Chapter 5

Computational Study

The computational study conducted consists of optimization of thermal performance and emissions constituents and ANN modeling of the variable compression ratio diesel engine. The optimization conducted using genetic algorithm technique is explained in Section 5.1 and ANN in Section 5.2.

Data obtained from experiments needs 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 essential.

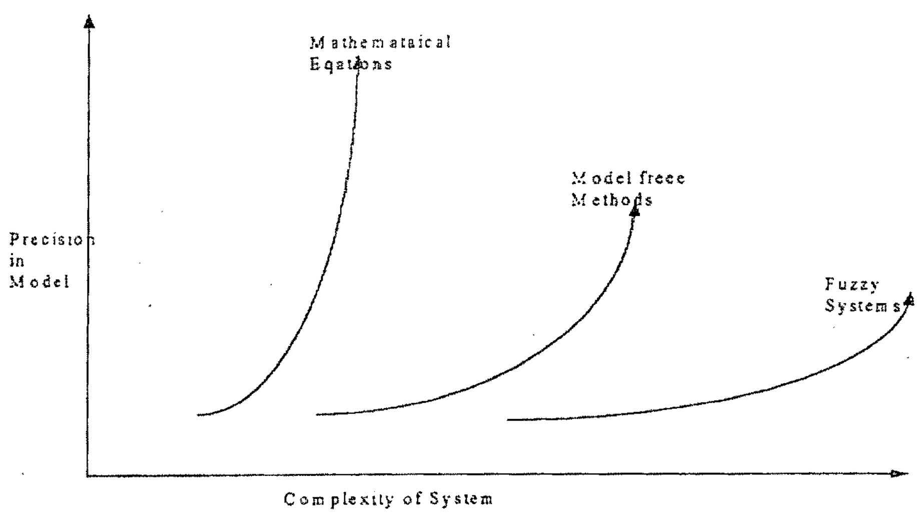

Figure 5.1 Complexity of System & Precision Level of Different Models

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 Figure 5.1, for systems that are little complex and hence little uncertain, closed form of mathematical models provide precise description of system. For systems little more complex but for which significant data is available, model free methods like ANNs 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 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 ANN modeling which 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. Artificial Intelligence (AI) techniques seem to be best solution for predicting engine emissions since they do not demand any additional sensor installation.

When mathematical models fail to capture the input/output relationship within the limits of permissible error and sufficient data regarding the system available, ANN 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.

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.

5.1 Multi-objective Optimization

Optimization is the task of finding one or more solutions which correspond to minimizing (or maximizing) one or more specified objectives and which satisfy all constraints (if any). A single-objective optimization problem involves a single objective function and usually results in a single solution, called an optimal solution. On the other hand, a multi-objective optimization task considers several conflicting objectives simultaneously. In such a case, there is usually no single optimal solution, but a set of alternatives with different trade-offs. Despite the existence of multiple optimal solutions, in practice, usually only one of these solutions is to be chosen. Thus, compared to single objective optimization problems, in multi-objective optimization, there are at least two equally important tasks: an optimization task for finding an optimal solution (involving a computer based procedure) and a decision making task for choosing a single most preferred solution. The latter typically necessitates preference information from a decision maker.

IC engines are the lightest power generating units known and therefore are of greatest applications in transportation. An engine is expected to give highest possible efficiency with least possible emissions in order to meet the environmental standards. Generally, it is observed that engine gives maximum efficiency and also maximum emissions at high loads. This creates a scenario wherein, to get maximum efficiency we must compromise on emissions or to get minimum emissions we must compromise on efficiency. This is a case of Optimization to strike an optimal combination of input parameters to achieve maximization of thermal performance and minimization of emission constituents.

The results obtained in the experimental study conducted at different preset compression ratios, different loads and different injection pressures show that as thermal efficiency of the engine increases, the harmful emissions constituents also increase. Hence, it is difficult to get the accurate minimum possible values of harmful emissions and maximum possible value of thermal efficiency. Hence an optimization is performed to obtain optimum values of load, compression ratio, injection pressure and blend which give minimum possible emissions and maximum possible thermal efficiency i.e. optimise thermal performance and emission constituents.

There are several algorithms which can be used to solve an optimization problem. The usage of these algorithms depends on the type of the problem, environment and the results required in real life situation. For engine applications, use of genetic algorithm (Refer Appendix VIII) is considered one of the best ways to solve the problem because of its inherent uniqueness. The optimization using genetic algorithm toolbox in MATLAB software is carried out to optimize the chosen engine input parameters to achieve specified priorities.

The genetic algorithm toolbox makes use of the correlations obtained by performing nonlinear regression analysis on the experimental data for all Karanja biodiesel and diesel blends at all loads, compression ratios and injection pressures. DATAFIT software which is developed by Oakdale engineering, USA is used to obtain the correlations.

The correlations evaluated are,

Square: $Y= A(x_1) + B(x_2) + C(x_3) + D(x_1)^2 + E(x_2)^2 + F(x_3)^2 + G(x_1)(x_2) + H(x_2)(x_3) + I(x_3)(x_1)$

Cubic: $Y= A(x_1) + B(x_2) + C(x_3) + D(x_4) + E(x_1)^2 + F(x_2)^2 + G(x_3)^2 + H(x_4)^2 + I(x_1)(x_2) + J(x_2)(x_3) + K(x_3)(x_4) + L(x_3)(x_4) + M(x_1)^3 + N(x_2)^3 + O(x_3)^3 + P(x_4)^3$

Exponential: $Y= e^{[A(X_1) + B(X_2) + C(X_3) + D]}$

Linear with Constant: $Y= A(x_1) + B(x_2) + C(x_3) + D$

The optimization process is carried out after fixing the upper and lower bounds for constraints, defining the fitness function and number of variables. The constraints are load, blend, compression ratio and injection pressure. The optimization is carried out considering full load condition and hence, both upper and lower bounds for loads are 12kg. The upper and lower bounds for the constraints are given in Table 5.1. The correlations obtained by nonlinear regression analysis of the experimental data are used as fitness functions and the number of variables are given as '4' viz. load, compression ratio, injection pressure, blend proportionand are varied during experimentation.

Table 5.1 Upper and Lower Bounds for Constraints

Constraints	Upper bound	Lower bound
Load (kg)	12	12
Compression Ratio	14	18
Injection Pressure (bar)	150	250
Blend	20	100

The Optimization is conducted considering three cases, namely

1. Thermal performance
2. Emission constituents
3. Both thermal performance and emission constituents together with equal weightages to each

The optimization of thermal performance, emission constituents and both thermal performance & emission constituents together giving equal weightages to each are, respectively, explained in sections 5.1.1, 5.1.2 and 5.1.3

5.1.1 Thermal Performance

The optimization of thermal performance is conducted by considering three important parameters viz. BTHE, BSFC and EGT. BTHE is always preferred to be maximum, BSFC and EGT to be minimum. Hence, this creates a multimodal scenario of optimization.

The solution procedure for optimization of thermal performance is as follows:

1. Three types of mathematical equations viz. Polynomials, exponentials and power functions are developed from the captured experimental data (Refer Appendix V) to form a relation between the input (Load, CR, IP, Blend) and output (BTHE, BSFC and EGT) parameters using the DATAFIT software which is developed by Oakdale engineering, USA.
2. The mathematical equation with best fit is selected based on best value of coefficient of determination (R^2) for all parameters. Cubic polynomial is found to be the best fit on both criterion and for all output parameters. Table 5.2 shows the cubic polynomials for thermal performance parameters, with their respective R^2 values.

Table 5.2 Polynomials for Thermal Performance Parameters with their Respective R^2 Values

Parameter	Polynomial	R^2
BTHE	$BTHE = -541317.7 - 3.34E\text{-}02\,(x_1) - 0.413\,(x_2) + 8480.6\,(x_3) - 5.03E\text{-}05\,(x_4) + 2.616E\text{-}03\,(x_1)^2 + 2.45E\text{-}02\,(x_2)^2 - 43.3\,(x_3)^2 + 2.27E\text{-}06\,(x_4)^2 + 3.39E\text{-}04\,(x_1)(x_2) + 4.14E\text{-}06\,(x_2)(x_3) - 2.26E\text{-}02\,(x_3)(x_4) + 2.26E\text{-}02\,(x_4)(x_1) - 8.46E\text{-}05\,(x_1)^3 - 4.89E\text{-}04\,(x_2)^3 + 7.21E\text{-}02\,(x_3)^3 - 1.026E\text{-}08\,(x_4)^3$	0.9408
BSFC	$BSFC = -541296.66 - 0.29(x_1) - 3.99(x_2) + 8480.68(x_3) - 8.84E\text{-}04(x_4) + 0.02(x_1)^2 + 0.23(x_2)^2 - 43.3(x_3)^2 + 2.77E\text{-}05(x_4)^2 + 3.02E\text{-}03(x_1)(x_2) - 3.4E\text{-}08(x_2)(x_3) + 0.03(x_3)(x_4) - 3.13E\text{-}02(x_3)(x_4) - 7.51E\text{-}04(x_1)^3 - 4.71E\text{-}03(x_2)^3 + 7.21E\text{-}02(x_3)^3 - 1.44E\text{-}07(x_4)^3$	0.9245
EGT	$EGT = -531591.25 + 13.7(x_1) - 1831.77(x_2) + 8487.49(x_3) + 0.24(x_4) - 6.27E\text{-}03(x_1)^2 + 111.28(x_2)^2 - 43.33(x_3)^2 - 7.98E\text{-}03(x_4)^2 - 0.16(x_1)(x_2) - 2.43E\text{-}06(x_2)(x_3) - 5.34E\text{-}03(x_3)(x_4) + 5.34E\text{-}03(x_4)(x_1) + 3.29E\text{-}02(x_1)^3 - 2.25(x_2)^3 + 7.22E\text{-}02(x_3)^3 + 6.45E\text{-}05(x_4)^3$	0.9723
x_1= Load, x_2= CR, x_3= IP, x_4= Blend		

3. The equations thus obtained are defined as a function in MATLAB and saved as a dot m (.m) file. This function is called as the fitness function for optimization in MATLAB. The GENETIC ALGORITHM tool box of MATLAB is used for defining and solving the problem. Figure 5.2 shows optimization problem definition screen.
4. Record the value of the optimum and the result after a few repeated trials to eliminate the effects of specific initialisation.

The problem definition screen is shown in Figure 5.2, while Figure 5.3 shows display screen of MATLAB program after optimization of thermal performance is carried out. The problem definition screen is where the solver, fitness function and bounds are defined. The optimization is carried out considering full load condition and hence, both upper and lower bounds for loads are 12kg. The set bounds for the constraints are given in Table 5.1. The same are entered in the order of 'Load, CR, IP, Blend' in the software. The options column on the left hand side is used to select pareto front display. The optimization is carried out by clicking the START button. After the optimization is done, number of iterations is displayed in the current iteration box.The the function values are also displayed suitably.

Figure 5.4 shows pareto front for optimization of thermal performance parameters to find maximum BTHE with minimum BSFC and EGT for the diesel engine operating on different Karanja biodiesel and diesel blends at different CRs, IPs and full load. Pareto front shows the trade-off between the two objectives. The objectives are the functions which the software forms inherently based on the maximising and minimising parameters given. Objective 1 is minimisation of BSFC and EGT and objective 2 is the maximisation of BTHE. The pareto front is plotted in objective function space. It gives a set of points corresponding to different values of objective 1 and objective 2. The software uses pareto front to strike a balance between objective 1 and objective 2 and picks up a point to suggest the optimum values of input parameters such as CR, IP and blend. The points appear to lie in the range -3472.3 to -3472.25 and -3800 to -3850 for objective 1 and objective 2 respectively. The values of objective 1 and objective 2 are used to determine the optimum input parameters by the software by following a set of complex calculations. The optimum values of CR, IP and blend suggested by the software after carrying the optimization run are 17, 228 bar, B70 respectively.

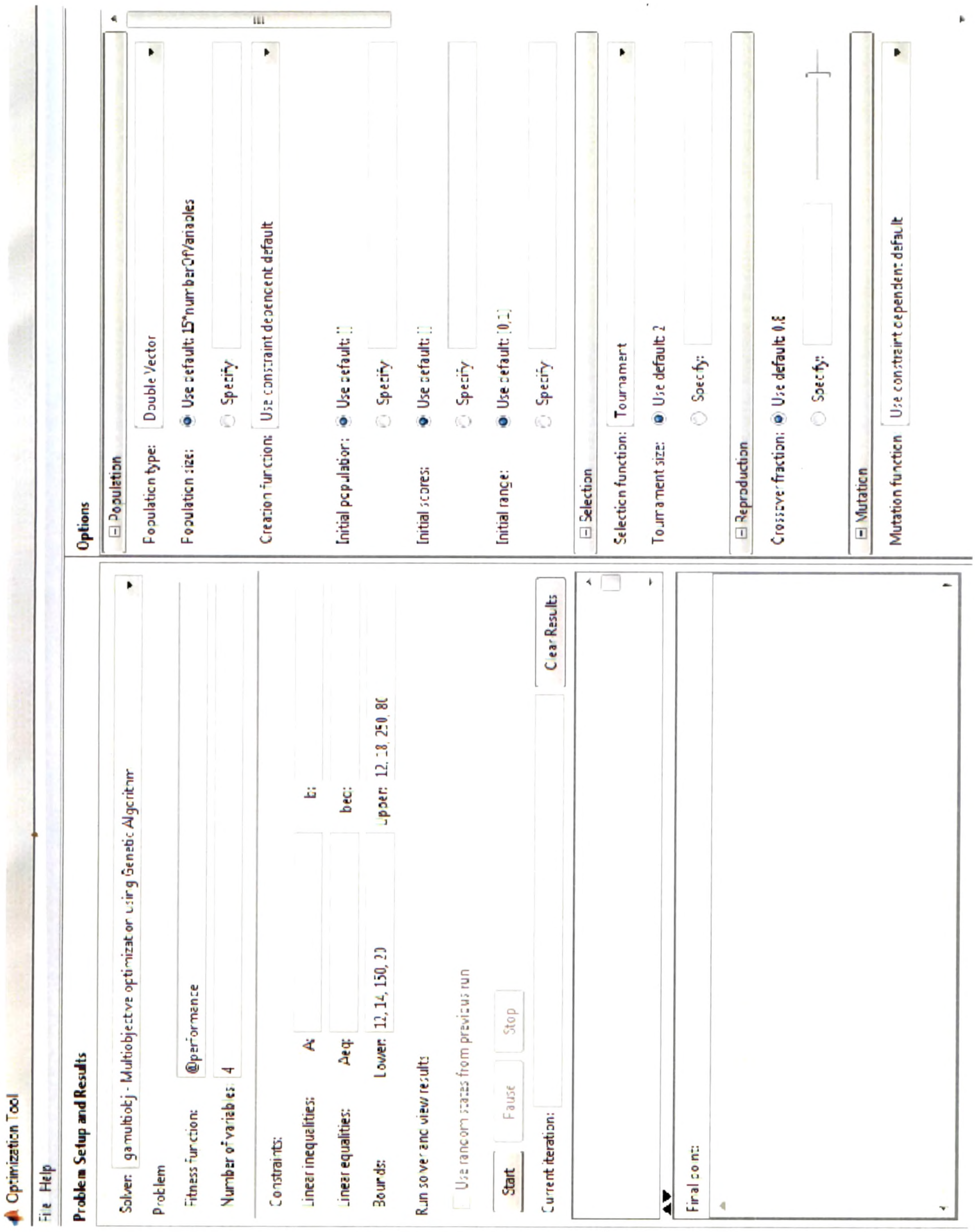

Figure 5.2 Problem Definition Screen

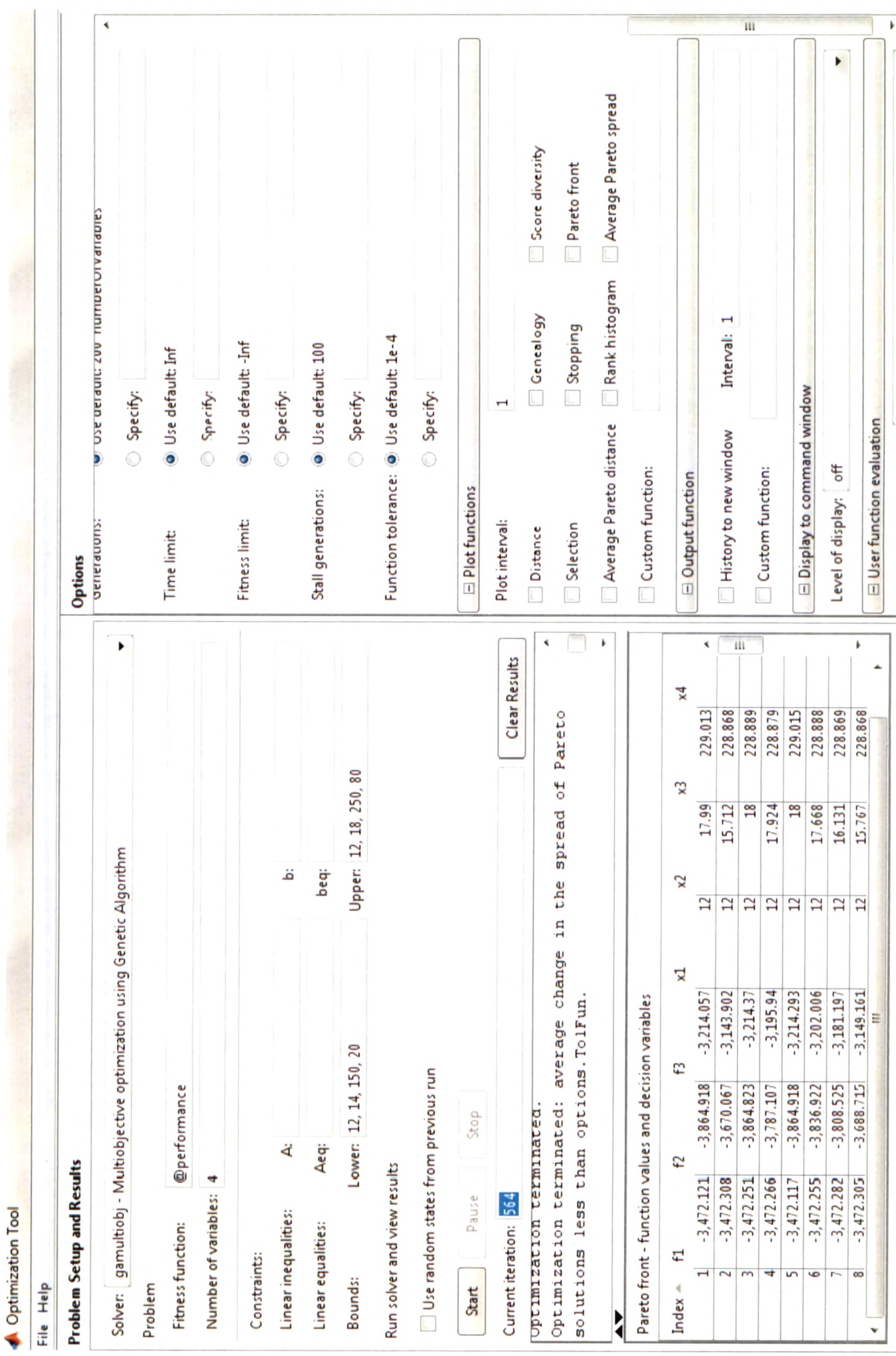

Figure 5.3 Display Screen of MATLAB Program for Optimization of Thermal Performance

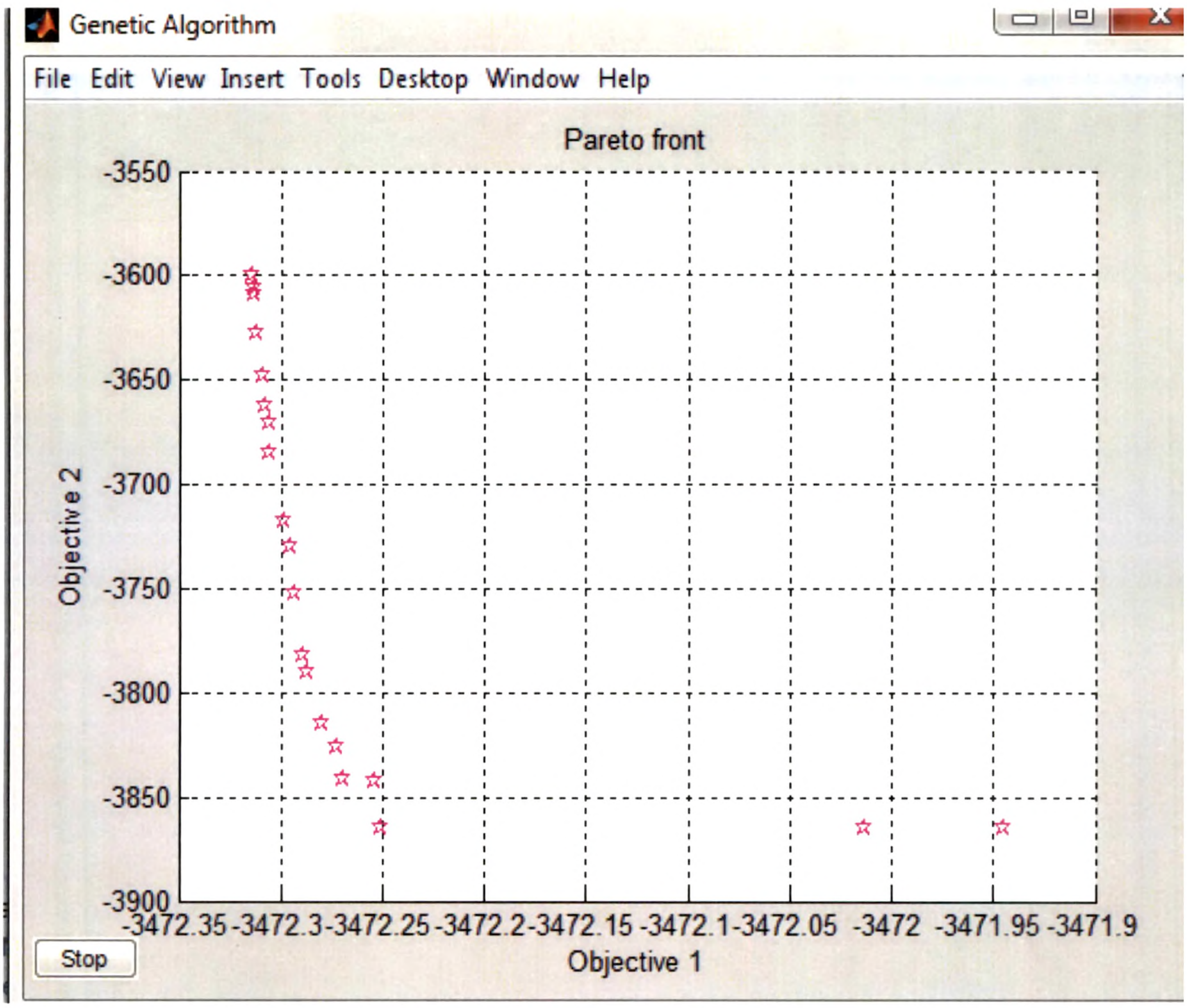

Figure 5.4 Pareto Front for Optimisation of Thermal Performance Parameters

5.1.2 Emission Constituents

The optimization of emission constituents is conducted by considering all the constituents of the exhaust gas measured in the experimental study. Among the emissions considered, oxygen is preferred to be maximum as it is not harmful to the environment and remaining emission constituents such as HC, CO, NO_x, SO_x and CO_2 to be minimum. This creates a multimodal scenario as oxygen is to be maximised at the expense of other constituents. The same steps adopted in solution procedure in section 5.1.1 of thermal performance are followed here also.

The polynomials for emission constituents are given in Table 5.3 with their respective R^2 values. Figure 5.5 shows the screen indicating process of optimization of emission constituents.

Table 5.3 Polynomials for Emission Constituents with their Respective R^2 values

Parameter	Polynomial	R^2
O_2	O_2 = -541388.21 -0.37 (x_1) + 15.41 (x_2) + 8480.75*(x_3) + 8.92E-03 (x_4) + 2.52E-02 $(x_1)^2$ -0.95 $(x_2)^2$ -43.30 $(x_3)^2$ -1.18E-04 $(x_4)^2$+ 5.63E-03 (x_1) (x_2)- 1.36E-06 (x_2) (x_3) -5.56E-02 (x_3) (x_4)+ 5.56E-02 (x_3) (x_4) -1.62E-03$(x_1)^3$+ 1.95E-02 $(x_2)^3$+ 7.21E-02 $(x_3)^3$+ 4.16E-07 $(x_4)^3$	0.9209
HC	HC = exp[-9.6E-02 (x_1) - 0.53 (x_2) - 1.38E-02 (x_3) - 1.29E-02 (x_4) + 14.016]	0.6638
CO	CO= -542389.53 - 121.82 (x_1) + 925.92 (x_2) + 8479.54 (x_3) - 5.63 (x_4) - 10.67 $(x_1)^2$ - 84.99 $(x_2)^2$ - 43.3 $(x_3)^2$ + 0.104 $(x_4)^2$ + 8.58 (x_1) (x_2) - 9.211E-06 (x_2) (x_3) - 0.27 (x_3) (x_4) + 0.27 (x_3) (x_4) + 0.66 $(x_1)^3$ + 2.1 $(x_2)^3$ + 0.072 $(x_3)^3$ - 5.57E-04 $(x_4)^3$	0.8668
NO_X	NO_X = -593.41 + 14.28 (x_1) + 70.25 (x_2) - 0.605 (x_3) - 0.311 (x_4) + 0.72 $(x_1)^2$ - 2.15 $(x_2)^2$ + 1.87E-03 $(x_3)^2$ + 4.13E-03 $(x_4)^2$ - 0.603 (x_1) (x_2) + 2.66E-02 (x_2) (x_3) + 1.53E-04 (x_3) (x_4) - 2.423E-02 (x_4) (x_1)	0.9495
CO_2	CO_2 = -541263.79 + 0.34 (x_1) -12.4 (x_2) + 8480.83 (x_3) -6.51E-03 (x_4) -2.12E-02 $(x_1)^2$+ 0.77 $(x_2)^2$-43.3 $(x_3)^2$ + 9.16E-05 $(x_4)^2$ - 6.87E-03 (x_1) (x_2) -1.44E-05 (x_2) (x_3) + 6.82E-03 (x_3) (x_4) -6.82E-03 (x_3) (x_4)+ 1.26E-03 $(x_1)^3$ -1.6E-02 $(x_2)^3$ + 7.21E-02 $(x_3)^3$ -3.25E-07 $(x_4)^3$	0.9258
x_1= Load, x_2= CR, x_3= IP, x_4= Blend		

Figure 5.6 shows pareto front for optimization of emission constituents after the application of multi-objective optimization of emission constituents for maximisation of O_2 emissions with minimisation of other emission constituents (HC, CO, NO_x, SO_x and CO_2) for the diesel engine operating on different Karanja biodiesel and diesel blends at varying compression ratios, injection pressures and full load. Objective 1 is maximisation of O_2 and objective 2 is the minimisation of other emissions viz. HC, CO, NO_x, SO_x and CO_2. The pareto front gives set of points corresponding to different values of objective 1 and objective 2. It can be observed that most of the points are close to objective 2 axis. The reason is that, objective 1 is only maximisation of O_2 whereas objective 2 is minimisation of HC, CO, NO_x, SO_x and CO_2. Hence, more preference is given to objective 2 due to more number of parameters involved. The software uses pareto front to strike a balance between objective 1 and objective 2 and picks up a point to suggest the optimum values of input parameters such as CR, IP and blend for optimum emissions. The point picked up by the software may lie between a value of 0 to 5 and -

4000 to -3000 for objective 1 and objective 2 respectively. The values of objective 1 and objective 2 are used to determine the optimum input parameters by the software by following a complex set of calculations. The optimum values of CR, IP and blend suggested by the software after carrying the optimization run are 18, 220 bar, B70 respectively.

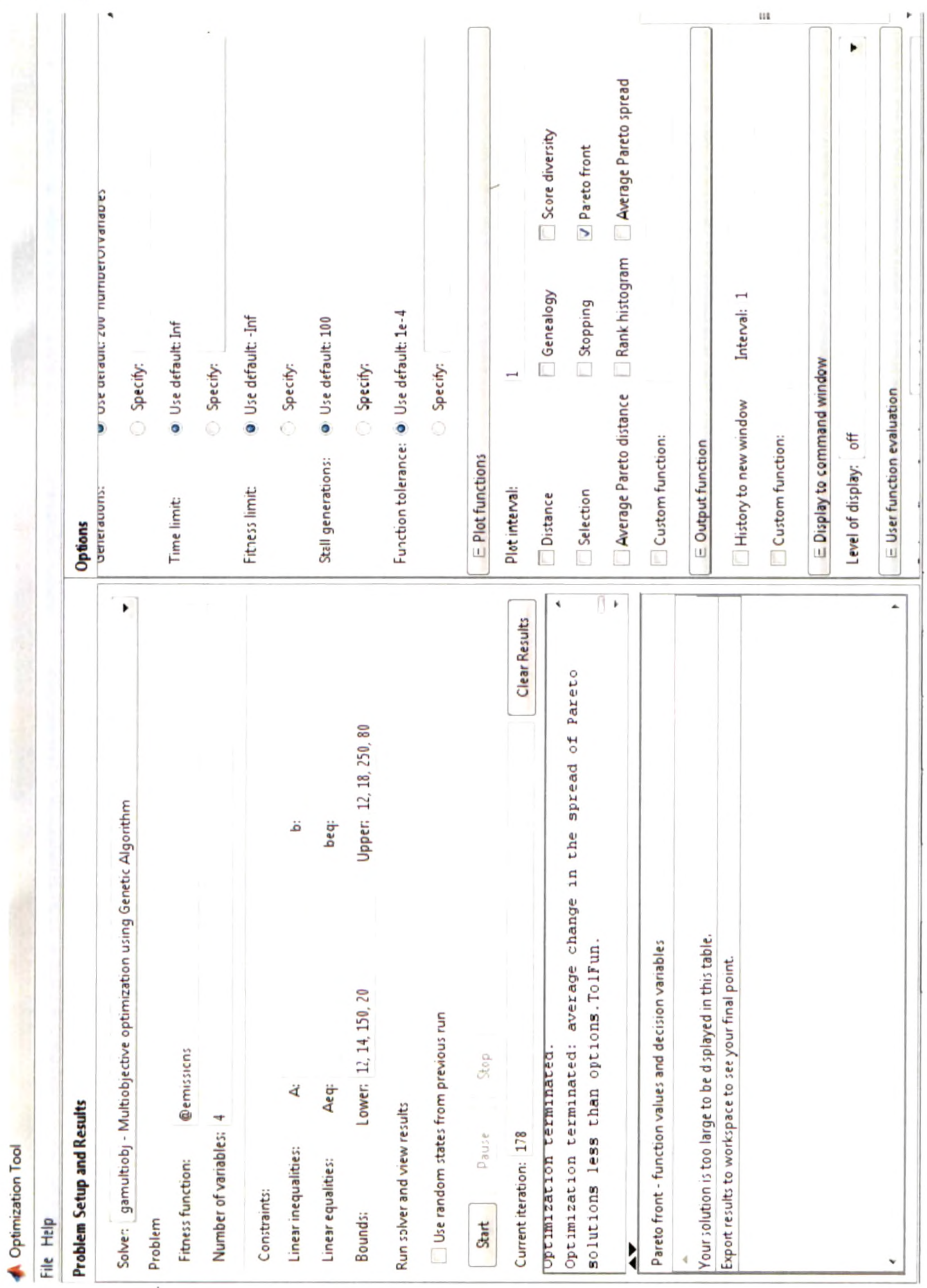

Figure 5.5 Display Screen of MATLAB Program for Optimization of Emission Constituents

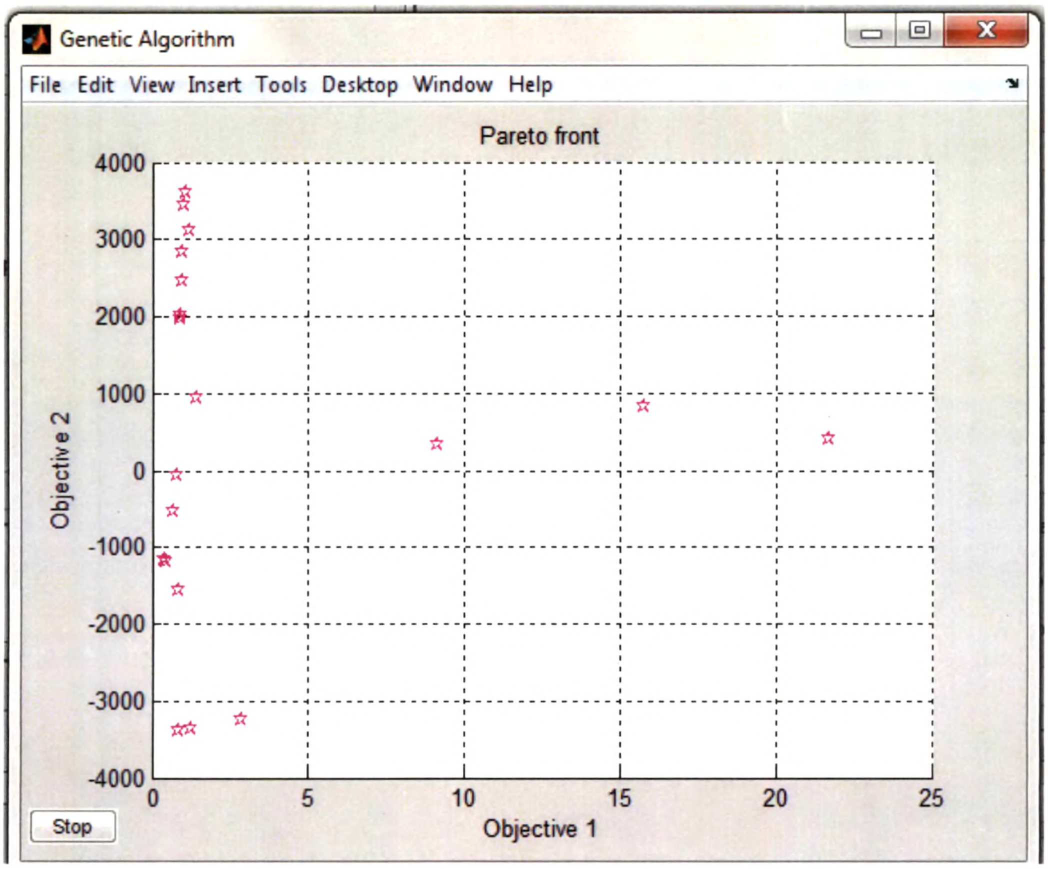

Figure 5.6 Pareto Front for Optimisation of Emission Constituents

5.1.3 Both Thermal Performance and Emission Constituents

The optimization of both thermal performance and emission constituents is conducted by considering all the performance parameters and emission constituents considered in sections 5.1.1 and 5.1.2. The solution procedure is also the same as followed for thermal performance optimization and emission constituents optimization.

Figure 5.7 shows the screen showing optimization of thermal performance and emission constituents.

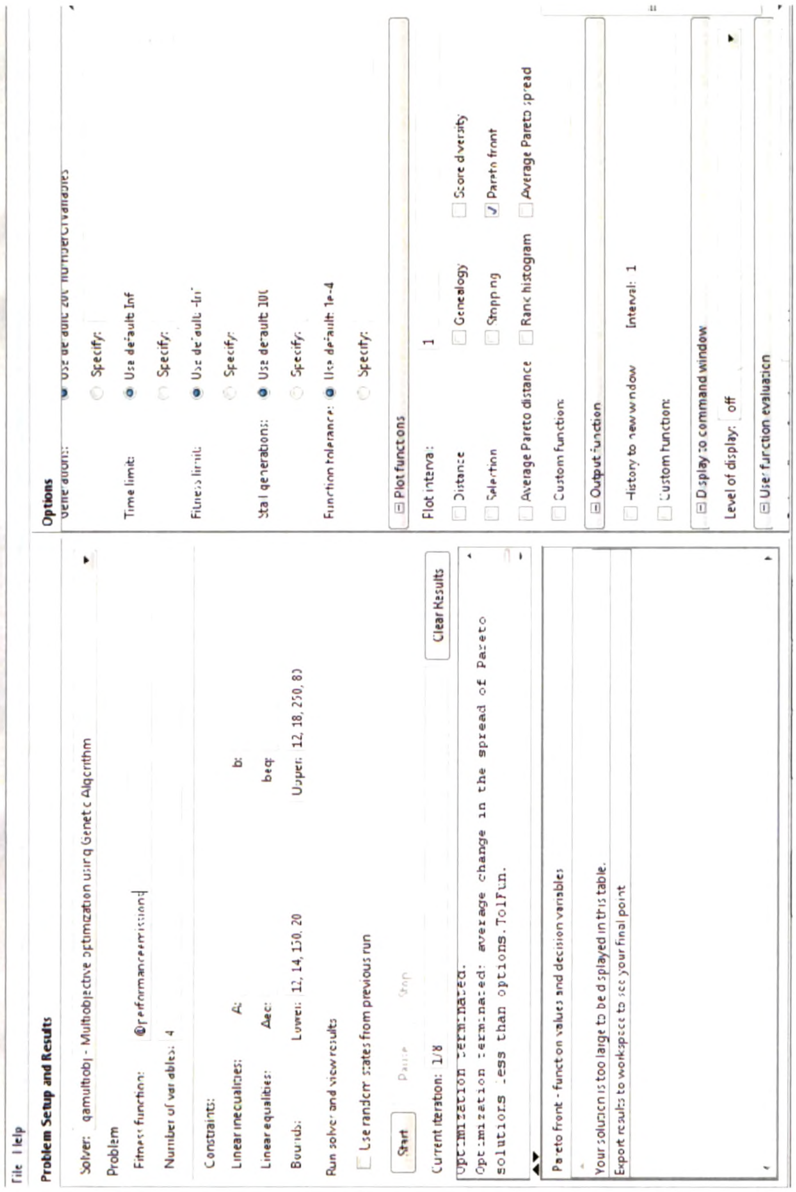

Figure 5.7 Display Screen of MATLAB Program for Optimization of Thermal Performance and Emission Constituents

Figure 5.8 shows pareto front for optimization of both thermal performance parameters and emission constituents giving equal weightages. Here, objective 1 is maximisation of thermal performance and objective 2 is the minimisation of exhaust emissions. The software uses a pareto front to strike a balance between objective1 and objective 2 and picks up a point to suggest the optimum values of input parameters such as CR, IP and blend. The point picked up by the software found to lie in a range of 0 to 5 and -4000 to -3000 for objective 1 and objective 2 respectively. The values of objective 1 and objective 2 are used to determine the optimum input parameters by the software by following a complex set of calculations. The optimum values of CR, IP and blend suggested by the software after carrying the optimization run are 18, 228 bar, B60 respectively.

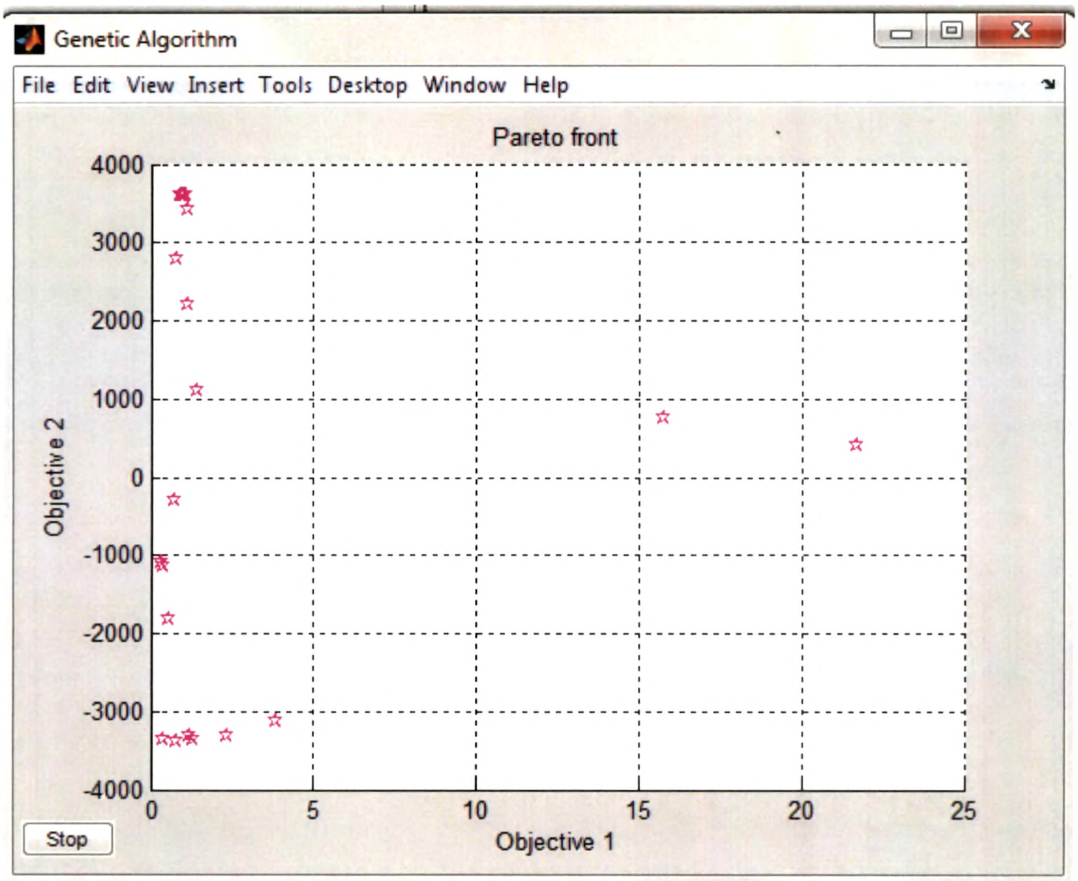

Figure 5.8 Pareto Front for Optimisation of Both Thermal Performance Parameters and Emission Constituents Giving Equal Weightages

5.1.4 Weighted Multi-objective Optimization

The multi-objective optimization carried out in the preceding section is conventional method. In such optimization equal preference is given to each individual parameter of both thermal performance and exhaust emissions. But, usually, the purpose of an IC engine is to operate with maximum thermal efficiency and at considerably lesser emissions. Rarely there may be cases where emissions are of more importance than efficiency. Under all such cases, weighted optimization** is to be carried out wherein suitable weights (preferences) are given to the thermal performance parameters and emission constituents.

The weighted optimization is carried out using genetic algorithm solver and the procedure is similar to that for conventional optimization. The only difference is that weights are defined for all the equations of output parameters which are obtained by nonlinear regression analysis (refer Table 5.2 and 5.3). Figure 5.9 shows the MATLAB editor which is used to define weights w (1) to w (8) for the equations f (1) to f (8).

Table 5.4 gives a few combinations of the results of weighted optimization of thermal performance and exhaust emissions. It is seen that the weightage given to thermal performance and exhaust emissions does not affect the values of CRs chosen. In all the cases, the optimum CR and IP are found to be 18 and 228bar respectively. Therefore, it can be inferred that the results obtained using optimization are in close agreement with those found in the experimental study. However the blend to be used appears to vary between B67 to B74 in most of the cases as observed from the table, based on the allotted weightages.

Further, it is also observed that the optimum values of CR and IP for equal weightages of 0.5 (50%) each to thermal performance and exhaust emissions match but blend do not match with those obtained from conventional multi-objective optimization*. The reason is that, in conventional optimization equal weightages are alloted to all parameters irrespective of whether they are related to thermal performance or exhaust emissions. But, in weighted optimization, 0.5 (50%) weightage given to thermal performance evaluation gets divided equally among BTHE, BSFC and EGT and the weightage given to exhaust emissions say gets divided equally among exhaust emissions constituents of HC, CO, NO_x, HSU, O_2, CO_2 and SO_x.

*Conventional multi-objective optimization: GA toolbox of MATLAB by default allots equal weightages to each individual parameter.

**Weighted optimization: Any selected value of weightage can be allotted collectively to a group of parameters or each individual parameter specifically

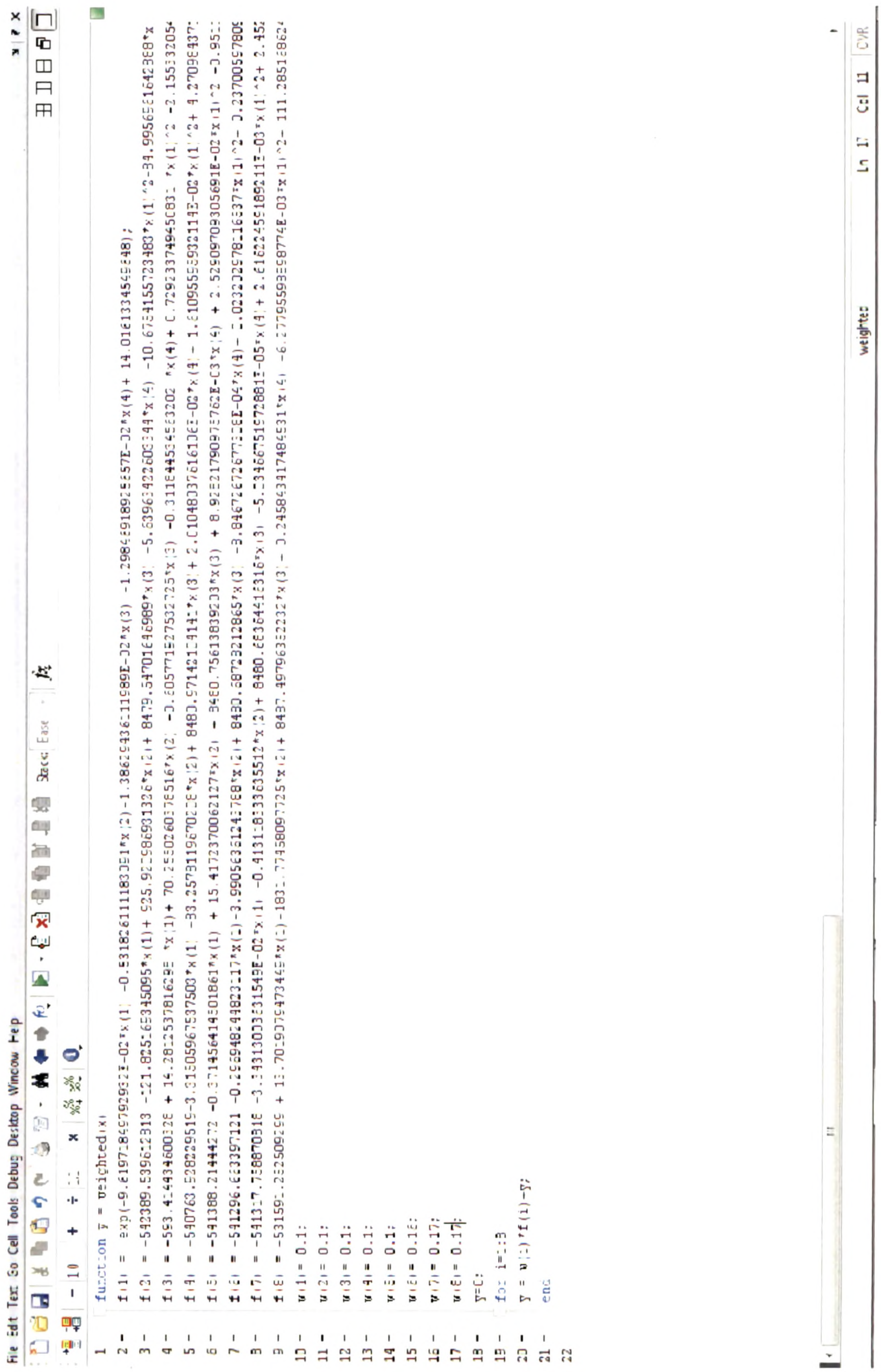

Figure 5.9 MATLAB Editor

It can also be noted that the optimum blend for 100% weightage to thermal performance is B72 which is in line with that obtained using conventional optimization (B70). But, when 100% weightage is given to exhaust emissions, the optimum blend through weighted optimization method is found to be B41. The value does not agree with that obtained by using conventional optimization. Here, in weighted optimization, highest weightage given to emissions indicate that B41 gives least emissions as compared to other higher blends.

Table 5.4 Weightages For Thermal Performance and Emissions In Multi objective Optimization

Weightage to Thermal Performance	Weightage to Emissions	CR	IP	Blend
1	0	18	228	72
0.8	0.2	18	228	74
0.7	0.3	18	228	72
0.6	0.4	18	228	75
0.5	0.5	18	228	71
0.4	0.6	18	228	72
0.3	0.7	18	228	70
0.2	0.8	18	228	67
0	1	18	228	41

Different optimization runs carried out considering thermal performance, emission constituents, both thermal performance and emission constituents giving equal and different weightages, show that the values of CR, IP and blend for optimum performance and emissions of the engine fuelled with Karanja biodiesel and diesel blends are found to be 18, 228bar and B70 respectively.

The experimental results presented in chapter 4 do not give the output parameters for the specified optimum values of CR, IP and blend as engine tests are not conducted for this configuration. Hence, there is a need to obtain the output parameters corresponding to the optimum values of inputs. An ANN can be used in order to obtain the corresponding output parameters, which is discussed in the following section.

5.2 ANN Modeling

An ANN is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system. ANNs are among the newest signal processing technologies nowadays. For further details Appendix IX can be referred.

In the present study, an ANN model is built to simulate the actual engine behaviour in order to obtain the output parameters of thermal performance and emission constituents corresponding to the optimum input parameters obtained. The model is built by using the data obtained by conducting a series of experiments on the four stroke, single cylinder, variable compression ratio, direct injection, diesel engine using blends of Karanja biodiesel and diesel as fuel. As discussed in chapter 4, the experiments are conducted by varying load, compression ratio, blend proportion and injection pressure. The experimental data is divided according to 80-20 rule, with 80% of the available data being used for training of the network and remaining 20% for validation.

Tables 5.5 and 5.6 represent a sample of input and output data that is used in the ANN modeling of engine performance and exhaust gas emission constituents respectively. The engine load is varied from 0kg to 12kg in steps of 3kg, compression ratios considered for conducting the experiments are 14, 15, 16, 17, 17.5 and 18, while the injection pressure is varied from 150bar to 250bar in steps of 50bar. The experiments are carried out for the blends of B20, B40, B60, B80, pure Karanja biodiesel and pure diesel. The data obtained by conducting these experiments is used to model the neural network for predicting thermal performance and exhaust gas emissions of the engine.

The software selected for neural network modeling in the present study is Easy NN. It is selected purely because of its simplicity in developing and training models involving feed forward multilayer neural networks with back-propagation training algorithm. Easy NN grows multilayer 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 the input and output layers can then be grown to hold the optimum number of nodes. Each node contains a neuron and its connection address. The whole process is automatic. 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, and comma separated files, bitmap files or binary files. The grid can also be produced manually using the Easy NN 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 validation data available in the grid for self validation at the same time. When training finishes the neural networks can be tested using the querying data in the grid, the interactive query facilities or querying data in separate files. The steps that are required to produce neural networks are automated in Easy NN. The learning can be terminated by specifying maximum number of cycles or the targeted maximum error.

Table 5.5 Neural Network Input Output Sample Data for Engine Thermal Performance

Input Parameters				Output Parameters		
Load (kg)	Fuel	Compression Ratio	Injection Pressure	BSFC (kg/kWh)	BTHE (%)	EGT (^{0}C)
0	B0	18	200	27.80	0.45	175.67
3	B0	18	200	0.6	15.72	196.27
6	B0	18	200	0.42	23.15	237.55
9	B0	18	200	0.35	26.17	288
12	B0	18	200	0.3	31.25	350.75
0	B20	18	200	21.25	0.43	185.56
3	B20	18	200	0.61	15.26	210.96
6	B20	18	200	0.45	22.35	254.67
9	B20	18	200	0.3	25.86	289.53
12	B20	18	200	0.31	30.5	348.56
0	B40	18	200	20.13	0.4	180.65
3	B40	18	200	0.63	15.04	201.85
6	B40	18	200	0.4	22.7	239.68
9	B40	18	200	0.3	25.42	286.53
12	B40	18	200	0.32	30.05	347.96
0	B60	18	200	34.36	0.38	182.89
3	B60	18	200	0.65	14.82	208.23
6	B60	18	200	0.44	20.38	247.9
9	B60	18	200	0.35	25.08	299.65
12	B60	18	200	0.32	29.32	356.04
0	B80	18	200	25.40	0.36	187.53
3	B80	18	200	0.67	13.63	209
6	B80	18	200	0.39	20.35	242.69
9	B80	18	200	0.36	25.46	290.62
12	B80	18	200	0.33	28.75	346.99
0	B100	18	200	22.05	0.32	179.35
3	B100	18	200	0.7	12.58	198.69
6	B100	18	200	0.45	20.03	240.38
9	B100	18	200	0.37	24.39	281.85

12	B100	18	200	0.34	28.65	343.77

Table 5.6 Input Output Sample Data of Emission Constituents For Neural Network

Input Parameters				Output Parameters				
Load (kg)	Fuel	Compression Ratio	Injection Pressure	CO_2 (%)	CO (%)	NO_x (ppm)	HC (ppm)	O_2 (%)
0	B0	18	200	0.83	0.012	9	6	19.81
3	B0	18	200	1.34	0.013	37	5	18.99
6	B0	18	200	1.65	0.014	75	5	18.67
9	B0	18	200	2.01	0.020	118	6	18.18
12	B0	18	200	2.57	0.022	160	8	17.51
0	B20	18	200	0.88	0.011	15	5	19.58
3	B20	18	200	1.4	0.012	42	4	18.97
6	B20	18	200	1.7	0.017	81	5	18.42
9	B20	18	200	2.11	0.018	118	6	18.22
12	B20	18	200	2.6	0.02	161	7	17.56
0	B40	18	200	0.87	0.01	15	4	19.87
3	B40	18	200	1.47	0.011	38	4	19.04
6	B40	18	200	1.75	0.013	82	3	18.69
9	B40	18	200	2.17	0.015	124	4	18.25
12	B40	18	200	2.65	0.016	163	6	17.43
0	B60	18	200	0.89	0.008	15	3	19.91
3	B60	18	200	1.52	0.009	44	3	19.15
6	B60	18	200	1.79	0.012	81	2	18.67
9	B60	18	200	2.19	0.015	129	4	18.21
12	B60	18	200	2.63	0.015	167	5	17.69
0	B80	18	200	0.92	0.005	17	2	19.94
3	B80	18	200	1.58	0.007	46	3	19.08
6	B80	18	200	1.82	0.013	84	2	18.56
9	B80	18	200	2.18	0.011	132	3	17.96
12	B80	18	200	2.68	0.013	175	4	17.59
0	B100	18	200	0.96	0.004	19	2	20.03
3	B100	18	200	1.6	0.006	58	3	19.33
6	B100	18	200	1.84	0.012	87	2	18.95
9	B100	18	200	2.24	0.009	135	2	18.44
12	B100	18	200	2.7	0.011	179	4	17.62

5.2.1 Thermal Performance

The neural network for predicting thermal performance is developed by considering the operating parameters like load, compression ratio, injection pressure and blend as input parameters. The output parameters considered are brake thermal efficiency, brake specific fuel consumption and exhaust gas temperature. Figure 5.10 shows the layout of simulation of actual engine using ANN model for engine performance. The ANN uses the same input parameters as received by the engine and gives corresponding outputs as that fron the engine. Therefore, the ANN model effectively replaces the engine.

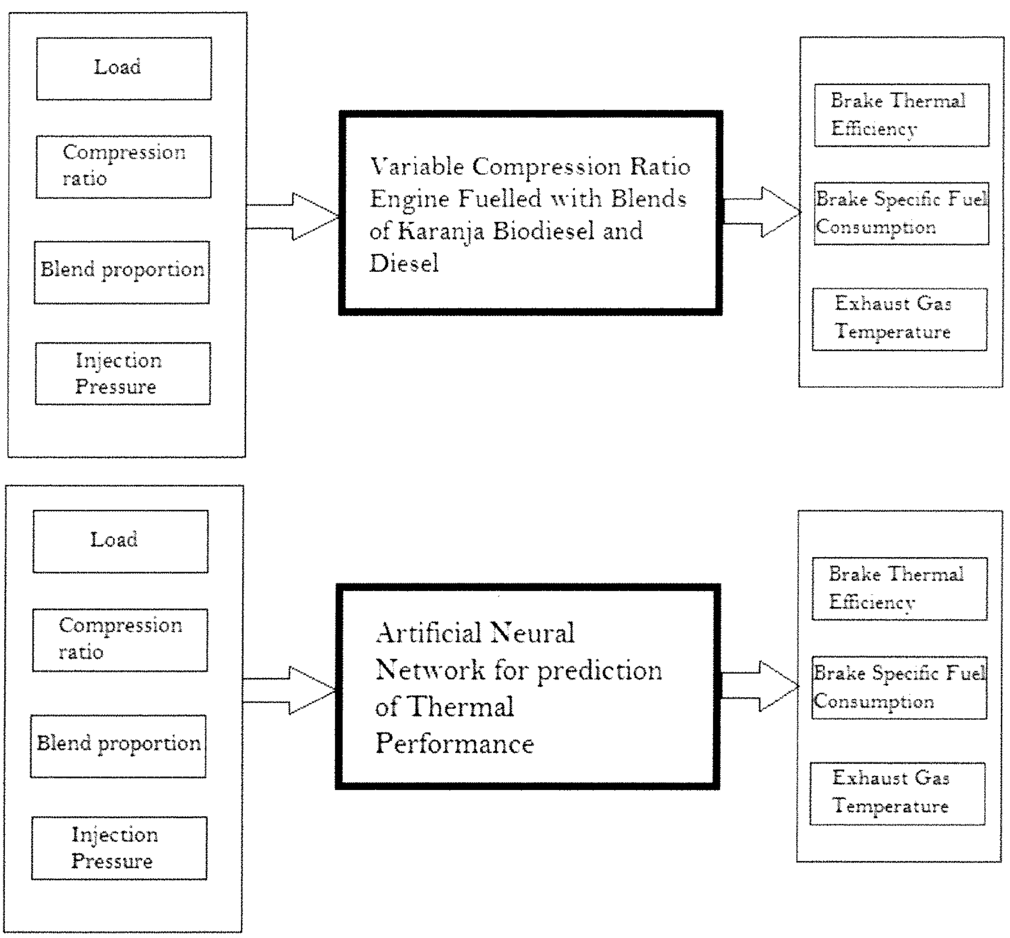

Figure 5.10 Layout of Simulation of Actual Engine using ANN Model for Engine Performance

The sample of results obtained experimentally by carrying out series of experiments on the variable compression ratio engine are listed in Table 5.5, which are used for developing the neural network model. Various architectures of neural networks are tried and an appropriate architecture is chosen such that the average error of the network for all outputs is within 5%. Table 5.7 gives the details used for modeling this neural network. According to the table, beginning from 2 hidden layered neural network model, having initially 8 cells in the hidden layer. The number of cells in the hidden layer is increased up to 30 while monitoring the error resulting at the end of training.

Table 5.7 Details Used to Model the Neural Network

Network Type	Feed Forward
Inputs for the neural network model	Load, Compression ratio, Blend, Injection pressure
Number of cells in input layer	4
Outputs from the neural network model	Brake thermal efficiency, Brake Specific Fuel Consumption, Exhaust Gas Temperature
Number of cells in output layer	3
Number of Hidden Layers	2
Initial Number of Cells in a Hidden Layer	8
Maximum Number of Cells in a Hidden Layer	30
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

The criteria for the termination of training selected are a) permissible error and b) maximum number of cycles in training and validation. The limiting value for all the errors over the entire data is selected as 0.05 (5%) 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 0.05, all validation points within 3% of target values or 1000000 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 3000. The number of validation cycles in one instance of validation is set to 100. These values are set in the control window of the software as shown in Figure 5.11.

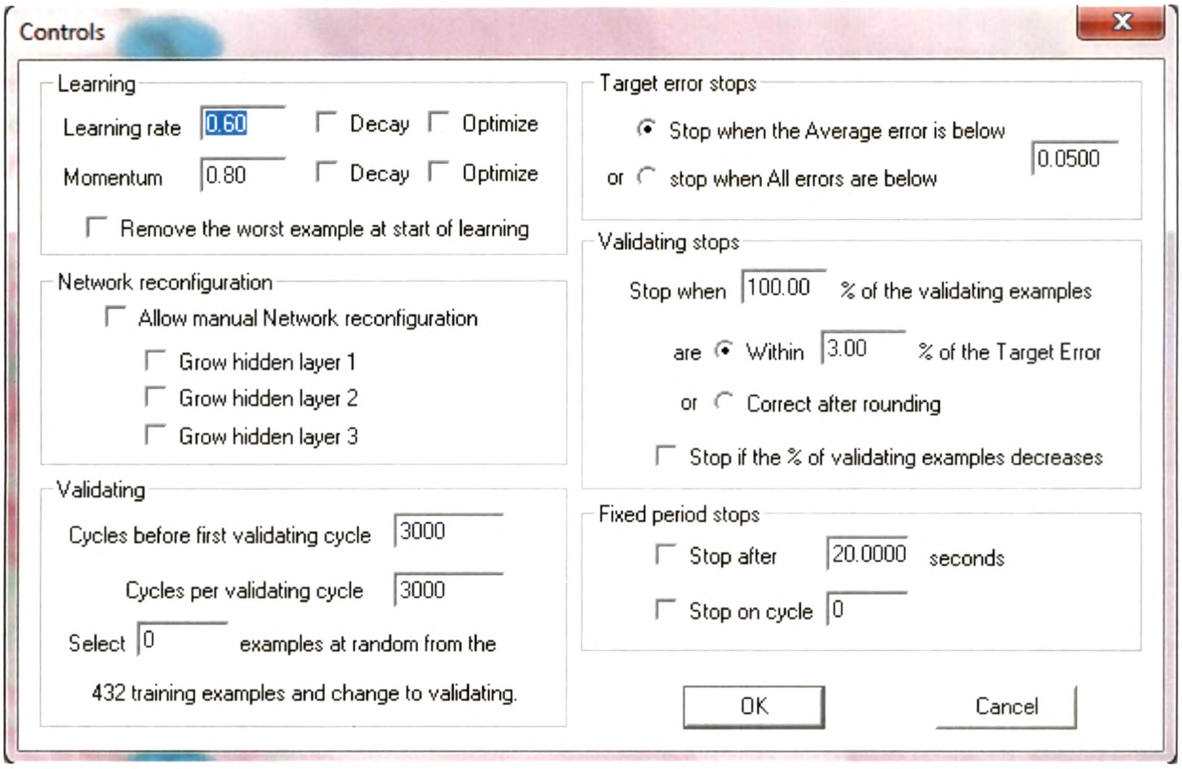

Figure 5.11 Setting Learning Control for Training of ANN Model

The neural network generated has 4 cells in the input layer, 8 cells in the first hidden layer, 10 cells in the second hidden layer and 3 cells in the output layer as shown in Figure 5.12. The architecture of such a neural network is denoted as 4.8.10.3 where the numbers denote the number of cells in the input layer, first hidden layer, second hidden layer and output layer respectively.

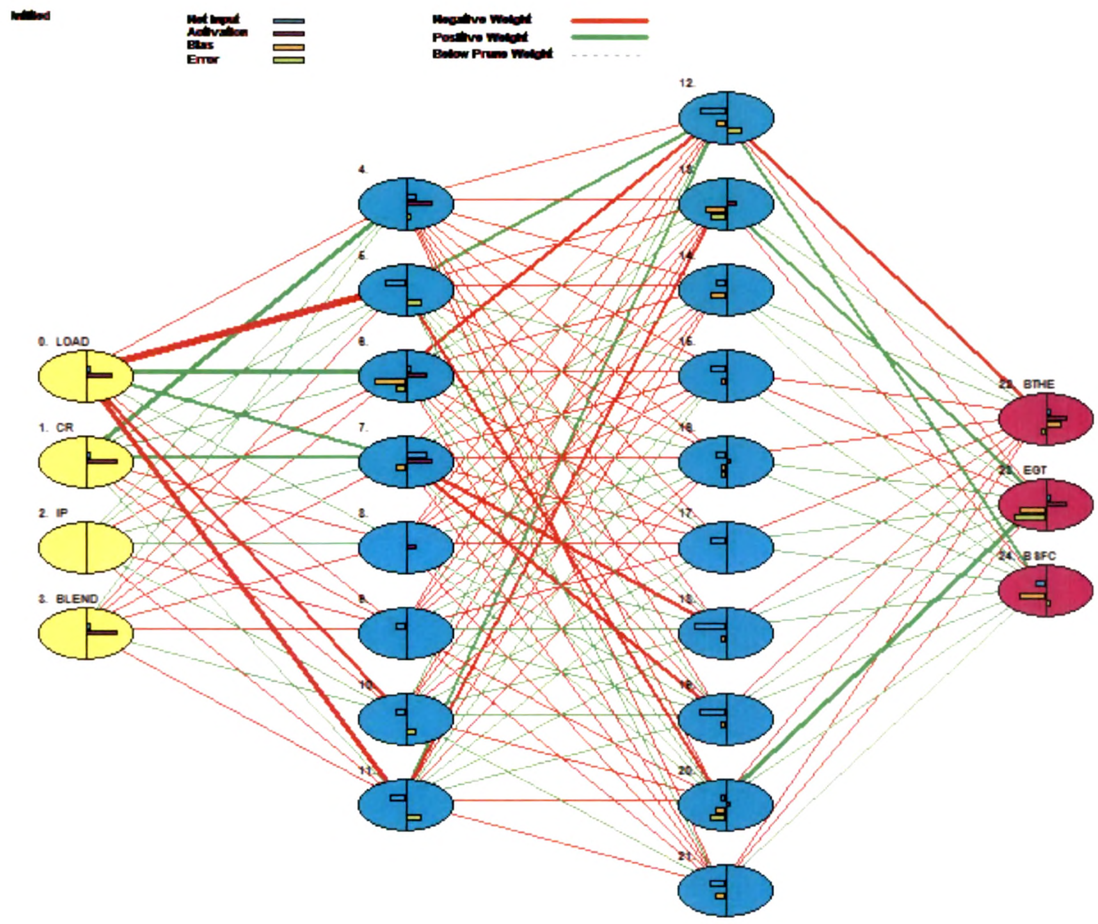

Figure 5.12 ANN Model for Predicting Thermal Performance with Architecture 4.8.10.3

On training of the network the error propagation graph for each training cycle is obtained as indicated in Figure 5.13. 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 the value of 5% 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 number 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.

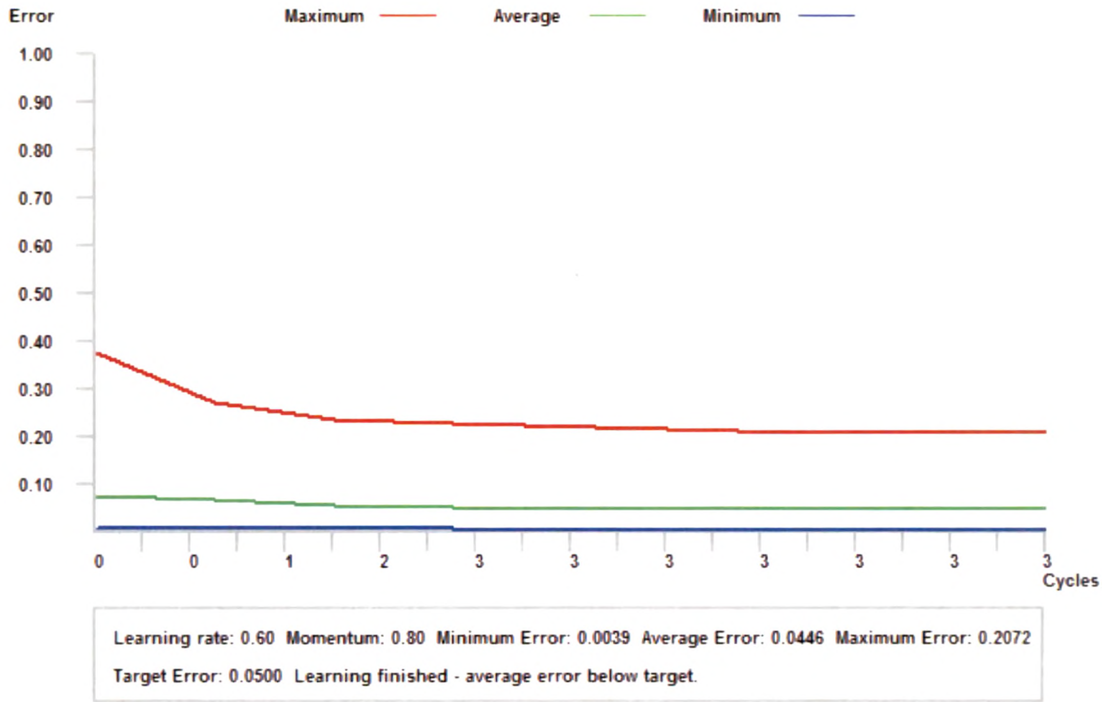

Figure 5.13 ANN Model Training & Error Propogation with Increasing Number of Training Cycles for the 4.8.10.3

Table 5.8 shows the average, minimum and maximum error for different architectures of the neural network. It can be observed that the average errors of all the architectures are almost identical and hence it becomes difficult to select the best architecture for the model. In such a case, the R test can be used in order to determine the best architecture. The values of rms error and R are evaluated by using Equations 5.1 to 5.6

Table 5.8 Errors for Different Architectures of Neural Network

Sr. No	Architecture of the Model	Average Error (%)	Minimum Error (%)	Maximum Error (%)	Validation stops within limiting Error (%)	Remarks
1	4.8.10.3	4.983	0.4482	22.6534	3	Training stopped with all errors within 5%
2	4.8.9.3	4.5806	0.3713	21.9288	3	
3	4.7.9.3	4.7719	0.2836	21.4245	3	
4	4.7.8.3	4.7719	0.2836	21.4245	3	
5	4.5.6.3	4.8108	0.3058	21.6008	3	

6	4.7.7.3	4.7889	0.3729	22.257	3	
7	4.22.3	4.7053	0.513	21.8532	3	
8	4.21.3	4.7962	0.6696	23.4381	3	
9	4.20.3	4.9679	0.2332	24.2883	3	
10	4.19.3	4.7524	0.4905	22.6710	3	

For error calculation, Equations 5.1 to 5.6 are used.

Error for each case is defined as

$$\%Error = \frac{|A_e - A_p|}{A_e} \tag{5.1}$$

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

$$\%Error_{av} = \frac{1}{N}\sum_{i=1}^{N}\frac{|A_{ei} - A_{pi}|}{A_{ei}} \tag{5.2}$$

The maximum error is defined as

$$\%Error_{max} = max\left(\sum_{i=1}^{N}\frac{|A_{ei} - A_{pi}|}{A_{ei}}\right) \tag{5.3}$$

and the minimum error is defined as

$$\%Error_{min} = min\left(\sum_{i=1}^{N}\frac{|A_{ei} - A_{pi}|}{A_{ei}}\right) \tag{5.4}$$

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

$$Error_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{|A_{ei} - A_{pi}|}{A_{ei}}\right)^2} \tag{5.5}$$

The confidence R (coefficient of determination) can be used to decide upon the best architecture. The R values can be determined as

$$R = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{A_e}{A_p} \tag{5.6}$$

The training and test errors for the networks are listed in Table 5.9. It can be observed that the values of errors are well within specified limits for all the neural network model architectures evaluated. On the basis of R test, it is found that the model having architecture 4.22.3 is a good model for which value of R is closest to unity among other models. Hence this model is selected as the best representative model for the prediction of thermal performance constituents.

Table 5.9 Training and Test Errors for Neural Network Architectures

Architecture of the Model	Average Error (%)	R
4.8.10.3	4.983	0.91517
4.8.9.3	4.5806	0.91637
4.7.9.3	4.7719	0.92456
4.7.8.3	4.7719	0.92092
4.5.6.3	4.8108	0.92916
4.7.7.3	4.7889	0.92428
4.22.3	4.7053	0.94355
4.21.3	4.7962	0.928815
4.20.3	4.9679	0.94024
4.19.3	4.7524	0.93864
4.23.3	4.5668	0.95002

5.2.2 Emission Constituents

The constituents of exhaust gas measured during the experiments are CO, CO_2, HC, O_2, NO_X, and SO_2. The exhaust gas emissions are directly dependent on input parameters like engine load, compression ratio, injection pressure, blend proportion. Thus, in order to develop a neural network which predicts the exhaust gas emission constituents for diesel engine working with Karanja biodiesel and its blends with diesel, the operating conditions such as engine load, CR, IP and blend proportion are given to the model as the input. The output parameters from the model are the exhaust gas constituents. Figure 5.14 shows the layout of simulation of actual engine using ANN model for exhaust emissions. The ANN uses the same input parameters as received by the engine and gives similar outputs as that of the engine. Therefore, the ANN model effectively replaces the actual engine.

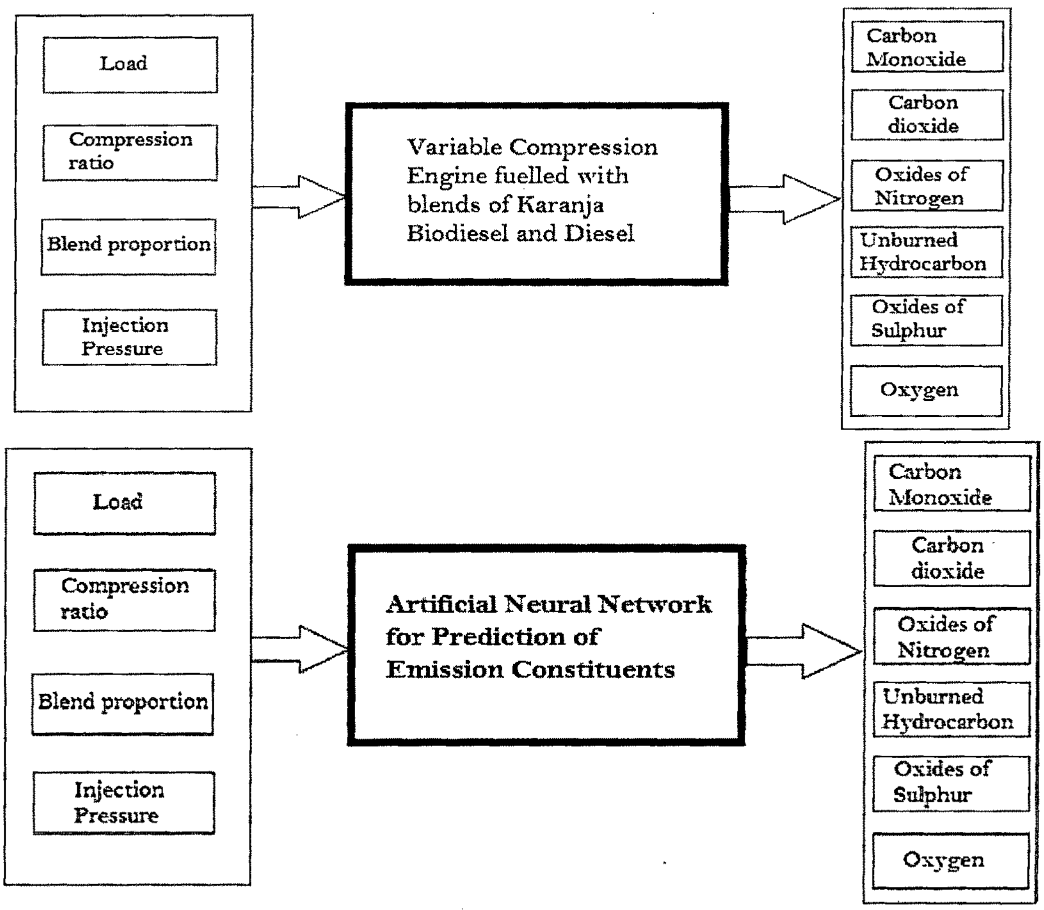

Figure 5.14 Simulation of Actual Engine Using ANN Model for Exhaust Emissions

The sample of results obtained experimentally by carrying out series of experiments on the variable compression ratio engine are listed in Table 5.6, which are used for developing the neural network model. Various architectures of neural networks are tried and an appropriate architecture is determined such that the average error of the network for all outputs is within 5%. Table 5.10 gives the details used for modeling this neural network. As per the table, beginning from 2 hidden layered neural network model, having initially 8 cells in the hidden layer, the number of cells in the hidden layer is increased up to 30 while monitoring the error, resulting at the end of training.

Table 5.10 Neural Network Modeling for Emission Constituents

Network Type	Feed Forward
Inputs for the neural network model	Load, Compression ratio, Blend, Injection pressure
Number of cells in input layer	4
Outputs from the neural network model	Brake thermal efficiency, Brake Specific Fuel Consumption, Exhaust Gas Temperature
Number of cells in output layer	3
Number of Hidden Layers	2
Initial Number of Cells in a Hidden Layer	8
Maximum Number of Cells in a Hidden Layer	30
Propagation Rule	Weighted Sum Rule
Activation Function	Logistic Function
Output Function	Identity Function
Learning Rule	Back Propagation

The limiting value for all the errors over the entire data is selected as 0.05 (5%) 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 0.05, all validation points within 3% of target values or 1000000 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 3000. 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 Figure 5.15.

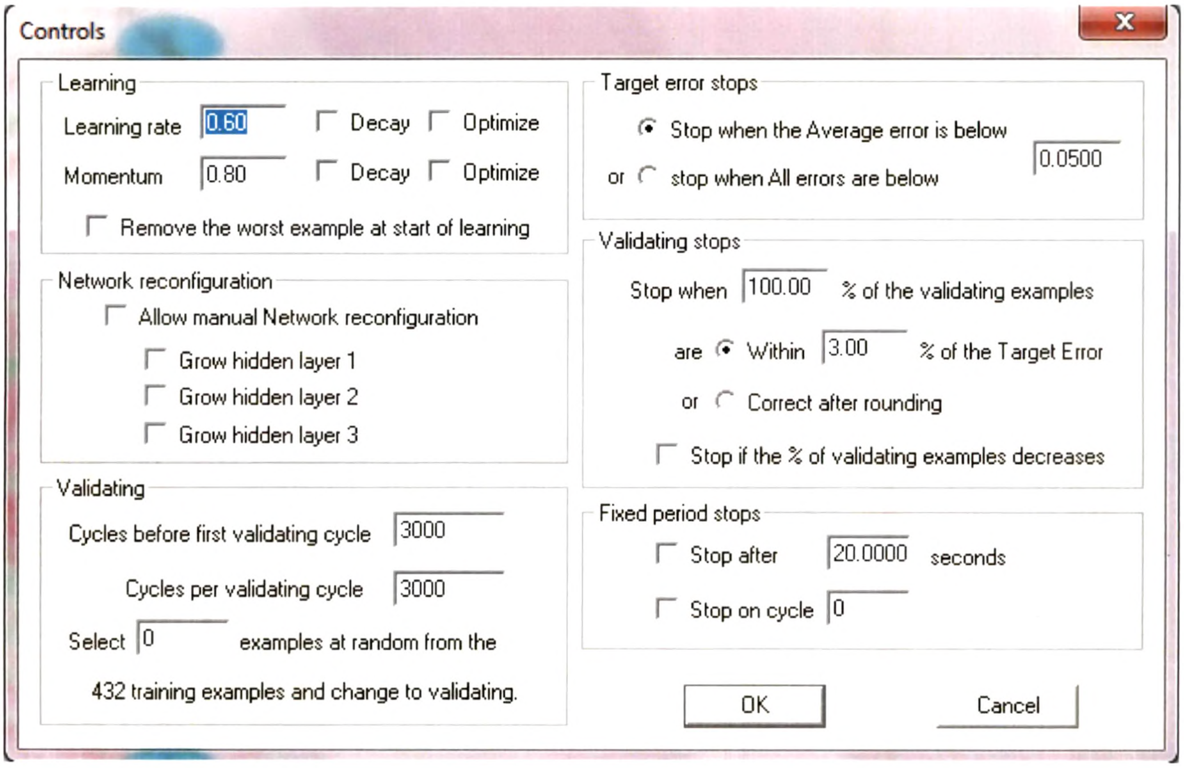

Figure 5.15 Setting Learning Controls for Training of ANN Model

The neural network generated has 4 cells in the input layer, 8 cells in the first hidden layer, 10 cells in the second hidden layer and 6 cells in the output layer as shown in Figure 5.16. The architecture of such a neural network is denoted as 4.8.9.5 where the numbers denote the number of cells in the input layer, first hidden layer, second hidden layer and output layer respectively.

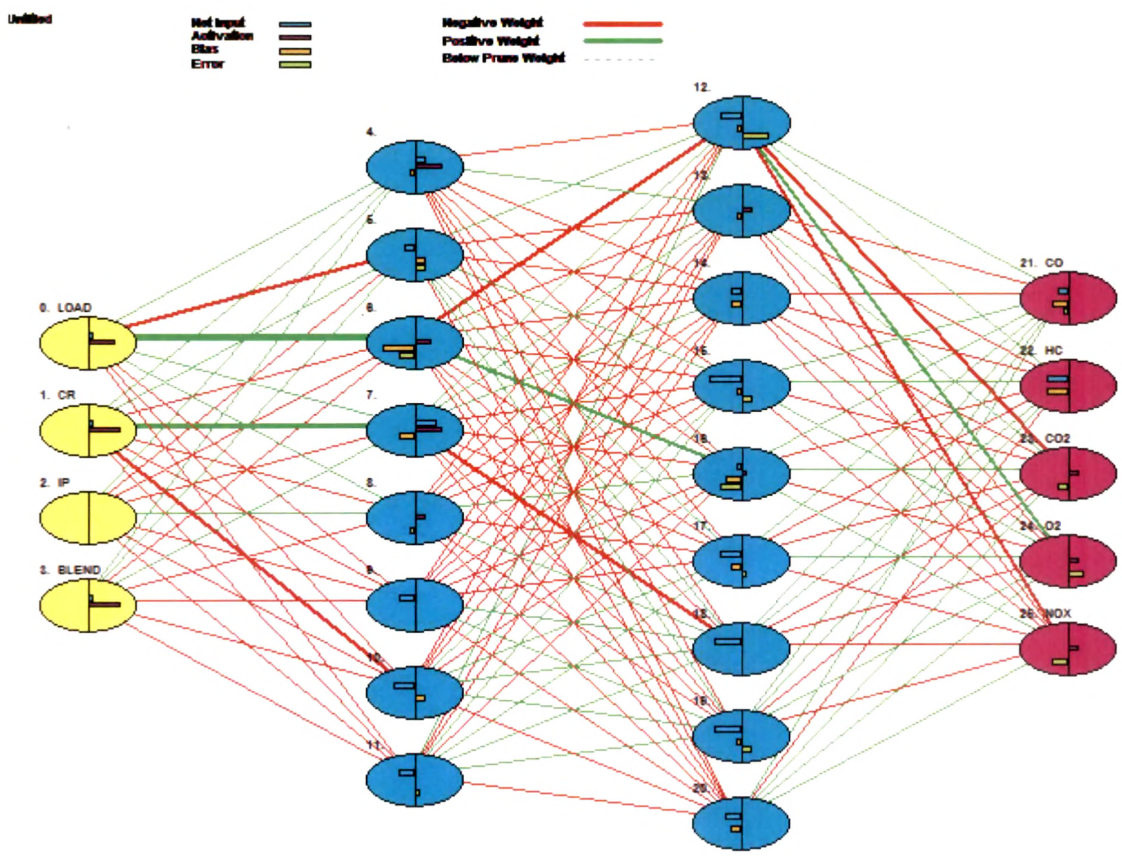

Figure 5.16 ANN Model of Exhaust Gas Constituents with Architecture 4.8.9.5

On training of the network the error propagation graph for each training cycle is obtained as indicated in Figure 5.17. 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 the value of 5% 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 number 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 5.11 gives the average, minimum and maximum errors for different architectures tested. It can be observed that the average errors of all the architectures are almost identical and hence it becomes difficult to select the best architecture for the model. In such a case, the R test can be used in order to determine the best architecture.

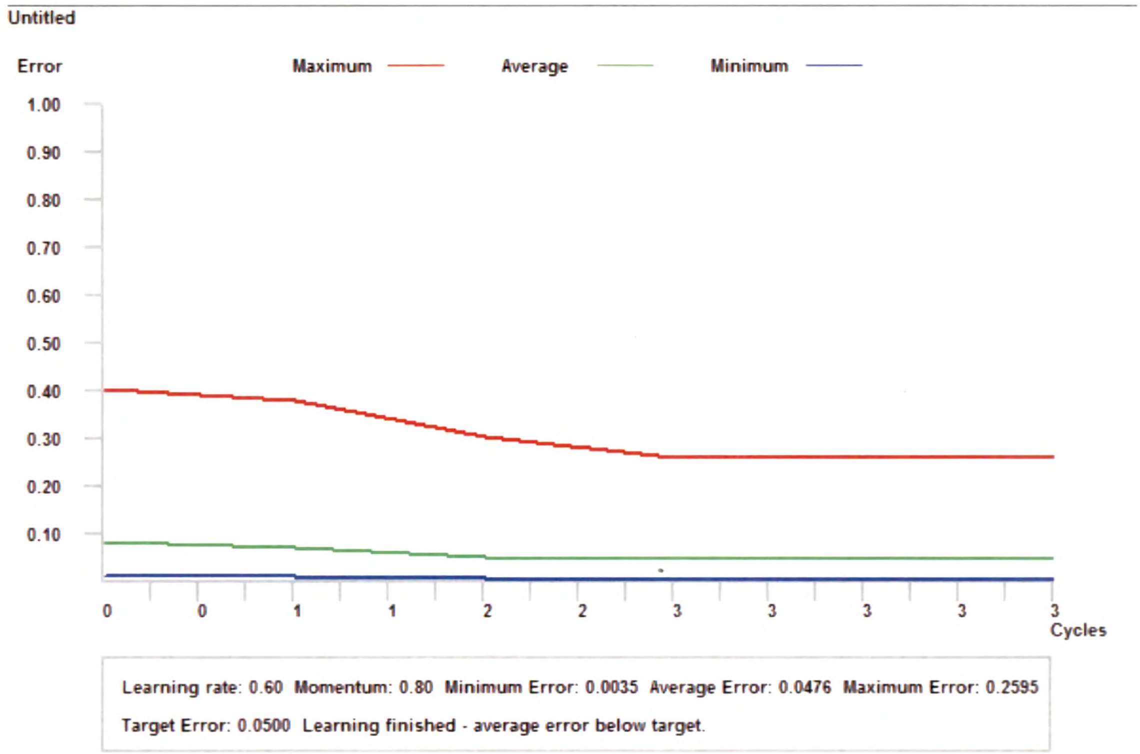

Figure 5.17 ANN Model Training & Error Propogation Graph With Increasing Number of Training Cycles for 4.8.9.5

Table 5.11 Neural Network Architecture & Corresponding Training Results for Gas Emissions

Sr. No	Architecture of the Model	Average Error (%)	Minimum Error (%)	Maximum Error (%)	Validation stops within limiting Error (%)	Remarks
1	4.8.10.5	4.6410	0.5076	22.3102	3	Training stopped with all errors within 5%
2	4.8.8.8.5	4.9514	0.7642	22.8478	3	
3	4.6.6.4.5	4.9928	0.648	26.9356	3	
4	4.6.6.5	4.9968	0.4639	22.9947	3	
5	4.6.7.5	4.9726	0.5657	23.3737	3	
6	4.20.20.5	4.8227	0.6691	22.9378	3	
7	4.6.7.5	4.7852	0.564	22.675	3	
8	4.6.6.6.5	4.6724	0.763	23.7865	3	
9	4.8.7.5	4.7895	0.7236	24.9720	3	
10	4.8.8.5	4.5463	0.7342	23.8765	3	

The training and test errors for the networks are listed in Table 5.12. It can be observed that the values of error are well within specified limits for all the neural network model architectures evaluated. On the basis of R test, it is found that the model having architecture 4.8.10.5 is a good model for which value of R is closest to unity among other models. Hence this model is selected as the best representative model for the prediction of thermal performance constituents.

Table 5.12 Training and Test errors for Different Architectures

Architecture of the Model	Average Error (%)	R
4.8.10.5	4.641	1.00288
4.8.8.8.5	4.9514	0.87712
4.6.6.4.5	4.9928	0.95073
4.6.6.5	4.9968	0.78219
4.6.7.5	4.9726	0.8043
4.20.20.5	4.8227	0.97175
4.6.6.6.5	4.7852	0.92968
4.8.9.5	4.6724	1.0028
4.8.7.5	4.7895	0.82335
4.8.8.5	4.5463	0.8976

It is seen from ANN modeling for prediction of exhaust gas constituents and thermal performance 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 thermal performance has architecture of 4.22.3. It has an average error of nearly 4.79%, minimum error of 0.66% and maximum error of 23%. The coefficient of determination is very close to unity being 0.92 and the spread is 0.1576. This ensures that in the test range if this model is subject to any condition for which experiment is not conducted, the error will not exceed 5% on an average and 23% maximum. This is shown by applying the model to a selected set of data. The results predicted by 4.22.3

ANN model are compared with experimental results and the error is evaluated (Refer Table 5.13)

On similar lines, the representative model selected for emission constituents has an architecture of 4.8.10.5. It has an average error of nearly 5%, minimum error of 0.5% and maximum error of 22%. The coefficient of determination is very close to unity being 1.0028 and the spread is 0.2876. This ensures that in the test range if this model is subject to any condition for which experiment is not conducted, the error will not exceed 5% on an average and 22% maximum. This is shown by applying the model to a selected set of data. The results predicted by 4.8.10.5 ANN model are compared with experimental results and the error is evaluated (Refer Table 5.14)

For the ANN models selected for both thermal performance and emission 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.

Tables 5.13 and Table 5.14 show that the ANN models developed for prediction of thermal performance and exhaust emission constituents have an acceptable error and hence can be used for obtaining the output parameters corresponding to optimized input parameters. The optimum values of CR, IP and blend obtained through optimization using genetic algorithm tool are 18, 228bar and B70 respectively. The output parameters corresponding to CR, IP and blend of 18, 228bar and B70 are given in Table 5.15.

Table 5.13 Comparison of Results of ANN Model and Experimental Data for Thermal Performance

Load (kg)	Fuel	CR	IP (bar)	BSFC (kg/kWh)			BTHE (%)			EGT (^{0}C)		
				Exp	ANN	Error (%)	Exp	ANN	Error (%)	Exp	ANN	Error (%)
3	Diesel	18	200	0.60	0.54	10.00	15.72	14.76	6.10	196.27	190.85	2.76
6	Diesel	18	200	0.42	0.39	7.14	23.15	24.65	-6.47	237.55	220.89	7.01
9	Diesel	18	200	0.35	0.36	-2.85	26.17	27.12	-3.63	288	267.43	7.14
12	Diesel	18	200	0.30	0.29	3.33	31.25	29.87	4.41	350.75	376	-7.19
3	B20	18	200	0.61	0.58	4.91	15.26	16.89	-10.68	210.96	195.46	7.34
6	B20	18	200	0.45	0.48	-6.66	22.35	23.06	-3.17	254.67	265.37	-4.20
9	B20	18	200	0.30	0.33	-10.00	25.86	23.87	7.69	289.53	300.78	-3.88
12	B20	18	200	0.31	0.35	-12.90	30.5	28.21	7.50	348.56	360.56	-3.44
3	B40	18	200	0.63	0.55	12.69	15.04	16.87	-12.16	201.85	225.46	-11.69
6	B40	18	200	0.40	0.42	-5.00	22.7	23.65	-4.18	239.68	245.67	-2.49
9	B40	18	200	0.30	0.28	6.66	25.42	25.12	1.18	286.53	295.43	-3.10
12	B40	18	200	0.32	0.36	-12.5	30.05	28.9	3.82	347.96	330.98	4.87

Table 5.14 Comparison of Results of ANN and Experimental Data for Emission Constituents

Load (kg)	Fuel	CR	IP (bar)	CO (%)			HC (ppm)			CO_2 (%)			O_2 (ppm)			NO_x (ppm)		
				Exp	ANN	Error (%)	Exp	ANN	Error (%)	Exp	ANN	Error (%)	Exp	ANN	Error (%)	Exp	ANN	Error (%)
3	Diesel	18	200	0.013	0.0134	-3.07	5	4.8	4.00	1.34	1.26	5.97	18.99	19.78	-4.16	37	35	5.40
6	Diesel	18	200	0.014	0.0142	-1.42	5	4.7	6.00	1.65	1.73	-4.84	18.67	18.28	2.08	75	69	8.00
9	Diesel	18	200	0.020	0.0213	-6.50	6	5.5	8.33	2.01	2.14	-6.46	18.18	17.38	4.40	118	109	7.62
12	Diesel	18	200	0.022	0.0224	-1.81	8	7.5	6.25	2.57	2.68	-4.28	17.51	16.32	6.79	160	171	-6.87
3	B20	18	200	0.012	0.013	-8.33	4	4.2	-5.00	1.4	1.54	-10.00	18.97	18.45	2.74	42	45	-7.14
6	B20	18	200	0.017	0.016	5.88	5	5.2	-4.00	1.7	1.54	9.41	18.42	18.67	-1.35	81	78	3.70
9	B20	18	200	0.018	0.0185	-2.77	6	6.5	-8.33	2.11	1.98	6.16	18.22	18.43	-1.15	118	113	4.23
12	B20	18	200	0.02	0.0211	-5.50	7	7.4	-5.71	2.6	2.89	-11.15	17.56	18.45	-5.06	161	169	-4.96
3	B40	18	200	0.011	0.0113	-2.72	4	3.8	5.00	1.47	1.34	8.84	19.04	18.67	1.94	38	39	-2.63
6	B40	18	200	0.013	0.0128	1.53	3	2.8	6.66	1.75	1.5	14.28	18.69	19.89	-6.42	82	75	8.53
9	B40	18	200	0.015	0.0146	2.66	4	4.3	-7.50	2.17	2.34	-7.83	18.25	17.3	5.20	124	118	4.83
12	B40	18	200	0.016	0.0159	0.62	6	6.2	-3.33	2.65	2.54	4.15	17.43	17.9	-2.69	163	169	-3.68

Table 5.15 Output Parameters Corresponding to CR, IP and Blend of 18, 228bar and B70

THERMAL PERFORMANCE	Output Parameters	Value
	BTHE (%)	27.49
	BSFC (kg/kWh)	0.33
	EGT (^{0}C)	345.56
EMISSION CONSTITUENTS	CO (%)	0.006
	HC (ppm)	3
	CO_2 (%)	3.08
	O_2 (%)	17.80
	NO_X (ppm)	160

Table 5.16 presents a comparison between the values of output parameters obtained through the ANN corresponding to the optimised input parameter for and those obtained through experimentation for Karanja biodiesel and Diesel oil. The experimental results given in the table correspond to a full load of 12kg, CR of 18 and IP of 200bar.

Table 5.16 Comparison of Thermal Performance and Emission Constituents for Diesel Oil, B70 and Karanja Biodiesel

THERMAL PERFORMANCE	Output Parameters	Diesel	B70	Karanja biodiesel
	BTHE (%)	29.20	27.49	26.64
	BSFC (kg/kWh)	0.31	0.33	0.34
	EGT (^{0}C)	350.75	345.56	343.77
EMISSION CONSTITUENTS	CO (%)	0.02	0.006	0.005
	HC (ppm)	5.00	3.00	2.00
	CO_2 (%)	2.62	3.08	3.26
	O_2 (%)	17.62	17.80	17.91
	NO_x (ppm)	125	160	166

It can be observed that thermal performance is best for Diesel oil and emission constituents are least for Karanja biodiesel. It can be also noted that the thermal performance and emission constituents for B70 are in between those for Diesel oil and Karanja biodiesel. The optimum values for blend B70 are obtained by striking a compromise or balance between Diesel oil and Karanja biodiesel. If the engine is operated with B70 blend, the values of BTHE, BSFC and EGT are found lesser by about 6%, 6% and 1.4% respectively as compared to Diesel oil and the emission constituents of CO, HC, CO_2, O_2 and NO_x are found more by about 20%, 50%, 5%, 0.6% and 4% respectively as compared to Karanja biodiesel.