON demand simulation using controller 1.

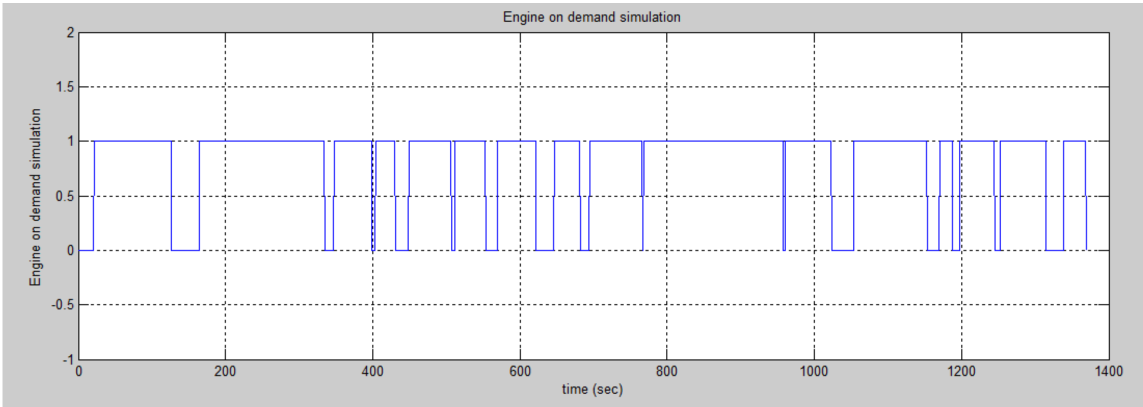

Figure 4.11 Engine ON demand simulation using controller 2.

Figures 4.10 and 4.11 show that the engine on demand simulation when controlled by the fuzzy logic controllers. By comparing both figures, it is clearly visible that when using controller 2, the total engine operating time is higher than when controller 1 is used. Engine on demand is controlled by the fuzzy logic controller. For example at any instant when the SOC of the battery is high, driver torque demand is low, vehicle speed either high or low, then according to the expert's knowledge engine should remain stopped or motor should run with higher torque. The fuzzy logic controller does the same thing. Basically the performance of the fuzzy logic controller depends on the expert's knowledge, it is a process of transferring human intelligence to machine intelligence.

Figure 4.12 and figure 4.13 show the engine fuel consumption by the vehicle during the complete cycle. The figures show that using controller 1, the total fuel consumption is nearly same as the total fuel consumption by using controller 2. At higher SOC, the fuel economy and efficiency is nearly same for both of the controller.

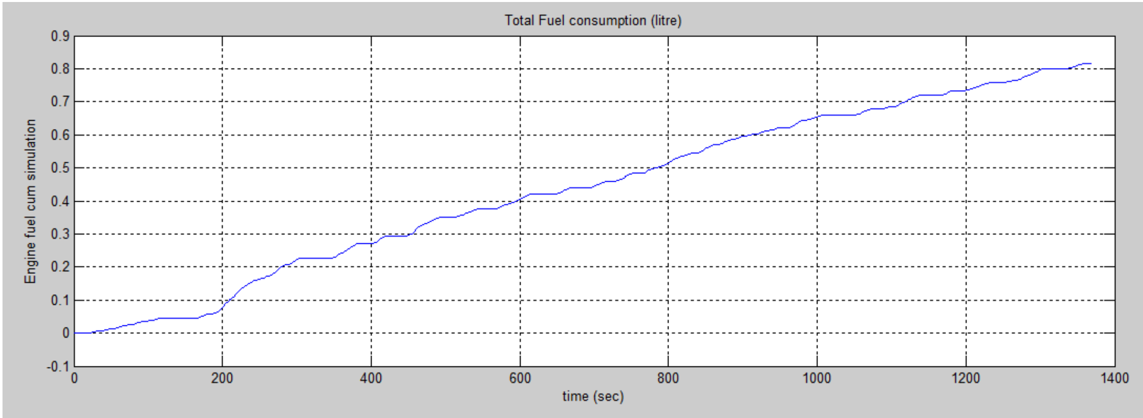

Figure 4.12 Total fuel consumption by engine using controller 1.

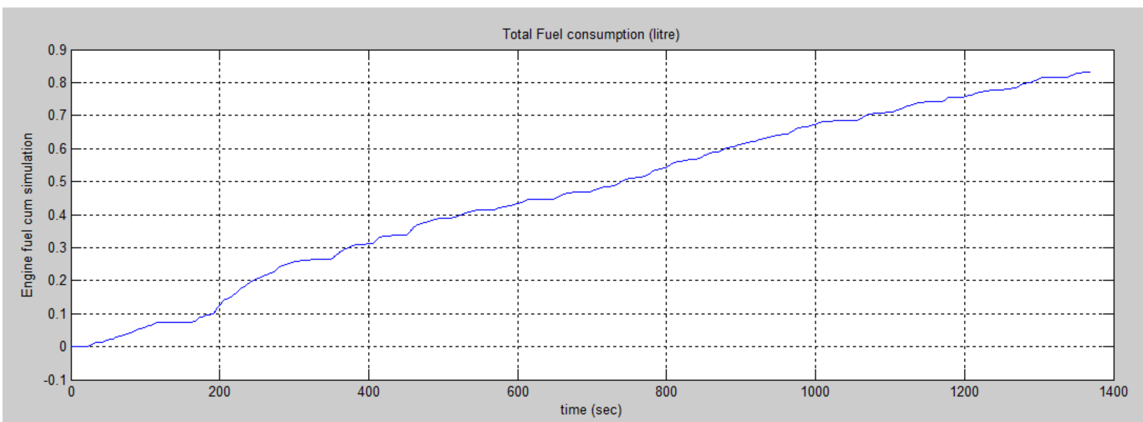

Figure 4.13 Total fuel consumption by engine using controller 2.

Figure 4.14 and figure 4.15 depict the engine fuel consumption rate along the UDDS drive cycle by using controller 1 and controller 2.

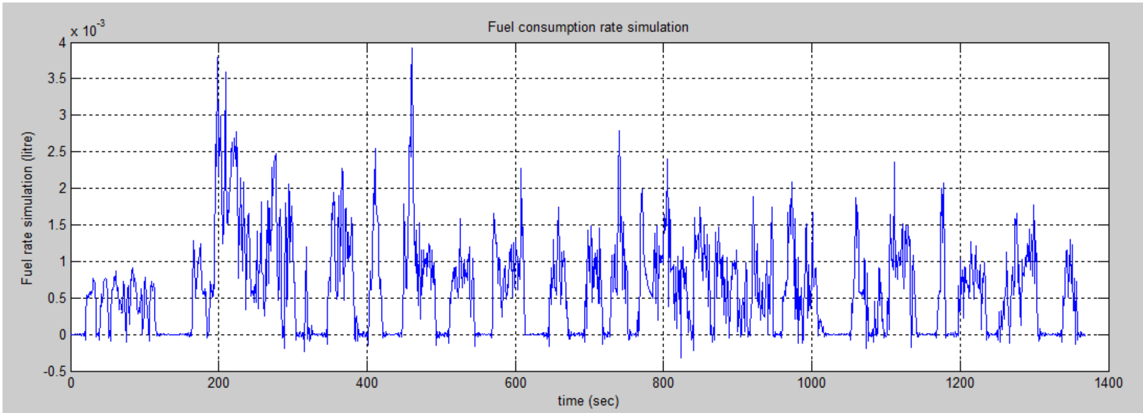

Figure 4.14 Engine fuel consumption rate using controller 1.

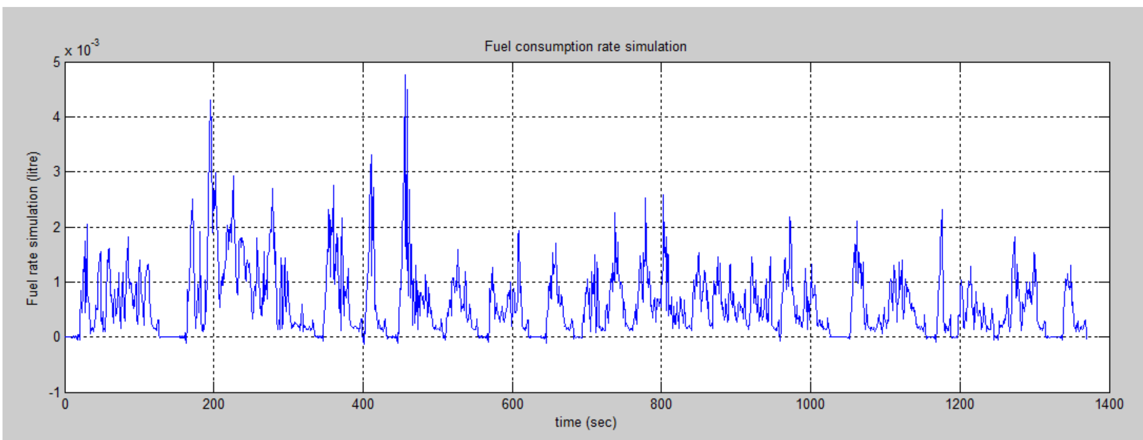

Figure 4.15 Engine fuel consumption rate using controller 2.

Figures 4.16 and 4.17 depicts the battery's output current flow during the UDDS cycle using controllers 1 and controller 2.

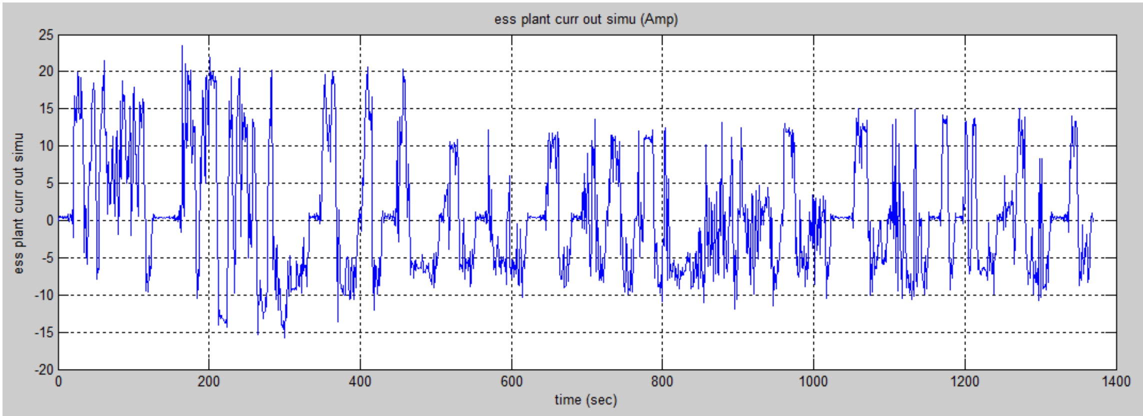

Figure 4.16 Battery output current simulation using controller 1.

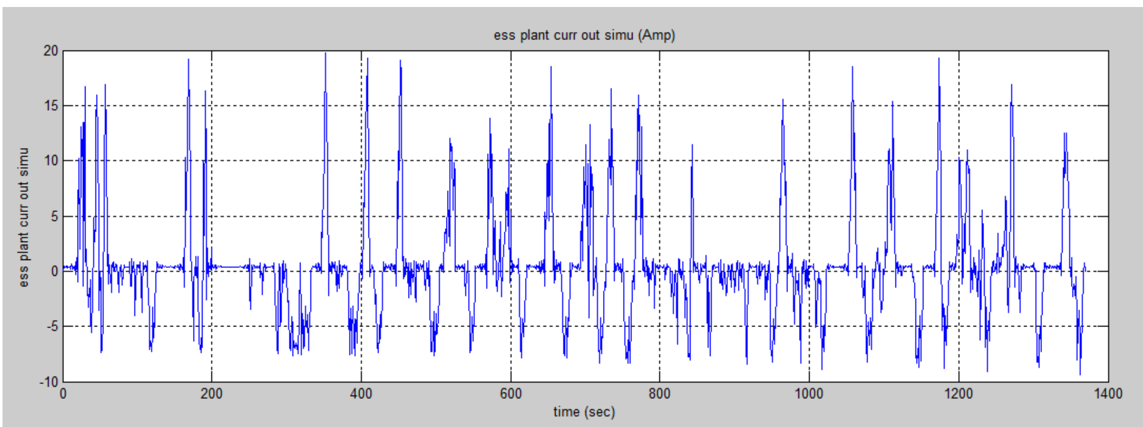

Figure 4.17 Battery output current simulation using controller 2

Figure 4.18 and figure 4.19 show the battery voltage variations. From figures 4.16 through figure 4.19, it can be seen that the current flow from the battery is proportional to the load (i.e. motor torque demand) and battery voltage is inversely proportional to the load.

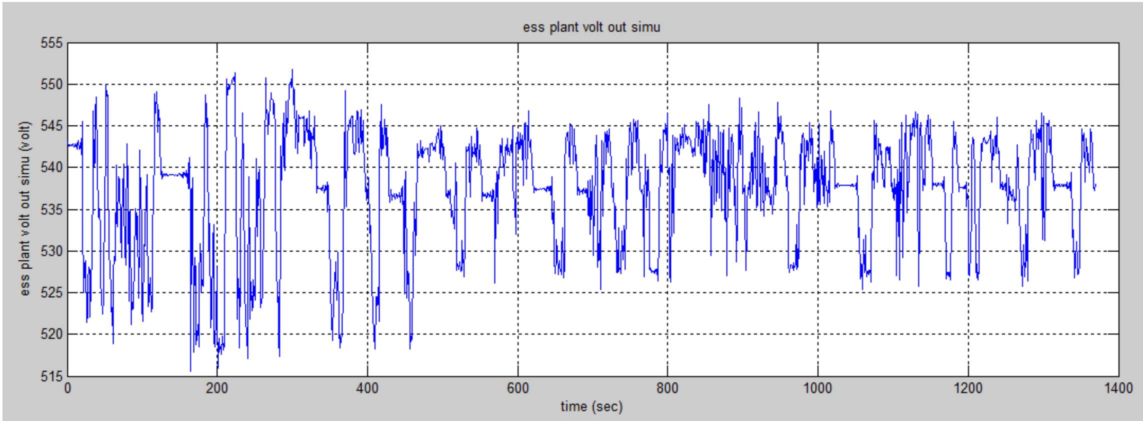

Figure 4.18 Battery output voltage simulation using controller 1.

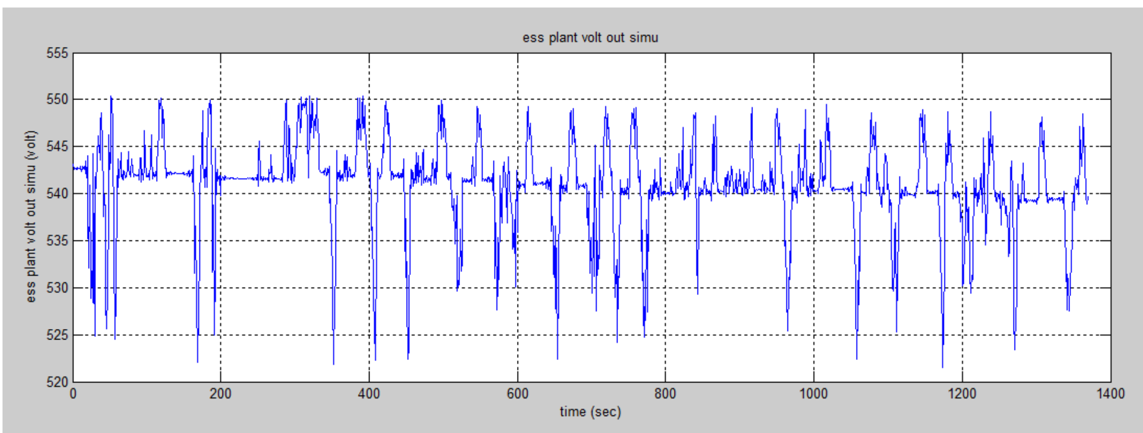

Figure 4.19 Battery output voltage simulation using controller 2

Figures 4.20 and 4.21 show the engine power loss during UDDS drive cycle using both of the fuzzy logic controllers.

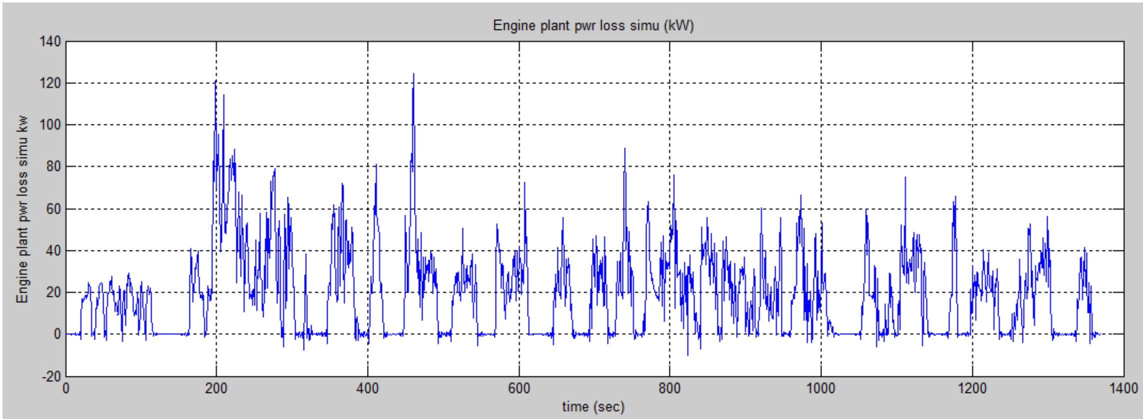

Figure 4.20 Engine power loss simulation using controller 1.

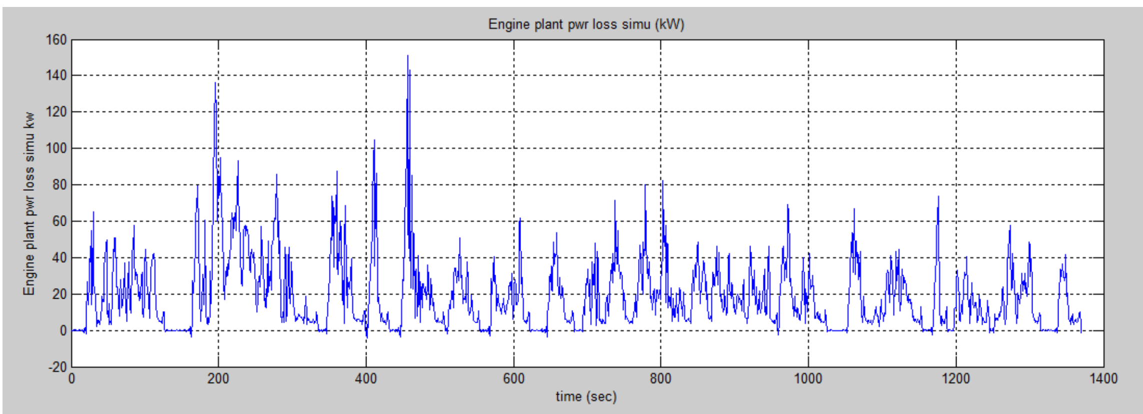

Figure 4.21 Engine power loss simulation using controller 2

Figure 4.20 and figure 4.21 shows the engine power loss simulations by using controller 1 and controller 2.

Figure 4.22 and figure 4.23 shows the engine brake specific fuel consumption map based on engine operating speed and torque when the vehicle controlled by the fuzzy logic controller 1 and fuzzy logic controller 2 respectively. The figure also shows the maximum torque line and maximum efficiency line based on speed and powers.

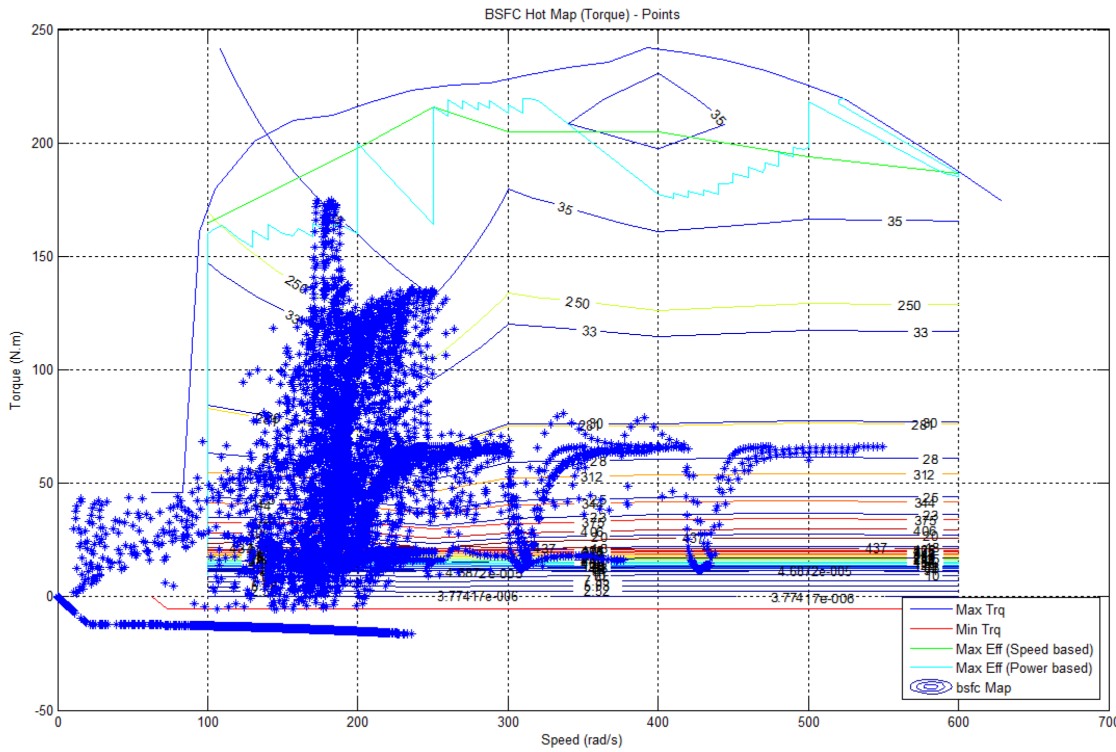

Figure 4.22 Engine brake specific fuel consumption for controller 1.

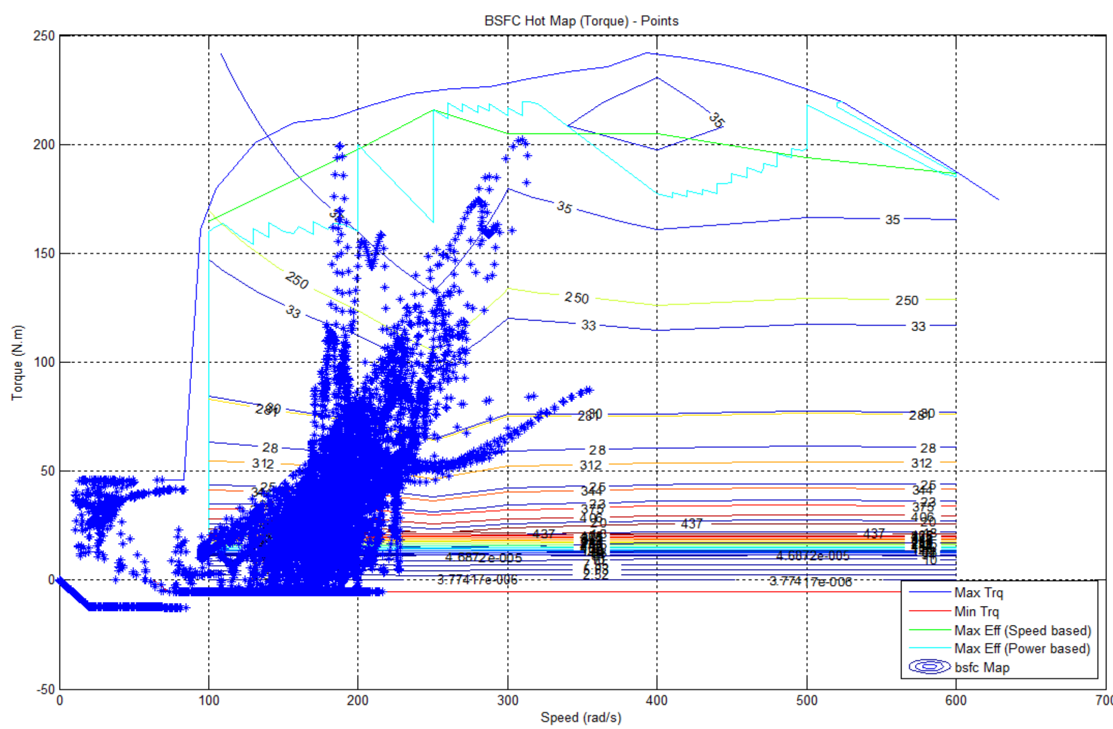

Figure 4.23 Engine brake specific fuel consumption for controller 2.

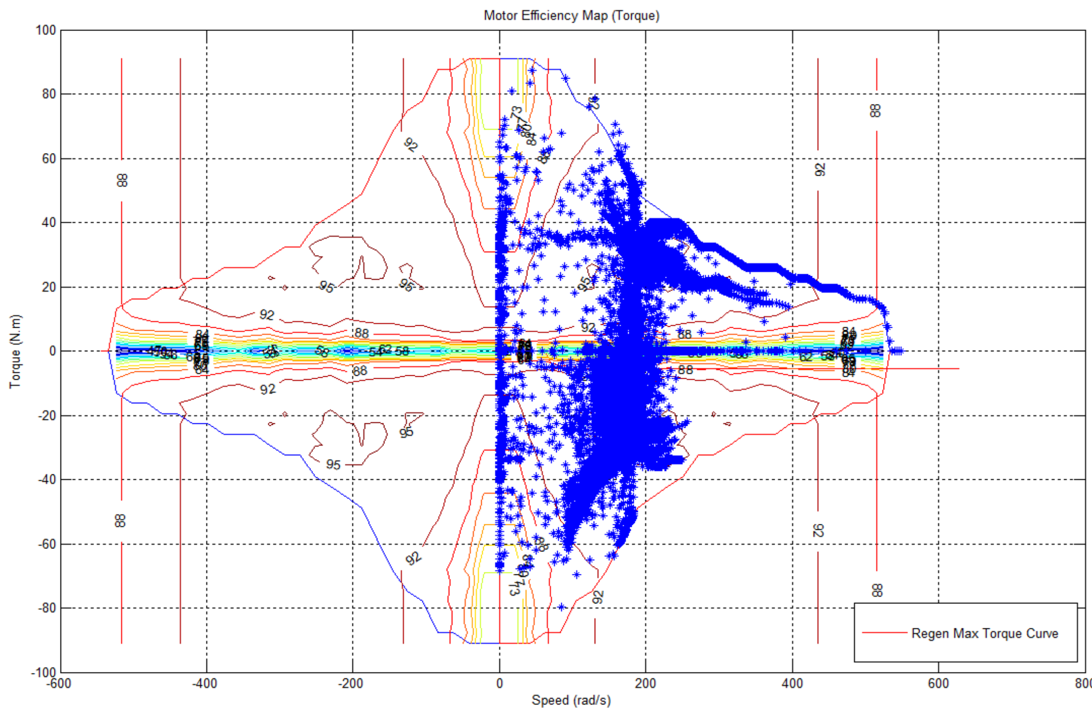

Figure 4.24 Motor efficiency maps using controller 1.

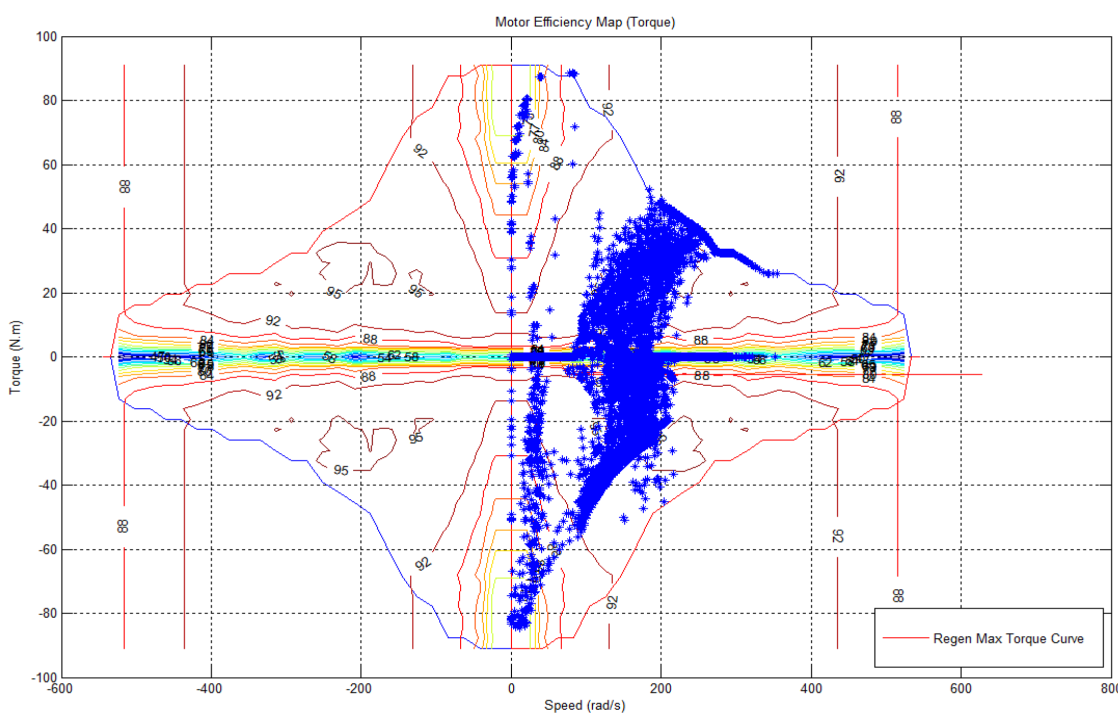

Figure 4.25 Motor efficiency maps using controller 2.

Figure 4.24 and figure 4.25 shows the motor efficiency map by using controller 1 and controller 2. Table 4.2 and figure 4.26 shows the performance of fuzzy logic controller developed for using parallel hybrid vehicle as plug-in hybrid vehicle. From the figure 4.24 it is evident that the equivalent fuel economy (which is the fuel equivalent energy of the sum of energy taken from the engine and the energy taken or given to the battery) and the SOC of the battery have strong relationship with each other. Both SOC and equivalent fuel economy vary up to 200 miles, after travelling this distance, both become constant.

Table 4.2 Simulation results using FLC by considering vehicle as plug-in hybrid.

Cycle number	Distance travelled per cycle	Total distance travelled	Initial SOC (%)	Final SOC (%)	Δ SOC (%)	Equivalent Fuel economy (mile/gallon)
0	44.72	0	100	100	0	52.81835
1	44.72	44.72	100	73.38	26.62	45.1973
2	44.72	89.44	73.38	51.61	21.77	46.6873
3	44.72	134.16	51.61	38.15	13.47	41.6131
4	44.72	178.88	38.15	38.15	1.94E-05	34.7077
5	44.72	223.6	38.15	38.15	-5.76e-7	34.6712
6	44.72	268.32	38.15	38.15	-1.52e-5	34.6540
7	44.72	313.04	38.15	38.15	1.49e-5	34.6706
8	44.72	357.76	38.15	38.15	-3.69e-7	34.6429

Table 4.3 and figure 4.27 present results obtained using the fuzzy logic controller when the engine is used to recharge the battery.

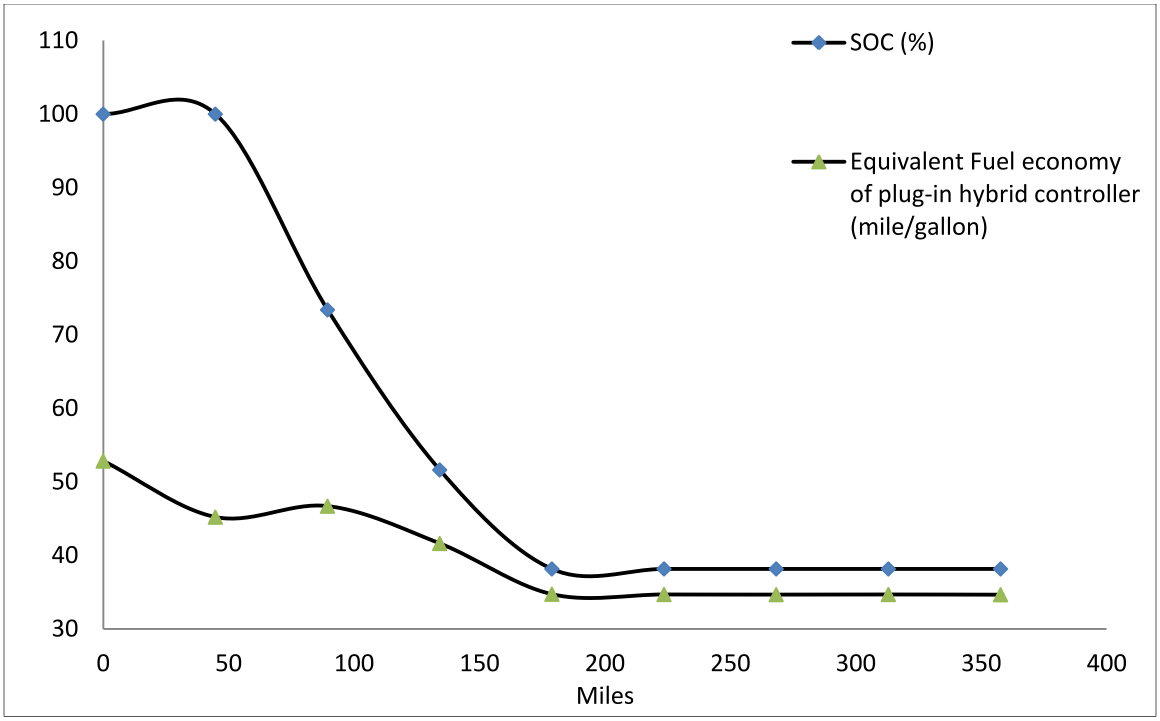

Figure 4.26 Simulation results of FLC by considering a plug-in hybrid vehicle.

Table 4.3 Simulation results using the FLC when the engine will recharge the battery.

Cycle number	Distance travelled per cycle	Total distance travelled	SOC (%)	Final SOC (%)	Δ SOC (%)	Equivalent Fuel economy of parallel hybrid controller (mile/gallon)
0	44.72	0	100	100	0	52.8183
1	44.72	44.72	100	74.98	25.02	42.8389
2	44.72	89.44	74.9803	74.94	2.8e-004	32.3952
3	44.72	134.16	74.94	74.93	1.117e-004	32.4131
4	44.72	178.88	74.93	74.93	-8.005e-006	32.4215
5	44.72	223.60	74.93	74.95	-1.866e-004	32.4017
6	44.72	268.32	0.7495	0.7494	1.438e-004	32.4013
7	44.72	313.04	0.7494	0.7493	2.779e-005	32.4246
8	44.72	357.76	0.7493	0.7496	-2.760e-004	32.4000

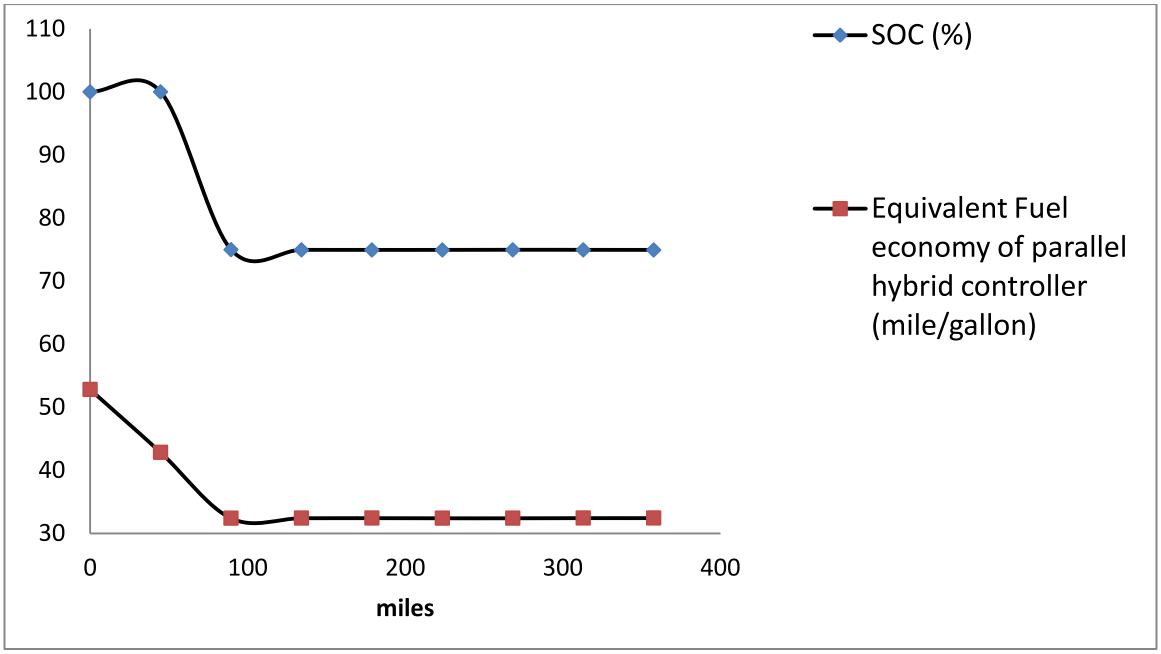

Figure 4.27 Simulation results of FLC by considering vehicle as parallel hybrid vehicle.

Table 4.3 and figure 4.27 show the simulation results for a parallel hybrid vehicle with fuzzy logic controller by considering the battery will never be recharged by the power grid; the engine will recharge the battery in all conditions. Figure 4.27 reveals the relationship between the SOC of the battery and the equivalent fuel economy. For up to a 74% SOC of the battery, the fuel economy varies with the SOC; after this limit both fuel economy and the SOC become constant.

Table 4.4 and figure 4.28 show the simulation results for a parallel hybrid vehicle with the default controller available in the AUTONOMIE software.

Table 4.4 Simulation result of parallel hybrid vehicle using default controller.

Cycle number	Distance travelled per cycle	Total distance travelled	Initial SOC (%)	Final SOC (%)	Δ SOC (%)	Equivalent Fuel economy (mile/gallon)
0.	44.72	0	100	100	0	37.2205
1.	44.72	44.72	100	85.14	14.86	36.6766
2.	44.72	89.44	85.14	78.93	6.21	34.2527
3.	44.72	134.16	78.93	75.92	3.01	33.4822
4.	44.72	178.88	75.92	74.35	1.57	33.1649
5.	44.72	223.60	74.35	73.45	0.90	33.0417
6.	44.72	268.32	73.45	72.93	0.0052	32.9813
7.	44.72	313.04	72.93	72.64	0.0029	32.9278
8.	44.72	357.76	72.64	72.48	0.0016	32.8963

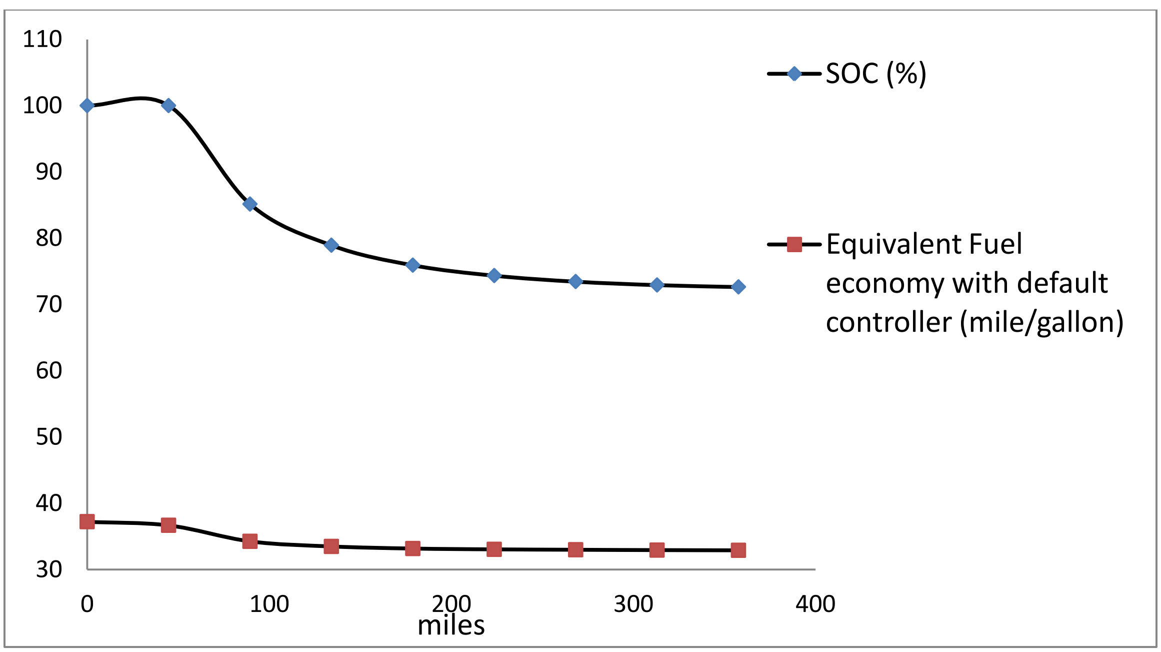

Figure 4.28 Simulation result of parallel hybrid vehicle using default controller.

Figure 4.28 shows the variation of the SOC of the battery and the fuel economy. From the data for the first 200 miles it can be seen that the variation of the SOC and the

equivalent fuel economy is comparatively slow from the other two developed controllers. The fuel economy varies by a small amount with the SOC of the battery. The maximum value of fuel economy is 37.22 miles per gallon.

Table 4.5 comparisons between two developed controllers with the default controller

Cycle number	Total distance travelled (mile)	Equivalent Fuel economy (mile/gallon) Plug-in hybrid	Equivalent Fuel economy (mile/gallon) Parallel hybrid	Equivalent Fuel economy (mile/gallon) Parallel hybrid with default controller
0.	0	52.81835	52.8183	37.2205
1.	44.72	45.1973	42.8389	36.6766
2.	89.44	46.6873	32.3952	34.2527
3.	134.16	41.6131	32.4131	33.4822
4.	178.88	34.7077	32.4215	33.1649
5.	223.6	34.6712	32.4017	33.0417
6.	268.32	34.6540	32.4013	32.9813
7.	313.04	34.6706	32.4246	32.9278
8.	357.76	34.6429	32.4000	32.8963

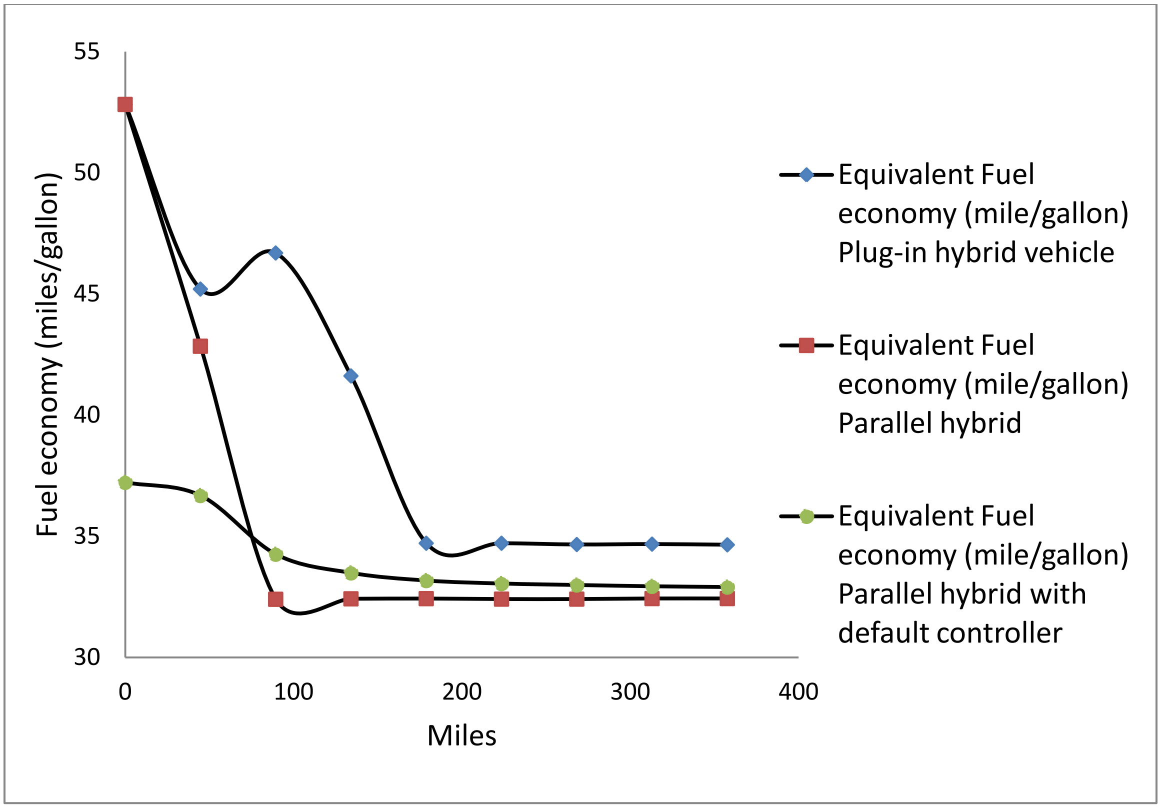

Figure 4.29 Comparison between three types of controller

Table 4.4 and figure 4.29 shows the comparison between two developed controllers with the default controller. It is very clear from the figure 4.29 that the fuel economy is the best for the controller developed by considering the vehicle as the plug-in hybrid vehicle, in all conditions its performance is better than the controller developed by considering the battery will be recharged by the engine and the default controller available in AUTONOMIE software. It is clear from figure 4.29 that fuel economy of the controller 2 is higher than the default controller up to 80 miles, after that it decreases by some amount and then remains constant. Although the performance of the default controller is better in some region but it is shown from the table 4.4 column 5 it is continuously downward trend.

Chapter 5

Conclusions and Recommendations

5.1 Conclusions

In this thesis, two fuzzy controllers have been developed for parallel hybrid vehicles. The first controller has been developed by considering the vehicle as the plug-in hybrid vehicle whereas for the second controller, it is assumed that the battery will recharged by the engine only. For testing and implementing the controllers, a model of mid-sized parallel integrated starter generator hybrid vehicle has been used. All details about the model were discussed in chapter two. After replacing the default controller in AUTONOMIE with the developed controller, the vehicle is driven through the UDDS cycle. All important data are measured and collected in order to determine the performance of the vehicle by using the developed controllers.

From the results discussed in chapter four, it is found that the controller developed by considering the vehicle as the plug-in hybrid vehicle gives better performance in all conditions. The maximum fuel economy achieved by the both developed controllers is around 52.8 miles per gallon (see figure 4.29). The maximum fuel economy possible by using the default controller is around 38 miles per gallon. Both controllers have been developed by assuming that the contribution of the motor drive system will be proportional to the state of the charge of the battery. As the performance of the electrical system is much higher than the mechanical propulsion system, so the equivalent fuel economy will be higher when the battery has a higher state of charge.

For both controllers, the main objective is to improve the fuel economy. The first controller always gives always better performance than the default controller whereas the second controller gives better performance than the default controller for the first 85 miles. The performance decreases little bit compared to the default controller and remains constant. The numerical value of the fuel economy using the second controller is 32.4 miles per gallon. The value default controller yields a fuel consumption rate of 32.8 and its trend is downward (table 4.4, column 5).

The first controller shows very high performance for the first 200 miles and then its performance tapers off to a value 34.64 miles per gallon in order to maintain the SOC of the battery above 70 %.

Beside the fuel economy, another objective is to maintain the state of charge of the battery. The state of charge of the battery has a strong relationship with the life of the battery. Continuous deep discharging destroys the battery life. The first controller has been developed by targeting that it will always maintain the battery state of charge more than 35% of the total battery capacity. The second controller is developed by insuring that battery that the charge will not drop below 70% of the capacity. The results (figures 4.27 and 4.28) show that the controllers satisfy these conditions.

5.2 Recommendations

1. As the fuzzy logic is a process of transferring human knowledge to the machine knowledge, a richer expert knowledge base can be used to make fuzzy rules database more efficient.

2. The fuzzy rules can be tuned with the help of neural networks; this would allow for a large set of input data has to be used which covers a wide range of driving conditions.

5.3 Scope of future work

The above problem has been solved based on translating expert knowledge into a set of fuzzy rules. There is no mathematical model behind it, if more refined rules are used, a potential improvement in system performance can result. The mathematical model can also be refined by considering the uncertainty and parameter variations and using robust control algorithms for solving the optimization problem.

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Appendix 1

UDDS cycle with default controller

This appendix presents vehicle performance results using the default controller in AUTONOMIE when used on a UDDS cycle.

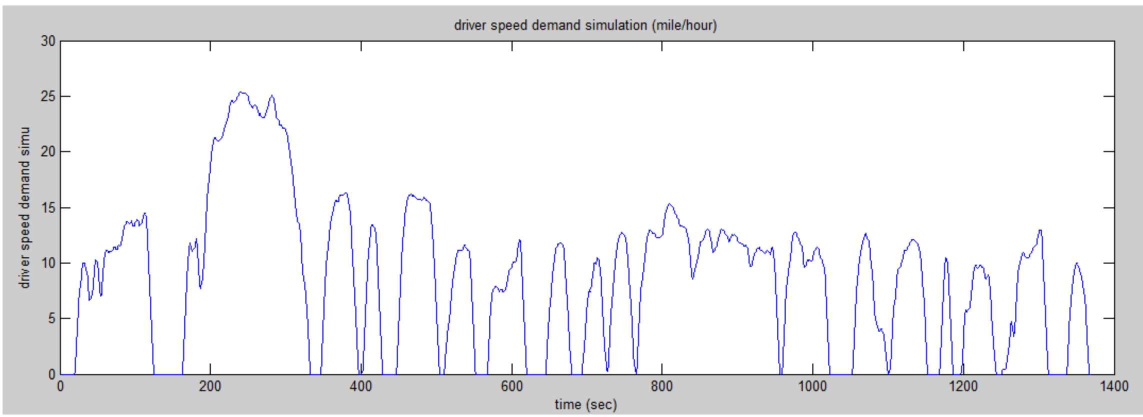

Figure A.1 UDDS driving cycle

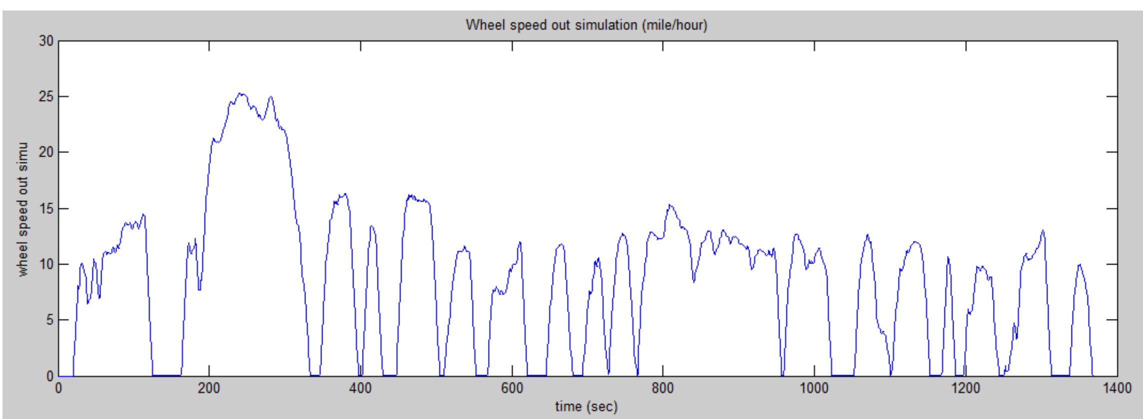

Figure A. 2 Output vehicle speed using default controller

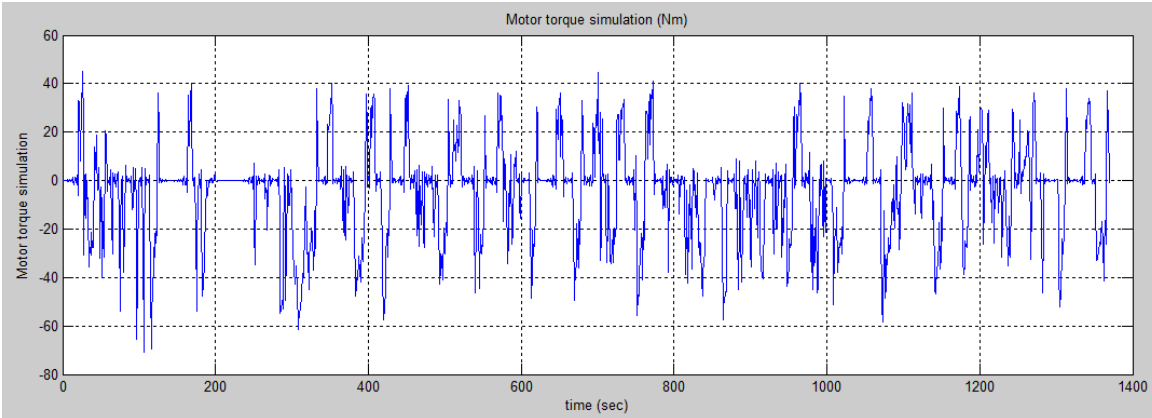

Figure A.3 Motor output torque using default controller

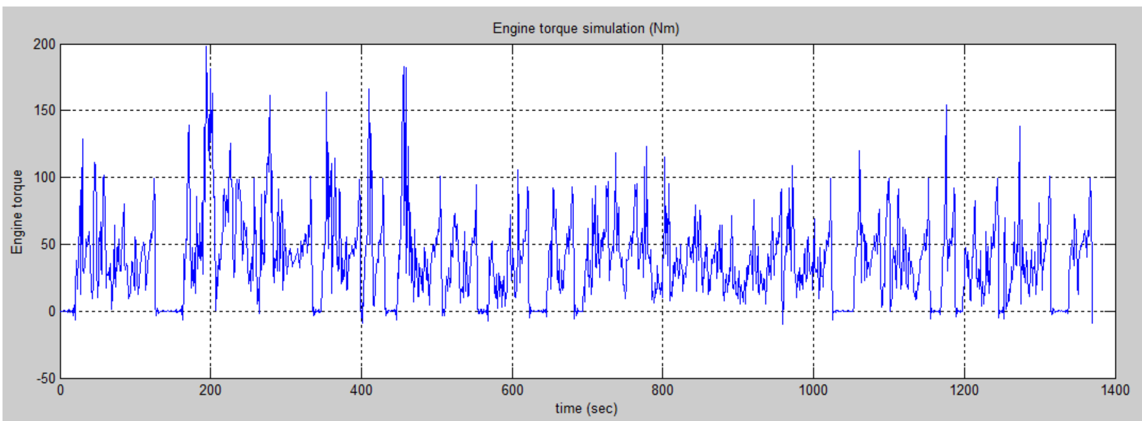

Figure A.4 Engine output torque using default controller

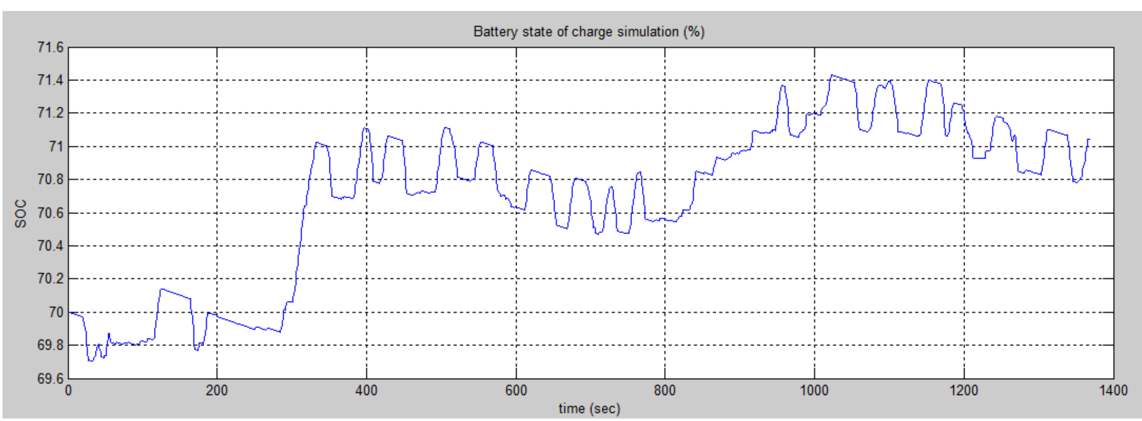

Figure A.5 Battery SOC using default controller

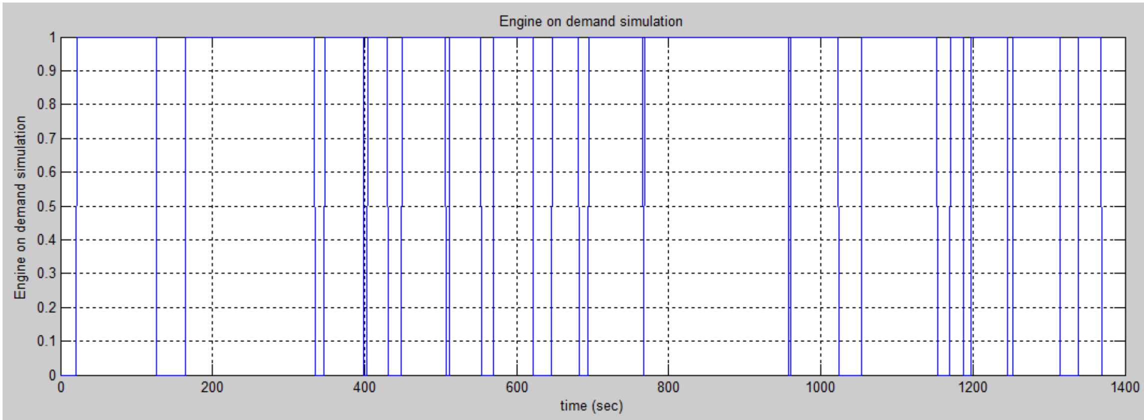

Figure A.6 Engine ON demand simulation using default controller

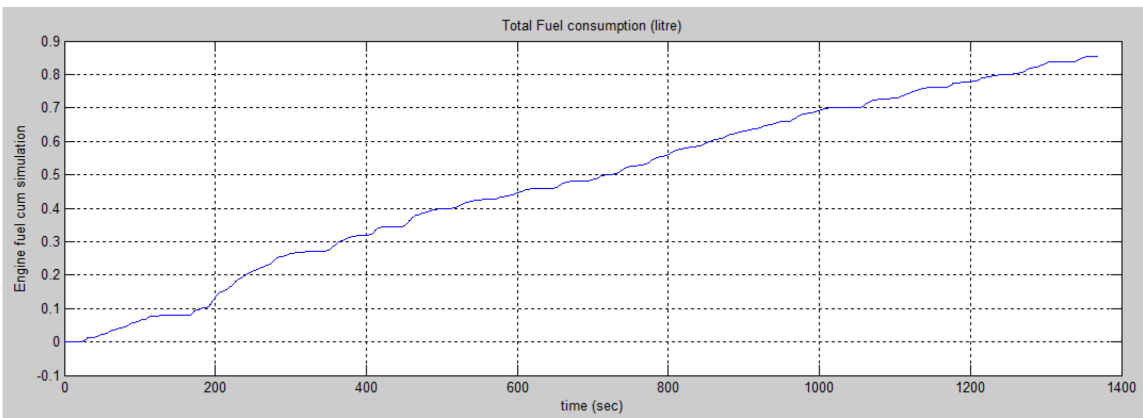

Figure A.7 Total fuel consumption by engine using default controller

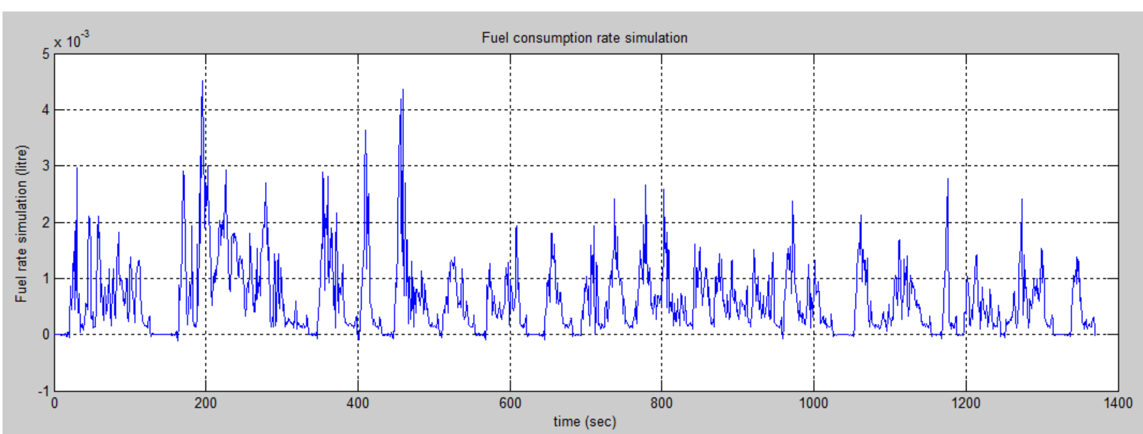

Figure A.8 Engine fuel consumption rate using default controller

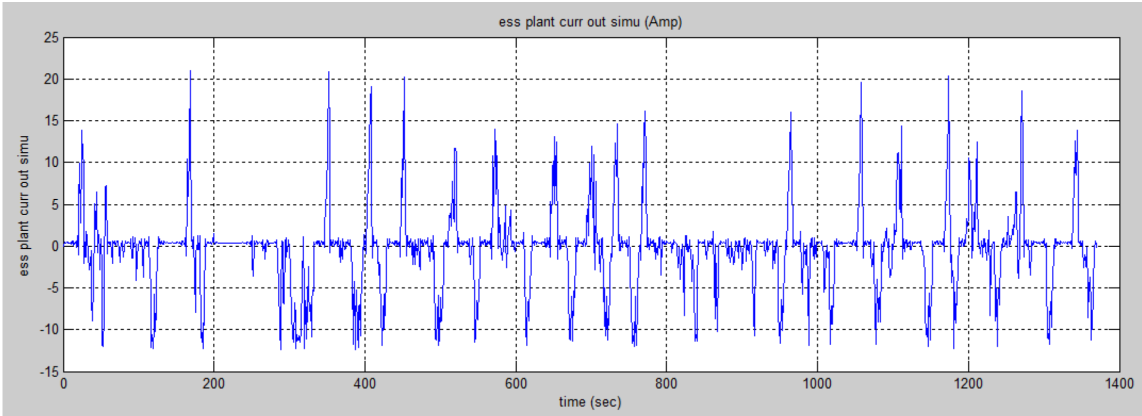

Figure A.9 Battery output current simulation using default controller

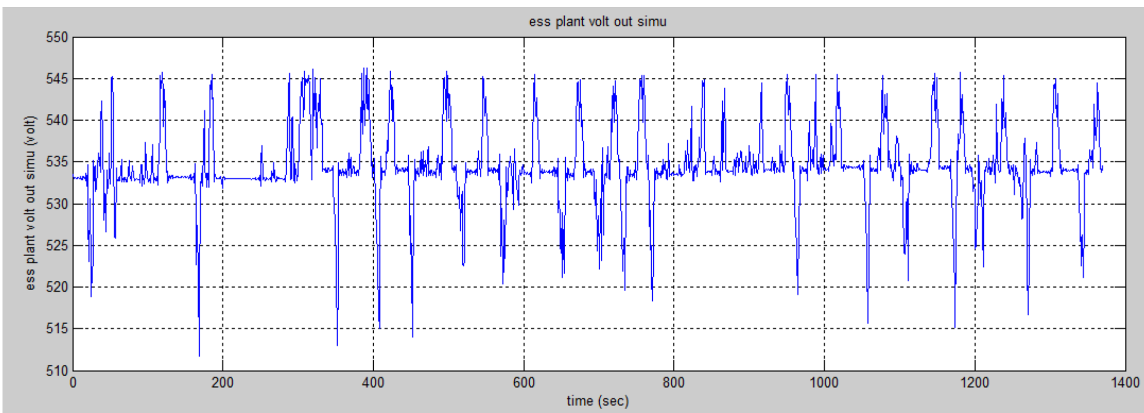

Figure A.10 Battery output voltage simulation using default controller

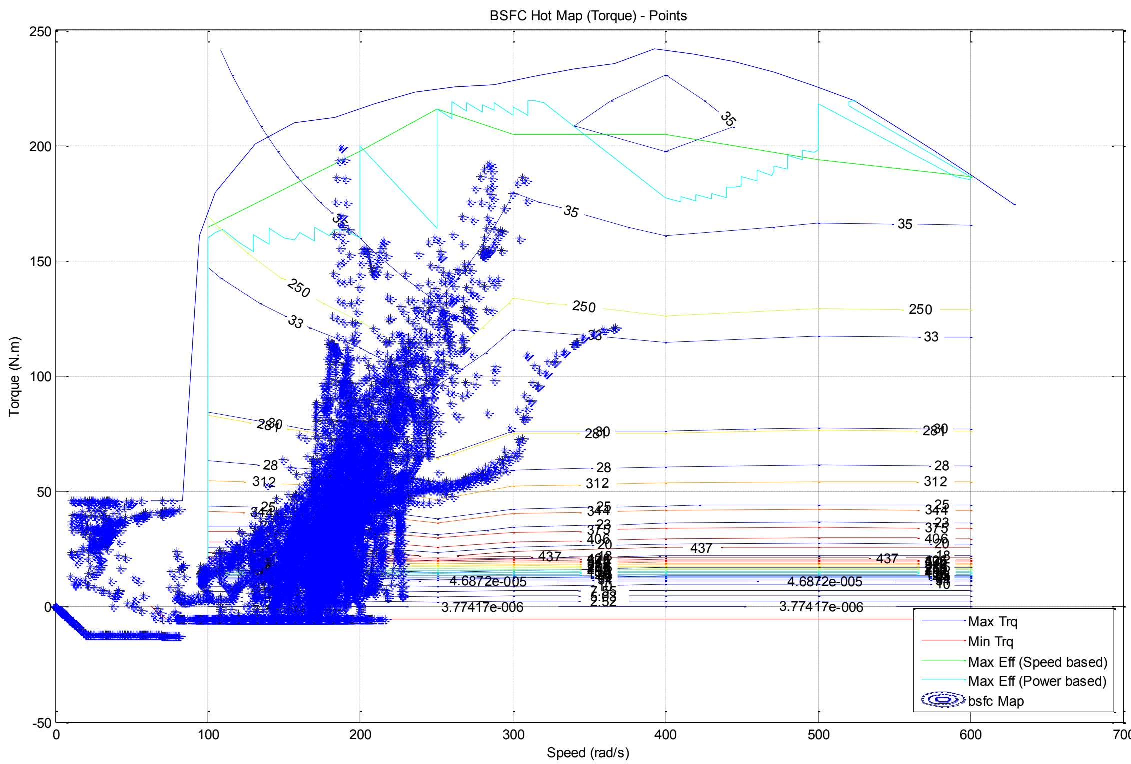

Figure A.11 Engine brake specific fuel consumption for default controller

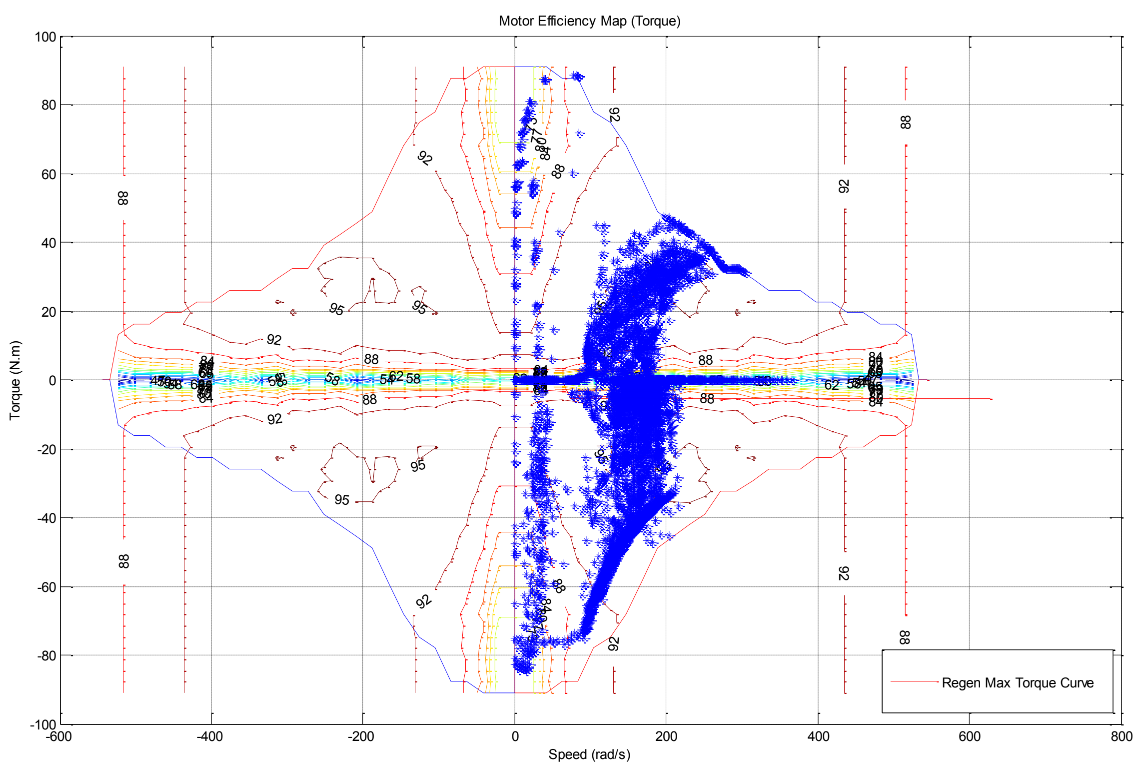

Figure A.12 Motor efficiency maps using default controller

Table A.1 shows vehicle running conditions and performance with default controller in UDDS cycle.

Table A.1 shows vehicle running conditions and performance

Name of the cycle	UDDS
Controller specification	Default controller comes with AUTONOMIE software
Total distance travelled	44.72 mile
Total duration	1369 sec
Maximum speed	56 mile/hr
Total fuel consumption	0.8651 liter
Fuel economy	32.6155 miles/gallon (miles/gallon)
Maximum engine efficiency	36.0018 %
Initial SOC	70 %
Final SOC	71.04 %
Equivalent fuel economy	32.6578 mile/gallon

Appendix B

Table B.1 show the 75 rules used for defining fuzzy logic controller 1.

Table B.1 Fuzzy rule base for controller 1

1		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	1	very_low	low	very_braking	high	very generator
	2	low	low	very_braking	high	very generator
	3	medium	low	very_braking	medium	very generator
	4	high	low	very_braking	medium	very generator
	5	very_high	low	very_braking	medium	very generator

2		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	6	very_low	low	braking	medium	generator
	7	low	low	braking	medium	generator
	8	medium	low	braking	medium	generator
	9	high	low	braking	medium	very_generator
	10	very_high	low	braking	medium	very_generator

3		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	11	very_low	low	zero	medium	neutral
	12	low	low	zero	medium	generator
	13	medium	low	zero	medium	generator
	14	high	low	zero	medium	very_generator
	15	very_high	low	zero	medium	very_generator

4		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	16	very_low	low	acclerating	very_high	generator
	17	low	low	acclerating	high	generator
	18	medium	low	acclerating	very high	generator
	19	high	low	acclerating	very high	motor

20	very_high	low	acclerating	high	motor

5

	Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
21	very_low	low	very_acclerating	Very_high	generator
22	low	low	very_acclerating	Very_high	motor
23	medium	low	very_acclerating	Very_high	motor
24	high	low	very_acclerating	Very_high	motor
25	very_high	low	very_acclerating	Very_high	motor

6

	Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
26	very_low	medium	very_braking	n/a	very generator
27	low	medium	very_braking	n/a	very generator
28	medium	medium	very_braking	n/a	very generator
29	high	medium	very_braking	n/a	very_generator
30	very_high	medium	very_braking	n/a	very_generator

7

	Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
31	very_low	medium	braking	n/a	generator
32	low	medium	braking	n/a	generator
33	medium	medium	braking	n/a	generator
34	high	medium	braking	n/a	very_generator
35	very_high	medium	braking	n/a	very_generator

8

	Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
36	very_low	medium	zero	n/a	neutral
37	low	medium	zero	n/a	generator
38	medium	medium	zero	n/a	neutral
39	high	medium	zero	n/a	very_generator
40	very_high	medium	zero	n/a	very_generator

9		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	41	very_low	medium	acclerating	low	very motor
	42	low	medium	acclerating	low	very motor
	43	medium	medium	acclerating	low	very motor
	44	high	medium	acclerating	high	very motor
	45	very_high	medium	acclerating	medium	very motor

10		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	46	very_low	medium	very_acclerating	medium	very motor
	47	low	medium	very_acclerating	medium	very motor
	48	medium	medium	very_acclerating	high	very motor
	49	high	medium	very_acclerating	medium	very motor
	50	very_high	medium	very_acclerating	medium	Very motor

11		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	51	very_low	high	very_braking	n/a	very generator
	52	low	high	very_braking	n/a	generator
	53	medium	high	very_braking	n/a	very generator
	54	high	high	very_braking	n/a	very generator
	55	very_high	high	very_braking	n/a	very generator

12		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	56	very_low	high	braking	n/a	generator
	57	low	high	braking	n/a	generator
	58	medium	high	braking	n/a	very generator
	59	high	high	braking	n/a	very generator
	60	very_high	high	braking	n/a	generator

13		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	61	very_low	high	zero	n/a	generator
	62	low	high	zero	n/a	neutral
	63	medium	high	zero	n/a	generator
	64	high	high	zero	n/a	very generator
	65	very_high	high	zero	n/a	very generator

14		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	66	very_low	high	acclerating	low	very_motor
	67	low	high	acclerating	low	very_motor
	68	medium	high	acclerating	low	very_motor
	69	high	high	acclerating	medium	very_motor
	70	very_high	high	acclerating	medium	very_motor

15		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	71	very_low	high	very_acclerating	medium	very motor
	72	low	high	very_acclerating	medium	very motor
	73	medium	high	very_acclerating	medium	very motor
	74	high	high	very_acclerating	high	very motor
	75	very_high	high	very_acclerating	low	very motor

Table B.2 given below shows the 75 rules used for defining for the second controller.

Table B.2 Fuzzy rule base for controller 2

1		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	1	very_low	low	very_braking	medium	generator
	2	low	low	very_braking	medium	generator
	3	medium	low	very_braking	medium	generator
	4	high	low	very_braking	medium	very generator
	5	very_high	low	very_braking	medium	very generator

2		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	6	very_low	low	braking	high	generator
	7	low	low	braking	high	generator
	8	medium	low	braking	medium	generator
	9	high	low	braking	medium	very_generator
	10	very_high	low	braking	high	very_generator

3		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	11	very_low	low	zero	high	very_generator
	12	low	low	zero	high	very_generator
	13	medium	low	zero	high	very_generator
	14	high	low	zero	high	very_generator
	15	very_high	low	zero	very high	very_generator

4		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	16	very_low	low	acclerating	very_high	generator
	17	low	low	acclerating	very_high	generator
	18	medium	low	acclerating	high	generator
	19	high	low	acclerating	high	generator
	20	very_high	low	acclerating	high	generator

5		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	21	very_low	low	very_acclerating	very_high	generator
	22	low	low	very_acclerating	very_high	generator
	23	medium	low	very_acclerating	very_high	generator
	24	high	low	very_acclerating	very_high	neutral
	25	very_high	low	very_acclerating	very_high	neutral

6		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	26	very_low	medium	very_braking	low	generator
	27	low	medium	very_braking	low	generator
	28	medium	medium	very_braking	low	generator
	29	high	medium	very_braking	low	very_generator
	30	very_high	medium	very_braking	low	very_generator

7		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	31	very_low	medium	braking	low	very_generator
	32	low	medium	braking	low	very_generator
	33	medium	medium	braking	low	generator
	34	high	medium	braking	low	very_generator
	35	very_high	medium	braking	low	very_generator

8		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	36	very_low	medium	zero	medium	very generator
	37	low	medium	zero	medium	very generator
	38	medium	medium	zero	medium	generator
	39	high	medium	zero	medium	generator
	40	very_high	medium	zero	low	very_generator

9		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	41	very_low	medium	acclerating	high	generator
	42	low	medium	acclerating	very high	generator
	43	medium	medium	acclerating	high	generator
	44	high	medium	acclerating	high	generator
	45	very_high	medium	acclerating	high	generator

10		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	46	very_low	medium	very_acclerating	medium	motor
	47	low	medium	very_acclerating	medium	motor
	48	medium	medium	very_acclerating	medium	motor
	49	high	medium	very_acclerating	medium	motor
	50	very_high	medium	very_acclerating	medium	motor

11		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	51	very_low	high	very_braking	n/a	neutral
	52	low	high	very_braking	n/a	neutral
	53	medium	high	very_braking	n/a	generator
	54	high	high	very_braking	n/a	generator
	55	very_high	high	very_braking	n/a	generator

12		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	56	very_low	high	braking	n/a	neutral
	57	low	high	braking	n/a	neutral
	58	medium	high	braking	n/a	generator
	59	high	high	braking	n/a	generator
	60	very_high	high	braking	n/a	generator

13		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	61	very_low	high	zero	n/a	neutral
	62	low	high	zero	n/a	motor
	63	medium	high	zero	n/a	motor
	64	high	high	zero	n/a	motor
	65	very_high	high	zero	n/a	very motor

14		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	66	very_low	high	acclerating	n/a	very_motor
	67	low	high	acclerating	n/a	very_motor
	68	medium	high	acclerating	low	motor
	69	high	high	acclerating	low	motor
	70	very_high	high	acclerating	n/a	very_motor

15		Speed	SOC	Drv_trq_dmd	Eng_trq	Mot_trq
	71	very_low	high	very_acclerating	n/a	very motor
	72	low	high	very_acclerating	low	very motor
	73	medium	high	very_acclerating	low	Very motor
	74	high	high	very_acclerating	low	very motor
	75	very_high	high	very_acclerating	low	motor