Chapter – 4

Modeling & Optimization

Data obtained from experiments need to be treated in a number of different ways to get meaningful insight into the system being studied. Numerous modeling techniques and multiple models may be developed for engines system. It is important to select a suitable modeling technique to capture the relationship between input and output of the system accurately and efficiently. For systems involving mutually conflicting out comes effected by a number of input variables, it is essential to determine the optimum state of the system to achieve desired output by setting appropriate levels of inputs. For this purpose, use of suitable optimization technique is an essential.

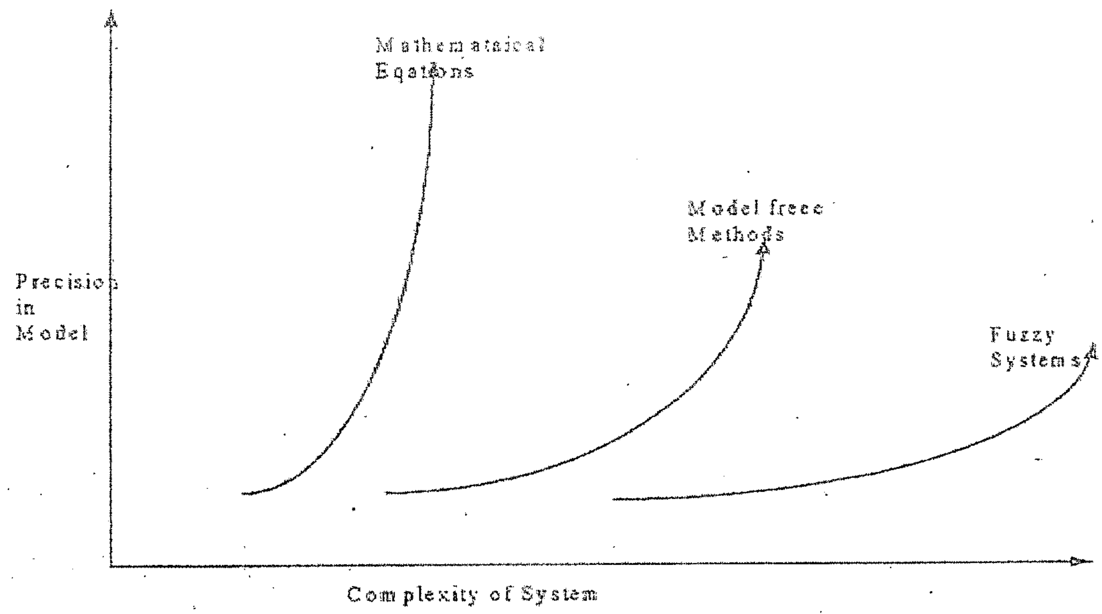


Fig.4.1 Complexity of System & Precision Level of Different Models

With increase in knowledge about a system or process, its complexity decreases and understanding increases. Decrease in complexity leads to increase in precision afforded by computational methods useful in modeling of the system or process. As seen in Fig. 4.1, for systems that are little complex and hence little uncertain, closed form mathematical models provide precise description of system. For systems little more complex but for which significant data is available, model free methods like artificial neural networks provide powerful and robust means to reduce uncertainty using pattern based learning. For most complex systems where little numerical data exists and where only ambiguous or imprecise information may be available, fuzzy models provide a method to understand and represent system behaviour by interpolation between observed inputs and outputs.

In order to use optimization algorithms in engineering design activities, the first task is to formulate the optimization problem. The formulation process begins with identifying the important design variables that can be changed in a design. The other design parameters are usually kept fixed. Thereafter, constraints associated with the design are formulated. The constraints may arise due to resource limitations such as deflection limitations, strength limitations, frequency limitations, and others. Constraints may also arise due to codal restrictions that govern the design. The next task is to formulate the objective function which the designer is interested in minimizing or maximizing. The final task of the formulation phase is to identify some bounding limits for the design variables.

The formulation of an optimization problem can be more difficult than solving the optimization problem. Every optimization problem requires different considerations for formulating objectives, constraints and variable bounds [77].

Section 4.1 is concerned with the ANN modeling applied to predict thermal performance and engine emission constituents using the extensive experimental data compiled during experimentation. Section 4.1.1 describes the approach adopted for both the thermal performance evaluation and constituents of engine emissions. The selection of modeling tool is presented in Section 4.1.2 while modeling strategy is given section 4.1.3. Section 4.1.4 gives the ANN modeling applied in the present investigation using the experimental data on the thermal performance. Using the experimental data on the exhaust gas emission constituents, ANN modeling is carried out and is given in Section 4.1.5 and finally the result and discussion is presented in Section 4.1.6.

The optimization of the CI engine performance in terms of both thermal performance and gas emission constituents carried out using genetic algorithm is discussed in Section 4.2. Single objective optimization is discussed in Section 4.2.1 while Section 4.2.2 deals with multi objective optimization.

4.1 Artificial Neural Network

In the recent years, many models and simulations have been tried to give a clear view about the diesel engine performance, fuel characteristics, emission etc. under varied conditions of speed, load and other operating parameters. One of these techniques is the artificial neural network (ANN). ANN modeling (neural networks) encompasses very sophisticated techniques capable of modeling complex functions and processes. The true power and advantage of neural networks lies in their ability to represent both linear and nonlinear relationships as well as having the capability of learning by example. For processes that have non-linear characteristics such as those found in diesel engine performance modeling, traditional linear models are simply inadequate. In comparison to traditional computing methods, neural networks offer a different way to analyze data and to recognize patterns within that data by being generic non-linear approximators [77, 78]. Artificial Intelligence (AI) techniques seem to be best solution for predicting engine emissions since they do not demand any additional sensor installation [81].

When mathematical models fail to capture the input/output relationship within the limits of permissible error and sufficient data regarding the system available, artificial neural network is a pertinent tool to model successfully the system behaviour. ANNs are called model free models since they don't rely upon a pre-defined mathematical equation to relate system input/output. A proper ANN structure is developed for each system to capture the system behavior of a complex system. With high complexity of combustion relations and emission phenomena, it is suitable to model by ANN. ANNs have been used for two main tasks: 1) function approximation and 2) classification problems. Neural networks offer a general framework for representing non-linear mappings. The application of neural networks to predict thermal performance and exhaust gas constituents belongs to the class of function approximation applications.

4.1.1 Neural Network Modeling Approach

Developing a suitable model for thermal performance and exhaust gas emissions of a compression ignition (CI) engine for evaluating the effect of hydrogen induction poses the problem of absence of widely accepted correlations. Artificial neural networks are found apt in such a scenario to capture the relationship between the response parameters and the control parameters selected as per the design of experiments. A model is desirable to simulate the engine performance and help predict the effect of load, speed and different hydrogen induction rates on the thermal performance and exhaust gas constituents to have a clear idea of benefits of hydrogen induction.

In correlation based analysis, the experimental data is normally converted into parameters such as brake power, diesel fuel consumption in order to get significance of variables and compact correlations. The problem often observed with such correlation based thermal analyses is that the parameters predicted strongly depend on the definition of these parameters and in absence of such established correlations as for exhaust gas constituents; an iterative procedure to obtain reasonable correlations becomes cumbersome.

An approach to development of a neural network model to simulate the functioning of the CI engine can help predict the same parameters. ANN does not need definition of experimental correlations and iterative methods. ANNs offer a method to simulate the nonlinear, complex and uncertain systems without any explicit knowledge about the input/output relationship. Developing an ANN with appropriate network architecture allows approximation of any continuous or nonlinear function as seen in complex systems like a CI engine. Looking at the analysis of the performance and engine emissions, it is observed that the analysis is much more complex, critical and involves a number of correlations. Based on this observation, the ANN modeling for the diesel engine operated by hydrogen diesel mixture is planned in two phases:

i) Development of ANN model for thermal performance, and
ii) Development of ANN model for gaseous emission constituents.

A multi layer feed forward ANN model also termed as a multi layer perceptron (MLP) is selected for two reasons. Firstly, a two layered network is not expected to handle the complex relationship between the inputs and outputs of a CI engine operated with hydrogen induction following the explanations of Minsky and Papert [93] regarding the limitations of two layered networks. Secondly, the recurrent network is preferred when the feedback system is to be simulated for dynamic regulation of inputs and outputs. This not being the case, a unidirectional feed forward network is preferred.

The most popular learning algorithm of error back propagation is selected for training purpose as seen in all the literature cited in Chapter 2.

4.1.2 Selection of Modeling Tool

There are many ways to implement artificial neural networks. It is difficult to find optimal network architecture, considering the uniqueness of each system or problem. Usually, a priori choice, such as selection of network topology, training algorithm and network size should be made based on experience in order to keep the task to a manageable proportion. Further, for modeling of systems an appropriate modeling platform is essential. Artificial neural network models for any system can be developed using one of the following three tools given in Fig. 4.2. There are numerous neural network simulation software available which allow fast development of neural networks. These software provide menus and graphics to define the network in terms of layers and cells in each layers, the propagation rule, activation rule, output function and learning algorithm.

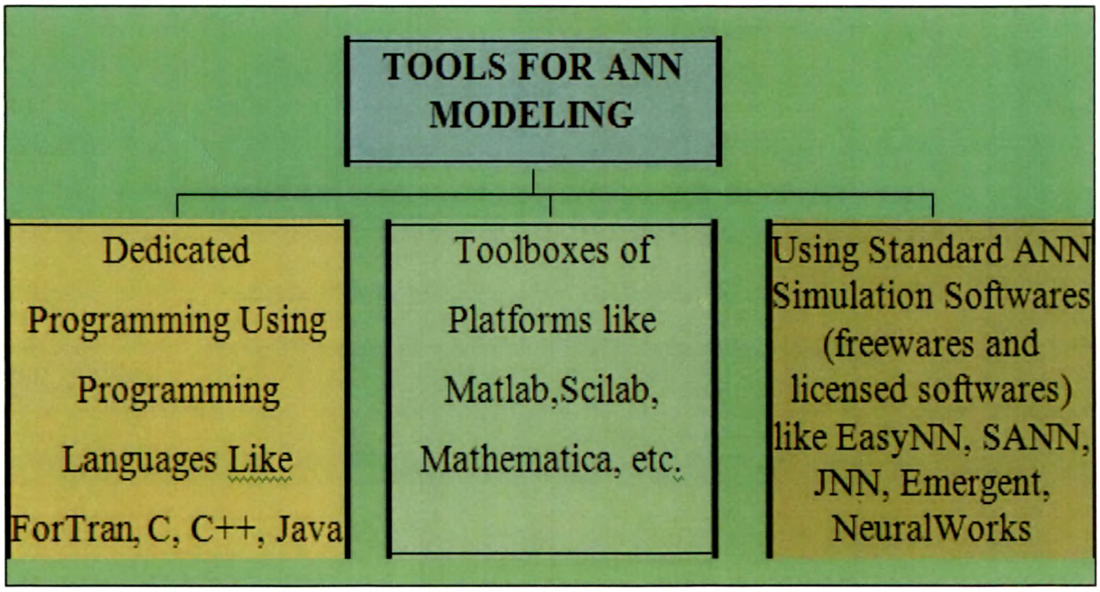


Fig. 4.2 Tools for ANN Modeling

They allow feeding of input/output matched pairs termed as patterns for learning and validation. The permissible error for the validation set can also be specified. The weights and bias are updated and the network is tuned. The learning terminates either on the basis of number of cycles permitted for learning and validation or on achievement of error values less than the target values specified.

Such simulation softwares can be further divided into executables and open source softwares. The executables like EasyNN, NeuralWorks etc. come with binary code and provide predefined functionality. This predefined functionality cannot be altered or extended by programming. The behaviour of the software in terms of definition of various network elements is predefined and cannot be modified if this behaviour is not satisfactory for a particular system. Further, the set of functions defined is also fixed. If neither of the functions in this set is suitable for the modeling of a particular system, the software is rendered inappropriate for modeling of that system. On the other hand, the open source softwares, in addition to providing some predefined functionalities, come with the source code and permit the modification and extension of the software definition. SANN, Genesis etc. are examples of such neural network simulation software with open source.

If these software do not satisfy the problem requirement, the next choice is to use the neural network modeling toolboxes available with programming platforms like MATLAB and Scilab. These toolboxes provide fast development platform since ready to use ANN specific functions are made available as library functions. Graphical functions of these platforms permit faster development. If these ready libraries do not satisfy certain peculiar system, the most flexible yet most time consuming option is to develop a dedicated program using any of the programming language syntax. All the graphics and other functionalities have to be defined in this case.

For the purpose of development of ANN model for thermal performance and exhaust gas constituents, the first choice is to use standard executable software. Comparative features of several simulation softwares are provided in Appendix V. The software selected for neural network modeling is EasyNN purely because of its simplicity in developing and training models involving feed forward multilayered neural networks with back-propagation training algorithm. EasyNN grows multi-layer neural networks from the data in a *Grid*. The neural network input and output layers are created to match the grid input and output columns. Hidden layers connecting to the input and output layers can then be grown to hold the optimum number of nodes. Each node contains a neuron and its connection addresses. The data grid containing input/output matched pairs for training and validation of the neural network is produced by importing data from spreadsheet files, tab separated plain text files, comma separated files, bitmap files or binary files. The grid can also be produced manually using the EasyNN grid editing facilities. Numeric, text, image or combinations of the data types in the grid can be used to grow the neural networks. The neural networks learn the training data in the grid and they can use the validating data in the grid to self validate at the same time. When training finishes the neural networks can be tested using the querying data in the grid, using the interactive query facilities or using querying data in separate files. The steps that are required to produce neural networks are automated in EasyNN. The learning can be terminated by specifying maximum number of cycles or the targeted maximum error.

4.1.3 Modeling Strategy

ANN requires matched pairs of inputs and outputs for the development of suitable network architecture and its training to simulate the system being modeled. The data is divided using the 80-20 rule, with 80% of the available data being used for training of the network and 20% being used for validation or pruning. The data required for the training of the neural networks is generated through series of experimental tests conducted on four stroke four cylinder compression ignition engine using hydrogen – diesel blends as fuel. This yields the data required for training and validation of the ANN model for the diesel engine. The data is generated from the experiments by varying speed and load of engine at various hydrogen induction rates. The sample of input and output experimental results for modeling purpose is listed in Table 4.1. (This experimental data set is the same as given in Appendix II).

The table represents a sample of input and output data that is used in the ANN modeling of engine performance and exhaust gas emission constituents. The engine speed is varied from 1000 to 2000 rpm with a step of 250 rpm, load in terms of Ampere is changed from 0 Amp. to 2 Amp with a step of 0.5 Amp., while the hydrogen induction rate is varied from 0 to 18 l/min with a step of 1 l/min. The data reduction is carried out for a constant engine speed of 1000 rpm under no load operating condition and 0 to 18 l/min hydrogen induction rate. By using the experimental data, a neural network model can be developed for gas emission constituents and engine performance. The general approach for ANN modeling of a given problem is described in Fig. 4.3. Once the type network topology and training algorithm is selected, the next task is to decide on some network parameters and operational rules. These can be listed as under:

1. **Identify Inputs:** The input variables to the system need to be identified which decides the number of cells in the input layer. For predicting thermal performance and exhaust gas constituents, the control variables such as speed, load and induction rate of hydrogen are the inputs. This implies that the number of inputs for ANN modeling is three.

2. **Identify Outputs:** The output variables for prediction of thermal performance considered are brake power and diesel fuel consumption. Brake thermal efficiency is the parameter conventionally used to represent thermal performance but this is not selected as output since the engine is operated with hydrogen - diesel fuel blend and objective is to determine the effect of

hydrogen induction on the performance. Further, the CI engine as a system allows control of speed and load and experimental setup is designed to control hydrogen induction which implies that the diesel fuel consumption is determined based on the power requirement and is effectively a response parameter to be treated as a direct outcome of the values of control variables. Hence, for thermal performance the number of outputs is two. For predicting the exhaust gas constituents five major constituents namely, CO, CO_2, HC, NO_X and SO_2 are selected as the five outputs.

3. Select the propagation rule: This decides how the net input to each cell is calculated. The commonly implemented weighted sum rule is selected as the propagation rule. The weights are initialized randomly and no weights are applied on the input connections of the cells in input layer.

4. Select the activation function: The logistic activation function is selected which allows scaling of the effect of inputs in a nonlinear fashion.

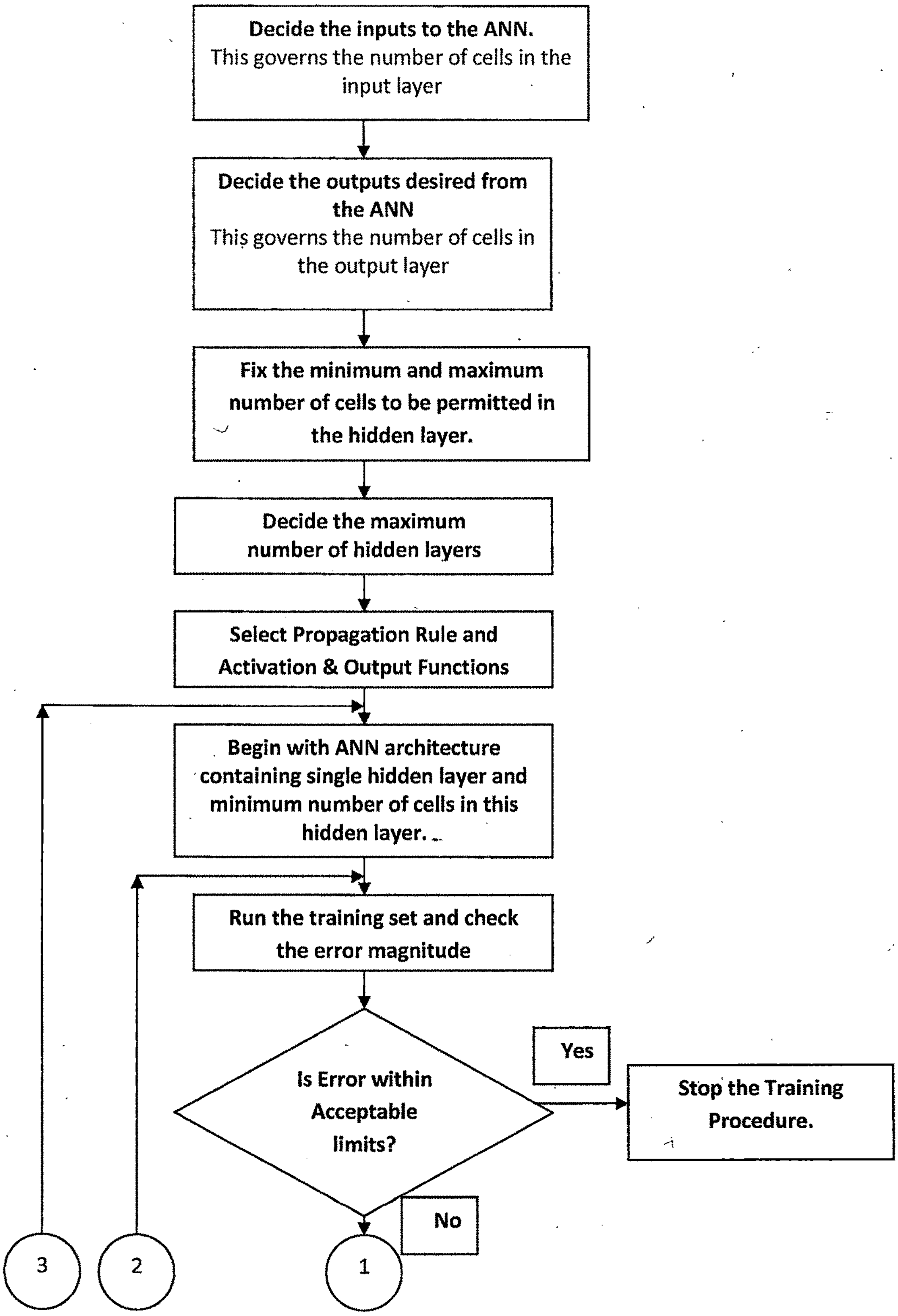
5. Select the output function: The identity function matches best with the logistic identity function in order to relay the output of the activated neuron as the response.

6. Number of layers & cells in them: Set the limits on minimum and maximum number of hidden layers and the least and most number of cells in each of these hidden layers. This requires some experience and trial & error on part of the modeler to achieve a suitable network. Usually a number of networks are tried and the one giving the least error after training and best coefficient of determination is selected as best model.

7. Termination Criteria: The training procedure is stopped when the error is within an acceptable value. The acceptable value is established on basis of practical needs or relevant literature. An error of 10% is generally acceptable for predictive models. However, infinite time cannot be allowed to a model to achieve the error and some models may not even be capable to capture the relationship and train to acceptable error. For this reason, a limit in number of training cycles is also specified.

Table 4.1 Neural Network Input and Output Data Sample for Engine Performance and Exhaust Gas Emissions Constituents

Input			Output							
			Thermal Performance		Emission Constituents					
Speed (rpm)	Load (Amp.)	Hydrogen Induction rate (l/min)	Diesel Fuel Consumption $\times 10^6$ (kg/s)	Brake Power (W)	CO	CO_2	HC	NO_X	SO_2
1000	0	0	183	0	0.09	2.15	0.16	78	141
1000	0	1	175	0	0.23	2.19	0.18	79	195
1000	0	2	173	0	0.36	2.22	0.19	80	249
1000	0	3	170	0	0.50	2.23	0.20	81	314
1000	0	4	167	0	0.63	2.23	0.22	79	378
1000	0	5	162	0	0.76	2.23	0.24	78	445
1000	0	6	156	0	0.89	2.23	0.26	78	512
1000	0	7	154	0	0.99	2.30	0.30	78	579
1000	0	8	152	0	1.10	2.37	0.35	77	645
1000	0	9	150	0	1.19	2.37	0.45	78	728
1000	0	10	150	0	1.29	2.37	0.56	77	811
1000	0	11	148	0	1.38	2.41	0.69	77	876
1000	0	12	147	0	1.47	2.45	0.83	75	941
1000	0	13	144	0	1.57	2.45	0.84	76	1032
1000	0	14	139	0	1.67	2.45	0.86	76	1123
1000	0	15	134	0	1.78	2.49	0.86	75	1219
1000	0	16	129	0	1.89	2.52	0.87	75	1315
1000	0	17	123	0	1.98	2.52	1.39	75	1407
1000	0	18	119	0	2.07	2.52	1.92	74	1499


Decide the inputs to the ANN.
This governs the number of cells in the input layer
Decide the outputs desired from the ANN
This governs the number of cells in the output layer
Fix the minimum and maximum number of cells to be permitted in the hidden layer.
Decide the maximum number of hidden layers
Select Propagation Rule and Activation & Output Functions
Begin with ANN architecture containing single hidden layer and minimum number of cells in this hidden layer.
Run the training set and check the error magnitude
Is Error within Acceptable limits?
Yes
Stop the Training Procedure.
No
3
2
1

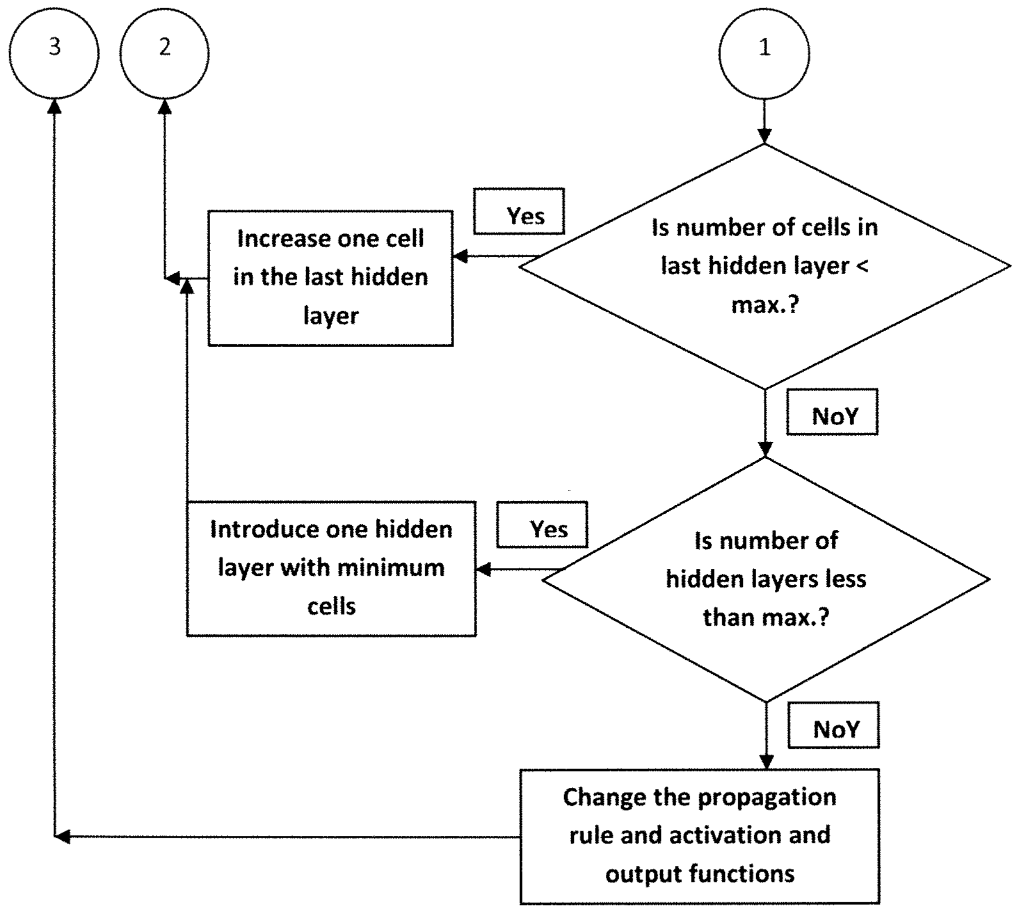


Fig. 4.3 Flow Chart for Neural Network Modeling Approach

The application of this general modeling approach to each of the cases of predicting thermal performance and exhaust gas constituents is discussed in subsequent sections.

4.1.4 ANN Model for Thermal Performance

The complete specification of engine performance comes in terms of diesel fuel consumption (DFC) and brake power (BP). Both are merely dependent upon engine speed, engine load, and hydrogen induction rate. Thus, in order to develop a model in neural network technique which predicts the performance of CI engine working with hydrogen – diesel blends, the operation condition such as engine rate speed, engine load, and hydrogen induction rates are accepted as the input while the diesel consumption rate and brake power are to be determined as the output variables. Fig. 4.4 shows the layout of the neural network model for engine performance.

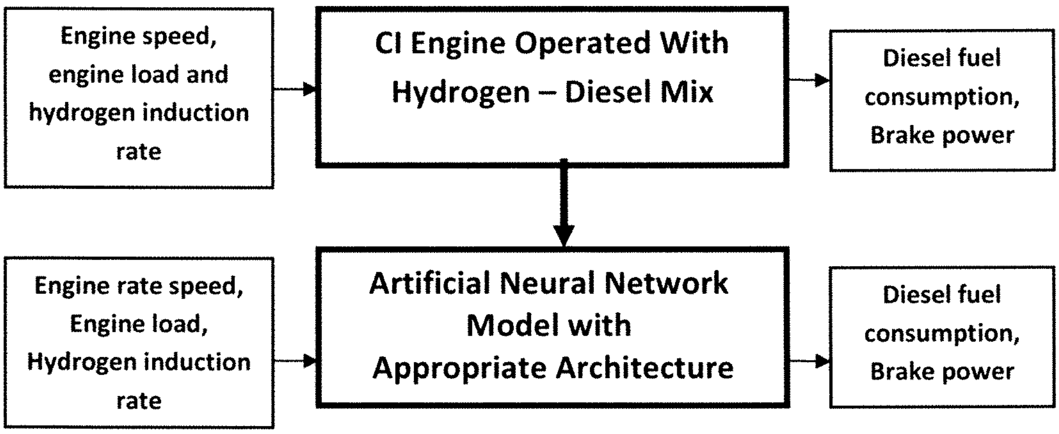


Fig. 4.4 Layout of Artificial Neural Network Model for Engine Performance

The neural network training data listed in Appendix II and Table 4.1 are used for developing individual neural network model. The central block representing CI engine in Fig. 4.4 is replaced by different architectures of neural networks and an appropriate architecture is determined which limits all the errors within 2%. The steps listed in the flow chart for development of neural network models shown in Fig. 4.3 are applied to this case as given in Table 4.2.

As per Table 4.2, beginning with a three layered neural network model having ten cells in the hidden layer, the number of cells in hidden layer is increased up to 50 while monitoring the error resulting at the end of training. The criteria for the termination of training selected are a) permissible error and b) maximum number of cycles in training and validation.

Error for each case is defined as

$$\text{Error\%} = \frac{|A_e - A_p|}{A_e} \tag{4.1}$$

where, A_e = The output value as obtained from theoretical analysis

A_p = The output value predicted by the neural network model

The average error for entire epoch (complete set of input-output pairs) is defined as

$$\text{Error}_{av}\,\% = \frac{1}{N}\sum_{i=1}^{N}\frac{|A_{ei} - A_{pi}|}{A_{ei}}$$

(4.2)

The maximum error is defined as

$$\text{Error}_{max}\,\% = \max\left(\sum_{i=1}^{N}\frac{|A_{ei} - A_{pi}|}{A_{ei}}\right\} \quad (4.3)$$

and the minimum error is defined as

$$\text{Error}_{min}\,\% = \min\left(\sum_{i=1}^{N}\frac{|A_{ei} - A_{pi}|}{A_{ei}}\right\} \quad (4.4)$$

For each architecture of neural network model the root mean square value of error is

$$\text{Error}_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{A^e - A^p}{A^e}\right)^2} \quad (4.5)$$

For determination of the rms error, the maximum error out of the five output nodes for CO, CO_2, HC, NO_X and SO_2 is used.

The confidence R and scatter σ test can be used to decide upon the best architecture. The R and σ values can be determined as

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{A^e}{A^p} \quad (4.6)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\{R - R_i)^2} \quad (4.7)$$

Table 4.2 Neural Network Modeling for Engine Performance

Network Type	Feed Forward
Input for the neural network model	engine speed, engine load, and hydrogen induction rate
Number of cells in input layer = Number of inputs to the neural network model	Three
Output from the neural network model	Diesel fuel consumption and brake power
Number of cells in output layer = Number of outputs from the neural network model	Two
Initial Number of Hidden Layers	1
Maximum Number of Hidden Layers	3
Initial Number of Cells in a Hidden Layer	10
Maximum Number of Cells in a Hidden Layer	50
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

For this model, the limiting value for all the errors over the entire data is selected as 0.02 (2%) while the permissible error for validation sets is specified as 3% of the target value. The maximum number of training cycles is limited to 1000000 for each learning set. The training stops when any one of the above criteria, namely, all errors being less than 0.005, all validation points within 0.3% of target values or 100000 training cycles being completed. The learning rate is kept as 0.6 and momentum as 0.8 for the stable learning and convergence of weights. The number of learning cycles before any validation cycle is executed is set to 1000. The number of validation cycles in one instance of validation is set to 100. These values are set in the ***controls*** window of the software as shown in Fig. 4.5. The 80-20 rule for neural networks are used for training and for validation similar to that employed in the case of ANN modeling on exhaust gas emission constituents.

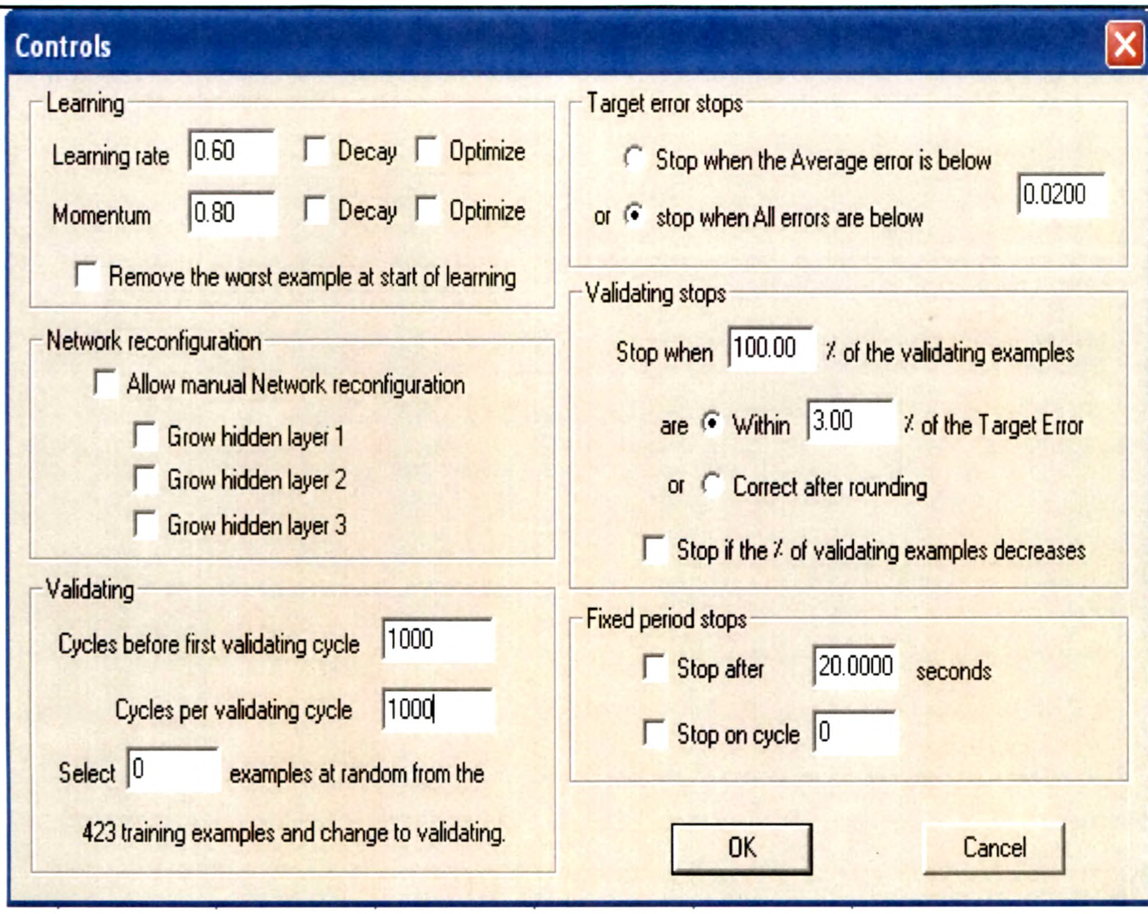


Fig. 4.5 Setting Learning Controls for Training of ANN Model

As given in Table 4.2, beginning with three cells in input layer, ten cells in the hidden layer, and two cells in output layer, the neural network model appears as indicated in Fig. 4.6. Such architecture is denoted as 3,10,9,2 architecture, the numbers denoting the number of cells in input layer, hidden layer and output layer respectively.

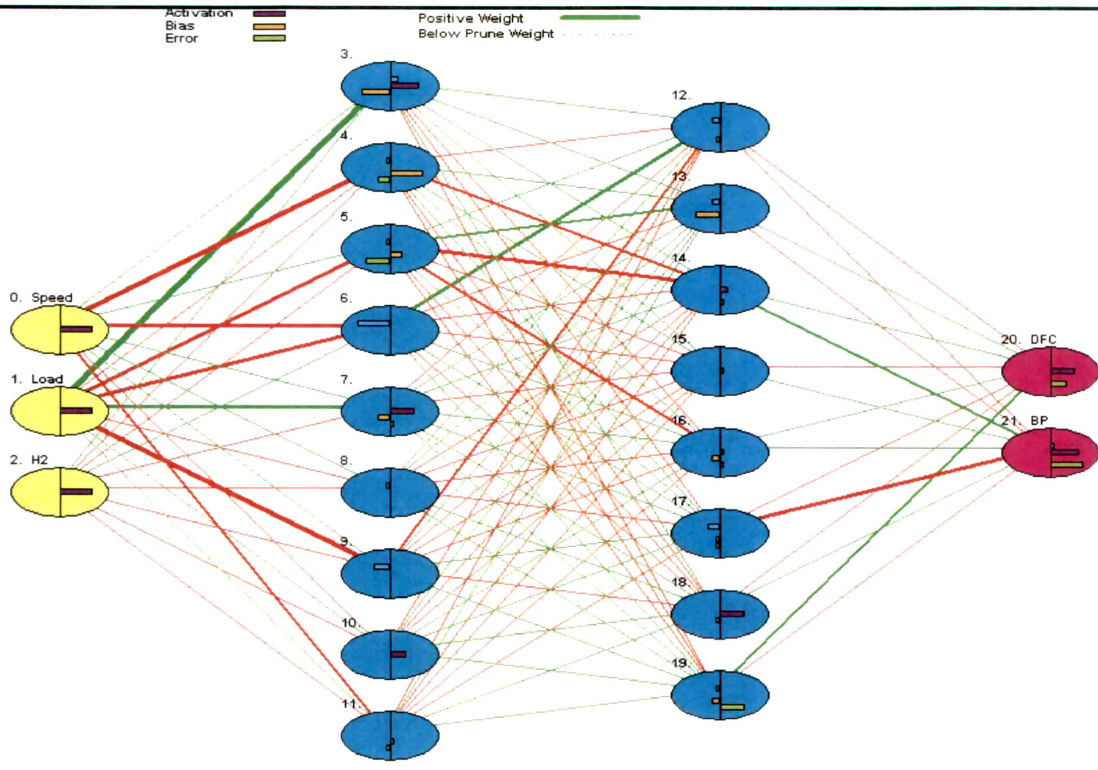


Fig. 4.6 ANN Model of Engine Performance with Architecture 3,10,9,2

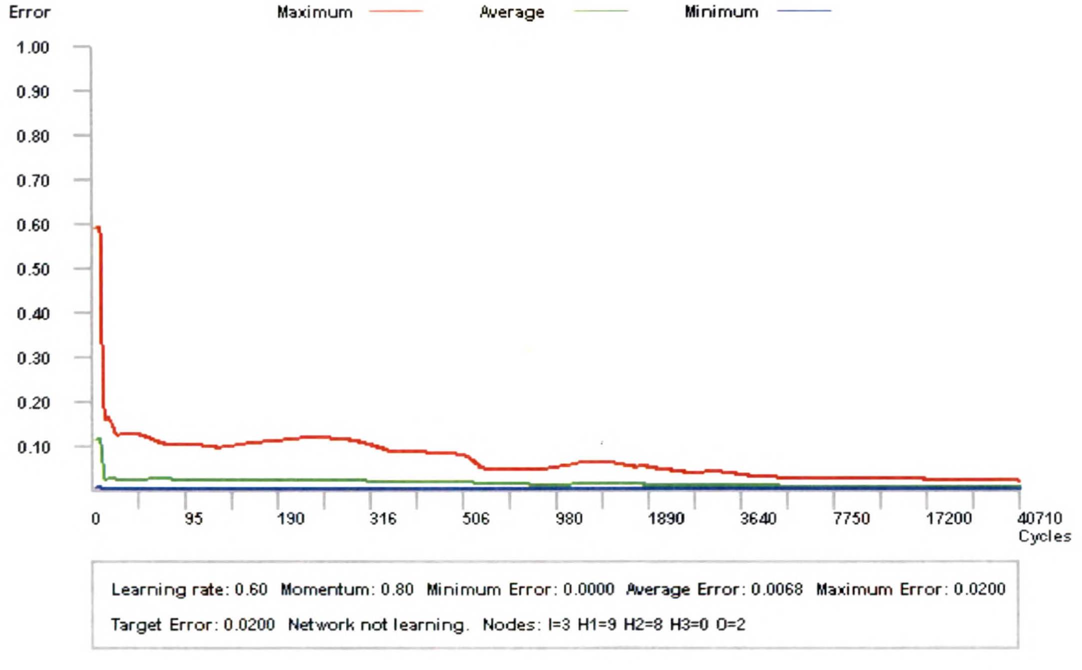


Fig. 4.7 ANN Model Training & Error Propagation With Increasing Number of Training Cycles for the 3,10,9, 2

On training of the network, the error propagation graph for each training cycle is obtained as given in Fig. 4.7. The maximum, average and minimum error are all seen to reduce at a fast pace in the early training period. But, towards the last training cycles, there is very small change in these error values. Further, the training ends with average error value less than 2% permitted as the target error value. The training does not achieve the limiting error value of 3% of target value selected for the validation set. The training stops after numbers of training cycles without the error limit set for validation points being achieved because no further reduction in error is seen for a number of consecutive cycles.

Table 4.3 shows the results for different architectures tried for the same data as in Table 4.1. Table 4.3 lists the training and test errors which can be used for selection of the most appropriate network architecture.

Table 4.3 Neural Network Architectures & Corresponding Training Results

NO.	Model Structure	Avg. Error %	Min. Error %	Max. Error %	Validation Set within Limiting Error%	Remarks
1	3,25,2	5.09	0.0601	0.059	3	Training Stopped with all errors being within 2%
2	3,26,2	5.17	0.0190	0.057	3	
3	3,27,2	5.28	0.0188	0.060	3	
4	3,28,2	5.02	0.0277	0.058	3	
5	3,29,2	5.13	0.0748	0.058	3	
6	3,9,8,2	5.06	0.0223	0.057	3	
7	3,10,10,2	5.02	0.0194	0.057	3	
8	3,9,9,2	5.14	0.0104	0.059	3	
9	3,10,8,2	5.10	0.0470	0.058	3	
10	3,10,9,2	5.09	0.0608	0.057	3	

As seen from Table 4.3, the error values and the percentage of validation sets within limiting error are almost identical. In such situation, deciding which architecture is best representative model of the system becomes difficult. The R and σ test is the most popular approach to handle this situation. The values of rms error, R and σ are evaluated using Eqs. (4.5) to (4.7). The training and test errors for the networks are listed in Table 4.4.

Table 4.4 Training and Test Errors for Neural Network Architectures for Engine Thermal Performance

Model Structure	Training Error		Test Error	
	Max. Error%	RMS Error%	R	σ
3,25,2	9.998	0.0590	1.0381	0.0331
3,26,2	9.971	0.0578	1.0420	0.0323
3,27,2	9.993	0.0601	1.0397	0.0321
3,28,2	9.975	0.0580	1.0405	0.0322
3,29,2	9.993	0.0581	1.0412	0.0317
3,9,8,2	9.997	0.0579	1.0399	0.0329
3,10,10,2	9.992	0.0577	1.0399	0.0318
3,9,9,2	9.976	0.0590	1.0393	0.0322
3,10,8,2	9.981	0.0581	1.0359	0.0309
3,10,9,2	9.995	0.0578	1.0413	0.0312

It is seen that the values of error are well within specified limits for all the neural network model architectures evaluated. On the basis of R and σ values, the 3,10,8,2 is the good model for which value of R is closest to unity and value of σ is least is selected as the best representative model for the engine gas emission constituents. Though few other models have lesser maximum and rms error values but the spread and accuracy of determination being better for this model, it is selected as the representative model.

4.1.5 ANN Model for Exhaust Gas Emission Constituents

For gas emission constituents completely specified in terms of CO, CO_2, HC, NO_X, and SO_2 are merely dependent upon engine speed, engine load, and hydrogen induction rate. Thus, in order to develop a neural network which rates the engine gas emission constituents for diesel engine working with hydrogen – diesel blends, the operation condition such as engine rate speed, engine load, and hydrogen induction rates are accepted as the input, while the variables of the gas emission constituents are to be determined as the output variables. However, the neural network model for CI engine gas emission constituents will schematically appear as indicated in Fig. 4.8.

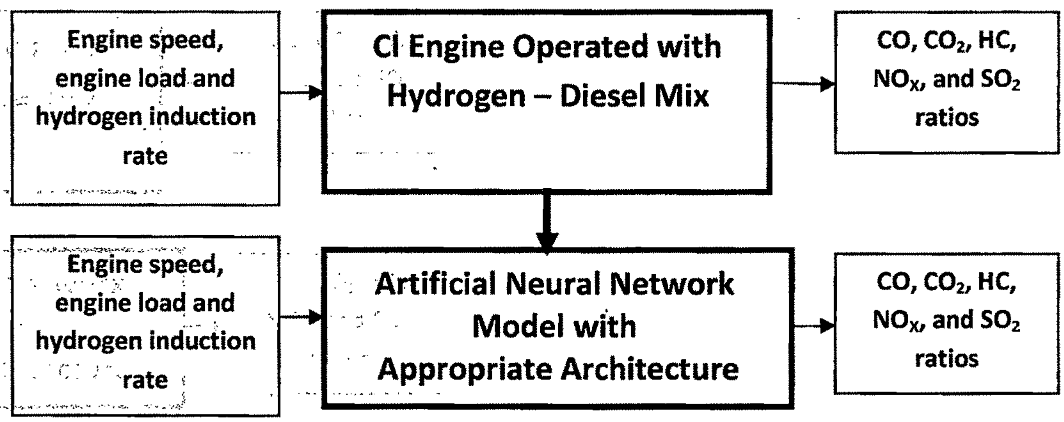


Fig. 4.8 Schematic of Artificial Neural Network Model for CI Engine Gas Emission Constituents

The neural network training data listed in Appendix II and Table 4.1 are used for developing individual neural network model. The CI engine operated during experimentation shown in central block in Fig. 4.8 is replaced by different architectures of neural networks and an appropriate architecture is determined which limits all the errors within **2%**. The steps listed in the flow chart for development of neural network models shown in Fig. 4.3 are applied to this case as given in Table 4.5.

Table 4-5 Neural Network Modeling for Emission Constituents

Network Type	Feed Forward
Input for the neural network model	Engine Speed, Engine Load, and Hydrogen Induction Rate
Number of cells in input layer = Number of inputs to the neural network model	Three
Output from the neural network model	CO, CO_2, HC, NO_X and SO_2 ratios
Number of cells in output layer = Number of outputs from the neural network model	Five
Initial Number of Hidden Layers	1
Maximum Number of Hidden Layers	3
Initial Number of Cells in a Hidden Layer	10
Maximum Number of Cells in a Hidden Layer	50
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

As per Table 4.5, beginning with a three layered neural network model having ten cells in the hidden layer, the number of cells in hidden layer is increased up to 50 while monitoring the error resulting at the end of training. The criteria for the termination of training selected are a) permissible error and b) maximum number of cycles in training and validation are discussed above and given by Eqs. (4.1) to (4.7).

The limiting value for all the errors over the entire data is selected as 0.02 (2%) while the permissible error for validation sets is specified as 3% of the target value. The maximum number of training cycles is limited to 1000000 for each learning set. The training stops when any one of the above criteria, namely, all errors being less than 0.02 , all validation points within 3% of target values or 100000 training cycles being completed. The learning rate is kept as 0.6 and momentum as 0.8 for the stable learning and convergence of weights. The number of learning cycles before any validation cycle is executed is set to 1000. The number of validation cycles in one instance of validation is set to 100. These values are set in the *controls* window of the software as shown in Fig. 4.9. The 80-20 rule for neural networks training and validation is used.

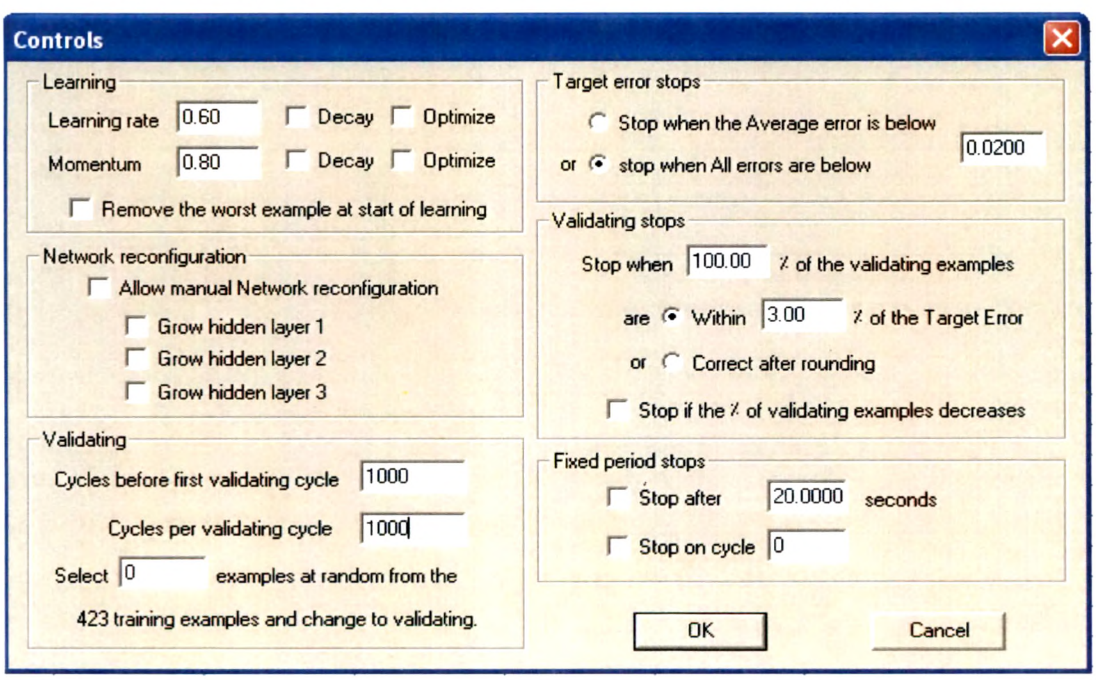


Fig. 4.9 Setting Learning Controls for Training of ANN Model

With three cells in input layer, starting by ten cells in the hidden layer and five cells in output layer, the neural network model appears as given in Fig. 4.10. Such architecture is denoted as 3,10,5 architecture. The numbers denote the number of cells in input layer, hidden layer and output layer respectively.

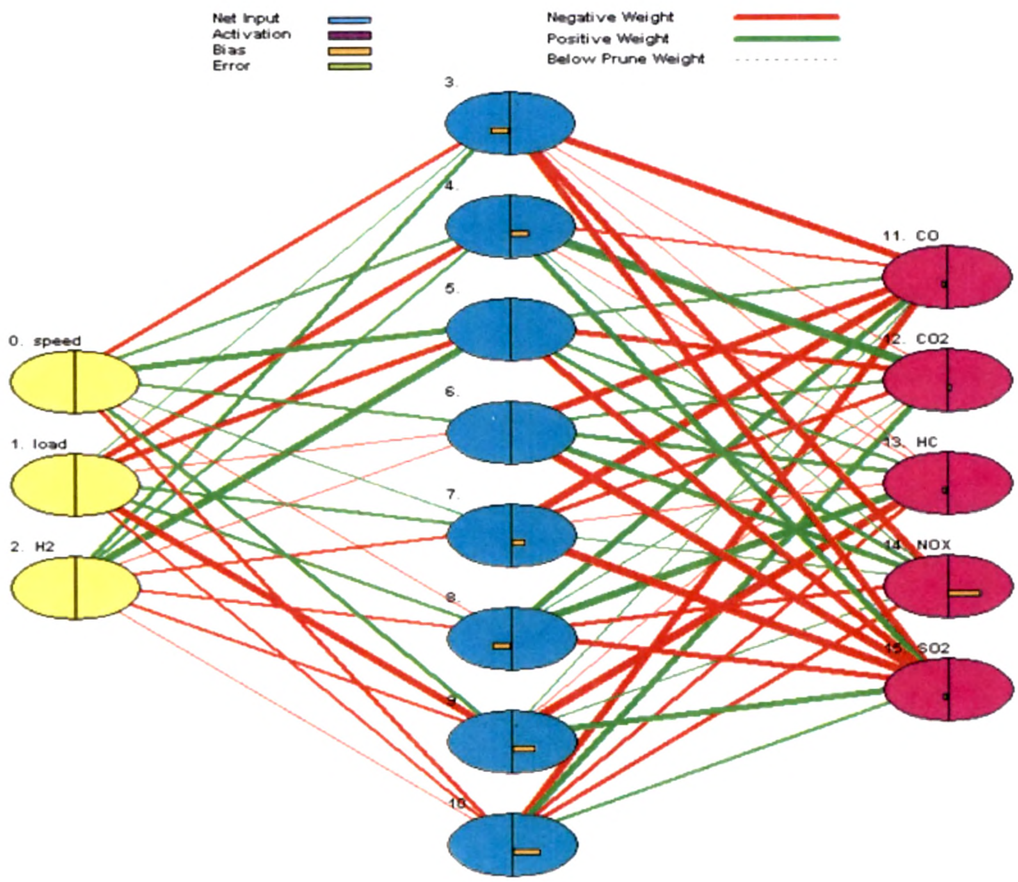


Fig. 4-10 ANN Model of Engine Gas Emission Constituents with Architecture 3,10,5

Table 4.6 Neural Network Architectures & Corresponding Training Results for Gas Emission

NO.	Model Structure	Avg. Error %	Min. Error %	Max. Error %	Validation Set within Limiting Error%	Remarks
1	3,28,28,5	5.048	0.0239	9.99	3	Training Stopped with all errors being within 2%
2	3,30,30,5	5.215	0.0484	9.98	3	
3	3,32,32,5	5.114	0.0432	9.99	3	
4	3,33,33,5	5.150	0.0613	9.99	3	
5	3,34,34,5	5.081	0.0504	9.99	3	
6	3,35,35,5	5.097	0.0063	9.99	3	
7	3,36,36,5	5.165	0.0180	9.99	3	
8	3,40,40,5	5.103	0.0629	9.99	3	
9	3,20,20,20,5	5.092	0.0345	9.99	3	
10	3,23,23,23,5	4.891	0.0090	9.99	3	
11	3,24,24,24,5	5.088	0.0302	9.99	3	
12	3,25,25,25,5	5.160	0.0375	9.99	3	
13	3,26,26,26,5	5.124	0.0601	9.99	3	
14	3,27,27,27,5	5.073	0.0382	9.99	3	

As seen from Table 4.6, the error values and the percentage of validation sets within limiting error are almost identical. In such situation, deciding which architecture is best representative model of the system becomes difficult. The R and σ test is the most popular approach to handle this situation. The values of rms error, R and σ are evaluated using Eqs. (4.5) to (4.7). The training and test errors for the networks are listed in Table 4.7.

It is seen that the values of error are well within specified limits for all the neural network model architectures evaluated. On the basis of R , σ, and rms test, the 3,28,28,5 is the good model for which value of R is closest to unity and value of σ is least is selected as the best representative model for the engine gas emission constituents.

Table 4.7 Training and Test Errors for Neural Network Architectures for Exhaust Gas Emission Constituents Model

Model Structure	Training Error		Test Error	
	Max. Error%	RMS Error%	R	σ
3,28,28,5	9.99	0.0582	1.0541	0.0322
3,30,30,5	9.98	0.0584	1.0548	0.0323
3,32,32,5	9.99	0.0589	1.0548	0.0326
3,33,33,5	9.99	0.0589	1.0551	0.0326
3,34,34,5	9.99	0.0583	1.0544	0.0326
3,35,35,5	9.99	0.0593	1.0547	0.0339
3,36,36,5	9.99	0.0591	1.0554	0.0325
3,40,40,5	9.99	0.0585	1.0547	0.0332
3,20,20,20,5	9.99	0.0582	1.0545	0.0324
3,23,23,23,5	9.99	0.0598	1.0564	0.0331
3,24,24,24,5	9.99	0.0587	1.0545	0.0332
3,25,25,25,5	9.99	0.0591	1.0553	0.0321
3,26,26,26,5	9.99	0.0587	1.0549	0.0324
3,27,27,27,5	9.99	0.0586	1.0543	0.0340

4.1.6 Results and Discussion

It is seen from the modeling for prediction of thermal performance and exhaust gas emission constituents that ANN models can successfully capture the complex input-output relationships and still provide small prediction errors. In order to determine the best ANN model, a number of architectures are tried and tested for error, spread and coefficient of determination. The representative model selected for exhaust gas constituents has an architecture of 3,28,28,5. It has an average error of nearly 5%, minimum error of 0.02%, maximum error of 10% and rms error value of 0.05%. The coefficient of determination is very close to unity being 1.054 and the spread is 0.032. This ensures that in the test range under consideration, if this model is subjected to any condition for which experiment is not conducted, the error will not exceed 5% on an average and 10% maximum. This is shown by applying the model to two cases: i) speed of 1300 rpm, no load condition equivalent to 0 Amp and the range of hydrogen induction rate experimentally investigated from 1 l/min to 18 l/min and ii) speed of 1800 rpm, a full load equivalent to 2 Amp and the range of hydrogen induction rate experimentally investigated from 1 l/min to 18 l/min. The results predicted by 3,28,28,5 ANN model are compared with values found by interpolating on graphical plot of experimental results and the error is evaluated and listed in Table 4.8 and Table 4.9.

Table 4.8 Comparison of Results of ANN Model and Experimental Data at 1300 rpm and No Load

Hydrogen Induction Rate (l/min)	Performance						Emission Constituents														
	m_f (kg/s)			BP (W)			CO (%)			CO_2 (%)			HC (%)			NO_X (ppm)			SO_2 (ppm)		
	Exp	ANN	Error (%)	Exp	ANN	Error (%)	Exp	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)
1	0.80	0.75	5.96	0	0	0	0.08	0.02	7.38	2.61	2.58	1.37	0.18	0.17	2.59	90.00	84.59	6.01	52.60	52.39	0.41
2	0.78	0.75	3.68	0	0	0	0.18	0.14	1.94	2.70	2.48	8.12	0.19	0.18	7.61	86.40	82.53	4.48	98.90	98.19	0.71
3	0.76	0.68	9.83	0	0	0	0.27	0.07	7.58	2.79	2.65	5.01	0.20	0.19	7.29	81.80	79.14	3.25	145.20	138.30	4.75
4	0.75	0.69	7.95	0	0	0	0.37	0.29	2.09	2.82	2.73	3.20	0.22	0.21	3.26	79.50	79.37	0.16	189.60	177.31	6.48
5	0.75	0.69	7.53	0	0	0	0.46	0.26	4.39	2.85	2.71	4.78	0.23	0.23	0.56	76.40	73.76	3.46	234.00	230.34	1.57
6	0.75	0.70	6.33	0	0	0	0.55	0.41	2.54	2.85	2.72	4.28	0.26	0.25	3.29	74.50	72.43	2.77	280.10	266.67	4.80
7	0.74	0.73	2.29	0	0	0	0.65	0.07	8.93	2.85	2.73	3.94	0.28	0.26	6.93	72.40	65.72	9.23	326.20	296.52	9.10
8	0.71	0.71	0.15	0	0	0	0.74	0.11	8.55	2.89	2.83	1.96	0.32	0.29	7.33	71.80	66.19	7.81	370.90	349.46	5.78
9	0.71	0.65	8.22	0	0	0	0.83	0.34	5.92	2.92	2.67	8.74	0.36	0.32	9.69	71.20	65.82	7.55	415.60	389.52	6.27
10	0.70	0.66	6.08	0	0	0	0.91	0.91	0.01	2.92	2.84	2.87	0.43	0.40	6.81	71.90	66.23	7.89	465.90	465.00	0.19
11	0.69	0.65	4.99	0	0	0	1.00	0.14	8.60	2.92	2.67	8.79	0.51	0.50	3.21	71.80	71.26	0.75	516.20	492.17	4.66
12	0.68	0.66	2.33	0	0	0	1.06	0.62	4.16	2.95	2.91	1.39	0.56	0.55	1.20	72.80	67.53	7.23	570.50	550.19	3.56
13	0.66	0.66	0.25	0	0	0	1.12	0.01	9.90	2.98	2.83	4.87	0.60	0.59	2.34	73.80	70.64	4.28	624.80	566.11	9.39
14	0.65	0.61	5.92	0	0	0	1.17	1.01	1.39	2.98	2.91	2.45	0.61	0.57	6.35	75.70	71.03	6.17	686.70	633.58	7.74
15	0.64	0.62	2.55	0	0	0	1.23	0.35	7.17	2.98	2.93	1.66	0.62	0.60	3.47	76.80	71.39	7.04	748.60	702.38	6.17
16	0.63	0.61	2.86	0	0	0	1.30	1.20	0.75	3.01	2.83	6.04	0.69	0.66	4.81	78.90	76.73	2.75	812.60	756.22	6.94
17	0.62	0.57	8.11	0	0	0	1.37	0.79	4.20	3.04	2.83	6.82	0.76	0.69	9.71	81.00	76.07	6.08	876.60	835.51	4.69
18	0.61	0.60	0.84	0	0	0	1.45	0.93	3.58	3.04	3.01	1.01	1.18	1.15	2.93	84.60	84.32	0.33	942.10	870.40	7.61

Table 4.9 Comparison of Results of ANN Model and Experimental Data at 1800 rpm and Full Load

Hydrogen Induction Rate (l/min)	Performance						Emission Constituents														
	m_f (kg/h)			BP (W)			CO (%)			CO_2 (%)			HC (%)			NO_X (ppm)			SO_2 (ppm)		
	Exp	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)	Exp.	ANN	Error (%)
1	3.63	3.63	6.82	11591	11155	3.77	0.02	0.02	3.04	8.26	7.84	5.07	0.04	0.04	9.09	90.00	84.59	6.01	2.00	1.84	8.19
2	3.60	3.60	6.20	11634	10891	6.39	0.03	0.03	1.70	8.35	7.79	6.68	0.05	0.04	6.41	86.40	82.53	4.48	5.00	4.85	3.01
3	3.57	3.57	1.34	11663	11195	4.01	0.05	0.05	2.18	8.46	7.89	6.65	0.05	0.04	5.63	81.80	79.14	3.25	8.00	7.63	4.60
4	3.54	3.54	5.15	11685	11561	1.06	0.07	0.06	6.15	8.50	8.11	4.59	0.05	0.05	3.98	79.50	79.37	0.16	16.80	16.19	3.64
5	3.51	3.51	1.78	11702	10960	6.34	0.08	0.07	9.45	8.50	7.85	7.62	0.05	0.05	0.80	76.40	73.76	3.46	25.60	23.86	6.78
6	3.48	3.48	6.15	11723	11328	3.37	0.10	0.09	3.58	8.48	8.18	3.53	0.05	0.05	8.25	74.50	72.43	2.77	32.70	32.37	1.00
7	3.46	3.46	5.80	11737	10581	9.84	0.11	0.11	5.66	8.45	8.30	1.81	0.06	0.05	5.40	72.40	65.72	9.23	39.80	36.77	7.62
8	3.43	3.43	8.90	11766	11178	5.00	0.13	0.12	6.80	8.48	8.45	0.35	0.06	0.05	3.69	71.80	66.19	7.81	54.70	50.38	7.89
9	3.40	3.40	1.44	11782	11520	2.22	0.14	0.13	5.70	8.52	8.30	2.64	0.06	0.06	3.71	71.20	65.82	7.55	69.60	68.67	1.33
10	3.37	3.37	4.27	11814	11688	1.06	0.15	0.14	6.26	8.49	7.76	8.67	0.06	0.06	0.50	71.90	66.23	7.89	82.40	79.85	3.09
11	3.34	3.34	5.62	11844	11484	3.04	0.16	0.15	4.92	8.47	8.12	4.18	0.06	0.05	8.18	71.80	71.26	0.75	95.20	93.44	1.85
12	3.32	3.32	7.10	11882	11124	6.38	0.18	0.17	4.44	8.50	7.96	6.32	0.06	0.05	9.00	72.80	67.53	7.23	112.60	108.73	3.44
13	3.29	3.29	8.69	11898	10746	9.68	0.19	0.18	5.46	8.52	8.13	4.57	0.06	0.06	1.17	73.80	70.64	4.28	130.00	120.73	7.13
14	3.26	3.26	2.99	11906	11799	0.89	0.20	0.20	2.40	8.55	7.79	8.85	0.06	0.06	1.59	75.70	71.03	6.17	143.20	140.96	1.57
15	3.23	3.23	0.64	11915	11619	2.49	0.22	0.21	2.64	8.60	8.38	2.54	0.06	0.06	3.77	76.80	71.39	7.04	156.40	145.35	7.06
16	3.20	3.20	5.39	11758	11219	4.58	0.23	0.21	6.09	8.60	8.17	5.01	0.10	0.10	4.86	78.90	76.73	2.75	161.70	155.10	4.08
17	3.18	3.18	5.41	11787	11308	4.07	0.24	0.22	7.59	8.60	8.11	5.69	0.14	0.14	3.96	81.00	76.07	6.08	167.00	158.80	4.91
18	3.15	3.15	3.15	11818	11520	2.52	0.25	0.23	7.23	8.61	8.53	0.97	0.15	0.14	6.65	84.60	84.32	0.33	172.30	167.75	2.64

On similar lines, the representative model selected for thermal performance has an architecture of 3,10,8,2. It has an average error of nearly 5.1%, minimum error of 0.01%, maximum error of 10% and rms error value of 0.06%. The coefficient of determination is very close to unity being 1.035 and the spread is 0.031. This ensures that in the test range, if this model is subjected to any condition for which experiment is not conducted, the error will not exceed 5% on an average and 10% maximum.

For the ANN models selected for both thermal performance and exhaust gas constituents, the average prediction error is hence close to 5% which is in line with the model errors reported in most literature reviewed. Further, the ANN model for thermal performance modeling required one hidden layer while that for exhaust gas constituents required two. The number of cells in these hidden layers is larger for exhaust gas constituents. This indicates a much more complex relationship between the exhaust gas constituents and the input parameters as compared to the thermal performance parameters.

4.2 Genetic Algorithm for Optimization

The problem of finding the optimum value of hydrogen induction from the point of view of maximizing brake power and minimizing fuel consumption and proportion of exhaust gas emission constituents poses a multi-objective and multimodal scenario. For all the reasons discussed, GA is selected as the optimization tool for the determination of optimum hydrogen induction rate. The procedure for implementing algorithms like GA can be represented in general as given in Fig. 4.12. Few aspects of GA are given in Appendix-V.

As mentioned earlier, the implementation of such algorithms requires computer implementation. Appropriate software is to be selected for implementing GA. Similar to the discussion for ANN modeling, possibility extends from ready freeware and open source softwares to toolboxes of celebrated platforms like MATLAB and requirement of hand coding where inbuilt facilities of these software do not satisfy peculiarity of the specific problem. The MATLAB Genetic Optimization toolbox is selected as the implementation tool. This toolbox

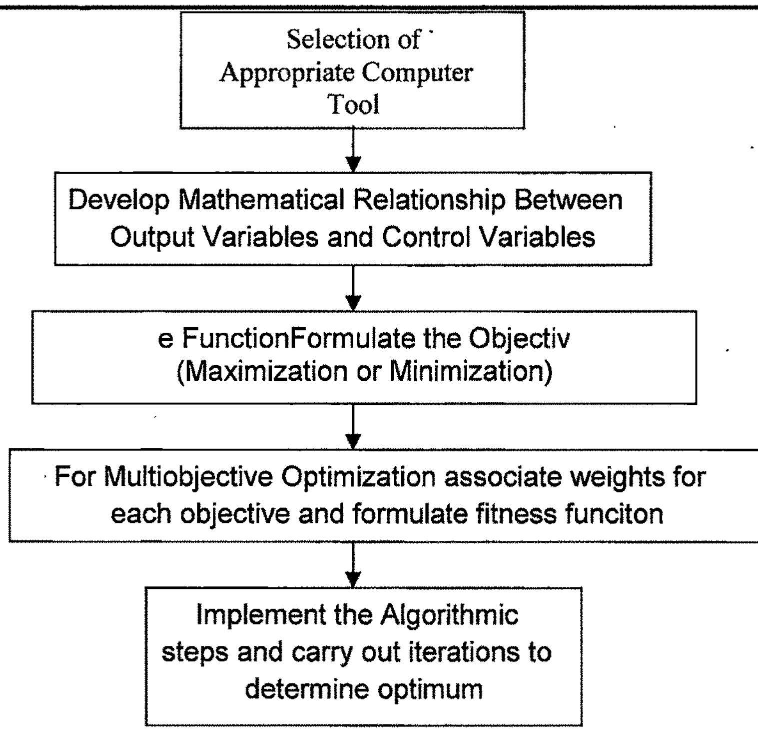


Fig. 4.12 Procedure to Implement GA

provides for solving the minimization problem. Hence, the optimization is carried out in three ways to determine the optimum hydrogen induction rate and corresponding load and speed values.

A correlation relating the output variables namely the brake power, diesel consumption and each of the exhaust gas constituents to the control variables namely speed, load and hydrogen induction rate is required. Feasible region is bounded by practical limit of control variables. These represent maximum and minimum values set in the design of experiment for each of the control variables. The optimization is carried out as single objective optimization treating minimization of exhaust gas constituents and diesel consumption, maximizing the brake power (actually minimizing the inverse of brake power) and a single fitness function to minimize emissions and inverse of brake power.

4.2.1 Single Objective Optimization

The following are the preliminary steps to be taken for the optimization of the performance of a compression ignition engine by taking in to consideration of thermal performance and exhaust gas emission constituents.

1. Select Single objective optimization function for minimizing individually CO, CO_2, NO_X, SO_2, HC and diesel fuel consumption.
2. Select single objective optimization function for maximizing brake power.

3. Formulate a single objective function (fitness function) to minimize emissions and fuel consumption and inverse of brake power.
4. Give different weights to different parameters in the objective functions. For example, since the primary reason for operating and CI engine is to generate power, the brake power is to be maximized if one considers it as the most important parameters and therefore, the contribution of this parameter is given maximum weightage.
5. Give next significant weightage to duel consumption rate as lowering the same will not only reduce the operating cost and conserve fuel but also reduce the emission constituents.
6. Give equal weightage to all emission constituents, keeping in mind that the sum of all weights is unity.

The procedure for the solution of the single objective optimization problem for the minimization of the exhaust gas content CO as a case study is as under: The same steps can be followed for all the other cases of exhaust gas constituents

1. Develop mathematical equation to relate the input and output parameters. The Datafit software developed by Oakdale engineering, USA is used to develop or obtain the mathematical function relating output parameters with the input control variables. Numerous functions are evaluated the best of which are

Square: $Y = aX_1^2 + bX_2^2 + cX_3^2 + dX_1 + eX_2 + fX_3 + gX_1X_2 + X_3 + iX_1X_3 + j$

Cubic: $Y = a_0 + X_1^3 + b_0X_2^3 + c_0X_3^3 + a\ X_1^2 + bX_2^2 + cX_3^2 + dX_1 + eX_2 + fX_3 + gX_1 + X_2 + hX_2X_3 + iX_1X_3 + jX_1X_2X_3 + k$

Exponential: $Y = e^{(aX1+bX2+cX3+d)}$

Linear with constant: $Y = aX_1 + bX_2 + cX_3 + d$

Linear without constant: $Y= aX_1+bX_2+cX_3$

The selection of best mathematical model fitting the data is made based on minimum error and best value of coefficient of determination (R^2) value for all parameters.

Cubic polynomial is found the best for both criterion and for all output parameters. Table 4.10 gives the cubic polynomial performance in comparison with other models fitted.

Table 4.10 Cubic Polynomial Error Test Coefficient in Comparison with Other Function Coefficient

Model	Standard Error	Residual Sum	Residual Average	RSS	R^2	Ra^2
Cubic	49.91	5.08773E-06	1.0711E-08	1148335	0.9652	0.9642
Square	57.27	1.06184E-10	2.23544E-13	1525251	0.9537	0.9528
Exponential	75.94	-3582.495	-7.542095612	2715892	0.9177	0.9171
Linear (no constant)	124.95	-4.43379E-12	-9.33429E-15	7353478	0.7771	0.7757
Linear	177.18	12229.050	25.74536975	14815220	0.5510	0.5491

The equation thus obtained is defined as a function in MATLAB and saved as a ***.m* file**. This function is called as the fitness function for optimization in MATLAB.

2. Use the single objective optimization function ***ga*** from the GENETIC OPTIMIZATION and DIRECT SEARCH tool box of MATLAB for defining and solving the problem. Fig. 4.13 shows the single objective optimization problem definition screen.

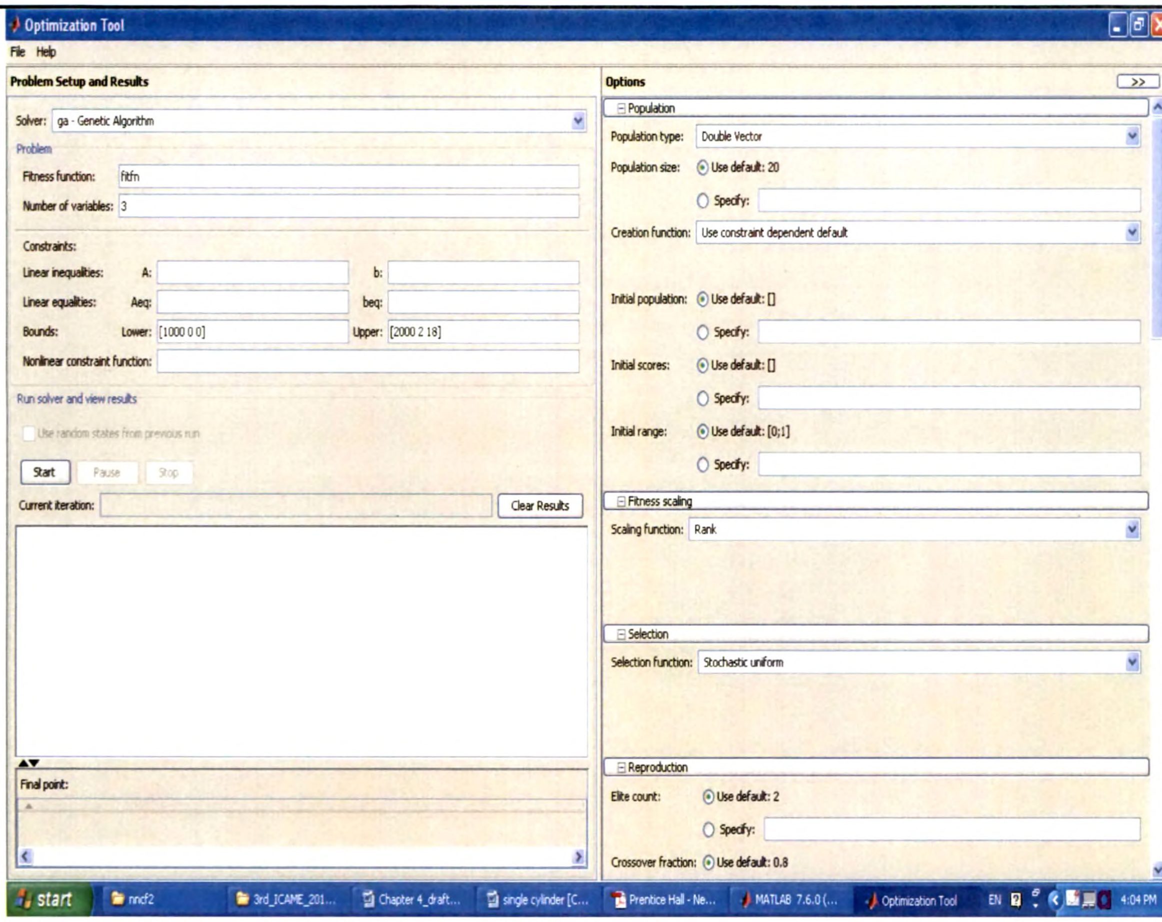


Fig. 4.13 Single Objective Genetic Optimization Editor from MATLAB

3. Record the value of the optimum and the result after a few repeated trials to eliminate the effects of specific initialization.

4.2.1.1 Results and Discussion

Fig. 4-14 shows the variation of fitness value with the generation for single objective optimization of compression ignition engine brake power when it is fuelled by hydrogen diesel blend. It can be noted that the fitness value varies linearly till the generation is about 63 and shows fluctuating trend thereafter till the generation of 100. The minimum optima shown at the generation of 100 indicates the maximum brake power. The program display result which indicates that the maximum brake power is at 2000 rpm and 2 Amp load with the hydrogen induction rate of 18 l/min is shown in Fig. 4.15.

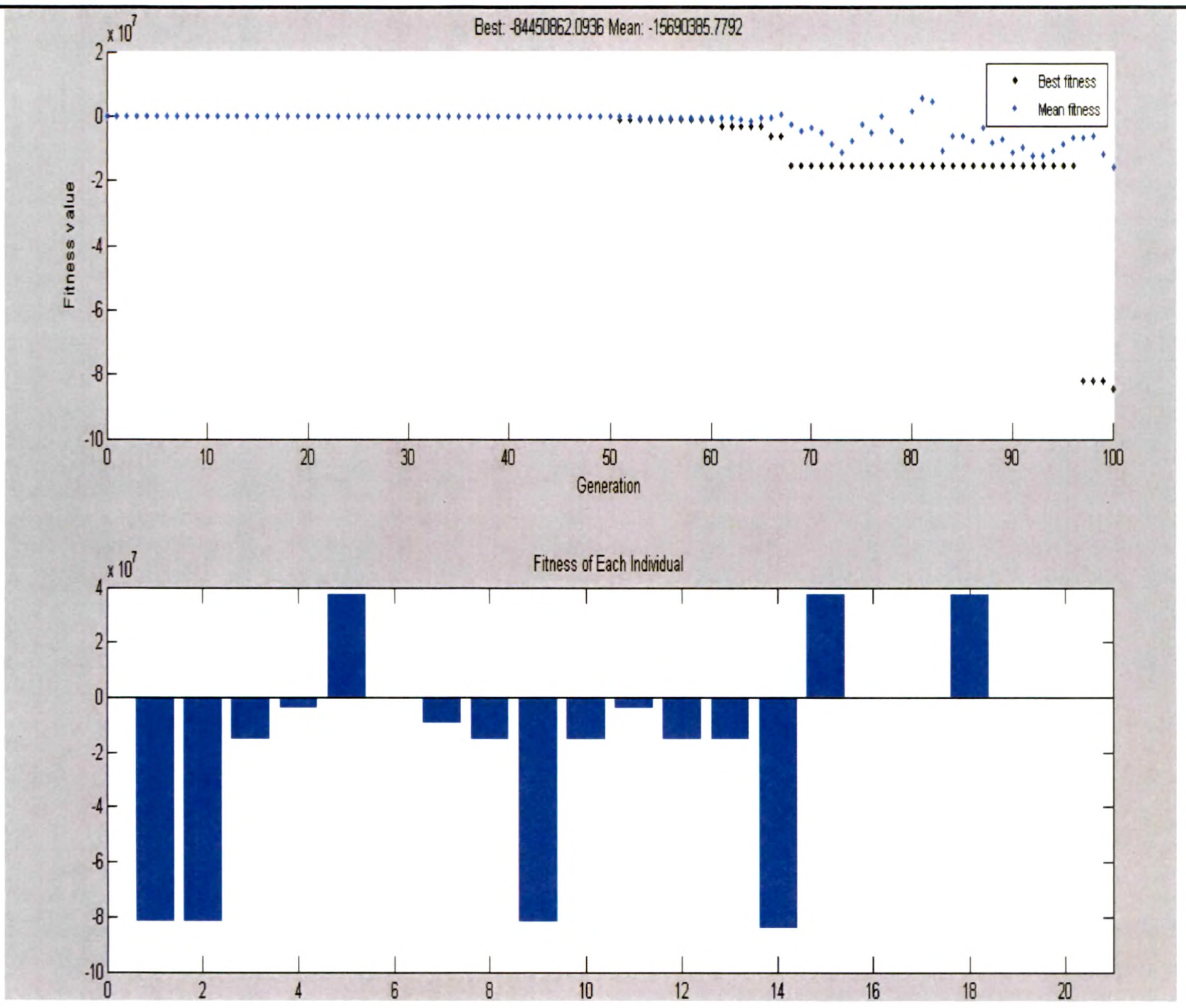


Fig. 4-14 Variation of Fitness Value with Generation Growth for Single Objective Optimization of Brake Power

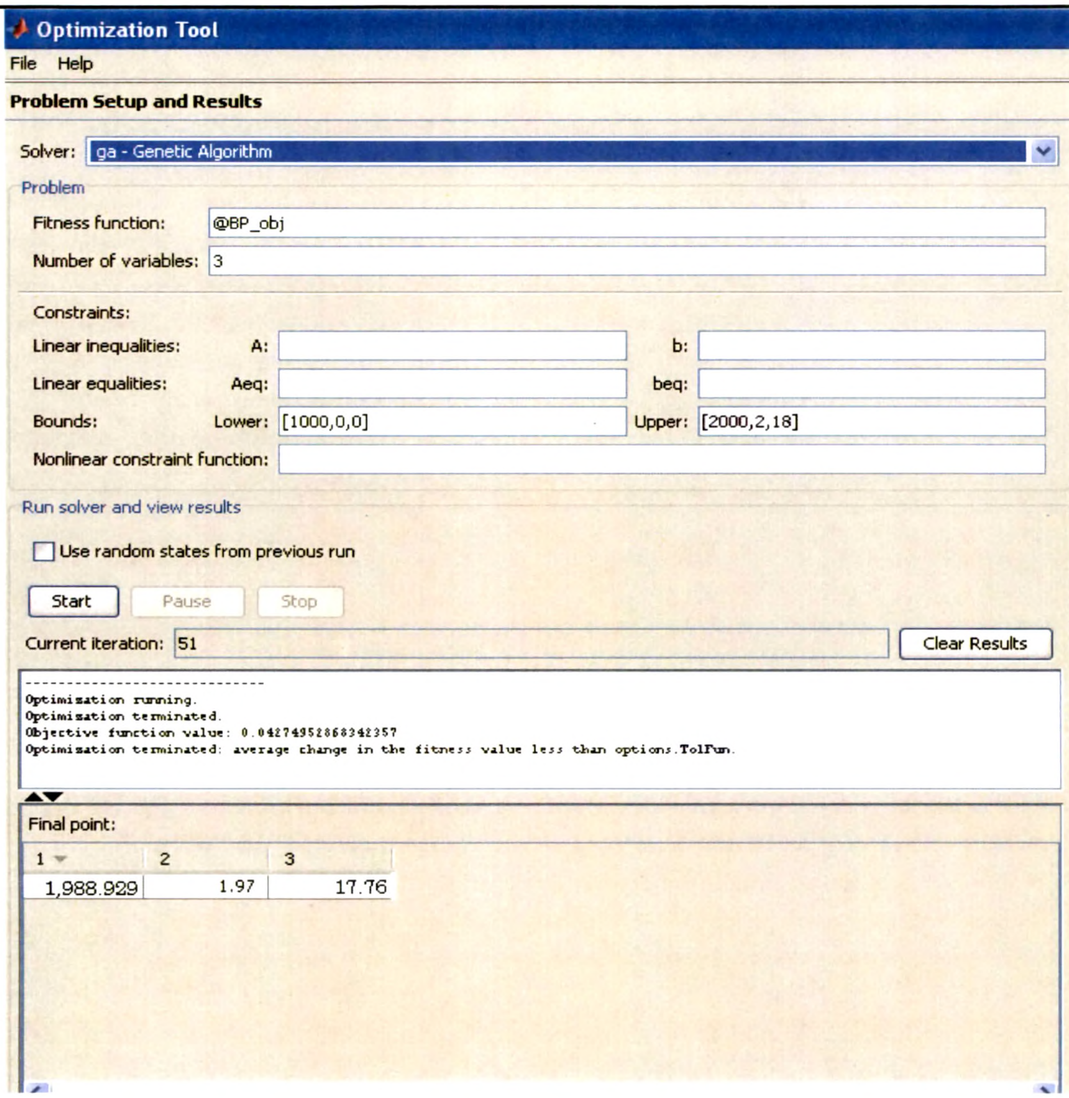


Fig. 4.15 MATLAB Screen to Show Single Objective Optimization of Brake Power

Fig. 4.16 presents the variation of fitness value with the generation for single objective optimization of compression ignition engine in the case of diesel fuel consumption when hydrogen diesel blend is used. The fitness value is found to continuously decrease from a high value of 0.27 at the smallest generation and then damped to reach the optimum value of diesel fuel consumption at about 54 generation with fitness value of about 0.12. Fig. 4.17 gives the corresponding program display result which indicates that the minimum diesel fuel consumption occurs at a speed of1000 rpm, with the load at 0 or 0.5 Amp when the hydrogen induction rate is 18 l/min.

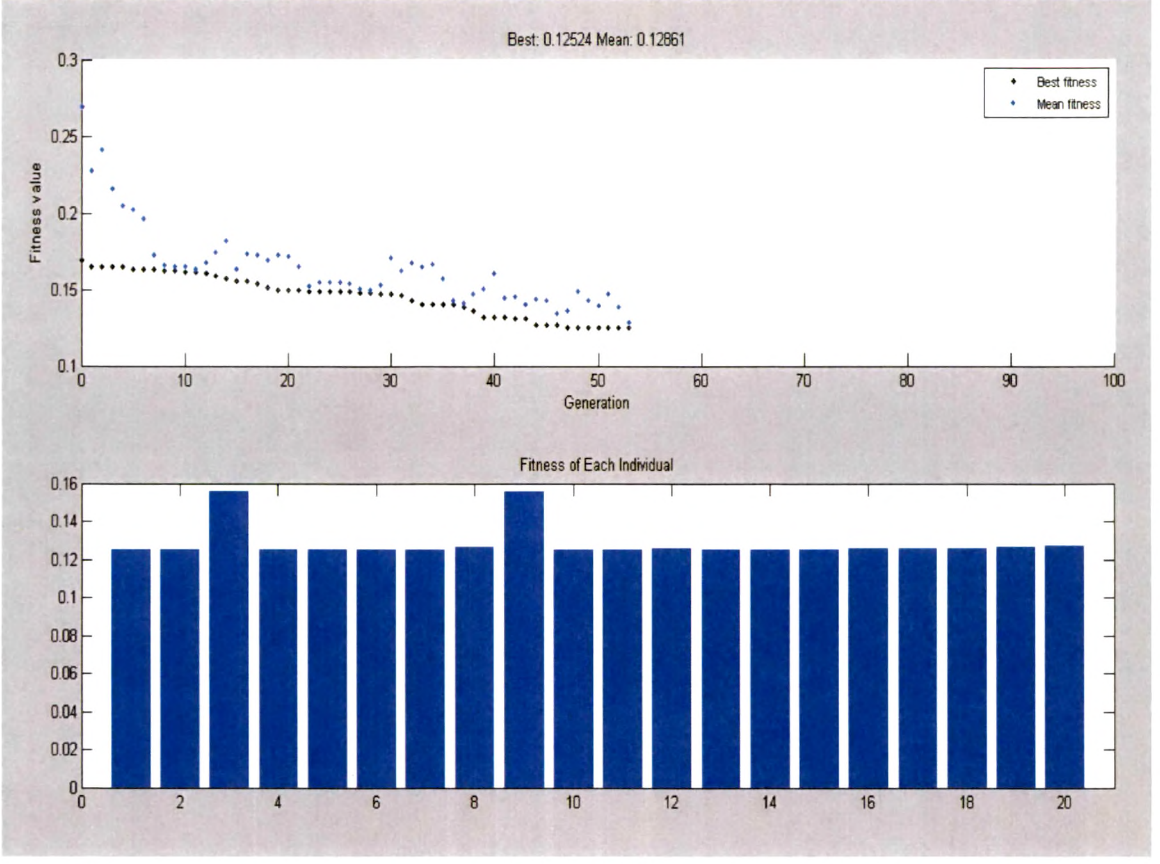


Fig. 4.16 Variation of Fitness Value with Generation Growth for Single Objective Optimization of Diesel Fuel Consumption

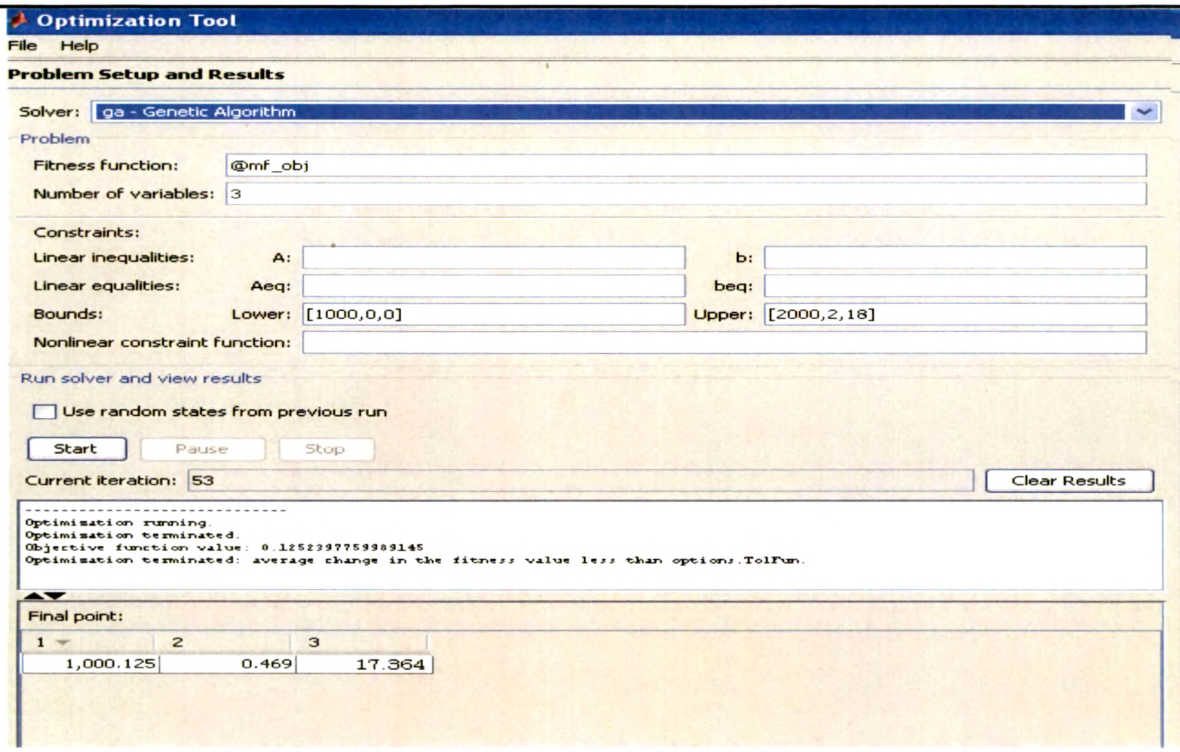


Fig. 4.17 MATLAB Screen to Show Single Objective Optimization of Diesel Fuel Consumption

Similar single objective optimization technique is also employed to find individually the optimal combination of speed, load and hydrogen induction rate needed to minimize each of the exhaust gas emission constituents. Figs. 4.18 to 4.27 show the variation of the fitness value with generation growth and program screen result for each of the constituent gas such as CO, CO_2, HC, SO_2 and NO_X respectively. It can be seen there is a convergent between the results obtained from single object optimization and that from experiment. Further, It can be noted that the fitness value reach to the optimum with generation between 50 and 60 which is relatively not high.

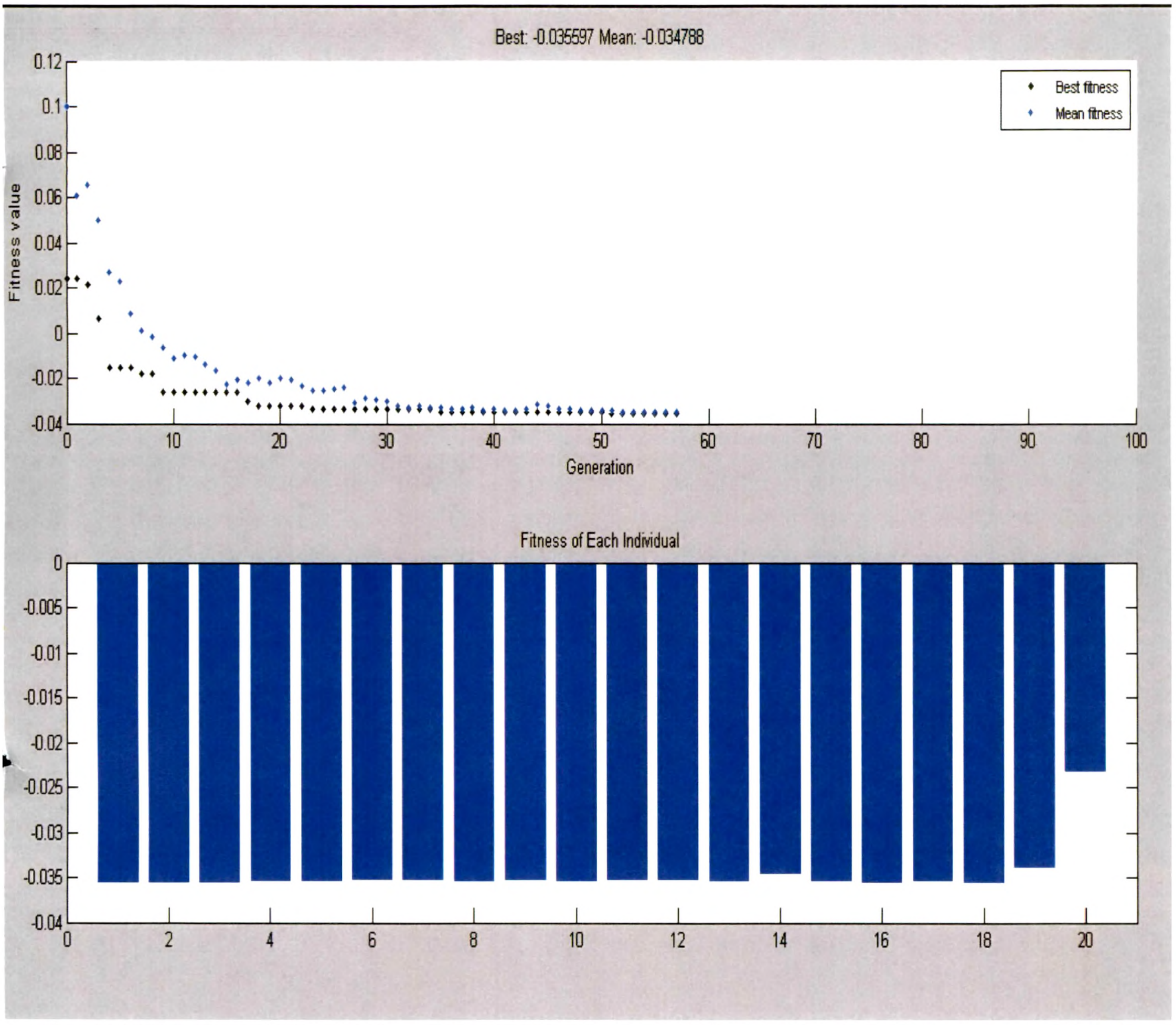


Fig. 4.18 Variation of Fitness Value with Generation Growth for Single Objective Optimization of CO

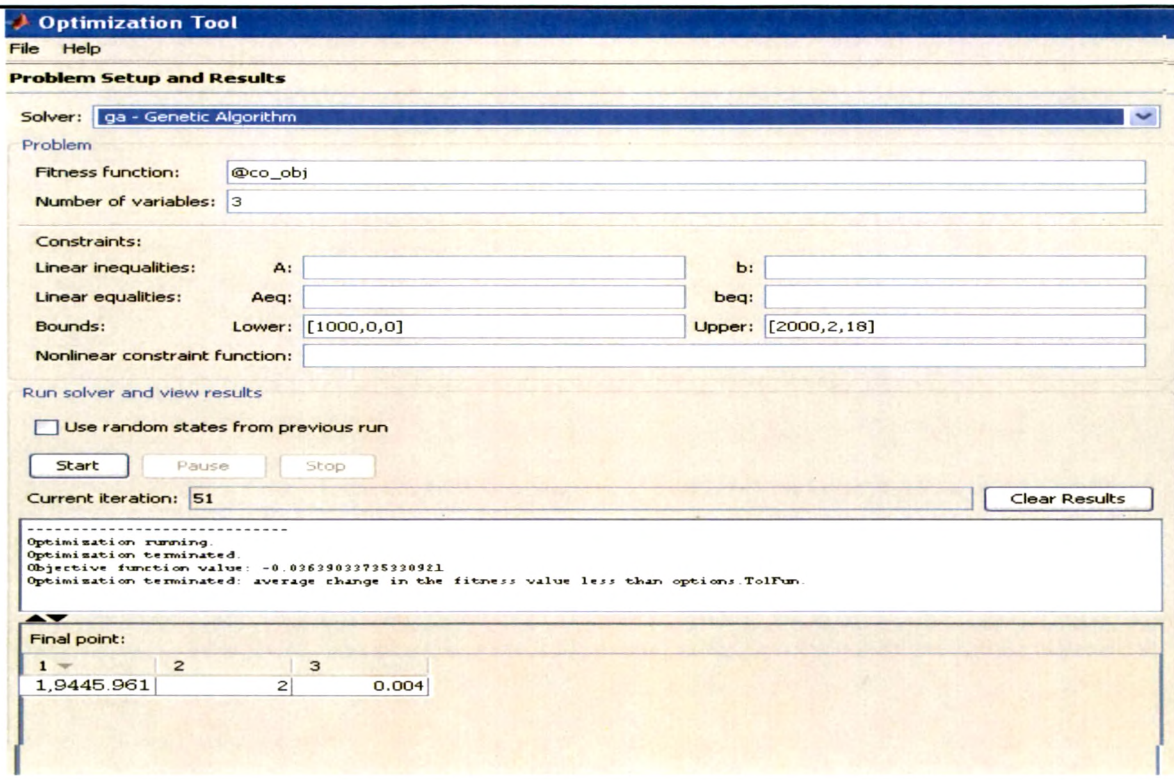


Fig. 4.19 MATLAB Screen to Show Single Objective Optimization of CO

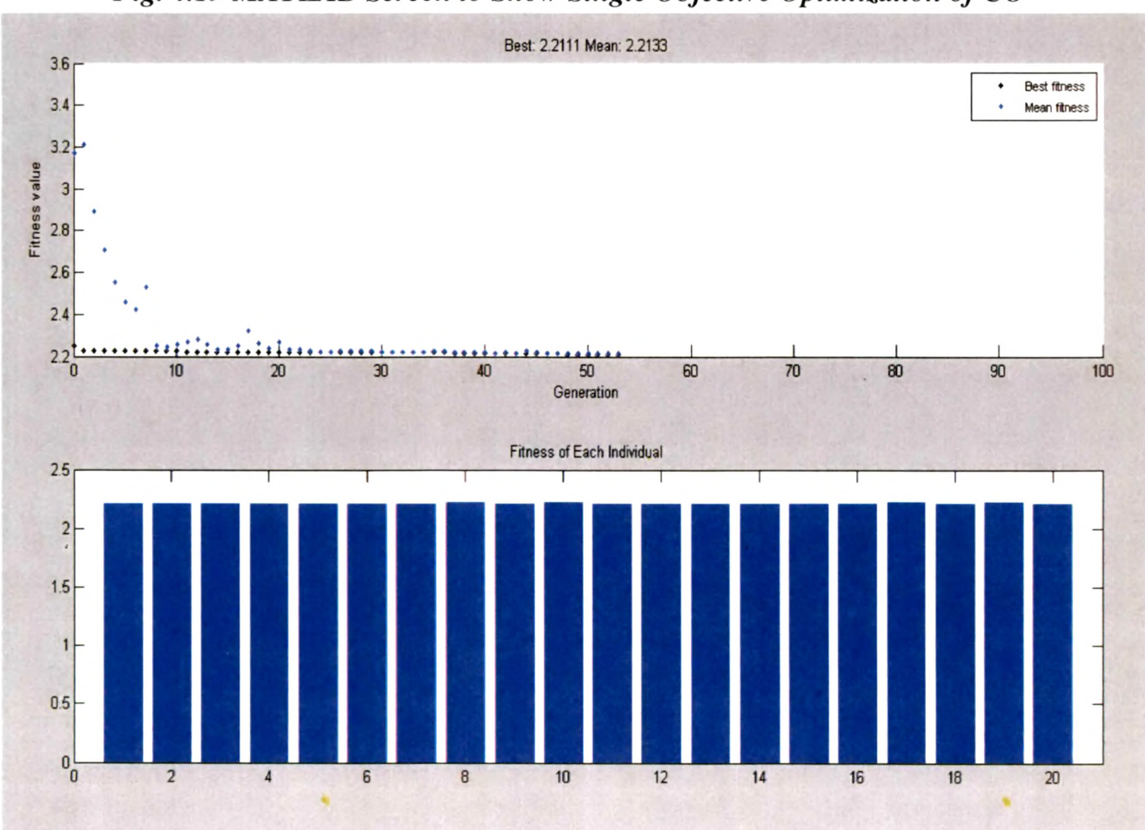


Fig. 4.20 Variation of Fitness Value with Generation Growth for Single Objective Optimization of CO_2

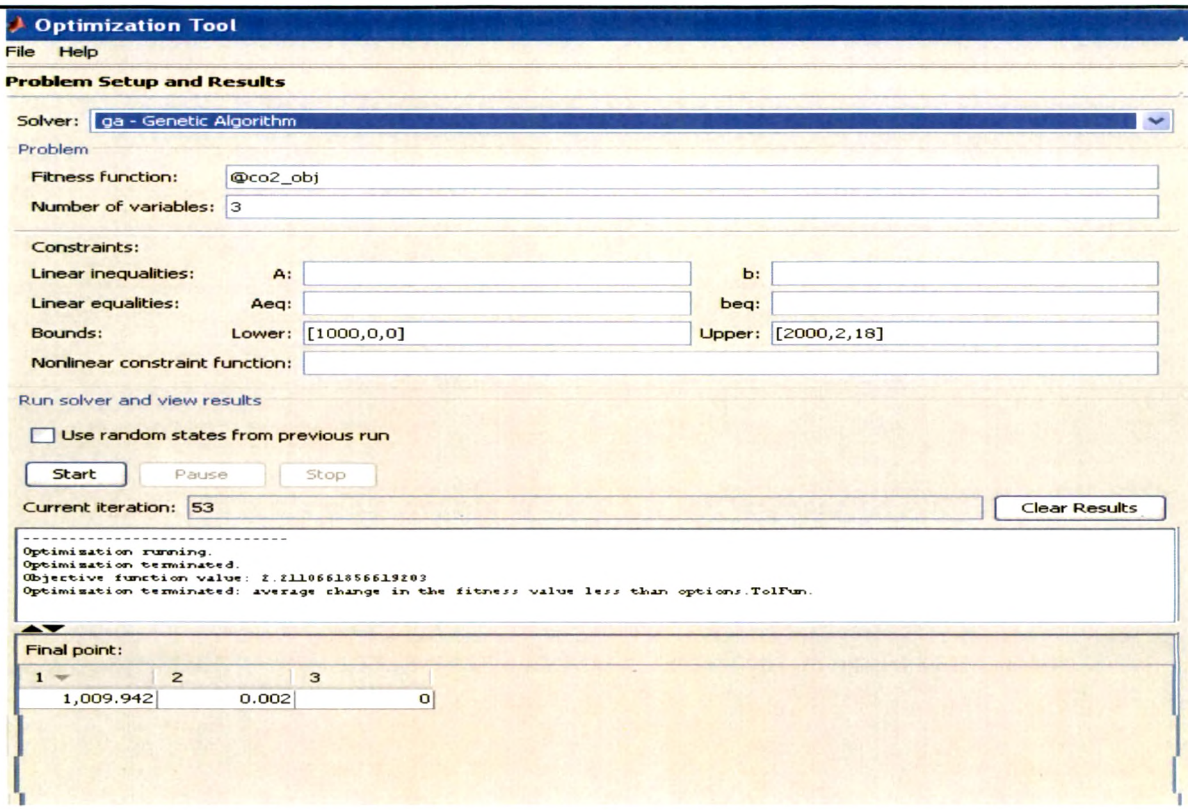


Fig. 4.21 MATLAB Screen to Show Single Objective Optimization of CO_2

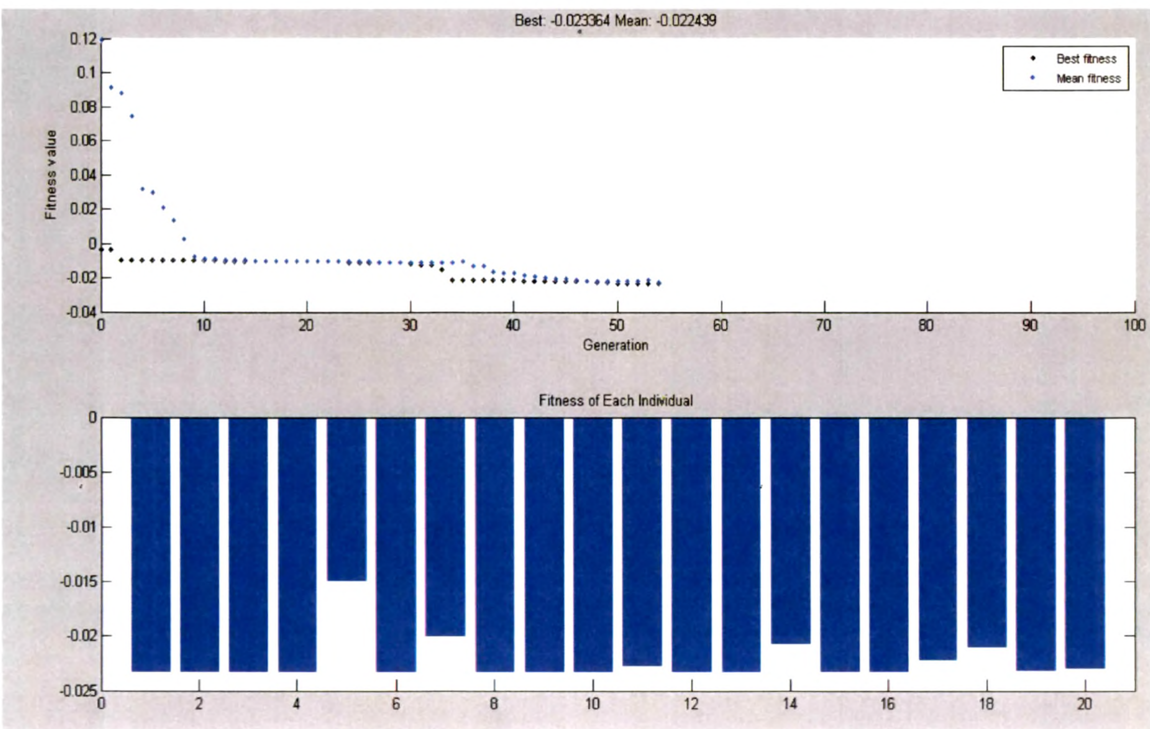


Fig. 4.22 Variation of Fitness Value with Generation Growth for Single Objective Optimization of HC

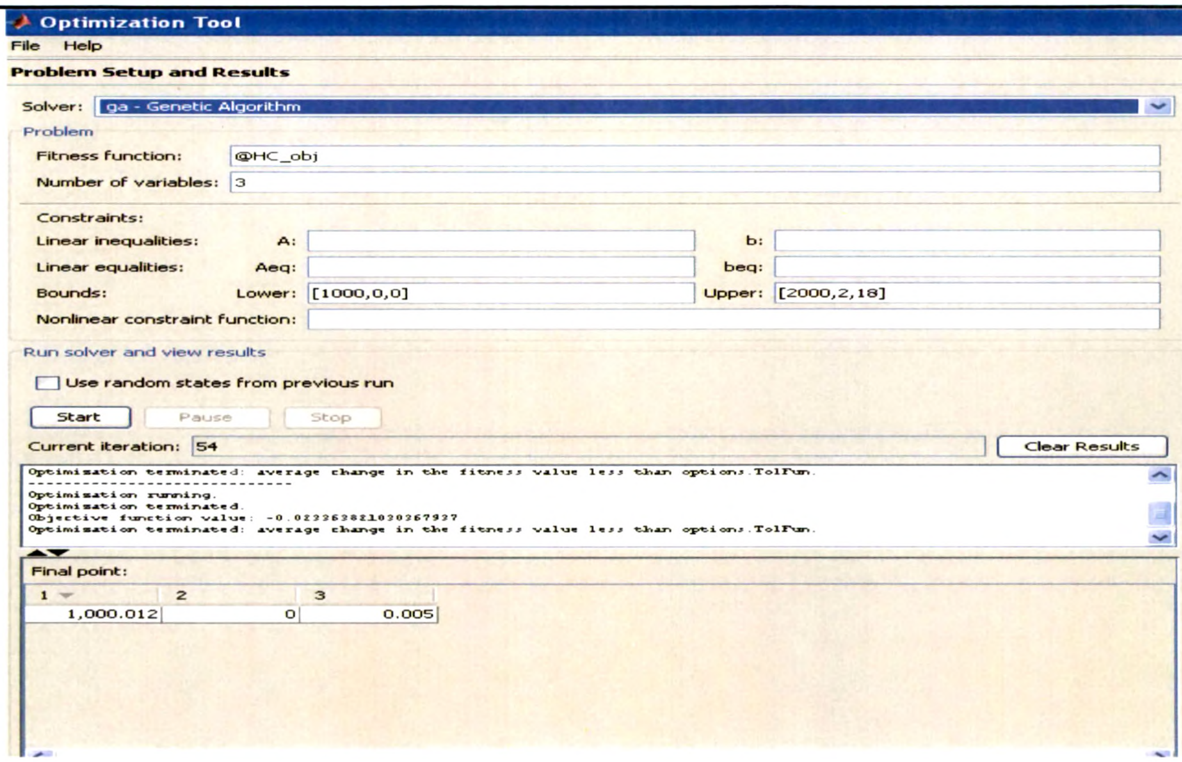


Fig. 4.23 MATLAB Screen to Show Single Objective Optimization HC

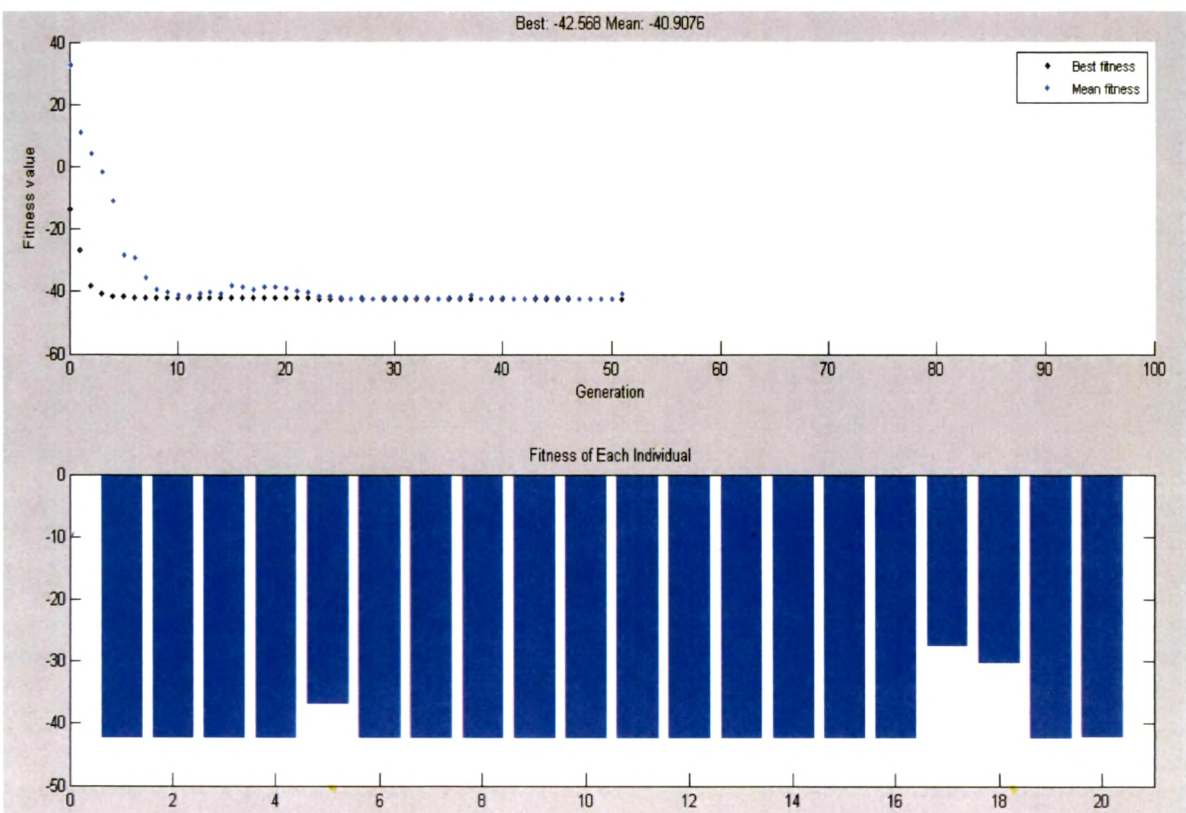


Fig. 4.24 Variation of Fitness Value with Generation Growth for Single Objective Optimization of SO_2

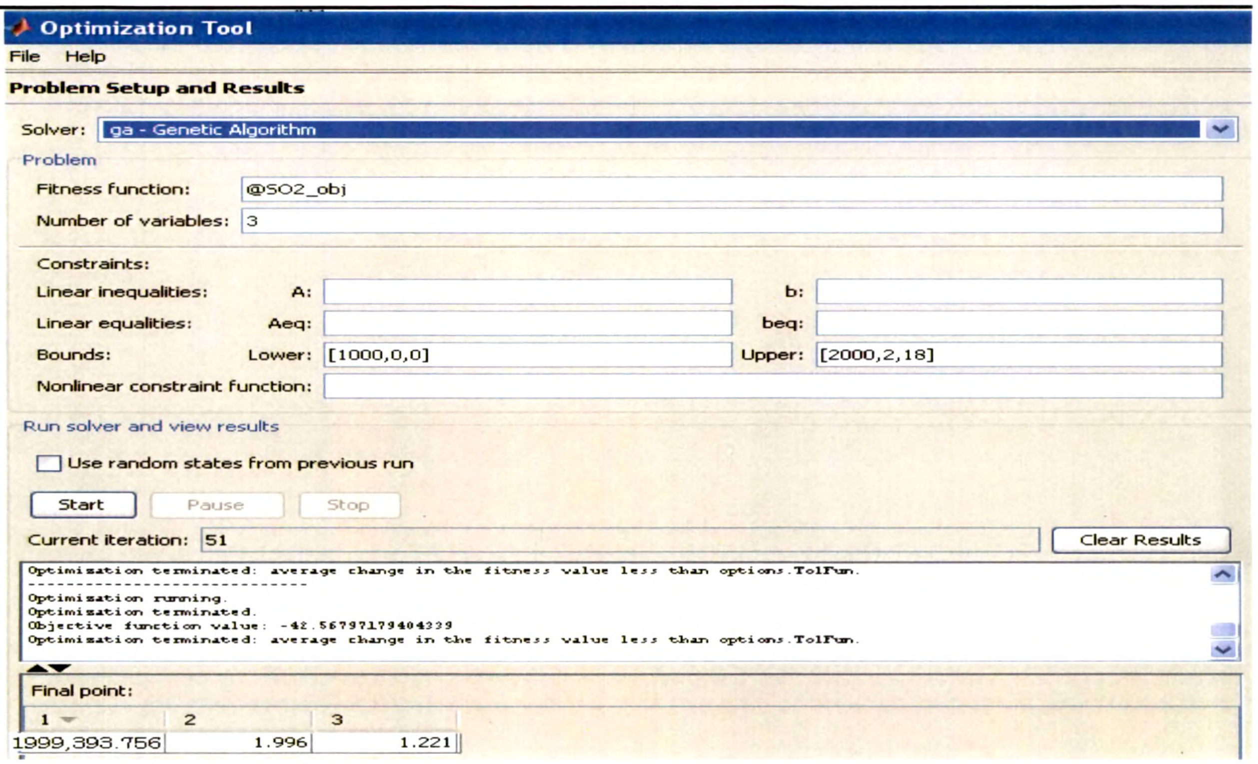


Fig. 4.25 MATLAB Screen to Show Single Objective Optimization of SO_2

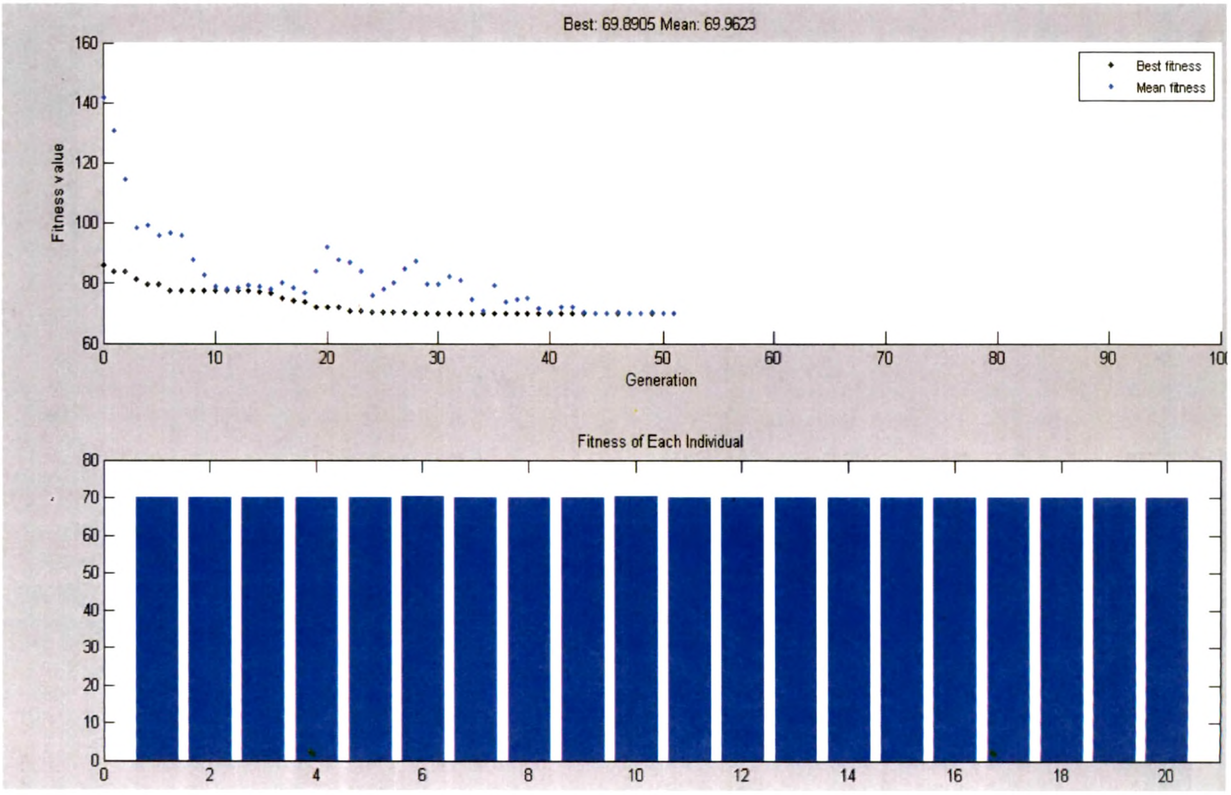


Fig. 4.26 Variation of Fitness Value with Generation Growth for Single Objective Optimization of NO_X

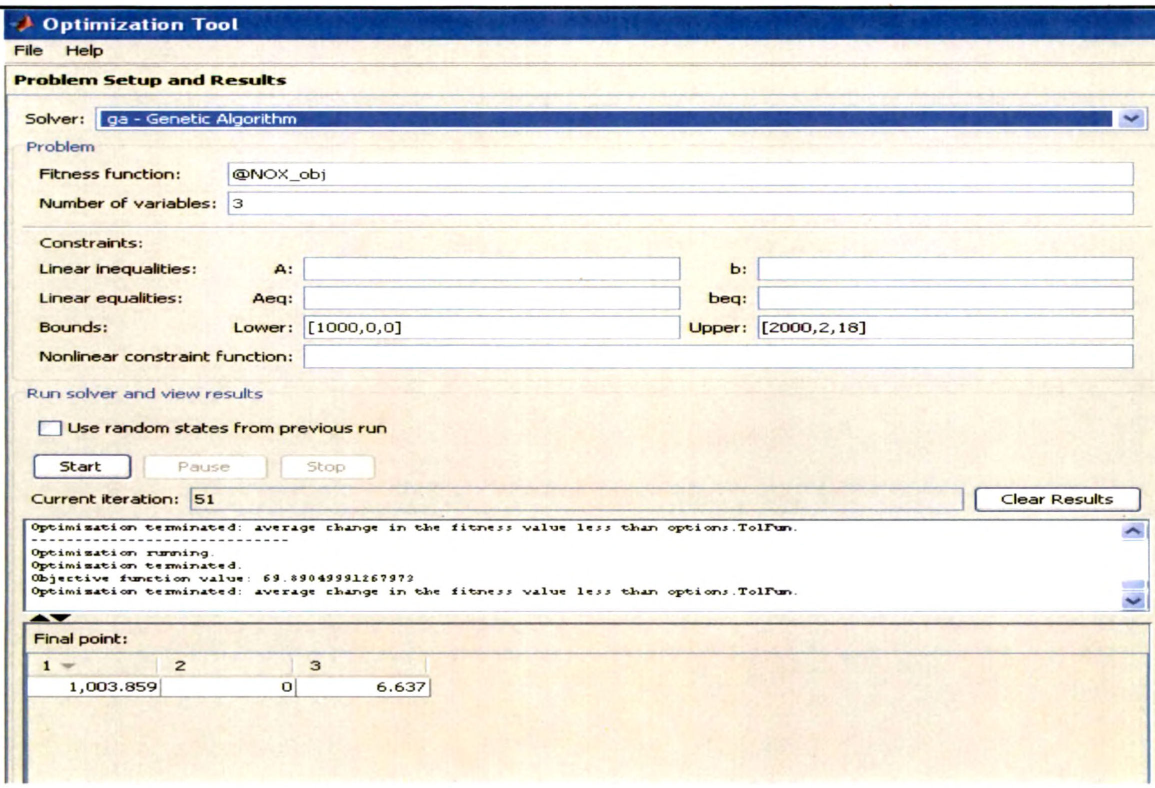


Fig. 4.27 MATLAB Screen to Show Single Objective Optimization of NO_X

Table 4.11 summarizes the results of the single objective optimization applied to minimize exhaust gas emission constituents like CO, CO_2, SO_2, HC, NO_x , and diesel fuel consumption and maximize brake power (minimizing the inverse of brake power is equivalent to maximizing brake power). It is seen that the constituents of exhaust gases such as CO, CO_2, SO_2, and HC are always minimum under no load condition when CI engine operates without hydrogen induction while NO_x emission is minimum when hydrogen induction at the rate of 6.67 l/min along with diesel. However, when the diesel fuel consumption is considered as the minimizing parameter, the optimum is found with diesel blended with hydrogen inducted at the rate of 16.87 l/min. Similarly, the brake power is maximum when the engine is operated at full load of about 2.0 A when the induction rate is 17.3 l/min. From the above observations for the engine running at 1000 rpm, it can be concluded that the optimum thermal performance of the compression ignition engine is possible with diesel blended with a higher rate of hydrogen induction to the tune of 16 to 17 l/min while exhaust gas emission is found to be minimum without hydrogen induction for CO, CO_2, SO_2, and HC. However, minimizing NO_x emission needs hydrogen induction at the rate of about 7 l/min. Single objective optimization, thus helps one to minimise or maximize parameters individually but not collectively.

Table 4.11 Single Objective Optimization for Brake Power, Diesel Fuel Consumption and Gas Emission Constituents

Minimize	Speed	Load	H_2	Remarks
CO	1000	0	0	Least emission at lowest fuel consumption and other minima captured around 7 lpm of Hydrogen induction
CO_2	1000	0	0	
SO_2	1000	0	0	
HC	1000	0	0	
NO_X	1000	0	6.67	
Diesel Consumption	1000	0	16.87	Minimum at lowest speed and load corresponding to maximum hydrogen induction rate
Inverse of Brake Power	1995	1.957	17.3	At highest speed and load with maximum H_2 induction

4.2.2 Multi Objective Optimization

As mentioned earlier, the problem of finding the optimum value of hydrogen induction from the point of view of maximizing brake power and minimizing fuel consumption and proportion of exhaust gas emission constituents poses a multi-objective and multimodal scenario. Therefore, multi objective optimization technique is selected as the optimization tool for the determination of optimum hydrogen induction rate simultaneously taking in to consideration of maximizing thermal performance parameters and minimizing exhaust gas constituents

The procedure for the solution of multi objective optimization problem is as follows:

1- Develop mathematical equation to relate the input and output parameters. Again, the Datafit software developed by Oakdale engineering, USA is used to develop or obtain the mathematical function relating output parameters with the input control variables. Polynomials, exponentials and power functions are evaluated. The selection of best mathematical model fitting the data is made based on minimum error and best value of coefficient of determination (R^2) value for all parameters. Cubic polynomial is found the best on both criterion and for all output parameters. Table 4.12 gives the comparison of the cubic polynomial performance with other models fitted.

Table 4.12 Cubic polynomial error test coefficient in comparison with other function coefficient

Model	Standard error	Residual Sum	Residual Average	RSS	R^2	Ra^2
power three	49.90	5.08773E-06	1.0711E-08	1148335	0.9652	0.9642
Square	57.27	1.06184E-10	2.23544E-13	1525251	0.9537	0.9528
exp(a*x1+b*x2+c*x3+d)	75.93	-3582.495	-7.542095612	2715892	0.9177	0.9171
a*x1+b*x2+c*x3+d	124.94	-4.4337E-12	-9.33429E-15	7353478	0.7771	0.7757
a*x1+b*x2+c*x3	177.16	12229.050	25.74536975	14815220	0.5510	0.5491

The equation thus obtained is defined as a function in MATLAB and saved as a ***.m* file**. This function is called as the fitness function for optimization in MATLAB.

2. Use the multi objective optimization function ***GA*** from the GENETIC OPTIMIZATION and DIRECT SEARCH tool box of MATLAB for defining and solving the problem. Fig. 4.29 shows the single objective optimization problem definition screen.
3. Record the value of the optimum and the result after a few repeated trials to eliminate the effects of specific initialization.

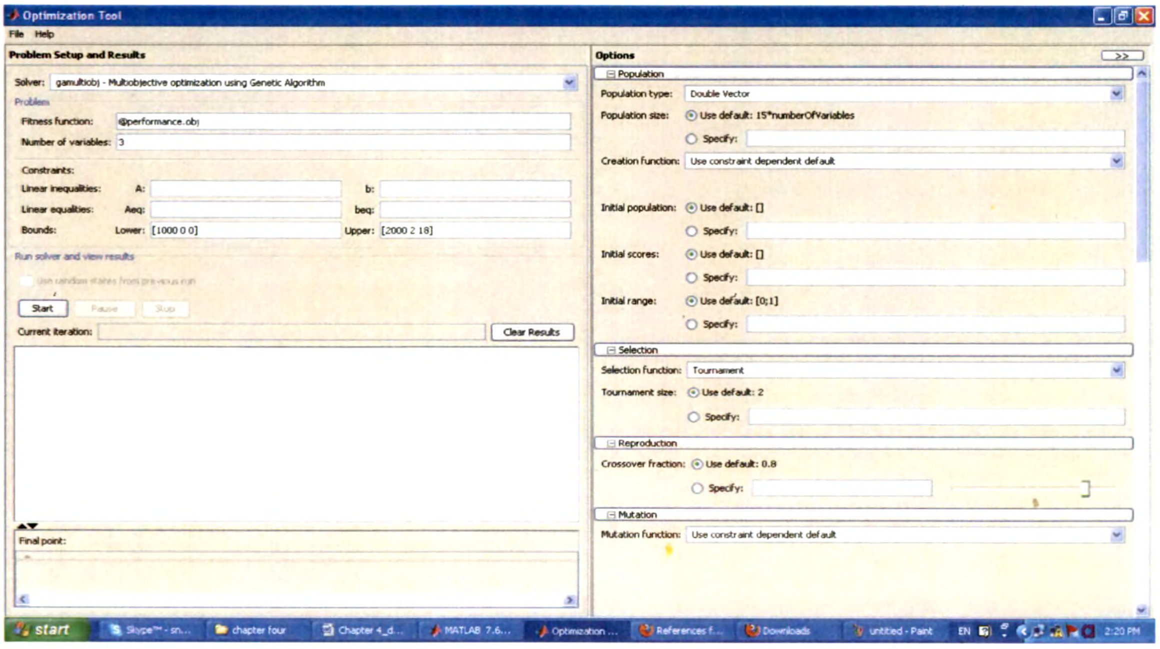


Fig. 4.28 Multi Genetic Editor from MATLAB.

4.2.2.1 Results and Discussion

Fig. 4.29 shows the application of multi objective optimization of thermal performance to find the maximum power with minimum diesel fuel consumption for the compression ignition engine operated by hydrogen-diesel blend. The multi objective genetic algorithm from MATLAB (GAMULTIOBJ) works on a population using a set of operators that are applied to the population. A population is a set of points in the design space. The initial population is generated randomly by default. The next generation of the population is computed using the non-dominated rank and a distance measure of the individuals in the current generation. The scatter of the average distance between individuals with respect to generation is depicted in Fig. 4.29 Brake power and fuel consumption are considered as objective 1 and objective 2 respectively in the *pareto-optimal* solution. The development of *pareto front* by mapping objective 2 with objective 1 is also given in the figure. The mapping depicts how objective 2 (fuel consumption rate) grow to a minimum level at 0.9 to match the maximum of objective 1 (brake power). It is also seen that the average distance between the individuals become closer and the number of generation increases to find the global optima in multi objective case.

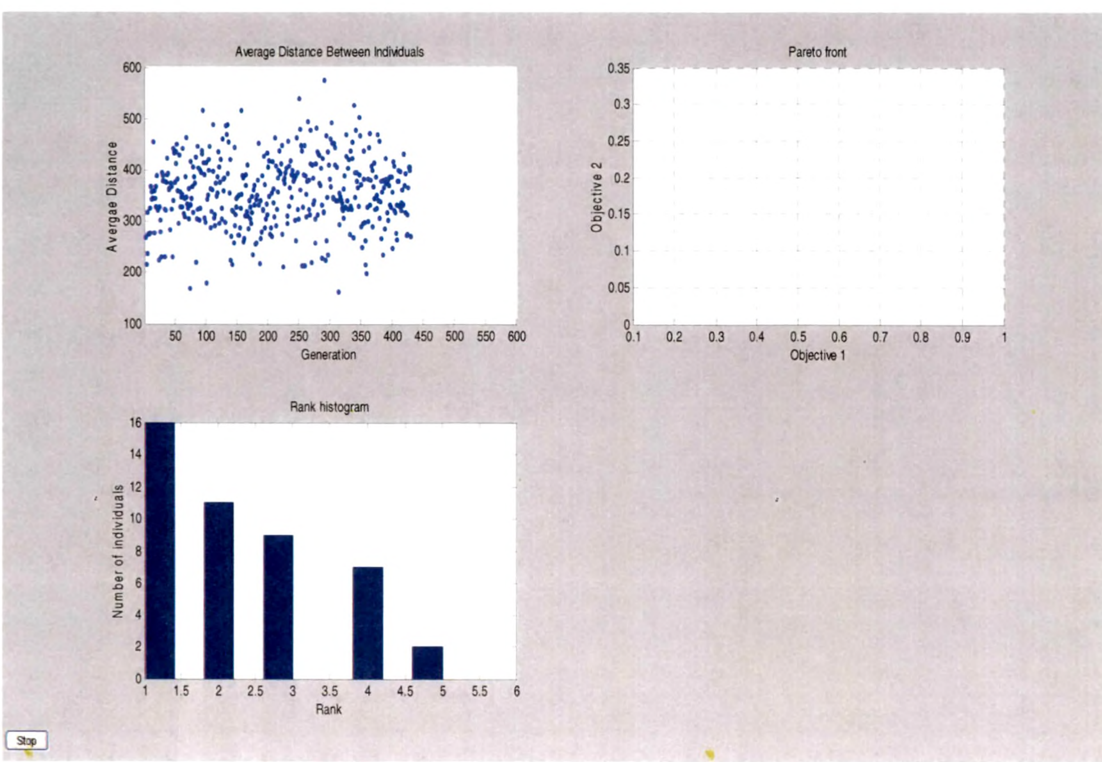
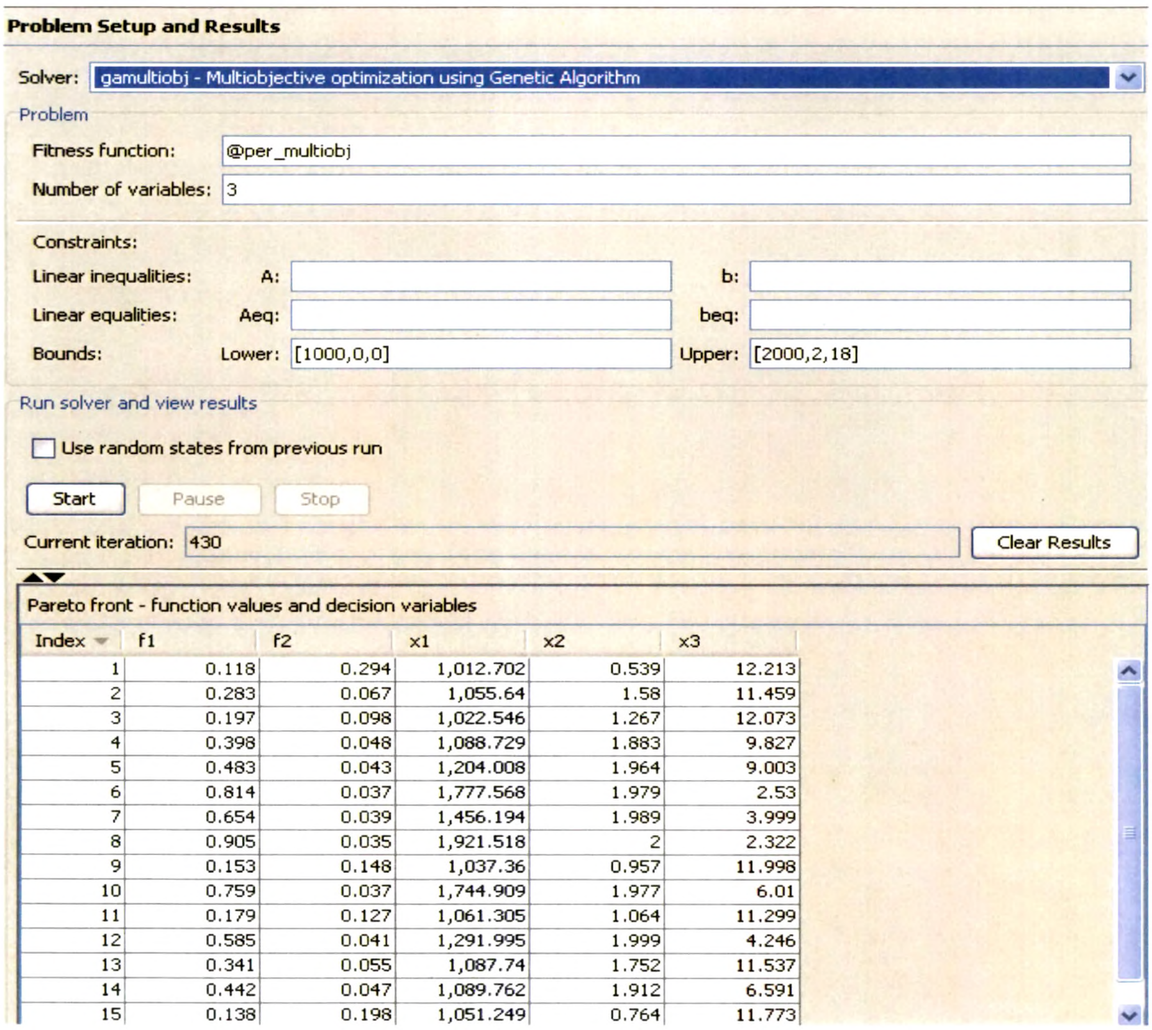


Fig. 4.29 Variation of Pareto Average Distance between Individual Point and Number of Individuals for Brake Power and Diesel Fuel Consumption

Fig. 4.30 shows the display screen of MATLAB program that illustrates a typical result of multi objective optimization of engine performance to find the maximum power and minimum diesel fuel consumption.



Index	f1	f2	x1	x2	x3
1	0.118	0.294	1,012.702	0.539	12.213
2	0.283	0.067	1,055.64	1.58	11.459
3	0.197	0.098	1,022.546	1.267	12.073
4	0.398	0.048	1,088.729	1.883	9.827
5	0.483	0.043	1,204.008	1.964	9.003
6	0.814	0.037	1,777.568	1.979	2.53
7	0.654	0.039	1,456.194	1.989	3.999
8	0.905	0.035	1,921.518	2	2.322
9	0.153	0.148	1,037.36	0.957	11.998
10	0.759	0.037	1,744.909	1.977	6.01
11	0.179	0.127	1,061.305	1.064	11.299
12	0.585	0.041	1,291.995	1.999	4.246
13	0.341	0.055	1,087.74	1.752	11.537
14	0.442	0.047	1,089.762	1.912	6.591
15	0.138	0.198	1,051.249	0.764	11.773

Fig. 4.30 Display Screen of MATLAB Program for Multi Objective Optimization of Maximum Brake Power and Minimum Diesel Fuel Consumption

Similar scheme can also be employed for determining the speed, power and hydrogen induction rate for the minimization of exhaust gas constituents.

Fig. 4.30 gives the variation of *pareto* average distance between individual points and number of individuals for maximum power, minimum diesel fuel consumption and minimum gas emission constituents using multi objective optimization technique. The trends to go for minimum level indicate that the program helps to find the optima values from different generation which have closed average distance. Fig. 4.32 shows the screen display of program for multi objective optimization in which the name of file and the specification of program run are indicated. It should be noted that the program handles a large number of data and thus unable to depict on the screen the *pareto- front* function values and decision variables.

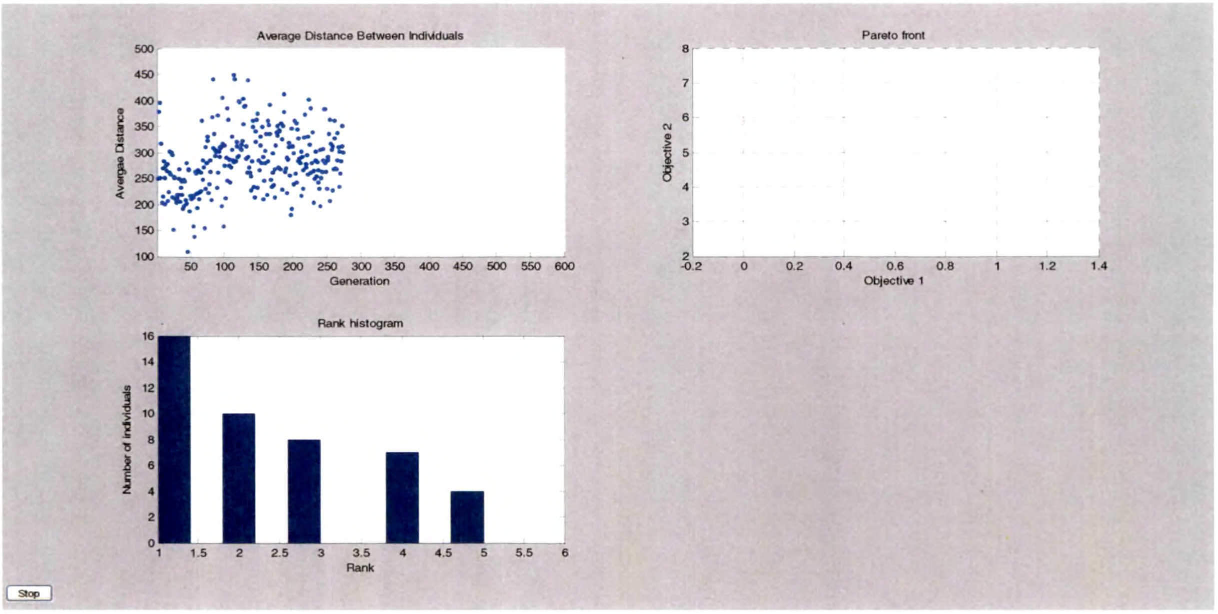


Fig. 4.31 Variation of Pareto Average Distance between Individual Point and Number of Individuals for Brake Power, Diesel Fuel Consumption and Gas Emission Constituents

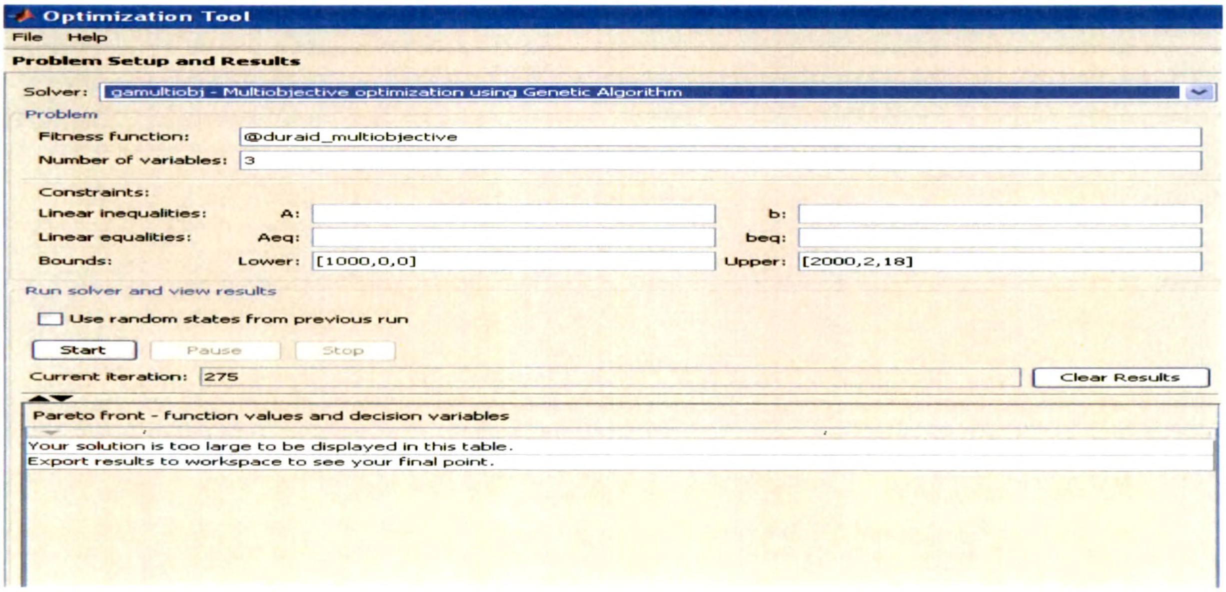


Fig. 4.32 Display Screen of MATLAB Program for Multi Objective Optimization of Maximum Brake Power and Minimum Diesel Fuel Consumption and Gas Emission Constituents

Table 4.13 gives few combinations of the results of the engine performance and exhaust gas emission constituents optimization through multi objective optimization method. It is seen that the hydrogen induction in to a compression ignition engine along with diesel oil helps not only improvement in thermal performance but decreases pollutant emission gases. Hydrogen induction rate of 7 l/min in to the engine with diesel oil as primary fuel minimises the exhaust gaseous pollutants such as CO, CO_2, SO_2, HC and NO_x giving equal weightage to each of them.

Table 4.13 Multi Objective Optimization for Thermal Performance and Gas Emission Constituents

Minimize	Speed	Load	H_2	Remarks
Emissions Y= Sum of CO + CO_2 + SO_2 + HC + NO_X considering equal weightage to each constituent	1000	0	6.67	Least emission at lowest fuel consumption and other minima captured around 7 l/min of Hydrogen induction
Diesel Consumption + Inverse of Brake Power (thermal performance maximization with equal weightage to fuel & power)	1500	0.5	6	At rated speed the fuel consumption is found minimum at 6 l/min without too much compromise on brake power
Minimize Emissions & Maximize thermal performance considering 40% weightage to emissions, 30% to brake power and 30% to fuel consumption	1000	0.5	8	Minimum speed low load and 8 l/min hydrogen induction for low emission.
Minimize Emissions & Maximize thermal performance considering 30% weightage to emissions, 20% to brake power and 50% to fuel consumption	1990	1.94	8	Highest weightage to power and less weightage to fuel consumption leads to higher speeds being favorable.

The thermal performance alone by considering the minimisation of diesel oil consumption and maximization of brake power on equal weightage basis shows that the hydrogen induction rate of 6 l/min in to the engine operated on diesel oil is the best option.

The combined optimum operation considering 40 % weightage to lower emissions and 60 % weightage to thermal performance with equal weightage to both brake power and diesel oil consumption is possible at lower speed and load with a hydrogen induction rate of 8 l/min. Full load operation of the

engine giving less weightage to gas emissions (30%) and more to thermal performance (50% to fuel consumption and 20% to brake power) demands higher speeds with 8 l/min hydrogen induction. In short, the operation of a compression ignition engine with diesel oil as primary fuel when blended with hydrogen by inducting in to the intake manifold at the rate of 6 – 8 l/min results in the optimum operation considering both thermal performance and exhaust gas emission constituents. The results of the optimization through GA agree well with the present experimental evidence and that of Saravanan et al. [52]. It should , however, be noted that Saravanan primarly used the technique of exhaust gas recirculation along with the hydrogen induction in the intake manifold and suggested an optimum hydrogen induction rate of 7 l/min.