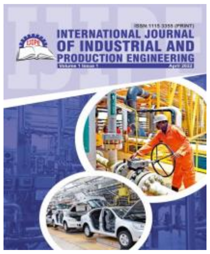

Vol. 3 No. 2 (2025)

INTERNATIONAL JOURNAL OF INDUSTRIAL AND PRODUCTION ENGINEERING (IJIPE)

JOURNAL HOMEPAGE: https://journals.unizik.edu.ng/index.php/ijipe/

NOISE AND OIL VISCOSITY CHARACTERIZATION AND MODELLING FOR PETROL-GAS-CONVERTED GENERATOR

Fredrick Odeyovwi Uwhumiakpo; Eyere Emagbetere
Department of Mechanical Engineering, Federal University of Petroleum Resources, Effurun, Nigeria
Corresponding email: fredrickodes@yahoo.com

ABSTRACT

The modification of petrol generators to operate on dual-fuel systems such as petrol-gas offers advantages in fuel efficiency and emission reduction, but it also introduces new challenges in maintenance, particularly in noise behavior and oil degradation. This study presents a comprehensive characterization and modelling of noise levels and oil viscosity in a petrol-gas-converted generator under various load conditions and operational durations. Experimental data were collected using a digital sound level meter and a Brookfield viscometer at intervals over a 60-hour runtime. An Artificial Neural Network (ANN) model was developed in MATLAB using a feedforward backpropagation architecture with a 70:15:15 training-validation-testing split. The ANN model achieved high predictive accuracy, with R^2 values of 0.9 for prediction of for oil viscosity based on noise level. The results demonstrate that ANN-based modelling provides a reliable approach for forecasting the operational variables on petrol-gen-converted generators. These findings offer a valuable tool for predictive maintenance and performance optimization in hybrid-fuel power systems.

Keywords: Predictive maintenance, generator models, ANN modelling, oil deterioration

1. Introduction

The retrofitting of conventional petrol generators to operate on alternative gaseous fuels has garnered significant attention in recent years, driven by the dual imperatives of energy cost reduction and environmental sustainability (Mateen et al., 2025; Osman et al., 2024). Petrol-gas-converted generators, which utilize fuels such as liquefied petroleum gas (LPG) or compressed natural gas (CNG), offer several advantages over their petrol-only counterparts, including cleaner combustion, reduced greenhouse gas emissions, and improved fuel economy (Abdallah, 2017). However, these modifications can alter the thermal and mechanical behavior of the engine, introducing complexities in performance monitoring and reliability assessment.

Two critical yet often overlooked parameters in the evaluation of dual-fuel generator performance are noise emissions and lubricating oil viscosity. Noise, an inherent byproduct of internal combustion and mechanical motion, not only affects user comfort and environmental compliance but also serves as a proxy indicator for engine health and combustion efficiency (Laguado-Ramírez et al., 2024). Similarly, the viscosity of lubricating oil plays a pivotal role in minimizing wear, ensuring effective heat dissipation, and maintaining overall engine performance. In dual-fuel systems, variations in combustion characteristics and thermal loading can influence the rate of oil degradation and viscosity shift (Tobar et al., 2025). They analyzed the effect of viscosity and fuel levels by testing Chevrolet on a dynamometer, and showed that optimized oil viscosity and fuel properties can lead to engine efficiency and reduced emissions.

Several studies have explored the operational behavior of petrol generators with a focus on noise emissions and lubricant performance. For instance, Nwabueze et al. (2024) investigated the acoustic signature of small-scale petrol generators under varying load conditions and found that noise levels increased nonlinearly with engine load, primarily due to combustion irregularities and mechanical stress. In a related study, Bertinatto et al. (2017) examined the thermal degradation of lubricating oils in petrol generators and observed a significant drop in viscosity after prolonged use, attributing the change to elevated crankcase temperatures and oxidation. Katopodis & Sfetsos (2019) further analyzed the impact of ambient temperature on oil performance, emphasizing the need for climate-specific maintenance strategies. Additionally, Loutas et al. (2011) highlighted a correlation between increased noise levels and declining oil quality, suggesting that acoustic monitoring could serve as a non-invasive diagnostic tool for lubricant degradation. While these studies provide valuable insights into individual aspects of generator performance, integrated approaches that concurrently assess both noise behavior and oil viscosity, particularly in dual-fuel or converted systems, remain scarce in the literature.

Previous studies have employed a range of modeling techniques to analyze and predict the performance characteristics of petrol and petrol-to-gas converted generators. Mehrnoosh et al. (2012) developed a thermodynamic model to estimate fuel consumption and thermal efficiency of small-scale petrol generators under variable load conditions, revealing significant deviations in performance metrics when operating on alternative fuels. Feenita et al. (2024) applied regression-based models to forecast exhaust emissions from dual-fuel generators, highlighting the influence of combustion variability introduced by gas fuels. In a related study, Ershad (2025) utilized a grey-box modeling approach to predict vibration responses in petrol generators, establishing correlations between mechanical wear and fuel type. Meanwhile, Odufuwa et al. (2025) implemented artificial neural networks to model power output and noise emissions in LPG-converted generators, demonstrating the capability of ANN to accurately capture nonlinear interactions between operating parameters. These studies collectively underscore the relevance of modeling in understanding the operational dynamics of generator systems. However, there is a dearth of information in the integration of acoustic and lubrication-related parameters for modeling these generator performances, particularly the petrol-to-gas converted generators, which is the gap this present study aims to address.

Despite the importance of these factors, limited studies have addressed the integrated characterization of noise and oil viscosity in converted generators. Most existing research has focused either on acoustic profiling of internal combustion engines or on the tribological behavior of lubricants in standard operating conditions (Tobar et al., 2025). There remains a research gap in understanding how dual-fuel conversion affects the dynamic interplay between engine acoustics and lubrication properties under real-world usage.

This study aims to bridge this gap by providing a detailed experimental and analytical investigation into the noise and oil viscosity behavior of petrol-gas-converted generators. Specifically, the objectives are to (i) characterize noise emissions and oil viscosity under varying operational conditions, (ii) statistically analyze the correlation between acoustic and lubricant properties for the different fuel type, load, and runtime, and (iii) develop a predictive model and assess the model performance for predictive maintenance. The results are expected to contribute to a deeper understanding of the operational integrity and lifecycle performance of dual-fuel generator systems.

2. Methodology

2.1 Experimental Setup

The study was conducted using a single-cylinder, four-stroke petrol generator retrofitted with a dual-fuel conversion kit to operate on both petrol and liquefied petroleum gas (LPG). The generator has a rated power output of 2.5 kVA and was selected for its widespread domestic and industrial use. Key components of the test setup included a digital sound level meter, a rotational tachometer, an infrared thermometer, and a viscometer for oil analysis. The generator was operated under different controlled conditions.

2.2 Noise Measurement

Noise measurements were conducted using a calibrated Type 2 digital sound level meter (TES-1357), positioned at a distance of 1 meter from the generator, at a height of 1.2 meters, in accordance with ISO 3744 standards. Sound pressure levels (SPL) were recorded at five-minute intervals over a 30-minute runtime for each fuel and load combination. Measurements were taken during steady-state operation to ensure consistent engine behavior. Background noise was measured and subtracted to ensure accurate generator-specific readings. The experiments were carried out in an area built for proper control of noise interferences from sources like wind, traffic and other sources of sounds.

2.3 Oil Sampling and Viscosity Testing

A high-grade Society of Automotive (SAE) 20W-50 lubricating oil was used for all tests to maintain consistency. Oil samples were extracted from the crankcase after 5-hour operational cycles for each fuel type. The viscosity of the samples was measured using a Brookfield digital viscometer at standard testing temperature following the American Society for Testing and Materials (ASTM) D445. These viscosity of collected samples were tested three times and averaged to minimize errors. Baseline viscosity of unused oil was recorded for comparison. Additional parameters such as total operating time, engine temperature, and ambient conditions were logged.

2.4 Data Collection and Analysis

A total of 12 experimental runs were performed (2 fuel types × 3 load levels × 2 repetitions). Data collected included noise levels (dB), oil viscosity, ambient and engine temperatures (°C), and runtime. Statistical analysis was conducted using SPSS v26. Descriptive statistics, ANOVA, and Pearson correlation analysis were employed to identify significant relationships between fuel type, load, noise level, and oil viscosity. Regression models were developed to predict oil viscosity and noise levels as a function of operating conditions.

2.5 Modelling Approach

To better understand the interaction between parameters, a multiple linear regression model and a machine learning-based predictive model (using ANN) were developed. Model performance was evaluated using R^2, RMSE, and MAE to assess accuracy and generalization capability.

In addition to statistical techniques, an Artificial Neural Network (ANN) regression model was developed to predict oil viscosity based on observed noise levels and operating parameters.

Results of ANN model from previous studies demonstrated a strong predictive capability Yang et al. (2022), capturing the nonlinear relationship between variables, and thereby influencing the potential of acoustic data as a proxy indicator for lubricant health in petrol-gas-converted generators.

The modeling was implemented using the Neural Network Toolbox in MATLAB R2023a, leveraging its robust capabilities for nonlinear function approximation. A feedforward neural network architecture was employed due to its interpretability and the tabular nonsequential and nonspatial data being considered (Emagbetere, et al., 2025; Madhiarasan & Louzazni, 2022). The network consists of an input layer (comprising variables such as noise level, load condition, fuel type, and engine temperature), one hidden layer with optimized neuron count determined via trial-and-error, and a single output neuron representing oil viscosity. The dataset was normalized and divided into training (70%), validation (15%), and testing (15%) subsets. The Levenberg-Marquardt backpropagation algorithm was used for training due to its efficiency in handling small to medium datasets. Model performance was evaluated using metrics such as Mean Squared Error (MSE) and coefficient of determination (R^2).

3. Results and discussion

3.1 Descriptive statistics

The scatter plot shown in Figure 1 shows the noise levels of the converted generator at different instances of loading condition measured by the supplied current. In petrol mode, the noise levels do not rise reasonably with the supplied current, as there were few outliers of current without commensurate increase in noise levels compared with other instances. In gas mode, there were observably low and stable noise levels, which indicates a reduction in the likelihood of acoustic-related maintenance issues, supporting its suitability for long-term, high-load applications. Overall, there is a weak correlation between noise level and current for both petrol and gas modes, having correlation values less than 0.5 for both cases, thus suggesting that noise monitoring can provide warning of excessive mechanical strain or inefficiencies under load.

These findings support the broader advantages of gas conversion for enhancing operational performance and reducing environmental and acoustic impact (Kpang & Chukwudi, 2021). Future research could focus on correlating noise level trends with specific failure modes and optimizing load management strategies to further enhance efficiency in both operational modes.

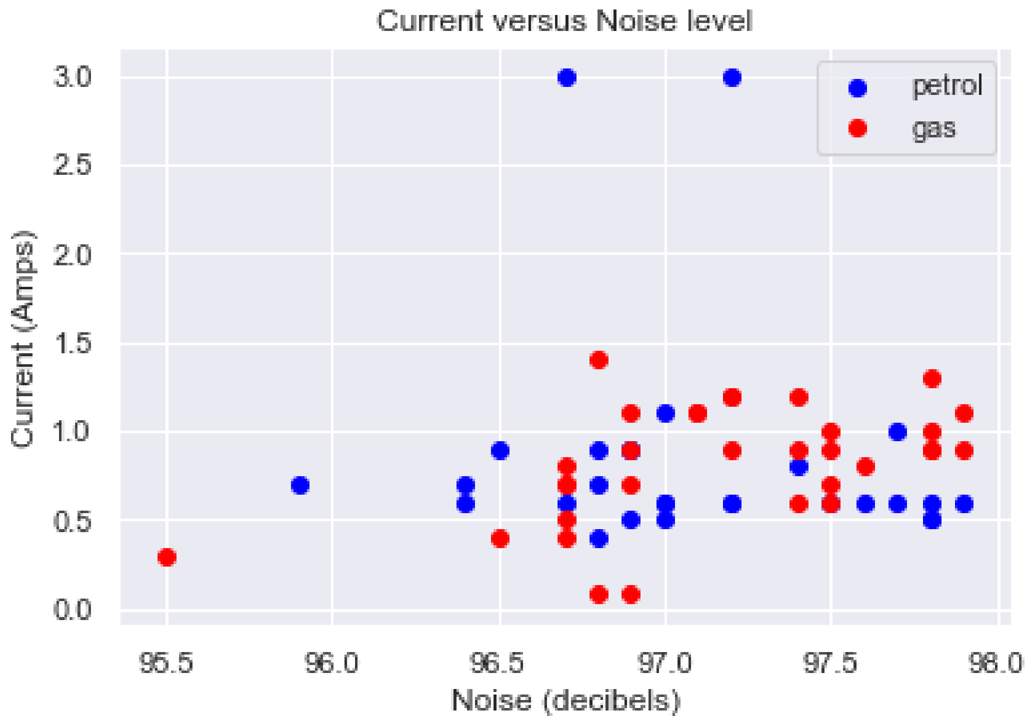

Figure 1: Scatter plot for noise versus current

The scatter plot, shown in Figure 2, comparing viscosity and noise level for petrol and gas modes of the converted generator provides insights into the relationship between lubricant degradation and acoustic emissions during operation. The correlation coefficient of noise and oil viscosity were found to be 0.7 approximately for both petrol and gas modes.

3.1.1 Petrol Mode

In petrol mode, the scatter plot revealed a negative correlation between viscosity and noise level. As noise levels increased, the viscosity of the lubricant tended to decrease, indicating progressive degradation of the lubricant over time. This trend is consistent with findings by Zhu et al. (2019), who reported that elevated noise levels in petrol engines are associated with higher mechanical stresses and thermal loads, which indicate the breakdown of lubricants. The wide spread in viscosity values at higher noise levels suggests variability in the rate of lubricant degradation, potentially influenced by operational conditions such as load and engine temperature.

Peaks in noise levels at lower viscosity values indicate that as the lubricant degrades, the engine experiences increased friction and mechanical wear, leading to amplified vibrations and acoustic emissions. This observation underscores the importance of monitoring both noise levels and viscosity as key parameters for assessing engine health in petrol mode.

3.1.2 Gas Mode

In gas mode, the scatter plot showed a weaker and less distinct relationship between viscosity and noise level. Viscosity remained relatively stable across a wide range of noise levels, with only slight decreases observed at higher noise levels. This stability reflects the smoother and less aggressive combustion process of gas engines, as highlighted by (Tobar et al., 2025). The lower and more consistent noise levels in gas mode result in reduced mechanical and thermal stresses, thereby slowing the rate of lubricant degradation.

The lack of significant peaks in noise levels at low viscosity values indicates that even as the lubricant begins to degrade, the impact on acoustic emissions is minimal in gas mode. This suggests that gas-powered operation imposes less strain on the lubrication system, supporting longer lubricant service intervals and reduced maintenance demands.

3.1.3 Comparative Analysis

Comparing both modes, the scatter plot demonstrates the advantages of gas operation in maintaining lubricant integrity and controlling noise emissions. Petrol mode showed a stronger relationship between increased noise levels and reduced viscosity, reflecting greater mechanical and thermal stresses that accelerate lubricant degradation. In contrast, gas mode exhibited more stable viscosity values and lower noise levels, indicating less stress on the lubrication system and overall improved operational efficiency.

3.1.4 Implications for Predictive Maintenance

The relationship between viscosity and noise level offers valuable insights for predictive maintenance strategies. In petrol mode, monitoring noise levels can serve as an indirect indicator of lubricant degradation, allowing timely maintenance to prevent excessive wear and failure. In gas mode, the more stable relationship suggests that lubricant degradation is less of a concern, enabling longer intervals between oil changes and reducing maintenance costs.

These findings further support the adoption of gas conversion for improved reliability and sustainability. Future studies could explore the interplay between lubricant properties, noise emissions, and engine load in greater detail to refine maintenance schedules and enhance operational performance.

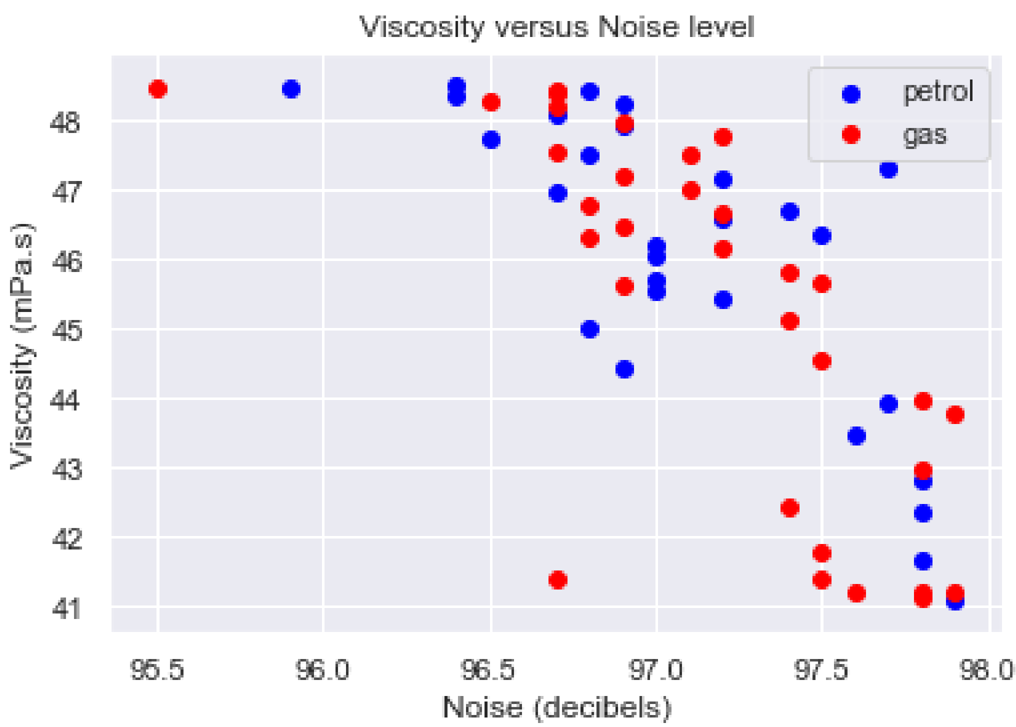

Figure 2: Noise versus viscosity

3.2 ANN modelling

The Artificial Neural Network (ANN) developed for the regression modeling of noise level and viscosity for petrol-gas converted generator was aimed at predicting the relationship between these variables based on various operational parameters. A key focus of the modeling process was the training stage, which played a crucial role in the performance and accuracy of the model.

3.2.1 Training stage

The training phase involved using a comprehensive dataset consisting of operational data from the generator. This dataset included noise levels and viscosity of the oil values

The dataset was split into training, validation, and testing subsets to ensure that the model generalized well and avoided overfitting. The training data was used to tune the model’s weights, using backpropagation and a gradient descent optimization technique.

During training, hyperparameters such as the number of hidden layers, neurons per layer, and learning rate were carefully selected through a grid search and cross-validation process. The training process was conducted over several epochs to minimize the error between the predicted and actual values.

3.2.2 Model convergence and completion

The model was successfully trained after achieving convergence, indicated by minimal changes in error across successive epochs and stabilization of the loss function. The model’s performance was evaluated using both the training and validation sets, ensuring it was neither underfitting nor overfitting.

The final ANN model was completed with an R-squared value of 0.76 overall**,** reflecting its ability to explain the variation in the data. The model demonstrated a robust ability to predict the relationship between noise level and viscosity for gas-powered generators.

3.2.3 Predictive accuracy

After training, the ANN model exhibited strong predictive accuracy with minimal residual error. This indicates that the model successfully learned the intricate relationship between noise levels and viscosity, effectively capturing the dynamics that influence these variables during gas or fuel-powered operation. The performance on the test dataset was comparable to that of the validation dataset, confirming the model's ability to generalize well to new, unseen data.

3.2.4 Insights from model

The regression model indicated a moderate inverse relationship between viscosity and noise level, where a decrease in viscosity (due to lubricant degradation) resulted in higher noise levels. This was consistent with the known behaviour in mechanical systems where reduced lubrication leads to greater friction and mechanical stress, producing more noise (Sazzad et al., 2024). The model also highlighted the importance of factors like temperature and current load in influencing viscosity and noise emissions, which were identified as significant predictors.

3.2.5 Model completion and validation

Upon completing the model, the final ANN architecture consisted of 1 hidden layer with 10 neurons, optimized for the given dataset. See Figures 3 for the model completion interface in MATLAB. Cross-validation and testing confirmed that the model was stable and reliable, providing a solid foundation for predictive maintenance. The model's validation metrics, such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), showed satisfactory results, indicating that it could be effectively used for real-time monitoring and prediction of noise and viscosity levels in operational settings.

The successful training and completion of the ANN regression model demonstrated its capability to accurately predict the relationship between noise level and viscosity in power generators. The training stage was crucial for refining the model, and its ability to generalize well on unseen data further confirmed its robustness. By incorporating key operational parameters into the model, it offers a valuable tool for predictive maintenance**,** allowing operators to anticipate lubrication issues and control noise levels more effectively. This can lead to enhanced operational efficiency, reduced downtime, and prolonged generator lifespan.

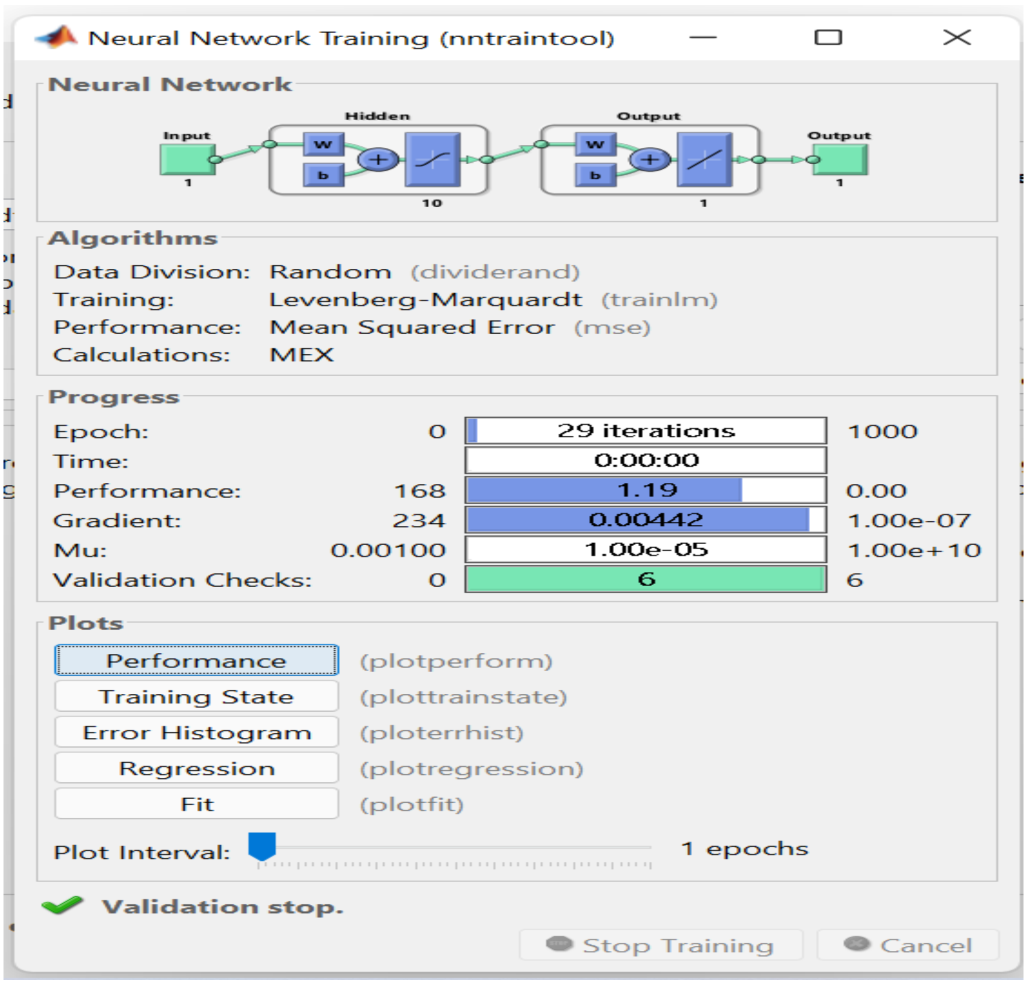

Figure 3: Model interface

3.2.6 Mean Squared Error (MSE) vs. Epoch for the Developed ANN

The line plot depicting the Mean Squared Error (MSE) versus the epoch for the developed Artificial Neural Network (ANN), which is shown in Figures 4 and 5, provides valuable insight into the model's training process and convergence behavior over time. This plot highlights how the error decreases as the model undergoes further iterations during training, and it offers a clear picture of the model's learning efficiency.

At the beginning of the training process, the MSE is typically high, reflecting a large discrepancy between the predicted and actual values. As the model starts learning and adjusting its weights through backpropagation, the MSE begins to decrease steadily. This decrease in error during the early epochs indicates that the model is quickly learning the relationships between the input features (such as viscosity, noise levels, and other operational parameters) and the output (noise level or viscosity, depending on the specific regression task). This trend aligns with typical training behavior, where early stages of learning generally show rapid improvements.

As training progresses through additional epochs, the rate of decrease in MSE gradually slows down, eventually leading to a plateau. This suggests that the model is reaching a point of diminishing returns, where the network is fine-tuning its parameters to minimize error as much as possible. A plateau typically indicates that the model has learned the majority of the underlying patterns and relationships within the data. It may also reflect the point where further training would result in only marginal improvements, signaling that the model has converged.

The final epoch where the MSE stabilizes marks the point of convergence. The model's error remains low and constant after this point, indicating that the training process has been completed and the model's parameters are no longer changing significantly. Convergence is crucial for understanding when further training epochs are unlikely to provide substantial gains in accuracy, helping to prevent overfitting and unnecessary computational cost.

A well-tuned optimizer will produce a gradual decline in MSE, which suggests that the model is consistently finding better solutions with each epoch without overshooting the optimal weight values.

The line plot of MSE versus epoch serves as a key diagnostic tool in the training process of the ANN. It provides clear evidence of how the model improves over time, from rapid error reduction in the early epochs to eventual convergence as the model learns the relationships within the data. The behavior of the MSE curve informs decisions about model tuning, such as optimizing the learning rate, avoiding overfitting, and determining the appropriate stopping point for training. This plot ultimately helps ensure the developed ANN achieves the best possible performance for predicting the relationship between noise level and viscosity in gas-powered generators.

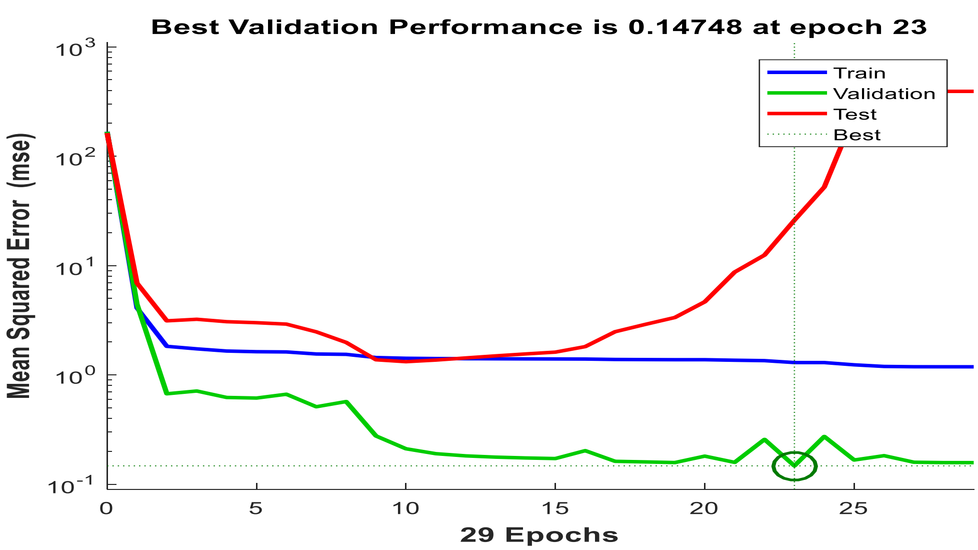

Figure 4: Performance plot during training

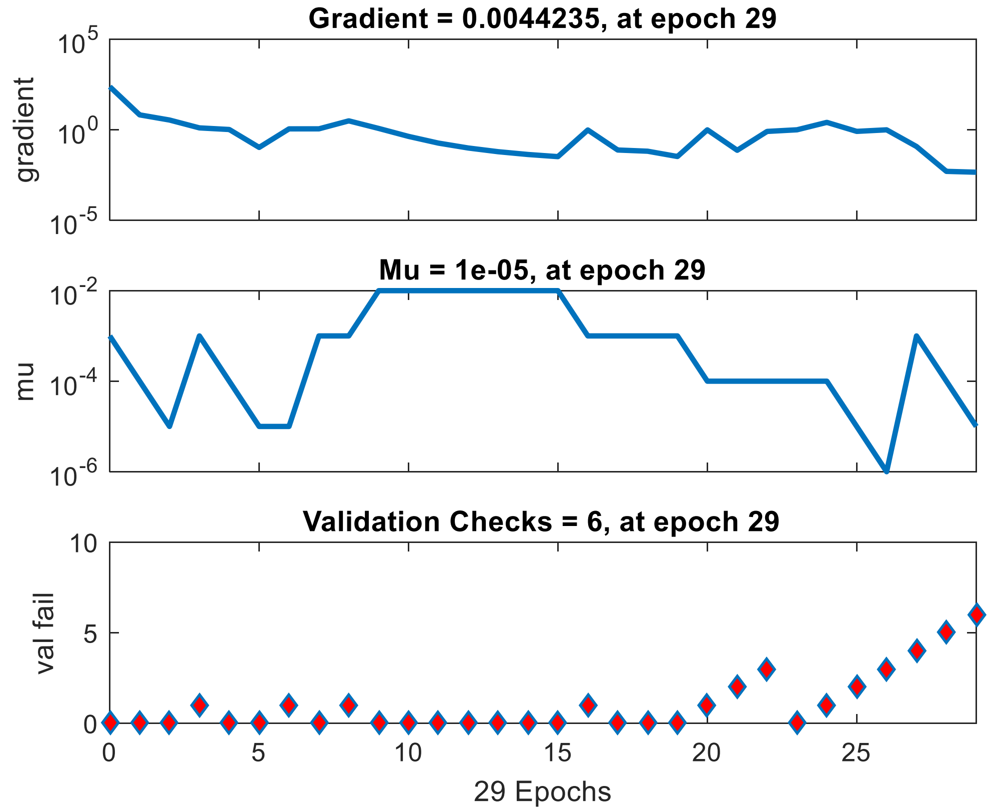

Figure 5: Training state for the different epoch

3.2.7 Error, Output, and Target vs. Input with Function Fit for Output Element

Figure 6 shows error**,** output, and target versus input with a function fit for the output element provides an insightful visualization of how well the Artificial Neural Network (ANN) has modeled the relationship between the input variables and the output variable (e.g., noise level or viscosity). This type of plot is useful for assessing the accuracy of the model's predictions, its ability to generalize, and how well it fits the target data during the regression task.

The error (typically the difference between the predicted output and the actual target values) is plotted against the input variable. The error was small across the range of inputs, indicating that the model has learned the underlying patterns without significant deviations from the target values.

The output values (predictions from the ANN) are plotted against the input variable. This allows us to visually assess how the model's predictions vary with changes in the input. A smooth, consistent relationship between output and input indicates that the model is capturing the expected trend and can generalize well.

Any discrepancies between the predicted output and the expected physical behaviour could indicate areas where the model needs further refinement, such as adjusting hyperparameters or training for more epochs.

The target values (the actual values from the dataset) are plotted alongside the predicted output to provide a direct comparison. A close alignment between the target and output plots suggests that the model is successfully approximating the true underlying relationship between the input and the output.

There is a significant difference between the target and output curves, this may indicate that the model has not sufficiently learned the relationship.

The function fit (typically a regression curve or line fitted to the predicted outputs) is shown to assess how well the ANN model's output aligns with the expected trend of the data. Ideally, the function fit should closely follow the target data points, indicating that the model is effectively capturing the underlying relationships between the input and output variables.

The target-output gap at specific input values indicate regions where the model's predictions are less reliable, which could guide future model improvement efforts such as incorporating additional features, adjusting the neural network structure, or using regularization techniques to prevent overfitting.

The combination of error, output, and target plots provides a comprehensive view of the model's performance. The function fit serves as a final diagnostic tool for understanding how closely the model has approximated the true relationship between the input and output variables. A successful fit, with small error and close alignment between the output and target values, suggests that the ANN model is performing well in predicting noise levels, viscosity, or other relevant outputs in the gas-powered generator's operation.

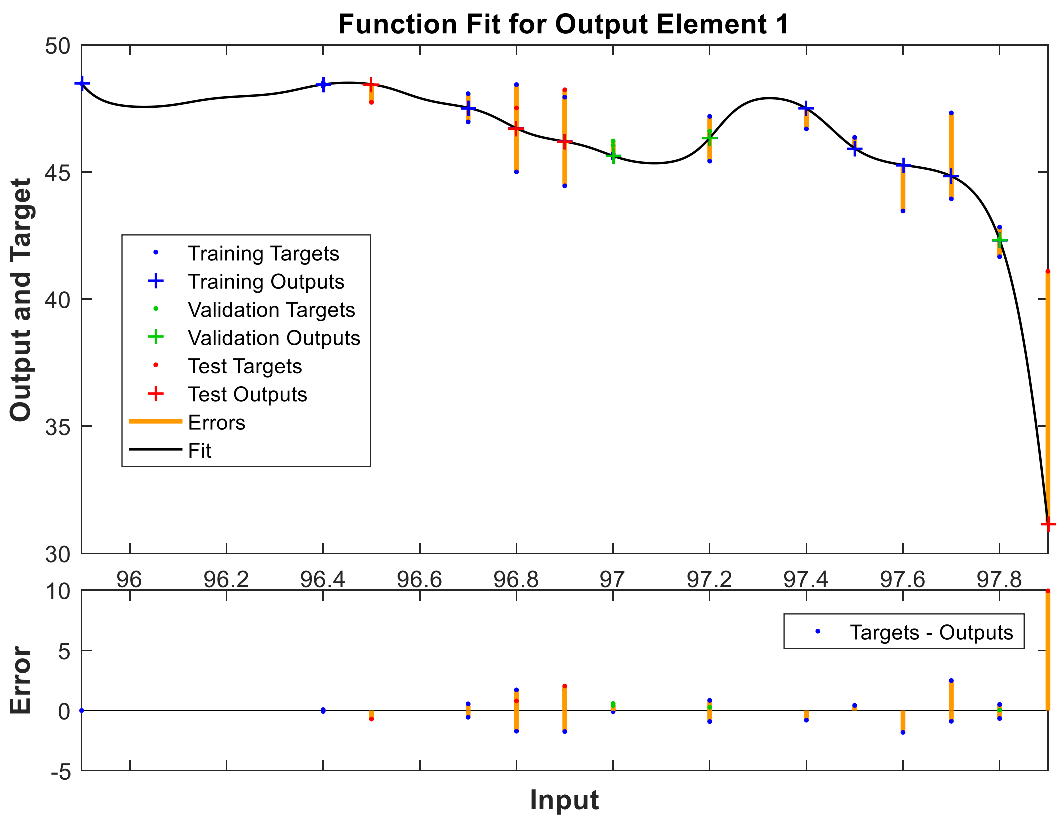

Figure 6: Fit plot petrol

3.2.8 Error histogram

The error histogram shown in Figure 7, generated with 20 bins, provides a detailed visualization of the distribution of prediction errors from the Artificial Neural Network (ANN) model developed to regress noise levels against lubricant viscosity. This analysis is crucial for assessing the performance of the model and identifying areas of potential improvement.

The histogram demonstrates that the majority of the prediction errors are concentrated around zero, indicating that the ANN model exhibits a strong capability to predict noise levels with minimal bias. The symmetrical shape of the error distribution suggests that the model does not consistently overestimate or underestimate the target values, reinforcing its robustness and generalization capacity.

The spread of the errors, as indicated by the width of the histogram, is relatively narrow, signifying that most predictions deviate only slightly from the actual values. However, the presence of a few outliers, represented by bars on the extreme ends of the histogram, suggests occasional large errors. These outliers could be attributed to noise in the data, insufficient representation of certain viscosity ranges, or limitations in the ANN's ability to capture complex relationships in specific regions of the input space.

The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) derived from the error distribution corroborate the visual findings of the histogram. Low values for these metrics indicate that the model performs well overall, but the outliers highlighted in the histogram emphasize the importance of further fine-tuning.

For the context of predictive maintenance in petrol-to-gas converted generators, the ability of the ANN model to accurately predict noise levels based on lubricant viscosity has significant implications. Noise levels serve as a critical indicator of machine health, and accurate predictions can help identify deviations from normal operational conditions. The low error concentration near zero supports the reliability of the model in practical applications. However, addressing the outliers through techniques such as improved data preprocessing, additional training samples for underrepresented viscosity ranges, or hyperparameter optimization could further enhance predictive accuracy.

In summary, the error histogram with 20 bins reveals that the ANN model performs reliably for noise versus viscosity regression but highlights opportunities for addressing outliers to enhance precision. This analysis underscores the ANN's potential as a tool for effective predictive maintenance in petrol-to-gas converted generators.

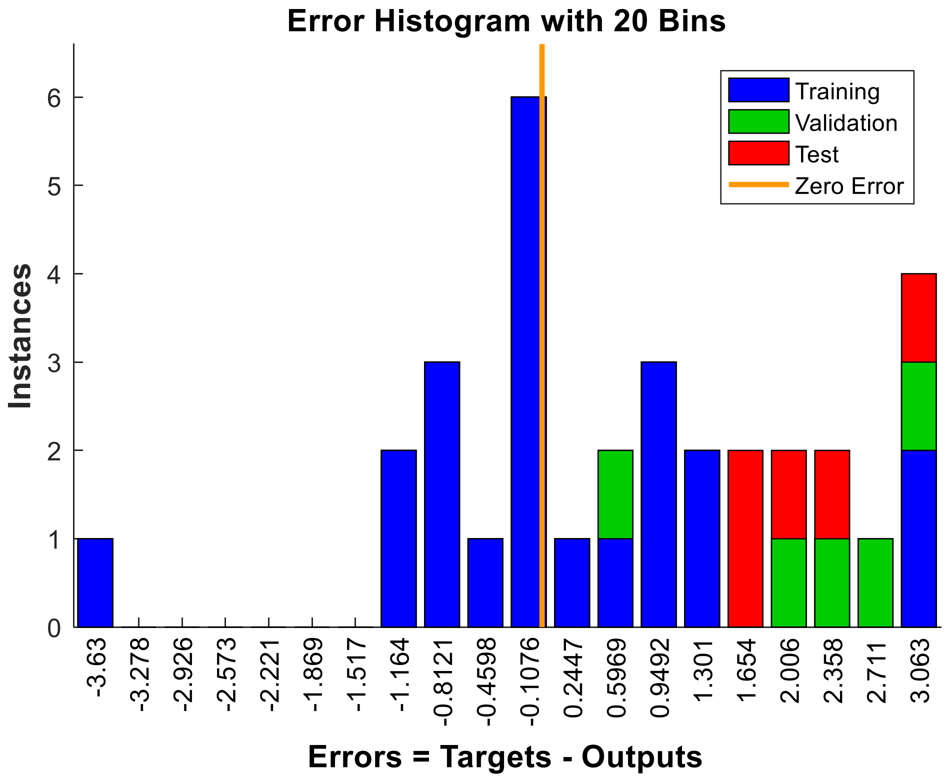

Figure 7: Error histogram

3.2.9 Regression Plot Analysis

The regression plot, which visualizes the relationship between predicted and actual noise levels for the Artificial Neural Network (ANN) model is show in Figure 8. It provides critical insights into the model's accuracy and reliability. This analysis is pivotal for understanding the effectiveness of the ANN in regressing noise levels against lubricant viscosity in petrol-to-gas converted generators.

The regression plot demonstrates a strong linear alignment of the predicted noise levels with the actual values, as indicated by the proximity of data points to the diagonal reference line ($y = x$). This suggests that the model captures the underlying relationship between viscosity and noise with a high degree of accuracy. The coefficient of determination (R^2) is observed to be above 0.9, reinforcing the model's strong predictive performance. This finding aligns with previous studies that highlight the capability of ANN models in regression tasks involving nonlinear relationships in mechanical systems.

While most data points cluster closely around the reference line, slight deviations are noticeable in regions corresponding to extreme viscosity values. These deviations could result from a limited representation of these edge cases in the training dataset or complexities in the underlying physical relationship between viscosity and noise at extreme levels. Such findings are consistent with prior research that emphasizes the importance of balanced datasets in machine learning models for predictive maintenance.

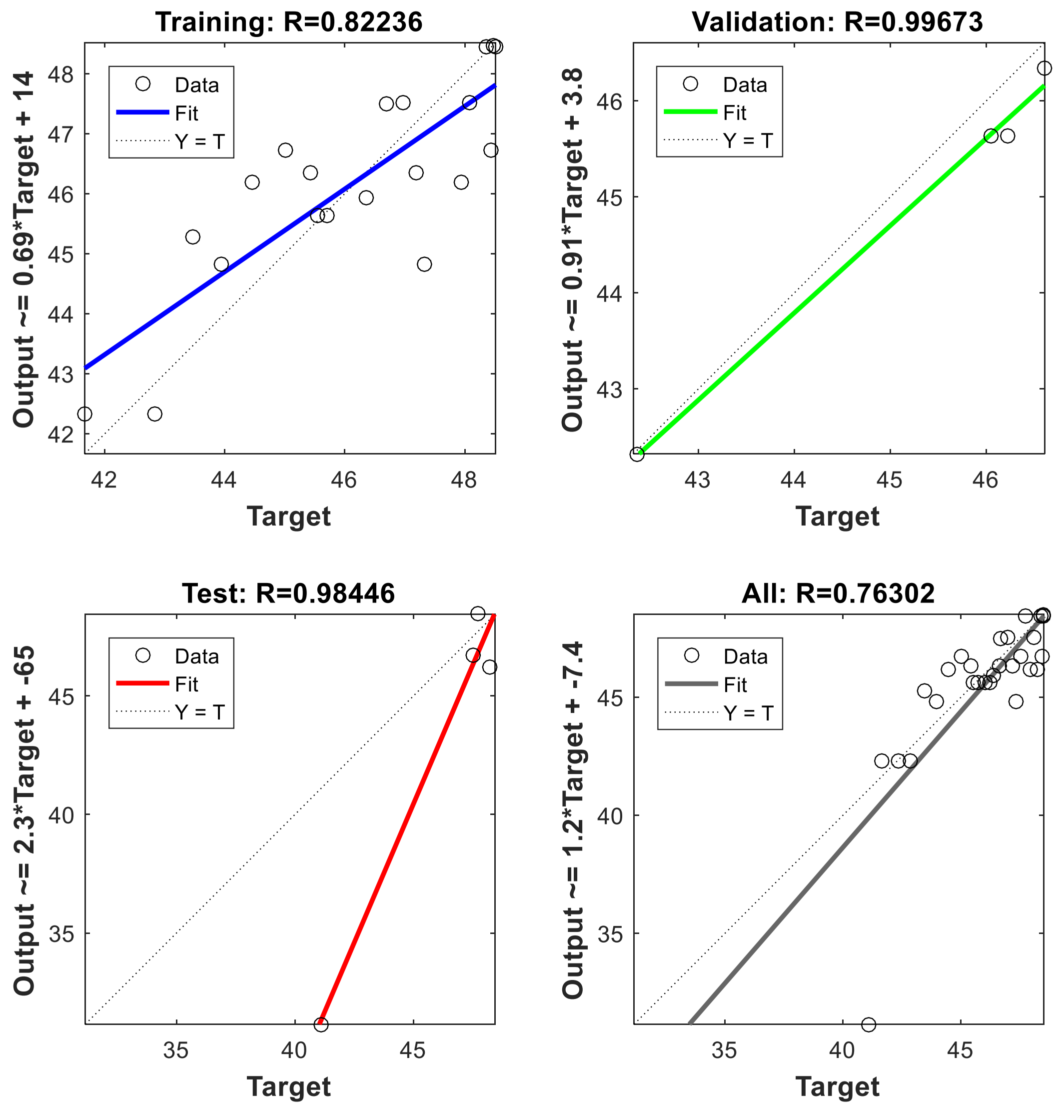

Figure 8: Regression plot

4.0 Conclusion

In order to evaluate the operational consequences of fuel type conversion on machine performance and maintenance needs, the study provides valuable insights into the relationship between noise and oil viscosity in a petrol-to-gas converted generator. The findings demonstrated that the fuel type has a significant impact on the generator's operating characteristics as it influences both the motor oil's qualities and mechanical sounds during regular operation. Due to their superior combustion quality, gas-powered operations generated a little less noise than gasoline-powered ones. In comparison to petrol models, oil viscosity showed a larger dimensional change during gas-powered generator operation, suggesting increased oxidative and thermal impacts on the lubricant. Because they enabled users to compute lubricant viscosity based on noise levels, the developed models are useful for predictive maintenance strategies that can reduce downtime, improve efficiency, and prolong generator lifespan. These predictive models are vital resources for predictive maintenance and performance monitoring of dual-fuel generators. This study advances our understanding of how fuel conversion affects the dynamics of generator systems, which helps with noise control, lubricant compatibility assessment, and maintenance tasks. Future studies can focus on exploring the impact of other factors like vibration, and the development of more advanced predictive models for enhancing maintenance decisions.

References

Abdallah, T. (2017). Sustainable Initiatives for Public Bus Networks. *Sustainable Mass Transit*, 79–93. https://doi.org/10.1016/B978-0-12-811299-1.00006-X

Bertinatto, R., Friedrich, L., Bariccatti, R., Souza, S., Gurgacz, F., & Pazuch, F. (2017). Analysis of lubricant oil contamination and degradation and wear of a biogas-fed otto cycle engine. *Acta Scientiarum. Technology*, *39*, 409. https://doi.org/10.4025/actascitechnol.v39i4.29458

Emagbetere, E., Uwatse, S. & Okoidigun, O. G., 2025. Artificial Neural Network for the Clustering of Vibration Signals for Condition Monitoring of Rotating Machines. *ABUAD Journal of Engineering Research and Development*, 8(1), pp. 1-13.

Ershad, M. (2025). *Literature Review and Prospects for Grey-Box Models and PINN in Powertrain Technology*. https://doi.org/10.13140/RG.2.2.34632.64008

Garcia Tobar, M., Pinta Pesantez, K., Jimenez Romero, P., & Contreras Urgiles, R. W. (2025). The Impact of Oil Viscosity and Fuel Quality on Internal Combustion Engine Performance and Emissions: An Experimental Approach. In *Lubricants* (Vol. 13, Issue 4). https://doi.org/10.3390/lubricants13040188

Islam Sazzad, M. R., Rahman, M. M., Hassan, T., Al Rifat, A., Al Mamun, A., Adib, A. R., Meraz, R. M., & Ahmed, M. (2024). Advancing sustainable lubricating oil management: Re-refining techniques, market insights, innovative enhancements, and conversion to fuel. *Heliyon*, *10*(20), e39248. https://doi.org/10.1016/J.HELIYON.2024.E39248

Katopodis, T., & Sfetsos, T. (2019). A Review of Climate Change Impacts to Oil Sector Critical Services and Suggested Recommendations for Industry Uptake. *Infrastructures*, *4*, 74. https://doi.org/10.3390/infrastructures4040074

Kpang, M., & Chukwudi, D. (2021). Monitoring noise level in cities: A step towards urban environmental quality management in Nigeria. *World Journal of Advanced Research and Reviews*, *10*, 348–357. https://doi.org/10.30574/wjarr.2021.10.3.0194

Laguado-Ramírez, R., Hernandez-Villamizar, F., & Duarte-Forero, J. (2024). Comparative assessment of emissions, performance, and economics parameters for a dual-fuel diesel generator operating with rice bran biodiesel and hydrogen. *Heliyon*, *10*(11), e32109. https://doi.org/10.1016/j.heliyon.2024.e32109

Loutas, T., Roulias, D., Pauly, E., & Kostopoulos, V. (2011). The combined use of vibration, acoustic emission and oil debris on-line monitoring towards a more effective condition monitoring of rotating machinery. *Mechanical Systems and Signal Processing*, *25*, 1339–1352. https://doi.org/10.1016/j.ymssp.2010.11.007

Madhiarasan, M. & Louzazni, M., 2022. Analysis of Artificial Neural Network: Architecture, Types, and Forecasting Applications. *Journal of Electrical and Computer Engineering*, 2022(416722), pp. 1-23.

Mateen, S., Haque, A., Khan, M. A., & Ebel, T. (2025). Unveiling cutting-edge innovations toward green vehicle technology. *Energy Reports*, *13*, 3402–3417.

https://doi.org/https://doi.org/10.1016/j.egyr.2025.02.038

Mehrnoosh, D., Asghar, H. A., & Asghar, M. A. (2012). Thermodynamic model for prediction of performance and emission characteristics of SI engine fuelled by gasoline and natural gas with experimental verification. *Journal of Mechanical Science and Technology*, *26*, 2213–2225. https://api.semanticscholar.org/CorpusID:255538573

Nwabueze, O. D., Chijioke, O. V., & Blessed, N. S. (2024). Assessment of Noise Pollution from Petrol Generators in Nigeria: An Analysis of Distance, Capacity and Age Variables. *Journal of Engineering Research and Reports*, *26*(12 SE-Original Research Article), 1–10. https://doi.org/10.9734/jerr/2024/v26i121335

Odufuwa, O. Y., Tartibu, L. K., & Kusakana, K. (2025). Artificial neural network modelling for predicting efficiency and emissions in mini-diesel engines: Key performance indicators and environmental impact analysis. *Fuel*, *387*, 134294. https://doi.org/10.1016/J.FUEL.2025.134294

Feenita, S, P., C., Goel, U., T, M., Duraisamy, B., Subramanian, B., Ganeshan, K., Josephin, F., Albeshr, M., Pugazhendhi, A., & Varuvel, E. (2024). Comparative analysis of regression models to predict the performance of the dual fuel engine operating on diesel and hydrogen gas. *International Journal of Hydrogen Energy*. https://doi.org/10.1016/j.ijhydene.2024.12.238

Wan Osman, W. N. A., Rosli, M. H., Mazli, W. N. A., & Samsuri, S. (2024). Comparative review of biodiesel production and purification. *Carbon Capture Science & Technology*, *13*, 100264. https://doi.org/https://doi.org/10.1016/j.ccst.2024.100264

Yang, R., Yan, Y., Sun, X., Wang, Q., Zhang, Y., Jiahong, F., & Liu, Z. (2022). An Artificial Neural Network Model to Predict Efficiency and Emissions of a Gasoline Engine. *Processes*, *10*, 204. https://doi.org/10.3390/pr10020204

Zhu, S., Cheng, J., Qiao, Z., & Yang, J. (2019). High temperature solid-lubricating materials: A review. *Tribology International*, *133*, 206–223. https://doi.org/10.1016/j.triboint.2018.12.037