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Development of Progressive Fuzzy Logic and ANFIS Control for Energy Management of Plug-In Hybrid Electric Vehicle

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ABSTRACT Hybrid electric vehicles are an effective alternative to the conventional fuel engine vehicles and thus efficient and intelligent energy management is the key for establishing a significant market for the hybrid electric vehicles globally. Recent developments in the field of intelligent techniques and demand to make the energy systems intelligent have become a means to develop energy efficient hybrid electric vehicles. The energy management issue becomes vital in order to enhance the autonomy of hybrid electric vehicles and to reduce the costs. Therefore, a novel approach with intelligent techniques, to control the plug-in hybrid electric vehicles, in front of different customer profiles has been presented. This paper presents the battery performance improvement of a plug-in hybrid electric vehicle using fuzzy logic controller and neural fuzzy logic controller with battery state of charge as a deciding parameter and consequently comparing the performance of both cases. The battery state of charge and engine speed as input has been selected and based on their values the advanced controller decides the accurate torque required to be converted to energy which could be used to charge the battery and this can be achieved by controlling the forward gain value. For this, an advanced fuzzy controller and advanced adaptive nuero fuzzy inference system controller are used to decide the value of forward gain. Simulink environment is used to simulate the performance of the proposed system. This could be helpful in deciding which type of intelligent system is to be used for the power efficient operation of the hybrid electric vehicle. The results of both the control techniques are compared and the better controller is recommended for energy management of a plug-in electric vehicles. The results indicate that advanced control techniques provide the good performance and improving the fuel budget of hybrid electric vehicles.

INDEX TERMS Artificial intelligence, artificial neural network, energy management strategy, fuzzy logic, hybrid electric vehicles.

NOMENCLATURE

Ah	Ampere hour.
ANFIS	Adaptive nuero fuzzy inference system.
ANN	Artificial neural network.
AQI	Air quality index.
E_{sys}	Electrical system
G_{shaft}	Gear shaft.
HEV	Hybrid electric vehicle.
ICE	Internal combustion engine.
kg	Kilogram.
kW	Kilowatt.
M_{shaft}	Motor shaft.
MUX	Multiplexer.
m	Meter.
Nm	Newton-meter.
P_b	Battery power.
$P_{eng-min}$	Minimum engine power.
$P_{eng-thr}$	Threshold engine power.
P_m	Motor power.
SOC	State of charge.

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T_{dgen} Generator torque demand
T_{gr} Gear torque
T_{mr} Motor torque.
T_{hr} Gear torque.

I. INTRODUCTION

The automobile industry is now transitioning to electric powered vehicles from the conventional combustion engine vehicles [1]. One of the major reasons for this transition is that a major portion of the carbon dioxide emissions comes from the conventional combustion engine vehicles. This emission is responsible for the rising air pollution levels especially in the metro cities where the number of vehicles are very high as compared to smaller cities. New Delhi is a very good example of the cities which have hugely impacted from the air pollution. The AQI (Air Quality Index) in some areas of Delhi in 2019 was as high as 858 which is considered hazardous for breathing and forced the government to shut down schools to protect the children from breathing problems. Besides, the rising CO_2 level is also responsible for global warming and consequently the melting of glaciers. Thus, there is an urgent need for an effective alternative to the conventional fuel based vehicles.

The hybrid electric vehicles are an effective alternative the conventional combustion engine automobiles. They have minimal carbon emissions which help reduce the carbon emissions and effectively combat air pollution especially in big cities. Due to this reason the government of India is planning to transition completely to the electric vehicles by 2030. Therefore, hybrid vehicles are set to be the future of transportation which contributes towards sustainable development.

But, the process of electrification of transport has its challenges. The biggest challenge is an effective energy management strategy for the hybrid electric vehicle [2]. The hybrid electric vehicles at the moment are limited by the distance that they can cover. Currently, the electric vehicles can travel a distance of about 150-200km with a single charge of battery, which is not enough if we are looking at the long term prospects. The major barrier that HEV technology has is the size, number of batteries and the ergonomics of having a bigger battery or more batteries. Thus, it becomes absolutely necessary to have an efficient energy management strategy in order to increase the distance the HEV can cover in electric mode [3]. This can be done by improving the battery state of charge (SOC) profile. Battery SOC is an indication of level of charge of the battery relative to its capacity and is expressed as a percentage. A better SOC profile indicates an efficient utilization of electrical energy. Higher values of SOC (>50%) are desirable at any instant of time. Battery can be charged by using regenerative braking while the vehicle is in motion. An efficient transfer of energy would result in faster battery charging and improved SOC profile. For this purpose, advanced and intelligent controllers have to be devised in order to improve the SOC profile [4].

Two advanced intelligent controllers are used in this study to devise an efficient energy management system for the hybrid electric vehicle. The goal of this study is to improve the SOC profile of the HEV so that it can cover longer distances in electric mode. A better SOC profile with smoother time domain curve means efficient energy transfer and better performance of the battery. This is achieved by using a fuzzy logic controller and an ANFIS controller which adjusts the value of the forward gain which is responsible for battery charging using regenerative braking. This forward gain controls how much part of generated torque can be used to charge the battery. The advanced intelligent controllers control the value of this forward gain according to the battery state of charge value and the engine speed at any particular instant of time. This results in real time battery charging whenever the battery SOC falls below a certain threshold value. The advanced controllers takes into account other factors like engine speed and required power output into account, and based on the predefined rules, it decides what will be the value of the forward gain. This results in improved SOC profile. This can be used in emerging plug-in hybrid electric vehicle technology for making power efficient cars, scooters and buses which can cover longer distances in electric mode.

Fuzzy logic has found its application in the operation of hybrid electric vehicle because this technology is simple, effective and it provides the option of real time supervisory control based on deterministic rule based approach [5]. On the other hand nuero-fuzzy controller is more advanced and is based on non linear and adaptive approach. Therefore, this adaptive can be used even more complex real time situations because of the accuracy, comprehensive supervisory control and less error [6].

In section II, circuit connections of series-parallel HEV is discussed, section III of this paper is discussed the battery charge controller, section IV and V are discussed the fuzzy controller and ANN controller respectively, section VI shows the simulation results and finally section VII discusses the Conclusions and comparison of two different type of controllers.

II. HYBRID ELECTRIC VEHICLE DYNAMICS AND CIRCUIT DISCRIPTION

The body diagram of the HEV is shown in figure 1 below.

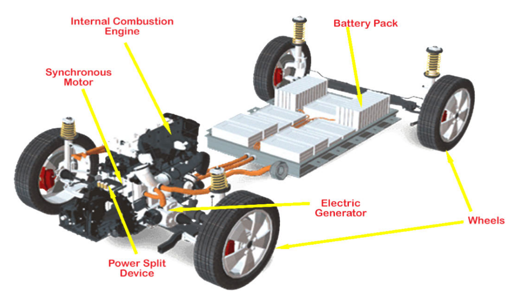


FIGURE 1. Hybrid electric vehicle body.

Figure 2 shows the functional block diagram of the HEV which consists of 5 major functional blocks. It consists of vehicle body, power split device, internal combustion engine, electrical system and energy management and control system block. The vehicle body consists of the vehicle dynamics i.e. assembly of mechanical parts which are responsible for vehicle motion. It includes body frame, wheels, tires, axle, gears, propulsion system, driver's inputs, aerodynamics, drivetrain, braking system, suspension, steering and ambient conditions etc.

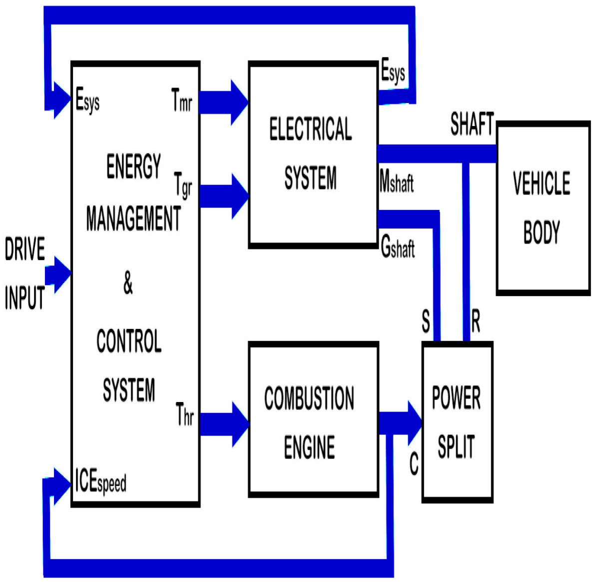


FIGURE 2. Functional block diagram of series-parallel HEV.

Power split device is a special type of gear which integrates the engine and motor drive together which allows the vehicle to be powered by the electric motor or the engine alone [7]. The combustion engine block consists of fuel based conventional 100kW internal combustion engine connected to the power splitting device with split ratio 2.5. Electrical system consists of a synchronous motor in a parallel connection with synchronous generator.

This arrangement is connected to the 20Ah and 250V nominal voltage battery pack through a 500V DC-DC converter. This assembly is capable of running the vehicle in electric mode. Electrical system is also connected to the power splitting device. The ICE and electrical system are connected in series-parallel mode of operation. Energy management and control system block controls the entire arrangement of electrical system and combustion engine and the mode of operation of hybrid vehicle. This block enables the hybrid vehicle to run in electric mode or engine mode or hybrid mode. The energy management and control system receives the drive input, then it checks the battery state of charge, engine speed and required power. Then based on these parameters the control signal is sent to motor to deliver motor torque T_{mr} if the vehicle is to be operated in electric mode or hybrid mode. If battery state of charge is low, then it enables the internal combustion engine to generate engine torque T_{hr}. T_{gr} denotes the gear torque.

The Table 1 below shows the various important parameters related to vehicle dynamics and electrical parameters.

TABLE 1. Vehicle parameters.

Parameter	Value	Unit
Vehicle mass	1000	Kg
Tire radius	0.25	m
ICE max power	100	kW
Motor max power	100	kW
Max torque motor	450	Nm
Motor efficiency	94	%
Battery capacity	20	Ah
Battery nominal voltage	300	V
Converter output voltage	500	V

Figure 3 shows the functional block diagram of the energy management and control system block. It consists of a state control block which is used to determine the state of the HEV by using the vehicle speed, battery SOC and engine speed as input, and based on this data it decides whether the HEV is going to operate in motor mode, generator mode or ICE mode which is then fed to the engine speed controller, generator controller and motor controller, which are used to control the hybrid electric vehicle. The next block is the battery

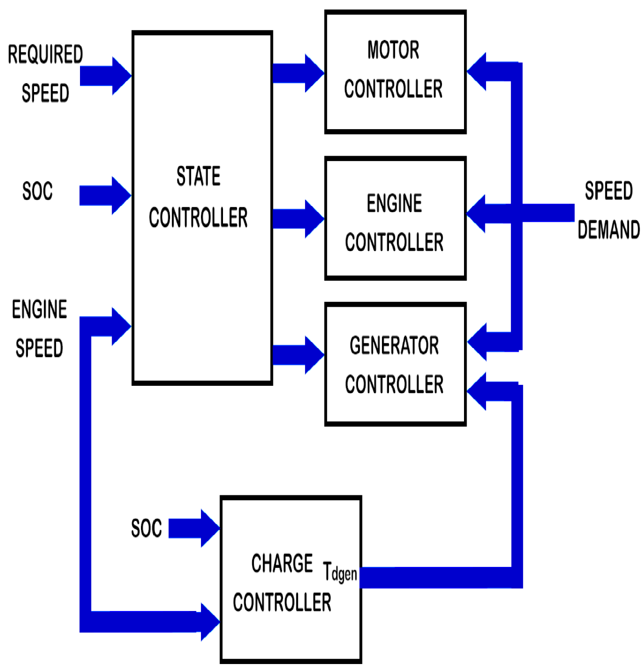


FIGURE 3. Energy management and control system.

charge controller which takes engine rpm and battery SOC as input. This block is the most important as far as energy management strategy is concerned, as it is the battery charge which decides how much distance this vehicle can travel in an electric mode. The more the battery charge, the more distance the vehicle can cover in electric mode. In this paper, we use regenerative breaking and real time engine rpm to decide how much percentage of available torque is used to charge the battery rather than keeping that percentage fixed. This can be done by keeping the percentage torque gain as variable and keeping its value in a particular range [8]. By making this variable gain auto-adjust according to the engine speed and battery SOC in real time, we can improve the SOC profile of the vehicle battery. This is the main goal of this work.

This work presents two different controllers in two different cases which control the battery state of charge.

The battery must be charged if the SOC falls below a certain threshold by transferring the available energy to charge the battery. Better fuel economy is likely to be achieved when the SOC is gradually depleted as compared to when there are sudden drops which yield not so good fuel economy and less km/kWh. The two controllers used are:

1. Fuzzy logic controller.
2. Artificial neural network (ANN) controller

In the next section, Battery charge controller is discussed in detail.

III. BATTERY CHARGE CONTROLLER FOR HYBRID ELECTRIC VEHICLE

The battery charge controller is the block which controls how the battery is charged and discharged while the vehicle is in the state of motion. As shown in figure 4 below, the battery charge controller takes the battery SOC and engine speed (rpm) as input from and outputs the generator torque demand as output based on the set of rules shown in algorithm in figure 4.

The flowchart in figure 4 shows how the operating mode of this hybrid vehicle changes from electric to HEV and vice versa [9]. The system takes the battery SOC and internal combustion engine speed (rpm) and then it checks if the SOC percentage is below a certain threshold value, and if this is the case then the part of energy from the engine is used to charge the battery and the vehicle is set to run in fuel mode or combustion engine mode while the battery is being charged [10]. If the battery SOC is above a particular threshold then, it proceeds further to check if the engine speed is above a set threshold, and if it is above the set threshold then the HEV continue to run in electric mode and battery is also charged at the same time. But if the engine speed is below a certain threshold value in this case, then the vehicle continues to run in the electric mode without charging thee battery [11]. This is the simplest case that we have taken to explain the algorithm where a threshold value is fixed for both the battery SOC and the engine speed. But this type of system is a typical operation of an HEV where these threshold values are fixed.

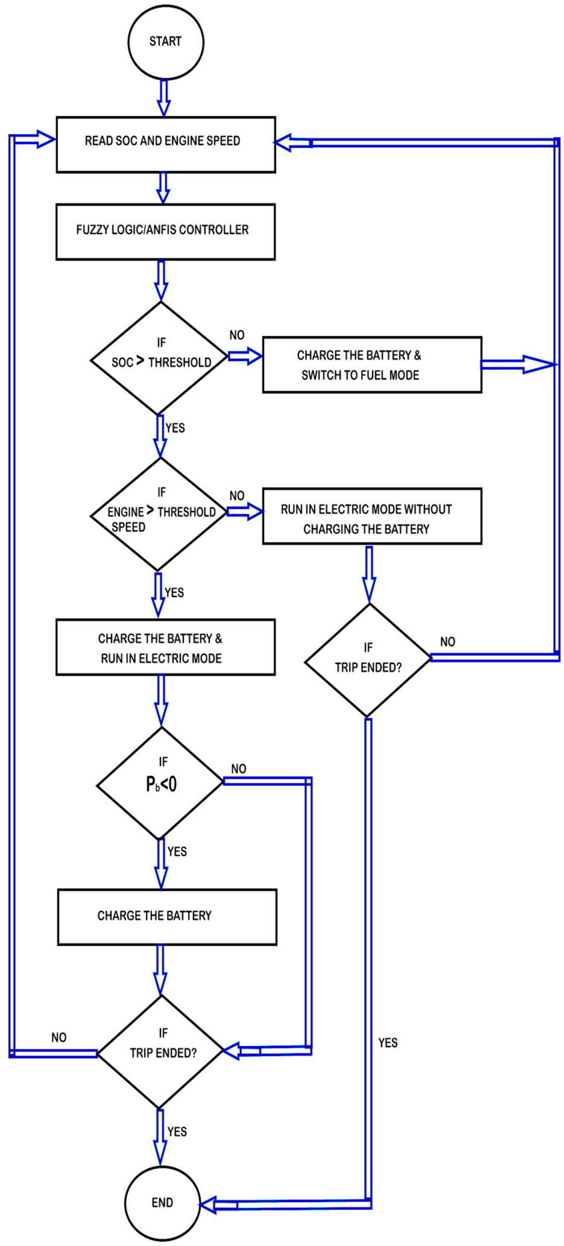


FIGURE 4. Operation of a battery charge controller.

Such a system is not an intelligent system. In this work, we want to make the threshold values dynamic and not fixed. If these values are dynamic, then the HEV can be made to operate intelligently by taking the values of battery SOC and engine speed while the vehicle is in operation. This can be used to control the vehicle state like an online system. There are two methods, mentioned in section II, which can be used to achieve the desired battery charge controller. The section IV will describe the fuzzy logic controller and its operation.

IV. FUZZY MODEL FOR CONTROLLING THE HYBRID ELECTRIC VEHICLES

The fuzzy logic controller is basically employed to control the different converters now it can also be used to control the battery SOC in hybrid electric vehicles. The various factors of system affects the overall performance of the controller. The controller should be capable to control all the parameters according the change of battery stage. The fuzzy logic controller is the best alternative for this condition which can easily control the battery SOC.

The main step of the fuzzy logic controller is to choose the input variables, output variables and membership functions.

The fuzzy logic uses different membership functions and then uses max-min composition along with the AND/OR rules to give the output. The figure 5 shows the functional block diagram of a fuzzy logics controller. The battery SOC and engine speed are given as input to the controller, the first step is the fuzzification, the fuzzifier then transfers the fuzzified output to the fuzzy inference system which then uses the rules [12] and applies them to the fuzzified input and gets the output. This output is then passed to the defuzzification block which gives the battery power as output.

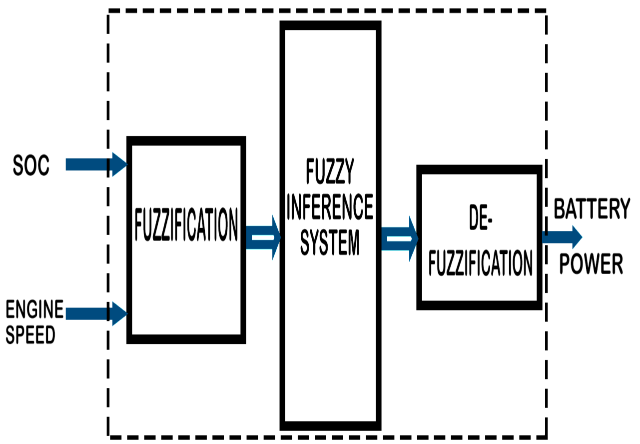


FIGURE 5. Fuzzy logic controller scheme for plug-in electric vehicles.

This type of system is a typical fuzzy logic controller which takes the input, fuzzifies it, applies the rules, and then gives the defuzzified output. The Table 2 shows how the control strategy is implemented.

TABLE 2. Rule strategy for estimation of gain.

Rule No.	SOC State	Speed State	Gain Output
1.	Low	Low	High
2.	Medium	Low	Medium
3.	High	Low	Low
4.	Very High	-	Low
5.	Low	Medium	Medium
6.	Medium	Medium	Medium
7.	High	Medium	Low
8.	Low	High	High
9.	Medium	High	High
10.	High	High	Medium
11.	Low	Very High	High
12.	Medium	Very High	High
13.	High	Very High	Medium

A. MEMBERSHIIP FUNCTIONS

There are three types of membership functions which are used to realize this fuzzy logic controller, namely, the Gaussian, triangular and trapezoidal membership functions which are shown below. The figure 6 below show the Gaussian membership functions for both inputs and output which are used in this study.

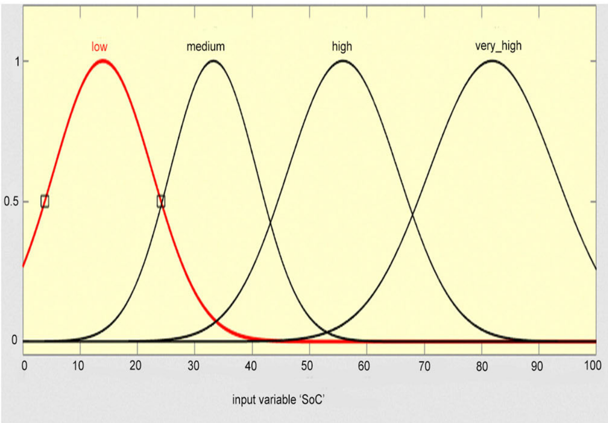
The figure 7 below shows the trapezoidal membership functions.

The figure 8 below depicts the triangular membership functions which are used in this study.

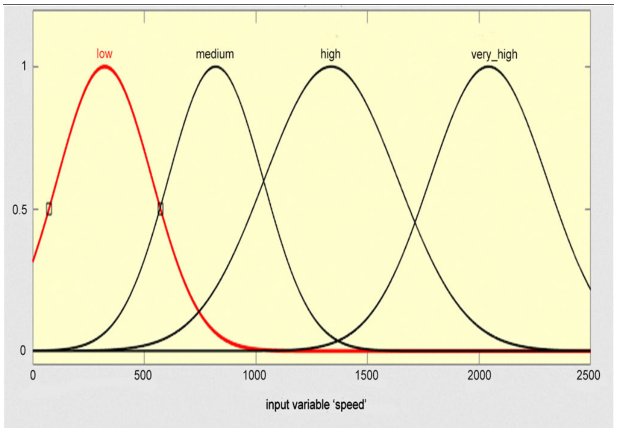
It is clear from figures 7, 8 and 9 that the SOC input is categorically divided into 4 categories, namely, low, medium, high and very high. The SOC value in range 0 to 30% is low SOC, from 30-50% is medium SOC, 50-70% is high SOC and 70-100% is very high SOC. Similarly, the speed input also uses 4 membership functions for each input. The speed in range 0-600 rpm accounts for low speed, in range 600-1200 rpm is medium speed, 1200-1800 rpm is high speed and above 1800 rpm accounts for very high speed. The output gain for this system varies between -0.1 to -0.25. The output also comes in 3 categories low, medium and high. The output gain -0.25 to -0.15 is high gain. This means that about 25% to 15% of energy generated is used to charge the battery. Between -0.15 to -0.1 is medium gain and from -0.15 to 0 is low gain. Table 3 shows the rule strategy which is followed for the inference system.

The Table 3 shows the rule based strategy for different range of the input values. This fuzzy charge control system uses mamdani system to evaluate the fuzzy output. The advantage of such systems is that machines follow the exact same rule which they are asked to perform and they perform the execution within the limit of the rules which are applied to them.

As the Table 3 shows, the sign of the required motor power determines the state of operation in both the charging and discharging state. Hence the control strategy for each state is different. If the power required by motor is positive, the batteries are therefore, in discharge state and power required by the motor is greater than $P_{eng-thr}$, the vehicle will be in hybrid state and required power is supplied by both the motor and the ICE engine generator. If the required motor power is less than the $P_{eng-min}$, then the power will be supplied by the electrical system. When the power required by the motor is negative, that means the generator power is used to charge the batteries. This is where the fuzzy logic can be used make the amount of power used to charge the battery SOC by using



(a)



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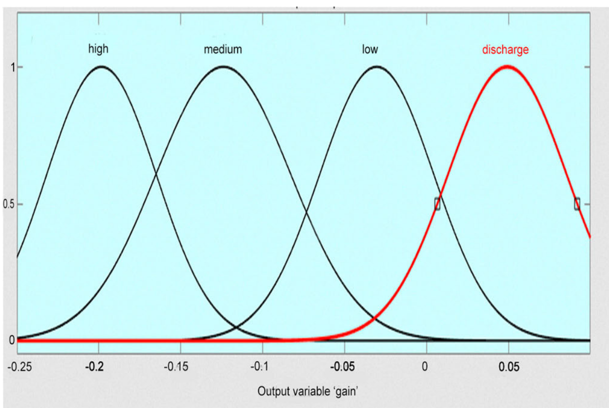
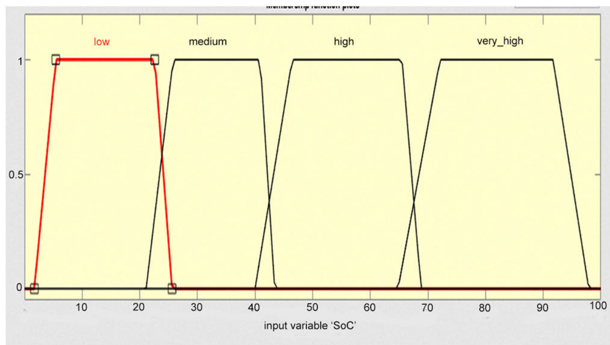


(c)

FIGURE 6. (a, b and c). Gaussian membership functions for SOC, Gaussian membership functions for speed (rpm), and Gaussian membership functions for gain output.



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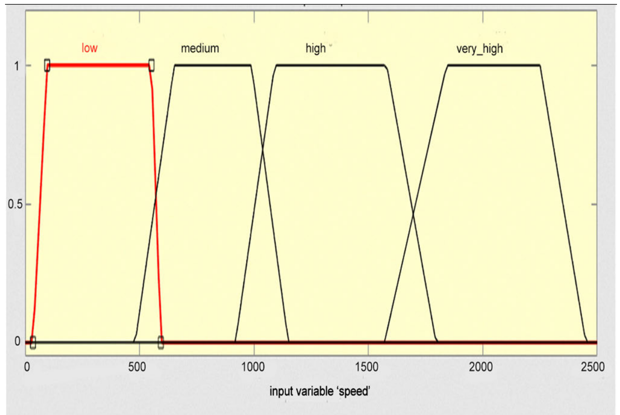

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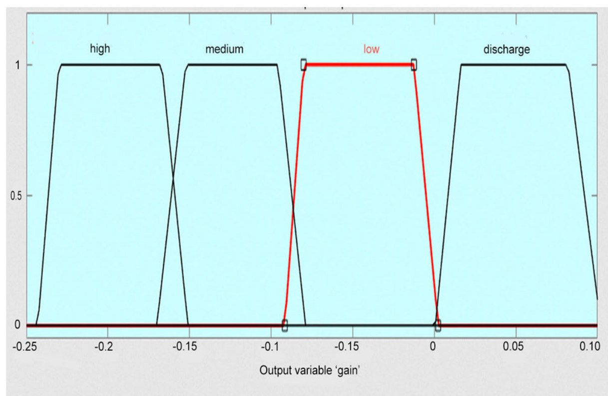


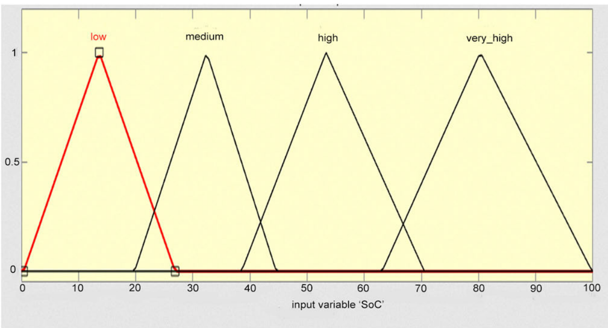
(c)

FIGURE 7. (a, b and c). Trapezoidal membership functions for SOC input, trapezoidal membership functions for speed input, and trapezoidal membership functions for gain output.

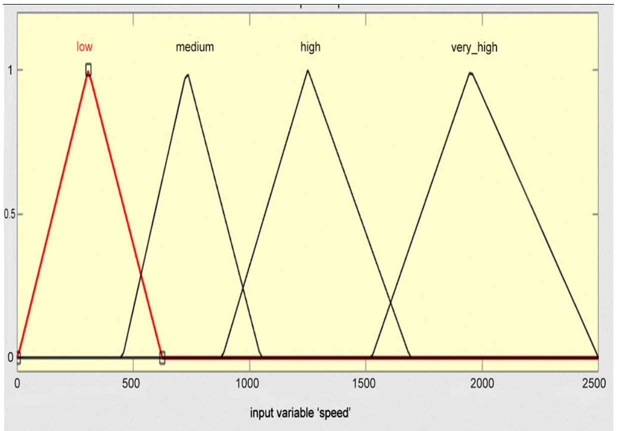
dynamic gain. The available battery state of charge (SOC) and the available generator power can be used to improve the SOC profile and consequently the electric mode can be used to travel on comparatively long distances.

The SIMULINK model used to simulate this logic is shown below figure 10.

The SIMULINK model in figure 6 shows that battery SOC and engine rpm are used as input to the fuzzy logic controller by using a 2 to 1 MUX block. The fuzzy logic controller decides the gain based on the values the values of the input given to the fuzzy logic controller. The output of the fuzzy logic controller decides how much part of the torque is available for charging the battery. The gain value varies between −0.1 to −0.3 meaning that the about 10% to 30% of the available torque can be used for charging the battery



(a)



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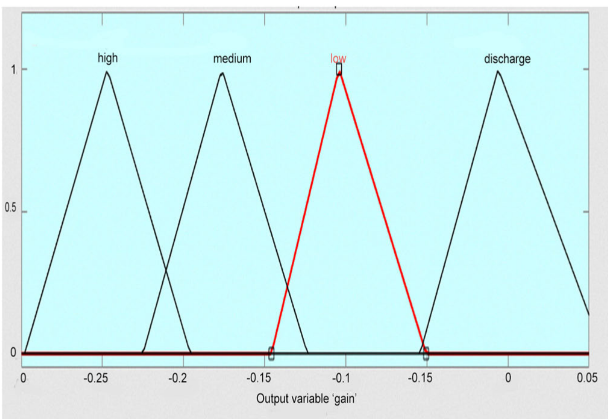


(c)

FIGURE 8. **(a, b and c). Triangular membership functions for SOC input, triangular membership functions for speed input, and triangular membership functions for gain output.**

depending on the drive time value of the SOC and engine speed. Now in order to implement the above model we use different membership functions and apply different rules to get an output which is the gain and the defuzzifier gives the desired output.

The extension of this type of system or more advanced fuzzy logic system called adaptive nuero fuzzy inference system or ANFIS system which will be discussed in detail in the next section.

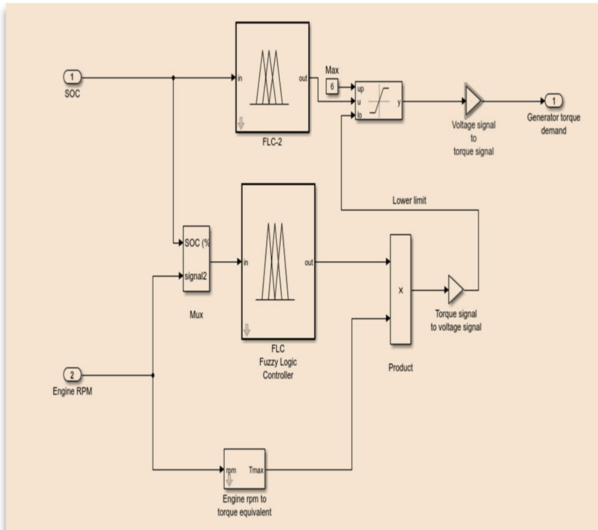


FIGURE 9. **SIMULINK circuit for Fuzzy logic controller.**

TABLE 3. **State of operation in both the charging and discharging state.**

S. No	SOC	Speed	Motor power	Mode of Operation
1.	low	Medium or high	$P_m \geq P_{eng-min}$	Engine mode
2.	Medium or high	Low or medium	$P_m > P_{eng-thr}$	Hybrid operation
3.	Very high	Low, medium or high	$P_m < P_{eng-min}$	Electric mode
4.	-	-	$P_b < 0$	Charging mode

V. ADAPTIVE NUERO FUZZY INFERENCE SYSTEM (ANFIS) FOR HYBRID ELECTRIC VEHICLES

The Adaptive nuero-fuzzy inference system is a type of artificial neural network and it is based on Takagi-sugeno fuzzy interference system. It is the more advanced and accurate system which is based on the data pairs of the input/output of the system which is under consideration. It is used for the modeling as well as control of the systems where there is hint of uncertainty in the system [13]. Thus, this is an intelligent system which can be used as an effective controller in the HEV energy management strategy. ANFIS system follows

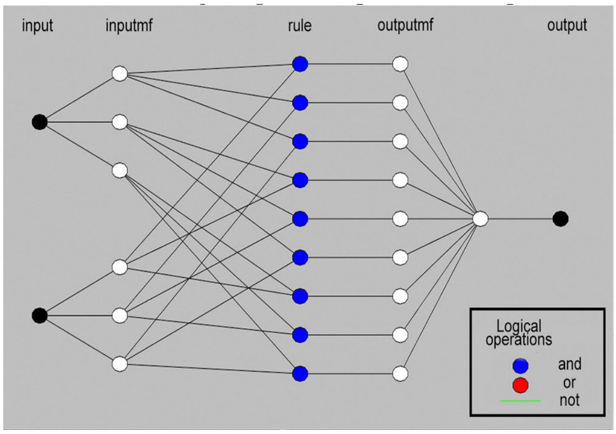


FIGURE 10. ANFIS rule structure for controlling the plug-in hybrid electric vehicles.

nonlinear and adaptive approach and based on real time data, the system can analyze, adapt and decide the response of the system. This controller provides better accuracy and better supervisory control even in complex real time simulations [14]. ANFIS controller uses precise fuzzy modeling concept and can handle and approximate highly complex non linear systems. The rule basis is obtained by using data driven clustering algorithms [15]. Thus, this controller finds its application in the hybrid electric vehicle. Therefore, this controller is used in this study to improve the SOC profile of the series-parallel operation of HEV.

In this work, 84 different entries are manually given and based on these values the system identifies low, medium and high values of the gain for different values of SOC and engine speed. The figure 11 below shows the structure ANFIS model for the SOC and engine speed as input and the output.

The value of the output gain varies from -0.1 to -0.3. In this case also 3 different membership functions are used, namely, Gaussian, trapezoidal and triangular. The training method used here is hybrid and number of epochs used are 3. The figure 11(a) below shows the training data for the fuzzy inference system for the Gaussian membership functions. This shows the response of the system for different values of inputs i.e. the SOC and the engine speed. Similarly, figures 11(b) and 11(c) shows the training data for the trapezoidal and the triangular membership functions.

Since ANFIS is an adaptive system, the system adapts to and trains the according to the data and the type of membership function which is used. The figure 12 below shows the simulink connections for this type of controller. The connections look similar to the fuzzy controller but they differ in the type of system used and their application.

The Table 4 below shows the training data for the ANFIS system used in this work.

VI. RESULTS AND DISCUSSIONS

The simulation results are recorded for both types of controllers discussed in sections IV and V. Figures 13(a) and 13(b) shows the SOC response and battery voltage for the fuzzy logic controller with Gaussian membership function.

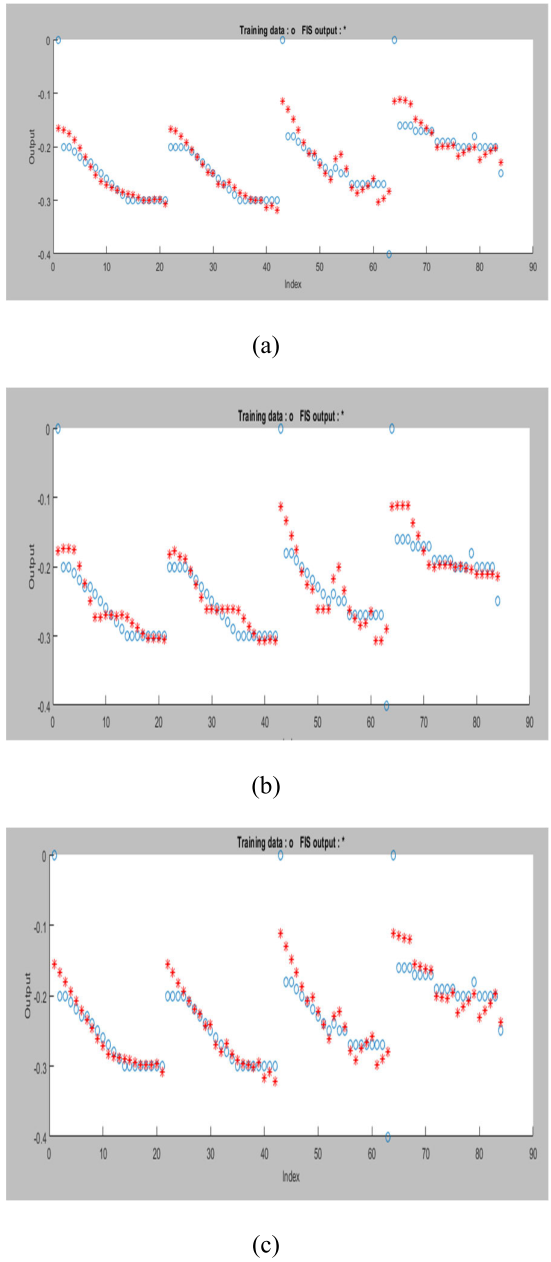


FIGURE 11. (a, b and c). Training data for Gaussian membership function, training data for trapezoidal membership function, and training data for triangular membership function.

The curve shows that SOC curve is initially smooth and remains fairly above 90%, but after 170 seconds of drive the curve takes a sudden drop and the SOC value drops to 70% and soon after, takes another sharp drop and rapidly drops to 32% within next 10 seconds. After this drop, the SOC value gradually increases and reaches 57% at 350 seconds. But at 350 seconds, the SOC curve dips suddenly to 20% within next 20 seconds. The curve slowly rises after 370 seconds and the SOC value reaches 23% at the end of the drive cycle.

Figures 14(a) and 14(b) shows the SOC response and output current for the fuzzy logic controller with trapezoidal

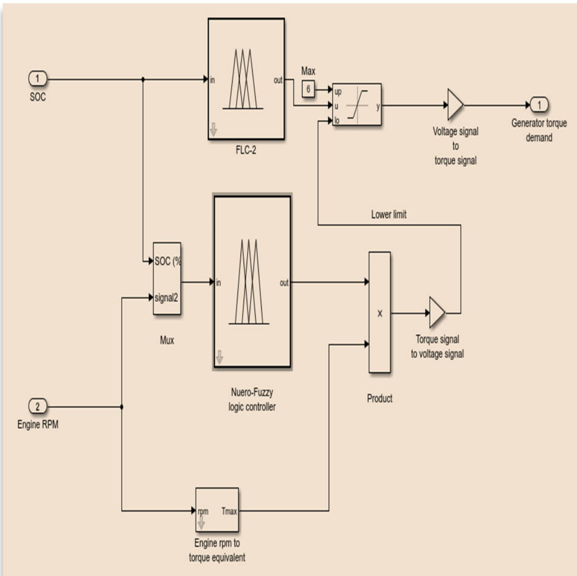
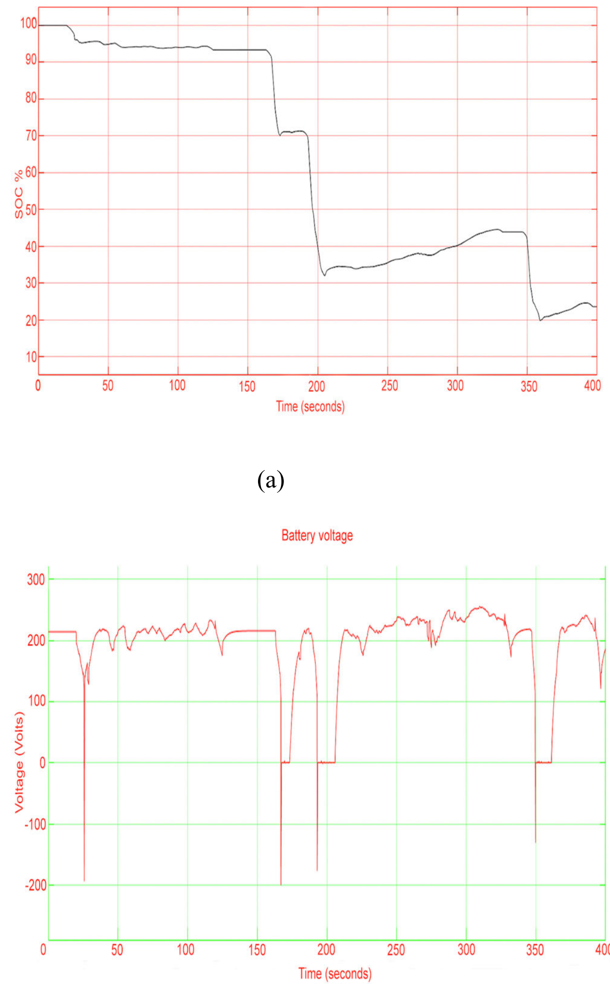


FIGURE 12. Simulink model for ANFIS system.

TABLE 4. Training data for the ANFIS system.

S. No	Information	Number
1.	Number of nodes	35
2.	Number of linear parameters	9
3.	Number of non linear parameters	18
4.	Total number of parameters	27
5.	Number of training data pairs	84
6.	Number of checking data pairs	0
7.	Number of fuzzy rules	9



(a)

(b)

FIGURE 13. (a and b). Battery SOC using FLC with Gaussian membership function and battery voltage for Gaussian membership function.

membership function. Initially the SOC profile is similar to the one in Gaussian membership function. The SOC curve takes a sudden dip at 160 seconds and within next 10 seconds, the SOC value drops to 80%. At 190 seconds, the curve suddenly drops once again to 43%. Thereafter, the SOC gradually rises to 60% at time 350 seconds. At 350 seconds, the SOC value drops to 33% and then slowly rises to 37% at the end of the drive cycle. The SOC profile for the trapezoidal membership function is slightly better than the Gaussian membership function.

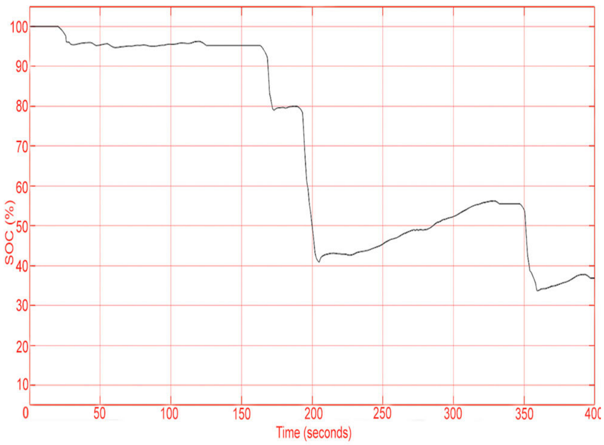
The drops are less steep and the final SOC value at the end of the drive cycle is slightly higher than the Gaussian membership function.

Figures 15(a) and 15(b) shows the SOC response and output current for the fuzzy logic controller with triangular membership function.

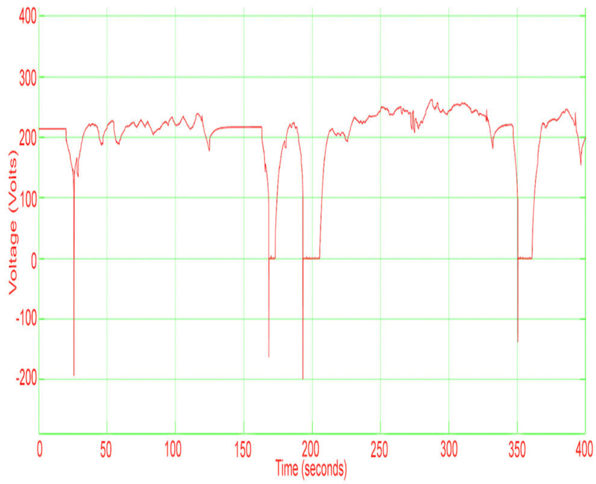
The best outcomes for the fuzzy logic controller were obtained using triangular membership function. The SOC profile is slightly better than the Gaussian and the trapezoidal membership functions. The drops are less steeper as compared to the Gaussian and trapezoidal membership functions. In this case, the SOC value at the end of 400 seconds drive cycle is 40%.

Figures 16(a) and 16(b) shows the SOC response and battery voltage for the fuzzy logic controller with Gaussian membership function using the ANFIS controller.

The SOC profile in this case is very smooth and drops are very small. Initially, the curve maintain a 100% state of charge value but takes a small drop at 25 seconds and state of charge decreases to 95%. Then SOC rises gradually to 100% and remains fairly above 96% till 170 seconds where the curve dips and the SOC value is reduced to 89% and then start to dip again at 190 seconds and the state of charge value reaches 78% at 200 seconds. The curve gradually rises again and reaches 100% at 250 seconds. The SOC value continues to be in the range of 96-100% till 350 seconds, after which the curve takes a sudden drop and the SOC value becomes 82%. At the end of the drive cycle, the state of charge is at 84%.

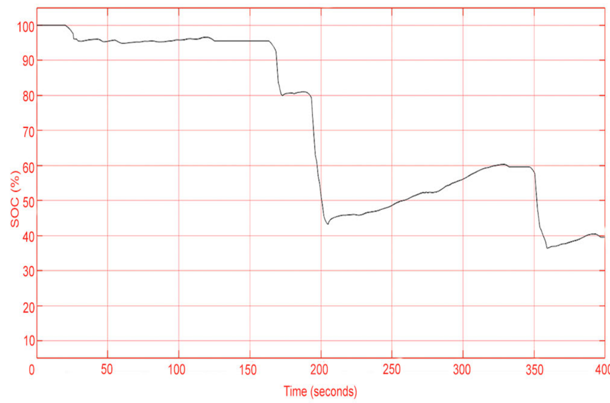


(a)

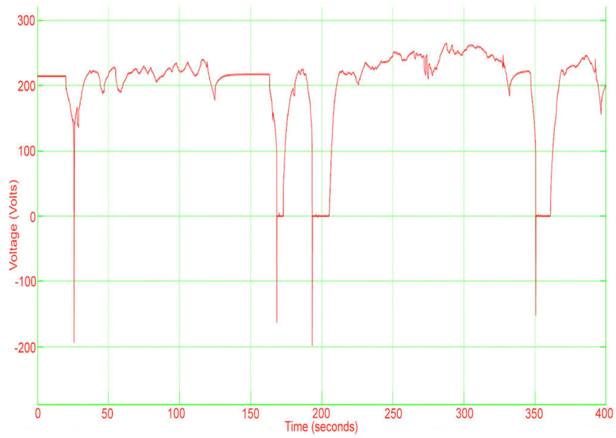


(b)

FIGURE 14. **(a and b). Battery SOC using FLC with trapezoidal membership function and battery voltage for Gaussian membership function.**



(a)



(b)

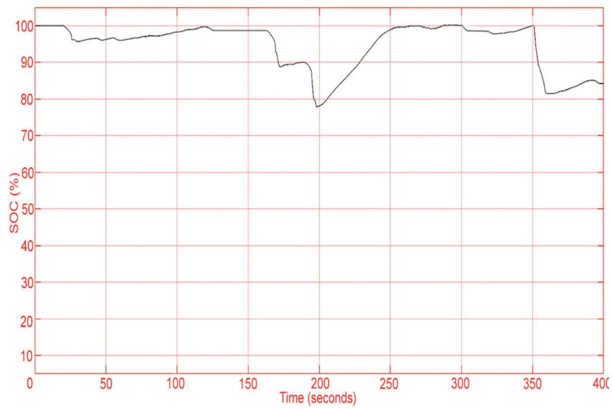
FIGURE 15. **(a and b). Battery SOC using FLC with triangular membership function and battery voltage for triangular membership function.**

Figures 17(a) and 17(b) shows the SOC response and battery voltage for the fuzzy logic controller with the trapezoidal membership function using the ANFIS controller.

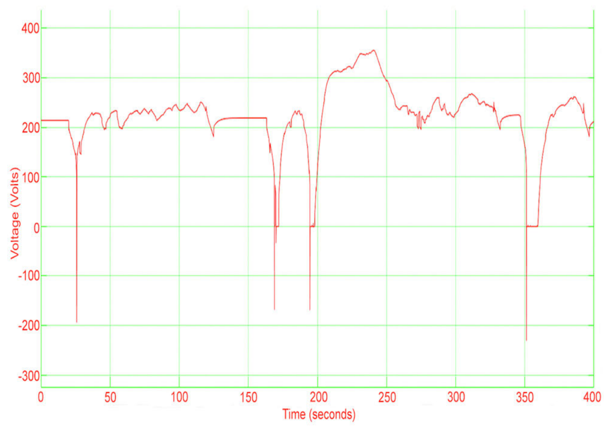
The SOC profile for ANFIS controller with trapezoidal membership function is similar to the SOC profile of the ANFIS controller with Gaussian membership function. The drops are slightly steeper as compared to the ANFIS controller with the Gaussian membership function. The SOC value remains mostly greater than 80% for most part of the drive cycle. At the end of the drive cycle, the SOC value is 79%.

Figures 18(a) and 18(b) shows the SOC response and battery voltage for the fuzzy logic controller with triangular membership function using the ANFIS system.

Figure 16(a) shows the SOC curve for nuero-fuzzy controller with Gaussian membership function. The SOC at the end of the drive cycle is about 84%, which is a lot higher as compared to normal fuzzy logic controller with any type of membership function. Also, the SOC curve is a lot smoother for this controller with Gaussian membership function. Figure 17(a) shows the SOC curve where ANFIS controller is used with trapezoidal membership function. The SOC at the end of the cycle in this case is about 79% which is less as compared to the Gaussian membership function with ANFIS controller. Figure 18 describes the battery performance using ANFIS controller with triangular membership function. The SOC at the end of the drive cycle in this case is 70% and the curve is also less smooth. The SOC performance is slightly better with the FLC using trapezoidal membership functions with SOC being 38% at the end of the drive cycle. Battery SOC, while using triangular membership function is only marginally better from the trapezoidal membership function and is about 39% at the end of the drive cycle. The SOC curve of the FLC with triangular membership function is similar to the FLC with trapezoidal membership function. Whereas, the SOC curve for neuro-fuzzy controller with Gaussian membership function shows that the SOC at the end of the drive cycle is about 84%, which is a lot higher as compared to normal fuzzy logic controller with any type of membership function. Also, the SOC curve is a



(a)

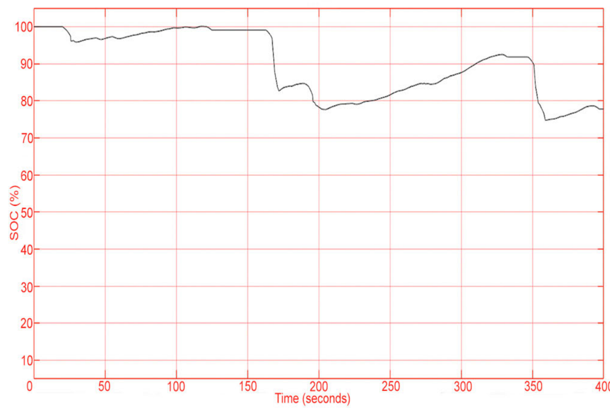


(b)

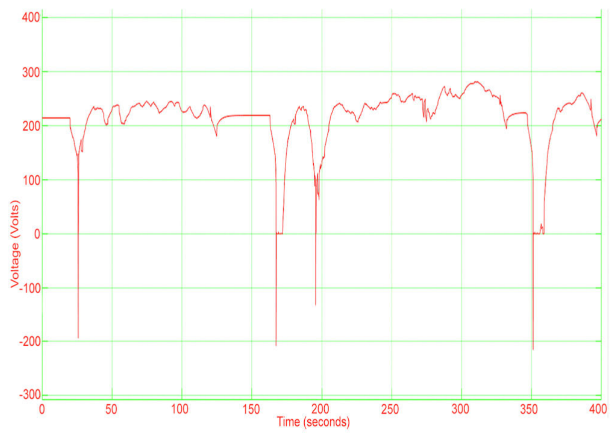
FIGURE 16. (a and b). SOC response for ANFIS controller with Gaussian membership function and battery voltage for ANFIS controller with Gaussian membership function.

lot smoother for this controller with Gaussian membership function. The SOC curve where ANFIS controller is used with trapezoidal membership function shows that the SOC at the end of the cycle in this case is about 79% which is less as compared to the Gaussian membership function with ANFIS controller. The SOC curve describes the battery performance using ANFIS controller with triangular membership function. The SOC at the end of the drive cycle in this case is 70% and the curve is also less smooth. On comparison, ANFIS controller is found to be more energy efficient as compared to the normal fuzzy logic controller.

When compared to the previous studies, the ANFIS controller used in this paper yields better results. In [13], ECMS (Equivalent consumption minimization strategy), A-ECMS (Adaptive equivalent consumption minimization strategy) and Fuzzy A-ECMS strategies were implemented. Out of these three, the A-ECMS was yielded better results as compared to the other two strategies in [19]. The table 5 below shows a comparison of the proposed study with the strategies implemented in [13].



(a)



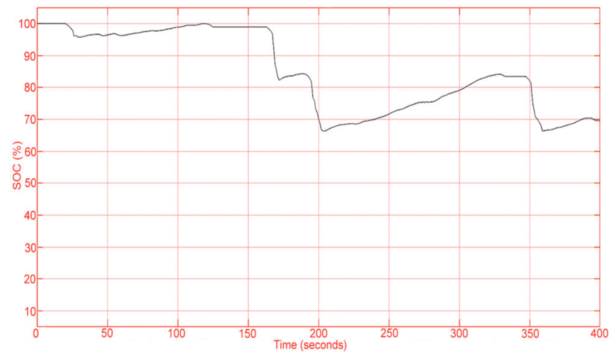
(b)

FIGURE 17. (a and b). SOC response for ANFIS controller with trapezoidal membership function and battery voltage for ANFIS controller with Gaussian membership function.

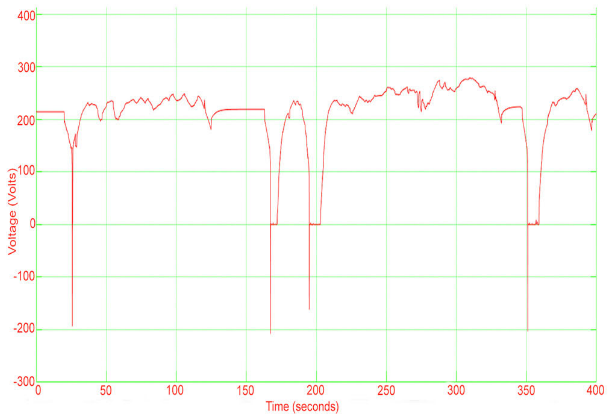
TABLE 5. Comparison of SOC profile using different energy management strategies.

Parameter	This Study controller		In [13] controller		
Controller	FLC	ANFIS	ECMS	A-ECMS	Fuzzy A-ECMS
Drive Cycle	FTP75	FTP75	NEDC	NEDC	NEDC
Time(sec)	400	400	1200	1200	1200
Initial SOC %	100	100	60	60	60
Final SOC %	40	84	60	60.4	60.2
SOC drop	Sharp	Small	Gradual	Sharp	Gradual

In [16], another study using GA-optimized fuzzy logic controller and non optimized fuzzy logic controller, the SOC profile showed good results. When compared to both GA-optimized fuzzy logic controller and non optimized fuzzy logic controller in [16], the ANFIS controller in this study yielded better results. The table 6 below shows the comparison of various parameters.



(a)



(b)

FIGURE 18. **(a and b). SOC response for ANFIS controller with triangular membership function and battery voltage for ANFIS controller with triangular membership functions.**

TABLE 6. **Comparison of parameters with proposed controllers.**

Parameter	**Proposed controllers**		**In** [16]	
Controller	**FLC**	**ANFIS**	**GA optimized FLC**	**Non optimized FLC**
Drive Cycle	FTP75	FTP75	WLTC	WLTC
Time(sec)	400	400	4500	4500
Initial SOC %	100	100	80	80
Final SOC %	40	84	81	81
SOC drop	Sharp	Small	Small	Small

In [17], three different energy management strategies were discussed. IHHCS (Intelligent hierarchical hybrid controller strategy), OFLC (optimal fuzzy logic control) and SF (state flow) energy management strategies were implemented in [17]. The IHHCS strategy produced slightly better results as compared to OFLC and SF strategies. The initial SOC was set to 95% in all the three cases, and at the of a 180 second drive cycle, the SOC in case of IHHCS strategy was 95.1%. In case of OFLC and SF strategies, battery state of charge was 95% at the end of the drive cycle.

ANFIS controller with Gaussian membership function, of all the configurations, is the most energy efficient controller with the SOC value highest at 84% and the SOC curve being the smoothest as compared to all the other cases. This performance is followed by the ANFIS controller with trapezoidal membership function whose performance is similar to the Gaussian membership function with SOC being 79% at the end and the curve also being as smooth as the ANFIS controller with Gaussian membership function.

Results reveals that adaptive nuero fuzzy inference system is the more progressive and accurate system which is based on the data pairs of the input/output of the system. Therefore, this work supports in working towards a controller which fulfills requirements of plug-in electric vehicles and taking a step further towards sustainable expansion.

VII. CONCLUSION

A fuzzy logic and ANFIS based energy management is established for suitably managing the power distribution in plug-in hybrid electric vehicles, which is equipped with a battery based hybrid energy storage system. The fuzzy logic scheme is used to control the amount of battery state of charge. The fuzzy logic based battery state of charge (SOC) control and generator power could be used to improve the SOC profile and consequently the electric mode could be used to travel on comparatively long distances. Whereas, an adaptive nuero fuzzy inference system is the more advanced and accurate technique which is based on the data pairs of the input/output of the system and this is also used for controlling the battery state of charge (SOC). The new advanced techniques are adopted in the optimization of fuzzy logic and ANFIS controllers, and their performances are compared.

The simulation results of fuzzy logic controller with the Gaussian membership function show that SOC at the end of the drive cycle is 23% and the curve had sudden drops during the accelerations. While in the previous studies [13], the SOC for a 1200 seconds drive cycle, the battery fluctuated in the range of 58%-63% and maintained the SOC value with these limits, in this study the battery SOC fluctuated within 60%-100%, overall the battery SOC at the end of the drive cycle was higher and remained above 70% for the ANFIS system, for all three membership functions. Further, In [17] the SOC profile for the proposed IHHCS strategy was similar to this study. Here the battery SOC fluctuated in the range 90%-96%, almost touching 96% mark for a significant time in the 180 second drive cycle while in the proposed study, the battery SOC fluctuated within 60%-100%. Considering that simulation in this study is done with a 400 second drive cycle, which is 2.25 times longer as compared to [17], the SOC profile was good and ended at about 89% using ANFIS controller with Gaussian membership function even after a 400 second drive.

The HEVs are set to be the future of transportation system. The need for making the HEV intelligent and power efficient is the key for this transition to happen smoothly. This work helps in working towards a controller which fulfills both the aforementioned requirements and taking a step further towards sustainable development.

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