Chapter 6

ANFIS Tuned Equivalent Consumption Minimization Strategy to Improve Fuel Economy in an HEV

This chapter proposes an adaptive network-based fuzzy inference system (ANFIS) EMS for an HEV. The proposed adaptive equivalent consumption minimization strategy (A-ECMS) decides the power to be drawn from ICE and EM based on the input parameters like the speed of the vehicle, state of charge (SoC) of battery, EM torque and ICE torque.

The whole system is simulated in advanced vehicle simulator (ADVISOR) tool which is developed by national renewable energy laboratory (NREL), USA. This is considered as a very significant for carrying out the research on XEVs. Many Sports vehicle designing industries uses this tool to verify their design. The proposed non-linear controller has also been tested for real-time behaviour using an FPGA based MicroLabBox hardware controller to compare its performance against existing controllers. Furthermore, the fuel economy obtained using the proposed method has been compared with other EMS. The result analysis clearly reveals that the proposed ANFIS based method provides better optimization of energy and hence offers better fuel economy.

The urban dynamometer driving schedule (UDDS) has been employed for this analysis.

6.1 Introduction

HEV is a non-linear, complex, and electro-mechanical-chemical system. The flow of energy and data transfer occur when HEV is in motion. The main agenda for HEV is the optimal power split between ICE and EM without compromising on the system performance. The power-split between ICE and EM depends upon the configuration and energy management strategy (EMS) adopted. EMS in HEVs is the key to boost the fuel economy (FE), reduce harmful emission and therefore, indispensable for optimal HEV design [290]. The inspiring features of the NN are its ability to learn and adapt, whereas the capability of a fuzzy system is to consider imprecision and prevailing uncertainties. To exploit the advantages of both methods, the ANFIS algorithm comprising of both the NN and the fuzzy logic is adopted for the proposed work.

In [291], the ANFIS based model has been proposed to optimize various parameters of HEV. In [287], artificial neural network (ANN)-based EMS has been employed for PHEVs with optimized parameters like demanded power, the ratio of the distance travelled to the total distance, and SoC. The energy consumption was found to be reduced by 29.6% for a SoC of 0.35. In [292], an EMS based on ANFIS with optimized parameters like Speed, driver demand and SoC has been used for series-parallel HEV and an improvement in FE have been proposed. In [293], an EMS based on ANFIS to optimize the energy flow in HEV has been proposed. An EMS based on hybrid multi-layer ANFIS with GA to optimize the torque and SoC for PHEV has been proposed [294], [295]. In [296], an EMS based on neuro-fuzzy-sliding mode control to optimize speed, quadrature current and vehicle dynamics for an (electric vehicle) EV has been proposed. In [297], an EMS based on NN algorithm to optimize the torque and speed for electrical variable transmission (EVT)-HEV and the efficiency optimization strategy of regenerative braking system (RBS) has been presented.

6.2 Powertrain structure and its control

The configuration employed in this work has been shown in Fig.6.1.

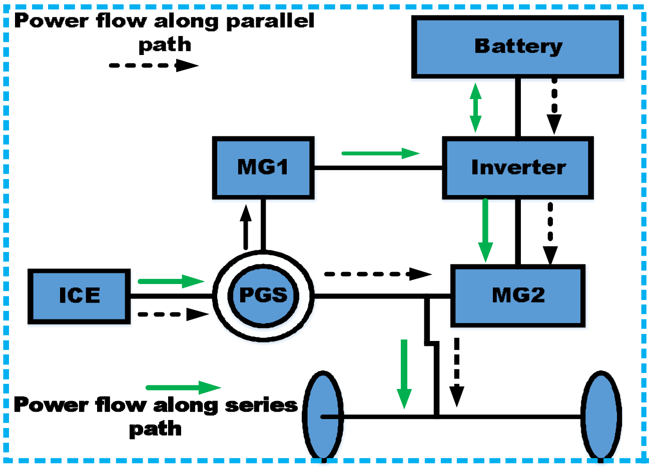


Fig. 6.1 Power-split hybrid architecture of Toyota Prius HEV

There are three power sources, i.e., ICE, EM and generator that exert force to keep the vehicle in motion. The ICE and EM torques are considered positive as they result in vehicle acceleration; on the other hand, the generator torque can be defined as positive to resist the vehicle motion. The HEV consists of two motor generators set, i.e. mg_1 and mg_2, ICE, and planetary gear set (PGS). The ICE and EM are responsible for supplying the required power as per the control strategy used. The switching (on/off) of ICE depends on the battery SoC, the energy required, the speed of the vehicle, the temperature of the coolant and ICE on/off periods. The on/off conditions of the sources depend on the following criteria:

(a) If the vehicle has sufficient SoC and demands less power as the vehicle speed is low and the coolant temperature is in the safe range, then the vehicle will work as BEV.

(b) If the vehicle requires high power and SoC is more than its predetermined value, then ICE and EM both provide propulsion power.

(c) If SoC is less than its predetermined value, then ICE provides the propulsion powers to the vehicle and also charge the battery simultaneously.

(d) If brakes are applied, the power becomes negative, and ICE is off, then this entire power is utilized to charge the battery by regenerative braking.

The controller is designed with a target that ICE and EM should operate in their efficient region leading to better FE. In order to achieve less fuel consumption, it is evident that battery power has to be large, or vehicle should be propelled more in the electric mode. Torques speeds and efficiencies of motor/generators are related to battery power as

$$\left.\begin{array}{l} P_{bat} = T_{mg1}\omega_{mg1}\eta_{mg1}^{k_{mg1}} + T_{mg2}\omega_{mg2}\eta_{mg2}^{k_{mg2}}, \\ k = \begin{Bmatrix} +1, T_i\omega_i > 0 \\ -1, T_i\omega_i < 0 \end{Bmatrix}, i = \{mg1, mg2\} \end{array}\right\} \tag{6.1}$$

Where T_{mg}, ω_{mg}, η are the torque of the motor-generator set, speed of motor-generator set and efficiency. Battery power (P_{bat}) is directly proportional to battery SoC which can be expressed as:

$$\left.\begin{array}{l} P_{bat} = OCV \times I_{bat} - I_{bat}^2 \times R_{bat} \\ SoC^{\bullet} = -\dfrac{I_{bat}}{Q_{bat}} \end{array}\right\} \tag{6.2}$$

Where OCV is open-circuit voltage, $SoC^{\bullet}$ is the rate of change of SoC, Q_{bat} is the battery capacity, and Rbat is the internal resistance of battery which can be obtained using the relation among mg_1, mg_2, ICE, and requested torques T_{mg1}, T_{mg2}, T_e, T_{req} and speeds ω_{mg1}, ω_{mg2}, ω_e, ω_{req} can be understood from the following equations.

$$T_{mg1} = -\frac{1}{1+R}[T_e] \tag{6.3}$$

$$\omega_{mg1} = -R \times \zeta \times \omega_r + (1+R) \times \omega_e \tag{6.4}$$

$$T_{mg2} = -\frac{1}{(1+R)}\left[-\frac{(1+R)\times T_{req}}{\zeta} + R \times T_e\right] \tag{6.5}$$

$$\omega_{mg2} = \zeta \times \omega_{req} \tag{6.6}$$

In the above equations R and ζ represents the gear ratio of PGS and the final drive ratio.

$$\left.\begin{array}{l} P_{bat} = T_{mg1}\omega_{mg1}\eta_{mg1}^{k_{mg1}} + T_{mg2}\omega_{mg2}\eta_{mg2}^{k_{mg2}} \\ where, k = \begin{Bmatrix} +1, T_i\omega_i > 0 \\ -1, T_i\omega_i < 0 \end{Bmatrix}, i = \{mg1, mg2\} \end{array}\right\} \tag{6.7}$$

For any smart control design, it is necessary to satisfy the constraints given in equation (6.8).

$$\left\{\begin{array}{l} \omega_{e,\min} \le \omega_e \le \omega_{e,\max} \\ \omega_{mg,\min} \le \omega_{mg} \le \omega_{mg,\max} \\ T_{e,\min} \le T_e \le T_{e,\max} \\ T_{mg,\min} \le T_{mg} \le T_{mg,\max} \\ SoC_{\min} \le SoC \le SoC_{\max} \end{array}\right\} \tag{6.8}$$

6.2.1. ICE Speed Control Strategy.

The control strategy design plays a vital role in improving FE. An efficient EMS should follow certain control objectives as below:

(a) Driver torque and speed requirement should be fulfilled in a way that it should not leave a missing trace (i.e., desired and the obtained response is in close resemblance) between them, (b) ICE and EM should operate in their efficient region.

(c) Target SoC level meets at the end of the trip, and

(d) Maximum braking energy is recuperated while braking or decelerating.

Vehicles can be categorized into three-speed regions, namely, (1) low, (2) medium, and (3) high vehicle speed, as shown in Fig. 6.2.

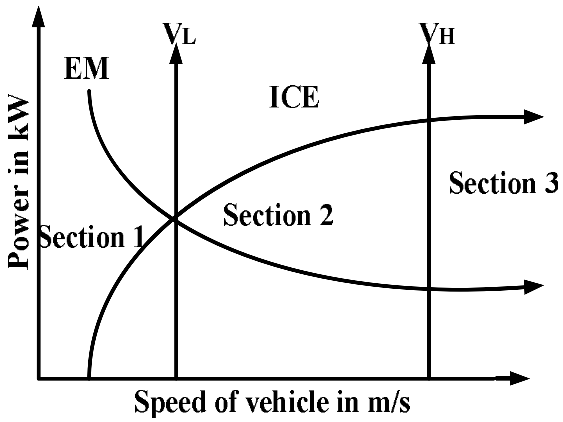


Fig. 6.2 Efficient operating region of the sources

During the low-speed region, it is advisable to use EM to provide the propulsion power to the vehicle as the use of ICE during this period is inefficient. Low vehicle speed i.e. V_L can be estimated by the expression given below [18]:

$$V_L = \frac{\pi k_{yr} n_{e\_\min} r_w}{30 i_{rw}} (m/s) \tag{6.9}$$

Where $n_{e\_\min}$ is the minimum allowable speed of ICE, rw is the wheel radius, k_{yr}=(1+i_g)/i_g, where, i_g is the gear ratio defined by r_r/r_s and i_{rw} is the gear ratio of the ring gear to drive train wheels. During this region, the motor/generator will operate with a positive speed (nm/g) given as:

$$\eta_{m/g} = k_{yr} \left[n_{e\_\min} - \frac{30 i_{rw} V}{\pi k_{yr} r_w} \right] \tag{6.10}$$

V is the vehicle speed in m/s ($V \leq VL$). The motor/generator absorbs a part of the engine power to charge the battery. Power on the motor/generator shaft $P_{m/g}$ can be expressed in terms of $T_{m/g}$ (motor/generator torque).

$$P_{m/g} = \frac{2\pi T_{m/g} n_{m/g}}{60} = \frac{2\pi T_e n_{e\_\min}}{60} - \frac{i_{rw}}{k_{yr} r_w} T_e V. \tag{6.11}$$

When the vehicle speed is higher than VL but lower than VH then it is given by the expression

$$V_H = \frac{\pi k_{yr} n_{e\_m\mathrm{ax}} r_w}{30 i_{rw}} (m/s) \tag{6.12}$$

Where $n_{e\_\max}$ is the maximum allowable revolution per minute (RPM) of ICE. In the medium-speed region, ICE is responsible for powering the vehicle for propulsion. When the vehicle speed is higher than the V_H, motor/generator has to operate in the direction opposite to the engine speed to limit the ICE speed below the maximum allowable ICE speed $n_{e\_\max}$. It can be expressed as follows:

$$\eta_{m/g} = k_{ys} \left[n_{e\_\max} - \frac{30 k_{ys} i_{rw} V}{\pi k_{yr} r_w} \right] \tag{6.13}$$

Where $V \geq V_H$. The motor/generator is in motoring mode, and motoring power can be expressed as follows:

$$P_{m/g} = \frac{2\pi T_{m/g} n_{m/g}}{60} = \frac{i_{rw}}{k_{yr} r_w} T_e V - \frac{2\pi i_{rw} T_e n_{ne\_\min}}{60 k_{yr} r_w}. \tag{6.14}$$

6.2.2 Torque based control.

In low-speed region when adequate SoC is available then EM torque T_{mt} can be expressed as follows:

$$\left.\begin{aligned} T_{mt} &= \frac{60 P_{m/g}}{2\pi n_{tm}} = \left(\frac{n_{e\_\min}}{n_{tm}} - \frac{i_{rw}}{k_{yr} i_{mw}} \right) T_e \\ &= \left(\frac{2\pi r_w n_{e\_\min}}{60 i_{mw} V} - \frac{i_{rw}}{k_{yr} i_{mw}} \right) T_e \end{aligned}\right\} \tag{6.15}$$

Where i_{mw} (traction motor to the driven wheels) is gear ratio, and n_{tm} is EM speed. PGS, mg_1 and mg_2 together function as an EVT, because no energy goes into or out of the battery. In the high-speed region, the ICE speed is governed by the max speed of engine $n_{e\_\max}$, and the motor/generator set works in motoring mode.

If the requested torque is higher than the torque that the ICE can deliver with its optimal throttle at the speed of n_{e_max} and SoC of the battery is lower than SoC_min, then ICE will be compelled to operate at a higher speed which will be out of its efficient operating region. In such a case, ICE alone has to propel the vehicle (neglecting all conditions of the optimal region), and it also charges the battery. By doing so it will help motor/generator set to work in generating mode to feed the traction motor which supports engine by providing additional torque, then speed will be.

$$n_e > \frac{30 i_{rw} V}{\pi k_{yr} i_w} \tag{6.16}$$

If SoC is more than the SoC_min, then the ICE should be operated in its optimal efficient region with ne_max and EM provides additional torque to support the ICE.

If the demanded torque is less than the engine torque and SoC is lower than SoC_min, the engine is operated according to (6.13), and EM works as a generator.

If SoC is in-between the range of SoC_min and SoC_max, ICE alone mode can be projected, and EM may be charged.

If SoC is greater than the SoC_max, the engine shuts down, and EM propels the vehicle alone. The vehicle component specifications are provided in Table 6.1.

Table 6.1 Vehicle component specification (Toyota Prius)

Component	**Values**	**Component**	**Values**
Motor	31kW	Average acceleration	1.66 ft/s^2
Engine	43kW	Average deceleration	-1.9 ft/s^2
Heating value of gasoline	42600 J/g	Idle time	259 s
Generator	15kW	Number of stops	17
Drag coefficient	0.3		
Battery	40kW		
Final drive ratio	3.93		
Frontal area	1.746m2		
Wheel radius	0.287m		
Vehicle glider mass	918 kg		
Total distance	7.45 miles		
Max speed	56.7 mph		
Average speed	19.58 mph		
Max acceleration	4.84 ft/s^2		
Max deceleration	-4.84 ft/s^2		

6.3 Proposed ANFIS based EMS

The presence of EM and ICE together makes it inevitable to decide engine/motor switching to split the power optimally between these sources in order to increase the FE. ANFIS is a non-linear dynamic system modelling technique, which uses a NN combination with fuzzy logic aimed to utilize the advantage of NN and fuzzy inference. Implementation of ANFIS architectures in various control algorithms have proved its advantages and approximating capabilities with great precision. It has the self-learning capability of ANN and the features of linguistic expression function of the fuzzy inference system. It is considered as an effective method for tuning the membership functions to minimize the output error. In the present work, the ANFIS architecture and Sugeno fuzzy model are used. ANFIS is an adaptive system that changes its structure based on internal, external information or data provided during the learning phase. Input data and a corresponding desired, or target response is fed to ANFIS. An error is generated due to the difference between the preferred response and the system output. This error is then feedback into the system, and the parameters are adjusted in a logical fashion. This process is repeated until the system performance is deemed acceptable, as shown in the flow chart in Fig. 6.3. The ANN parameters are fixed on completion of this learning process.

The inputs are: namely, m and n and the output is f. For a Sugeno fuzzy model (first-order), a typical rule set with two fuzzy if/then rules are given below.

Rule 1: If (m is A1) and (n is B1) then $f_1= p_1m+ q_1n +r_1$

Rule 2: If (m is A2) and (n is B2) then $f_2= p_2m+ q_2n +r_2$

Where, x and y are crisp inputs and A1, A2, B1 and B2 are linguistic variables.

Layer 1. Each node i in layer 1 represents the fuzzy membership function. The output of each node is given as:

$$\rho_j^1 = \alpha_{Ai}(x); i = 1, 2.. \tag{6.17}$$

$$\rho_j^1 = \alpha_{Bi-2}(y); i = 1, 2, 3.. \tag{6.18}$$

ρ_j^1 must be the membership grade for x and y

$$\alpha_A(x) = \frac{1}{1 + \left| \dfrac{x - c_i}{a_i} \right|^{2b_i}}, \tag{6.19}$$

Where a_i, b_i, c_i are the premise parameters.

Layer 2. All nodes in this layer are fixed. Here, t-norm is used to 'AND' the membership grades, as shown in (6.20).

$$\rho_j^2 = w = \alpha_{Ai}(x)\alpha_{Bi}(y); i = 1, 2,. \tag{6.20}$$

Layer 3. Determination of the ratio of the firing strengths of the rules is done as below:

$$\rho_j^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \tag{6.21}$$

Layer 4. It is an adaptive layer which performs the subsequence of the rules, and it is performed based on (6.22).

$$\rho_j^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{6.22}$$

The parameters in this layer (pi, qi, ri) are called consequent parameters.

Layer 5. It is a single node layer which determines the final output, as shown in (6.23).

$$\rho_j^5 = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6.23}$$

ANFIS parameters are trained by alternatively using the forward and backward pass, which uses least square estimation (LSE) algorithm and gradient descent algorithm, respectively. The schematic diagram of ANFIS shown in Fig. 6.4 with four input parameters to determine one output which is the torque of ICE/EM. As the ANFIS structure produces one output at a time, it was necessary to use the ANFIS algorithm separately for ICE and EM. During the torque produced by ICE, there were; 193 nodes, 117 parameters (81 linear and 36 non-linear), hence, 1370 training data pairs, 81 fuzzy rules, 10 epoch numbers and 16.58 root mean squared error (RMSE). During the torque produced by EM, all the above parameters were the same except for RMSE, which was 0.448534.

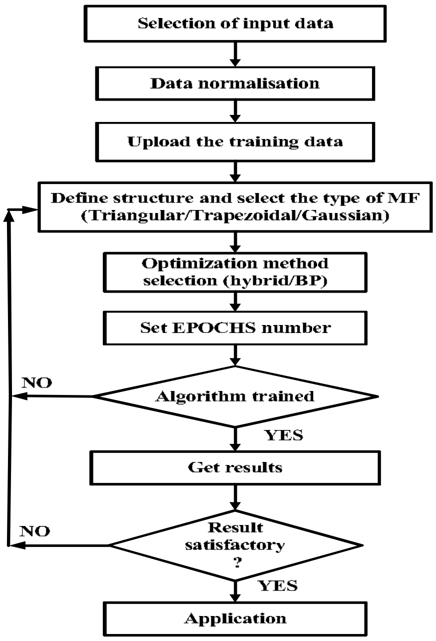


Fig. 6.3 Flowchart of the ANFIS algorithm operation

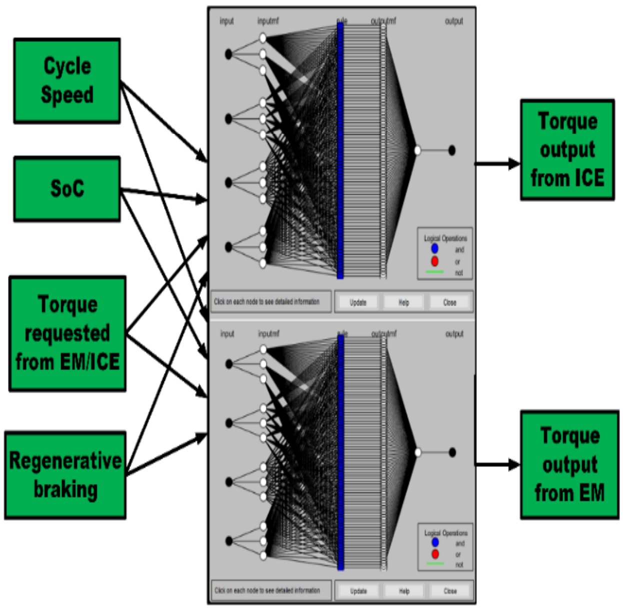


Fig. 6.4 Schematic diagram of the proposed ANFIS Based EMS

6.3.1 Computational cost:

ANFIS is good when the number of inputs are not more than five [298]. The more the inputs, the higher will be computational expense of ANFIS-based model. In the presented approach since the number of inputs are four therefore the issue of computational cost is not going to affect the performance of designed EMS.

ANFIS is susceptible to the "curse of dimensionality". The training time increases exponentially with respect to the number of fuzzy sets per input variable used. To illustrate this let us understand from the Table 6.2. Suppose there are 8 input variables that are coded into two fuzzy sets (e.g. low, high) and has 256 rules (28) and if there are three linguistic variables instead of two (say low, medium, high) the number of fuzzy rules becomes 6561 (38). This phenomenon limits in practice the choice of input variables as well as the expression of those variables into meaningful fuzzy sets. In our case the rules are 81 so curse of dimensionality will not affect the performance of the system. The overfitting problem with artificial intelligent technique is not going to be encountered as the model is simple (rules were 81 only) and regularization was done [299].

Table 6.2 Curse of dimensionality for fuzzy set with three linguistic variables

No. of inputs	1	2	3	4	5	6	7	8
No. of rules	3	9	27	81	243	729	2187	6561

6.4 Simulation results

The simulation has been carried out on ADVISOR tool (for Toyota Prius). The block diagram of the vehicle used in this study is shown in Fig. 6.5. The energy management unit (EMU) takes SoC, cycle speed, demanded torque and constraints [as in eq (8)] as input and based upon the efficient region of the sources, it switches on the source(s) appropriately to fulfil the demanded torque. The fulfilment of the demand is reflected based on the missed traces. Significant trace missing indicates inefficient EMS. The simulation is carried out using ADVISOR tool on the Toyota Prius model.

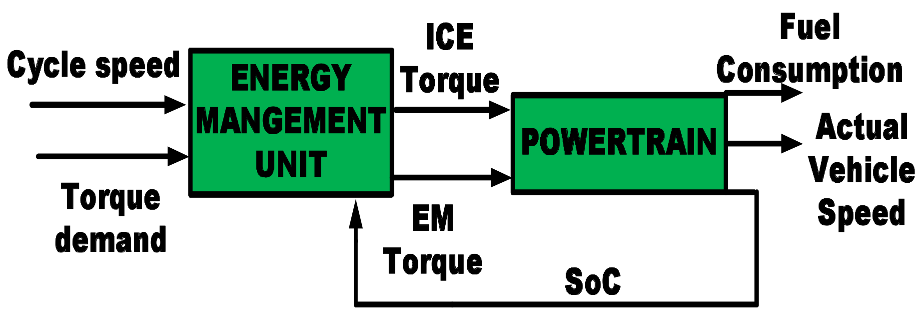


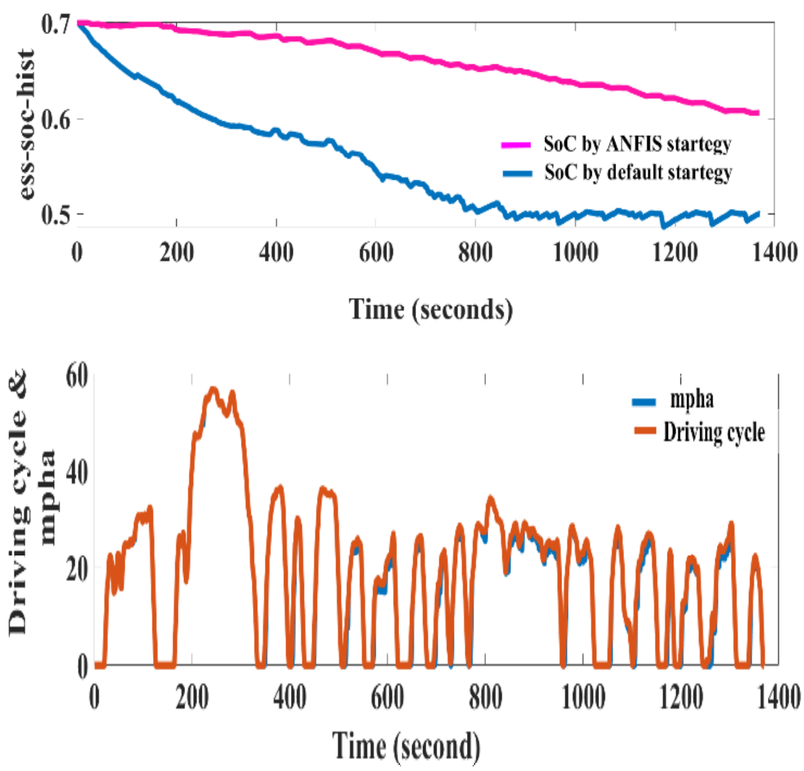
Fig. 6.5 Block diagram of the vehicle used in the study

Figure 6.6 presents the variation in ESS SoC (ess-soc-hist), demanded and achieved speeds, and variation in emissions over time for the default and ANFIS based strategies. The interpretation of these results including the major contribution of this work, is as below:

i) SoC changes from 0.7 to 0.5 with default strategy, and from 0.7 to 0.6 with ANFIS based EMS. It infers that the decay in SoC is lesser using proposed strategy which minimizes the frequent charging and discharging of the battery and hence enhance its lifecycle.

ii) The demand of the driving cycle is matched (almost coinciding) with the miles per hour achieved (mpha) i.e., the demanded speed has been achieved. It signifies the effectiveness of the proposed algorithm.

iii) From the emission graph it can be concluded that the emission are quite high at cold start and then gets mitigated with an increase in the catalyst efficiency. Also, the frequent start and stop of ICE should be avoided as it produces more emissions during the transient engine regime (start-up until the engine reached working temperature). The proposed EMS has reduced the emission as shown in Table 6.3.



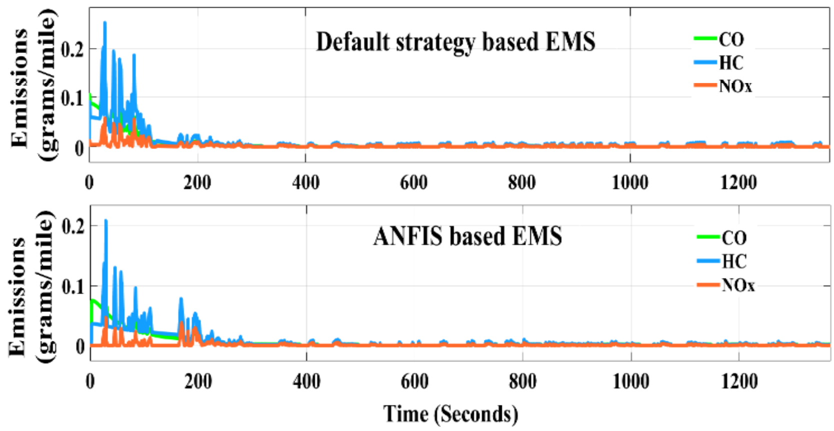


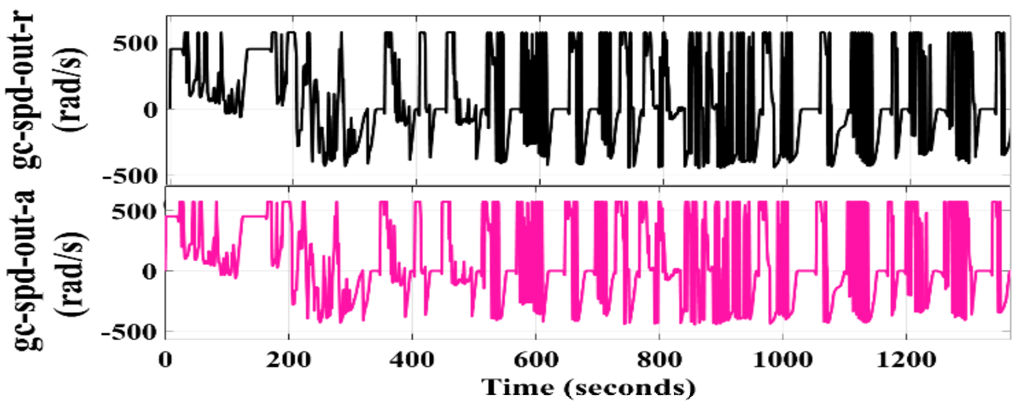
Fig. 6.6 Various Results obtained for Toyota Prius using default EMS as in ADVISOR.

Further, the FE obtained using proposed EMS is quite high as compared to default, PSO and GA tuned EMS (Table 6.3).

Table 6.3 Emissions (Toyota Prius)

Emission	**HC**	**CO**	**NOx**
ANFIS	1.133	1.273	0.245
Default	1.239	1.632	0.43

Figure 6.7 represents the generator behavior. The generator torque input required (gc-trq-in-r) by the vehicle to charge the battery required and generator torque input achieved (gc-trq-in-a) both are equal without a trace miss. The similar condition can be seen with the generator speed output required (gc-spd-out-r) and generator speed output achieved (gc-spd-out-a). These conditions will improve the FE of the vehicle as well as make the driver feel comfortable to drive the vehicle since it smoothens the driving scenario.



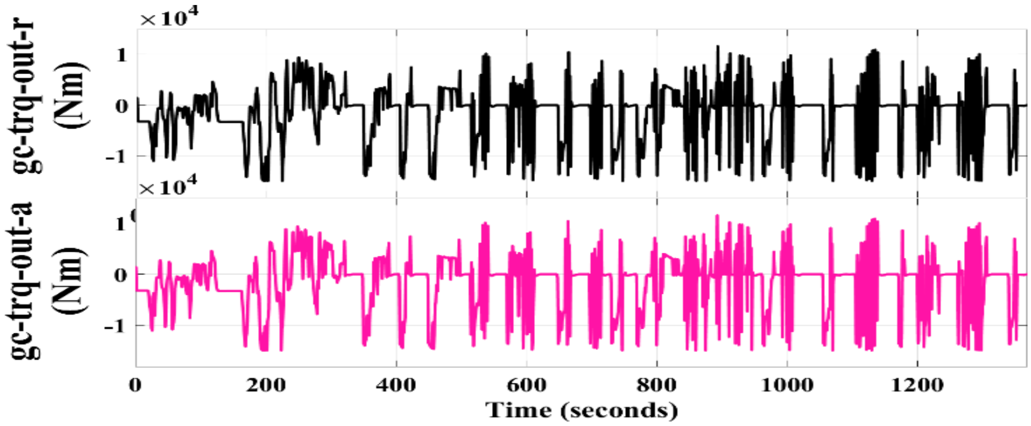


Fig. 6.7 Generator behaviour using ANFIS

Figure 6.8 represents the EM behaviour as per the driving cycle chosen. When EM provides power for propulsion it drains out the battery. Therefore, from the time EM provide the propulsion power the SoC level keeps on decreasing. In Fig. 6.8 the motor power input required (mc-pwr-in-r) is equal to the motor power input achieved (mc-pwr-in-a) which shows that the demanded power has been met up without having any mismatch. Similarly, motor speed out required (mc-spd-out-r) and motor speed out achieved (mc-spd-out-a) are also met up.

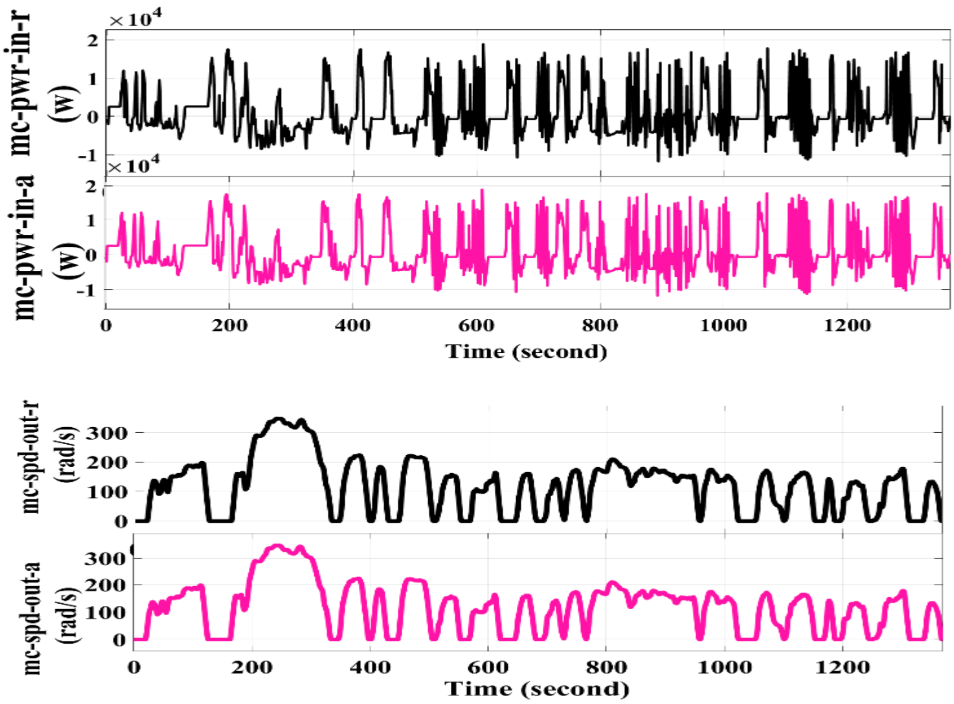


Fig. 6.8 Motor behaviour using ANFIS

Figure 6.9 shows the behaviour of the energy storage system. The required and achieved ESS powers have been represented by the ess-power-out-r and ess-power-out-a, respectively. Both the parameters are overlapping, which proves the accountability of the proposed algorithm. The SoC (Fig.6.6) is gradually decreasing with time using ANFIS compared to the default strategy. It infers that ANFIS has reduced the frequent charging and discharging of the battery and hence the SoC is being preserved for longer time while prolonging the life of battery.

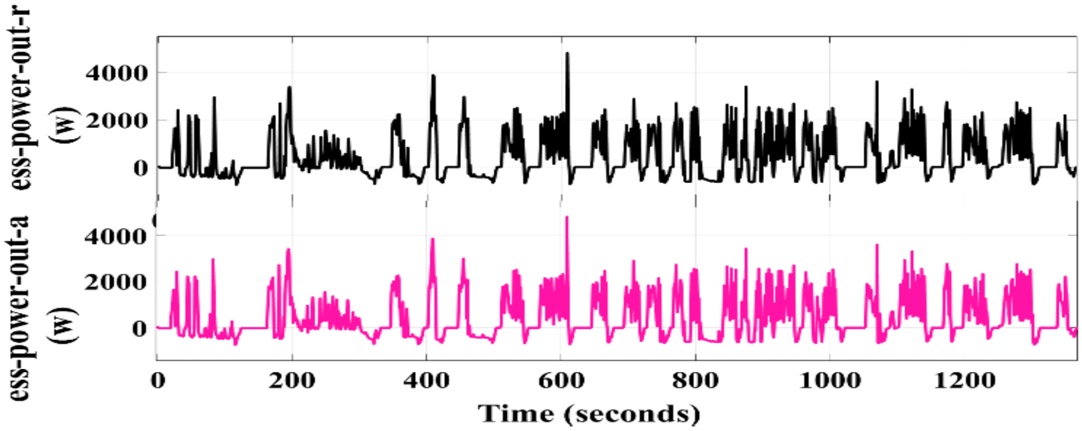


Fig. 6.9 Energy storage system behaviour using ANFIS

Figure 6.10 displays the response of the fuel converter. The fuel converter represents the behaviour of the ICE. The fuel converter speed out required (fc-spd-out-r) equals with the fuel converter speed out achieved both the quantities represents the demanded speed can be achieved without delay. Hence making ICE operation efficient and fast.

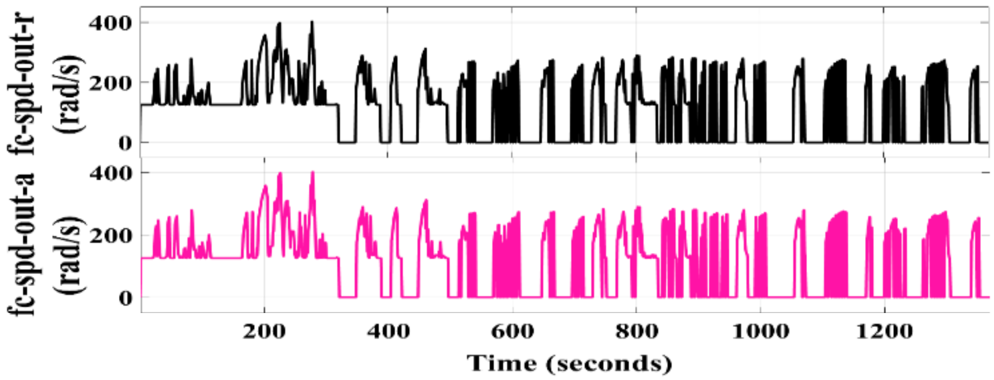


Fig. 6.10 Fuel converter behaviour using ANFIS

Figure 6.11 shows the working of the various sources based upon the driving cycle. In this figure, the amount of energy supplied by each source i.e. fuel converter (fc), generator controller (gc) and motor control (mc) has been shown. The energy produced by various sources until t=100s has been shown here.

Table 6.4 represents the energy usage in kilo Jules (kJ) in terms of input and output of various components which are utilized during the power and the regenerative mode. As the units of consumption of various components are different like i.e. the fuel consumption in

L/km or mpg and motor power is kilowatt so it is better to define the overall efficiency. The overall system efficiency is 0.114 for the vehicle with default EMS available in ADVISOR, whereas it rises to 0.168 by employing ANFIS based EMS. The overall drive train efficiencies are vastly influenced based on the resultant traction motor-controller efficiency, inverter efficiency and fuel converter efficiency. The overall efficiency has increased from 0.114 (11.4%) to 0.168 (16.8%) i.e. an increase of 47.36%. The is due to the fact that various component of HEV have worked at high efficiency while applying the proposed algorithm. The proposed approach proves to be much more accurate than the existing efficiency analysis.

Table 6.4 Energy usage in the vehicle by various component (kJ)

Parameter	**With default EMS**								**With ANFIS EMS**							
	Power mode (kJ)				**Regen. Mode (kJ)**				**Power mode (kJ)**				**Regen. Mode (kJ)**			
	In	**Out**	**Loss**	**Eff.**	**In**	**Out**	**Loss**	**Eff.**	**In**	**Out**	**Loss**	**Eff.**	**In**	**Out**	**Loss**	**Eff.**
Fuel	0	18607							0	12717						
Fuel converter	18607	5219	13388	0.28					12717	8138	4579	0.64			101	
Generator	662	457	204	0.69					1415	664	751	0.47				
ESS	1201	2215	319	0.82					159	758	31	0.88				
Energy stored	-1334								-630							
Motor	2476	1998	478	0.81	1562	1305	257	0.84	3385	2748	637	0.81	2663	2598	65	0.98
Final drive	4723	4723	0	1	1004	1004			5892	5892	0	1	1363	1363	0	1
Wheel/axle	4723	4387	336	0.93	2111	2098	13	0.99	5892	5512	381	0.94	2454	2449	5	1
Braking							1094								1086	
Auxiliary load	958	0	958	0					958	0	958	0				
Aerodynamic			826								817					
Rolling resistance			1448								1430					
Overall system efficiency	**0.114**								**0.168**							

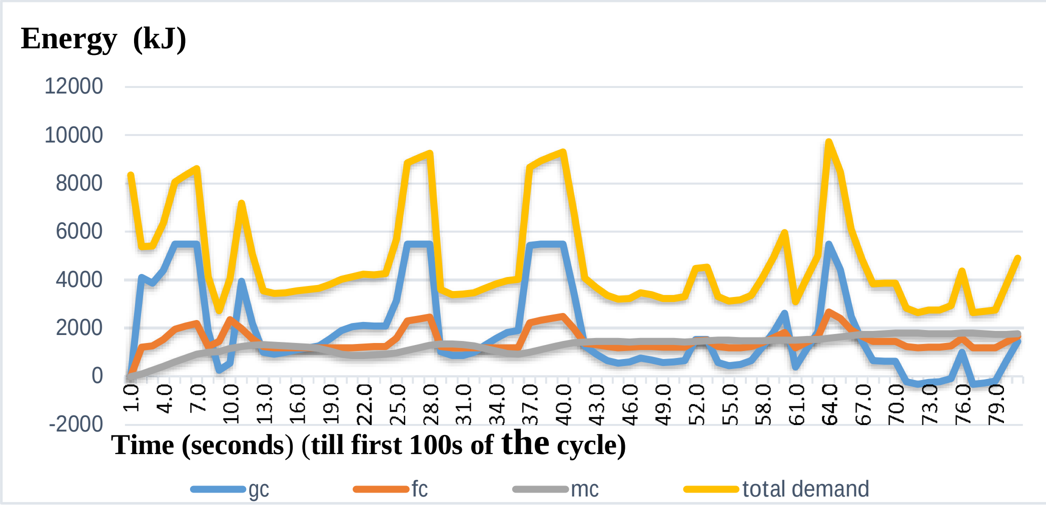


Fig. 6.11 Amount of energy released by available sources at the various instant of the speed requirement/driving cycle.

6.5 Real-time (CHIL-setup) implementation

The CHIL setup of the proposed system is shown in Fig. 6.12. The proposed system is developed in ADVISOR tool and then validated in real-time on CHIL testing platform using FPGA based MicroLabBox. Real-time is used to describe time-critical technology in various industries. MicroLabBox uses real-time in reference to an embedded system. These systems are devices which interface with the real world and provide control. The embedded device is given a pre-set time, like 1,5,20 ms to read input signals, to perform all necessary calculations and to write all outputs. The interval size is called the step size, Ts. Fixed-step solvers solve the model at regular time intervals from the beginning to the end of the simulation. Physical test system setup serves the purpose quite well, but they are large, costly and require highly experienced people to handle the repetitive occupations of setting up networks and maintaining extensive inventories of difficult hardware. With the improvement and advancement in microprocessor and floating-point digital signal processing technologies, physical test systems have been replaced with completely real-time simulator. The hybrid vehicles are highly non-linear and complex in nature and therefore testing on the actual network is very expensive, tedious, and risky. Hence, a speedier approach is to test and validate a new algorithm or research in a real-world environment using a real-time simulator as validation in real-time is an essential part of the design and improvement of the electrical system.

MicroLabBox controller helps in realizing the complex control concepts. It provides a high computation power with very low I/O latencies, which results in significant real-time performance. CHIL laboratory was setup for the validation of the simulated results in real-time. The results obtained through ADVISOR simulation and real-time CHIL are in close resemblance. This proves that the simulated results will be obtained in a real-world scenario as well.

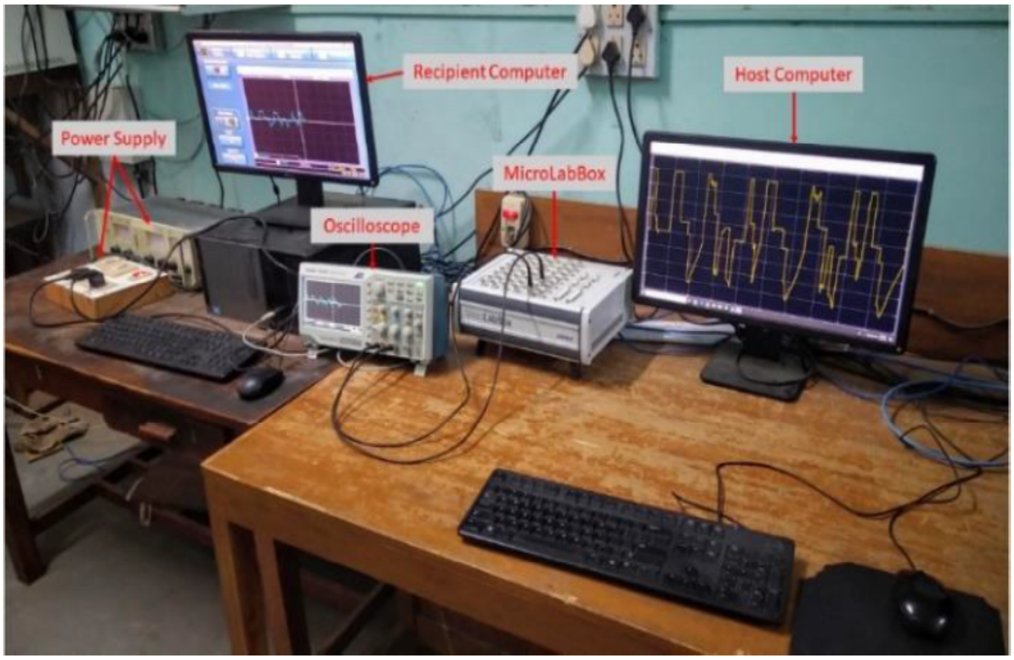


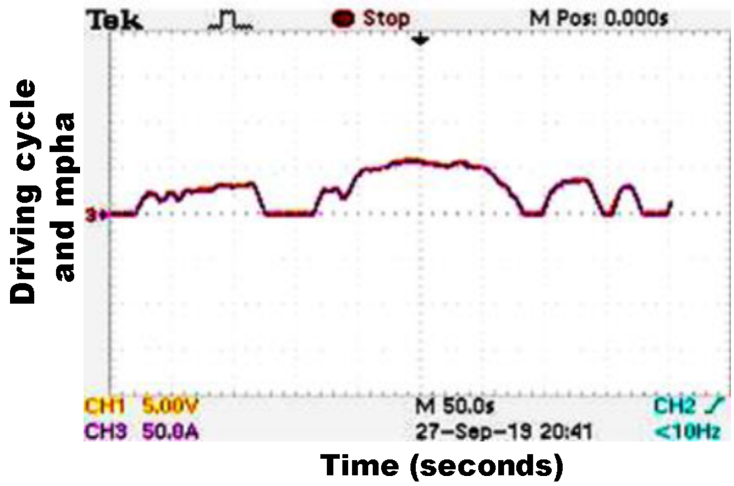
Fig. 6.12 CHIL Setup of the System

Figure 6.13 shows the results of the CHIL implementation. The whole system is burned in the field-programmable gate array (FPGA)-based MicroLabBox. Various settings have been done like feeding the host with the provided internet protocol (IP) address then the dSpace will recognize the personal computer, thereafter, setting the sampling time to 50 microseconds (user-defined) and then burning all the simulation files into it. If the files are burned successfully a message appears. Thereafter by means of dSpace controlDesk the results need to be verified and to verify the results, it needs to be checked by digital storage oscilloscope (DSO). Figure 6.13A shows that the driving cycle and the achieved speed (mpha) are coinciding. Figures 6.13B and 6.13C shows the ESS power and generator power, which are same as in the simulated results. Figure 6.14A show the results of motor power whereas Figure 6.14B shows the results of SoC which is a very important parameter to measure the condition in the ESS unit. It can be clearly seen that all the real-time results are in close resemblance to the simulated results provided in section 4. The results shown below are for 500s because in DSO the maximum sampling time is the 50s so it can display the result up to 500s only.

Table 6.5 shows the FE in mpg comparison for the same vehicle with the same parameters. The various algorithm used are Direct PSO, GA and ANFIS. It can be safely concluded that ANFIS based is having the highest mpg, which proves the accountability of the proposed algorithm over other algorithms.

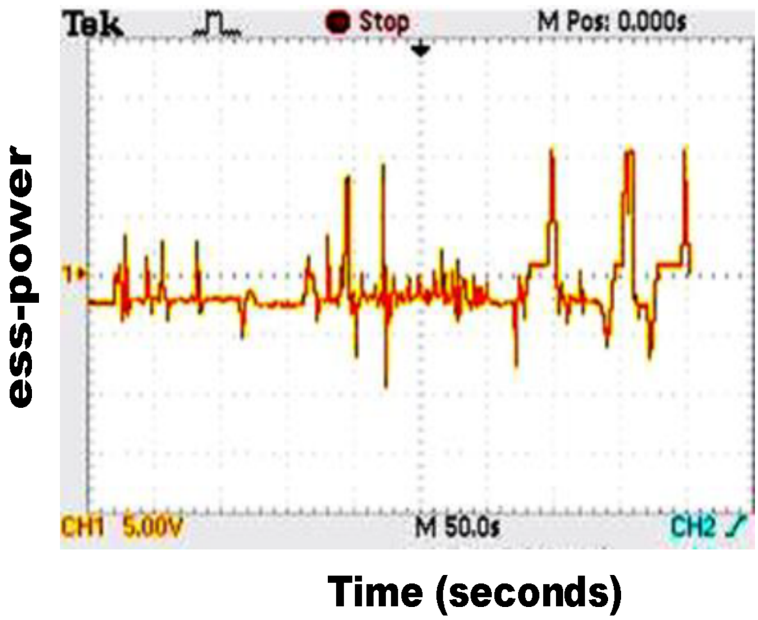
Table 6.5 Fuel Economy comparison in mpg by various EMS with same parameters and over the same vehicle [171].

EMS	Direct	Default strategy	PSO	GA	ANFIS
FE (mpg)	43.49	48.4	51.4	54.17	69

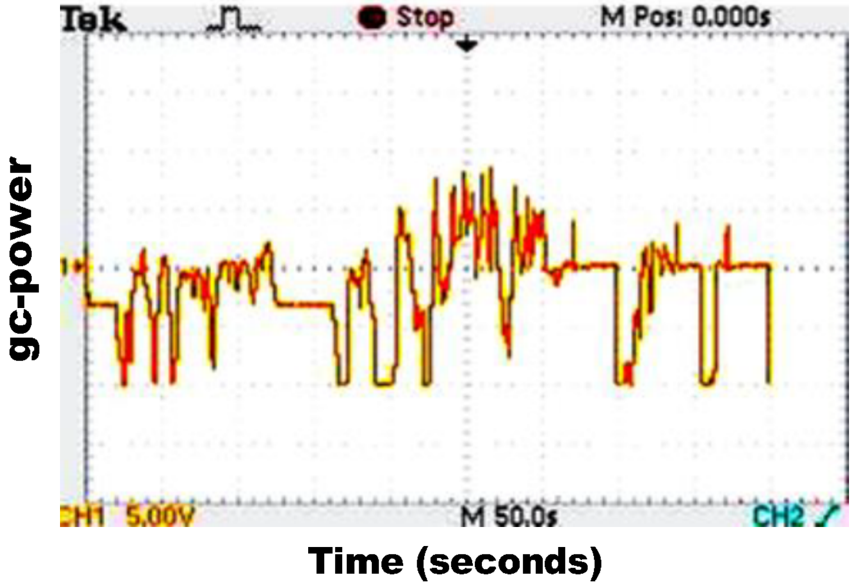


**** CH1 is driving cycle and CH3 is mpha. CH1 and CH3 are overlapping/coinciding.**

A) Driving cycle and speed achieved

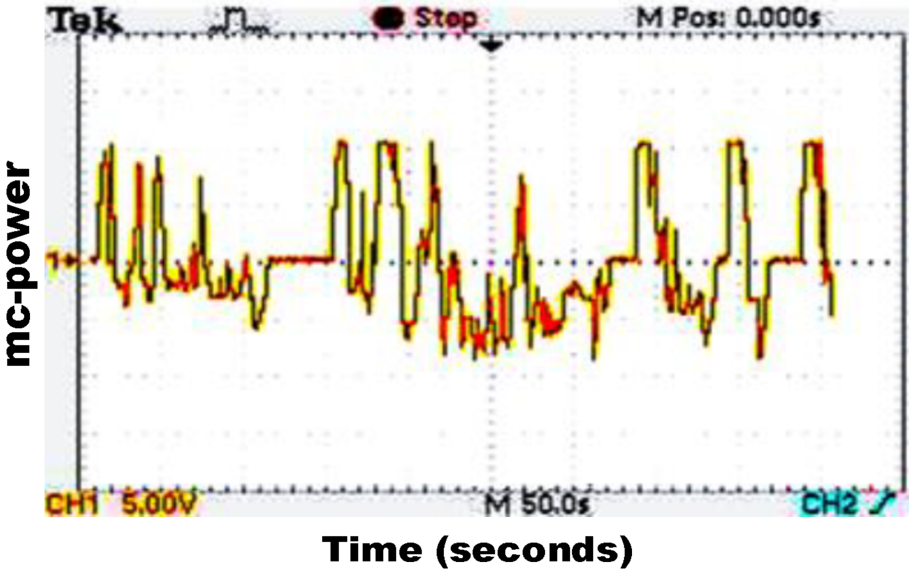


B) ESS power

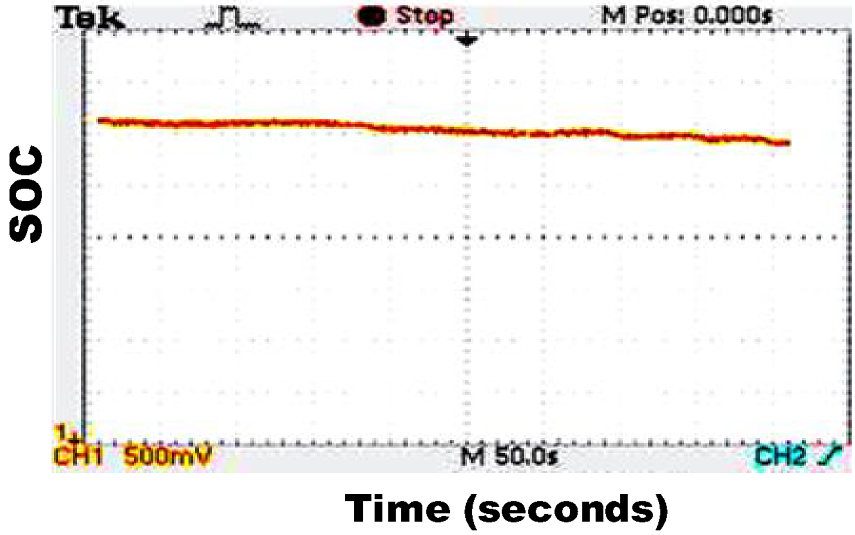


C) Generator power

Fig. 6.13 Results obtained from CHIL setup of the system.



A) Motor power



B) SoC

Fig. 6.14 CHIL Results of battery SoC and motor power

The proposed EMS has been tested on various driving cycle to check the FE of the vehicle and the results have been summarized in Table 6.6

$$overall\ efficiency = \frac{losses\ on\ account\ of\ aerodynamic\ of\ the\ vehicle(kJ) + losses\ on\ account\ of\ rolling\ resistance(kJ)}{energy\ stored(kJ) - ESS\ storage(kJ)} \tag{6.24}$$

Table 6.6 Fuel economy of various driving cycle based on ANFIS EMS

	HWFET (mpg)	**HWY (mpg)**	**NEDC (mpg)**	**NYCC (mpg)**	**US06 (mpg)**	**FTP (mpg)**
Default strategy	65.6	43.2	46.2	29.8	38.7	46.9
ANFIS	195.1	63.6	94.7	39.7	40.9	53.3

6.6 Summary

This chapter proposes an ANFIS tuned adaptive EMS for a power split HEV. The whole system is simulated in ADVISOR and validated in real-time using FPGA based MicroLabBox hardware controller. It has been observed that the results obtained from ANFIS based EMS are very encouraging as compared to GA and PSO based strategies. The detailed analysis of the working of HEV and its component has been presented by means of simulation results. The emission has gone down to a large extent, and the fuel economy has improved from default 48.4 mpg to 69 mpg by applying the proposed EMS.

The proposed EMS has also resulted in an overall system efficiency of 16.8% against 11.4% using default strategy. The simulation and real-time results are in close resemblance, which proves the potential of the algorithm to perform well in real-time as well. The emission has been reduced of HC from 1.239 to 1.133, CO from 1.63 to 1.273 NOx 0.43 to 0.245 by ANFIS.