IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

COMPARATIVE ANALYSIS OF DIFFERENT STATISTICAL REGRESSION TECHNIQUES THROUGH PYROOIL FUELED SPARK IGNITION ENGINE RESPONSE OPTIMIZATION

[1]Manickavelan K, [2]Sivaganesan S, [3]Sivamani S, [4]Mithun V Kulkarni

[1]Research Scholar, [2]Associate Professor

[1]Department of Mechanical Engineering,

[1]Vels Institute of Science Technology & Advanced Studies (VISTAS), Chennai, India

Abstract: Statistical regression is vital for thoroughly analyzing and optimizing Internal Combustion engine performance, serving various functions like providing predictive insights and aiding data-driven decision-making. In this study, two methodologies, no transform and square root transformation are compared for their effectiveness in predicting engine performance indicators brake thermal efficiency and specific fuel consumption in spark ignition engines fueled with pyro oil and gasoline blends. Analysis of Variance (ANOVA), the statistical analysis tool was used to find the significant of the model. The findings consistently favor the square root transformation, which demonstrates higher R-squared values and better alignment with actual values compared to no transform regression technique. Notably, it offers more accurate predictions of critical metrics such as brake thermal efficiency and specific fuel consumption compared to the traditional no transform approach. Overall, this research significantly contributes to refining engine performance prediction models, offering valuable insights for decision-making in automotive engineering and design.

Index Terms **- Statistical regression, spark ignition engine, no transformation, square root transformation**

I. INTRODUCTION

Research and experimentation into the utilization of plastic oil in internal combustion (IC) engines have provided avenues for exploring sustainable fuel sources. Investigations have delved into the potential of plastic pyrolysis oil (PPO) as a feasible substitute for conventional diesel fuel in compression ignition (CI) engines[1,2]. Findings suggest that PPO exhibits comparable performance and combustion traits to petroleum diesel. Extensive research and experiments have been conducted to investigate the feasibility of utilizing pyro oil generated from plastic waste as an alternative fuel for SI engines. According to studies, pyrooil can efficiently replace standard gasoline while maintaining identical performance characteristics[3,4]

The incorporation of optimization methodologies, regression modeling, and cutting-edge technologies within IC engines is pivotal for elevating performance, mitigating emissions, and enhancing overall efficiency[5,6].

Statistical optimization involves the use of mathematical and statistical techniques to identify the optimal settings for various parameters within an IC engine. This process typically begins with the formulation of an objective function, such as maximizing fuel efficiency or minimizing emissions, subject to constraints like engine operating limits and regulatory standards[7,8]. Techniques such as response surface methodology (RSM), factorial designs, and Taguchi methods are often used to systematically explore the parameter space and identify the optimal combination of settings[9].

By collecting experimental data or using simulation results, regression models can be developed to predict how changes in input variables impact engine behavior[10]. These models can take various forms, including linear regression, nonlinear regression, and multivariate regression, depending on the complexity of the relationships being studied(11). Figure 1 illustrates the fundamental steps of a simple regression process.

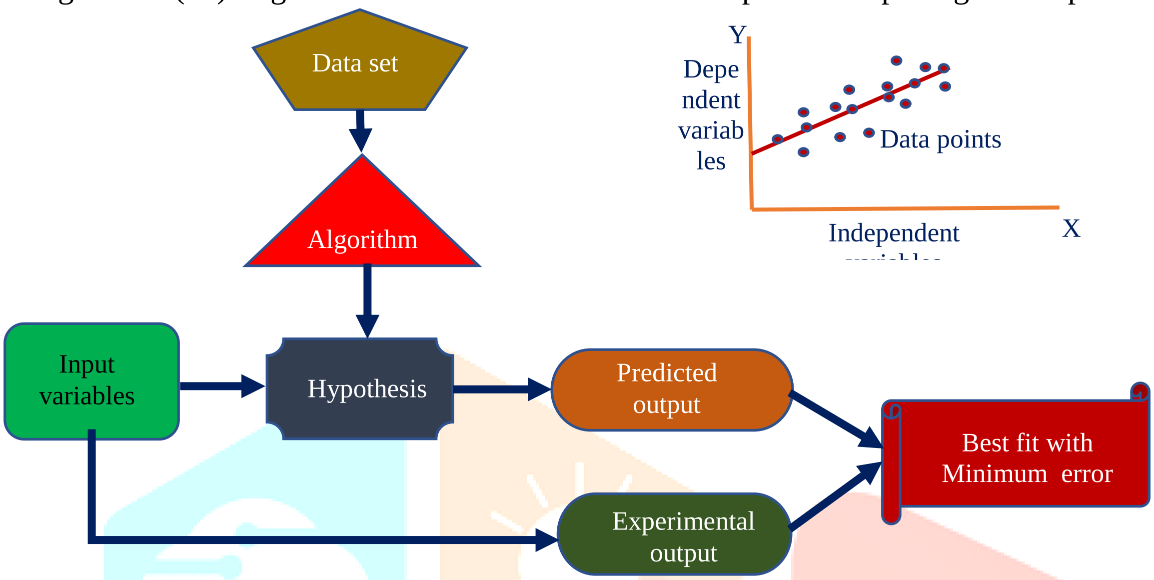


Figure.1 Regression technique layout

II. THEORETICAL ANALYSIS

Four modeling methods, encompassing both linear and non-linear regression, were employed in regression analysis. Non-linear regression comprised quadratic, logarithmic, and exponential regression models(12). These four models were identified based on the equations 1-4 outlined in the table 1.

Table 1. Equation of vegetation index(12)

Regression model	Equation	
Simple linear	$Y = a + bX$	(1)
Quadratic	$Y = a + bX + bX^2$	(2)
Logarithmic	$Y = a + b \log X$	(3)
Exponential	$Y = ae^{bx}$, $e = 2.7183$	(4)

(a and b are co-efficient, X is dependent variable, Y is independent variable)

Gad & Alenany (2024)[13] developed two mathematical models, an extreme learning machine (ELM) and quadratic regression, to forecast engine parameters and emissions across various engine speeds and biodiesel concentrations. Quadratic regression outperformed ELM in predicting engine performance and emissions for most variables, yielding lower root-mean-square and mean absolute percentage errors. Maheshwari et al. (2011)[14]used nonlinear regression to predict brake thermal efficiency, NOx, HC, and smoke emissions from experimental data with different blending ratio of Karanja biodiesel . The results showed correlation coefficients (R) of 0.95 to 0.99 and minimal root mean square errors, allowing them to assess the optimization process within the 0-20% blend range. Alsuwian et al. (2022)[15] compared Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and a Nonlinear Regression-based observer model in Fault Detection and Isolation (FDI) to find the most cost-effective and precise method. The found that the nonlinear regression approach yielded accurate results and lower response times. Dey et al. (2023)[16] employed regression analysis to enhance the performance and minimize emissions of a CI engine fueled by alcohol-biodiesel blends.

Tosun et al. (2016) [17]used linear regression and artificial neural network modeling to predict engine performance, torque, exhaust emissions, and carbon monoxide levels in a naturally aspirated diesel engine fueled with diesel, peanut biodiesel, and biodiesel-alcohol. They found that ANN provided more accurate results. The same author analyzed operational parameters of a four-stroke turbocharged SI engine using a threelayer feed-forward ANN with back-propagation and his results showed its superior predictive accuracy over both linear and non-linear regression techniques[18]. Many researchers used nonlinear regression meddling of IC engines by using ANN and optimized the outputs[19–21]. Other algorithms like Random Forest Regression[22], Gaussian Processes[23], Kernel Regression[24], Generalized Additive Models[25] also extensively used in the field of IC engine technology. Different optimization techniques like Gradient Descent[26], Root Mean Squared Prop[27], Adaptive Moment Estimation[28] used the regression methods for different applications in IC engines. The integration of statistical optimization and regression modeling in IC engines is a powerful approach to optimizing engine performance and emissions control. Regression models can be used to understand the relationships between engine parameters and performance metrics, which can then be leveraged in the optimization process. Statistical optimization techniques can guide the search for optimal engine settings based on the insights gained from regression models, leading to improved efficiency, reduced emissions, and enhanced overall performance of IC engines.

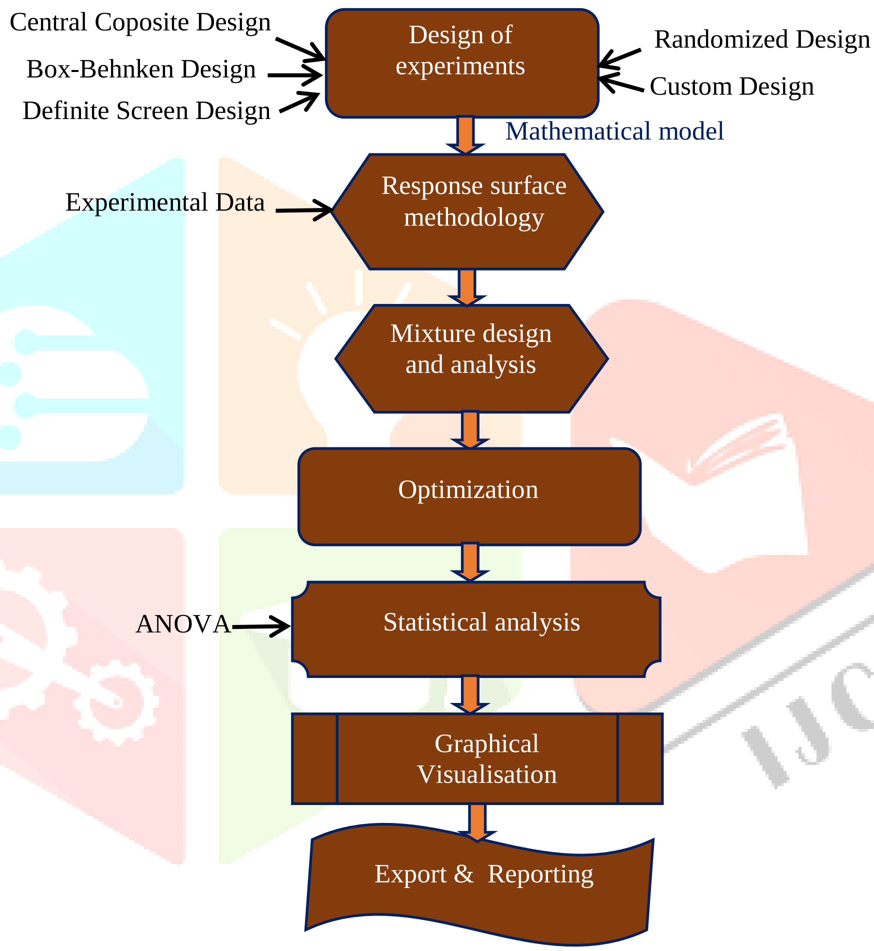


Figure 2. Deign expert process flowchart

Design-Expert is a powerful software tool used for design of experiments (DOE), statistical analysis, and optimization of processes and products[29]. It is developed and distributed by Stat-Ease, Inc. Design-Expert offers a user-friendly interface and a wide range of features to help researchers, engineers, and scientists design experiments, analyze data, and optimize processes efficiently. Figure 2 provides an illustrative overview of the diverse processes encompassed within Design Expert. This visual representation offers a comprehensive depiction of the intricate steps and functionalities integral to the Design Expert software. This study aims to evaluate the optimized performance of blends containing pyro oil and gasoline in a spark ignition (SI) engine, with a focus on determining the most effective analysis method for optimization. Two distinct analysis methodologies were employed: one utilizing no-transformation techniques, and the other employing square root methods. The experimentation phase was conducted using Design Expert 13.0 software, enabling a thorough comparative evaluation of the performance characteristics of these fuel blends within the SI engine context.

Through this investigation, the study seeks to identify the analysis technique that yields the most accurate optimization process for the fuel blends. By systematically comparing the outcomes of both no transformation and square root methods, the study aims to provide valuable insights into the optimal approach for achieving enhanced performance and efficiency in SI engines utilizing pyro oil and gasoline blends. This research contributes to advancing our understanding of the optimization process for alternative fuel blends, ultimately supporting efforts towards sustainable and efficient energy utilization in automotive applications.

III. MATERIAL AND METHODS

Waste HDPE plastics were subjected to pyrolysis within a fixed bed reactor, operating at temperatures reaching up to 450°C. The output from this process yields an oil product, which is then subjected to distillation for the purpose of separating gasoline and diesel fractions based on temperature gradients. This separation process allows for the isolation of distinct gasoline fractions. Following distillation, the gasoline fraction is blended with pure gasoline at varying ratios, specifically at 2%, 4%, 6%, and 8%, yielding blends designated as DPO2, DPO4, DPO6, and DPO8, respectively. These blends are meticulously formulated to offer a range of compositions suitable for further evaluation and analysis.

To assess the performance characteristics of these blends, initial testing is conducted using the engine fueled solely with pure gasoline (DPO). For the testing procedures, a four-cylinder single ignition (SI) engine equipped with a hydraulic dynamometer is employed. The layout of the test rig. is exhibited in the figure 3. Subsequently, the engine undergoes comprehensive testing utilizing each of the different blends.

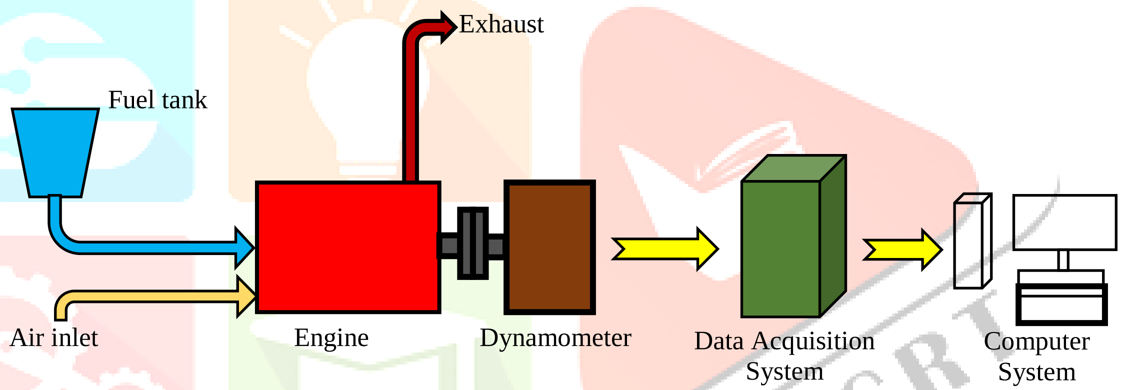


Figure. 3 Experimental set up

A comprehensive mathematical model was formulated and meticulously examined through the utilization of Design Expert 13.0 software based on the experimental outputs. The design process was approached from two distinct angles, employing both no transformation and square root methods. With the aid of user-defined parameters, the models were intricately crafted and subjected to rigorous analysis via Analysis of Variance (ANOVA). Following this detailed analysis, the outcomes of the two optimization approaches were meticulously compared, leading to conclusive insights and findings.

IV. RESULTS AND DISCUSSION

The optimization of BTE and SFC of pyro-oil and gasoline blends were analyzed by tow distinguish techniques no transformation and square root transformation techniques.

4.1 No-transformation analysis

In the realm of Design Expert software, a "no transformation model" typically denotes a statistical model or analytical approach in which the response variable (also known as the dependent variable) remains unaltered before analysis.

When handling experimental data, it's frequent to encounter scenarios where the response variable exhibits characteristics that don't necessitate transformation to conform to assumptions such as normality, linearity, or homoscedasticity. In such instances, analysts can proceed with analyzing the data directly without resorting to any transformation techniques.

Design Expert offers a suite of tools to facilitate analyses on both transformed and no transformed datasets. The decision to opt for a transformed or no transformed model hinge on the specific attributes of the data and the analytical requirements at hand. Should the assumptions of the analysis be met satisfactorily without the need for transformation, analysts can confidently pursue a no transformed model.

No transformation models within Design Expert encompass various methodologies, including but not limited to Analysis of Variance (ANOVA), regression analysis, response surface methodology (RSM), and a plethora of multivariate analysis techniques. These approaches enable analysts to explore the relationships between factors (independent variables) and the response variable without introducing alterations to the original data through transformations[30]. In Design-Expert software, when no standard transformation is recommended within the confidence interval, a Power transformation is suggested with the best lambda value.

A user-defined quadratic model has been employed to analyze the responses of brake thermal efficiency (BTE) and specific fuel consumption (SFC), utilizing speed (A) and torque (B) as input factors. The speed range spans from 1390 to 3400 rpm, while the torque range varies from 1 to 12 Nm across all blending ratios. A total of 45 runs were conducted, each involving different combinations of input variables, and subsequently analyzed.

In the analytical process, the "no transform" option coupled with a quadratic model was chosen in Design Expert. This decision allows for the examination of the relationship between the input factors and the response variables without applying any transformations to the data. The quadratic model is particularly advantageous as it enables the exploration of potential nonlinear relationships between the inputs and outputs, offering a more comprehensive understanding of the system's behavior[30].

In the analysis of brake thermal efficiency (BTE), the model demonstrates strong predictive performance, with an exceptionally high R-squared value of 0.9954. This indicates that the model effectively captures a significant portion of the variability in BTE explained by the input variables[31]. The adjusted R-squared value remains high at 0.9925, suggesting that the model's performance remains robust even when considering the number of predictors involved. Additionally, the predicted R-squared value of 0.9854 reflects the model's effectiveness in making accurate predictions on new data, reinforcing its reliability and utility in the analysis of BTE.

For the analysis of specific fuel consumption (SFC), the R-squared value of 0.9728 indicates a strong relationship between the input variables and SFC. The adjusted R-squared value, while still high at 0.9556, suggests that the model accounts for a substantial amount of variability in SFC while considering the complexity of the model. However, the predicted R-squared value of 0.9120, though respectable, is lower than the R-squared and adjusted R-squared values, suggesting some potential limitations in the model's predictive capability on new data. Table 2 exhibits the values of R squared for BTE and SFC in no transformation analysis.

Table 2. Fit statistics for no transformation analysis

BTE		SFC	
Regression co-efficient	**Value**	**Regression co-efficient**	**Value**
R^2	0.9954	R^2	0.9728
Adjusted R^2	0.9925	Adjusted R^2	0.9556
Predicted R^2	0.9925	Predicted R^2	0.9120

Overall, both analyses demonstrate the significance of the models in explaining the variability in BTE and SFC. While the BTE model exhibits stronger predictive performance with higher R-squared values, further investigation and refinement may be necessary to enhance the predictive capability of the SFC model on new data.[31].

The resulting regression equations 5-9 and 10-14 derived from ANOVA serves as a valuable tool for identifying optimal conditions that yield maximum BTE and minimum SFC, aligning with the specified requirements. In the equations, A represents Speed, B represents Torque.

4.1.1 Brake thermal efficiency regression equations

$$DPO0 = -4.95923 + 0.004499 * A + 2.70443 * B + 0.000131 * A * B - 5.12485E^{-07} * A^2 - 0.119436 * B^2 \quad (5)$$

$$DPO2 = -5.63525 + 0.004601 * A + 2.92347 * B + 0.000131 * A * B - 5.12485E^{-07} * A^2 - 0.119436 * B^2 \quad (6)$$

$$DPO4 = -1.99421 + 0.004341 * A + 2.73573 * B + 0.000131 * A * B - 5.12485E^{-07} * A^2 - 0.119436 * B^2 \quad (7)$$

$$DPO6 = -4.57811 + 0.004466 * A + 2.64282 * B + 0.000131 * A * B - 5.12485E^{-07} * A^2 - 0.119436 * B^2 \quad (8)$$

$$DPO8 = -5.84532 + 0.004455 * A + 2.65477 * B + 0.000131 * A * B - 5.12485E^{-07} * A^2 - 0.119436 * B^2 \quad (9)$$

4.1.2 Specific Fuel Consumption regression equations

$$DPO0 = +4.32058 - 0.001197 * A - 0.596215 * B + 0.000069 * A * B + 1.04469E^{-07} * A^2 + 0.024498 * B^2 \quad (10)$$

$$DPO2 = +4.83776 - 0.001267 * A - 0.627066 * B + 0.000069 * A * B + 1.04469E^{-07} * A^2 + 0.024498 * B^2 \quad (11)$$

$$DPO4 = +4.74005 - 0.001257 * A - 0.622665 * B + 0.000069 * A * B + 1.04469E^{-07} * A^2 + 0.024498 * B^2 \quad (12)$$

$$DPO6 = +4.53086 - 0.001188 * A - 0.623454 * B + 0.000069 * A * B + 1.04469E^{-07} * A^2 + 0.024498 * B^2 \quad (13)$$

$$DPO8 = +6.97488 - 0.001548 * A - 0.756772 * B + 0.000069 * A * B + 1.04469E^{-07} * A^2 + 0.024498 * B^2 \quad (14)$$

4.2 Square root transformation analysis

Transformation is crucial in data analysis, particularly when error (residuals) depends on the magnitude of the response (predicted values). Design-Expert offers robust diagnostic tools to validate statistical assumptions. The normal plot assesses residual normality, while patterns in the residuals versus predicted response plot signal issues. Transformation is typically unnecessary unless there's a significant range between maximum and minimum responses.

The Diagnostics button in Design-Expert features a Box-Cox plot recommending transformations from the power family. For specific data types like bounded or proportional data, non-power transformations such as logit and arcsin-sqrt are recommended. Square-root transformations are often suggested for proportion data, while log transformations suit bounded data.

Design-Expert offers a diverse range of transformations, predominantly from the power family, with additional options like logit and arcsine square root. These transformations generally adhere to the power function, ensuring equal variance in statistical models. The same dataset utilized in the no transformed analysis is also employed in the square root analysis conducted through Design Expert. Table 3 presents the regression coefficients for BTE and SFC. In the BTE analysis, the Predicted R^2 of 0.9934 closely aligns with the Adjusted R^2 of 0.9965, with a difference of less than 0.2. Similarly, for SFC analysis, the Predicted R^2 of 0.9297 is reasonably consistent with the Adjusted R^2 of 0.9613, with a difference of less than 0.2.

Table. 3 Fit statistics for square root analysis

BTE		SFC	
Regression co-efficient	**Value**	**Regression co-efficient**	**Value**
R^2	0.9978	R^2	0.9763
Adjusted R^2	0.9965	Adjusted R^2	0.9613
Predicted R^2	0.9934	Predicted R^2	0.9297

The regression coded equations 19-24 and 25-29 the relationship between the variables for maximizing BTE and minimizing SFC.

4.2.1 Brake thermal efficiency regression equations

$$DPO0 = +0.397010 + 0.000837 * A + 0.497729 * B - 4.39236E^{-06} * A * B - 8.60240E^{-08} * A^2 - 0.021293 * B^2 \quad (15)$$

$$DPO2 = +0.262986 + 0.000849 * A + 0.527530 * B - 4.39236E^{-06} * A * B - 8.60240E^{-08} * A^2 - 0.021293 * B^2 \quad (16)$$

$$DPO4 = +0.973712 + 0.000795 * A + 0.482683 * B - 4.39236E^{-06} * A * B - 8.60240E^{-08} * A^2 - 0.021293 * B^2 \quad (17)$$

$$DPO6 = +0.476842 + 0.000831 * A + 0.487762 * B - 4.39236E^{-06} * A * B - 8.60240E^{-08} * A^2 - 0.021293 * B^2 \quad (18)$$

$$DPO8 = +0.162144 + 0.000847 * A + 0.501583 * B - 4.39236E^{-06} * A * B - 8.60240E^{-08} * A^2 - 0.021293 * B^2 \quad (19)$$

4.2.2 Specific Fuel Consumption regression equations

$$DPO0 = +2.35268 - 0.000476 * A - 0.253175 * B + 0.000024 * A * B + 4.19327E^{-08} * A^2 + 0.010632 * B^2 \quad (20)$$

$$DPO2 = +2.54163 - 0.000500 * A - 0.263757 * B + 0.000024 * A * B + 4.19327E^{-08} * A^2 + 0.010632 * B^2 \quad (21)$$

$$DPO4 = +2.50522 - 0.000498 * A - 0.262878 * B + 0.000024 * A * B + 4.19327E^{-08} * A^2 + 0.010632 * B^2 \quad (22)$$

$$DPO6 = +2.37711 - 0.000455 * A - 0.263571 * B + 0.000024 * A * B + 4.19327E^{-08} * A^2 + 0.010632 * B^2 \quad (23)$$

$$DPO8 = +3.14314 - 0.000569 * A - 0.298300 * B + 0.000024 * A * B + 4.19327E^{-08} * A^2 + 0.010632 * B^2 \quad (24)$$

The regression equations aimed at maximizing BTE and minimizing SFC satisfy the necessary conditions. This implies that the mathematical models derived from these regression equations effectively capture the relationships between the input variables and the desired outcomes.

Based on the results obtained from both analysis methods, the R-squared value for BTE is 0.9978 in the square root analysis, compared to 0.9954 in the no transformation technique. Similarly, for SFC, the square root analysis yields a higher value of 0.9763, whereas the no transformation technique shows a comparatively lower value of 0.9728. Additionally, the Adjusted and Predicted R-squared values for BTE are 0.9965 and 0.9934 respectively in the square root analysis, while they are 0.9925 and 0.9856 in the no transformation analysis, indicating lower values in the latter method as shown in Table 4. This trend is mirrored in the SFC Adj. R-squared and Pred. R-squared values, with the square root analysis exhibiting more accurate results than the no transformation analysis.

Table 4. comparison of regression coefficients between no transform and square root transform techniques

Response	Regression co-efficient	No transformation	Square root transformation
BTE (%)	R^2	0.9954	0.9978
	Adjusted R^2	0.9925	0.9965
	Predicted R^2	0.9859	0.9934
SFC (kg/kW.hr)	R^2	0.9728	0.9763
	Adjusted R^2	0.9556	0.9613
	Predicted R^2	0.9120	0.9297

This discrepancy is further evident in the response optimization values presented in Table 5.

Table 5. Comparison of optimized response values between no transform and square root transform techniques

Variables	No transform optimized values	Square root optimized values
Speed (A) (rpm)	3400	3400
Torque (B) (Nm)	10.2595	10.2595
Brake thermal efficiency (BTE) (%)	26.9023	27.4505
Specific fuel consumption (SFC)(kg/kW.hr)	0.262507	0.300141

Both analyses identify the same optimized input variables at 3400 rpm and 10.2595 Nm. However, the optimized BTE value in the square root transformation is 27.4505%, whereas it is 26.9023% in the no transformed analysis, indicating approximately 2% lower accuracy for the same inputs. Moreover, the square root analysis yields a specific SFC of 0.300141 kg/kW.hr, compared to 0.262507 kg/kW.hr in the no transformation method as illustrated in fig.4. Despite the higher R-squared value and BTE in the square root analysis, it emerges as the superior technique compared to the no transformation analysis.

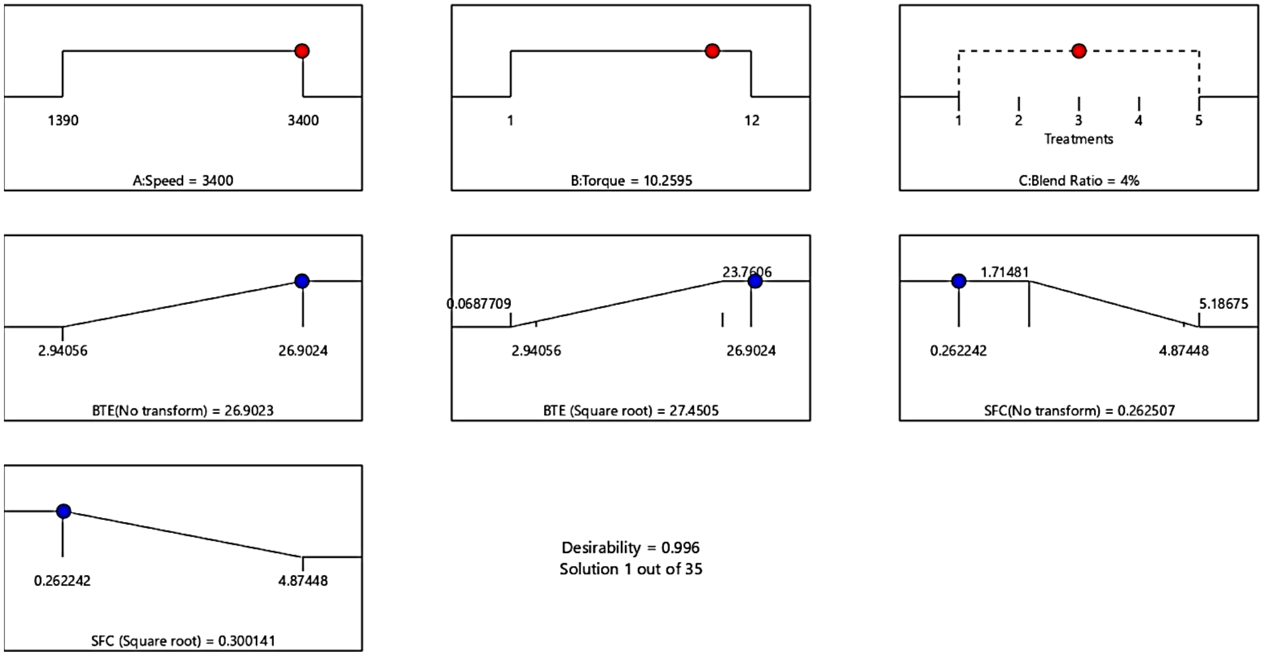
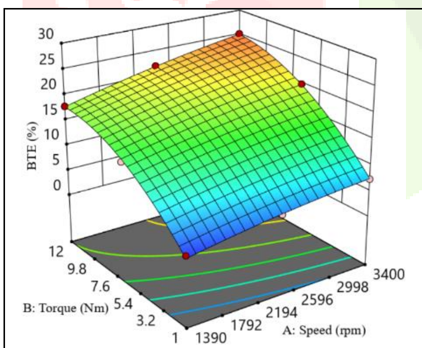
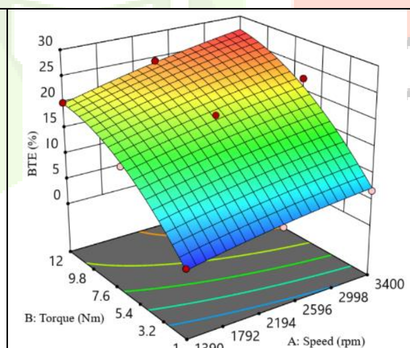
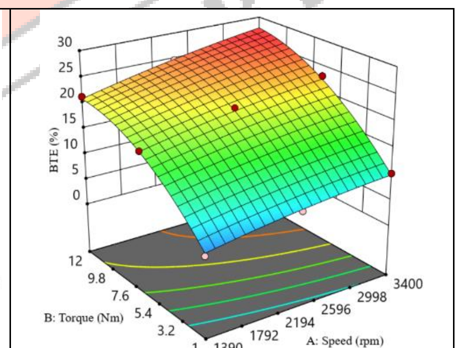
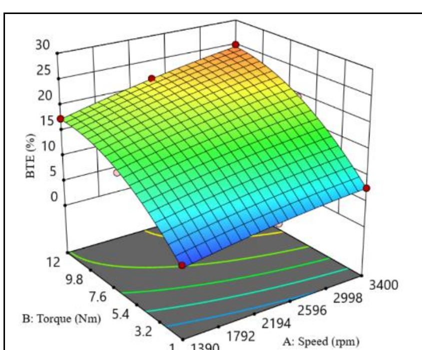
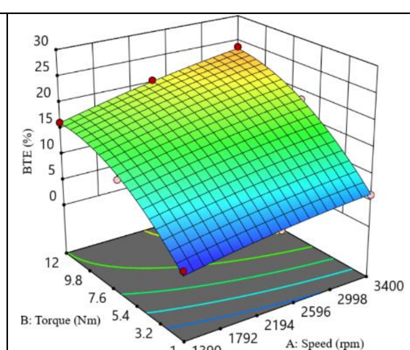
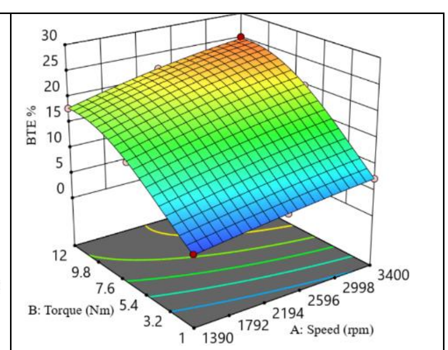
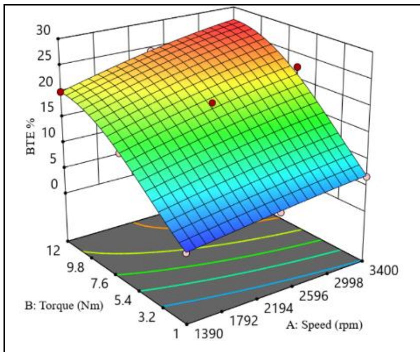


Figure 5. Ramp output diagram of optimized values

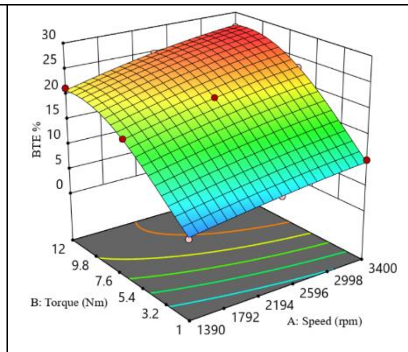
The 3-Dimensional response surface diagram for BTE and SFC obtained through the two techniques, no transformation and square root transformation are shown in fig. 6

		
BTE of DPO0-no transform	BTE of DPO2-no transform	BTE of DPO4-no transform

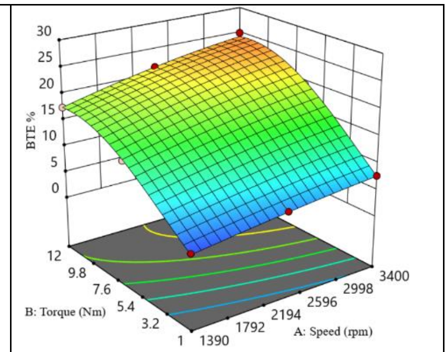
		
BTE of DPO6-no transform	BTE of DPO8-no transform	BTE of DPO0-square root transform



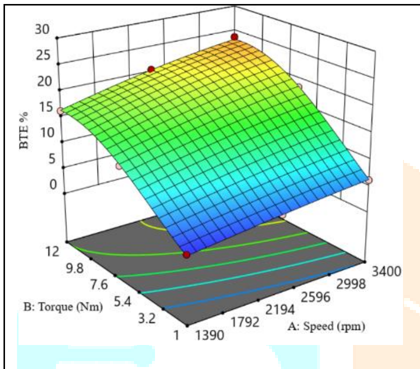
BTE of DPO2- square root transform



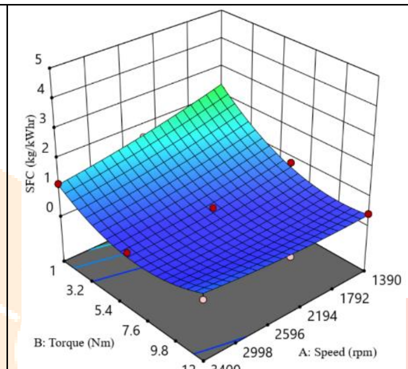
BTE of DPO4- square root transform



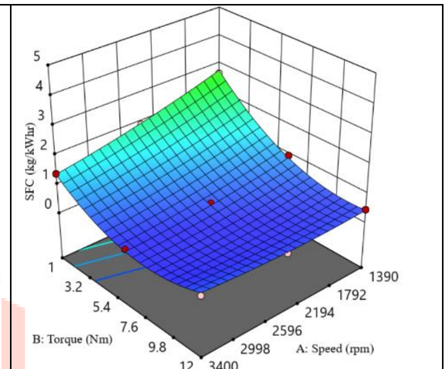
BTE of DPO6-square root transform



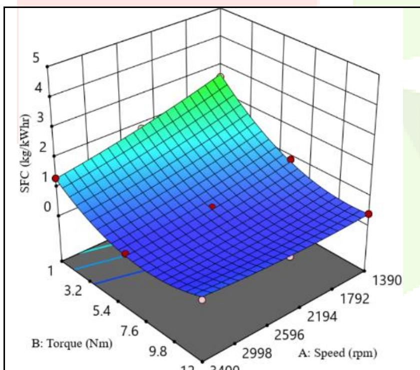
BTE of DPO8- square root transform



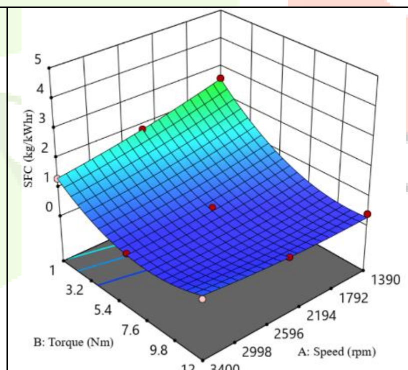
SFC of DPO0- no transformation



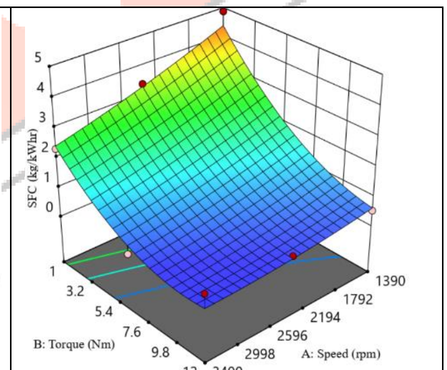
SFC of DPO2- no transformation



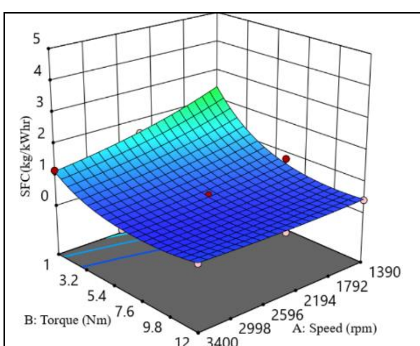
SFC of DPO4- no transformation



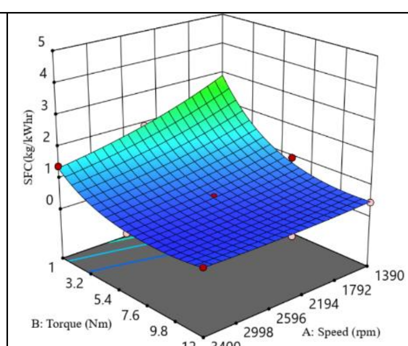
SFC of DPO6- no transformation



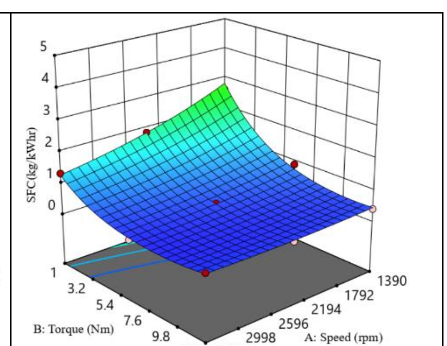
SFC of DPO8- no transformation



SFC of DPO0- square root



SFC of DPO2- square root



SFC of DPO4- square root

transform	transform	transform

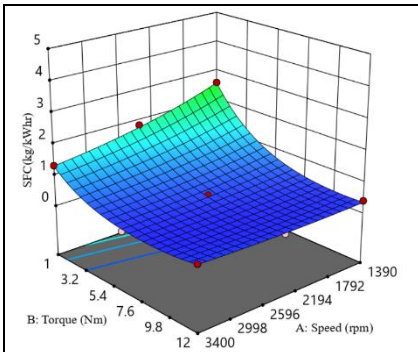
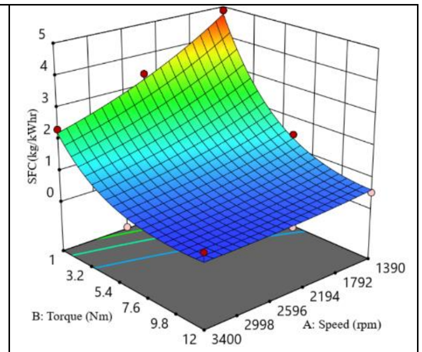
	
SFC of DPO6- square root transform	SFC of DPO8- square root transform

Fig.6 3-D surface diagrams for BTE and SFC from no transform and square root transform technique

V. CONCLUSION

The performance test was conducted successfully using various blending ratios (DPO0, DPO2, DPO4, DPO6, DPO8) of distilled plastic oil and gasoline in a Spark Ignition engine across different speeds and torque levels. A mathematical design was developed based on the outcomes obtained from these experiments using Design Expert software. Subsequently, the model underwent analysis using both no transformation and square root transformation techniques. The results from the square root transformation analysis demonstrated higher accuracy in terms of R-squared, Adjusted R-squared, and Predicted R-squared values for both BTE and SFC compared to the no transformation analysis. This method revealed optimal response values, indicating 27.4505% BTE and 0.300141 kg/kW.hr SFC at a speed of 3400 rpm and a torque of 10.2595 N.m. Thus, based on the conclusive evidence, it can be affirmed that square root analysis stands out as the superior approach, providing invaluable insights and facilitating more precise predictions in the assessment of IC engine performance.

REFERENCES

[1] Singh RK, Ruj B, Sadhukhan AK, Gupta P, and Tigga VP. 2020. Waste plastic to pyrolytic oil and its utilization in CI engine: Performance analysis and combustion characteristics. Fuel, Feb 15;262.

[2] Kumar A, Pali HS, and Kumar M. 2024. Effective utilization of waste plastic derived fuel in CI engine using multi objective optimization through RSM. Fuel, Jan;355:129448.

[3] Khairil, Riayatsyah TMI, Bahri S, Sofyan SE, Jalaluddin J, and Kusumo F. 2020. Experimental Study on the Performance of an SI Engine Fueled by Waste Plastic Pyrolysis Oil–Gasoline Blends. Energies, Aug 14;13(16):4196.

[4] Sunaryo, Efendy M, Sarjito, and Kamarrudin NS. 2019. Pyrolysis of plastic waste as an alternative fuels in spark ignition engine. Int J Emerg Trends Eng Res, Nov 1;7(11):454–459.

[5] Tornatore C, and Marchitto L. 2021.Advanced Technologies for the Optimization of Internal Combustion Engines. Appl Sci,11(22):10842.

[6] Yu X, Zhu L, Wang Y, Filev D, and Yao X. 2022. Internal combustion engine calibration using optimization algorithms. Appl Energy, 305:117894.

[7] Sathish Kumar T, Vignesh R, Ashok B, Saiteja P, Jacob A, Karthick C. 2022. Application of statistical approaches in IC engine calibration to enhance the performance and emission Characteristics: A methodological review. Fuel, 324:124607.

[8] Badra J, Owoyele O, Pal P, and Som S. 2022. A machine learning-genetic algorithm approach for rapid optimization of internal combustion engines. In: Artificial Intelligence and Data Driven Optimization of Internal Combustion Engines. Elsevier, 125–158.

[9] Veza I, Spraggon M, Fattah IMR, and Idris M. 2023.Response surface methodology (RSM) for optimizing engine performance and emissions fueled with biofuel: Review of RSM for sustainability energy transition. Results Eng, 18:101213.

[10] Sepehrnia M, Mohammadzadeh K, Hemmati Rozbahani M, Ghiasi MJ, and Amani M. 2024. Experimental study, prediction modeling, sensitivity analysis, and optimization of rheological behavior and dynamic viscosity of 5W30 engine oil based SiO2/MWCNT hybrid nanofluid. Ain Shams Eng J, Jan;15(1):102257.

[11] Rodríguez del Águila MM, and Benítez-Parejo N. 2011. Simple linear and multivariate regression models. Allergol Immunopathol (Madr),. May;39(3):159–173.

[12] Umarhadi DA, and Muammar A. 2018. Regression model accuracy comparison on mangrove canopy density mapping. In: The 3rd International Conference on Science and Technology, 1–11.

[13] Gad MS, and Alenany A. 2024.Comparative diesel engine performance and emission forecasting using extreme learning and quadratic regression techniques burning waste cooking biodiesel. Int J Hydrogen Energy, Mar; 60:94–106.

[14] Maheshwari N, Balaji C, and Ramesh A. 2011. A nonlinear regression based multi-objective optimization of parameters based on experimental data from an IC engine fueled with biodiesel blends. Biomass and Bioenergy, May;35(5):2171–183.

[15] Alsuwian T, Iqbal MS, Amin AA, Qadir MB, Almasabi S, and Jalalah M. 2022. A Comparative Study of Design of Active Fault-Tolerant Control System for Air–Fuel Ratio Control of Internal Combustion Engine Using Particle Swarm Optimization, Genetic Algorithm, and Nonlinear Regression-Based Observer Model. Appl Sci, Aug 4;12(15):7841.

[16] Dey S, Singh AP, Gajghate SS, Pal S, Saha BB, Deb M. 2023. Optimization of CI Engine Performance and Emissions Using Alcohol–Biodiesel Blends: A Regression Analysis Approach. Sustainability. Oct 10;15(20):14667.

[17] Tosun E, Aydin K, and Bilgili M. 2016. Comparison of linear regression and artificial neural network model of a diesel engine fueled with biodiesel-alcohol mixtures. Alexandria Eng J, Dec;55(4):3081–3089.

[18] Tosun E, Aydin K, Merola S, and Irimescu A. 2017. Estimation of operational parameters for a direct injection turbocharged spark ignition engine by using regression analysis and artificial neural network. Therm Sci, 21(1 Part B):401–412.

[19] Yusaf TF, Buttsworth DR, Saleh KH, and Yousif BF. 2010. CNG-diesel engine performance and exhaust emission analysis with the aid of artificial neural network. Appl Energy, May;87(5):1661–1669.

[20] Duan H, Yin X, Kou H, Wang J, Zeng K, and Ma F. 2023. Regression prediction of hydrogen enriched compressed natural gas (HCNG) engine performance based on improved particle swarm optimization back propagation neural network method [(IMPSO-BPNN). Fuel, Jan;331:125872.

[21] Sun P, Zhang J, Dong W, Li D, and Yu X. 2023 .Prediction of oxygen-enriched combustion and emission performance on a spark ignition engine using artificial neural networks. Appl Energy, Oct;348:121466.

[22] Yun Q, Wang X, Yao C, and Wang H. Random forest method for estimation of brake specific fuel consumption. Sci Rep. 2023 Oct 18;13(1):17741.

[23] Shi X, Jiang D, Qian W, and Liang Y. 2022. Application of the Gaussian Process Regression Method Based on a Combined Kernel Function in Engine Performance Prediction. ACS Omega, Nov 15;7(45):41732–41743.

[24] Shi C, Ji C, Wang H, Wang S, Yang J, and Ge Y. 2021 Comparative evaluation of intelligent regression algorithms for performance and emissions prediction of a hydrogen-enriched Wankel engine. Fuel, Apr;290:120005.

[25] Brandsæter A, and Vanem E. 2018. Ship speed prediction based on full scale sensor measurements of shaft thrust and environmental conditions. Ocean Eng, Aug;162:316–330.

[26] Huang Y, Wang J, and He W. 2024. Study on momentum gradient descent on-line engine calibration algorithm combined with search space division. Int J Engine Res., Mar 13;25(3):424–434.

[27] Jason Brownlee. Gradient Descent With RMSProp from Scratch. machine learning mastery. 2021 Oct 12;

[28] Liang K, and Zhao H. 2019. Automatic Evaluation of Internal Combustion Engine Noise Based on an Auditory Model. Shock Vib,. Jul 11;2019:1–9.

[29] Luiz Caleffo Piva Bigão V, Ruiz Brandão da Costa B, Joaquim Mangabeira da Silva J, Spinosa De Martinis B, and Tapia-Blácido DR. 2024. Use of statistical design of experiments (DoE) in Forensic Analysis: A tailored review. Forensic Chem., Mar;37:100554.

[30] Ling TY, and Kumar JR. 2017. DESIGN, OPTIMIZATION AND CHARACTERIZATION OF AZILSARTAN NANOPARTICLES USING DESIGN-EXPERT® SOFTWARE VERSION 11. Rapp

Pharm., 3(3):395–407.

[31] Colin Cameron A, and Windmeijer FAG. 1997. An R-squared measure of goodness of fit for some common nonlinear regression models. J Econom., Apr;77(2):329–342.