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COMPARATIVE STUDY BETWEEN MFIS BASED APPROACH AND ANN BASED APPROACH OF ENERGY MANAGEMENT OF HYBRID VEHICLES FOR IMPROVING PERFORMANCE PARAMETERS

ZOONUBIYA ALI[a1], S. L. BADJATE[b] AND R. V. KSHIRSAGAR[c]

[a]CSVTU, Bhilai, Chhattisgarh, India
[bc]Nagpur University, Maharashtra, India

ABSTRACT

The proposed MFIS and ANN based EMS is a holistic approach which considered all the important modules require for efficiently managing energy in PHEV. The driver command interpreter is the important aspect of driving considered in this work. Most of the previous approaches have not given any consideration to this vital aspect. Another important feature of proposed approach is the generation of battery charging discharging instances and performance parameters of the EMS. The proposed MFIS and ANN based strategy is implemented in this paper to various driving Cycles and it was observed that the proposed methodology works well for any type of driving cycle irrespective of its length, speed profile and variety of road as well as wind condition acting on the vehicle.

KEYWORDS: EMS, Emission, MFIS, PHEV.

The global scenario of environmental conditions is very alarming. The continuous and uncontrolled use of fossil fuels is responsible for deterioration of the habitat. The large number of vehicles around the world has caused and continues to cause serious environmental problems and health issues for human. More and more countries all over the world are contributing towards development of greener vehicles with the ultimate objective of eliminating hazardous tail pipe emissions. HEV (Hybrid Electric Vehicles) have thrives as a lucrative solution to the above mentioned global crises. HEV achieves superior mileage and low exhaust emissions as compared to conventional Internal Combustion Engines (ICE). The main issue in the HEVs in the management of power flow between fuel and energy supply system that is responsible for vehicle motion. The difficulty arises in generating balance between limited energy supply from battery system and the requirement to minimize fuel consumption and exhaust emissions. The main objective of this work is to deal with the external information about driving conditions and modes of driver as well as state of charge of battery. Additionally, it decides the fuel consumption and exhaust emissions based on algorithm. Control strategy is the main key objective which is to be held responsible for achieving the improved performance of hybrid vehicle. One of the future technologies of the hybrid electric vehicle (HEV), typically featuring both an internal combustion engine and an electric motor, with the goal of producing lower emissions while obtaining superior fuel economy.

LITERATURE REVIEW

ANFIS (adaptive neuro-fuzzy inference system) integrate the best features of fuzzy logic and neural network and so it has attracted the interest of researchers to synthesis controllers and to develop the models to explain past data and predict future behavior. ANFIS based online SOC (State of Charge) correction considering cell divergence for the EV (electric vehicle) traction batteries is developed [Ehsani et. al., 2005]. To indicate the actual charging level of the battery, the State of Charge (SOC) is often used. The control strategy involves the calculation of various parameters including battery SOC. Battery state of charge indicator (SOC) is used for both online and off-line type control strategy [Sabri et. al., 2016]. A study was proposed to solve the common problem of SOC of not considering the difference among individual cells. They consider the whole battery pack as an averaged cell and thus employ the averaged SOC as the state of charge of the pack to increase the life of battery by avoiding over charging or over discharging of battery. They used kalman filtering based estimator for determining the averaged SOC and then using ANFIS or correcting it online with the information of cell differences and loading current which was trained offline. As the power source, battery plays an important role in EV systems, and recently, Lithium-ion batteries have been widely adopted in EV systems due to their high energy and power density, low self-discharge, high energy efficiency and long service life and lot more advantages [Cacciabue, 2007] [Balakrishnan and Indulal, 2009].

To achieve promising solutions for worldwide environmental problems, battery management strategy is also one important algorithm to look for development in HEV. One of the most significant of battery management strategy is to estimate the SOC since batteries are sensitive to overcharge which can definitely

[1]Corresponding author

results in irreversible damages [Dai et. al., 2015] [Kang et. al., 2014] [Liu and Duan, 2012] so SOC correction measures are also done during charging and discharging.

ANFIS is used to optimize the performance of hybrid vehicle compares the dynamics of hybrid vehicle with real time data to remove the drawbacks of normal PI vehicles by intelligent adaptive neuro- fuzzy controller. An Adaptive Neuro-Fuzzy Inference systems (ANFIS) controller performs better for variable load condition is used to control the speed of the IC Engine.

Real time control strategy based of Elman neural network for the parallel hybrid electric vehicle is used by Liu and Duan, 2012, their work discuss about equivalent fuel consumption function under charging and discharging conditions of batteries. In one approach a neural network based trip model for highway portion [Khayyam, 2013] [Khayyam and Bab-Hadiashar, 2014], 3 inputs, 2 outputs network was developed for the fitting of the driving pattern on highway near on/off ramps. The trained neural network can obtain a good fitting of the driving pattern. The simplified approach makes the trip model on highway much easier. The interpolation model with NN is used and the fuel economy is greatly improved. The NN model presents a simplified and effective way for this detailed model of trip model considering the on/off ramp flows. The main objective of HEV or the governing EM is to attain the goal of minimum fuel consumption and minimum exhaust emission at various operating conditions. For this purpose the performance of EMS is to be tested under different driving modes and conditions.

Modeling of energy management strategy to control ICE and motor, poses a considerable challenge. Due to various non linear parameters which are included in developing hybrid electric vehicles. Many a time to develop and achieve this new emerging technology, is time consuming analytical procedure and it requires simplifying assumption. One practical alternative to analytical and empirical method that is easy and more accurate is fuzzy Inference system (FIS) and Artificial Neural Network (ANN).In light of Hybrid Electric Vehicle being viewed as promising technology, the existing Energy Management Strategy may not be capable to integrate various aspects of HEV control efficiently and optimally. This necessitates the needs for holistic approach for control of HEVs in real time and under uncertainties. Such systems has to consider issues like -

a) Static and dynamic parameters of vehicle
b) Interpretation of driver behavior
c) The road conditions
d) Wind conditions
e) Battery parameters like SOC and
f) The tradeoff between varieties of power sources.

All these issues are important to achieve the objective of minimum fuel consumption, minimum exhaust emission that to without compromising performance of the vehicle. The few aspects of major concern are first analyses to ensure holistic nature of EMS for HEV.

PROPOSED FRAME WORK OF ADAPTIVE ENERGY MANAGEMENT STRATEGY USING ARTIFICIAL INTELLIGENCE

The proposed framework is outlined in Fig 1. It essentially considers the specifications of the vehicle, the configuration of drive train, the nature and condition of road as well as wind as an input to generate an optimal tradeoff between power sources for variety of driving condition. In this work HONDA INSIGHT first generation is selected as parallel hybrid vehicle under study.

VARIOUS MODULES OF THE FRAMEWORK

Driver Command Interpreter

In this particular model, roadway type, driver style, driving trend and driving mode are used as inputs to determine the various factors and torque requirement given by the driver. This being a very crucial model, parameter like vehicle speed, average acceleration, average speed, number of stoppages, instantaneous velocity was considered. These parameters are co related with torque requirement from driver using Mamdani Fuzzy Inference System (MFIS) and Artificial Neural Network (ANN) [Khayyam, 2013] [Khayyam and Bab-Hadiashar, 2014].

Wind Condition Module

This module finds out the drag force that will be experienced by the vehicle during propulsion. For this purpose wind conditions are modeled using exponential distribution, Weibull distribution and uniform distribution. Both MFIS and ANN based architecture are utilized.

Road Condition Module

To model road condition Gaussian and exponential distribution is utilized. The data base generated using this distribution is utilized to design MFIS and ANN framework to predict road condition. This data is further utilized to determine the power required to drive the vehicle.

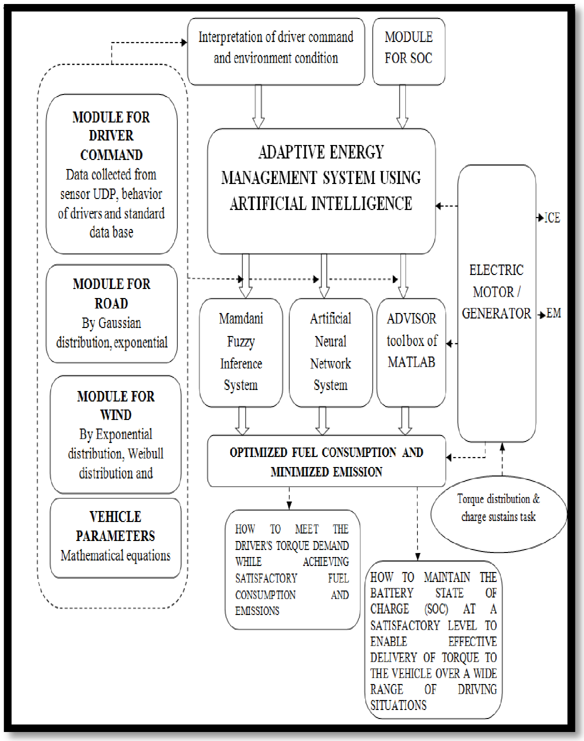

Figure 1: Developed Framework of Adaptive Energy Management of PHEV using Artificial Intelligence

Battery State Of Charge (SOC)

Battery State of Charge (SOC) is necessary data required to deciding the power source for propulsion. In real time this data is directly available from the battery monitoring system. In this work for simulation purpose, a mathematical model which tells about the SOC using the value of battery Open circuit voltage and other parameter of the battery. The MFIS as well as ANN based framework is designed from the data thus generated

ADAPTIVE ENERGY MANAGEMENT STRATEGY FOR HYBRID VEHICLE USING ARTIFICIAL INTELLIGENCE

This system utilizes the four modules discuss in previous section that is driver command interpreter, wind condition, road condition and SOC to determine the mode of propulsion for optimal utilization of fuel and minimum emissions. The optimization is done using Mamdani Fuzzy Inference System [De Vlieger et. al., 2000] [Ehsani et. al., 2005] [Sabri et. al., 2016] [Balakrishnan and Indulal, 2009] and Artificial Neural Network. The study is conducted with the parameters of Honda Insight .In order to access the performance of designed adaptive energy management strategy both strategies are compared. The details of ADVISOR tool box and its result are not included in this paper to limit the comparison between only MFIS and ANN [Cacciabue, 2007]. The output of EMS is in form of command for the drive train. Two types of artificial intelligent techniques are utilized by EMS. The applicability of developed EMS and its effectiveness is tested in different conditions. The results thus obtained and the analysis is presented in next section.

MFIS FOR PERFROMANCE PARAMETERS

After splitting the power optimally among various sub systems of the hybrid vehicle, the next important job of EMS is to determine three performance parameters. These parameters reflect the fuel consumption, exhaust emissions and efficiency of the engine. For this purpose road power demand state of the charge of battery and mode of battery (charging/discharging) are selected as input to determine levels of fuel consumption, exhaust emissions and engine efficiency. These relations are given in the Table 1. The rule base is designed by referring to work of Rajagopalan et. al., 2003 of NREL. Three levels for input and output parameters are considered. The output is in the form of level and hence to determine its numeric equivalent de-fuzzification using centroid methods is done.

Table 1: Rule Base for the Performance Parameter of MFIS Based EMS

PRPD	SOC	Battery Charge (BC)/ Battery Discharge(BD)	Fuel consumption	Exhaust emission	Efficiency
M	L	BC	M	M	H
M	M	BD	M	M	H
M	H	BD	M	M	H
L	L	BC	H	H	L
L	M	BC	L	L	H
L	H	BD	L	L	H
H	L	BC	H	H	L
H	M	BC	H	H	L
H	H	BD	L	L	H

To estimate the effectiveness and efficiency proposed MFIS based EMS, three cases are studied. The performance is tested and compared with ANN based EMS and

PROPOSED ANN BASED EMS

The ANN based EMS consists of many ANNs for various modules of the EMS. The scheme used for this EMS is given in Fig 2. The details of neural network used to know the performance parameters are explained in the next section.

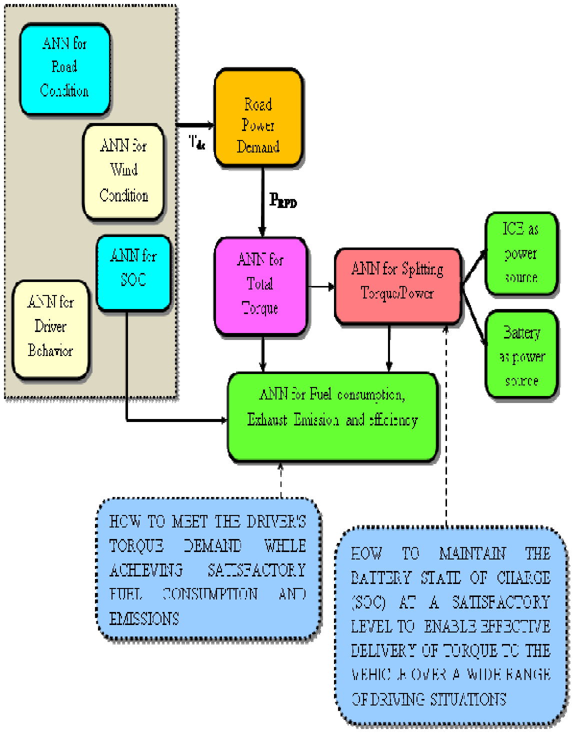

Figure 2: Frame Work of ANN Based Energy Management System

NEURAL NETWORK FOR PERFORMANCE PARAMETERS OF ANN BASED EMS

The ultimate aim of ANN based EMS is to determine fuel consumption, exhaust emissions and efficiency of the vehicle. So for this purpose, neural network is designed which takes input as road power demand, SOC , battery charging/ discharging mode to predict performance parameters. The data and relationships between inputs and outputs required for this neural network are taken from Rajagopalan et. al., 2003. The output of this neural network comes in the form of levels as these parameters cannot be computed using simple empirical relationships. To determine the exact value of each of the performance parameters, these levels are converted into numeric value using appropriate scale.

To assess the performance of ANN based EMS, it is implemented to three different cases and compared with MFIS based EMS.

SIMULATION STUDIES USING PROPOSED MFIS FOR PHEV

The assessment of the performance of the developed Mamdani fuzzy inference system for control of the PHEV is done in the next sections by considering various driving cycles subjected to simulated road conditions, wind conditions and battery state of the charge information. The three case studies are considered from Indian driving perspective. The input information required for the analysis is extracted from the drive cycle which consists of time and the speed of the vehicle measured using dynamometer. These drive cycles are the standard data available on the website of ARAI (www.araiindia.com)

Case Study 1

The drive cycle which consist of information regarding time and speed of the vehicle is necessary as an input to assess the energy management system. For simulation purpose, varieties of drive cycles are consider which cover the different driving situation, road conditions and wind conditions. In this first case study, Indian urban driving situation is selected for simulation purpose. The speed and the time required are available from the drive cycle data. The plot of the Drive Cycle-I : Indian Urban Driving given in the Fig 3 is used for evaluation of performance of MFIS based EMS.

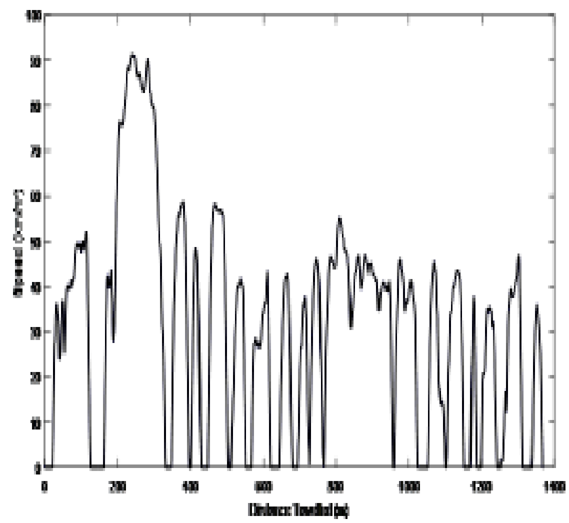

Figure 3: Drive Cycle-I

From Fig 3 it is evident that the data is collected at every second. Hence, for simulation purpose same time interval is considered. In order to use this drive cycle for analysis purpose, following information is extracted. To show the working of the MFIS based system, average values of the parameters are considered however, the analysis is done for every time step for which data is available. The number of data point in every cycle istoo many and hence results obtained after every analysis is presented in the form of graphs. From the drive cycle shown above, following data is extracted. The detail information is given in Table 2.

Table 2: Data Extracted from the Drive Cycle-I

Parameter	Value
Time	1369 seconds
Distance	13.79 Km
Maximum Speed	91.25 Km/hr
Average Speed	31.53 Km/hr
Maximum acceleration	1.48 m/s2
Maximum deceleration	-1.48 m/s2
Average acceleration	0.5 m/s2
Average deceleration	-0.5 m/s2
Standard deviation of acceleration	0.25
Idle time	259 seconds
No. of stops	17
No. of data points	1370

The performance of this MFIS based energy management system was evaluated based on fuel consumption for Drive Cycle-I exhaust emission and vehicle efficiency. The vehicle efficiency is also computed using same MFIS. The defuzzified values of this efficiency are obtained. In Table 3, the average value of fuel consumption (L/100 Km), the exhaust emissions (gm/Km) and efficiency of the vehicle for Drive Cycle-I are listed.

Table 3: Performance of the MFIS based EMS for Drive Cycle-I

Fuel Consumption	Exhaust emissions(gm/km)	Vehicle Efficiency
5.0679L/100 Km (PetrolEquivalent)	HC : 0.32321	31.9792%
5.8053L / 100 Km (Diesel Equivalent)	CO : 0.14658	
	NOx : 0.25266	

The average values of fuel consumption exhaust emissions and vehicle efficiency obtained from ANN based simulation are presented in Table 4.

Table 4: Performance of the ANN Based EMS for Drive Cycle-I

Fuel Consumption	Exhaust emissions	Vehicle Efficiency
3.2798L/100 Km (Petrol Equivalent)	HC : 0.26151	35.3972%
3.757L / 100 Km (Diesel Equivalent)	CO : 0. 12869	
	NOx : 0.10488	

Case Study 2

In this case study, the road inside the Indian town is considered. The drive cycle associated with this case study is given in Fig 4. The number of data points is 1030. The information extracted from this drive cycle for simulation purpose is presented in the Table 5.

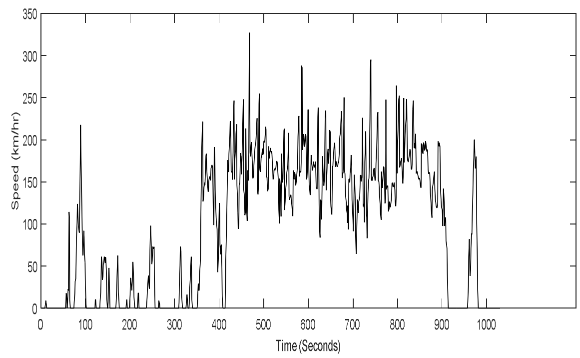

Figure 4: Drive Cycle-II

Table 5: Data extracted from Drive Cycle II

Parameter	Value
Time	1029 seconds
Distance	4.03 Km
Maximum Speed	57.94 Km/hr
Average Speed	14.1 Km/hr
Maximum acceleration	4.11 m/s2
Maximum deceleration	-3.88 m/s2
Average acceleration	0.47 m/s2
Average deceleration	-0.54 m/s2
Standard deviation of acceleration	0.25
Idle time	341 seconds
No. of stops	19
No. of data points	1030

The performance of MFIS based EMS is checked for Drive Cycle-II and the values of these parameters are obtained. In Table 6, the average value of fuel consumption (L/100 Km), the exhaust emissions (gm/Km) and efficiency of the vehicle for Drive Cycle-II are listed.

Table 6: Performance of the MFIS based EMS for the Drive Cycle-II

Fuel Consumption	Exhaust emissions (gm/km)	Vehicle Efficiency
4.3 L/100 Km (Petrol Equivalent)	HC : 0.932	32.5274%
3.7601 L / 100 Km (Diesel Equivalent)	CO : 0.4042	
	NOx : 0.368	

The average values of fuel consumption, exhaust emissions and vehicle efficiency obtained from ANN based simulation are presented in Table 7.

Table 7: Performance of the ANN based EMS for the Drive Cycle II

Fuel Consumption	Exhaust emissions	Vehicle Efficiency
4.9798 L/100 km (Petrol Equivalent)	HC : 0.79377	31.5274%
4.3473 L/100 km (Diesel Equivalent)	CO : 0.30224	
	NOx : 0.17479	

Case Study 3

Previous two case studies have, longer road were considered and urban style of driving as well as urban driving situations were assumed. In order to understand the behavior of MFIS based EMS when implemented to the roads inside the city or rather crowded city, an arterial road moving through residential township is considered. It is represented as shown as Drive Cycle-III in Fig 5. The information extracted from thisdrive cycle is given in Table 8. Similarly simulated wind condition, road condition and battery state of the charge are generated using MFIS. These simulated operating conditions along with the drive cycle are given input to the various modules of the MFIS based EMS. These inputs are processed in MATLAB environment. The defuzzified values of the driver torque requirement for Drive Cycle-III are used. The defuzzified values of wind drag, road friction and power required to keep battery at a specific charge level is also obtained. The battery charging / discharging sequence adapted by the EMS as well as total torque required for propulsion for Drive Cycle-III is obtained. These results are given input for estimation of the performance parameters and the Fuel Consumption thus obtained for Drive Cycle-III.

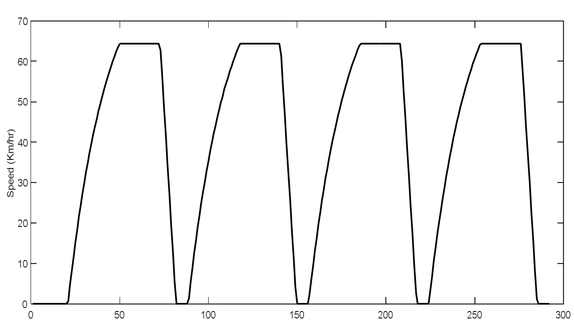

Figure 5: Drive Cycle-III

Table 8: Data Extracted From the Drive Cycle-III

Parameter	Value
Time	291 seconds
Distance	3.22 km
Maximum Speed	64.37 km/hr
Average Speed	39.71 km/hr
Maximum acceleration	1.07
Maximum deceleration	-2.01
Average acceleration	0.6
Average deceleration	-1.79
Standard deviation of acceleration	0.45
Idle time	48
No. of stops	4
No. of data points	292

In Table 9, the average value of fuel consumption (L/100 Km), the exhaust emissions (gm/Km) and efficiency of the vehicle for Drive Cycle-III are listed.

Table 9: Performance of the MFIS based EMS for the Drive Cycle-III

Fuel Consumption	Exhaust emissions (gm/km)	Vehicle Efficiency
5.92 L/100 Km (Petrol Equivalent)	HC : 0.9984	30.3955%
5.18L / 100 Km (Diesel Equivalent)	CO : 0.46406	
	NOx : 0.56469	

The average values of fuel consumption, exhaust emissions and vehicle efficiency obtained from ANN based simulation are presented in Table 10.

Table 10: Performance of the ANN Based EMS for the Drive Cycle-III

Fuel Consumption	Exhaust emissions (gm/Km)	Vehicle Efficiency
2.2987L/100 Km (Petrol Equivalent)	HC : 0.72343	32.3955%
2.9798L / 100 Km (Diesel Equivalent)	CO : 0.40352	
	NOx : 0.22346	

CONCLUSION

The developed MFIS based and ANN based approaches consist of various modules based on their functionality. In order to make the developed approaches adaptive and flexible, the modules responsible for driver command interpretation, road condition prediction and wind condition prediction are of major importance. Hence, they were included in the developed approaches. The major findings of this work are as follows.

- The modeling of PHEV and its environment is an important aspect to be considered while carrying out EMS study. In this work, for simplicity, the HONDA INSIGHT model was considered. To get the feel of actual driving conditions, road condition and wind condition were simulated using established relationships. This facilitates accurate model of the vehicle and its environment.
- The ANN based EMS for control of PHEV seems to be most efficient in terms of fuel consumption, exhaust emissions and vehicle efficiency.

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