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Emission Value Estimation to Achieve Best Performance Gas Engine Generator Set using Artificial Neural Network

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Abstract— *Exhaust gas emissions resulting from the combustion of a combustion engine can determine the efficiency of the engine. Recently, the use of Artificial Neural Network (ANN) methods has been explored to predict exhaust gas output from combustion processes. This research aims to predict exhaust emissions produced by considering factors such as fuel type, torque, and engine speed by developing an ANN model trained using the Levenberg-Marquardt (LM) algorithm. The results indicate that the ANN model trained with the LM algorithm successfully predicted exhaust emissions with high accuracy, yielding a Correlation Coefficient (R) of 0.99514, a Determination Coefficient (R^2) of 0.9903, and a low Root Mean Squared Error (RMSE) of 0.0017. These findings suggest that ANN models can be effective tools for predicting exhaust gas emissions, potentially contributing to improvements in engine efficiency and environmental sustainability.*

Keywords— *Generator set; Liquified Petroleum Gas; Artificial Neural Network; Fuel properties, emissions*

I. INTRODUCTION

Currently, Fuel Oil is increasingly popular among Indonesian people as a source of energy. However, the use of fuel oil causes negative impacts on the environment because it increases exhaust emissions and contributes to global warming. In 2018, there was an increase in greenhouse gas emissions of 14% GHG emissions, 73% of which was caused by the transportation sector [1]. The effort taken is to increase existing standards, namely nitrogen oxides (NOx), which contributes greatly to the formation of air pollution, will be reduced.[2]

Various studies have been carried out to reduce emissions caused by the combustion process [3][4][5]. There are several studies that have been carried out using spark ignition (SI) engines with various alternative fuels, one of them that is considered good is compressed natural gas [6]. Therefore, Indonesia has great potential to replace transportation fuels such as natural gas. One option for Fuel Oil is LPG (Liquified Petroleum Gas), which is obtained from natural gas. Indonesia has abundant natural gas reserves. LPG has a high octane value, around 112, so it is suitable for use in petrol engines (spark ignited). LPG can be an alternative fuel for Spark-ignition (SI) engine, especially for vehicle applications, because has easy liquefaction capability and high knock resistance with low pressure and lower costs [7]

Fuel quality has a significant influence on engine performance results. If we can predict the emissions that will be generated then the engine can be at good performance. One of the methods that can be used is ANN. Previous research on neural networks to can determinated diesel engine emissions shows that NOx emissions results can be found by knowing the fuel composition and workload.[8]

The ANN used was based on LM which worked well to predict NOx emission data in previous research. Abaut emission performance prediction using an ANN has developed to predict torque, hydrocarbons (HC), carbon monoxide (CO) and NOx emissions based on the LM model with a correlation coefficient value of > 0. 99 and a MSE value of less than 0.001, which effectively predicts difficult to determinated NOx emission data.[9] By knowing the amount of fuel used, torque and the speed of the engine, the amount of emissions produced can be known.

There are many study is use of LPG as a fuel for generator set engine.

TABLE 1. Literatures related to “engine”, “prediction” and “emission”.

Title	Ref	Emission	Model
Application of artificial neural network to forecast engine performance and emissions of a spark ignition engine	Fu et al. (2022) [10]	Carbon monoxide, hydrocarbons, nitrogen oxides	Neural Networks
A novel modal emission modelling approach and its application with on-road emission measurements	Wang et al.(2022) [11]	Carbon monoxide, carbon dioxide, nitrogen oxides	Modal emission models
Designing a steady-state experimental dataset for predicting transient NOx emissions of diesel engines via deep learning	Shin et al. (2022) [12]	Nitrogen oxides	Deep learning
Optimizing model parameters of artifcial neural networks to predict vehicle emissions	Seo and Park (2023)[13]	Carbon monoxide, carbon dioxide, nitrogen oxides	Neural Networks
NOx emissions prediction based on mutual information and back propagation neural network using correlation quantitative analysis	Wang et al. (2020) [14]	Nitrogen oxides	Neural Networks
Neural network models for virtual sensing of NOx emissions in	Arsie et al. (2017) [15]	Nitrogen oxides	Neural networks

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automotive diesel engines with least square-based adaptation			
Prediction of engine NOx for virtual sensor using deep neural network and genetic algorithm	Kim et al. (2021) [16]	Nitrogen oxides	Deep neural networks and genetic algorithms
An Artifcial Neural Network Model to Predict Effciency and Emissions of a Gasoline Engine	Yang et al. (2022) [17]	Carbon monoxide, nitrogen oxides	Neural networks
Prediction of instantaneous real-world emissions from diesel light-duty vehicles based on an integrated artifcial neural network and vehicle dynamics model	Seo et al. (2021) [18]	Carbon dioxide, hydrocarbons, nitrogen oxides	Neural networks
Deep neural network model with Bayesian hyperparameter optimization for prediction of NOx at transient conditions in a diesel engine	Shin et al. (2020) [19]	Nitrogen oxides	Bayesian Hyperparameter Optimization for Deep Neural Networks

From Table 1 we see that a lot of research has been developed in the last 5 years regarding engines, emissions and ANN, using advanced machine learning techniques, namely ANN, to predict the emission characteristics of LPG-fueled engines. ANN training uses the LM method. This research aims to provide predictions of emissions to determine engine performance by providing input data in the form of fuel consumption, torque and engine speed as given in the following Figure 1.

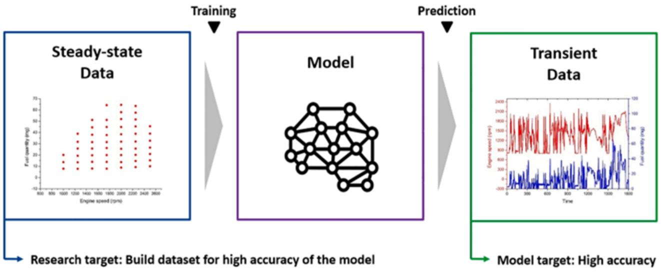

Fig. 1. Objective of this study.

The process of accurately predicting the performance of gas engine generator sets, particularly in terms of emissions, involves the development of a model that leverages both steady-state and transient data. The overall methodology can be broken down into three distinct phases: steady-state data collection, model training, and transient data prediction. These phases are crucial for achieving high prediction accuracy and optimizing engine performance.

1. Steady-State Data Collection

The first phase involves the acquisition of steady-state data, which is collected when the engine operates under constant conditions. This data typically includes variables such as engine speed (in RPM) and fuel consumption, among others. As illustrated in the left-hand section of the diagram, this steady-state data forms the basis for the initial dataset. The research target at this stage is to build a high-quality dataset to ensure that the model, when trained, is highly accurate. High-accuracy data allows the model to generalize effectively across various operating conditions.

2. Model Training

Once a sufficient dataset of steady-state conditions has been gathered, the next phase involves training the model using this data. In this case, an artificial neural network (ANN) is used, as depicted in the center of the diagram. ANNs are well-suited for handling complex, non-linear relationships, such as those found between engine operational parameters and emission outputs.

The steady-state data is fed into the neural network, and a training process is conducted to allow the model to learn the underlying relationships between input features (e.g., engine speed, fuel type) and target outputs (e.g., emissions, fuel consumption). During this training process, various parameters of the model are adjusted to minimize prediction errors and enhance model accuracy.

3. Transient Data Prediction

Following model training, the next step involves using the trained model to predict engine performance under transient conditions—where the engine's operational parameters are changing dynamically over time. The transient data, as shown in the right section of the diagram, reflects how variables such as engine speed and fuel consumption fluctuate over time in non-steady conditions (e.g., during acceleration or deceleration).

The model target at this stage is to maintain high accuracy in predicting transient performance. Accurately modeling transient conditions is more challenging due to the non-linear and rapidly changing nature of the data. However, with the neural network already trained on steady-state data, the model can provide highly accurate predictions of engine performance even in dynamic environments.

Research Implications

The approach of using steady-state data to train an artificial neural network for transient data prediction has several significant implications. First, the method allows for the efficient use of available data to create a robust prediction model, capable of generalizing to real-world scenarios. Second, by achieving high accuracy in transient data prediction, the model can be instrumental in optimizing engine performance while minimizing emissions. This has direct relevance to industries aiming to meet stringent environmental regulations without compromising on operational efficiency.

II. Material and Method

A. Material

The materials used in this research include both hardware and software components, as well as the data utilized for model training and validation:

1. Gas Engine Generator Set: The gas engine generator set used for the study operates under various load conditions.

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The key parameters measured during the engine's operation include engine speed (RPM), fuel consumption, and emission outputs (NOx, CO2, and HC emissions).

2. Sensors and Data Acquisition System: The system includes various sensors for measuring real-time engine performance. These sensors include:
3. Engine Speed Sensor: Captures the revolutions per minute (RPM) of the engine.
4. Fuel Consumption Sensor: Measures the fuel consumed during engine operation.
5. Emission Sensors: NOx, CO2, and hydrocarbon (HC) sensors to quantify the pollutant levels. The data is collected via a 12-bit ADC (Analog-to-Digital Converter), ensuring high accuracy in the recorded values.
6. Microcontroller (STM32Fx LQFP64): An STM32Fx microcontroller in the LQFP64 package is used to manage data collection and processing. This microcontroller is known for its efficiency in handling real-time data from multiple sensors.
7. Artificial Neural Network (ANN) Software: The ANN model is implemented using MATLAB and Python programming environments, which provide robust tools for neural network design, training, and testing. The model architecture consists of multiple layers of neurons trained using the backpropagation algorithm.
8. Data Acquisition Interface (USB-Serial FT232RL): The communication between the data acquisition system and the processing unit is facilitated through a USB-Serial FT232RL interface, allowing for seamless transfer of data for model training.

B. Engine setup

Experimental work set as a schematic and diagram following Table 2 and Figure 2. A flow and ventilation brake dynamometer was used to determinated torque. Varying the amount of fuel, torque and speed is done by controlling the existing load. A gas analyzer is used to record the NOx produced.

TABLE 2. The specific parameters of the test engine.

Description	Specification
Type	OHV,4 Stroke, Single cylinder,
Volume	389 cc
Compression ratio	8.2
Power	8.7kW (11.7 HP)/3600 min-1 rpm

The table describes the specifications of an engine. Here's the explanation:

Type: The engine is an OHV (Overhead Valve), 4-stroke, single-cylinder engine. This means the engine operates on a four-stroke cycle, and the valves are located in the cylinder head above the combustion chamber.

Volume: The engine has a displacement of 389 cc (cubic centimeters), which refers to the total volume of all the cylinders in the engine.

Compression ratio: The engine has a compression ratio of 8.2:1. This is the ratio of the volume of the combustion chamber at its maximum capacity to its minimum capacity, which describes how the fuel-air mixture is pre-burned.

Power: The engine produces a power output of 8.7 kW (11.7 horsepower) at 3600 revolutions per minute (rpm), which reflects its capability to generate energy at this engine speed. This specification provides an overview of the engine's design and performance characteristics.

C. Data Gathering

Data is taken from a gas-fueled generator set with a self-made Electric Control Unit (ECU) is given in the following Table 3 and Figure 3. Data is taken using an ECU with electrical wiring as in Figure 4. By carrying out 100 data variations, data was obtained in the form of variations in fuel, torque, speed and emissions produced.

TABLE 3. Technical specification of ECU.

Description	Specification
Type	OHV,4 Stroke, Single cylinder,
Volume	389 cc
Compression ratio	8.2
Power	8.7kW (11.7 HP)/3600 min-1 rpm

Here's an explanation of each part in the table:

1. Power Voltage (12 V):

The system operates at a power voltage of 12 volts. This voltage powers the main components, such as the microcontroller and peripheral devices. It is common in embedded systems and automotive electronics.

2. Main Chip (STM32Fx LQFP64):

The main processing unit is an STM32Fx microcontroller in an LQFP64 package (64 pins). STM32Fx is part of STMicroelectronics' STM32 family, known for their performance in controlling embedded systems. The "Fx" series typically supports ARM Cortex-M cores, offering high processing capabilities for real-time applications.

3. Storage (Internal EEPROM):

The system has built-in EEPROM (Electrically Erasable Programmable Read-Only Memory) for non-volatile storage. EEPROM stores critical data such as settings or calibration parameters, ensuring data retention even when the power is off.

4. USB Data Interface (USB-Serial FT232RL):

This interface allows communication between the system and a computer or other devices using a USB connection. The FT232RL chip is commonly used for USB-to-serial communication, converting USB signals to serial communication protocols (UART), making it easy to transfer data between the microcontroller and external devices.

5. Engine Control Transistor (IRF540N):

The IRF540N is an N-channel MOSFET (Metal-Oxide-Semiconductor Field-Effect Transistor) used for controlling high-power components in the engine control system. It can handle high currents and voltages, making it suitable for switching operations and driving heavy loads.

6. TPS Input (12-bit ADC):

The TPS (Throttle Position Sensor) input is connected to a 12-bit ADC (Analog-to-Digital Converter), which converts the analog signal from the sensor to a digital value for the microcontroller to process. A 12-bit ADC provides high-

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resolution measurements, ensuring more accurate throttle control in engine applications.

7. PULSER Input (Any pulsed signals):

This input can accept various types of pulsed signals. Pulsers generate pulse-width modulation (PWM) or other digital pulses, which can be used for controlling the timing and synchronization of certain system components or monitoring engine performance metrics.

D. Electric Control Unit (ECU)

In addition to the previously mentioned materials, a self-made Engine Control Unit (ECU) was utilized in this research. The ECU was custom-built to provide real-time control and data acquisition capabilities for the gas engine generator set. The key features of the custom ECU are as follows:

1. Main Controller (STM32Fx Microcontroller):

The self-made ECU is based on the STM32Fx microcontroller in the LQFP64 package, which allows for efficient processing of sensor data and engine control operations. The microcontroller's versatility and processing speed make it well-suited for handling real-time control of the engine parameters, such as fuel injection and ignition timing.

2. Signal Input and Processing:

The ECU is designed to accept a variety of inputs from the engine, including:

a. Throttle Position Sensor (TPS): The ECU processes signals from the TPS using a 12-bit ADC, allowing for precise throttle control in response to real-time conditions.
b. Pulser Input: The ECU can handle any pulsed signals, such as those from crankshaft position sensors, which are critical for timing control.
c. Fuel Consumption and Emission Sensors: Inputs from sensors measuring fuel flow and emissions (NOx, CO2, HC) are fed into the ECU for processing and real-time adjustments to engine operations.

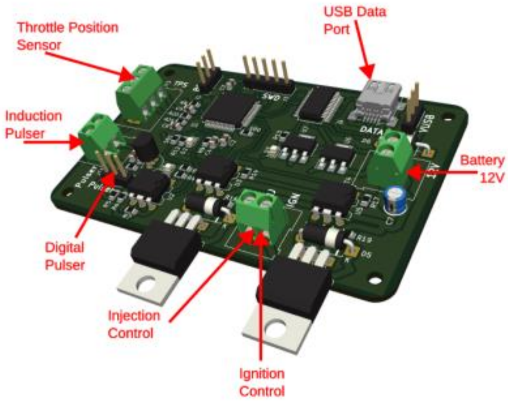
3. Control Output:

The ECU is equipped with an IRF540N MOSFET to handle high-power outputs for controlling various engine components, such as fuel injectors and ignition coils. The ECU can modulate the fuel delivery and engine timing to optimize performance and minimize emissions under varying load conditions.

4. Data Communication Interface (USB-Serial FT232RL):

The self-made ECU integrates a USB-Serial FT232RL interface to communicate with a computer for real-time data logging and monitoring. This interface allows the ECU to transmit operational data such as engine speed, fuel consumption, and emissions to external monitoring systems or a neural network model for further analysis.

This custom ECU design is an integral part of the engine control system, managing critical engine parameters such as fuel injection, ignition timing, and throttle position. It collects real-time data from multiple sensors, processes it using the STM32Fx microcontroller, and makes dynamic adjustments to optimize engine performance and minimize emissions. The integration of high-precision sensors, powerful control transistors, and data communication capabilities allows the ECU to interact with machine learning models (such as ANNs) for advanced engine tuning and performance optimization.



(a) Mockup

(b) Actual

Fig. 2. (a) Mockup Electric Control Unit (ECU) (b) Actual Electric Control Unit.

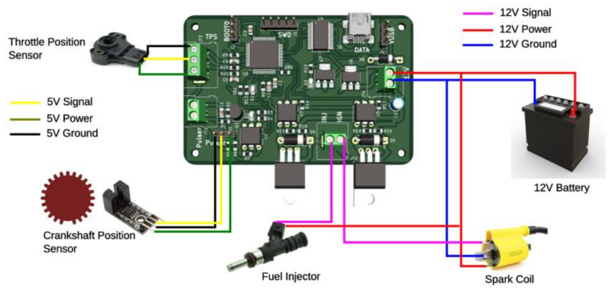


Fig. 3. Electrical Wiring

The diagram illustrates a microcontroller-based control system for the ignition and fuel injection processes in a gas engine. The system integrates multiple sensors and actuators to ensure precise control over the engine's operational parameters. The components are described as follows:

1. Throttle Position Sensor (TPS)

The Throttle Position Sensor measures the angle of the throttle valve, which is used to control the amount of fuel injected into the engine. The sensor provides real-time data to the microcontroller, which processes the information to adjust fuel injection accordingly. The sensor operates using a 5V signal, with connections for power (5V), signal (5V), and ground (5V).

2. Crankshaft Position Sensor

This sensor detects the position and rotational speed of the crankshaft, providing critical input for determining the engine's ignition timing and fuel injection intervals. The sensor operates with a 5V power supply and communicates with the microcontroller via signal and ground connections.

3. Fuel Injector

The fuel injector is responsible for delivering fuel to the combustion chamber of the engine. It is controlled by the microcontroller based on input from the sensors, which ensures an optimal air-fuel mixture for combustion. The microcontroller signals the injector to release fuel at the appropriate time and quantity.

4. Spark Coil

The ignition coil produces the high voltage required to ignite the air-oil mixture in the engine's cylinders. The microcontroller governs the timing of the spark, ensuring precise ignition based on the data provided by the position sensors.

5. 12V Battery

The 12V battery powers the entire system, supplying energy to both the sensors and the microcontroller. It has connections for power (12V), signal (12V), and ground (12V), ensuring the steady operation of the electronic components.

This system allows for enhanced engine control by monitoring and adjusting key operational parameters in real time, ultimately improving engine efficiency and emission control.

III. Results and Discussion

NOx emissions refer to nitrogen oxide gas (NO and NO2), which is formed during the combustion process in internal combustion engines. Generally, LPG generator set engines tend to produce higher levels of NOx emissions than gasoline engines. Additionally, NOx levels increased with increasing engine load for all mixtures tested. From these data we can observe that the increase in NOx emissions is consistent with increasing fuel proportions. This can indicate the influence of engine load on NOx emissions, where after a certain point, an increase in load does not significantly affect NOx emissions. These data highlight the potential of fuel reduction to reduce NOx emissions in generator set engines at different engine loads.

From the Figure 8 it can be seen that the correlation coefficient (R) and determination (R2) in artificial neural networks were examined in this study. R is used to measure the closeness of the relationship between points to the linear regression line according to the resulting value. The R value can vary from -1 to +1, with a value of -1 indicating perfect linear inverse correlation and +1 indicating that the correlation is perfect positive. The detailed R value of the LM algorithm for training, validation, testing and everything is presented in Figure 8. In addition, the coefficient of determination is a prediction criterion used to measure how much variability a particular factor is triggered by its relationship to other factors.

Correlation is also usually called "goodness of fit", which has a value ranging between 0 and 1, with a value of 1 indicating perfect suitability, and this makes the model contently usable, while 0 indicates that the prediction results cannot be used in general. accurate.

The correlation value uses the LM Algorithm. With an R value of 0.99514, the LM algorithm sign is almost perfectly linear positive correlation. Furthermore, the LM algorithm with an R2 value of 0.9903 shows that the dependent variable is predicted well is presented in Figure 7. These results can be obtained because LM has a faster ability to adjust the algorithm. in general LM is able to handle models better rather than free parameters that are not known exactly. If the initial estimate is far from the target, then the LM algorithm can find the optimal solution. However, LM sometimes has some weaknesses. For linear functions, the LM algorithm will take a long time to find a solution. In some cases, these algorithms can be very slow to assemble due to bulk the model has more than ten parameters that the algorithm needs to move slowly.

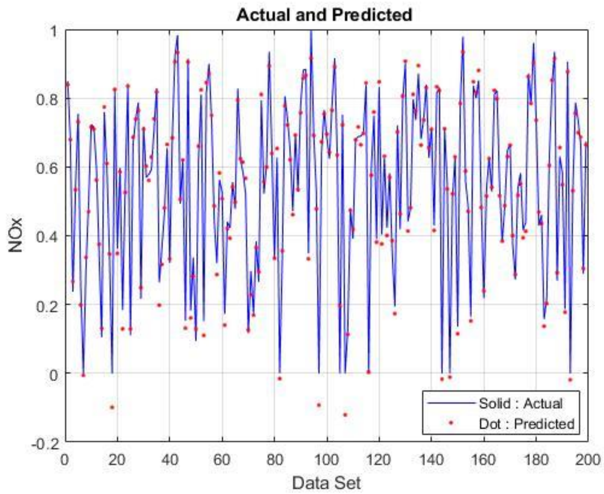


Fig. 4. Actual and predicted for various test LM training algorithm

The graph presents a comparison between the actual and predicted values of NOx emissions (nitrogen oxides) using a machine learning or statistical model, likely an Artificial Neural Network (ANN) model. Here's a breakdown of the key components:

1. X-Axis (Data Set): This axis represents the data points or samples used in the analysis, ranging from 0 to 200. These could be different instances or time intervals during which NOx emissions were recorded and predicted.
2. Y-Axis (NOx): This axis represents the NOx values, ranging from approximately -0.2 to 1.0. The NOx values are typically measured in ppm (parts per million), although the exact unit is not specified.
3. Solid Line (Actual): The blue solid line represents the actual measured NOx values in the system.
4. Dotted Points (Predicted): The red dots correspond to the predicted NOx values calculated by the ANN or another prediction model.

The graph demonstrates how closely the predicted values (red dots) align with the actual values (blue line). A good model would show a close match between the two, indicating that the model is accurately predicting NOx emissions.

The slight variations between the red dots and blue line may indicate some prediction error, which is common in such

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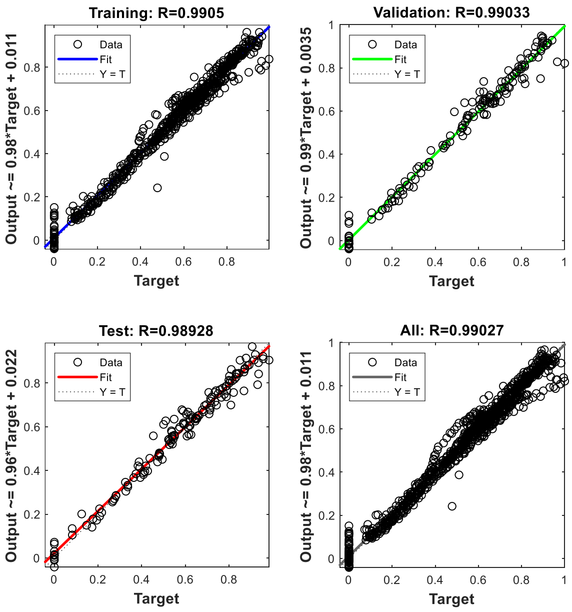
models.

This figure likely demonstrates the effectiveness of the predictive model (such as an ANN) in estimating NOx emissions from a gas engine generator set. The closeness of the predicted points to the actual line suggests the model's accuracy, though there are visible discrepancies at certain data points, which might require further model refinement.



The image consists of four scatter plots, each comparing predicted output values from a model Artificial Neural Network to actual target values. These types of plots are commonly used to evaluate how well a model is performing in terms of its predictions. Here is a detailed breakdown of each subplot:

1. X-Axis (Target): This axis represents the actual target values, ranging from 0 to 1.
2. Y-Axis (Output): This axis represents the model's predicted output values, also ranging from 0 to 1.
3. Circles (Data): Each black circle represents a pair of target and predicted values. Ideally, these points should fall along the diagonal line, indicating a perfect match between predictions and actual values.
4. Lines
5. Fit Line (Colored): The colored line represents the best-fit line of the model's predictions.
6. Diagonal Line (Y=T): This is the dashed diagonal line where the predicted output equals the target value (Y = T). The closer the data points are to this line, the more accurate the model is.

Subplot Descriptions:
1. Top Left Plot:
Fit Line (Blue): Shows a linear fit of the data with an equation of `Output = 0.89 * Target + 0.011`. This suggests that the model is underestimating the target slightly, as the slope is less than 1. The points are relatively well distributed along the diagonal, indicating reasonable performance but some underprediction for higher target values.
2.Top Right Plot
Fit Line (Green): The equation is `Output = 0.99 * Target + 0.0036`, with a slope much closer to 1. This indicates that the model is performing better, with predictions more closely matching the actual values. The points align quite closely with the diagonal, suggesting strong predictive accuracy in this set.
3.Bottom Left Plo:
Fit Line (Red): The equation here is `Output = 0.96 * Target + 0.022`, indicating slightly lower predictions compared to the actual values. There are a few points where the predictions deviate from the diagonal, indicating minor prediction errors, especially for some higher target values.
4.Bottom Right Plot:
Fit Line (Grey): The equation is `Output = 0.98 * Target + 0.001`, showing a very close fit between the model's predictions and actual values. Similar to the other plots, most points lie near the diagonal, indicating a high degree of accuracy.

These plots show how well the model predicts NOx emissions based on the given targets. The closer the points are to the diagonal (Y=T line), the better the model's predictions align with the actual values.

Across the four plots, the model performs quite well, with only slight deviations in the predicted output. In general, the fit lines indicate that the model slightly underestimates the true values (slope < 1), but the differences are minor.

In summary, the plots indicate that the predictive model is effective in estimating NOx emissions with some small deviations, particularly for larger target values. Further refinement of the model might reduce these small prediction errors.

IV. Conclusion

A conclusion section is research from 100 data sets used to build the ANN model. In predicting the emissions produced based on variations in speed, torque and fuel used, a training algorithm using the LM algorithm uses an artificial neural network structure with 3 inputs and 1 output using 10 hidden layers. Results ANN trained with LM provided the better accuracy and succeeded in predicting emissions with correlation and determination coefficients (R = 0.99514, R2 = 0.9903) and the lowest error RMSE = 0.0017.g

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