

# Review studies on the Prediction of Engine Performance and Exhaust Emissions with Statistical Parametric Optimization Techniques of Ethanol-Gasoline Blended Fuel.

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**Abstract :** Recent trends depict depletions of petroleum fuels and this situation of energy crisis needs exigent attention towards innovative alternative fuels which may be engendered from biomass such as alcohol. Experiments were conducted to examine the gasoline engine at different operating conditions the two engines were utilized for investigation of the performance. Investigation was conducted experiments to examine the operating variables at different speeds, fuel quantities in the range of 5%, 10%, 15%, 20%, 25%, 30% and 35%. Statistical techniques like Replication Surface Methodology (RSM) and Artificial Neural Network (ANN) used to optimize the performance parameters of a four-stroke SI engine which operates with ethanol coalesced gasoline as fuel. The main objective was to optimize the engine performance for minimum BSFC. Tests were also conducted by various researchers on a variable compression ratio engine test rig with different coalescences of Compression Ratio (CR), Blend Ratio (BR) and load. The experimentation was designed with statistical implements withal kenneled as the design of experiments (DOE) predicated on RSM and ANN.

**Index Terms -** DOE, RSM, ANN, Gasoline, Spark Ignition Engine, Methanol, Ethanol.

## I.INTRODUCTION

Fuels from fossil origin are depleting at faster rate, stringent environmental regulations and environment degradation [1] are forcing internal combustion engine researchers to anticipate the need to find sustainable, eco-friendly, and renewable alternative fuel to the existing conventional automotive fuels. Excess use of gasoline leads to global warming, acid rain, ozone depletion, climate change etc.[2]. Problem of environmental degradation aggravates when non-eco-friendly octane boosters are added to the gasoline like Tetraethyl lead (TEL) [3]. Performance of S.I (petrol) engine is greatly influenced by octane number of the fuel. Blend of petrol and TEL was used in early model cars (beginning in 1920) to boost octane ratings [4]. Every gallon of gasoline with 1 gram of TEL boosts octane rating by 10 times [5]. One gram of TEL contains 640.6 milligrams of lead. However, use of TEL was slowly reduced and usage stopped in all on-road vehicles in the U.S. in 1995 because TEL is toxic and poison catalytic converters [6]. Toluene was tried as an octane booster but it generates huge amount of smoke and smog because it is an aromatic hydrocarbon [7] [8]. Another additive called MTBE (methyl tertiary butyl ether) was used as an octane booster. MTBE emerged as a promising additive because; it not only enhances the octane rating but also reduces carbon monoxide (CO) and ozone emissions [9]. In addition, MTBE is insensitive to water and has no effect on volatility of fuel [10]. However, MTBE contaminates ground water when petrol tank leaks [10]. Alcohols are emerging as promising octane boosters. Alcohols can either be blended with petrol and burned in regular automobile, or used straight, in modified engines [11]. Alcohols are clean burning resulting in low oxides of nitrogen, hydrocarbon and carbon dioxide emissions than other biomass fuels [12] [13]. However, the combustion of alcohols may lead to increase in aldehyde emissions, which are undesirable for health reasons [14]. Small modifications to the fuel systems are also needed, since ethanol damages several plastics and metals [15]. In addition, use of 100% ethanol results in cold start problem in unmodified petrol engine [16]. To solve the problems of phase separation, corrosion, and change in air requirement and vapour pressure, it is concluded that lower quantity of alcohol can be blended with petrol fuel [17].

Motor cycles are highly popular in local transportation which leads to enormous vehicular emissions. In Asian countries, the emissions from these vehicles CO, NO<sub>x</sub>, Non Methane Hydro Carbon (NMHC) and Particulate Matter (PM) are the superior air pollutants. These pollutants can be minimized and combustion efficiency can be increased by modern engines. Around 6 times more CO emissions can be seen in older engines and even NO<sub>x</sub> emission also greater. As the global community gears up for the crucial Paris climate summit, World Resources Institute (WRI) a global research organization has come out with its latest analysis of the country wise emissions that lead to climate damaging GHG. Countries like China, Mexico, Brazil and India are the top countries that emit larger GHG. India is prominent fossil fuel importer and second most populous country. Worldwide usage of renewable energy policy has become

prominent hence it aims in reduction of GHG emission caused by fossil fuels, which there is a threat of prominent reason for global warming. Certainly, there is a higher energy demand annually, India is the world's largest fossil fuel importer because of second most populous country even though India's per-capita sits in 10<sup>th</sup> place in emissions, and it is around 2.44. Around 13% of the country's energy related GHG emissions. This problem needs immediate attention to identify the better fuel generating sources to attain the demand goals by providing better market for biofuels [18]. Blending renewable sources of bio-ethanol for automobiles minimizes the CO emissions compared to gasoline alone. Blending bio-ethanol with gasoline minimises the substantial total volume of gasoline usage and also current infrastructure for circulating fuels may be utilised majorly unaltered. The blends of fuels affect the performance qualities of the individual engines. So it also depends on engine design, fuel, engine control system and emission controlling devices. An ethanol-Gasoline blend reduces the heating value, enhances in torque power and minimizes the emissions. Favourable consequences of ethanol contain more percentage of oxygen it is possible for complete combustion, thereby power and torque enhancement power and torque. It is observed that higher volumetric efficiency and lower intake manifold temperature is majorly due to pure gasoline will have lesser latent heat of evaporation for blended fuels. The Government making policy mandating 5% ethanol blending in petrol is currently being implemented in the country. A significant target of minimum 20% ethanol-blended gasoline across the country has been set for the year 2017. The preparedness of the automobile industry is a major part in the successful implementation of this policy, given the fact that gasoline run vehicles account for the majority of vehicles registered [19].

The Air Fuel (A/F) mixture into the engine directly affects the torque and power [20]. The structured multivariate analysis definitely furnishes a clear cut and extreme apprehension in the engine combustion characteristics compared to single variable transient study [20]. Multivariate analysis considers usually nonlinear analysis techniques like DOE best suitable to investigate the influenced effects of experimental variables. Amid referred techniques, DOE is highly powerful and economical to evaluate the independent and integrated consequences of experiment variables on output responses [20]. For better simulation studies between on-road conditions on in-use motorcycles chassis dynamometer is better selection, around 30% of motorcycle was under emission limits. As S.I engines are meant for speed it is observed that particle total number concentrations emitted from 4-stroke motorcycles found increased with speed [21]. Poly cyclic aromatic hydrocarbon and particulate matter emissions factors were found to be higher in new engines. Modern methods of fuel injections like electronic fuel injection (EFI) and modified combustion chambered engine or alternative fuels can only address the problems which are under investigation [21]. Recent investigations are on alternative fuels because of better engine performance and minimum emissions [21]. It is proved that biofuels are favourable over gasoline due to better antiknock features, minimum CO and UHC emissions [21]. Emission tests on multicylinder SI engines with ethanol- blended fuels revealed that CO minimises slightly, but NO<sub>x</sub> decreased appreciably due to lower heat release rate for blended fuels [21]. Increased engine displacement uniformly for oxygenated fuel around 3% to 5% at a rated speed of 2200RPM reduction of CO emissions about 8-15% were observed [21]. Volumetric efficiency increases about 3 to 5 times more for ethanol compared to gasoline due to better evaporation. Even though the heating values of ethanol is lower and it needs 1.5 to 1.8 times excess ethanol fuel to gain the equivalent engine power [21]. It is observed that reduced BSFC and higher BP with using ethanol – gasoline blended fuels. It can be considered that the higher indicated mean effective pressure for higher ethanol content [21]. The study of optimum operating parameters for tolerable pollutant emission and maximum engine performance is an important issue when ethanol blended fuels are used.

## II. PARAMETRIC OPTIMIZATION TECHNIQUES.

Response Surface Methodology is a collection of statistical and mathematical techniques useful for developing, improving and optimizing products and processes. The most extensive applications of RSM are particularly in situations where several input variables have high influence on some performance measures or quality characteristics of the product or process. RSM initially from Design of Experiments (DOE) to determine the factors, values for conducting experiments and collecting data. The data is then used to develop an empirical model that relates the process response to the factors. Sub sequentially; the model with RSM is a very prominent tool for product and process improving in the development phase of engines. Use of statistics in engine performance evaluation with the help of DOE, RSM explores the relationships between several explanatory variables and one or more response variables [18]. These methods were developed by G.E.P.Box and K.B.Wilson in 1951. The prominent idea of RSM is applied in a sequence of designed experiments to obtain an optimum response. RSM uses statistical models; practitioners need to be aware that even the best statistical model is an approximation to reality. In response development models and considered parameters are to be analysed and concern to uncertainty on top of ignorance. Actually, estimated optimal values need not be optimum because of the errors of the estimates and deficiencies in the designed model. So RSM definitely has an effective proven history towards the favourable improvement in products and services for researchers. The investigation of the optimum biofuel ratio at which there is high fuel conversion efficiency and low exhaust emissions are absent. The main technical advantages of optimization for percentage of bio-origin components in gasoline fuel is improving engine performance exhaust emissions and utilizing optimized blends in a gasoline engine without any engine modifications [20]. For the attainment of these impetus DOE techniques like RSM, Taguchi Method, Factorial design and ANN can be adopted.

RSM is used for non-linear relationships between the input factors and the outputs RSM is best suited techniques [20]. A determinant support methodology selected to contrast engine torque between values and the designed latest mean approach called response surface [20]. RSM manifests to be a substantial tool for optimization of biofuel extraction. Second order model can be successfully developed to define the relationships between biofuels yield and test variables [20].

Statistical tool like RSM can be used in DOE; optimization of compression Ratio (CR) and injection system parameters was performance using the desirable approach of the RSM for superior performance and lesser smoke emissions. A CR of 17.99, indicated pressure (IP) of 250bars and indicated Temperature (IT) of 27°C BTDC was found to be optimal values. At optimal input parameters, the values of the BTE, BSFC, EGT and smoke capacity were found to be 29.76%, 0.289kg/kwh, 298.52°C and 56.49HSU respectively [20]. RSM has been employed to optimize the engine power, torque, BSFC and emission components based on the variable gasoline-ethanol blends and speed. The main objective of researchers is to investigate the capability of RSM for optimization of engine performance in modelling. In this research, the optimum values for the parameters of RSM were found and the performances of this method were thoroughly evaluated. The complex and multivariate models were considered to analyse the engine performance and emission in the non-linear conditions [21]. The engine speed, load and static injections timing were used to optimization of the operation parameters of diesel engine. Selected bio- fuel blends ratio using RSM and showed that the suitable blend ratio could be obtained at the balance among exhaust emissions and engine performance. RSM is better method to optimise the multi objective goals and minima-maxima problems [21]. In the recent testing procedures statistical methods better suited for gasoline-ethanol blended fuels on motorcycles [21]. The aim of the research is to study and develop analytical model equation for content the exhaust emissions of a retrofitted CNG engine using RSM. To determine the model adequacy by using the F-test analysis of variances (ANOVA) and error estimations are used for checking the error. Based on experiment result, contours and response surfaces are plotted by using MATLAB 6.5 that shows the combined effect of the engine parameters of each effect of the independent input variables to the output response of emissions. Through analysis of variance F-test (ANOVA) and 95% confidence interval, the calculation of F-test static value estimates models are larger than tabulated F-value. The test Regression models has successfully proved that at least one independent regression variable of no zero coefficient. From HC, CO and CO<sub>2</sub> emissions models, engine speed and throttle position are found significant influence on the emissions with small effect of operation time. HC and CO<sub>2</sub> emissions equations show the major effect of engine speed but CO emissions mostly effected by the engine throttle position. The error estimations with 95% confidence interval, the equations are within ranges. The dual response contours of the emissions models which obtained in place of two responses. Engine speed and throttle position are provided useful information about minimum attainable exhaust content [23].

Statistical methods like RSM, Taguchi, ANOVA and artificial neural networks (ANN) from artificial intelligent (AI) techniques are recent favourite's analysis tools for researchers. ANNs are used to solve a wide variety of problems in science and engineering particularly for some areas where the conventional modelling methods fail. A well trained ANN can be used as a predictive model for a specific applications, which is a data processing system inspired by biological neural system. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. An ANN has the ability to re-learn to improve its performance if new data are available [24]. An ANN model can accommodate multiple input variables to predict multiple output variables. It differs from conventional modelling approaches in its ability to learn the system than can be modelled without prior knowledge of the process relationships. The prediction be a well-trained ANN is normally much faster than the conventional simulation programmes or mathematical models as no lengthy iterative calculations are needed to solve the differential equations using numerical methods but the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. Along with it is also possible to add or remove input and output variables in the ANN if it is needed. Some researchers studied this method to predict internal combustion engine characteristics.

The ANNs are applied to estimate specific fuel consumption and exhaust temperature for diesel engine [24]. Few investigators investigated combustion analysis of IC engines performance using biofuels with an artificial neural network [24]. Yuan Wang concluded the effect of cetane number on exhaust emissions from engine. The valve timing diagram effects in a spark ignition engine on the performance and fuel consumption economy was investigated [24]. Say-in investigated the performance and exhaust emissions of a gasoline engine using ANN. Kalogirou reviewed artificial intelligence for the modelling and control combustion process. A number of AI techniques have been described. ANN is used in the thermal system analysis this approach was used to predict the performance and exhaust emissions of internal combustion engines [24]. ANN is a powerful modelling tool that has the ability to identify complex relationships from input – output data. Using ANN model for predicting the BP, torque and emissions of CO, CO<sub>2</sub> and HC, NO<sub>x</sub> of the engine in relation to input variable including engine speed, engine load and fuel blends. At different varying conditions ANN modelling can predict suitable models. ANN is fairly simple and small in size when compared to human brain and has some powerful knowledge and information processing characteristics due to its



similarity to human brain [24]. ANN is one such effort and is perceptibly utilised as prognostic tool In the automotive sector to afford rapid predictions of various engine parameters when new strategies on engine operating conditions to be tested. ANN is more attractive engine optimisation tool because it is robust and less expensive in terms of required time and resources [24]. Currently, with the developments in computer technologies, ANN has been applied to many automotive engineering problems with some degree of success. In automotive technology problems neural networks have been applied to different engine investigations such as predictions of exhaust emissions and modelling of engine performance parameters [24]. An ANN model to predict a correlation between BP, torque, BSFC, BTE, volumetric efficiency and emission components using different gasoline –ethanol blends and at different speeds. A standard back propagation algorithm for the engine was used in most conditions. Another study conducted by Deh-kiani et.al [24] dealt with ANN modelling of a spark ignition engine to predict the engine BP, output torque and exhaust emissions (H, CO, CO<sub>2</sub> and NO<sub>x</sub>) of the engine. Results showed that ANN provided the best accurate values from the modelling the emission indices with correlation coefficient equation to 0.98, 0.96, 0.90, and 0.71 for CO, CO<sub>2</sub>, HC and NO<sub>x</sub> and 0.99 and 0.96 for torque and BP respectively. The changes in exhaust emissions and engine performance have been observed by using ethanol, gasoline blended fuel without any modifications on the SI engine and the impact of the fuel on the exhaust emissions and BSFC have be examined by developing ANN model for the fuel type, torque, engine speed and fuel flow in the input layer so prediction of some parameter such as CO, HC, BSFC and AFR was concentrated [24].

### III. STATISTICAL METHODOLOGIES IN THE DETERMINATION OF ENGINE VARIABLES AND EMISSION CHARACTERISTICS

#### 3.1 Response Surface Methodology (RSM)

RSM has an effective track record of helping researchers to develop innovative modern products and services. In RSM there are various parameters available for maximization of performance of IC engine like CR, BR, load, speed, AFR, injection pressure, spark timing and etc. for predicting the optimum point in the combustion process a second order polynomial model is developed to a established relationship between engine parameters and the response (BSFC). The result achieved through the 13 experimental runs design based on BOX- Behnken design with 3 engine parameters (CR, BR and Load) and 3 levels (-1, 0 and +1), indicating these replicate at centre point is used for fitting a 2<sup>nd</sup> order polynomial equation. The model is cross checked with an F-test and the determination coefficient R<sup>2</sup>. The ANOVA (analysis of variants) has been analysed and developed the model is highly significant (P<0.0001) with F value. In testing C, C<sub>2</sub> are significant model terms. For these variable factors the equations obtained are,

$$Y = BSFC = \beta_0 + \beta_1A + \beta_2B + \beta_3C + \beta_{12}AB + \beta_{13}AC + \beta_{23}BC + \beta_{11}A^2 + \beta_{22}B^2 + \beta_{33}C^2 \quad (1)$$

Where, Y= predicted response (BSFC),  $\beta_0$ = Model constant A, B, C= engine parameters (CR, BR and Load),  $\beta_1, \beta_2, \beta_3$  =Linear coefficient,  $\beta_{12}, \beta_{13}, \beta_{23}$  = cross product co-efficient,  $\beta_{11}, \beta_{22}, \beta_{33}$  =quadratic coefficients

Validation of the model is done by comparing the experimental value with the predicted values. The difference between the experimental values and predicted value is very less. Analysis based on BOX- Behnken response surface analysis suggested that the optimum combination engine parameters for minimum BSFC is CR 9.5, BR10, load 6.5 kg. The experiment with minimum number of experimentation, BOX- Behnken design based on RSM is powerful and useful tool to understand the interactive effect of various engine parameters on the response (BSFC). A quadratic model developed which establishes relationship between the response (BSFC) an the parameters. Verification of the model is done with ANOVA; also validation of the model is done comparing the experimental data and the predicted from the model [18]. Minitab software includes four types of designed experiments, which are Factorial, RSM, Factorial and RSM and Taguchi. The procedure to get an experimental design with graphs is same for all types of design. Experimental design is generated as per selection of experimental points, number of runs and blocks, then the model equation is specified and coefficients of the model equations are predicted. The test data and the predicted data are compared with each other to understand whether the model is making a good prediction. In order to compare these data the statistical method of root mean square error (RMSE) and coefficient of multiple determination (R<sup>2</sup>) value are used, these values are determined by following equations,

$$RMSE = [1/n \sum |a_j - p_j|^2 \sum n_j = 1]^{1/2} \quad (2)$$

$$R^2 = 1 - \sum |a_j - p_j|^2 \sum n_j = 1 / \sum |p_j|^2 \sum n_j = 1 \quad (3)$$

Where,  $a_j$  = Experimental Specific consumption

$p_j$  = Predicted Specific consumption

Using Minitab-17 software, insert the 3 factors with 3level in RSM of BOX- Behnken got the design of steps to perform experiment. In statistics RSM explores the relationship between several explanatory variables and one or more response variables. This method was also introduced for optimal response. BOX and Wilson suggest using second degree polynomial methods to do this. RSM consists of a group of mathematical and statistical methods are used in the development of adequate functional relationship between the response of interest (y) and number of associated control(input) variables denoted by  $X_1, X_2, X_3, \dots, X_k$ . In general such a relationship is unknown but can be approximated by a low degree polynomial model of the form,

$$Y = f'(X)\beta + \varepsilon \tag{4}$$

Where,  $X=(X_1, X_2, X_3, \dots, X_k)$ ,  $f(x)$  is a vector function of  $p$  elements that consists of power and cross product of powers of  $X_1, X_2, X_3, \dots, X_k$ . Up to a certain degree denoted by  $d(>1)$ ,  $\beta$  is a vector of  $P$  unknown constant coefficients referred to as a parameter and  $\varepsilon$  is a random experimental error assumed to have a zero mean. This is conditioned on the belief that model provides an adequate representation of response. In this case, the quantity  $f'(X)\beta$  represents the mean response that is expected values of  $y$  and is denoted by  $\mu(x)$ . We are using two important models in RSM. There are special cases of model and include the first-degree model ( $d=1$ ):

$$y = \beta_0 + \sum_{i=1}^k \beta_i X_i + \varepsilon \tag{5}$$

And the second degree model ( $d=2$ );

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i < j} \beta_{ij} x_i x_j + \sum_{i=1}^k \beta_{ij} x_i^2 + \varepsilon \tag{6}$$

The model for a multiple regression may take different forms; it was in previous research that the second order models are nominally applied as shown.

$$\text{Power, Torque} = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i < j} \beta_{ij} x_i x_j + \sum_{i=1}^k \beta_{ij} x_i^2 + \varepsilon \tag{7}$$

Above equation assumes that the response surface  $Y$  contains free terms ( $\beta_0$ ), linear term ( $x_i$ ), squared term ( $x_i^2$ ) and cross product term ( $x_i x_j$ ) which have the coefficient ( $\beta$ ).

RSM was conducted to analyse the relationships among explanatory variables, response variables and obtained an optimal response by using a sequence of designed experiments. These experimental factors, includes the ethanol blend ratio, the speed of motor cycle and the throttle position were selected. The experiments were designed to use the model of three variables BOX- Behnken design (BBD), the set points of the design were the midpoints of the edges of the design space and the centre point. A factor, 3- level designs retained, expressed in coded and natural units. In the experimental design, the ethanol blend ratios were prepared at 0, 10, 20, volume percentage the speeds of motorcycles were selected as 30, 45, 60 Km/h and the throttle positions were set at 30, 60, and 90%. At total of 17 experiments were necessary for this model [21].

### 3.2 Artificial Intelligence (AI) [24][25][26]

To get the best prediction by the network, several structures were evaluated and trained using the experimental data. Back propagation is a network created by generalised by the Widrow-Holf learning rule to multiple-large networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vector are used to transfer a network until it can approximate a function. Networks with biases, assigned layer and a linear output layer are capable of approximating any functions with a finite number of discontinuities. Back-propagation is a network created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Standard back-propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. Each neuron computes a weighted sum of its  $n$  input signals,  $x_j$ , for  $j= 1, 2, \dots, n$ , and then applies a nonlinear activation function to produce an output signal

$$y = \varphi\left(\sum_{j=1}^n w_j x_j\right) \tag{8}$$

$$E = \frac{1}{p} \sum_p \sum_k (d_{pk} - o_{pk})^2 \tag{9}$$

The input variables are engine speed in rpm and the percentage of ethanol blending with the conventional gasoline fuel and engine load as percentage. The six outputs for evaluating engine performance include engine torque and brake power and emission parameters as shown in Fig. 1. Therefore the input layer consisted of 3 neurons while the output layer had 6 neurons.

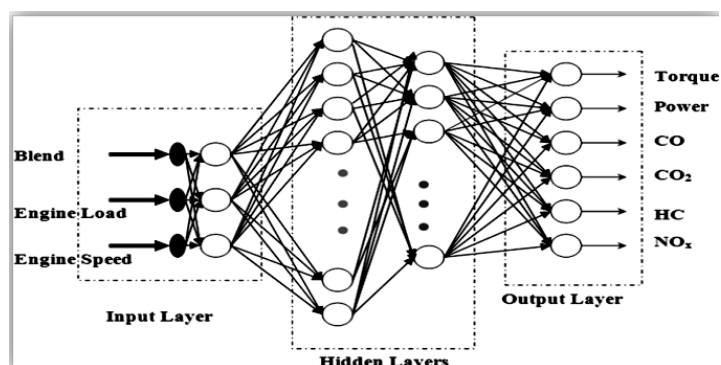


Fig.1. Configuration of multilayer neural network for predicting engine parameters

The number of hidden layers and neurons within each layer is determined by the complexity of the problem and dataset. In this study, the number of hidden layers varied from one to two. To ensure that each input variable provides an equal contribution in the ANN, the inputs of the model were pre processed and scaled into a common numeric range (1, 1). The activation function for hidden layer was selected to be the tangent-sigmoid transfer function. The performance of the network can be evaluated by comparing the error obtained from converged neural network runs and the measured data. Error was calculated at the end of training and testing processes based on the differences between targeted and calculated outputs. The back-propagation algorithm minimizes an error function defined by the average of the sum square difference between the output of each neuron in the output layer and the desired output. ANNs are a logic programming technique developed with the purpose of automatically performing skills such as learning, remembering, deciding, and inference, which are features of the human brain, without receiving any aid. By simply imitating the operation of the human brain, ANNs have various important features, such as learning from data, generalisation, working with an infinite number of variables, etc. The smallest units that form the basis of the operation of ANNs are called artificial neural cells. The artificial neural cells consist of mainly five elements; namely inputs, weights, summation functions, activation functions and outputs (Fig. 2). ANN has three main layers; namely, the input, hidden and output layers. The inputs are data from the external world. Neurons (processing elements) in the input layer transfer data from the external world to the hidden layer. The data in the input layer is not processed in the same way as the data in the other layers. The weights are the values of connections between cells. The outputs are produced using data from neurons in the input and hidden layers, and the bias, summation and activation functions.

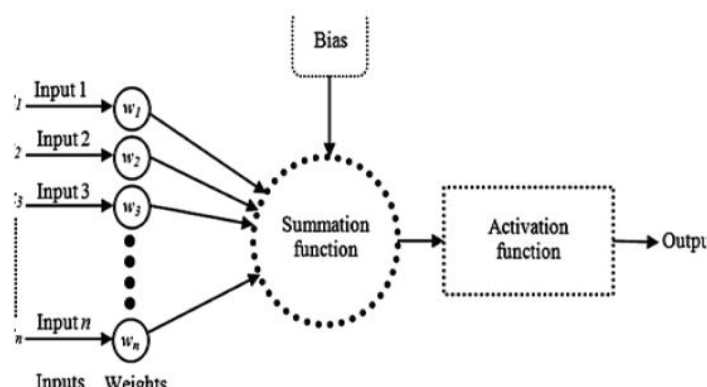


Fig. 2. The structure of an artificial neural cell

The summation function is a function which calculates the net input of the cell. The summation function used in this study is given in Eq. (10).

$$NET_i = \sum_{j=1}^n w_{ij}x_j + w_{bi} \quad (10)$$

The activation function provides a curvilinear match between the input and output layers. In addition, it determines the output of the cell by processing the net input to the cell. The selection of an appropriate activation function significantly affects network performance. There are many ways to define the activation function, such as the threshold function, step activation function, sigmoid function, and hyperbolic tangent function. The type of activation function depends on the type of neural network to be designed. A sigmoid function is widely used for the transfer function. Logistic transfer function of the ANN model in this study is given in Eq. (11). In the output layer, the output of network is produced by processing data from hidden layer and sent to external world.

$$f(NET_i) = \frac{1}{1+e^{-NET_i}} \quad (11)$$

The significant advantages of artificial neural networks are learning ability and the use of different learning algorithms. The most important factor which determines its success in practise, after the selection of ANN architecture, is the learning algorithm. In order to obtain the output values closest to the numerical values, the best learning algorithm and the number of optimum neurons in the hidden layer must be determined. In the training stage, to obtain the output precisely, the number of neurons in the hidden layer was increased step by step [25]. For this purpose, BFGS (Quasi-Newton back propagation), LM (Levenberge Marquardt learning algorithm), RP (resilient back propagation) and SCG (scaled conjugate gradient learning algorithm) learning algorithms were used in the building of the network structure. As a result of the conducted trials, the best learning algorithms for CO, HC, BSFC and AFR were found to be the LM, RP, SCG and BFGS learning algorithms respectively. The best network structures for CO, HC, BSFC and AFR were also found to be 4-7-1, 4-14-1, 4-7-1 and 4-11-1 respectively. The best ANN architecture built for the prediction of carbon monoxide is shown in Fig. 3.

The mean prediction accuracy represents validity of prediction. It is calculated by the formula in Eq. (12). Also, the mean prediction accuracies of CO, HC, BSFC and AFR for four learning algorithms,

$$\text{MPA} = 100 - \text{MEP} \quad (12)$$

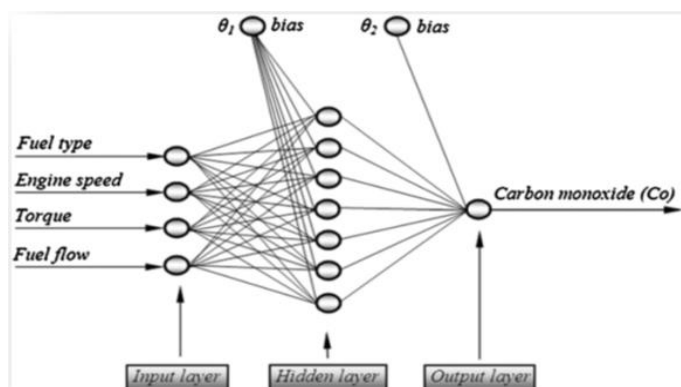


Fig. 3. ANN architecture with a single hidden layer for carbon monoxide

ANN is an analytical method for simulating system performance. The method relies on experimental data that is used to ‘train’ the ANN so that it can precisely predict the system performance at other conditions. This technique has found application in situations where the simulation of complex systems is required but limited experimental data is available. ANN is a powerful, nonlinear tool and since many phenomena in industry have non-linear characteristics, ANN has been applied widely. The performance of the ANN-based predictions is evaluated by regression analysis of the network outputs (predicted parameters) and the experimental values [15]. The error identified during the learning process is called the root-mean-squared-error (RMSE).

$$RMSE = \left( \frac{1}{p} \sum_j |t_j - o_j|^2 \right)^{1/2} \quad (13)$$

$$MEP(\%) = \frac{\sum_j ((t_j - o_j) / t_j) \times 100}{p} \quad (14)$$

$$R^2 = 1 - \left( \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \quad (15)$$

There were two input and nine output parameters in the experimental tests. The two input variables are engine speed in rpm and the percentage of bioethanol blending with the conventional gasoline fuel.

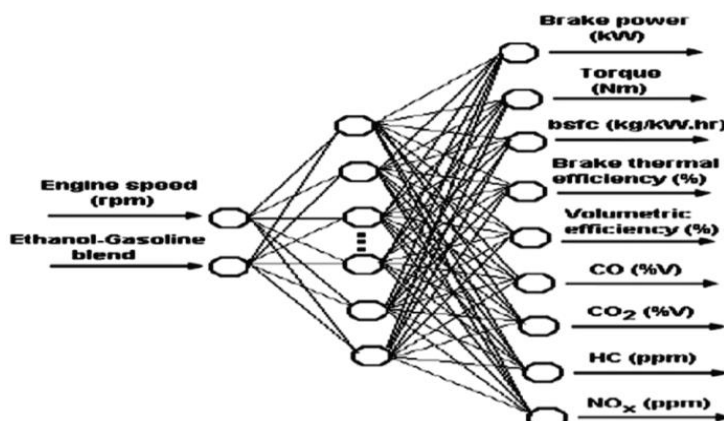


Fig. 4. The structure of ANN for gasoline engine with gasoline–ethanol blended fuels.

The nine outputs for evaluating engine performance are indicated in Fig. 4. There is 1 neural network structure with 2 inputs and 9 outputs; the input layer consisted of 2 neurons which corresponded to engine speed and levels of biofuel blends and the output layer had 9 neurons. The number of hidden layers and neurons within each layer can be designed by the complexity of the problem and data set. In this study, the network was decided to consist of one hidden layer with 20 neurons. The activation function for hidden layer was selected to be sigmoid function. A linear function was best suited for the output layer. However, many other networks with several functions and topologies were examined.

#### IV. CONCLUSION

The important objective of this paper is to review the work done previously. The study of performance and emissions characteristics of spark-ignition (SI) engine fuelled with ethanol- gasoline blended fuels under different operating conditions has been reviewed using the statistical Techniques the analysis based on different analytical models prominent engine parameters are optimized. At wide range of experimental data offers minimum experimentation. BBD based on RSM is powerful tool to understand the iterative effects for wide range of engine parameters and exhaust emissions of



engine parameters on the response. A quadratic model developed between response and the parameters verification of the model with ANOVA is very good. RSM is ultimate helpful tool in designing the experiments and to identify statistical analysis and to identify the significant parameters. The performance parameters for ethanol gasoline blends were found to gasoline and emission characteristics improved prominently. Modified BBD array in response surface optimization techniques predicted engine parameters are very closer to experimental results. Operating conditions like fuel conversion efficiency greatly influence the responses while CO emissions are majorly affected by the blend ratio. Designed regression model has successfully proved that one independent or regression variations of non-zero coefficient. In error estimation for emission models the regression model are best suited and in the linear range. In error estimation with 95% confidence interval, the equations are in the limits. Engine speed and throttle position are predicted in dual response contour of the emission modelling which are obtained in plane of two responses. ANN proves to be powerful modelling tool which can predict engine performance and emission parameters under nonlinear and sophisticated conditions. 3 layers feed forward neural networks achieved a desirable mapping between the inputs and outputs. Predicted and measured data yields Wide range of regression coefficients during the development of a regression line. ANN modelling predicts BSFC, CO, HC and AFR for blended SI engine. ANN models with learning algorithms, training algorithm and testing sets are notably close to unity with error less than 5%. So ANN is better alternative tool to other conventional modelling techniques such as RSM, Taguchi, ANOVA etc., in prediction of engine performance and exhaust emissions.

## REFERENCES

1. M.C.Math, Sudheer Prem Kumar, Soma V. Chetty.2010. Energy for Sustainable Development Technologies for biodiesel production from used cooking oil — A review Volume 14, Issue 4, December 2010, 339–345.
2. The Harmful Effects of Vehicle Exhaust – A case for policy change, Environment & Human Health, Inc. 1191 Ridge Road. North Haven, CT 06473 Phone: (203) 248-6582. Fax: (203) 288-7571. www.ehhi.org
3. William Kovarik, Ethyl-leaded Gasoline: How a Classic Occupational Disease Became an International Public Health Disaster. International Journal of Occupational and Environmental Health, VOL 11/NO 4, OCT/DEC 2005, 384 – 397
4. <http://www.todayifoundout.com/index.php/2011/11/why-lead-used-to-be-added-to-gasoline/>
5. Robert D. Entenberg and Albert L. Menard, Jr.1966. Future Octane Number Requirements for Future Market Demand, Journal of Marketing, Vol. 30, No. 1 (Jan. 1966), 28-32.
6. <https://en.wikipedia.org/wiki/Avgas>
7. Marin, D. Kodjak. 1998. Relative Cancer Risk of Reformulated Gasoline and Conventional Gasoline Sold in the Northeast, the Northeast States for Coordinated Air Use Management, Book, NESCAUM, 1998.
8. K.A. Kourtidis, I. Ziomas, C.Zerefos, E.Kosmidis, P.Symeonidis, E.Christophilopoulos, S. Karathanassis, A. 2002. Mploutsos, Benzene, toluene, ozone, NO<sub>2</sub> and SO<sub>2</sub> measurements in an urban street canyon in Thessaloniki, Greece, Atmos. Environ. 36 (2002) 5355-5364.
9. P. Grimshaw, the Gothenburg bible & Volvo Performance Handbook, 1995.
10. M.Koç, Y.Sekmen, T.Topgu, H.S.Yu. 2009. The effects of ethanol unleaded gasoline Blend on engine performance and exhaust emissions in a spark-ignition Engine, Renew. Energy 34 (2009) 2101-2106.
11. V.R. Surisetty, A.K. Dalai, J. Kozinski. 2011. Alcohols as alternative fuels: an overview, Appl. Catal. A: General 404 (2011) 1-11.
12. Elfasakhany.2013. Investigation on performance and emissions characteristics of An internal combustion engine fuelled with petroleum gasoline and a hybrid Methanol-gasoline fuel, IJET-IJENS 13, 2013, 24-43.
13. Elfasakhany. 2014. The effects of the ethanol-gasoline blend on performance and Exhaust emission characteristics of spark ignition engines, Int. J. Automotive.Eng. 4 (2014) 608-620.
14. Roger L. Tanner. et.al. 1988. Atmospheric Chemistry of Aldehydes: Enhanced Peroxyacetyl Nitrate Formation from Ethanol-Fueled Vehicular Emissions - Environ. Sci. Technol. 1988, 22, 1026-1034
15. Brinkman.N. 1981. Ethanol Fuel-A Single-Cylinder Engine Study of Efficiency and Exhaust Emissions," SAE Technical Paper 810345, 1981, doi: 10.4271/810345.
16. [http://www.theicct.org/sites/default/files/publications/ICCT\\_ethanol\\_revised\\_02\\_03\\_format.pdf](http://www.theicct.org/sites/default/files/publications/ICCT_ethanol_revised_02_03_format.pdf)
17. [http://www.iea-etsap.org/web/E-echDS/PDF/T06\\_Ethanol%20ICES\\_final\\_18Jun10\\_GS\\_OK\\_NH.pdf](http://www.iea-etsap.org/web/E-echDS/PDF/T06_Ethanol%20ICES_final_18Jun10_GS_OK_NH.pdf)
18. Mr. G. A. Kapadia, 2Prof. P. D. Patel, 3 Prof. T. M. Patel, “Parametric Optimization of 4-Stroke Spark Ignition Engine Fuelled with Ethanol Blended Gasoline using Response Surface Methodology” IJSDR, IISN:2455-2631, , June 2016 IJSDR, volume 1, Issue 6, P 367-375.
19. Nikunj B Prajapati<sup>1</sup>, Prof. Pragna R Patel<sup>2</sup>, Dr. Tushar M Patel<sup>3</sup>, Prof. Gaurav P Rathod<sup>4</sup> Optimization of SFC Using Mathematical Model Based On RSM for SI Engine Fueled with Petrol-Ethanol Blend IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE) e-ISSN: 2278-1684,p-ISSN: 2320-334X, Volume 13, Issue 2 Ver. IV (Mar- Apr. 2016), PP 57-63
20. Gholamhassan Najafi<sup>1</sup>, Barat Ghobadian<sup>1</sup>, Talal Yusaf<sup>2</sup>, Seyed Mohammad Safieddin Ardebili<sup>3</sup>, Rizalman Mamat<sup>4</sup>,”Optimization of performance and exhaust emission parameters of a SI (spark ignition) engine with gasoline ethanol blended fuels using response surface methodology, energy(2015), <http://dx.doi.org/10.1016/j.energy.2015.07.004>



21. Chen YL<sup>1</sup>, Chen S, Tsai JM, Tsai CY, Fang HH, Yang IC, Liu SY. Optimization of suitable ethanol blend ratio for motorcycle engine using response surface method, ISSN 1093-4529, journal of environmental science and health, part A(2012) 47.101-108, DOI:10.1080/10934529.2012.629949.
22. Nikunj B Prajapati<sup>1</sup> Prof. Pragna R Patel<sup>2</sup> Dr. Tushar M Patel<sup>3</sup> Prof. Gaurav P Rathod<sup>4</sup>, Mathematical Modeling of NOX for SI Engine Working with Petrol-Ethanol Blend, IJSRD - International Journal for Scientific Research & Development| Vol. 4, Issue 02, 2016 | ISSN (online): 2321-0613.
23. R. Saidur, M.I. Jahirul, M. Hasanuzzaman and H.H. Masjuki. analysis of exhaust emissions of natural gas engine by using response surface methodology, ISSN 1812-5654, journal of applied sciences 8(19): 3328-3339,2008.
24. Kiani Deh Kiani M, et al., Application of artificial neural networks for the prediction of performance and exhaust emissions in SI engine using ethanol-gasoline blends, Energy (2009), doi:10.1016/j.energy.2009.08.034
25. Yusuf Çay a,\* , Ibrahim Korkmaz b, Adem Çiçek c, Fuat Kara Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network, Energy (2012), Energy 50 (2013) 177e186.
26. Najafi G, et al., Optimization of performance and exhaust emission parameters of a SI (spark ignition) engine with gasoline ethanol blended fuels using response surface methodology, Energy (2015), <http://dx.doi.org/10.1016/j.energy.2015.07.004>

