AI-Based Prognostic Modeling and Performance Optimization of CI Engine Using Biodiesel-Diesel Blends

Prabhakar Sharma*‡, Avdhesh Kr. Sharma**

**Mechanical Engineering Department, DCR Univ. of Science & Technology, Murthal, Haryana, INDIA-131039
(psharmahal@gmail.com, avdhesh_sharma35@yahoo.co.in)

‡ Corresponding Author; Prabhakar Sharma, Mechanical Engineering Department, DCR Univ. of Science & Technology, Murthal, Haryana, INDIA-131039, psharmahal@gmail.com

Received: 09.03.2021 Accepted:04.04.2021

Abstract- This article describes aspects of the development of an artificial intelligence (AI)-based prognostic modeling and performance optimization of a single-cylinder CI engine powered by biodiesel-diesel blends. It is a tool based on gene expression programming (GEP) followed by response surface methodology (RSM). RSM is employed to establish an explicit mathematical relationship between input and outputs. A database of experimental data on a computerized engine test bench was collected for model development and its testing. The prognostic ability of the GEP model was verified by error analysis, where the coefficient of determination (R^2) and mean absolute percentage error (MAPE) varied marginally within the range of 0.979 ± 0.020 and 2.15 ± 0.25, respectively. The model captures adequate trends. Optimum input conditions of engine load, biodiesel-diesel blending ratio, fuel injection pressure, and fuel injection timing are observed to be 60.49 %, 14.32 %, 231.35 bar, and 23.7° bTDC, respectively, while optimized results of brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), and peak in-cylinder pressure (P_{max}) are found to be 24.28 %, 0.3135 kg/kWh, and 58.95 bar, respectively. GEP approach followed by RSM is observed to be a robust tool.

Keywords Artificial Intelligence; Gene Expression Programming; Response surface methodology; diesel engine.

1. Introduction

Diesel engines are extensively used in industries, agriculture, mining, marine, and surface transport due to their high efficiency, economical fuel to power ratio, and ease of operation. However, diesel engine using conventional diesel fuel emits very harmful exhaust emissions causing global warming and harmful health effects on flora and fauna. Thus, there is an urgent need for alternative fuel with a high potential for diesel engines [1]. Biodiesel or fatty acid methyl ester is one such option for diesel engines. Numerous studies on biodiesel-fuelled diesel engines were reported in past. Laboratory-based experimental testing of waste cooking oil methyl ester (WCOME)/diesel blends powered diesel engine is carried out by Sharma and Sharma [2]. The thermal and combustion performance results of biodiesel blends (20% WCOME + 80% diesel) were close to 100% diesel fuel. They reported that biodiesel-diesel blends up to W20 (20% WCOME + 80% diesel) can be used without any harmful effects on engine hardware. Pinto et al. [3] used tire-extracted oil blended with diesel to fuel a diesel engine. The results published show that a small quantity of used tire-derived oil (up to 5%) helps in the reduction of oxides of nitrogen (NOx) and carbon monoxide (CO) while a small decrease in brake thermal efficiency was also reported.

The use of any new alternative fuel requires extensive investigations in the laboratory in different engine operating conditions include health monitoring on a long-term basis. This leads to a comprehensive escalation in cost in terms of material and man-hours. A feasible solution may be to establish empirical relations among inputs/outputs using AI-based modeling techniques compounded with high-end computational facilities [4]–[7]. There are newer artificial intelligence techniques and easy availability of the efficient computational facility. Studies were reported on AI/soft computing methods like artificial neural network (ANN) [8], gene expression programming (GEP), response surface methodology (RSM), and fuzzy logic-based tools. RSM (a mathematical technique) is being extensively used to study the effects of engine input (control variables) on output (response factors). It can help to select the best operating parameters to achieve optimized engine performance [9]–[11].

Singh et al. [12] used RSM for parametric optimization of Pongamia biodiesel-diesel blends powered diesel engine and suggested that peak cylinder pressure, BTE, and BSFC can be chosen as response variables and reported that reported best input parameters of fuel injection advance, fuel injection pressure, engine load, and biodiesel-diesel blends at 25 crank angle degree before top dead center (CA °bTDC), 226 bar, 74% engine load. Roy et al. [13] developed a prognostic model for a common rail direct ignition (CRDi) engine by establishing an explicit relationship between input and output parameters. The engine load, exhaust gas recirculation (EGR), fuel injection line pressure, and fuel-injected/cycle were selected as input while BTE, BSFC, CO_2, NO_x, and particulate matter were chosen as output. The GEP model was compared with the ANN model and found that the GEP model was relatively superior to the ANN model. A multi-input and multi-output optimization study, reported by Roy et al. [14], employed GEP to optimize the trade-off between performance and emission. Elkelawy et al. [15] optimized the experimental and RSM-based engine parameters using sunflower and soybean biodiesel/diesel blends, where engine load and blending ratio were taken as input while BTE, unburnt hydrocarbon (UHC), and NO_x were chosen as response variables. Best engine performance was reported with 13.7% BTE, 120.7 ppm UHC, and 234.9 ppm NO_x at 2.05 kW engine power at 70% biodiesel.

The literature survey reveals that AI-based predictive models are available to analyze the impacts of biofuel-diesel blends on the performance and exhaust emission of the diesel engine [16]–[18]. Nevertheless, the ability of the combined application of AI-based methods, for instance, GEP, and RSM tool to prognosticate and optimize the diesel engine parameters has not been reported in the open literature. Thus, the experimental-based model-cum-optimization study may be undertaken in the present investigation. Thus, for the present work, a comprehensive laboratory-based experimental study was carried out on biodiesel-diesel blend-powered-diesel engines to acquire the combustion data. This experimental data was used for the development of the GEP model and testing. The RSM module is integrated with GEP to obtain optimal operating conditions. This forms the focus in the present work.

2. Materials and Methods

A computerized test engine set up coupled with an eddy current dynamometer is used in the present study for acquiring precise combustion performance data. The test set up comprises a 5.2kW single-cylinder water-cooled diesel engine. The airflow is measured with an airbox installed with an orifice plate. The fuel flow is measured with a glass burette on a volumetric basis per unit time. KiBox (Kistler Instruments AG) has been used for the reception of input signals of in-cylinder pressure and crank angle with a crank angle encoder. The raw data collected is supplied fed to KiBox cockpit software installed on laptop/PC. The cockpit software is capable of carrying out all the necessary calculations to provide the combustion characteristics measurement viz, pressure-crank angle graph, peak pressure, etc. The schematic arrangement of the test engine and dynamometer is shown in **Fig. 1.** The important technical details of the setup used during experiments are listed in **Table 1.** In the present study, four blends of test fuel W0 (100% diesel), W10 (10% WCOME + 90% diesel), W20 (20% WCOME + 80% diesel), and W30 (30% WCOME + 70% diesel) have been used. The diesel engine used in the study was initially fuelled with B0 and operated for 30 minutes to stabilize the cooling and lubrication system. The engine load was varied at constant engine speed using a mechanical speed governor. In the next step all the engine input parameters viz, engine load, blend ratio, fuel injection timing (FIT), and fuel injection pressure (FIP) were varied and output data was recorded.

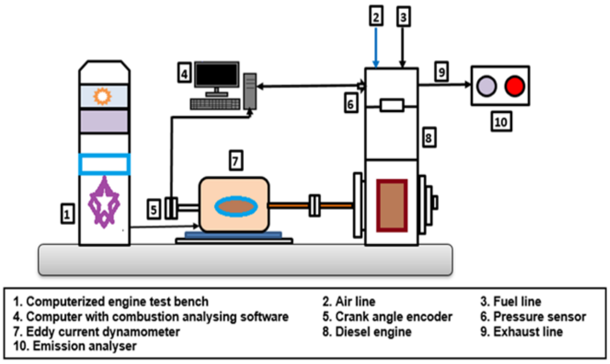

Fig. 1. Schematics of test engine set up

Table 1. Test engine set up specifications

Part name	**Specifications**
Engine	TV1 model, Kirloskar, single-cylinder
Engine cooling type	Water-cooled
Engine capacity	661 cubic cm
Engine power & speed	Rated power 5.2 kW @ 1500 rpm
Fuel	Diesel
Bore & stroke	0.0875 m & 0.110 m
Compression ratio	17.5/1
Engine Load gauge	Digital (0-50) Kg
Dynamometer	Sutlej, eddy current type
Dynamometer power	20 kilowatts, max at 2450 rpm

Application of gene expression programming

GEP is an artificial intelligence technique based on genotype/phenotype code, capable of generating computer programs with linear chromosomes having a fixed length. It is a genetic algorithm in the sense that it uses a population of individuals, chooses them according to their fitness, and then uses genetic operators (transposition, mutation, root transposition, and gene transposition, etc.) to create genetic variation [19]. Each gene is composed of a distinct head and a tail, where the head comprises both terminal and function but the tail comprises only terminals. The information encoded in a chromosome is displayed through the expression tree [20]. The decoding of the gene contained information is called translation.

An efficient model evolution depends on the careful selection of model parameters. Therefore, only those input variables that have profound effects on the engine output variables are selected for the model development. Literature survey, as well as experiments for the present study, reveals biodiesel blending composition, engine loading, and fuel injection largely influence the engine combustion indices [21], [22]. Thus, the WCOME-diesel blending ratio, engine loading, FIP, and FIT have been selected as input (control variables) to examine their effects on diesel engine output (response variables) viz., brake specific fuel consumption (BSFC), brake thermal efficiency (BTE), and peak in-cylinder pressure (P_{max}). A database of 60 test runs was randomly divided into two portions, 40 data sets were used for model training while the remaining 20 were used for testing and evaluation. [23].

The GEP model developed in the present study is assessed on statistical metrics such as determination coefficient (R^2), coefficient of correlation (R), and mean absolute percentage error (MAPE) [13], [18]. The mathematical expressions of the statistical measures used are given below as Eqn (1) to Eqn (3):

$$R^2 = \left(1 - \frac{\sum_{i=1}^{n}(t_i - o_i)^2}{\sum_{i=1}^{n} o_i^{\,2}}\right) \quad \text{.........} \quad (1)$$

$$R = \sqrt{\left(1 - \frac{\sum_{i=1}^{n}(t_i - o_i)}{\sum_{i=1}^{n} o_i}\right)} \quad \text{.........} \quad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{t_i - o_i}{t_i}\right|\right) \quad \text{..........} \quad (3)$$

where, n = total data; o_i = model predicted value; t_i = experimental value; $\bar{t}$ = experimentally measured mean value.

3. Results and Discussion

In this prognostic investigation, a GEP based predictive model has been developed utilizing the experimental data collected through lab-based experiments. The collected experimental data sets (total 60) were randomly divided into two sub-sets; out of which, ~40 data sets were used in model development while the remaining ~20 were used for testing and evaluation [23]. Details of the set of functions employed for model development are enumerated in **Table 2**. Once the model is developed it is used to test on statistical metrics namely R, $R^{2,}$ and MAPE, their values are listed in Table 3. The GEP developed model is tested on statistical metrics viz., R, R^2, and MAPE, and their output is listed in Table 3. The GEP models for output and their prognostic capabilities are discussed in the following paragraphs.

Name	Weight	Definition	Symbol
Addition	4	(x+y)	+
Multiplication	4	(x*y)	*
Subtraction	4	(x-y)	-
Division	1	(x/y)	/
Power	1	pow(x,y)	Pow
Cube root	1	x^(1/3)	3Rt
Square root	1	sqrt(x)	Sqrt
x to the power of 2	1	x^2	X2
Inverse	1	1/x	Inv
x to the power of 3	1	x^3	X3

Table 2. Set of the function used for GEP simulation

Table 3. Statistical metrics of GEP model efficiency

Parameter	R	R^2	MAPE
BTE	0.9951	0.9890	2.4 01
BSFC	0.9794	0.9592	1.902
P_{max}	0.9989	0.9986	2.101

The developed GEP models for BTE are shown as expression trees (ETs) in **Fig. 2a.** Each expression tree is made up of three sub-ET and their sum denotes the mathematical relationship between input and BTE. Different symbols and letters are used in the ET: letter d_0, d_1, d_2, and d_3 denotes input viz., engine load, blending ratio, FIP, and FIT respectively, letter 'c' represents constants. A comparison between GEP predicted and experimentally acquired values and mathematical relation in form of the equation are presented in **Fig. 2b**. It is seen from **Fig. 2b,** that most of the correlation values scattered close to 45^0 line. Pearson's coefficient of correlation (R) and R^2 values as 0.9951 and 0.9890 respectively shows the very high prognostic capability of GEP based BTE model. MAPE as 2.401 further establish the BTE model as highly efficient [18]. The absolute value basis comparison of GEP model-predicted and experiment-based BTE for the entire 60 test run is illustrated in **Fig. 2c**.

BSFC model using GEP techniques has been developed as shown in the form of three ETs as shown in **Fig. 3a**. The correlation graph and mathematical relation between experimental & GEP predicted brake specific fuel consumption is presented in **Fig. 3b**. High goodness of fit measure (R) as 0.9794 and R^2 value at 0.9592 demonstrates the high predictive capability of the BSFC model. Furthermore, the low value of MAPE as 1.902, depicts the closeness between observed and predicted results. Similar outcomes are also reported by Roy and Banerjee [14]. The is shown as **Fig. 3**.

The GEP model for P_{max} is shown in **Fig. 4a** in the form of three ETs. The correlation between GEP predicted P_{max} entire data set experimentally observed and model-predicted and experimentally recorded P_{max} is shown in **Fig. 4b**. An outstanding curve fitting could be achieved in this case at 99.99%. R^2 as 0.9998, which is close to 1,

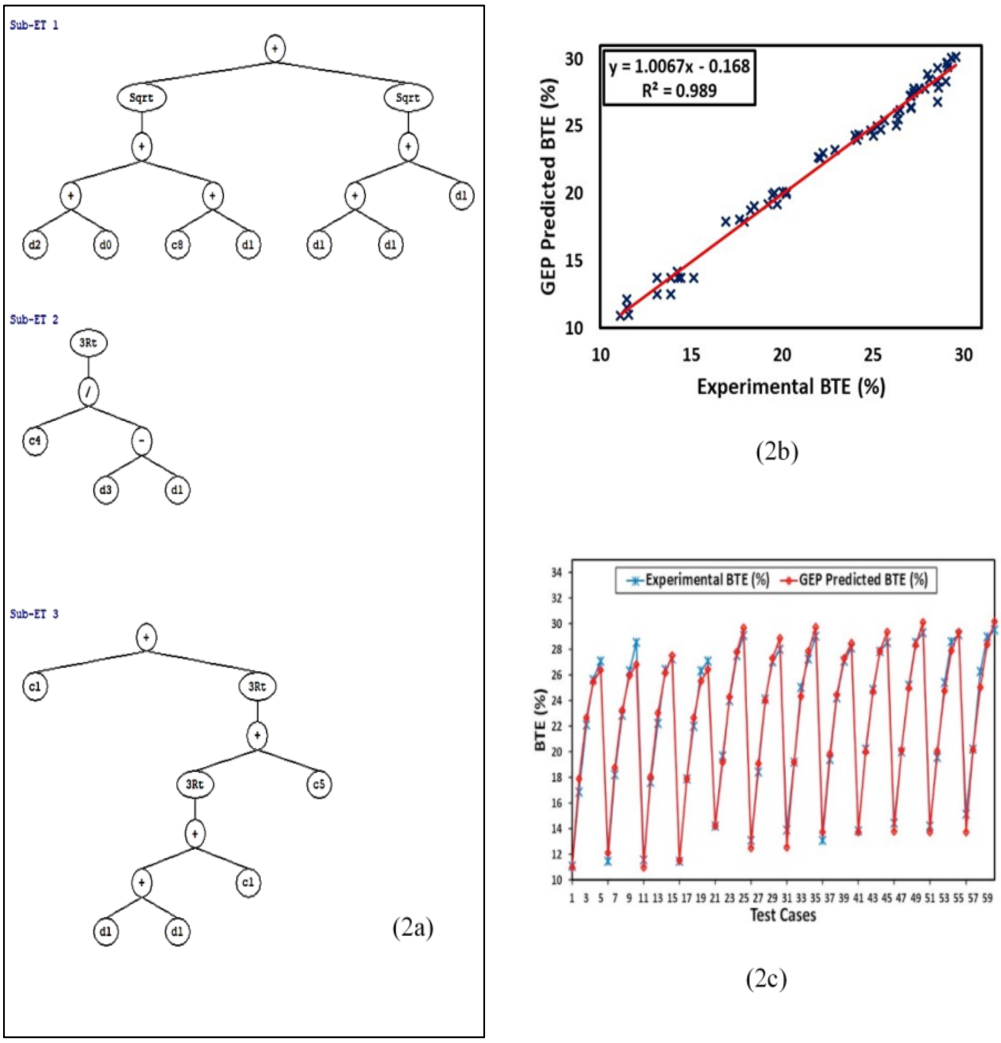

Fig. 2. BTE Model using GEP approach (2a) GPE model (2b) Comparison GEP and experiments and (2c) GEP predicted BTE values for all test cases

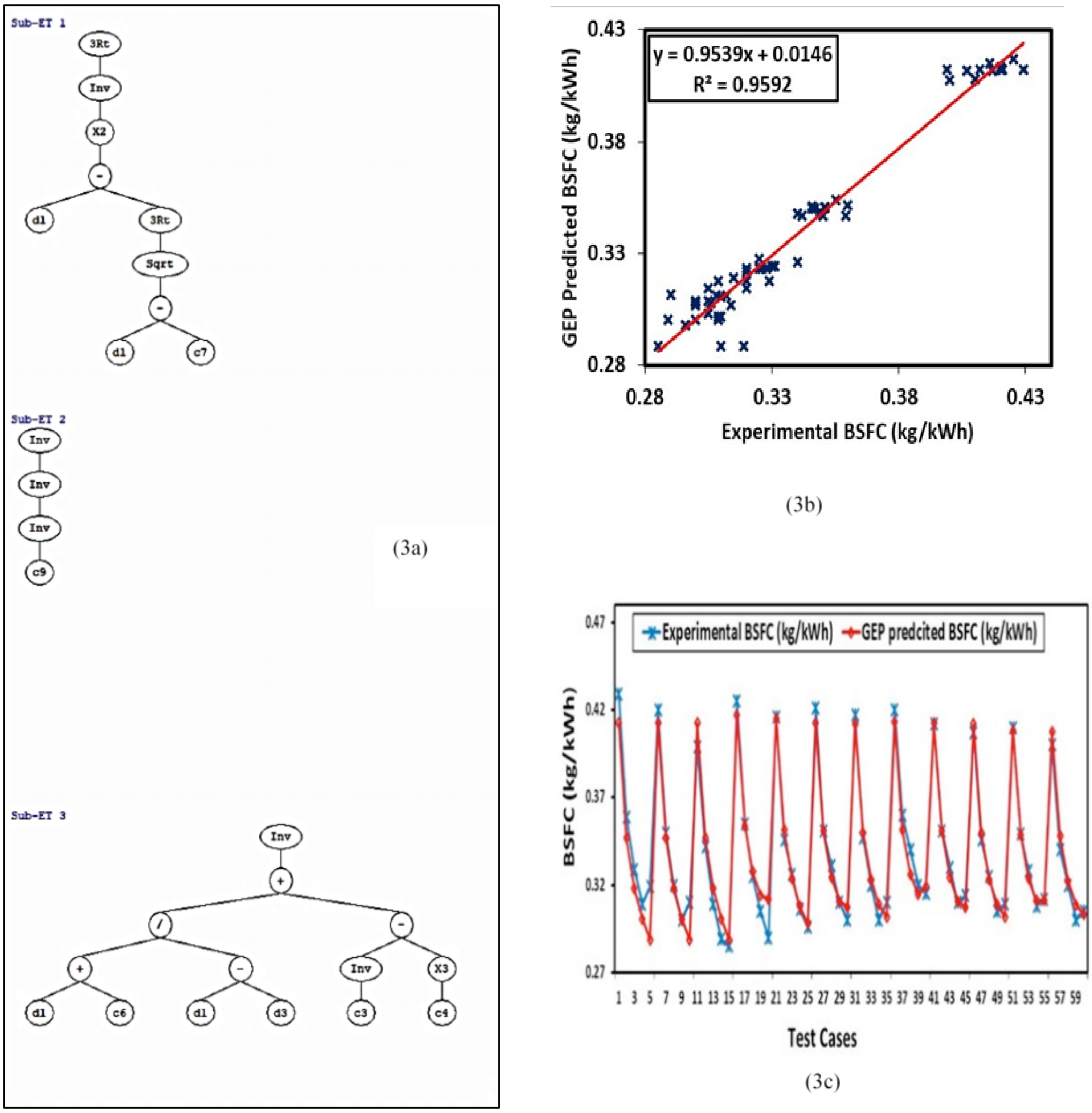

Fig. 3. BSFC Model using GEP approach (3a) GPE model (3b) Comparison GEP and experiments and (3c) GEP predicted BSFC values for all test cases.

Optimization with response surface methodology

The purpose of optimization in a model prediction study is to achieve the optimized performance based on the desirability approach. Parametric optimization helps in solving this kind of problem to obtain an input parameter for optimized output. Among many parametric optimization techniques, RSM has been extensively used as a statistics-based mathematical technique to optimize multi-input multi-output (MIMO), type engineering problems [24]. In the present research study, RSM is employed to optimize to attain maximum BTE, P_{max}, and lowest BSFC. The desirability approach, an inbuilt feature of RSM is used to combine multi-output into a unitary dimensionless criterion named as desirability function. As the data involved in the present study is nonlinear due to the complex nature of engine combustion, a quadratic model is used in the present study. Central composite design (CCD) was used for RSM to ensure precise results with fewer amounts of data. Commercial software Design-Expert version 10 is used for RSM-based optimization. The data was fed in the design matrix and analysis of variance (ANOVA) of the data is carried out to check the difference between predicted and adjusted R^2. ANOVA is also used to check the F-value (comparison of source and residual mean square) and p-value (chances of ensuring correctness of the null hypothesis). After ANOVA analysis, the functional relation between engine controllable input parameters and GEP predicted outputs was developed using second-order equations as given in Eqn. (4) to (6).

$$BTE = -26.977 + 0.36639L - 1.2867B + 0.293P + 0.617T + 0.000125LB + 0.00058LP - 0.0021LT + 0.002BP + 0.0352BT - 0.0078PT - 0.0021L^2 - 0.0001B^2 - 0.00036P^2 + 0.0196T^2 \quad ......(4)$$

$$BSFC = 1.63857 - 0.0085L - 0.0116B + 0.00083P - 0.08827T + 0.0000043LB + 0.0000068L + 0.00011LT + 0.000046BP + 0.000091BT - 0.0000077PT + 0.000027L^2 + 0.000015B^2 - 0.0000046P^2 + 0.00178T^2 \quad (5)$$

$$P_{max} = 1139.52253 + 6.219L - 6.856B - 7.537P - 32.698T + 0.0182LB - 0.244LP + 0.109LT + 0.0057BP + 0.1447BT + 0.0523PT + 0.0064L^2 + 0.0366B^2 + 0.0165P^2 + 0.474T^2 \quad (6)$$

where, L = engine load (%); B = blending ratio (%) ; P = fuel injection pressure (in bar) ; T= fuel injection timimg (in degrees CA bTDC)

Thereafter, the RSM method was employed to investigate the optimized engine operating parameters to achieve the best engine output in terms of performance and exhaust emission.

A combined desirability function of 0.6635 was used. The optimum values of operating conditions i.e., engine load, WCOME-diesel blending ratio, fuel injection pressure, and fuel injection timing are observed to 60.49%, 14.32%, 231.35 bar, and 23.7°bTDC, respectively. At these operating conditions, the optimized results i.e., BTE, BSFC, and P_{max} are found to be 24.28%, 0.3135 kg/kWh, and 58.95 bar, respectively.

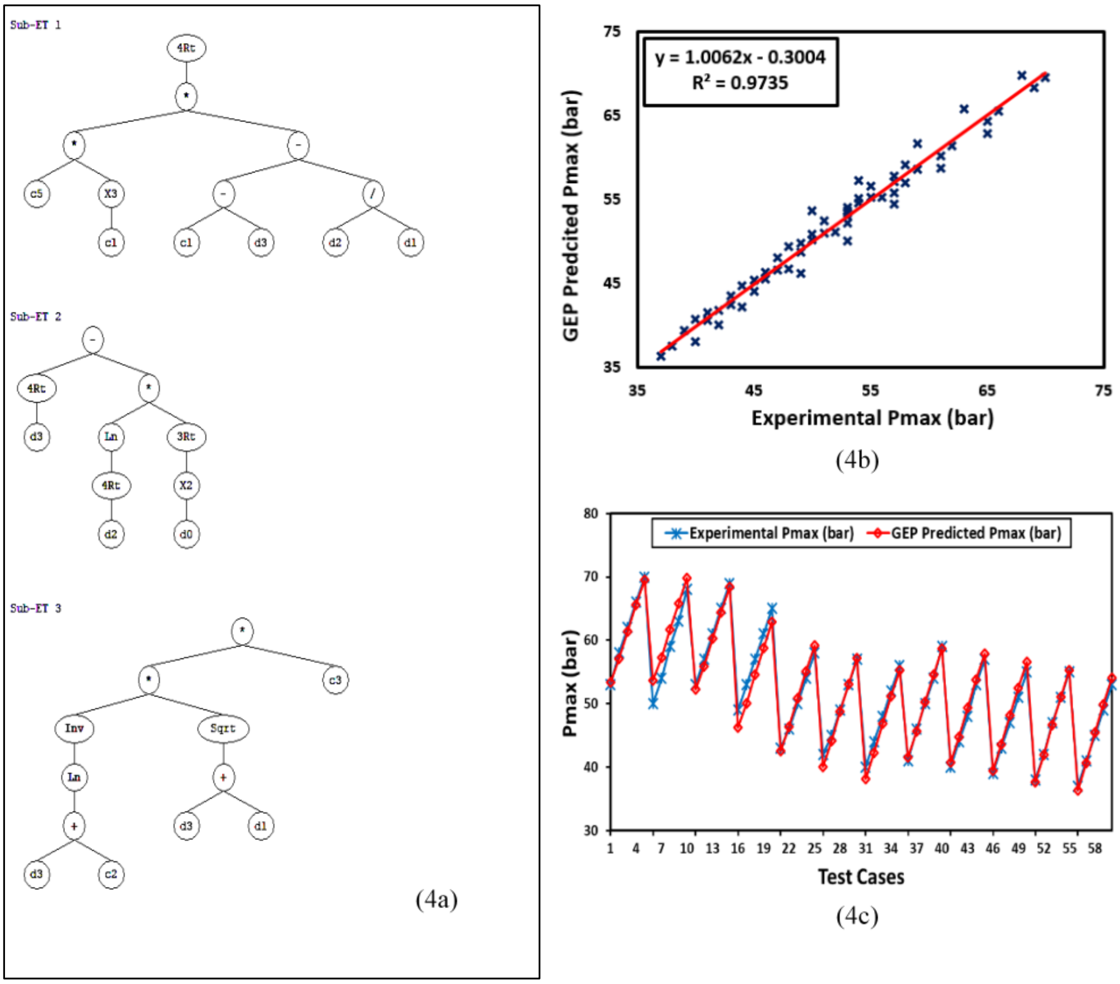

Fig. 4. P_{max} Model using GEP approach (4a) GPE model (4b) Comparison GEP and experiments and (4c) GEP predicted Pmax values for all test cases.

Finally, an experimental validation test was also conducted to validate the RSM-based optimization results. The engine output on these operating conditions was recorded as BTE and BSFC were 25.15% and 0.3268 kg/kWh respectively while P_{max} was 61.98 bar. The results of the validation test, RSM precited results, and error % are listed in **Table 4**. The error was well within an acceptable range of 5% [1].

Table 4. RSM optimized values and validation test results

Engine load (%)	Blending ratio (%)	FIP (bar)	FIT (ºCA bTDC)	Type of value	BTE (%)	BSFC (kg/kWh)	Pmax (bar)
60.49	14.32	231.35	23.70	Experimental	25.15	0.327	61.98
				RSM optimized	24.28	0.314	58.95
Error (%)					3.46	4.07	4.89

4. Conclusion

In the present study, an AI-based GEP model was created to predict the WCOME/diesel-fuelled CI engine combustion performance. Out of the total test runs 60 runs, about 60% experimental data sets were used for the development of the GEP model while the remaining 30% data was used for validation and verification of the model. The model established an explicit relationship in form of expression trees between engine input and output parameters. Following conclusions are derived out of the present work as:

(i) The overall uncertainty in the measuring instruments is deduced to be ± 1.81, which is quite reasonable.

(ii) An experimental validation test was conducted on optimized operating parameters. All validation results were within 5% of the RSM predicted results.

(iii) Predictions of the GEP model have high prognostic accuracy in the range of validity. It is evident from the error analysis as the correlation coefficient, R and coefficient of determination, R^2, values varied marginally within the range of 0.989 ± 0.010 and 0.979 ± 0.020, respectively, while MAPE values vary within the range of 2.15 ± 0.25.

(iv) GEP model is used to predict optimized results. The optimum values of operating conditions i.e., engine load, WCOME-diesel blending ratio, fuel injection pressure, and fuel injection timing are observed to be 60.49%, 14.32%, 231.35 bar, and 23.7°bTDC, respectively. At these operating conditions, the optimized results i.e., BTE, BSFC, and P_{max} are found to be 24.28%, 0.3135 kg/kWh, and 58.95 bar, respectively.

Therefore, the present model based on GEP coupled RSM can consistently emulate the real engine combustion performance with high accuracy over the encountered range of engine operation. GEP approach followed by RSM is observed to be a robust tool.

References

[1] M. Aydın, S. Uslu, and M. Bahattin Çelik, "Performance and emission prediction of a compression ignition engine fueled with biodiesel-diesel blends: A combined application of ANN and RSM based optimization," Fuel, vol. 269, 117472, February 2020.

[2] P. Sharma and A. K. Sharma, "Experimental Evaluation of Thermal and Combustion Performance of a DI Diesel Engine Using Waste Cooking Oil Methyl Ester and Diesel Fuel Blends," In Yadav S., Singh D., Arora P., Kumar H. (eds) Proceedings of International Conference in Mechanical and Energy Technology. Smart Innovation, Systems and Technologies, vol. 174, pp. 551-559, 2020

[3] G. M. Pinto, T. A. Z. de Souza, C. J. R. Coronado, L. F. V. Flôres, G. R. A. Chumpitaz, and M. H. da Silva, "Experimental investigation of the performance and emissions of a diesel engine fuelled by blends containing diesel s10, pyrolysis oil from used tires and biodiesel from waste cooking oil," Environ. Prog. Sustain. Energy, vol. 38(5), 13199, March 2019.

[4] N. Shrivastava and Z. M. Khan, "Application of Soft Computing in the Field of Internal Combustion Engines: A Review," Arch. Comput. Methods Eng., vol. 25 (3), pp. 707–726, 2018.

[5] G. M. Gilbert, N. Shililiandumi, and H. Kimaro, "Evolutionary Approaches to Fog Node Placement in LV Distribution Networks," International Journal of Smart Grid-ijSmartGrid., vol. 5(1), pp. 1–14, 2021.

[6] H. Bakiri, H. Maziku, N. Mvungi, N. Hamisi, and M. Libe, "Towards the Establishment of Robust Load Forecasting Mechanism in Tanzania Grid : Effect of Air Temperature and Daytime on Electricity Consumption in Residential Buildings," International Journal of Smart Grid-ijSmartGrid., vol. 5(1), 2021.

[7] A. I. Nusaif and A. L. Mahmood, "MPPT Algorithms (PSO, FA, and MFA) for PV System Under Partial Shading Condition, Case Study: BTS in Algazalia, Baghdad," International Journal of Smart Grid-ijSmartGrid., vol. 4(3), pp. 100–110, 2020.

[8] H. Benbouhenni and O. Maurice, "Utilization of an ANFIS-STSM Algorithm to Minimize Total Harmonic Distortion," International Journal of Smart Grid-ijSmartGrid., vol. 4(2), 2020.

[9] S. Simsek and S. Uslu, "Determination of a diesel engine operating parameters powered with canola, safflower and waste vegetable oil based biodiesel combination using response surface methodology (RSM)," Fuel, vol. 270,

117496, February 2020.

[10] A. Dolara, A. Gandelli, F. Grimaccia, S. Leva, and M. Mussetta, “Weather-based machine learning technique for Day-Ahead wind power forecasting,” in 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), pp. 206–209, 2017.

[11] L. P. Di Noia, F. Genduso, R. Miceli, and R. Rizzo, “Optimal integration of hybrid supercapacitor and IPT system for a free catenary tramway,” in 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), pp. 949–954, 2017.

[12] A. Sharma, Y. Singh, S. K. Gupta, and N. K. Singh, “Application of response surface methodology to optimize diesel engine parameters fuelled with pongamia biodiesel/diesel blends,” Energy Sources, Part A Recover. Util. Environ. Eff., vol. 0, pp. 1–12, 2019,

[13] S. Roy, A. Ghosh, A. K. Das, and R. Banerjee, “Development and validation of a GEP model to predict the performance and exhaust emission parameters of a CRDI assisted single cylinder diesel engine coupled with EGR,” Appl. Energy, vol. 140, pp. 52–64, 2015,

[14] S. Roy and R. Banerjee, “Multi-objective optimization of the performance-emission trade-off characteristics of a CRDI coupled CNG diesel dual-fuel operation: A GEP meta-model assisted MOGA endeavour,” Fuel, vol. 211, pp. 891–897, 2018.

[15] M. Elkelawy, H. Alm Eldin, K. Khodary Esmaeil, A. Mohamed Radwan, H. Panchal, K. Kumar Sadasivuni, S. Muthusamy, M. Israr, “Maximization of biodiesel production from sunflower and soybean oils and prediction of diesel engine performance and emission characteristics through response surface methodology,” Fuel, 2020, vol. 266, 117072, 2020.

[16] S. Bhowmik, R. Panua, D. Debroy, and A. Paul, “Artificial Neural Network Prediction of Diesel Engine Performance and Emission Fueled With Diesel-Kerosene-Ethanol Blends: A Fuzzy-Based Optimization,” J. Energy Resour. Technol. Trans. ASME, vol. 139(4), 042201, 2017.

[17] N. Kumar Singh, Y. Singh, A. Sharma, and S. Kumar, “Diesel engine performance and emission analysis running on jojoba biodiesel using intelligent hybrid prediction techniques,” Fuel, vol. 279, 118571, 2020.

[18] S. Roy, A. Ghosh, A. K. Das, and R. Banerjee, “A comparative study of GEP and an ANN strategy to model engine performance and emission characteristics of a CRDI assisted single cylinder diesel engine under CNG dual-fuel operation,” J. Nat. Gas Sci. Eng., vol. 21, pp. 814-828, 2014.

[19] C. Ferreira, "Gene Expression Programming: A New Adaptive Algorithm for Solving Problems," Complex Systems., vol. 13(2), pp. 87-129, 2001.

[20] C. Ferreira, “Gene expression programming and the evolution of computer programs,” Med. Informatics Concepts, Methodol. Tools, Appl., vol. 4–4, no. Holland 1975, pp. 2154–2173, 2008.

[21] M. N. Nabi and M. G. Rasul, “Influence of second generation biodiesel on engine performance, emissions, energy and exergy parameters,” Energy Convers. Manag., vol. 169, pp. 326–333, 2018.

[22] C. Patel, A. K. Agarwal, N. Tiwari, S. Lee, C. S. Lee, and S. Park, “Combustion, noise, vibrations and spray characterization for Karanja biodiesel fuelled engine,” Appl. Therm. Eng., vol. 106, pp. 506–517, 2016.

[23] S. Bhowmik, A. Paul, R. Panua, S. K. Ghosh, and D. Debroy, “Artificial intelligence based gene expression programming (GEP) model prediction of Diesel engine performances and exhaust emissions under Diesosenol fuel strategies,” Fuel, vol. 235, pp. 317–325, 2019.

[24] P. Sharma and A. K. Sharma, “Application of Response Surface Methodology for Optimization of Fuel Injection Parameters of a Dual Fuel Engine Fuelled with Producer Gas- Biodiesel blends,” Energy Sources, Part A Recover. Util. Environ. Eff., vol. 00, pp. 1–18, 2021.