Performance and Emission Prediction of Hybrid Electric Vehicle Using Software Tools- ADVISOR and Artificial Neural Networks

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Abstract - *In the event of combating harmful emissions and saving petroleum fuels, the importance of electrical vehicles is increasing due to the advantages of zero local emissions and respective governments' incentives. However, going fully electric in a short period is a challenging task because of inevitable limitations. Hybrid vehicles act as a suitable linkage between conventional and pure electric vehicles. The present work aims to evaluate the harmful pollutant emissions from a hybrid electric vehicle using ADVSIOR for 3 different driving cycles viz; UDDS, NEDC and US06 and to compare the emissions of these driving cycles by varying the initial state of charge. Also, the pollutant emissions of hybrid vehicles are compared with that of the conventional vehicle of the same model. For comparison purposes, the Toyota Prius vehicle model (parallel Hybrid) was chosen. In order to predict different performance parameters i.e. Brake Power, Brake Thermal Efficiency, and Harmful emissions (HC, NOx, and CO), the help of an Artificial Neural Network with ethanol-gasoline blend type, and the ethanol blend varied from E0 to E20. The final developed ANN model delivered the best correlation coefficient ranging from 0.96567 to 0.99989 for all the performance parameters and exhaust emissions. The mean square errors and the correlation coefficients for different performance parameters were calculated.*

Key Words: **Emissions, Hybrid vehicle, ADVISOR, Driving cycle, Ethanol-gasoline blend, Artificial Neural Networks**

1. INTRODUCTION

The fossil fuel automobiles have been serving the community in light, medium and heavy duty applications for over one and half a century. The automotive industry has also given a provision for other industries to grow. However, due to its large scale use, it has led to the difficulty of uneven supply of petroleum fuels and more importantly air pollution related issues. Many parts of major cities in the world are in the grab of high levels of air pollution mostly from passenger vehicles. The sole aim is to minimize the negative impact on the nature. Efforts have been made to overcome the difficulties with conventional vehicles by using alternative fuels either in neat or blended form and exhaust gas aftertreatment devices. However, due to stringent emission norms of EURO or BSVI, it is becoming imminent to switch over to electric mobility in a phased manner. As a solution to these complex issues now focus is being laid on electric vehicles. But a quick transition to pure battery electric vehicles from conventional internal combustion engine driven vehicles seems difficult to be feasible owing to many constraints. The key constraints include poor infrastructure and availability of charging station service where the EVs are operated. Also, the range anxiety is a major concern too which dissuades many customers from swaying away from using EVs. As the automotive industry of the entire globe is in a transition phase i.e. we are moving from conventional vehicles to pure battery electric vehicles. Hence, in order to make the transition smoother a Hybrid vehicle may act as a suitable linkage to act as a suitable medium of transport. Hybrid electric vehicles as the definition above suggests, a hybrid vehicle is simply the one that relies on two different power sources for undergoing motion. The two different power sources are basically gasoline and energy storages for electricity.

1.1 Components of hybrid electric vehicle

The major components of HEV includes Electric motor, Internal combustion engine, Battery pack, converter, control board and gasoline/diesel fuel tank. All these key components of hybrid electric vehicles can be broadly classified into three categories. They are:

1. Drive train

2. Energy storage system

3. Control system

Drivetrain helps to combine the power source of ICE and electrical drive in a physical manner. The energy storage system prioritizes the energy storage and power capacities whether they are large or small. The control system, as the name suggests, controls and manages the ICE, electrical system and energy storage system of hybrid vehicles.

1.2 Function of different components

1. **Traction motor-** In its simple form, an electric motor aids the vehicle wheel to move by supplying power from the traction battery pack. In some vehicles motor generators are employed to perform both the drive and regeneration duties.

2. **Internal Combustion Engine (spark-ignited):** In this component, the fuel used is gasoline which is pumped into either the intake manifold or the combustion chamber, where it gets mixed with air and ignited with the help of a spark plug.

3. **Battery Pack or Stack-** The battery pack or stack has the function to store electricity which is to be consumed by the electric traction motor. The battery embedded in the traction battery pack, helps to provide electricity to start the vehicle before the engagement of the traction battery pack. Adding to that, the auxiliary battery also provides power to vehicle accessories for their operation

4. **Converter-** The conversion of higher-voltage DC power from the traction battery pack to the lower-voltage DC power is taken place with the help of a converter. The converted lower DC voltage is utilized by the vehicle accessories to drive them and for recharging purpose of the battery pack

5. **Electric Generator:** This is implemented to serve the purpose of regenerative braking. While braking, the moving wheels generate electricity, which is then transferred to the traction battery pack.

6. **Gasoline or Fuel Tank-**This tank is used to store gasoline and remains preserved till the engine needs it.

1.3 Classification of Hybrid Electric Vehicles

1.3.1 Classification on the basis of degree of hybridization

There are four types of hybrid vehicle based on their **degree of hybridization** values.

i. A **Micro hybrid** possesses a degree of hybridization value which lies below 5%. The embedded electric motor has the function of starting and stopping the vehicle. Adding to that the vehicle has the ability to stop the engine in an impulsive manner too. Mild hybrids would not provide with any extra torque by the electrically powered motor.

Example: BMW 1 series, Fortwo Mercedes.

ii. A **full hybrid** can run on just the combustion engine (i.e. diesel/petrol), the electric source (i.e. power from batteries), or a combination of both the power sources. FHEVs are the most fuel efficient type of hybrid vehicle. They are also capable of operating in **series mode**, **parallel mode** or **all-electric mode.** The all-electric mode as it explains itself and is used to run the FHEVs at a low vehicle speed. Series mode also makes use of the electric motor to drive the wheels but the internal combustion engine is used at the same time as an on-board generator. Parallel mode utilizes both the internal combustion engine and the electric motor together to drive the wheels.

Example: Ford Fusion Hybrid, Toyota Prius.

iii. A **mild hybrid** consists of electric motor and Internal combustion engine which always work together to propel the vehicle. A mild hybrid is limited to parallel mode so can really be looked upon as having a battery and a helper motor.

Example: Ferrari LaFerrari, Chevrolet Malibu.

iv. A **plug-in hybrid**, as the name suggests, it does require plugging action into the mains to get its battery fully recharged. PHEVs can run in just electric mode. These hybrids use all the technologies of a FHEV but possess a relatively larger capacity battery which can be plugged into the mains for charging purpose. The key advantage of plug-in hybrid vehicles is that their range in all electric modes is higher than that of an average FHEV.

Example: BMW i8, Kia Optima, Porsche Cayenne S

The real goal of a hybrid vehicle is to utilize the electric portion of the drive-train as much as it can without compromising on its performance. This basically aims to cut down the harmful emissions and improve the fuel efficiency. This is because the electric motor is relatively more efficient as compared to an internal combustion engine and produces zero emissions locally. In order to power the electric portion of a hybrid engine, a hybrid vehicle has to carry a battery pack. In the battery pack, the size of the battery varies depending on the degree to which the vehicle is designed to rely on it, and the way the battery gets recharged. The hybrid vehicles also can be classified on the basis of their degree of hybridization value.

Table-1.1 shown below depicts the summary of classification of hybrid vehicles depending on the values of their degree of hybridization (DoH).

Table 1.1-classification of hybrid vehicles based on DoH.

Type	DoH
Micro	<5%
Mild	Up to 10%
Full Hybrid: Parallel Series	 10% to 50% 50% to 75%

1.3.2 Classification on the basis of vehicle architecture

Based on vehicle architecture the hybrid vehicles are of 3 types. These are:

1. Parallel hybrid
2. Series hybrid
3. Series-Parallel hybrid

Since the chosen vehicle configuration is a parallel type hybrid-Toyota Prius, description of parallel hybrid is only presented here.

1.3.2.1 Parallel hybrid

A parallel hybrid possesses the flexibility of using more than one power source to deliver the propulsive power to the wheels. Here both the IC engine and electric motor are configured in parallel with a suitable mechanical coupling that utilizes the torque coming from both the sources. This vehicle requires less motor power as compared to series hybrid and electric vehicles as the IC engine which is connected in parallel with it contributes to the total power demanded by the vehicle. Fig.1.1 illustrates the detailed mechanical and electrical connection between the major components of the parallel hybrid configuration.

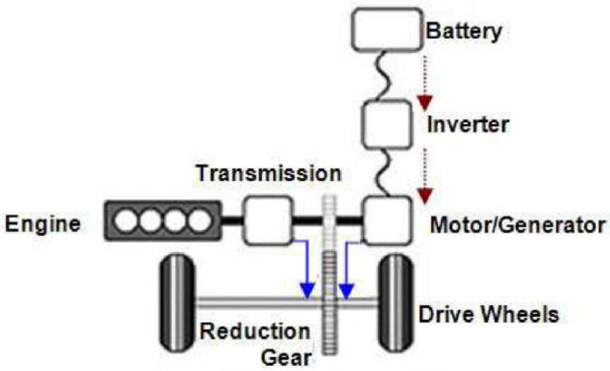

Figure 1.1- Configuration of parallel hybrid vehicle [4]

1.4 Driving cycle

For evaluation of vehicle performance and emissions in a laboratory, a chassis dynamometer is used and the vehicle is allowed to run simulating normal road and load conditions. Driving cycle represents a series of data points which show the variation of speed versus time.

For different countries and organizations, various driving cycles are implemented to assess the performance of a standard vehicle model. For example, it can be used to assess the fuel consumption, vehicle emissions, acceleration and gradeability test.

In addition, driving cycles are also utilized in propulsion system simulations to predict the performance of internal combustion engines (petrol and diesel type), electric vehicle, hybrid electric vehicle, fuel cell electric vehicle etc.

Driving cycles are divided into two categories. They are:

1. Transient driving cycles
2. Modal driving cycles

In transient driving cycle, the continual speed variations typical of on-road driving which include several alterations are represented whereas, long durations of continuous speed are involved in modal driving cycles.

The "Drive-cycle" is essentially a representation of the road where the concerned vehicle is operated. Drive cycles are used to reduce the cost of on-road tests, test time, and test engineer fatigue. The entire concept is to bring the road to the test lab (a chassis dynamo-meter) or to a computer simulation.

There are two types of driving cycles that can be created. One is time dependent, whereas the other is distance dependent (speed versus distance versus altitude) (speed versus time versus gear shift). The time dependent is a compressed representation of the actual time taken to conduct the test on the road, whereas the distance dependent is an exact reproduction of the test route. The European NEDC cycle and FTP-75 are examples of time dependent driving cycles. Time dependent driving cycles are utilized specifically for chassis dynamometer testing since the results may be obtained in a short amount of time and repeated tests are simple.

The popular driving cycles are UDDS, NEDC and US06.

UDDS is an acronym for Urban Dynamometer Driving Schedule and it refers to dynamometer test on fuel economy mandated by the US Environmental Protection Agency that simulates city driving conditions only. It’s shown in Fig. 1.2.

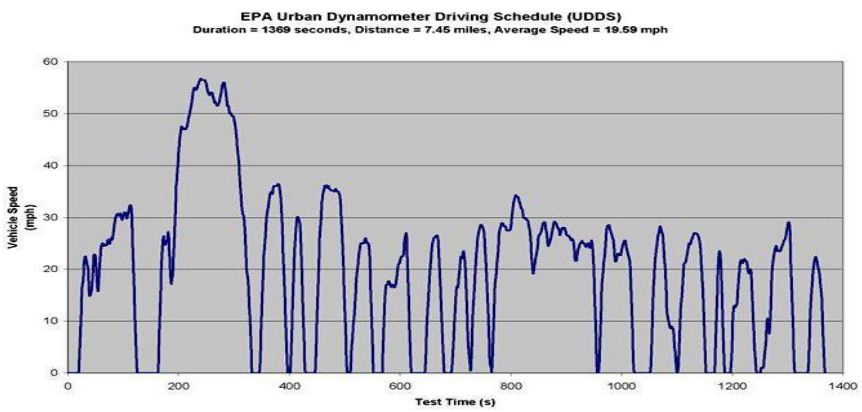

Figure 1.2- Urban Dynamometer Driving Schedule

NEDC is an acronym for new European driving cycle which is developed to evaluate automotive engine emissions and fuel economy in passenger cars (which excludes light trucks and commercial vehicles). It's also known as the MVEG cycle (Motor Vehicle Emissions Group). Initially it was designed to predict the performance of gasoline based engines but now it’s widely used to estimate the electric power consumption and range of hybrid and battery electric vehicles, as represented in Fig. 1.3

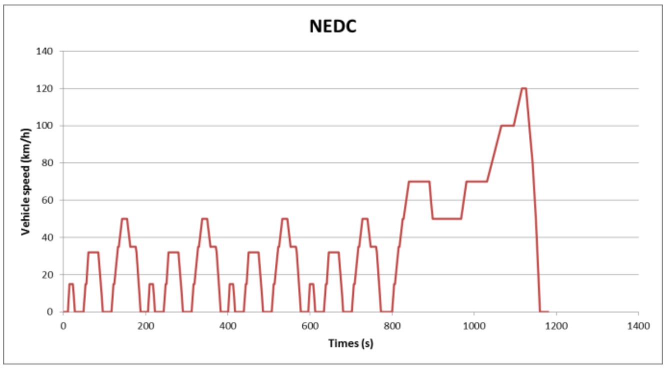

Figure 1.3: New European Driving Cycle

The US06 Supplemental Federal Test Procedure (SFTP) was developed to solve the FTP-75 test cycle's limitations in order to represent an aggressive, high-speed, and/or high-acceleration driving behavior, fast speed fluctuations, and driving behavior after starting, shown in Fig.1.4

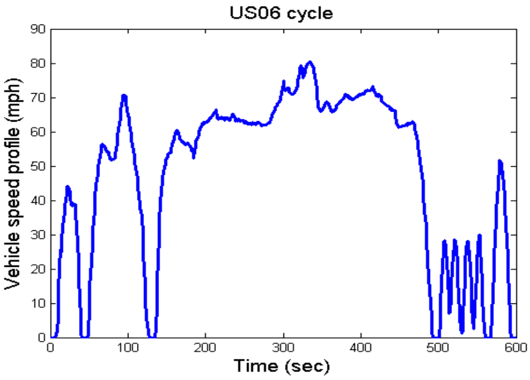

Figure 1.4- US 06 driving cycle

1.5 Mathematical formulae

1.5.1 **Degree of Hybridization (DOH)-**The ratio of power developed by an electric motor in a hybrid vehicle to the total power developed by two sources of the vehicle is known as degree of hybridization.

Here total power refers to the sum of the contribution of power from the motor and the internal combustion engine.

Mathematically, DoH= Motor Power / (Motor Power + Engine Power)

For conventional vehicle Motor power=0 hence, the DoH for a conventional vehicle=0

For a pure Electric vehicle there is no contribution of power from engine, hence the DoH for a pure electric vehicle=1

For a hybrid electric vehicle, it has both electric motor and IC engine, so

DoH of hybrid vehicle lies in between 0 and 1

1.5.2. **State of Charge (SOC)-**The SOC of the battery may be defined as the ratio of the current remaining battery capacity to the available capacity under certain operating conditions i.e. temperature, charge and discharge ratio, etc.

Mathematically, SOC= (Qc/Q)*100

Where Qc = Residual charge of the battery at the moment of calculation

State of charge (SOC) at any instant,

$$SOC(t+1) = SOC(t) - \frac{(\int_t^{t+1} i*dt)}{Q}$$

where, SOC(t) represents the state of charge at t seconds and *i* represents the electric current at that instant. Q represents the maximum charge storing capacity of the battery.

1.5.3 **Root Mean Square Error (RMSE)**

It measures **error between two data sets**. It compares a predicted value and an observed or known value. The smaller an RMSE value, the closer predicted and observed values are. Root mean square error takes the difference between each observed and predicted value.

Mathematically, it can be written as,

$$RMSE = \sqrt{\frac{\sum_i^n (Pi-Oi)^2}{n}}$$

Pi= Predicted value*, Oi*=Observed value and n=no. of samples

1.5.4. **Correlation coefficient(R)**

Correlation coefficient is a measure of the strength of linear relationship existing between two variables. When the value of linear correlation coefficient is greater than zero, then it indicates a positive relationship. But when the correlation coefficient is less than zero, it indicates a negative relationship. If the correlation coefficient is zero then it indicates no relation between the two variables which are compared. In case of less error between the predicted and observed experimental values, the correlation coefficient lies closer to 1.

2.LITERATURE REVIEW

In order to arrive at the scope and objectives for the present work, literature review has been done.

A dynamic dynamic model was simulated in ADVISOR of a split plug in hybrid electric vehicle which included a detailed representation of a hybrid electric vehicle. Based on the simulation, they proposed a vehicle controller. With the use of the proposed controller it was shown that working in different modes of operation, the engine was operated in high efficient areas of the efficiency map which indicated a relatively higher efficiency as compared to the conventional drive-train configuration [5]. Bhatikar et al [2000] proposed a model for the energy storage system of a hybrid electric vehicle using Artificial Neural Network. The ANN model dealt with regression analysis to calculate the Mean square error. They also demonstrated the effectiveness of smart selection techniques to design the training data for an ANN model.

Markel et al [2002] gave a detailed introduction to ADVISOR software which was developed by the National Renewable Energy Laboratory of the USA. Adding to that it was briefly described how ADVISOR provides the vehicle engineering community with an easy-to-use and flexible, yet robust and supported analysis package for advanced vehicle modeling. Andrew et al [2004] proposed a model to combine the battery in parallel with an ultracapacitor. They observed that the storage and peak current characteristics could be achieved without degrading the standards of the vehicle. Mariam Khan et al [2009] described the drawbacks of conventional vehicles and the harmful impact resulting from emissions. They observed that HEVs would reduce the harmful emissions like CO, HC, NOx and demonstrated the growing need for sustainable transportation and the role of HEVs as a possible solution.

Kiani Deh Kiani et al [2009] focused on predicting the performance parameters like brake power, brake thermal efficiency, brake specific fuel consumption and emissions-HC, NOx, CO and Particulate Matter. The implemented ANN model and utilized ethanol gasoline blend fuel and load at the input layer. Theo Hofman et al analyzed the drivetrain configurations of Toyota Prius. The overall goal of the research was to find the minimal specifications for the Primary power source, Secondary power source, and Transmission technology in order to achieve a predetermined fuel economy and performance while keeping cost and lifetime limits in to account.

Duarte et al [2013] carried out work on the effect of battery State of Charge on fuel consumption and gaseous pollutant emissions in a complete Hybrid Electric Vehicle. They used Vehicle Specific Power (VSP) methods and a portable laboratory to characterize the vehicle's energy and environmental footprint based on its power demand. On-road energy and pollutant mass emission rates according to VSP mode were coupled with NEDC VSP time distribution, allowing certification data to be compared to acquire data under real-world operation. Imdat Taymaz et al [2014] focused on the importance of hybrid vehicles and how it could play a major role in the future by reducing the emissions along with a greater fuel economy. They calculated the emissions of a standard hybrid vehicle model in different modes of operation-normal driving mode, acceleration mode, deceleration mode and charging mode. Apart from that they determined fuel consumption of a vehicle through simulation methods in different driving cycles to compare the performance of a vehicle.

Hannan et al [2014], emphasized the importance of energy management techniques which were depicted along with renewable energy technology as a potential solution to environmental pollution. Apart from that they elaborated the classification of hybrid electric vehicles on the basis of their degree of hybridization values.

Zou Yuan et al [2014] proposed a model that can be used to optimize the control development of a power split hybrid vehicle. In order to get the benefits of series and parallel hybrid vehicles, they proposed use of a power-split planetary gear arrangement in hybrid vehicle models. They conducted a trade-off study between fuel economy and emissions and the results were compared with the simulation results of the ADVISOR.

Panday et al [2015] explained how the variation of temperature affects the battery's current, voltage, and state of charge (SOC), which in turn affects the engine's on/off transition. The effect of temperature was studied in order to limit the operational range of the vehicle to optimize fuel efficiency and have a longer battery life.

Srinath Pai et al [2016] developed an ANN model to predict the emissions of NOx, HC for a diesel engine. Using the predicted model performance parameters like correlation coefficients, mean square error were calculated and comparative analysis was made in a graphical form between the predicted and actual values. It was also shown that owing to its simplicity and flexibility, ANN could be successfully implemented to predict the parameters with desired accuracy in lesser time.

Jianfei et al [2016] demonstrated the advantages of using a power-split plug-in hybrid electric vehicle which basically takes the advantages of both series and parallel combination of vehicles. They performed a simulation regarding the energy management strategy of power split hybrid vehicles. On the basis of simulation results, they showed the maximum power of the engine corresponding to the most fuel economical area and its dependency on velocity variation.

Dibakor Boruah et al [2016] tried to quantify the utility of an artificial neural network as a black-box model for internal combustion engine performance. As a result, an artificial neural network (ANN)-based model for a four-cylinder, four-stroke internal combustion diesel engine has been built using particular input and output variables based on some experimental data for various load and engine speed conditions. They calculated the RMSE and correlation coefficient and explained the importance of ANN tool in predicting certain outputs with greater accuracy.

Ojas [2017] presented the classification of hybrid electric vehicles on the basis of parameters viz; degree of hybridization and the vehicle architectural design. The author classified the hybrid vehicle into 4 types like micro, mild, fully and plug-in hybrids depending on their degree of hybridization values. Similarly on the basis of vehicle architecture the vehicles were classified as hybrid vehicles into parallel, series and series-parallel hybrids.

An ANN model developed by Samet Uslu et al [2018] to predict the parameters like exhaust gas temperature, brake thermal efficiency, NOx, CO, HC and smoke. Experimental data showed that the addition of diethyl ether to diesel fuels increases brake thermal efficiency and brake specific fuel consumption but on the contrary if the engine performance was considered it reduced the exhaust gas temperature. Significant reduction in CO, NOx, HC and smoke emission concentrations were seen with the use of Diethyl Ether-diesel fuel blends.

Thakur et al [2018] envisaged a model using ANN to predict the performance parameters like brake power, brake thermal efficiency, brake specific fuel consumption and emissions like HC, NOx, CO. The implemented ANN model and utilized ethanol-gasoline blend fuel and load at the input layer. Using ANN as a tool in MATLAB, they calculated correlation coefficients and root mean square error. Singh et al [2019] laid importance on hybrid vehicles which has progressed from its infancy to become a possible answer to the planet's major existential crisis. The paper extensively described different components of a standard hybrid vehicle and how HEVs would combine the propulsion capabilities of an internal combustion engine and an electric motor.

Jan Dizo et al [2021] made a study about the importance of plug-in hybrid and electric vehicles and the key areas where they could serve better than the conventional vehicle. They emphasized on the availability of a sufficient number of charging stations and infrastructural growth so that the future of hybrid and electric cars would be viable.

Anh Tuan Hoang et al [2021] emphasized on the ANN model which would help to optimize the engine performance and emission characteristics fueled with biodiesel-based fuels. At the input layers the parameters like load, cetane number, density and speed were taken to predict the output parameters like brake thermal efficiency, brake specific fuel consumption and emission parameters like CO, HC, NOx and smoke.

2.1 Observations from literature review

From the above literature review, the following points were noted:

- The initial State of charge and driving cycles have a profound impact on the emissions of a hybrid vehicle model which requires some additional research for comparative study.
- There is a scope of evaluation of emissions for a parallel hybrid and conventional vehicles to compare their performance for a particular standard driving cycle.
- Implementation of some tools like ANN can be a handy approach in the automotive industry to predict the performance of a vehicle to arrive reasonably accurate and simple without involving expensive experimental setup.

2.2 Objectives

1. To evaluate the emission characteristics of a hybrid vehicle using ADVISOR software for different driving cycles.
2. To compare the emissions of Hybrid electric vehicles with Conventional vehicles with gasoline-ethanol blends as fuel.
3. To predict the performance of a hybrid vehicle using Artificial Neural Network.

3. MODELING AND SIMULATION

3.1 Emission evaluation using ADVISOR software

The present work deals with a simulation process for the performance and emissions evaluation of hybrid electric using ADVISOR software-ADvanced VehIcle Simulator developed at the National Renewable Energy Laboratory(NREL),USA. The software possesses the capability to simulate different kinds of vehicles i.e. conventional, electric, or hybrid vehicles (series, parallel, or fuel cell). ADVISOR software serves as the backbone for the detailed simulation and analysis of a definite user defined drivetrain components, a starting point of verified vehicle data and algorithms from which it takes the full advantage of the modeling flexibility of SIMULINK and analytic power of MATLAB. It can be used for predicting the fuel economy, acceleration performance grade sustainability and emission evaluation. In order to evaluate the emissions of a hybrid vehicle model this software demands certain input variables which play an essential role to evaluate the harmful pollutants.

3.1.1 Structure of ADVISOR for simulation

Following steps are involved in the software to evaluate the emissions of a hybrid electric vehicle. ADVISOR works on the MATLAB/SIMULINK based environment. SIMULINK can be used to graphically represent complex systems using block diagrams, while MATLAB provides the flexibility of an easy-to-use matrix-based programming environment for executing calculations. The links between various components are graphically portrayed in the ADVISOR car model using SIMULINK block diagrams. During the simulation, the model reads the input data from the MATLAB workspace, and the results are displayed in the results window.

- ADVISOR provides the flexibility to the user to select the car at one's interest in the ADVISOR vehicle input window, as shown in Fig. 3.1. The various pull-down choices are used to select a certain vehicle configuration, which can be a conventional vehicle, a pure electric vehicle, or a hybrid vehicle with a series/parallel configuration.
- The characteristic performance maps for the various components are presented in the lower left of the window and can be accessed using the pull-down menu.
- In this work the simulated vehicle configuration has parallel hybrid configuration, hence parallel hybrid configuration is chosen at the input window.

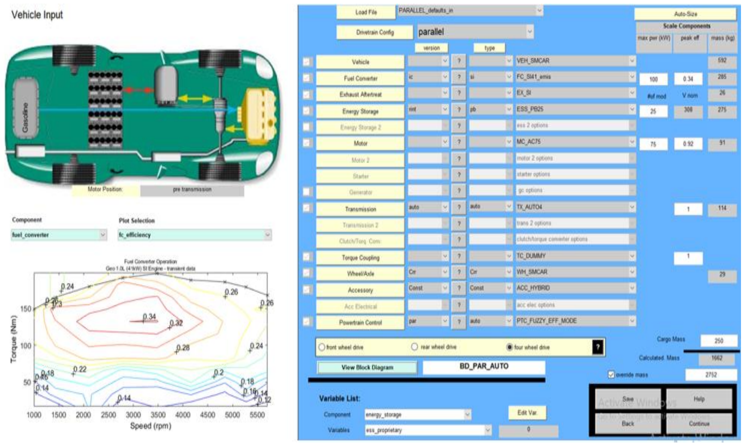

Figure 3.1: Input window of ADVISOR

- To guide the user through the simulation process, ADVISOR employs three key graphical user interface (GUI) windows. The GUIs allow the user to examine the effects of vehicle specifications and driving cycle requirements on vehicle performance, emissions and fuel economy in an iterative manner. The graphical user interfaces (GUIs) make it easier to deal with the raw input and output data in the MATLAB workspace. To define the connections between various components, the vehicle model is graphically shown using SIMULINK block diagrams. During the simulation, the model reads the input data from the MATLAB workspace and outputs the results to the workspace, which may be examined in the results window.

- The user defines the event over which the car will be modeled in the ADVISOR simulation setup window (Fig.3.2). The following are some of the occurrences that could be simulated: A single drive cycle, several cycles, and unique testing techniques are all available. The upper right corner of the set-up window gives the opportunity to choose different driving cycles as per desire of the user which the user can again see in the right-hand corner of the window. In the simulation mode, it allows the user to select cycles and define simulation parameters information about the selected cycles which are presented in the left portion.

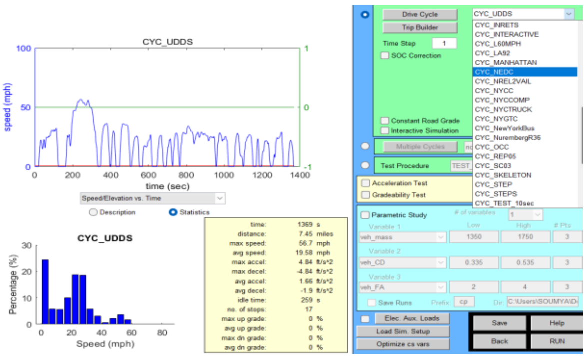

Figure 3.2: Setup window of ADVISOR

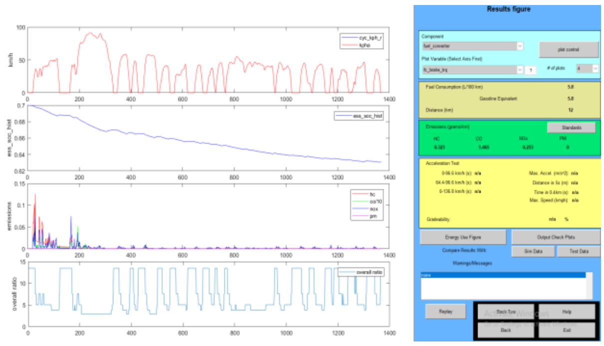

Figure 3.3: Results window of ADVISOR

Fig.3.4 illustrates the complete block diagram of a hybrid vehicle which is developed in the MATLAB/**SIMULINK** environment. This diagram extensively describes each and every component of the vehicle.

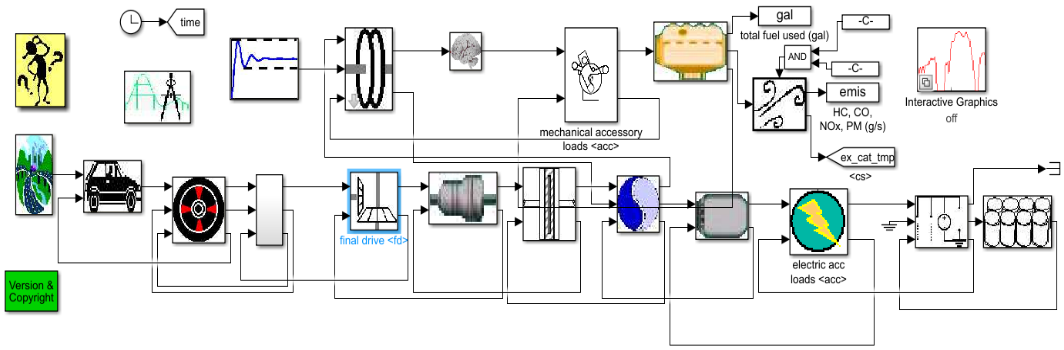

Figure 3.4: SIMULINK block diagram of a hybrid vehicle

- For a Hybrid electric vehicle, Fuel converter, Motor controller, Torque coupling, Energy storage, Vehicle, Power train control, Exhaust after treat, Accessories etc. are the input variables for initiating simulation.

- For a conventional vehicle, at the input, the numerical values of different variables under fuel converter, power-train, Vehicle, Wheel axle, Trans-mission, Accessories, Exhaust after-treatment etc. are to be entered. After entering the desired input variables then we proceed to simulation by clicking on run and the results of simulation are shown in the output screen. Similarly, the ADVISOR output screen gives us results based on vehicle architecture selected and the test parameters that we provide such as drive cycle, exhaust emission characteristics.

- In order to proceed to simulation some essential numerical data are required by the ADVISOR software. These numerical data play a vital role in determining the emission parameters like HC, CO, NOx and PM of a standard vehicle model.

- Table 3.1 describes the numerical data demanded by ADVISOR to proceed towards simulation.

Table 3.1- Input parameters for hybrid vehicle

(Toyota Prius)

S No.	Parameter name	Value
1	Torque(Nm)	142
2	Power(kW)	73
3	Gross Vehicle weight(kg)	1725
4	Coefficient of drag (Cd)	0.24
5	Frontal projected area(m^2)	2.587
6	Engine displacement volume(cc)	1798
7	Compression ratio	13:1
8	Lower heating value of fuel(kJ/kg)	45200
9	Wheel base(m)	2.7
10	Overall length(m)	4.54
11	Overall width(m)	1.76
12	Overall height(m)	1.47

13	No. of cylinders	4 in-line
14	Kerb weight(kg)	1380
15	No of battery modules	28
16	Battery capacity(kWh)	1.31
17	Battery Nominal voltage(V)	201.6
18	Battery capacity (Ah)	6.5

4. PERFORMANCE PREDICTION USING ANN

- It's really time consuming and costly to test an automotive vehicle engine under different operating conditions and with a variety of fuels. In this regard, ANN helps to model the performance and exhaust emissions of an engine with a good accuracy.
- To predict a few performance characteristics of HEV such as brake power, brake thermal efficiency, and pollutant emissions (HC, CO, NOx) which are essentially the ANN model's output in this paper. At the input the provided parameters are Speed, Ethanol blend, Gasoline flow rate and Load. The number of hidden layers in each case of simulation is 20.
- MATLAB has a provision to use ANN as a tool. In ANN model there are 3 different layers. They are basically input layer, output layer and hidden layer.
    - Input layer- This layer has the same number of neurons as the number of inputs to neural network. This layer is made up of passive nodes, which do not participate in signal modification but just pass the signal on to the next layer
    - Hidden layer- This layer has an arbitrary number of layers, each with an arbitrary number of neurons.
    - Output layer- This layer's nodes are active because they participate in signal modification. The number of neurons in the output layer is the same as the number of output values in the neural network. This layer contains only active nodes.

4.1. Steps involved

The following steps are involved in ANN modeling in MATLAB.

Step-1: Neural Layer fitting
Step-2: Data selection
Step-3: Conversion from column matrix to row matrix
Step-4: Division of data into training, test and validation
Step-5: Selection of hidden layers
Step-6: Selection of algorithm

The steps involve the Fitting of different layers of ANN. In this step, the architecture of ANN is depicted which includes input, hidden layer, output layer and output. This neural layer fitting helps to select data, create and train a network and to evaluate the performance by calculating mean square error and regression analysis. This step includes the input and output data selection in form a column matrix

As the selected data(input and target) are in form of a column matrix, this step helps to convert the column matrix to row matrix so that the dataset can be trained in the next step.

The selected data are divided into 3 training, testing and validation and the respective weight percentages are 70%, 15% and 15%.This indicates the division of total no of samples into training, validation and testing. The total no of samples selected for training, validation and testing are 211, 45 and 45 respectively. The number of hidden layers chosen is 20 for each performance parameter.

The algorithm used in this step is **Levenberg-Marquardt**. After selection of algorithms the network is trained to proceed towards simulation. This yields the mean square error as well as the correlation coefficient after a certain no of iteration.

4.2 Levenberg-Marquardt Algorithm-

1. This algorithm is basically used in the cases when there exists a non-linear relation between inputs and outputs.

2. It's a back propagation algorithm which is used in an artificial neural network to predict the results based on the input data set provided to it.

3. This Algorithm is a technique which is iterative in nature and it helps to locate the minimum of a multivariate function that can be expressed as the sum of squares of non-linear real-valued functions.

4. In this case the used input variables i.e. load, speed, gasoline blend, fuel flow rate and these are used in the algorithm to predict the output variables i.e. the performance parameters which are Brake power, Brake Thermal Efficiency, Pollutants missions- HC, NOx and CO.

5. The ANN model utilizes this algorithm to predict the performance so that the errors can be calculated. Basically 2 kinds of parameters are calculated here. They are **RMSE** (Root mean square error) and **R** (Correlation coefficient)

Properties of gasoline and ethanol [13].

Table- 4.1- properties of Gasoline and Ethanol

Fuel property	Fuel	
	Gasoline	Ethanol
Molecular formula	C_4-C_{12}	C_2H_5OH
Molecular weight	100-105 grams/mole	46.07 grams/mole
Density at 20°C	740kg/m^3	790kg/m^3
Lower heating value	45.26MJ/kg	25.12MJ/kg
Specific heat	1.99 kJ/kg K	2.38kJ/kg K

5. RESULTS AND DISCUSSION

5.1 Evaluation of emissions of a conventional vehicle

The standard urban dynamometer schedule test driving cycle test mode was chosen for a time period of 6000 seconds (approximately 100 minutes). The plot helps to find the value of any harmful pollutant at any instant of time during the operation of a hybrid vehicle.

The conventional vehicle was subjected to testing as per chosen driving cycle urban dynamometer driving schedule (UDDS) for comparison purposes. Fig.5.1. shows the emission plot for a conventional vehicle.

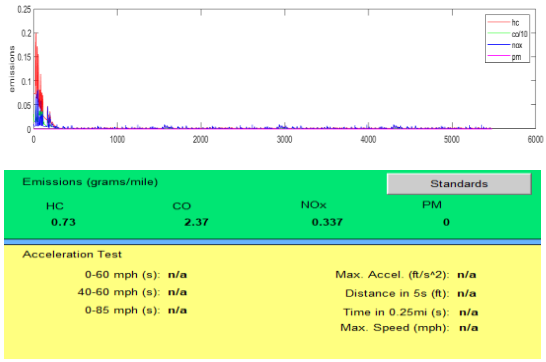

Figure.5.1. Variation of emissions with time on UDDS Driving cycle for a conventional vehicle

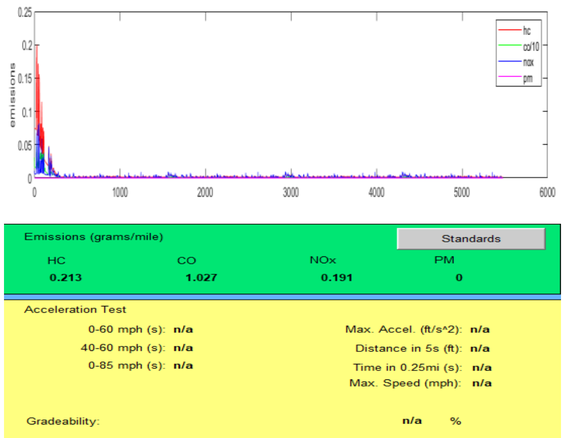

Figure 5.2. Variation of emissions on UDDS Driving Cycle for Hybrid Electric vehicle

5.2 Emissions test on UDDS Driving Cycle for a HEV

The chosen vehicle configuration under hybrid electric mode was allowed to perform for predicting emissions on UDDS driving cycle. The Fig. 5.2 shows the magnitude of emissions over a certain period of time for a standard Toyota Prius hybrid model. The magnitude of CO and NOx are within the limits of BS VI norms whereas the HC emission magnitude is little more than the BS VI 6 norms. As the selected hybrid model is a petrol engine driven, hence the magnitude of emissions satisfy the BS VI norms except HC emission whose range is little bit more than the BSVI i.e. 0.1gram/km.

Table 5.1- Comparison of emissions between hybrid and conventional vehicle

Vehicle Type	HC (gram/mile)	CO (gram/mile)	NOx (gram/mile)	PM (gram/mile)
HEV	0.213	1.027	0.191	0
Conve-ntional	0.73	2.37	0.337	0

Table 5.1 gives the comparison of differences of emissions between conventional and hybrid electric vehicle.The comparative analysis suggested that the harmful pollutant emissions from hybrid vehicles were lower than that of conventional vehicle operation. The reduction in HC emissions were about 70%, 57% For CO and NOx were reduced by 45%.

5.3 State of charge history versus time:

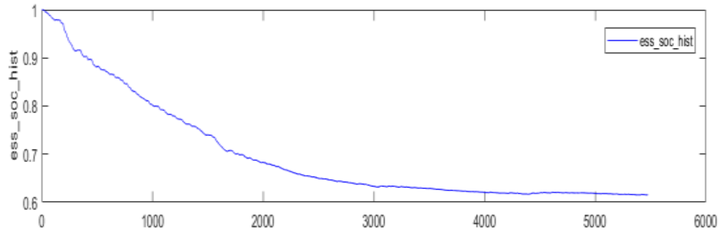

Figure 5.3 Variation of state of charge with time

The plot in Fig. 5.3 shows the variation of state of charge with respect to time for a period of 6000 seconds (approx.100 min). At the start of vehicle operation, the battery is fully charged but once the vehicle starts to run, the battery gets to discharge and there is a gradual fall in the state of charge after some period of time. State of charge plot gives a warning about the battery with respect to time, as battery charging is a vital aspect in hybrid electric vehicles.

5.4 Comparison of emissions by varying initial state of charge

The state of charge of a hybrid vehicle plays a vital role as far as the emissions of a hybrid vehicle is concerned. The variation of state of charge has a profound impact on the engine emissions. The three different driving cycles (UDDS, NEDC and US06) were chosen whose initial state of charge was varied to evaluate the emissions of a standard hybrid electric vehicle. The Figs-5.4, 5.5 and 5.6 represent the variation of pollutant emissions versus state of charge in case of all the driving cycles. From the above histogram it's seen that as the state of charge decreases gradually, there is a rise in emission values of the pollutants. All the harmful pollutants show an increase in their values as the state of charge decreases.

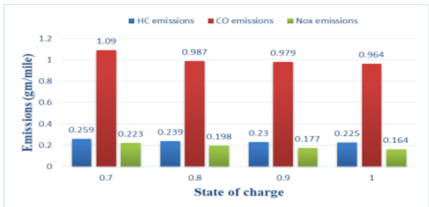

Figure 5.4: Variation of Emissions with SOC in UDDS driving cycle

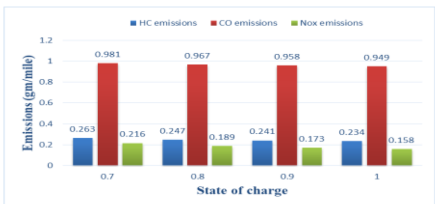

Figure 5.5: Variation of Emissions with SOC in NEDC driving cycle

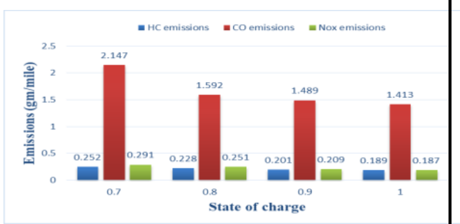

Figure 5.6: Variation of Emissions with SOC in US06 driving cycle

It is known that a parallel hybrid vehicle draws its propulsive power from 2 power sources to propel itself. As the state of charge decreases the contribution of power supplied from the battery reduces too. So, the vehicle tends to draw more power from the IC engine which is petrol/gasoline driven. Hence more power is consumed from petrol/gasoline than before. Thus this makes the vehicle emit more and more harmful pollutants. That's why the magnitude of pollutant emissions increases with decrease in the state of charge values for a particular driving cycle.

The percentage increase in the emissions of various pollutants as **SOC** decreases from **1 to 0.7** is shown in tabular formats below for different driving cycles.

It can be seen from Figs.5.4 to 5.6 that the rise in NOx percentage is maximum among all the pollutants under all three Driving Cycles. The rise in NOx emission is maximum in the US06 driving cycle which lies in the range of 55-60%. Out of all the driving cycles US06 driving cycle has seen the maximum increase in the emissions of all the individual pollutants. This is because of the nature of the US06 driving cycle which is basically designed for aggressive, high-speed with great-acceleration driving behavior, fast speed variations after the start of the engine.

5.5 **Performance prediction of HEV using ANN.**

For prediction of the performance of a hybrid vehicle model, a well known tool- Artificial Neural Network was taken. The ANN model basically considers two important parameters to predict the performance of a vehicle. The values of correlation coefficient and mean square error are calculated for training, test and validation in each performance parameter and they are shown in a tabular form.

5.5.1 Prediction for brake power using ANN

Correlation coefficient (R) performance

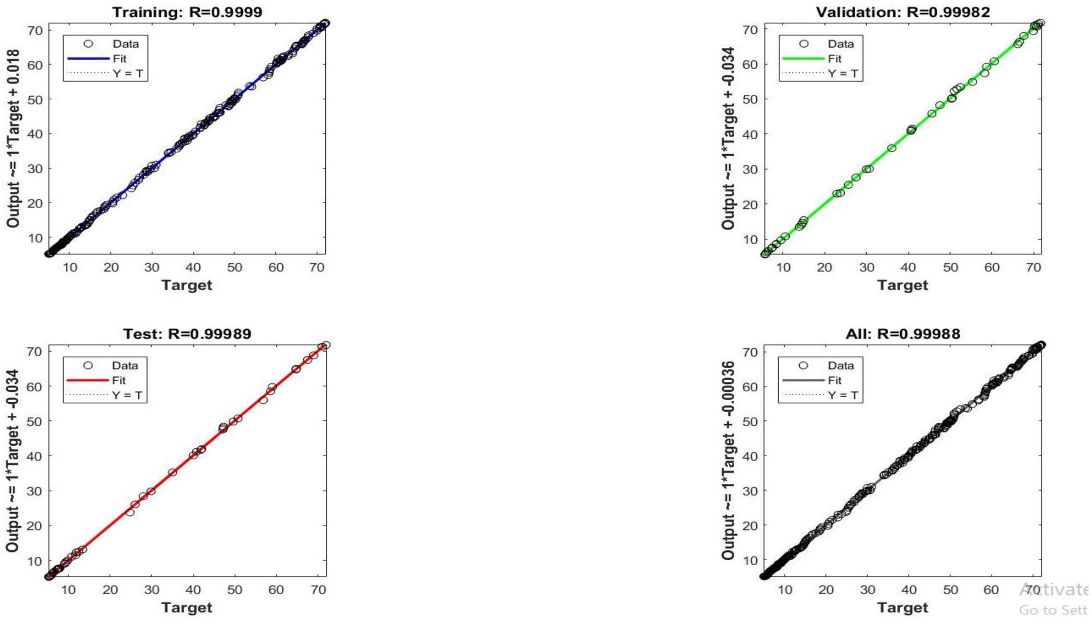

Figure 5.7: Performance of correlation coefficient for Brake power

Referring to Fig.5.7, for predicting the correlation coefficient for Brake Power , a maximum value of power of 72kW, as per the specifications of chosen vehicle configuration was selected. The target represents the experimental values and output represents the predicted values which were obtained from the ANN. From the above plot the values of correlation coefficient (R) for training, validation and test stages for brake power which were 0.9999, 0.99982 and 0.99989 respectively. The value of correlation coefficient(R) in each stage is closer to 1. This indicates the predicted results obtained in the training, test and validation stages were positive and strong and hence there exists a perfect correlation between the predicted and experimental values.

Table 5.2 shown below represents the RMSE and R values for brake power.

Table 5.2-R and RMSE values for Brake Power prediction

Stage of model	Correlation coefficient(R)	Root Mean square error(RMSE)
Training	0.9999	0.3236
validation	0.99982	0.4604
test	0.99989	0.3441

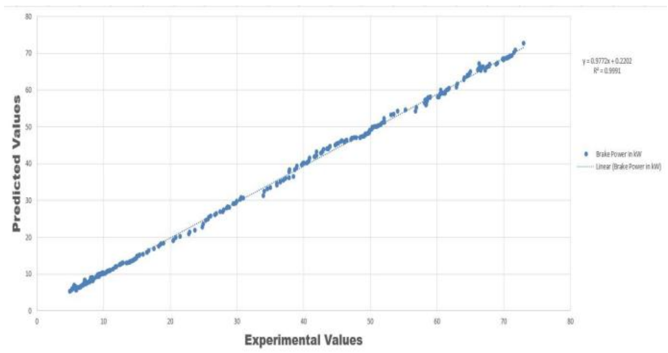

Figure 5.9- Comparison between experimental and predicted values for brake power

The above plot represents the variation of predicted values versus experimental values for brake power. The correlation coefficient of the brake power shows a value of 0.998 which is pretty close to 1. Thus it indicates the relation between the predicted values and Experimental values is positive and strong and they were closer to each other. As the R value lies closer to 1 which means there exists a perfect correlation between the predicted and experimental values in predicting the brake power using ANN. There is a rise in brake power value as the ethanol blend percentage increases and due to that, there occurs a slight deviation between the experimental and predicted values.

5.5.2 Prediction of Brake Thermal Efficiency

using ANN Correlation coefficient (R) performance

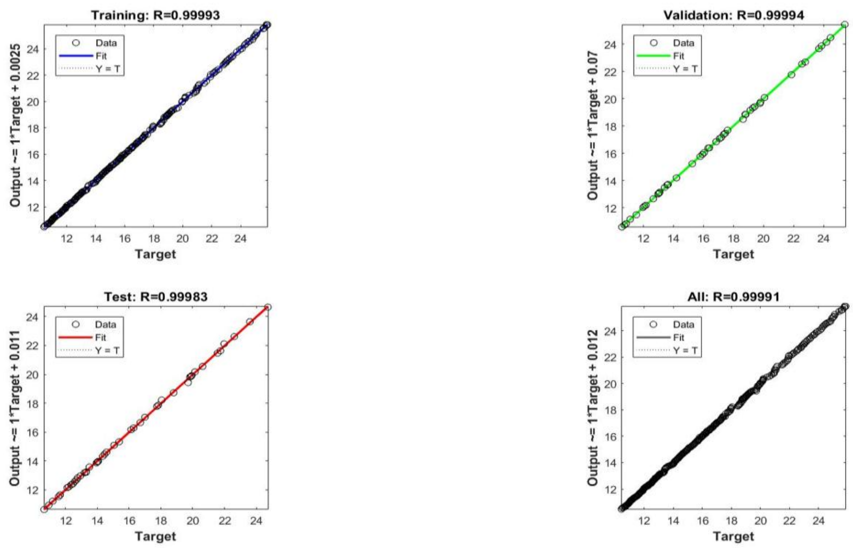

Figure 5.8:Correlation coefficient for brake thermal efficiency

Fig.5.8 shows the graphical variation of the output versus target for brake thermal efficiency and the limit of brake thermal efficiency was taken as 26%. From the above plot the values of correlation coefficient (R) for training, validation and test stages for predicting the brake thermal efficiency are 0.99993, 0.9994 and 0.99983 respectively. The value of correlation coefficient (R) in each stage is closer to 1. It indicates the predicted results obtained in the training, test and validation stages are positive and strong and there exists a perfect correlation between the predicted and experimental values. Table 5.3 shown below represents the RMSE and R values for brake power.

Table 5.3-R and RMSE values for Brake Thermal Efficiency

Stage of model	Correlation coefficient(R)	Root Mean square error (RMSE)
Training	0.99993	0.0513
Validation	0.99994	0.05015
Testing	0.99983	0.07163

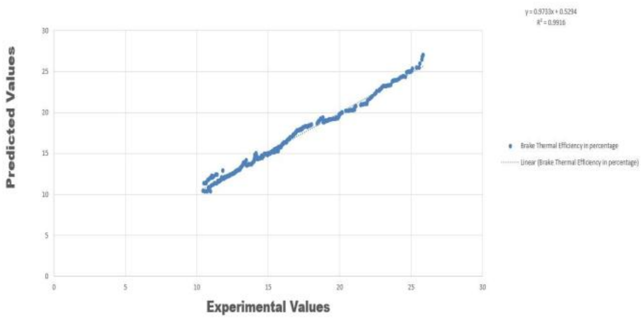

Figure 5.14

Figure 5.10: Variation of Predicted values versus Experimental values for Brake Thermal Efficiency

Fig.5.10 shows the variation predicted values versus experimentally obtained values for brake thermal efficiency. The maximum limit of brake thermal efficiency is 26% in the plot. The magnitude of correlation coefficient is 0.995. It can be seen that there is an increase in brake thermal efficiency which was due to the addition of ethanol blend gasoline. The addition of ethanol aided in improved combustion efficiency. The initial fluctuation arises because of the error introduced in the predicted but the error lies in the decimal range and it is minimal as the ethanol blend percent increases.

5.5.3 Prediction of HC emission using ANN

Correlation coefficient performance

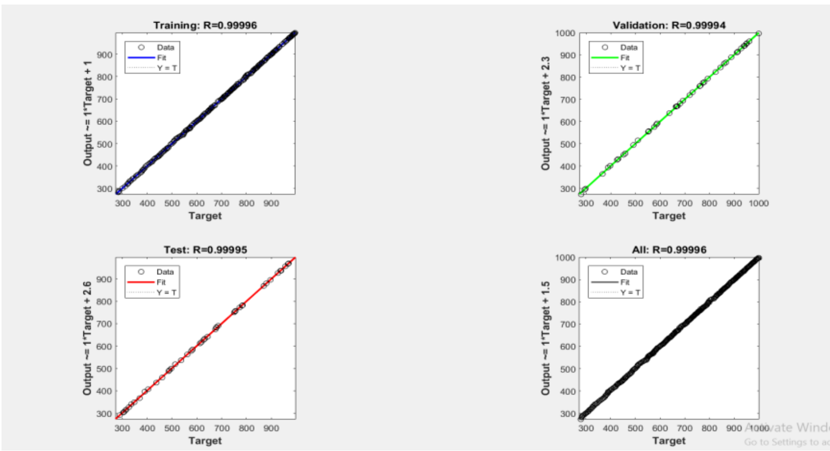

Figure 5.11- Correlation coefficient for HC emission

Fig.5.11 shows the variation of the output versus target for HC emission where the limit of HC emission was taken till 1000 PPM. The target represents the experimental values and output represents the predicted values which were predicted by the ANN. From the above plot the values of correlation coefficient (R) for training, validation and test stages for predicting the brake thermal efficiency are 0.9996, 0.99994 and 0.99995 respectively. The value of correlation coefficient(R) in each stage is closer to 1. This indicates the predicted results obtained in the training, test and validation stages are positive and strong and there exists a perfect correlation between the predicted and experimental values.

5.5.4 Prediction for CO emission using ANN

Correlation coefficient performance

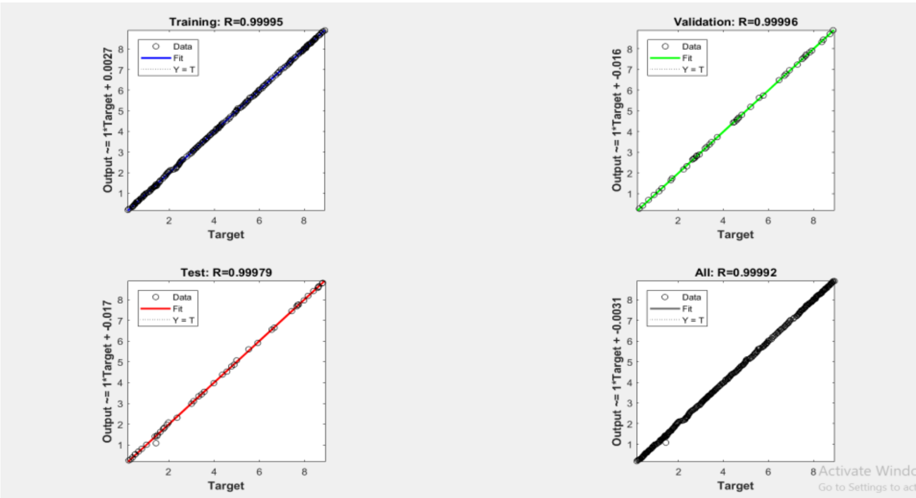

Figure 5.12-Correlation coefficient performance for CO emission

Fig. 5.12 shows the graphical variation of the output versus target for CO emission where the limit of HC emission is taken till 10%. Here the target represents the experimental values and output represents the predicted values which were predicted by the ANN. From the above plot the values of correlation coefficient (R) for training, validation and test stages for predicting the brake thermal efficiency are 0.99995, 0.99996 and 0.99979 respectively. The value of correlation coefficient(R) in each stage is closer to 1. This indicates the predicted results obtained in the training, test and validation stages are positive and strong and there exists a perfect correlation between the predicted and experimental values.

5.5.5 Prediction of NO_X emission using ANN

Correlation coefficient(R) performance

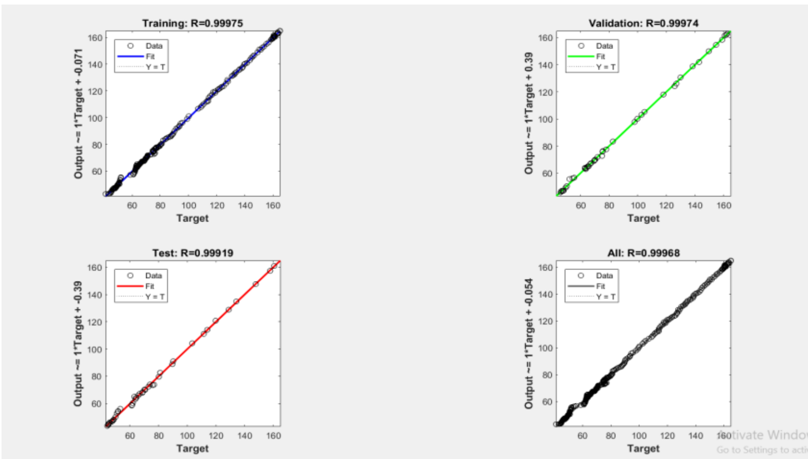

Figure 5.13:Correlation coefficient performance for NOx emission

Fig. 5.13 shows the graphical variation of the output versus target for HC emission where the limit of HC emission is taken till 170 PPM. Here the target represents the experimental values and output represents the predicted values which are forecasted by the ANN. From the above plot the values of correlation coefficient (R) for training, validation and test stages for predicting the brake thermal efficiency are 0.99975, 0.99974 and 0.99919 respectively. The value of correlation coefficient(R) in each stage is closer to 1. This indicates the predicted results obtained in the training, test and validation stages are positive and strong and there exists a perfect correlation between the predicted and experimental values.

6. Conclusions

1. Presently, hybrid electric vehicles would be a better option for combating local pollution levels.
2. The harmful emissions from a hybrid vehicle lie between the conventional vehicle and pure electric vehicle.
3. The CO emission in US06 driving cycle is more than that of in urban mode dynamometer schedule and New European driving cycle.
4. Owing to aggressive, high speed and/or high acceleration driving behavior, quick fluctuations in speed, the US06 driving cycle produces more carbon monoxide than the corresponding UDDS and NEDC driving cycle.
5. State of charge of a battery has a profound impact on the emissions of a hybrid electric vehicle. As the initial state of charge decreases, the emission of harmful pollutants increases in all the driving cycles for a hybrid electric vehicle.
6. The percentage rise in NOx emission is maximum in all the driving cycles of the hybrid vehicle and the rise is maximum in US06 driving cycle i.e. 55.61%
7. The ANN model used for prediction brake power, brake thermal efficiency of a hybrid model using ethanol-gasoline blend gives satisfactory results as the correlation coefficient values lie in the range of 0.97 to 0.99
8. For prediction of emissions like HC, CO and NOx, the correlation coefficient value lies in the range of 0.96 to 0.99 which indicates the relation between the predicted and target values is positive and strong.
9. Through ANN tool, good correlation is observed between predicted and experimental values. Present model's R values are very near to one, and the RMSE value is quite low.

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