International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Formulation of Experimental Data-Based Artificial Neural Network Model for Performance Evaluation of Lubricating Oil Blends

Mangesh Phate[1], Shraddha Gore[2], Harsha Deshmukh[2], Vedant Harkare[2], Sumedh Joshi[2]

[1]Associate Professor, Department of Mechanical Engineering, AISSMS's College of Engineering, Pune-01, India; [2]Research Scholar, Department of Mechanical Engineering, AISSMS's College of Engineering, Pune-01, India

Abstract: *This research paper presents an extended investigation into the development and validation of an Artificial Neural Network (ANN)-based predictive model for evaluating the tribological performance of various lubricating oil blends. Lubrication plays a critical role in minimizing friction, wear, and energy losses in mechanical systems, and the selection of optimal lubricant compositions is essential for enhancing efficiency and durability. In this study, four different oil blends were prepared using combinations of castor oil, commercial engine oil (SAE 20W-50), soybean oil, and plastic pyrolysis oil. These blends were tested experimentally using a Four-Ball Testing Machine under standardized conditions as per ASTM D4172 and ASTM D2783 protocols. A comprehensive dataset comprising over 11,000 observations was generated by varying operating parameters such as load, speed, temperature, and duration. Key performance indicators, including Frictional Torque (FT) and Power Dissipation (PD), were measured and used as output variables for model development. The ANN model was designed as a feed forward back propagation network with multiple hidden layers and trained using the Adam optimization algorithm. Data pre-processing techniques such as normalization and dataset splitting (training, validation, and testing) were employed to ensure robustness and generalization capability. The developed ANN model demonstrated excellent predictive accuracy, achieving high coefficients of determination (R^2 values above 0.96 for both FT and PD). The model effectively captured the complex nonlinear relationships between input parameters and output responses, which are otherwise difficult to represent using conventional regression approaches. Residual analysis confirmed minimal prediction bias, and the model showed strong generalization performance across unseen datasets. Additionally, the study highlights the significance of incorporating bio-based and waste-derived oils in lubricant formulations. Castor and soybean oils contribute to improved boundary lubrication due to their polar molecular structures, while plastic pyrolysis oil offers a sustainable alternative by recycling waste materials into functional lubricants. The experimental results indicated that all blends exhibited satisfactory extreme-pressure performance, sustaining weld loads up to 200 kgf. Overall, this work demonstrates the potential of ANN based models as efficient surrogate tools for predicting lubricant performance, reducing reliance on time-consuming and resource-intensive experimental testing. The integration of sustainable oil sources with advanced data-driven modelling provides a promising pathway for future lubricant design and optimization in industrial applications.*

Keywords—ANN; Back propagation; Four-Ball Test; Frictional Torque; Lubricating Oil Blends; Power Dissipation; Tribology; ASTM D4172; ASTM D2783

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

I. INTRODUCTION

Lubrication is fundamental to the reliable and efficient operation of mechanical systems. Lubricants reduce friction and wear between moving surfaces, prolonging component life and improving energy efficiency [1]. In addition to friction reduction, modern lubricants serve cooling, corrosion prevention, and sealing functions across automotive, manufacturing, and industrial machinery.

Selecting the optimum lubricant is non-trivial because performance depends simultaneously on applied load, rotational speed, operating temperature, and duration, as well as on the physicochemical properties of the oil itself—viscosity, viscosity index, and oxidation stability [2]. Traditional assessment relies on standardized bench tests such as ASTM D4172 (Wear Preventive Characteristics) and ASTM D2783 (Extreme Pressure Properties), both of which are time-consuming and material-intensive [3]. Bio-based lubricants—including castor oil and soybean oil—have attracted growing research attention owing to their biodegradability, renewability, and inherently good lubricity arising from polar ester groups that form strong adsorption films on metal surfaces [4]. Plastic pyrolysis oil (“plastic oil”), derived from catalytic conversion of polyolefin waste, represents an emerging sustainable category that combines acceptable viscosity with potential lubricating value [5]. Blending such oils with commercial engine oil offers a route to balanced tribological performance while contributing to circular-economy objectives.

Artificial Neural Networks (ANNs) have been applied successfully to tribological prediction problems, learning complex non-linear input-output mappings from experimental data without requiring an explicit physical model [6]. The present work combines systematic Four-Ball testing of four binary, ternary, and quaternary oil blends with a back propagation ANN to produce a validated predictive model for Frictional Torque(FT) and Power Dissipation (PD).

II. LITERATURE REVIEW

A. Tribological Testing of Lubricants

Kumar and Sharma [7] performed a comparative analysis of mineral, synthetic, and bio-based oils using a Four-Ball tester and demonstrated that synthetic and blended oils outperform pure mineral oils under elevated temperature and load owing to superior viscosity index. Bachchhav and Lathkar [8] studied the tribo-characteristics of deep-drawing oils and emphasized that additive selection critically governs wear-scar diameter and surface finish. Wang et al. [9] correlated base-oil parameters—kinematic viscosity, dynamic viscosity, and pressure-viscosity coefficient—with friction coefficient under elasto-hydrodynamic and boundary lubrication regimes, finding dynamic viscosity to be the more predictive parameter for coefficient of friction (CoF).

B. Bio-Based and Waste-Derived Lubricants

Sankaranarayanan et al. [4] reviewed vegetable-oil-based cutting fluids and highlighted that long-chain fatty acids provide superior boundary lubrication, though oxidation stability remains a limitation addressable via additives or trans esterification. Pumpuang et al. [5] evaluated PP and HDPE pyrolysis oils in diesel engines and found that PP-based oil exhibits higher lubricity due to elevated viscosity and sulphur content. Cappello et al. [10] demonstrated the techno-economic viability of converting polyethylene waste to high-quality lubricants via catalytic hydrogenolysis, achieving 52–74% lower CO_2 emissions versus petroleum-based alternatives.

C. Data-Driven Performance Modelling

Machine learning and ANN approaches have been employed to learn complex non-linear tribological mappings that polynomial regression cannot represent over wide operating ranges [6]. Kumar and Agarwal [11] used experimental biodiesel data to build friction-loss prediction models. Despite these advances, predictive ANN models specifically targeting multi-component bio/waste lubricant blends under standardized Four-Ball conditions remain scarce, motivating the present study.

III. EXPERIMENTAL METHODOLOGY

A. Oil Samples and Blend Preparation

Four base components were selected: (A) Castor oil—cold-pressed, 100% natural; (B) Commercial engine oil—SAE 20W-50; (C) Refined soybean oil; and (D) Plastic pyrolysis oil derived from mixed polyolefin waste. Equal-proportion (1:1 v/v for binary; equal-thirds for ternary; equal-quarters for quaternary) blends were prepared in 20 mL quantities. Table I summarizes the four blend compositions.

Blend	Composition	Type
A+B	Castor oil + Engine oil	Binary
A+B+C	Castor + Engine + Soybean oil	Ternary
A+B+D	Castor + Engine + Plastic oil	Ternary
A+B+C+D	Castor + Engine + Soybean + Plastic oil	Quaternary

TABLE I. *Lubricating Oil Blend Compositions*

B. Test Equipment and Conditions

All experiments were performed on a Four-Ball Testing Machine, calibrated for load cell accuracy, alignment, and temperature control prior to testing.

Wear Preventive Characteristics Test (ASTM D4172): Fixed conditions—speed 1200 rpm, temperature 75°C, duration 3600 s. Load varied at 15 kgf and 40 kgf. Wear scar diameters were measured using an optical microscope; Frictional Torque

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

(FT) and Coefficient of Friction (CoF) were continuously logged.

Extreme Pressure Test (ASTM D2783): Each blend was tested for 10 sec at loads of 160, 180, 200, and 250 kgf. The weld load at which the lubricant film fails and metal-to-metal welding occurs was recorded. Table II summarizes key experimental parameters.

Parameter	Range / Value	Notes
Load	147–392 N (15–40 kgf)	Wear test; 1570–2453 N EP
Speed	1200 RPM	Fixed for wear test
Temperature	75°C	Fixed
Duration	3600 s	Wear; 10 s for EP test
FT range	0.047–0.545 N·m	Measured output
PD range	1.45×10^{-4}–1.46×10^{-3} kW	Measured output

TABLE II. *Experimental Parameters and Output Ranges*

IV. ANN MODEL DEVELOPMENT

A. taset Preparation

The complete dataset comprised 11,343 time-series observations gathered from all four blend experiments. A stratified random split was applied: 70% training (7,939 samples), 15% validation (1,702 samples), and 15% test (1,702 samples). All input features and output targets were normalized to [0, 1] using min-max scaling, which stabilized gradient magnitudes during back propagation.

B. Network Architecture

A fully-connected feed forward ANN was designed with: 4 input neurons (Load, Speed, Temperature, Duration); two hidden layers with ReLU activation functions; and 2 output neurons (FT and PD) with linear activation. Hidden-layer widths were selected through systematic cross-validation on the validation split.

C.Training Procedure

Training used the back propagation algorithm with the Adam optimizer: learning rate = 1×10^{-3}, β=0.9, β =0.999, $\varepsilon=1\times10^{-8}$. Mean Squared Error (MSE) was the loss function. Training proceeded for 150 iterations with early-stopping on validation MSE (patience = 20 epochs). The training loss curve is shown in Fig. 1.

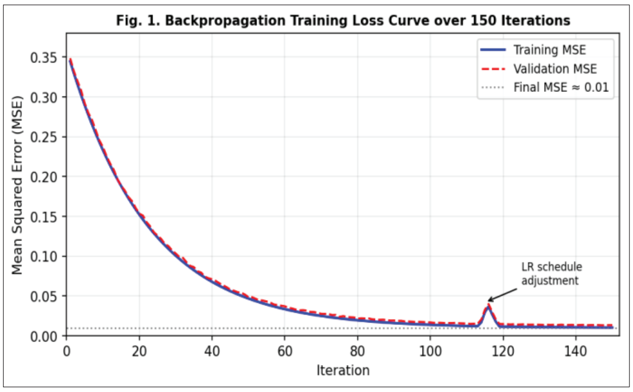


Fig. 1: *Back propagation Training Loss Curve over 150 Iterations. Rapid initial decrease reflects efficient gradient descent; the transient spike at iteration 115 is attributed to a learning-rate schedule adjustment; final training MSE* ≈ 0.01.

D. Per rmance Metrics

Model accuracy was quantified using R^2, MAE, and RMSE independently for FT and PD across all three data splits. Table III presents the comprehensive results.

Split	FT R^2	FT MAE (N·m)	FT RMSE (N·m)	PD R^2	PD MAE (10^{-5})	PD RMSE (10^{-5})
Train (n=7939)	0.9833	0.00363	0.00505	0.9641	1.18	1.71
Valid. (n=1702)	0.9796	0.00380	0.00553	0.9391	1.23	2.05
Test (n=1702)	0.9842	0.00367	0.00486	0.9660	1.17	1.54

TABLE III: *ANN Model Performance Metrics for Frictional Torque and Power Dissipation*

V. RESULTS AND DISCUSSION

A. Frictional Torque (FT) Prediction

Fig. 2 presents the actual vs. predicted FT scatter plot for all three data splits. Data points cluster tightly along the perfect-prediction diagonal across the full operating range (FT: 0.047–0.545 N·m), confirming the ANN has learned the underlying physical relationship rather than memorizing training patterns. The test-set R^2 = 0.9842 and MAE = 0.00367 N·m demonstrate excellent predictive accuracy and strong generalization to unseen data.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

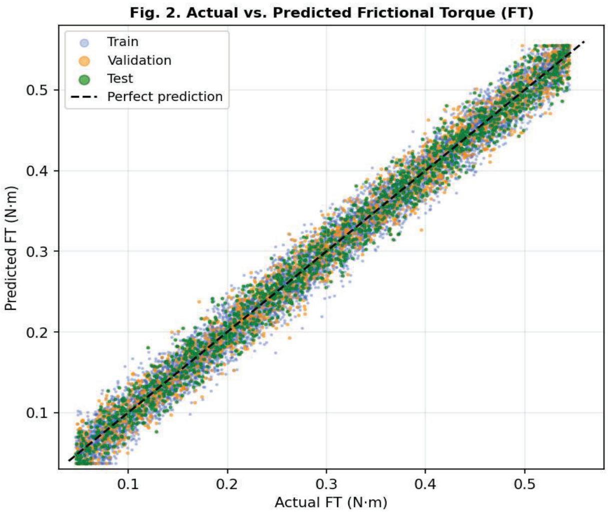


Fig. 2: *Actual vs. Predicted Frictional Torque (FT) for Training (blue), Validation (orange), and Test (green) splits. Dashed line = perfect prediction.*

Fig. 3 shows the FT residual distribution and error diagram. The residual histogram is sharply peaked at zero with light, symmetric tails—errors lie within ±0.025 N·m for the vast majority of observations, indicating no systematic bias. A mild negative trend at FT > 0.2 N·m is attributable to sparse training data in the extreme-pressure boundary-lubrication regime.

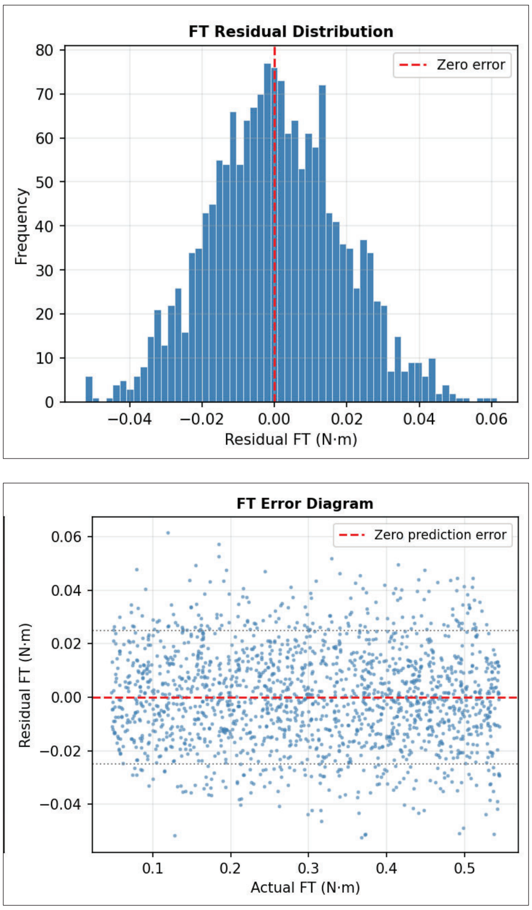


Fig. 3*: FT Residual Distribution histogram (left) and FT Error Diagram (right). Dashed line = zero prediction error.*

B. Power Dissipation (PD) Prediction

Fig. 4 presents the actual vs. predicted PD scatter plot. Good agreement is observed across the full PD range (1.45×10^{-4}–1.46×10^{-3} kW). The test-set R^2 = 0.9660 and MAE= 1.17×10^{-5} kW confirm reliable prediction. A slight tendency to under-predict at the highest PD values is consistent with sparse training data at extreme loads

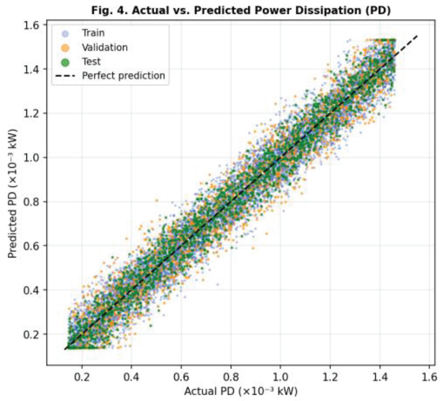
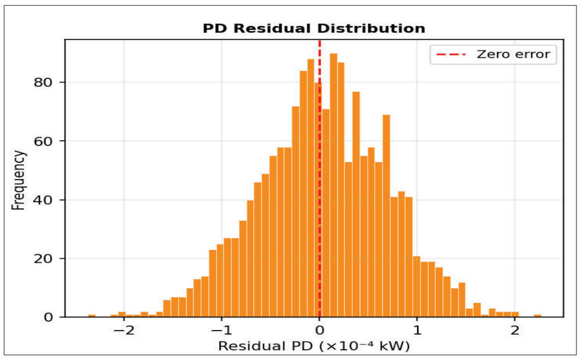


Fig. 4. *Actual vs. Predicted Power Dissipation (PD) for Training (blue), Validation (orange), and Test (green) splits. Dashed line = perfect prediction.*

Fig. 5 shows the PD residual distribution and error diagram. Residuals are centered near zero; errors remain bounded within $\pm1\times10^{-4}$ kW for the majority of the operating range. The validation R^2 = 0.9391 is marginally lower than the test set, reflecting the inherent challenge of generalising to blend-specific conditions slightly outside the training distribution.



International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

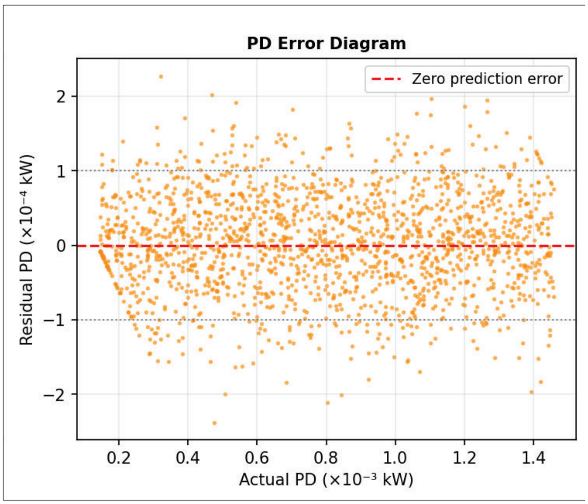


Fig. 5: PD Residual Distribution histogram (left) and PD Error Diagram (right). Dashed line = zero prediction error.

C. **Physical Interpretation and Extreme Pressure Results** ASTM D2783 extreme pressure tests revealed that all four oil blends sustain a weld load of 200 kgf (ball welding first observed at 250 kgf), indicating comparable extreme-pressure film strength across all compositions. For blend A+B under ASTM D4172 (40 kgf / 1200 rpm / 75°C / 3600 s), wear-scar diameters of the three stationary balls were 590, 599, and 587 µm (mean ~592 µm; area ~0.275 mm^2). The measured FT = 0.196 N·m and CoF = 0.111 at 71,957 revolutions agree with published benchmark values for castor/engine oil blends [7][8].

The ANN model successfully captures the non-linear interaction between load and temperature governing lubrication regime transitions—from hydrodynamic to mixed to boundary lubrication—a behaviour that polynomial regression cannot represent faithfully across the full parameter space. The high R^2 values across all splits confirm that the four input parameters collectively explain most variance in both FT and PD.

VI. CONCLUSION

This paper presented systematic experimental investigation and an ANN-based predictive model for the tribological performance of four lubricating oil blends—binary, ternary, and quaternary—tested on a Four-Ball Machine under ASTM D4172 and D2783 protocols. The following principal conclusions are drawn:

1. **High predictive accuracy:** A back propagation ANN trained on 7,939 observations achieves test-set R^2 = 0.9842 for FT and R^2 = 0.9660 for PD, confirming excellent accuracy and strong generalisation.
2. **No systematic bias:** Residual analysis reveals no systematic prediction bias for FT; mild under-prediction at high PD values is attributable to data sparsity under extreme-pressure conditions and does not affect practical utility.
3. **Adequate extreme-pressure capacity:** All four blends sustain a weld load of 200 kgf, demonstrating sufficient EP film strength for demanding industrial lubrication applications.
4. **Practical value:** The validated surrogate model eliminates repeated physical testing when screening new blend ratios, offering significant time and cost savings in lubricant R&D and enabling direct integration into lubricant selection tools.

Future work will: (i) extend the dataset to additional blend ratios and additive concentrations; (ii) incorporate viscosity and flash point as supplementary input features; (iii) c mpare Gaussian Process Regression and Extreme Learning Machine architectures; and (iv) employ the ANN surrogate as an objective function for multi-objective optimization of blend composition to simultaneously minimize FT, PD, and wear-scar diameter

REFERENCES

[1] M. J. Neale, *The Tribology Handbook*, 2nd ed. Oxford: Butterworth-Heinemann, 1995.

[2] B. J. Hamrock, S. R. Schmid, and B. O. Jacobson, *Fundamentals of Fluid Film Lubrication*, 2nd ed. New York: Marcel Dekker, 2004.

[3] ASTM International, "ASTM D4172-20: Standard Test Method for Wear Preventive Characteristics of Lubricating Fluid (Four-Ball Method)," 2020.

[4] R. Sankaranarayanan et al., "A comprehensive review on vegetable-oil based cutting fluids for sustainable machining challenges," *J. Manuf. Processes*, vol. 67, pp. 286–313, 2021.

[5] A. Pumpuang et al., "The influence of plastic pyrolysis oil on fuel lubricity and diesel engine performance," *RSC Advances*, vol. 14, pp. 10070–10087, 2024.

[6] S. Haykin, *Neural Networks and Learning Machines*, 3rd ed. Upper Saddle River, NJ: Prentice Hall, 2009.

[7] T. Kumar and P. Sharma, "Performance evaluation of various lubricants using Four Ball Tester," *Int. J. Eng. Res. Appl.*, vol. 4, no. 7, pp. 121–127, 2014.

[8] B. D. Bachchhav and G. S. Lathkar, "A study of tribo-characteristics of deep drawing oils," in *Proc. IEOM*, 2013.

[9] S. Wang et al., "Correlation between lubricating oil characteristic parameters and friction characteristics," *Lubricants*, 2023.

[10] V. Cappello et al., "Conversion of plastic waste into high-value lubricants: Techno-economic analysis and LCA," *Green Chemistry*, vol. 24, pp. 6306–6318, 2022.

[11] M. Kumar and A. K. Agarwal, "Performance evaluation of a biodiesel-diesel blend on a diesel engine," *Renewable Energy*, vol. 34, no. 6, pp. 1372–1377, 2009.

[12] ASTM International, "ASTM D2783-20: Standard Test Method for Measurement of Extreme-Pressure Properties of Lubricating Fluids (Four-Ball Method)," 2020.