

Multi-Objective Optimization of PLTMG Duri Engine 4-7 Operations Using RSM (Response Surface Methodology) – MOGA (Multi-Objective Genetic Algorithm) Methods for Efficiency Improvement and Emission Reduction

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ARTICLE INFO	ABSTRACT
Received: 22 Dec 2024	The Balai Punggut-Duri Gas Engine Power Plant (PLTMG) plays an important role in meeting the electricity needs in Central Sumatra. However, its flexible operation causes significant variations in efficiency and emissions between units. This study aims to optimize the operation of units 4-7 of the Duri PLTMG by considering efficiency, NPHR, and NOx emissions. The Response Surface Methodology (RSM) method models the relationship between load and power factor variations with plant performance. Furthermore, the Multi-Objective Genetic Algorithm (MOGA) is applied to find the optimal solution that simultaneously considers efficiency, NPHR, and NOx emissions. The results show that optimization with MOGA-RSM successfully identified the optimal start-up pattern for each unit. The priority order of start-up based on efficiency, NPHR, and NOx is units 5, 7, 4, and 6. This study provides a new contribution by integrating RSM and MOGA for PLTMG operation optimization, which has not been widely done in previous studies. This approach improves energy efficiency and reduces environmental impacts by reducing NOx emissions. The resulting start-up pattern recommendations are expected to support more efficient and environmentally friendly PLTMG Duri operations.
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INTRODUCTION

The Balai-Punggut Duri Gas Engine Power Plant (PLTMG) is one of Central Sumatra's supporting facilities for electricity needs, especially in Riau province. The working principle of PLTMG is almost the same as PLTD, with the difference that PLTMG uses a mixture of 99% gas and 1% HSD fuel. The following are the specifications of the Balai Punggut-Duri PLTMG.

Table 1. Spesification PLTMG Balai Punggut -Duri

Parameters	Specification
Manufacturer	Wärtsilä
Engine type	W18V50DF
Installed Power	7x16,1 MW
Net Capable Power (DMN)	7x14,3 MW
Speed	500 Rpm
Cylinder Bore	500 mm

Piston stroke	580 mm
BMRP	20/19,5 bar

Figure 1 shows the main stages in the electricity generation process at the Balai Punggut-Duri PLTMG, from the use of fuel to the distribution of power to the electricity network.

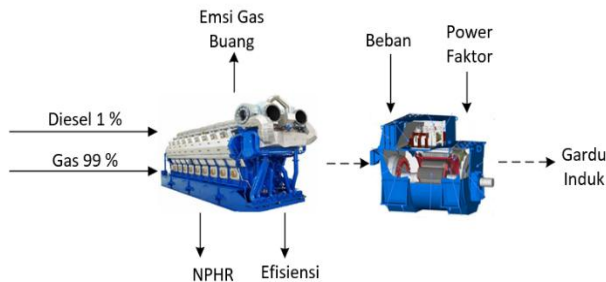


Figure 1. Electricity Generation Process at Balai Punggut-Duri PLTMG

Figure 1 shows the workflow of PLTMG Duri, which uses 99% gas and 1% diesel as fuel. The engine produces electricity through a generator by converting the mechanical energy of the fuel. This process generates parameters such as Efficiency and Net Plant Heat Rate (NPHR), which indicate the plant's performance. During combustion, exhaust gases such as NOx are produced. After that, the generated electricity is then sent to the substation to be distributed to the grid.

PLTMG Duri consists of 7 engines and two power transformer blocks: transformer 1 serves engines 1, 2, and 3, while transformer 2 serves engines 4, 5, 6, and 7. PLTMG Duri is a flexible power plant that adjusts electricity production according to the electricity network's load needs, often called a "picker" power plant.

However, in its operation, the operator only considers the condition of the equipment and the readiness of the unit without considering the efficiency, NPHR, and exhaust emissions of the PLTMG engine. The picker operation method, which is designed to activate generating units according to fluctuations in electricity demand in the Sumatra system, causes variations in running hours on each unit. This affects the differences in efficiency, NPHR, and NOx emissions between units because units that are operated more frequently experience more intense operational conditions than units that are rarely activated. This study aims to identify the optimal start-up pattern on engines 4, 5, 6, and 7 with load variations of 10 MW, 12 MW, and 14 MW and power factors of 0.90, 0.95, and 0.99. By considering efficiency, NPHR, and NOx exhaust emissions. The results of this study can provide a basis for operators to determine the priority of optimal unit operation, especially in the context of picker operations that affect each unit's performance and environmental impact.

This study uses the Response Surface Methodology (RSM) method used in this study because of its ability to evaluate complex relationships between input variables, such as load variations (10 MW, 12 MW, 14 MW) and power factors (0.90, 0.95, 0.99), on efficiency, NPHR (Net Plant Heat Rate), and NOx exhaust emissions. RSM allows the development of second-order polynomial-based mathematical models to analyze variable interactions and identify optimal operating patterns on engines 4, 5, 6, and 7. With experimental designs such as Central Composite Design (CCD), RSM reduces the number of experiments required, making it more efficient in time and cost, and provides a scientific basis for decision-making on operating patterns.

After obtaining the mathematical model from RSM, this study uses a Multi-Objective Genetic Algorithm (MOGA) to find the optimal solution by considering efficiency, NPHR (Net Plant Heat Rate), and NOx emissions. MOGA is chosen because of its ability to handle multi-objective optimization, producing a Pareto Front that reflects various optimal trade-offs between objectives. This method is effective in complex and non-linear solution spaces, allowing operators to choose solutions that suit operational priorities. With MOGA, this study

produces comprehensive start-up pattern recommendations, supporting the energy efficiency and operational sustainability of PLTMG Duri.

This study aims to optimize efficiency, Net Plant Heat Rate (NPHR) value and NO_x exhaust emissions at the Duri Gas Engine Power Plant (PLTMG) Unit 4, 5, 6, and 7 with load variations of 10 MW, 12 MW, and 14 MW, and power factors of 0.90, 0.95, and 0.99. The Multi-Objective Optimization Genetic Algorithms (MOGA) method utilizes the Response Surface Methodology (RSM) model. The steps in this study are as follows:

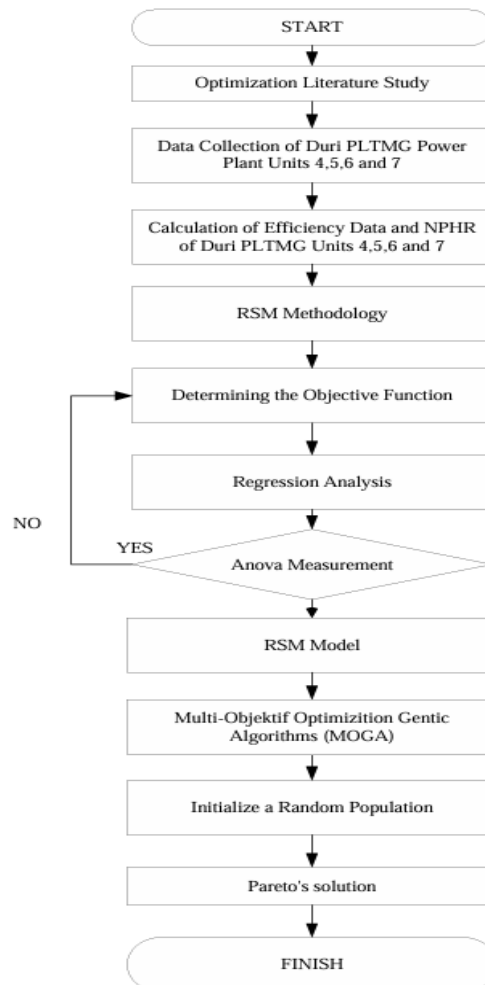


Figure 2 Optimization Process

PLTMG Balai Punggut-Duri

PLTMG Balai Punggut-Duri is located in Balai Punggut Village, Pinggi District, Bengkalis Regency, Riau Province. This power plant uses a gas engine to produce electricity, which is distributed on the island of Sumatra, especially in Riau Province.

The working principle of PLTMG is almost the same as that of PLTD, but the difference lies in the fuel used. Generally, PLTD uses 100% HSD fuel, while PLTMG uses 99% natural gas fuel with 1% HSD fuel, which is used for the initial combustion ignition. Gas fuel, HSD and air enter simultaneously into the combustion chamber. Where the gas flow is regulated by the Solenoid actuating gas valve (SOGAV). In contrast, the incoming HSD is regulated by the Main Fuel Injection (MFI), a small portion of gas enters the pre-camber chamber, and

the injector provides ignition, which is regulated by the coil drive on the pre-camber at the time of TDC (Top Dead Center) compression of the piston so that combustion in compressed gas air (Marhaini et al., 2022).

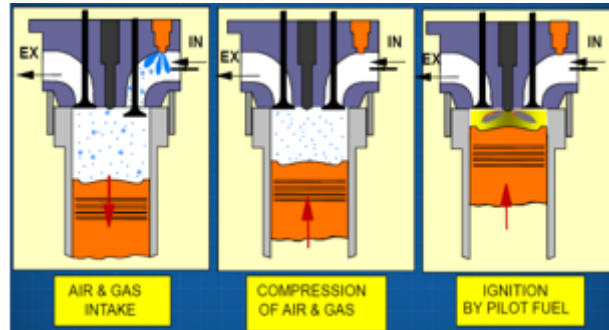


Figure 3. Working Principle of Combustion in PLTMG

Thermal Efficiency of PLTMG

Thermal Efficiency is an important indicator parameter that determines how well the system can convert fuel energy into electrical energy. Fuel quality, engine condition, and control technology used affect the Efficiency of gas engine power plants (PLTMG) (Wahyudi et al., 2021).

The Thermal PLTMG Efficiency Formula: (Novi Gusnita & Bayu Prima, 2017)

$$\text{Thermal Efficiency } (\eta) = \frac{p_{out} (KW)}{m \left(\frac{kg}{s} \right) \cdot LHV \left(\frac{kJ}{kg} \right)} \times 100\% \quad (1)$$

Net Plant Heat Rate (NPHR)

Net Plant Heat Rate (NPHR) One of the important indicators is calculated by connecting the input energy from the fuel with the electrical energy produced. A lower NPHR value indicates a more efficient energy conversion. The increase in NPHR value in PLTMG is largely due to optimization efforts such as load regulation and improvement of combustion control technology (Alber & Kiono, 2022; Saini et al., 2021; Santoso et al., 2021).

The formula for calculating NPHR in PLTMG: (Davidy, 2022)

$$NPHR = \frac{m \left(\frac{kg}{s} \right) \cdot LHV \left(\frac{kJ}{kg} \right)}{p_{netto} (kW)} \quad (2)$$

NOX Emissions

Nitrogen oxide (NOx) emissions from gas engine power plants (PLTMG) are caused by the combustion process of fuel at high temperatures. NOx causes air pollution and the formation of tropospheric ozone, which is detrimental to human health and the environment. A continuous Emission Monitoring System (CEMS) is a measurement system used to monitor exhaust emissions in power generation facilities continuously; technologies such as low-temperature burners, steam injection, and Selective Catalytic Reduction (SCR) are used to reduce NOx emissions and make power plant operations more environmentally friendly (Dahal & Hastings, 2016; Huber et al., 2023).

METHOD

Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a statistically based approach to develop empirical models through systematic experimental design. The goal of RSM is to find the optimal combination of factors in a microprocessor to influence a process, focusing on the interaction effects between variables (Veza et al., 2023).

RSM Formula:

$$Y = \beta_0 + \sum_{i=1}^k \beta_i X_i + \sum_{i=1}^{k-1} \sum_{j=1}^k \beta_{ij} X_i X_j + \sum_{i=1}^k \beta_{ii} X_i^2 + \varepsilon_{er} \quad (3)$$

Although RSM can model linear and quadratic relationships between variables well, it cannot model complex non-linear relationships.

Multi-Objective Genetic Algorithm (MOGA)

Multi-Objective Genetic Algorithm (MOGA) is an evolution-based optimization method used to solve problems with various conflicting objectives, such as maximizing efficiency and minimizing emissions from gas engine power plants (PLTMG). By utilizing mechanisms such as mutation, crossover, and selection, MOGA uses the concept of natural selection to develop optimal solutions through successive generations (Kaviri et al., 2012).

MOGA exploits Pareto dominance to find the Pareto front, which is the optimal solution for multiple objectives. No solution can be improved for one objective without sacrificing another. This method allows for a more efficient investigation of the relationship between emissions and efficiency in energy systems (Hu et al., 2016).

Multi objective formula

Minimize/maximize

$$F(x) = [F_1(x), F_2(x), \dots, F_m(x)] \quad (6)$$

Where $[F_1(x), F_2(x), \dots, F_m(x)]$ is the objective function such as efficiency, NPHR and NOx emission.

MOGA has proven to be superior in finding balanced optimal solutions for multiple criteria, making it a very suitable tool for optimizing the performance of PLTMG (Chen et al., 2018).

Validation and Comparative Analysis

After the modelling is completed, validation of the results between the RSM and ANN models is carried out to ensure prediction accuracy with a high R2 value (above 0.90). In addition, a comparison is made between the Pareto-optimal solutions of the RSM and ANN models to determine the best method that can be implemented in optimizing PLTMG operations.

RESULTS AND DISCUSSION

Analysis parameter

Experimental data used operational performance test data in June 2024. Input data consists of Engines 4, 5, 6, and 7, cos pi, and load, while response data consists of Efficiency, NPHR, and NOx. The data obtained is presented in Figure 5 below.

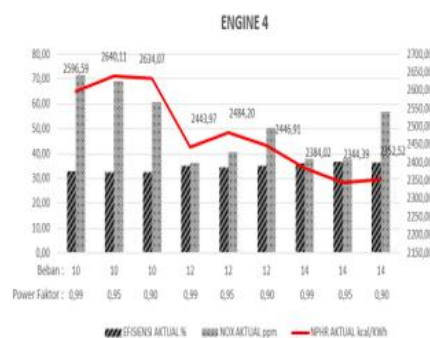




Figure 5. Duri PLTMG performance test data

RSM Optimization

This study analyzes the relationship between three independent variables and three response variables using Response Surface Methodology (RSM). RSM involves a series of stages, from model determination, factor level identification, experimental design selection, evaluation, validation, and optimization. As a method used to predict and construct higher-order polynomials, RSM aims to model the non-linear relationship between input variables and output responses. The main purpose of implementing RSM is to identify the optimal combination of input variables that produce the desired or optimal response value. This process is carried out by systematically designing experiments, collecting relevant data, and building a mathematical model that describes the relationship between input and response factors.

In this experiment, three objective functions, namely engine 4,5,6 and 7 Cos pi, Load, and Mode Load, are tested. These functions are related to three main responses: Net Plant Heat Rate (NPHR) efficiency and exhaust emissions Nox and. Central Composite Design (CCD) is used in this experiment as an approach to designing an empirical model that can explain the relationship between input variables and responses.

The analysis of variance (ANOVA) obtained from the RSM application, presented in Table 2, indicates a significant role of input variables, quadratic terms, and interactions between factors in influencing the variation of output responses. These findings strengthen the statistical validity of the model used, given the importance of the relationship between input parameters and their interactions in determining the observed response behaviour.

Table 2. ANOVA Results of RSM Design Expert

Efeisiensi			
Std dev.	0,4270	R ²	0,9703
Mean	34,88	Adjusted R ²	0,9506
C.V%	1,22	Predicted R ²	0,9148
		Adeq Precision	24,7368
NPHR			
Std dev.	26,76	R ²	0,9752
Mean	2472,41	Adjusted R ²	0,9586
C.V%	1,08	Predicted R ²	0,9280
		Adeq Precision	26,3683
Emisi Nox			
Std dev.	5,27	R ²	0,9397
Mean	27,25	Adjusted R ²	0,8994
C.V%	19,32	Predicted R ²	0,7915
		Adeq Precision	16,7716

From the data obtained, the following equation for simulation is derived to perform optimization using MOGA, here is the equation:

$$\text{Engine 4 EFF} = (-38.72939) + (2.35652 * x_1) + (114.32386 * x_2) + (-1.0958 * x_1 * x_2) + (-0.016875 * x_1^2) + (-53.61111 * x_2^2) \quad (7)$$

$$\text{Engine 4 NPHR} = 7749.63449 + (-220.99892 * x_1) + (-7521.19876 * x_2) + (73.48566 * x_1 * x_2) + (3.56719 * x_1^2) + (3504.25926 * x_2^2) \quad (8)$$

$$\text{Engine 4 Nox} = 344.21804 + (-4.93953 * x_1) + (-404.46283 * x_2) + (-18.88166 * x_1 * x_2) + (0.709896 * x_1^2) + (289.25926 * x_2^2) \quad (9)$$

$$\text{Engine 5 EFF} = (-46.56354) + (3.09569 * x_1) + (114.28834 * x_2) + (-1.0958 * x_1 * x_2) + (0.016875 * x_1^2) + (-53.61111 * x_2^2) \quad (10)$$

$$\text{Engine 5 NPHR} = (8211.02597) + (-256.60225 * x_1) + (-7507.03482 * x_2) + (73.48566 * x_1 * x_2) + (3.56719 * x_1^2) + (3504.25926 * x_2^2) \quad (11)$$

$$\text{Engine 5 Nox} = (146.40421) + (3.18047 * x_1) + (-331.01747 * x_2) + (-18.88166 * x_1 * x_2) + (0.709896 * x_1^2) + (289.25926 * x_2^2) \quad (12)$$

$$\text{Engine 6 EFF} = (-35.16665) + (2.06069 * x_1) + (133.55337 * x_2) + (-1.0958 * x_1 * x_2) + (-0.016875 * x_1^2) + (-53.61111 * x_2^2) \quad (13)$$

$$\text{Engine 6 NPHR} = (7480.3728) + (-201.17142 * x_1) + (-7435.62772 * x_2) + (73.48566 * x_1 * x_2) + (3.56716 * x_1^2) + (3504.25926 * x_2^2) \quad (14)$$

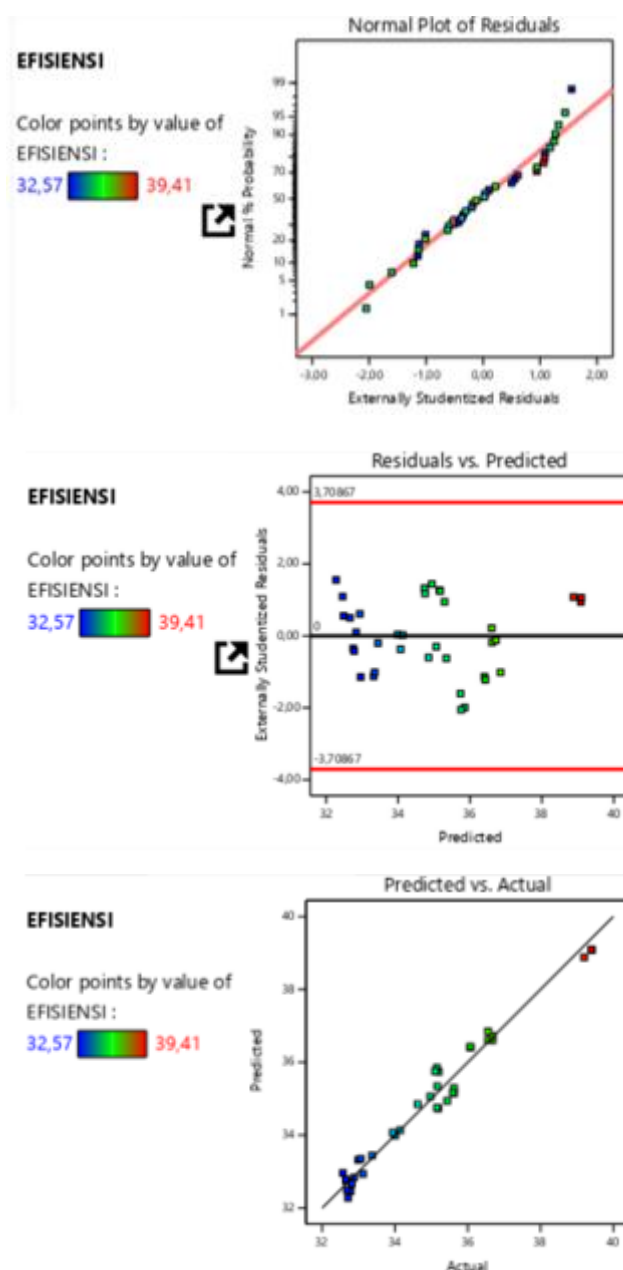
$$\text{Engine 6 Nox} = (149.35252) + (0.532136 * x_1) + (-310.1131 * x_2) + (-18.88166 * x_1 * x_2) + (0.709896 * x_1^2) + (289.25926 * x_2^2) \quad (15)$$

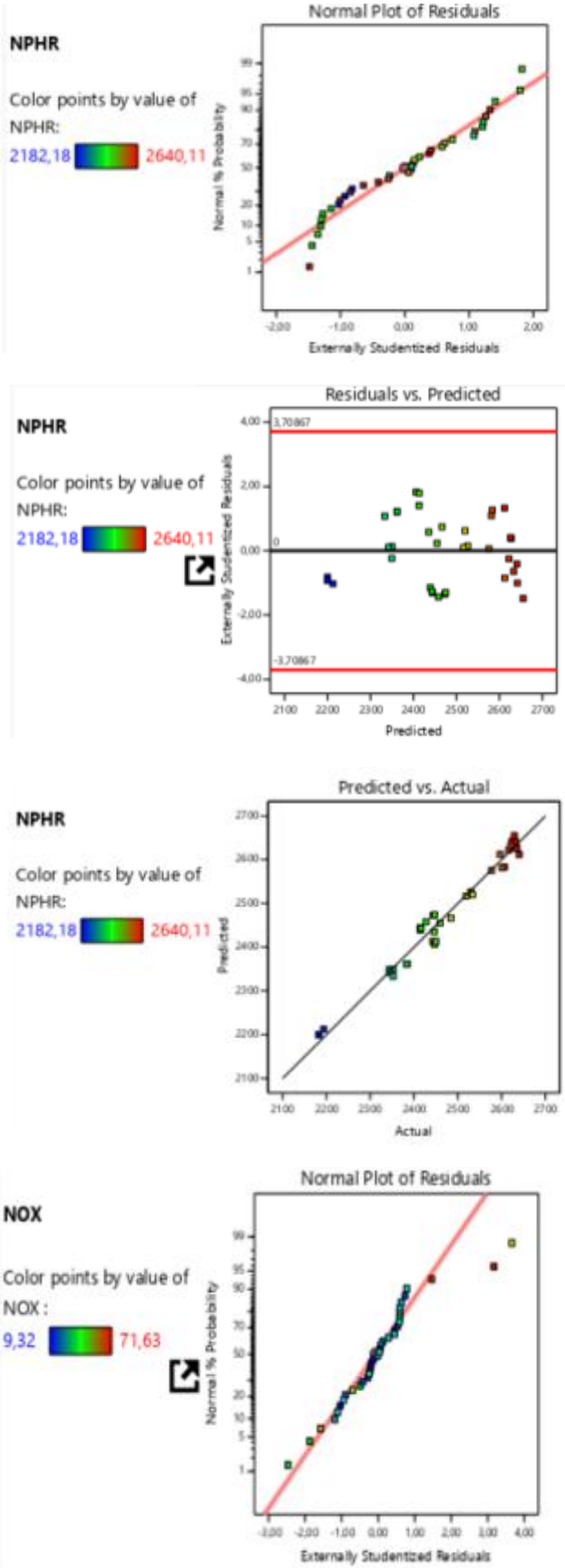
$$\text{Engine 7 EFF} = (-35.1002) + (2.26652 * x_1) + (111.95501 * x_2) + (-1.0958 * x_1 * x_2) + (-0.016875 * x_1^2) + (-53.61111 * x_2^2) \quad (16)$$

$$\text{Engine 7 NPHR} = (7465.34493) + (-213.81392 * x_1) + (-7335.83537 * x_2) + (73.48566 * x_1 * x_2) + (3.56719 * x_1^2) + (3504.25926 * x_2^2) \quad (17)$$

$$\text{Engine 7 Nox} = (151.96705) + (-0.088695 * x_1) + (-289.73878 * x_2) + (-18.88166 * x_1 * x_2) + (0.709896 * x_1^2) + (289.25926 * x_2^2) \quad (18)$$

The model generated through the Response Surface Methodology (RSM) approach is then tested to ensure the data's suitability and detect abnormalities, using normal probability plots against residuals and outliers. In this case, a good model should not show a particular pattern or trend, and the resulting data is expected to be well distributed along a straight line.





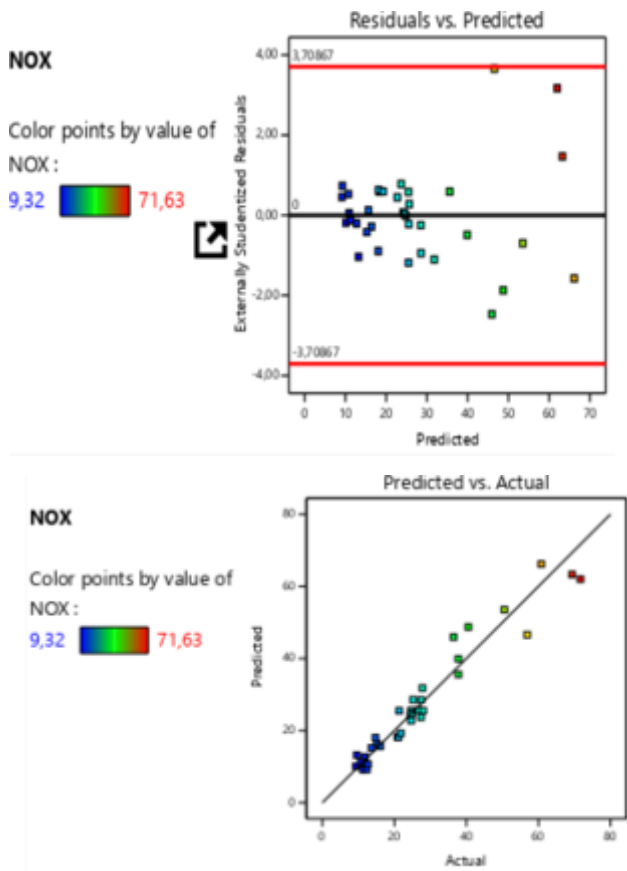
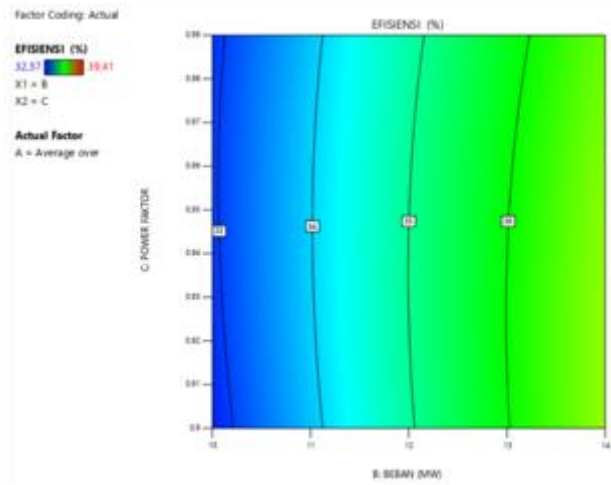
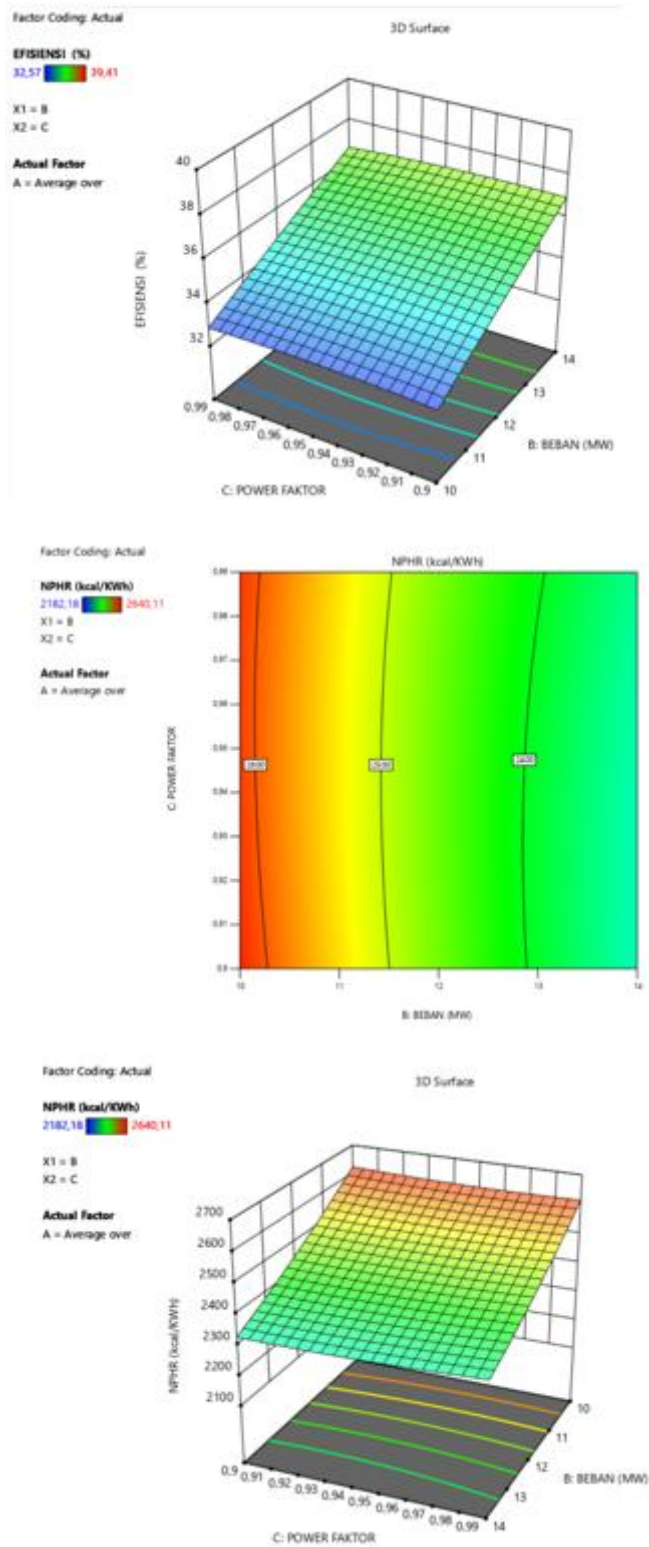


Figure 6. 2D plot of Design Expert Efficiency, NPHR and NOx

The following figure illustrates 3D profiles for Efficiency, Net Plant Heat Rete (NPHR), and data. These profiles visually depict the interrelationships between these parameters, allowing a better understanding of how variations in one factor can affect the others. Such visualizations are critical in optimizing performance and improving the operational efficiency of the system under study.





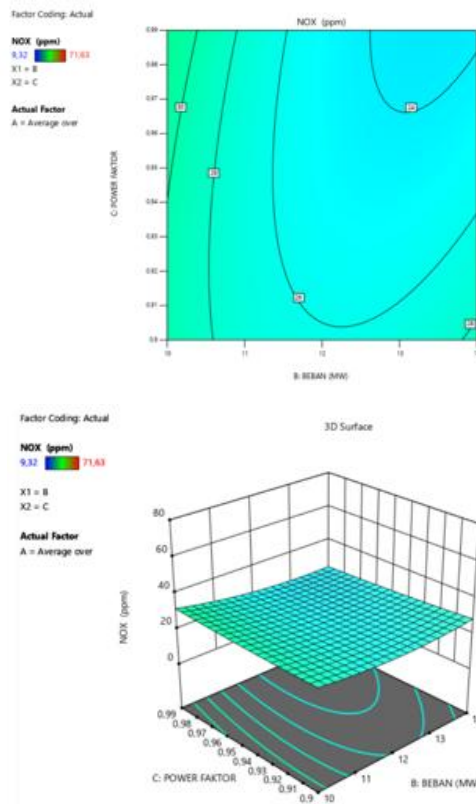
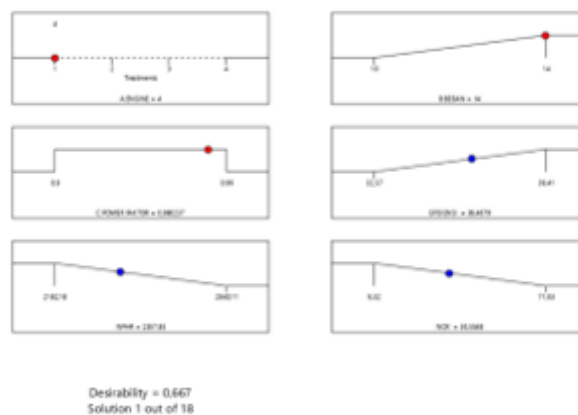


Figure 7. 3D plot of Design Expert Efficiency, NPHR and NOx

This experiment illustrates the challenges in determining the optimal operating parameters for Engines 4, 5, 6 and 7 at the Balai Punggut-Duri PLTMG. To achieve this, the Response Surface Methodology (RSM) is used to identify the most suitable operating conditions. RSM is an effective statistical technique for modelling and optimising complex processes by examining the relationship between input and output variables. By implementing RSM, this study aims to improve the operational efficiency of engine performance and reduce exhaust emissions amidst the challenging conditions of the Balai Punggut-Duri PLTMG.



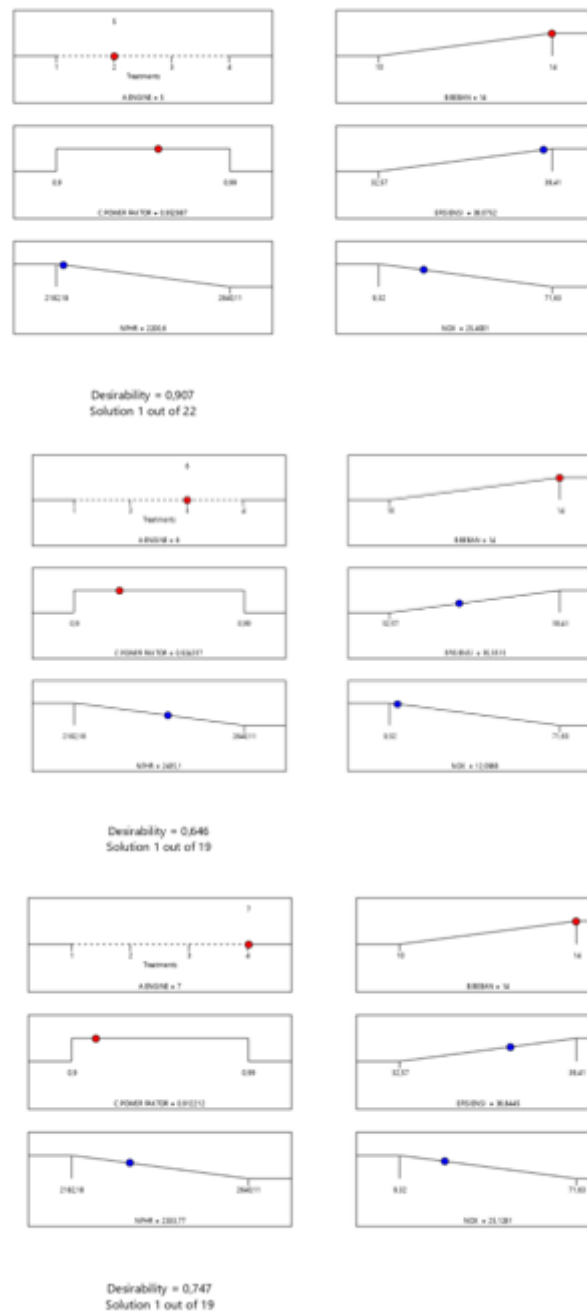


Figure 8. Optimization Results of Design Expert for Efficiency, NPHR and Nox.

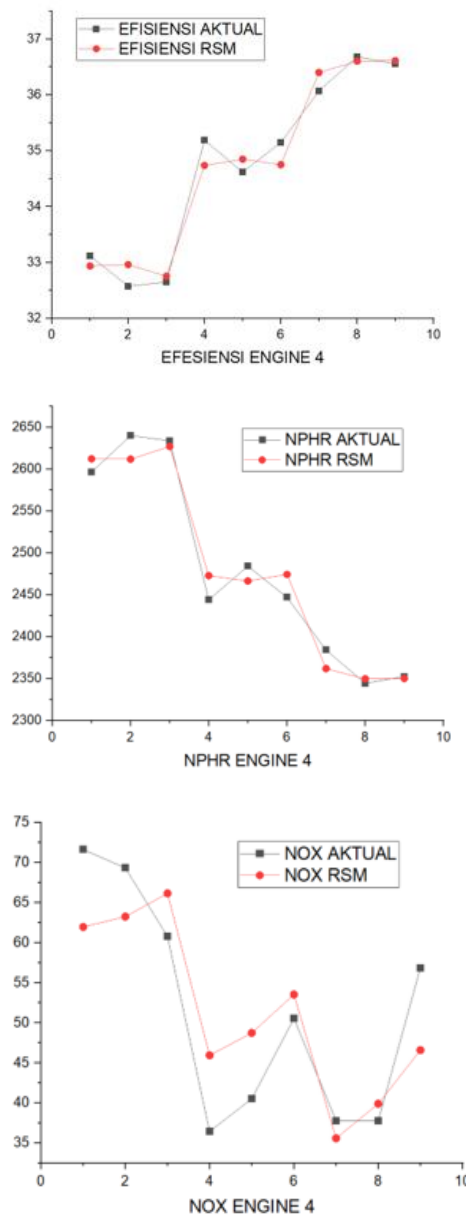
Desirability is a statistical indicator used in the optimization process to assess the level of solution fulfilment against predetermined criteria. The desirability value ranges from 0 to 1, where zero indicates that the solution does not meet the desired optimization criteria or objectives. 1 indicates that the solution fully meets the desired objectives or criteria or is in optimal condition

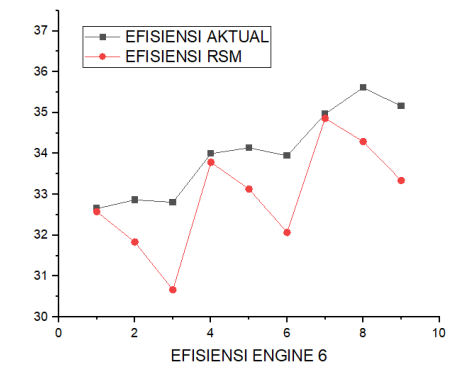
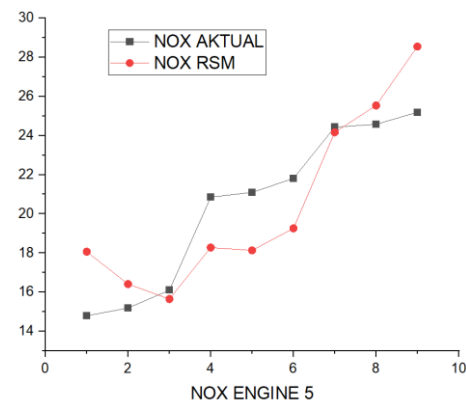
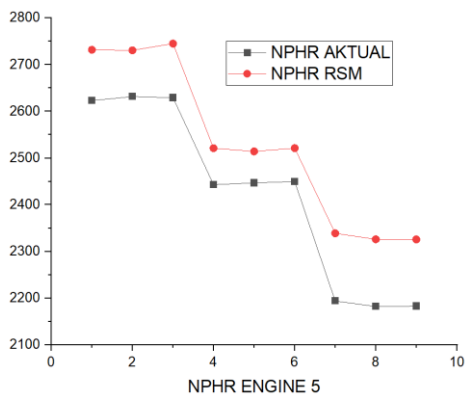
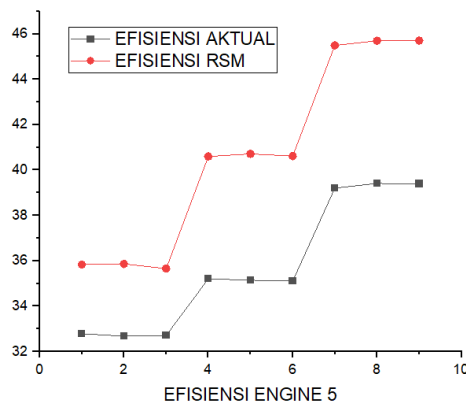
To achieve the optimal objective function value among the variables, Engine 4 is set at a load of =14 MW, $\cos \pi = 0.98$, for the response Efficiency = 36.46%, NPHR = 2357.85 kcal/kWh, Nox = 36.55 ppm. Meanwhile, for Engine 5 it is set at a load of = 14 MW, $\cos \pi = 0.95$, for an Efficiency response of = 39.08%, NPHR = 2200.60 kcal/kWh, Nox = 25.40 ppm, while for Engine 6 it is set at a load of = 14 MW, $\cos \pi = 0.92$, for an Efficiency

response of = 35.35%, NPHR = 2435.10 kcal/kWh, Nox = 12.10 ppm, while for Engine 7 it is set at a load of = 14 MW, for an Efficiency response of = 36.84%, NPHR = 2333.77 kcal/kWh, Nox = 25.13 ppm.

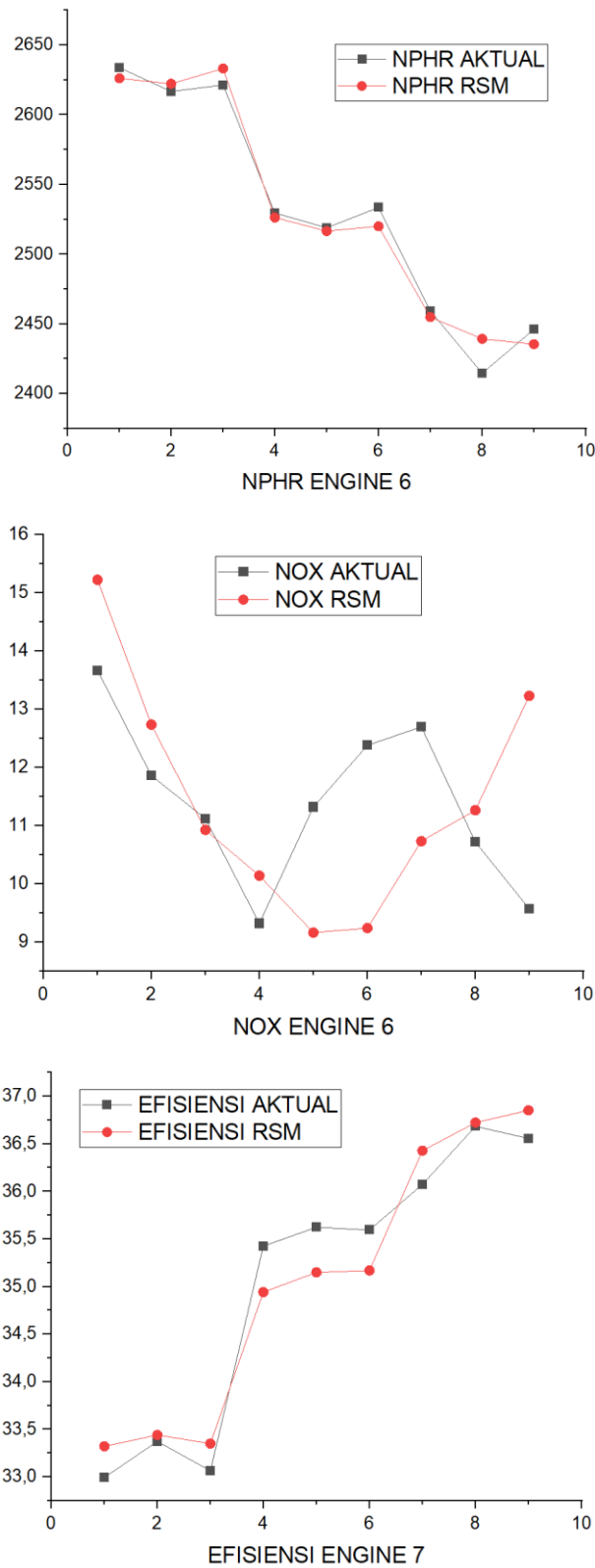
MOGA Optimization Analysis

Analysis Multi-Objective Genetic Algorithm (MOGA) was performed using MATLAB to obtain Pareto graphs of three objective functions, Load and Cos pi, and three responses: Efficiency, NPHR, and Nox. Optimization was also performed on the Design of Experiments (DoE) results, especially the Response Surface Methodology (RSM) presented in equations 7-18. Figure 9. Shows a comparison between the actual and RSM predictions.





Research Article



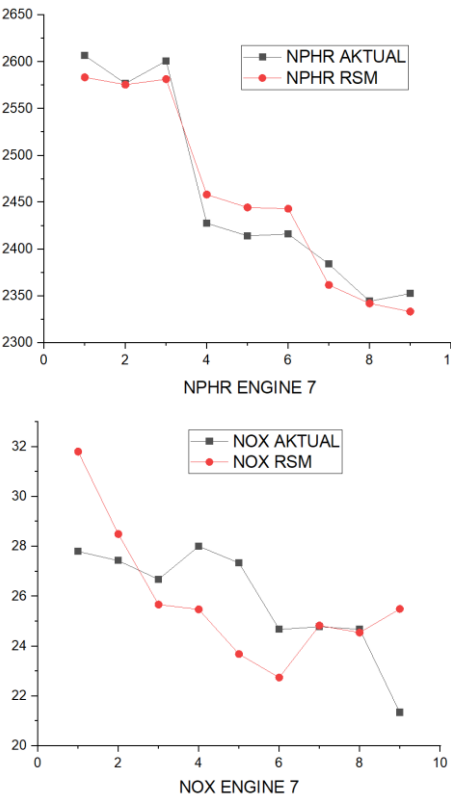
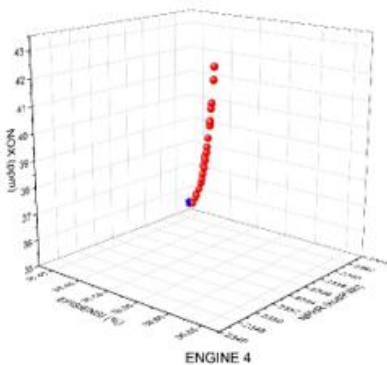


Figure 9. Comparison of Actual and RSM

Figure 10 shows the Pareto front obtained from the Response Surface Methodology (RSM) optimization process for Engines 4,5, 6, and 7. The red dots on this three-dimensional graph represent non-dominated solutions, which illustrate the trade-off between the three optimized objectives: efficiency (%), NPHR (kcal/kWh), and NOx (ppm). The blue dot shows the optimal solution selected based on the Design Expert 13 application.



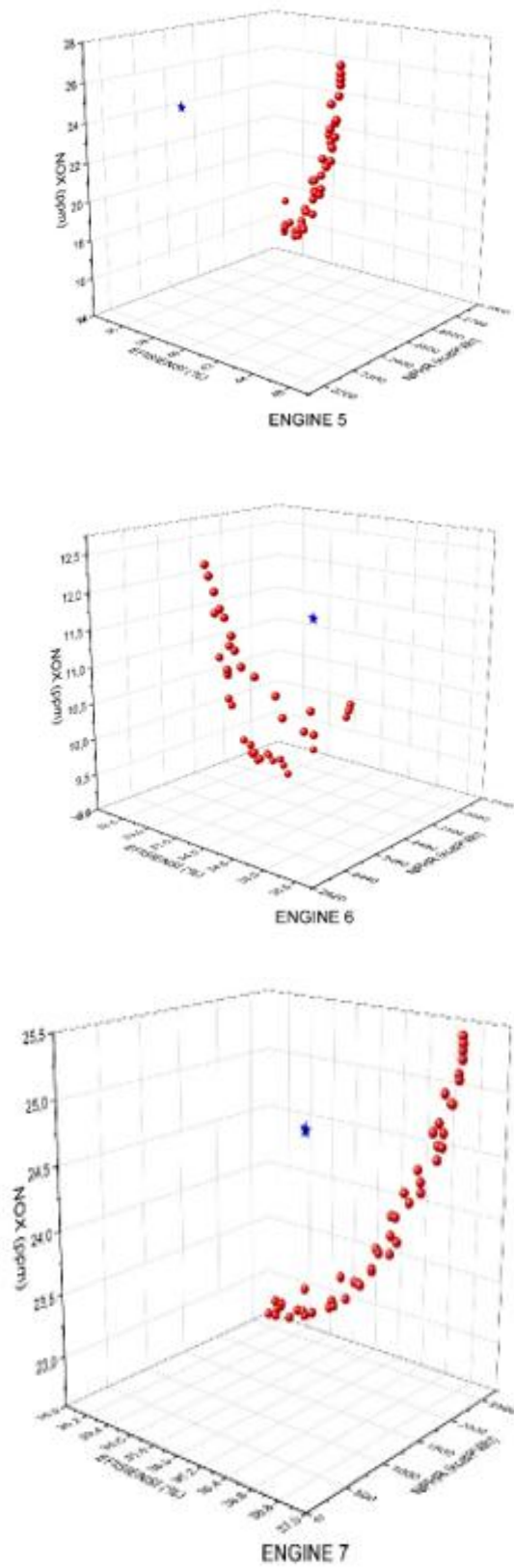


Figure 10. MOGA RSM

CONCLUSION

This study identifies the optimal start-up pattern to improve the performance of PLTMG Duri Units 4, 5, 6, and 7. The methods used are Response Surface Methodology (RSM) and Multi-Objective Genetic Algorithm (MOGA). RSM describes the relationship between load and power factor with efficiency, NPHR, and NOx. MOGA produces the optimal combination of the three parameters. As a result, the optimal settings for each unit are:

Unit 4: Load = 14 MW, Cos Pi = 0.98 (Efficiency = 36.46%, NPHR = 2357.85 kcal/kWh, NOx = 36.55 ppm.

Unit 5: Load = 14 MW, Cos Pi = 0.95 (Efficiency = 39.08%, NPHR = 2200.60 kcal/kWh, NOx = 25.40 ppm.

Unit 6: Load = 14 MW, Cos Pi = 0.92 (Efficiency = 35.35%, NPHR = 2435.10 kcal/kWh, NOx = 12.10 ppm.

Unit 7: Load = 14 MW, Cos Pi = 0.90 (Efficiency = 36.84%, NPHR = 2333.77 kcal/kWh, NOx = 25.13 ppm.

TOPSIS shows the priority order of unit start-up based on the highest efficiency, lowest NPHR, and lowest NOx are 5, 7, 4, 6. Unit 5 is the best choice with the highest efficiency. This information is useful for PLTMG Duri operators in determining more efficient and environmentally friendly operating strategies.

List of Notations

PLTMG: Gas Engine Power Plant

RSM : Response Surface Methodology

ANN : Artificial Neural Network

MOGA : Multi-Objective Genetic Algorithms

Thermal Efficiency (η): Parameter that shows the conversion of fuel energy into electrical energy (%)

NPHR: Net Plant Heat Rate, an indicator of energy conversion efficiency in power plants (kcal/kWh)

Nox: Nitrogen Oxide, emissions resulting from the combustion process (PPM)

R^2 : Coefficient of determination for model validation (ratio between 0–1).

N : Number of data.

MSE : Mean Squared Error

$Y_{p,i}$: ANN model predictions, output values produced by Artificial Neural Network models.

$Y_{exp,i}$: Experimental values or actual values, are used for comparison with the ANN model results.

Y_{av} : The average of experimental values, used in the evaluation of the ANN model.

P_{out} : Electricity output from the generator. (KW)

$\dot{m}$: Fuel mass flow rate (kg/s)

LHV : Low heating value of fuel, which is the amount of energy released when the fuel is completely burned. (kJ/kg)

P_{netto} : Net power (kW).

X1= Load

X2= Power factor

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