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OPTIMIZATION OF LOAD DISTRIBUTION AND FUEL CONSUMPTION FOR DIESEL GENERATOR 1000 KW FOR REMOTE AREA USING BIODIESEL B35 POWER STATION

Dhimas Adi Purbandono
Master's Candidates in Mechanical Engineering*
Muhammad Arif Budiyanto
Corresponding Author
Doctoral*
E-mail: arif@eng.ui.ac.id
Firman Ramdan
Bachelor of Engineering
PLN Indonesia Power UBP Mahakam
Ulin str., 1, Karang Anyar, Kec. Sungai Kunjang, Kota Samarinda, East Kalimantan, Indonesia, 75243
Muhamad Iqbal Felani
Magister of Engineering
PT PLN (Persero) Pusat Penelitian dan Pengembangan Ketenagalistrikan
Duren Tiga Raya str., 102, RT.8/RW.1, Duren Tiga, Kec. Pancoran, South Jakarta, Jakarta Special Capital Region, Indonesia, 12760
*Department of Mechanical Engineering
Universitas Indonesia
Margonda Raya str., Pondok Cina, Kecamatan Beji, Depok, West Java, Indonesia, 16424

This study focuses on the operational optimization of a 1000 kW high-speed diesel generator (Mitsubishi S16R) located at PLTD Muara Wahau, a remote power station in East Kalimantan, Indonesia. The generator operates with Biodiesel B35, a national renewable fuel standard containing 35% biodiesel and 65% petroleum diesel. While B35 offers environmental benefits, its lower heating value and distinct combustion characteristics result in an 18% reduction in generator output and increased specific fuel consumption (SFC), posing challenges to performance and fuel efficiency in isolated areas. To address these issues, a hybrid modeling and optimization framework is proposed, combining response surface methodology (RSM), artificial neural networks (ANN), and multi-objective genetic algorithm (MOGA). A multi-criteria decision-making approach using TOPSIS is applied to evaluate alternative operating scenarios. The study investigates two modes: base load (cos φ = 0.96, load = 698 kW) and load share (cos φ = 0.97, load = 829 kW). The RSM model in base load mode achieves a fuel consumption of 0.21 l/kWh and efficiency of 42.78%, while the ANN-MOGA model in load share mode records 0.24 l/kWh and 39.42% efficiency. The results demonstrate that parameter optimization can significantly improve the performance of B35-fueled generators. The integrated methodology provides a practical solution for enhancing operational efficiency and sustainability in remote, off-grid power systems, with potential for broader application in similar decentralized energy contexts

Keywords: diesel generator, biodiesel B35, remote power systems, efficiency, renewable energy

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1. Introduction

Phenomena of economic development and growth generate both urbanization and a structural transformation that increases energy consumption as a consequence of evolving patterns of production and consumption [1]. Energy demand in many emerging markets, including Indonesia, is rising rapidly, requiring substantial investment in energy infrastructure-particularly in power generation. The World Energy Outlook 2023 projects that 45% of vehicle engines in Southeast Asia will be converted to electric by 2030 [2]. In response to these challenges, various propulsion technologies have been explored to support low-emission and energy-efficient operations, a performance analysis was conducted on a combined cycle generator indicate that the system can achieve a maximum power output of approximately 28.122,23 kW, with a fuel consumption rate of 1,173 kg/s and an overall thermal efficiency of about 48,49% under fully loaded conditions [3].

Another study focused on dual-fuel medium-speed diesel engines. Mean Effective Pressure (MEP), obtained through simulation, served as the main performance indicator, allowing for the calculation of power and thermal efficiency using empirical equations. The performance was assessed under five different gas mixture ratios – 30%, 40%, 50%, 60%, and 70% – to examine how varying fuel compositions affect engine behavior [4]. A simulation-based comparative analysis was also carried out to evaluate emissions from medium-speed diesel engines using alternative fuels. Results show that biodiesel and ultra-low sulfur fuel oil (ULSFO) produce higher NO_x emissions than heavy fuel oil (HFO), with an average increase of 51.4%. However, both fuels result in lower CO_2 and SO_2 emissions – by approximately 3 and 98,8%, respectively – due to their higher oxygen content, which supports more efficient combustion, and significantly lower sulfur content [5].

In the face of these challenges, biomass-based biofuels offer a strategic solution. Indonesia, as the world's leading palm oil producer, has aggressively adopted biodiesel – especially the B35 blend (35% biodiesel, 65% diesel) – which has been nationally mandated since 2023. Biodiesel's adoption has steadily increased since 2006, showing growth in quality, production capacity, blend ratios, and industry participants [6]. It supports energy diversification while reducing greenhouse gas emissions and dependency on fossil fuels, offering advantages such as renewability, biodegradability, lower emissions, and potential economic benefits [7].

Electricity generation is increasingly strained as demand outpaces infrastructure development. Reliability concerns-frequent blackouts, voltage instability-necessitate the deployment of supplementary systems like diesel generators, especially in remote areas [8]. These generators, while practical, face new technical hurdles when using B35. Biodiesel has a higher oxygen content, cetane number, and viscosity than petroleum diesel, but also a lower heating value, resulting in increased brake specific fuel consumption (BSFC) and lower power output [9].

Despite global momentum toward renewable technologies, full-scale deployment in remote and archipelagic regions remains impractical in the short term. Diesel generators will continue to play a pivotal role in hybrid and isolated systems. Therefore, optimizing their performance with biodiesel fuels, particularly B35, is crucial for achieving fuel efficiency, cost reduction, and sustainability in decentralized energy systems. Therefore, research on the optimization of biodiesel-fueled diesel generators in remote power systems remains a highly relevant and urgent scientific topic.

2. Literature review and problem statement

The study [10] presents the results of research on the optimization of diesel–biodiesel hybrid engine performance using response surface methodology (RSM). It is shown that under optimal conditions such as a 20% biodiesel blending ratio (BBR), 15% EGR, and 74,52% load – the engine achieves improved brake thermal efficiency (BTE) and reduced emissions (BSFC, NO_x, CO). However, there were unresolved issues related to the applicability of these results to B35-fueled diesel generators in remote operational contexts.

The papers [11, 12] present performance analyses of diesel power plants used in grid systems and microgrids, highlighting their essential role in supplying backup and remote electricity. However, both studies reveal key challenges such as low efficiency, high operational costs, and the absence of effective optimization strategies – especially when alternative fuels like Biodiesel 35% (B35) are used. These limitations may stem from difficulties in collecting real-time data, the complexity of modeling interrelated operational parameters, and the high computational demands of advanced optimization methods. To address these issues, a hybrid approach integrating response surface methodology (RSM), artificial neural networks (ANN), and multi-objective genetic algorithms (MOGA) offers a promising solution for optimizing key performance indicators such as specific fuel consumption (SFC), net plant heat rate (NPHR), and thermal efficiency under diverse field conditions.

In [13], a genetic algorithm was applied to optimize fuel use in spark-ignition engines running on butanol-gasoline blends, highlighting the value of evolutionary optimization for multi-objective problems. However, the study did not consider diesel engines or the complex behavior of biodiesel blends like B35 under real-world constraints.

Work [7] examined the integration of exhaust gas recirculation (EGR) and biodiesel blends for emission reduction in diesel engines. Although RSM was used to optimize performance, the study lacked consideration of generator derating effects or the impact on net plant heat rate (NPHR), which are essential when assessing the practicality of B35 in high-speed diesel generators.

Research [9] combined RSM and artificial neural networks (ANN) to predict performance and exergy metrics of a diesel engine fueled with Bael biodiesel. Their hybrid modeling approach improved prediction accuracy, supporting the argument for integrating data-driven and empirical models. However, their work was limited to laboratory-scale analysis and did not extend to optimization under multiple criteria or field validation.

The paper [14] is a review of diesel generator systems in remote areas emphasized the need for performance improvement due to challenges in fuel delivery, emission control, and system reliability. Despite this, optimization models specific to B35 use were not explored, leaving a gap in application-driven solutions.

The study [6] described the national framework for biodiesel implementation in Indonesia, confirming the widespread adoption of B35. However, it did not provide insights into operational strategies or performance modeling to improve efficiency at the generator level.

Furthermore, [15] proposed the use of multi-criteria decision making (MCDM) with the TOPSIS method to aid energy prioritization in marine systems. The findings suggest that integrating decision models with technical analysis improves system evaluation and can be adapted for operational optimization in off-grid power systems.

Despite the growing interest in biodiesel and optimization techniques, the current literature lacks a comprehensive approach that integrates operational performance indicators such as derating, SFC, NPHR, and thermal efficiency under realistic constraints using B35. The main reasons for this gap may include:

– objective difficulties associated with real-time data collection and monitoring in remote locations;

– the fundamental complexity of modeling multi-response, interdependent systems;

– the high computational burden of training and validating hybrid models (such as ANN-MOGA combinations) using operational datasets.

To overcome these challenges, a unified modeling framework that combines RSM and ANN supported by a multi-objective genetic algorithm (MOGA) for optimization and a decision-support mechanism such as TOPSIS is proposed. This method allows for greater flexibility, accuracy, and applicability in real-world scenarios.

Elements of such an approach have been demonstrated in [7, 9], but their applications were limited either by the optimization scope (single-objective) or the absence of real-world validation and full parameter integration.

All this suggests that it is advisable to conduct a study on the multi-objective optimization of high-speed diesel generators operating with B35 biodiesel in remote energy systems. Such a study should integrate RSM, ANN, and MOGA within an MCDM framework to address the practical limitations of current generator operations and to deliver actionable insights for fuel-efficient and sustainable electricity production in isolated areas.

3. The aim and objectives of the study

This study aims to improve the operational performance of a 1000 kW high-speed diesel generator using Biodiesel B35 in remote power systems by increasing fuel efficiency, reducing specific fuel consumption (SFC), and enhancing thermal performance under real-world conditions.

To achieve this aim, the following objectives are accomplished:

– to analyze the effect of operational parameters (load, power factor, and load mode) on performance indicators (SFC, net plant heat rate, and efficiency) based on actual field data;

– to develop predictive models for performance indicators using response surface methodology (RSM) and artificial neural networks (ANN);

– to perform data normalization and validation of ANN models to ensure consistent scaling and accurate prediction;

– to generate optimal operational scenarios using multi-objective genetic algorithm (MOGA) based on the trained ANN models;

– to evaluate and rank the generated scenarios using the TOPSIS method within a multi-criteria decision-making framework.

4. Materials and methods

4. 1. Object and hypothesis of the study

The object of this study is a 1000 kW high-speed diesel generator (Mitsubishi S16R) operated at PLTD Muara Wahau, a remote power station located in East Kalimantan, Indonesia. This generator plays a vital role in supplying electricity to off-grid communities and operates using Biodiesel B35, a nationally mandated blend consisting of 35% biodiesel and 65% petroleum diesel. The main hypothesis of this study is that the performance degradation caused by the use of B35 – manifested in reduced effective output and increased specific fuel consumption – can be mitigated through optimization of key operational parameters, namely load, power factor, and operation mode, using a hybrid modeling and optimization framework. In conducting this study, several assumptions are made, including that the fuel quality complies with the national standard, environmental conditions remain relatively stable during operation, and that the measured data reflects real-world usage scenarios with calibrated instrumentation. To simplify the scope of analysis, the study focuses on steady-state operation and excludes transient behavior, engine aging effects, and emissions analysis. Additionally, the results are based on a single generator unit and are generalized only to similar high-speed diesel engine applications in remote settings.

4. 2. Biodiesel B35

Indonesia leads the world in biodiesel usage, with B35 (a mixture of 35% biodiesel and 65% diesel fuel) as its nationwide standard. The success of biodiesel program is primarily influenced by factors such as encompassing supply, demand, regulatory frameworks, economic considerations, and environmental impact [6]. The complete specifications of B35 on Table 1 can be found in the standard regulatory document Decree of the Director General of Oil and Gas No. 170.K.HK.02.DJM.202 [16].

These specifications indicate that B35 is a high-quality biofuel with physical and chemical properties that meet international ASTM testing standards. For instance, the minimum cetane number of 52 ensures good ignition quality and combustion efficiency, while the maximum sulfur content of 0.005% supports emission reductions. The viscosity range (2.0–4.5 mm^2/s) and density range (815–860 kg/m^3) reflect compatibility with diesel engine injection systems, though slightly higher than fossil diesel, which can affect atomization and combustion.

Table 1

B35 specifications

No.	Characteristic	Unit	Limit (Min–Max)	ASTM test method	Others
1	Cetane number	–	≥ 52	D613	–
2	Density (at 15°C)	kg/m^3	815–860	D1298/D4052	–
3	Viscosity (at 40°C)	mm^2/s	2.0–4.5	D445	–
4	Sulfur content	% m/m	≤ 0.005	D2622/D4294/D5453	–
5	Distillation (90% vol. evaporation)	°C	≤ 370	D86	–
6	Flash point	°C	≥ 55	D93	–
7	Cloud point	°C	≤ –18	D2500/D5771/D5773/D7683	–
8	Pour point	°C	≤ –18	D5949/D5950/D6749	–
9	Carbon residue	% m/m	≤ 0.1	D189/D4530	–
10	Water content	mg/kg	≤ 300	D6304	–
11	FAME content	% v/v	35	D7371/D7806/D8274	–
12	Copper strip Corrosion	Class	– Class 1	D130	–
13	Ash content	% m/m	– 0.01	D482	ISO EN6245
14	Sediment content	% m/m	– 0.01	D473	–
15	Strong acid number	mgKOH/g	– 0.6	D664	–
16	Total acid number	mgKOH/g	– 0.6	D664	–
17	Visual appearance	–	Clear and Bright	Visual	–
18	Color	ASTM No.	–	D1500	–
19	Lubricity (HFRR wear scar dia.@ 60°C)	micron	– 460	D6079	–
20	Oxidation stability	Hours/minutes	≥ 35 hours/≥ 45 minutes	D7545	EN15751/EN16091

The relatively low cloud and pour points (≤ –18°C) make B35 suitable for tropical climates, but potentially challenging in colder environments without pre-heating systems. Importantly, the fatty acid methyl ester (FAME) content is standardized at 35% v/v, contributing to reduced net CO_2 emissions compared to conventional diesel.

These characteristics, while environmentally favorable, also present technical challenges when applied to high-speed diesel engines, especially in remote area applications. The higher viscosity, oxygen content, and lower energy density compared to petro-diesel can lead to increased specific fuel consumption and power derating. Therefore, understanding and optimizing engine performance parameters under these altered fuel conditions is critical to ensure the operational reliability and economic viability of B35-powered diesel generators in isolated systems. This sets the foundation for the modeling and optimization methodologies employed in this study.

4. 3. Plant description

Power generating stations in which diesel engines are used as the prime movers for electric generators are known as diesel power plants [8]. PLTD Muara Wahau is a Diesel Power Plant located in Muara Wahau, a subdistrict in the Kutai Timur Regency of East Kalimantan, Indonesia. In recent years, almost all isolated communities (e. g. remote areas and islands) heavily depend on diesel power generation because of its reliable diesel operation and low fuel cost. However, the importance of diesel engines increases day by day because of their superior fuel economy, longer lifetime, and larger power range operations (e. g. hybrid power systems in isolated areas) [14]. Electricity supply and consumption directly support economic activities, with energy being an input in almost all major economic activities in all countries [17]. As the sole PLN power plant in the region, PLTD Muara Wahau plays a crucial role in providing electricity for the local community and supporting regional development and economic growth.

With the rapid socio-economic growth of the Muara Wahau community, the Diesel Power Plant is expected to operate reliably, safely, and efficiently. The plant has a net capacity of 7.9 MW, consisting of 16 high-speed engines operating at 1500 rpm, with capacity variants ranging from 300 kW to 1000 kW. Among these engines, the S16R stands out as the largest engine in the isolated system of Muara Wahau, capable of supplying 1000 kW of power.

Diesel power plants, characterized by their use of diesel engines as the main drivers for electricity generators, are essential for providing power in off-grid locations. The primary function of a diesel engine is to convert the working fluid, fuel, into mechanical energy through a four-stroke diesel cycle, which includes intake, compression, expansion, and exhaust strokes. The diesel engine drives an alternator that converts mechanical energy into electrical energy, which is subsequently distributed to consumers. Despite their crucial role, the operational costs of diesel power plants are relatively high due to the expense of diesel fuel. Therefore, they are often deemed suitable for small-scale power generation in the short term [18]. The PV diagram of Diesel cycle of this study shown in Fig. 1.

The experimental site for this study is PLTD Muara Wahau, a diesel power plant located in Muara Wahau, a subdistrict in Kutai Timur Regency, East Kalimantan, Indonesia. This plant is operated by PT PLN (Persero) and serves as the primary electricity provider for a remote and isolated community. Given the region's limited infrastructure and its distance from the national power grid, diesel-based generation remains the most viable option for ensuring consistent and reliable electricity supply.

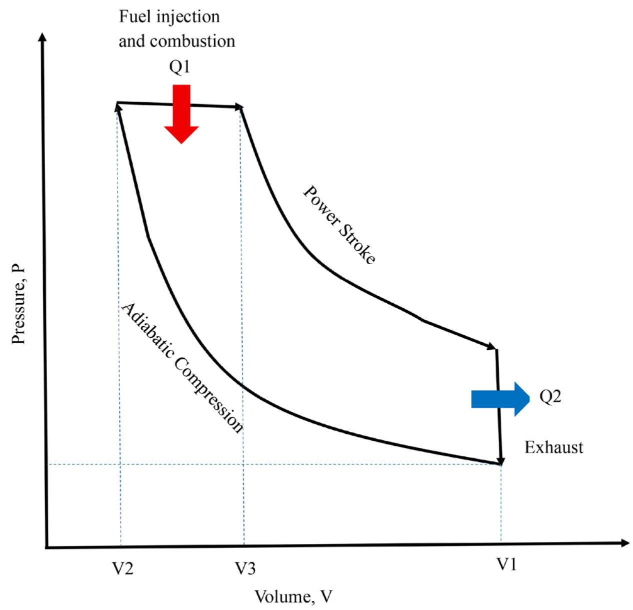

Fig. 1. PV diagram of the diesel cycle

PLTD Muara Wahau has a total installed capacity of 7.9 MW, comprised of 16 high-speed diesel engines operating at 1500 rpm, with individual unit capacities ranging from 300 kW to 1000 kW. Among these, the S16R engine capable of producing up to 1000 kW, is the largest and most critical unit for base and peak load operations. However, since the national implementation of B35 biodiesel, the effective power output of this engine has decreased by approximately 18% due to the fuel's lower heating value and different combustion characteristics, resulting in a new effective output of 820 kW.

The plant operates in two primary load modes: baseload and load sharing. In baseload mode, a single engine operates continuously at a relatively constant load, providing stability and fuel efficiency. In contrast, load sharing involves multiple engines working together to meet fluctuating demand, often leading to operational complexities and increased fuel consumption. The S16R engine, because of its size and load-bearing capacity, plays a strategic role in both modes, making it an ideal subject for performance optimization.

The harsh operational environment in remote areas-characterized by high ambient temperatures, limited technical support, and logistical challenges in fuel delivery further emphasizes the need for improving engine efficiency and reliability. By optimizing engine parameters such as load, power factor (cos φ), and operation mode under real-world conditions, this study seeks to enhance fuel economy and thermal performance without requiring costly hardware modifications. The following sections describe the analytical and computational methods used to achieve these objectives.

4. 4. Analysis of specific fuel consumption

One of the key performance indicators in evaluating diesel generator efficiency is specific fuel consumption (SFC), which represents the amount of fuel consumed per unit of electrical energy produced. In this study, let's model and observe fuel usage based on actual generator operation data to determine the generator's real-world fuel efficiency [19]. SFC is routinely monitored as a daily operational parameter at PLTD Muara Wahau to assess fuel economy and support performance optimization.

To calculate SFC, fuel consumption data is obtained from a digital flow meter attached to the engine's fuel line, while electrical energy output is measured using a calibrated kWh meter. The SFC is then calculated using the following equation

$$SFC = \frac{V_f}{E}. \quad (1)$$

This ratio, expressed in liters per kilowatt-hour (l/kWh), provides a direct measure of how efficiently the generator converts fuel energy into electrical energy. A lower SFC indicates better fuel efficiency, which is especially critical in remote applications where fuel supply is logistically complex and expensive. Understanding and minimizing SFC is essential not only for cost reduction but also for reducing the environmental footprint of diesel-based generation systems operating with biodiesel blends such as B35.

4. 5. Net plant heat rate analysis

Net plant heat rate (NPHR) is a critical metric for evaluating the thermal efficiency of a power generation system. It represents the amount of heat energy from fuel that is required to produce one kilowatt-hour of electricity. Specifically, NPHR is defined as the ratio between the heat input chargeable to power and the net electrical energy generated. The heat input chargeable to power is calculated by multiplying the volume of fuel consumed by its gross heating value (GHV), then dividing the result by the total electrical energy output [20].

In this study, NPHR is treated as a derived parameter, as it cannot be measured directly through standard instrumentation. Instead, it is calculated using data obtained from operational measurements. Fuel consumption is determined using a flow meter installed on the generator's fuel line, while energy production is tracked using a digital kWh meter. The GHV of the B35 biodiesel used in this study is obtained from certified laboratory tests according to national fuel standards. The NPHR in kilocalories per kilowatt-hour (kcal/kWh) is calculated using the following equation

$$NPHR = \frac{V_f \times GHV}{E}, \quad (2)$$

where V_f – the volume of fuel consumed (liters), GHV – the gross heating value of B35 fuel (in kcal/L), and E – the net electrical energy output (in kWh).

A lower NPHR value indicates that the power plant is utilizing fuel more efficiently to generate electricity, which is particularly important in remote area operations where fuel logistics are challenging and operational costs are high. Since biodiesel generally has a lower GHV compared to conventional diesel, accurate monitoring and optimization of NPHR is essential to ensure that the adoption of B35 does not compromise system efficiency. This metric also enables comparative analysis across different engine loads and operational modes, serving as a key parameter in performance modeling and optimization efforts carried out in this study.

4. 6. Thermal efficiency analysis

Thermal efficiency is a fundamental metric that quantifies the effectiveness of a power generation system in converting the chemical energy of fuel into usable electrical energy. In diesel generator systems, thermal efficiency is closely related to the Net Plant Heat Rate (NPHR), where an inverse relationship exists – lower NPHR values correspond to higher thermal efficiency. This study calculates thermal efficiency as a derived parameter using the measured NPHR values and a standardized energy conversion factor.

The thermal efficiency (η) is calculated using the following formula

$$\eta(\%) = \frac{1}{NPHR} \times 860 \times 100^{\circ} = \frac{86000}{NPHR}. \quad (3)$$

Alternatively, using the conversion factor between kilocalories and kilowatt-hours (1 kWh = 860 kcal), the formula used in this study is expressed as

$$\eta(\%) = \text{Conversion Factor} \frac{1}{NPHR}, \quad (4)$$

where

Conversion factor = 0.0011622.

This formulation allows for consistent computation of thermal efficiency based on operational data, yielding results in percentage (%) that reflect the proportion of input fuel energy successfully transformed into electrical output. Thermal efficiency is particularly critical when evaluating the impact of B35 fuel, which has a lower energy density compared to pure diesel. The fuel's higher oxygen content and different combustion behavior can result in suboptimal performance if operating conditions are not properly tuned. Through systematic monitoring and analysis of thermal efficiency under varying load and power factor conditions, this study aims to identify operational strategies that can maximize energy conversion and ensure the economic viability of B35-fueled generators in remote environments.

4. 7. Modelling methodology

4. 7. 1. Response surface methodology (RSM)

Response surface methodology (RSM) has been widely utilized as a statistical analysis tool and empirical methodology for developing mathematical models and providing a better analysis of the interaction effects among operational parameters [21]. RSM is a useful statistical tool for design, optimization and analysis of experiments in any process [22]. RSM consists of two types of designs, namely central composite design (CCD) and BoxBehnken design (BBD), which are used to study the process variables at five and three levels respectively. CCD is a successful and widely used design reported in the literature for optimization of various processes [22]. The designed matrix is suitable for process optimization because experimental data can be compared with predicted values. In this context, the studentized residual represents the ratio of the residuals to their standard deviation. Conventional ANOVA is used to determine if the results of a given data or analysis are significant and to disregard the null hypothesis. ANOVA was chosen in this study because it provides a robust statistical framework to quantitatively evaluate the significance of each factor and interaction in the developed RSM model. Specifically, ANOVA enables identification of the most influential variables affecting generator performance, assessment of model adequacy and quality, and confirmation that the observed relationships are statistically significant rather than random.

Given the complex and nonlinear interactions among operational parameters such as load, power factor, and operation mode in this diesel generator system using B35 fuel, applying ANOVA ensures that the fitted second-order polynomial model is both valid and reliable for optimization purposes. Usually, a second-order polynomial equation is used to describe the relationship between the variables and the responses [23]. Usually, a second-order polynomial equation is used described the relation between the variables and the responses [22]

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_0 X_i + \sum_{i=1}^{k-1} \sum_{i=1}^{k} \beta_{ij} X_i X_j + \sum_{i=1}^{k} \beta_{ij} X_i^2 + \varepsilon_{er}. \quad (5)$$

Response surface methodology is a statistical and mathematical tool used to model and analyze problems in which a response of interest is influenced by multiple variables. RSM is particularly useful for identifying optimal conditions in complex systems and understanding interactions between input factors. In this study, central composite design (CCD) is used to structure the experiments, allowing for efficient exploration of the operating space defined by load, power factor, and operating mode.

Using experimental data, RSM generates second-order polynomial regression models that describe the relationships between inputs and outputs. These models are then validated through analysis of variance (ANOVA) to ensure their statistical significance. The RSM approach allows the study to identify not only the main effects of each input variable but also the interaction effects that might influence performance metrics.

4. 7. 2. Artificial neural network (ANN)

Artificial neural networks (ANNs) [24] have emerged as a promising alternative to simulate systems due to their successful applications in several engineering and science fields, such as signal processing, image processing, control systems, associative memory, to name a few. Besides, fractional calculus (FC) is an extension and generalization of the integer-order calculus, which its main characteristic is the memory description [25]. Neurons in each layer are interconnected by weights, which are summed with a bias value and then passed through a transfer function. Several transfer functions are commonly used in ANNs, such as Linear (Purelin), Log-Sigmoid (Logsig), and Tan-Sigmoid (Tansig). To train the network and determine the optimal weights of the neurons, algorithms such Structured Quasi-Newton method (SQN), GaussNewton (GN) and Levenberg-Marquardt (LM) are frequently employed [26]. ANN was chosen in this study because of its superior capability in modeling complex and highly nonlinear relationships between operational parameters and performance metrics of the diesel generator operating with B35 fuel. Traditional statistical models often fall short when the interactions among variables exhibit strong nonlinearities and cross-dependencies, which are typical in real-world generator operations. ANN, through its multi-layered architecture and adaptive learning ability, enables accurate prediction of key responses (SFC, NPHR, efficiency) across varying operational scenarios. This makes ANN particularly suitable for capturing the dynamic behavior of the system and providing a high-fidelity model that supports optimization and decision-making in this challenging application domain.

In this study, the ANN model is developed using the most popular architecture, the multi-layer backpropagation neural network. The Levenberg-Marquardt **(**LM) incorporates gradient descent and the Gaussian Newton method's advantages. It possesses the property of global approximation and is capable of producing local convergence. Not only does it accomplish the global nature of the gradient descent method, but it also achieves convergence at a rate comparable to the Gauss-Newton method [27]. LM was especially developed for faster convergence in backpropagation algorithms [28]. It also achieves a lower mean squared error (MSE) compared to other algorithms in many applications, making it the best-performing option.

For model evaluation, commonly used metrics such as the coefficient of determination (R^2) and mean squared error (MSE) are utilized. These metrics are selected for their sensitivity to small variations, which helps ensure accurate model assessment:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(\left| y_{p,i} - y_{exp,i} \right| \right)^2,$$

$$R^2 = \frac{\sum_{i=1}^{N} \left(\left| y_{p,i} - y_{exp,i} \right| \right)}{\sum_{i=1}^{N} \left(\left| y_{p,i} - y_{av} \right| \right)}. \quad (6)$$

Fig. 2 demonstrates the artificial neural network (ANN) architecture and its optimal topology used in the study to predict generator performance indicators based on three input parameters: power factor (Cos φ), load (kW), and operation mode (base load or load share).

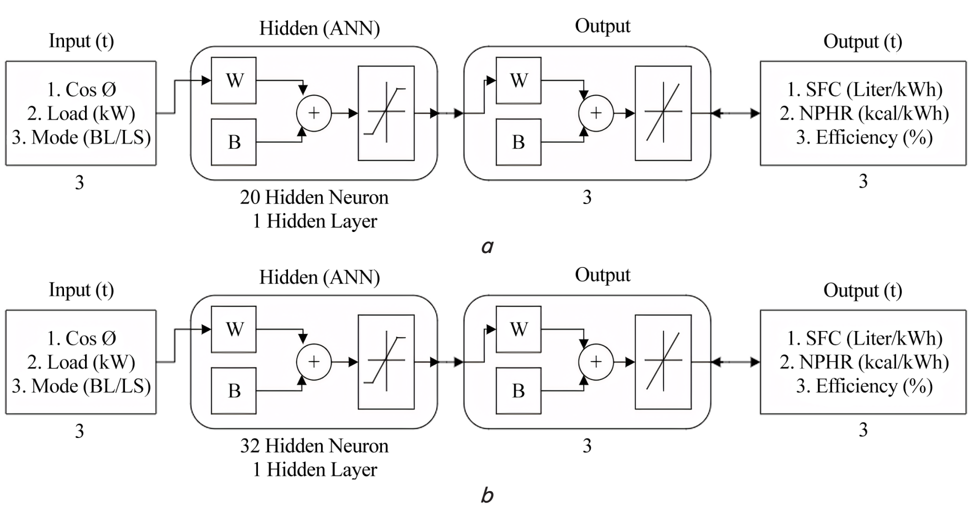

Fig. 2. Architecture of the ANN and optimal topology: *a* – baseload 20 neuron; *b* – loadshare 32 neuron

Artificial neural networks provide a non-linear modeling approach based on data-driven learning, making them well-suited for predicting outcomes in systems with complex, interdependent parameters. In this study, a multi-layer perceptron (MLP) architecture is applied, trained using the Levenberg-Marquardt (LM) algorithm, which offers fast convergence and high accuracy.

ANN is developed using historical and experimental data collected from the S16R generator. The model learns to map the relationship between input parameters (load, power factor, operation mode) and output variables (SFC, NPHR, efficiency) through training and validation processes. Performance of the ANN model is assessed using metrics such as mean squared error (MSE) and the coefficient of determination (R^2), ensuring reliability and robustness for use in optimization.

4. 7. 3. Multi objective genetic algorithm (MOGA)

Multi objective genetic algorithm (MOGA) [29] may be attributed as method for optimizing the search tool for difficult problems based on genetics selection principle. In additions to optimization, it also serves the purpose of machine learning and for Research and development [30]. The point of multi-objective optimization problems is how to find all possible tradeoffs among multiple objective functions that are usually conflicting. Since it is difficult to choose a single solution for a multi-objective optimization problem without iterative interaction with the decision maker, one general approach is to show the set of Pareto optimal solutions to the decision maker [31].

A multi-objective problem consists of optimizing (i.e. minimizing or maximizing) several objectives simultaneously, with a number of inequality or equality constraints. The problem can be formally written as follows [32]:

$$\text{Find } x = (x_i)\ \forall i = 1, 2, ..., N_{pa}, \tag{7}$$

$$\text{Minimizing or maximizing } f_i(x)\ \forall i = 1, 2, ..., N_{obj}, \tag{8}$$

$$g_j(x) = 0\ \forall i1, 2, ..., m, \tag{9}$$

$$h_k(x) = 0\ \forall k1, 2, ..., n. \tag{10}$$

Equation (6), (9) are explained that *Npar* is the number of decision variables, $f_i(x)$ represents the objective functions, N_{obj} is the total number of objective functions, x contains the decision variables, $g_j(x)$ and $h_k(x)$ denote the inequality and equality constraints, respectively. m and n represent the number of equality and inequality constraints, respectively.

4. 7. 4. Technique for order preference by similarity to ideal solution (TOPSIS)

The technique for order preference by similarity to ideal solution (TOPSIS) is a common method used in multi-criteria decision making (MCDM). It works by selecting the best option based on its closeness to the ideal solution and distance from the worst (non-ideal) solution. The ideal solution maximizes the benefit criteria and minimizes the cost criteria, while the non-ideal solution does the opposite. TOPSIS is useful when there are multiple and conflicting objectives. To improve objectivity, it can be combined with design of experiments (DoE) to determine the weight of each criterion statistically. It can also use Chebyshev polynomial regression to better understand how each criterion affects the final decision [33]. There are several steps involved in applying the TOPSIS method.

To enhance decision-making, the technique for order preference by similarity to ideal solution (TOPSIS) is applied to rank the optimization scenarios generated by RSM and ANN-MOGA. TOPSIS evaluates each alternative based on its distance from an ideal solution and a negative-ideal solution, enabling a comprehensive comparison that considers all objectives simultaneously. This method ensures a balanced and objective selection of the most effective configuration for operating B35-fueled diesel generators in remote systems.

5. Research results of performance analysis and optimization of a b35-fueled diesel generator

5. 1. Analysis of operational parameters on generator performance

This subsection analyzes how operational parameters namely load, power factor, and operation mode affect the performance indicators: specific fuel consumption (SFC), net plant heat rate (NPHR), and thermal efficiency. Using 600 data samples from 50 hours of field operation, the study reveals that stable high-load conditions and high-power factor values significantly improve efficiency and reduce SFC, especially in base load mode. These empirical findings form the basis for developing accurate predictive models in subsequent sections.

The experimental data on Table 2 used operational data from the period of August 2024 for 50 hours, consisting of 600 samples. The input data includes cos pi, load, and load mode, while the response data consists of SFC, NPHR, and efficiency.

Table 2

Experimental data engine #9

Hour	BBM	mode	cos φ	load (kW)	SFC (Litre/kWh)	NPHR (kCal/kWh)	Gross efficiency (%)
1	100	1	0.96	290	0.34	3140.90	27.39
2	120	1	0.94	381	0.31	2868.86	29.99
3	135	1	0.98	429	0.31	2866.35	30.02
4	150	1	0.96	485	0.31	2817.10	30.54
5	170	1	0.96	541	0.31	2862.23	30.06
6	190	1	0.95	620	0.31	2791.35	30.82
7	190	1	0.93	621	0.31	2786.86	30.87
8	195	1	0.98	639	0.31	2779.63	30.95
9	197	1	0.96	648	0.30	2769.13	31.07
10	197	1	0.96	649	0.30	2764.87	31.12
1	80	2	0.81	250	0.32	2914.76	29.52
2	120	2	0.78	329	0.36	3322.29	25.90
3	110	2	0.93	343	0.32	2921.13	29.46
4	140	2	0.77	411	0.34	3102.69	27.73
5	140	2	0.88	430	0.33	2965.60	29.01
6	160	2	0.92	516	0.31	2824.38	30.46
7	180	2	0.93	573	0.31	2861.35	30.07
8	188	2	0.96	600	0.31	2854.03	30.15
9	188	2	0.96	601	0.31	2849.29	30.20
10	188	2	0.96	602	0.31	2844.55	30.25

The dataset reveals consistent patterns regarding the relationship between load, power factor, and the performance metrics. Under base load conditions (mode 1), particularly at power factor values of 0.96–0.98 and load levels between 620–649 kW, the SFC stabilizes around 0.30 l/kWh, with efficiency peaking at 31.12% and NPHR declining to as low as 2764.87 kcal/kWh. These values suggest that the generator performs more efficiently at higher, steady loads and when operated with a high-power factor.

Conversely, under load share conditions (mode 2), lower power factor values (down to 0.77) and moderate load levels (250–602 kW) result in higher SFC values up to 0.36 l/kWh and reduced efficiency, with the lowest recorded at 25.90%. This indicates suboptimal combustion and thermal conversion due to load instability or inefficient engine synchronization across multiple units.

These findings confirm that the most fuel-efficient and thermally effective operation occurs during stable, high-load scenarios with optimized power factors. Variations in efficiency and fuel consumption under different operational modes underscore the need for a systematic optimization approach to identify ideal load and power configurations especially when using alternative fuels like B35, which inherently affect combustion behavior due to their physical and chemical properties.

This analysis provides a solid empirical foundation for the development of predictive models and optimization algorithms, as presented in the subsequent sections.

5. 2. Development of predictive models using response surface methodology (RSM)

Here, second-order polynomial models are constructed using RSM to estimate SFC, NPHR, and efficiency as a function of operational parameters. The models demonstrate good statistical validity (Adjusted $R^2 \approx 0.74$), and ANOVA confirms significant interaction effects. Contour and 3D surface plots are used to visualize trade-offs between variables, and optimization through RSM identifies operating points with minimized SFC and maximized efficiency under base load and load share scenarios.

In this study, three independent variables and three responses are analyzed using the response surface methodology (RSM). Among the most relevant multivariate techniques used in analytical optimization is response surface methodology (RSM) [34]. Some stages in the application of RSM as an optimization technique are as follows:

1) the selection of independent variables of major effects on the system through screening studies and the delimitation of the experimental region, according to the objective of the study and the experience of the researcher;

2) the choice of the experimental design and carrying out the experiments according to the selected experimental matrix;

3) the mathematic–statistical treatment of the obtained experimental data through the fit of a polynomial function;

4) the evaluation of the model's fitness;

5) the verification of the necessity and possibility of performing a displacement in direction to the optimal region;

6) obtaining the optimum values for each studied variable [34].

In this experiment, there are three objective functions: cos pi power factor (Cos φ), load, and load mode, along with three responses: specific fuel consumption (SFC), net plant heat rate (NPHR), and efficiency. The CCD model is an integral part of response surface mythology. The biggest advantage of this type of optimization model is, it is more accurate, and no need for a three-level factorial experiment for building a second-order quadratic model [35].

The ANOVA results from the response surface methodology (RSM), presented in Table 3, illustrate the importance of the input variables, their quadratic terms, and interactions in the analysis of the output responses. These results reveal that these factors contribute significantly to the variation observed in the responses. This highlights that the chosen model is statistically valid, as the relationships between the input parameters and their interactions have a crucial role in determining the response behavior.

Table 3

ANOVA results of RSM design expert

Fit Statistics			
SFC			
Std. Dev.	0.0155	R^2	0.761
Mean	0.2895	Adjusted R^2	0.74
C. V. % 5.34		Predicted R^2	0.6723
		Adeq precision	30.9402
NPHR			
Std. Dev.	140.79	R^2	0.761
Mean	2636.6	Adjusted R^2	0.74
C. V. % 5.34		Predicted R^2	0.6723
		Adeq precision	30.9402
EFFICIENCY			
Std. Dev.	1.83	R^2	0.7598
Mean	33	Adjusted R^2	0.7387
C. V. % 5.56		Predicted R^2	0.6852
		Adeq precision	29.8015

From the obtained data, quadratic RSM equations were generated to correlate the input and output. (10), (11) represent the formulas for calculating SFC baseload and loadshare. (12), (13) represent the formulas for calculating NPHR baseload and loadshare. (14), (15) represent the formulas for calculating efficiency baseload and loadshare:

$$\text{SFC Base Load} = \begin{pmatrix} 0.595549 + -0.705015 \cdot A + \\ +0.000528032 \cdot B \pm \\ \pm 7.99703e-05 \cdot A \cdot B + \\ +0.350297 \cdot A^2 \pm \\ \pm 5.81072e-07 \cdot B^2 \end{pmatrix}, \quad (10)$$

$$\text{SFC Load Share} = \begin{pmatrix} 0.564669 \pm 0.697652 \cdot A + \\ +0.000589757 \cdot B \pm \\ \pm 7.99703e-05 \cdot A \cdot B + \\ +0.350297 \cdot A^2 \pm \\ \pm 5.81072e-07 \cdot B^2 \end{pmatrix}, \quad (11)$$

$$\text{NPHR Base Load} = \begin{pmatrix} 5424.63 \pm 6421.71 \cdot A + \\ +4.80964 \cdot B \pm \\ \pm 0.728419 \cdot A \cdot B + \\ +3190.72 \cdot A^2 \pm \\ \pm 0.00529277 \cdot B^2 \end{pmatrix}, \quad (12)$$

$$\text{NPHR Load Share} = \begin{pmatrix} 5143.35 \pm 6354.65 \cdot A + \\ +5.37187 \cdot B \pm \\ \pm 0.728419 \cdot A \cdot B + \\ +3190.72 \cdot A^2 \pm \\ \pm 0.00529277 \cdot B^2 \end{pmatrix}, \quad (13)$$

$$\text{EFF Base Load} = \begin{pmatrix} 33.2141 \pm 7.18849 \cdot A \pm \\ \pm 0.0487795 \cdot B \pm \\ \pm 0.0171047 \cdot A \cdot B + \\ +16.8365 \cdot A^2 + \\ +7.89845e-05 \cdot B^2 \end{pmatrix}, \quad (14)$$

$$\text{EFF Load Share} = \left(\begin{array}{l} 40.5848 \pm 11.2648 * A \pm \\ \pm 0.0569871 * B \pm \\ \pm 0.0171047 * A * B + \\ +16.8365 * A^2 + \\ +7.89845e-05 * B^2 \end{array}\right). \tag{15}$$

The model generated from the response surface methodology (RSM) was subsequently tested for data adequacy and abnormalities using normal probability plot [36] for residuals and outliers. In this context, an acceptable model is expected not to follow any specific trends or patterns, and the points should be closely aligned with a straight line. Fig. 3 shows the data plot from RSM, the normal plot of residuals, and the residuals vs. predicted.

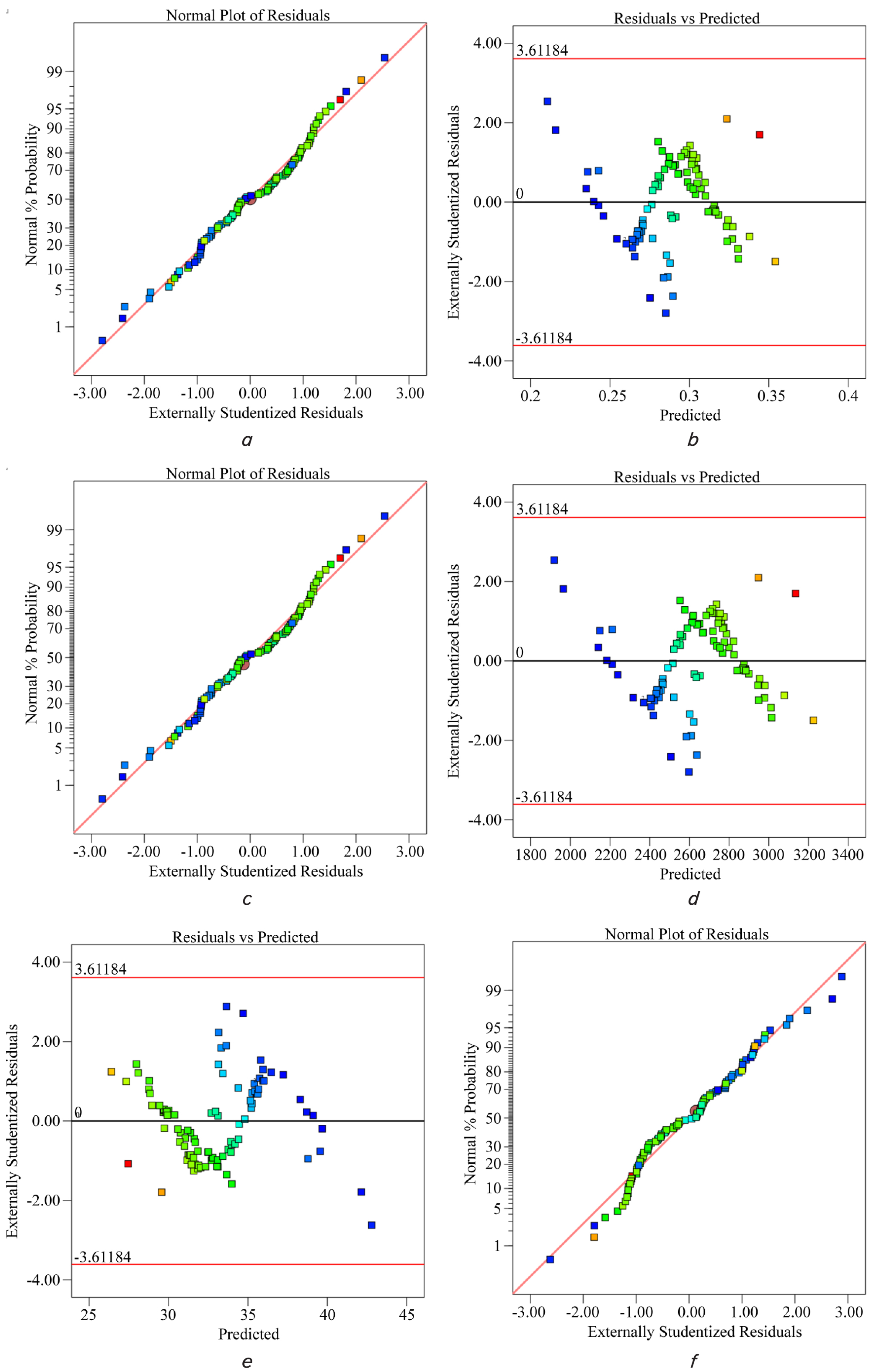

Fig. 3. 2D Normal plot of residual, residual vs. predicted design expert: *a, b* – specific fuel consumption; *c, d* – net plant heat rate; *e, f* – efficiency

A check on the normal probability plot depicts that the residuals generally fall on a straight line implying that the errors are distributed normally. Also, the plot of residuals vs. predicted response revealed that it has no obvious pattern and unusual structure. This implies that the models proposed are adequate and there is no reason to suspect any violation of the independence or constant variance assumption [37].

Fig. 4 illustrates the 3D profiles for the data on specific fuel consumption (SFC), net plant heat rate (NPHR), and efficiency. These profiles visually represent the interrelationships among these parameters, allowing for a better understanding of how variations in one factor can influence the others. Such visualizations are essential in optimizing performance and enhancing the operational efficiency of the system under study.

From the all-factor graph in Fig. 5, it is shown that there is a trade-off between the output parameters, where SFC and NPHR have a negative polarity, while Efficiency has a positive polarity.

This experiment highlights the challenges of achieving optimal operating parameters for Unit #9 of the S16R in Muara Wahau. To address this goal, Response Surface Method (RSM) is useful mathematical and statistical technique to achieve optimum condition [38]. By utilizing RSM in Fig. 6, this study aims to enhance operational efficiency and performance of the engine in the challenging conditions of Muara Wahau.

To achieve optimal objective function values among its variables, Unit #9 S16R Muara Wahau is set at Cos pi = 0.98; Load = 838 kW; Mode = load share. This configuration results in responses of SFC = 0.24 liters/kWh; NPHR = 2158 kcal/kWh; Eff = 39%.

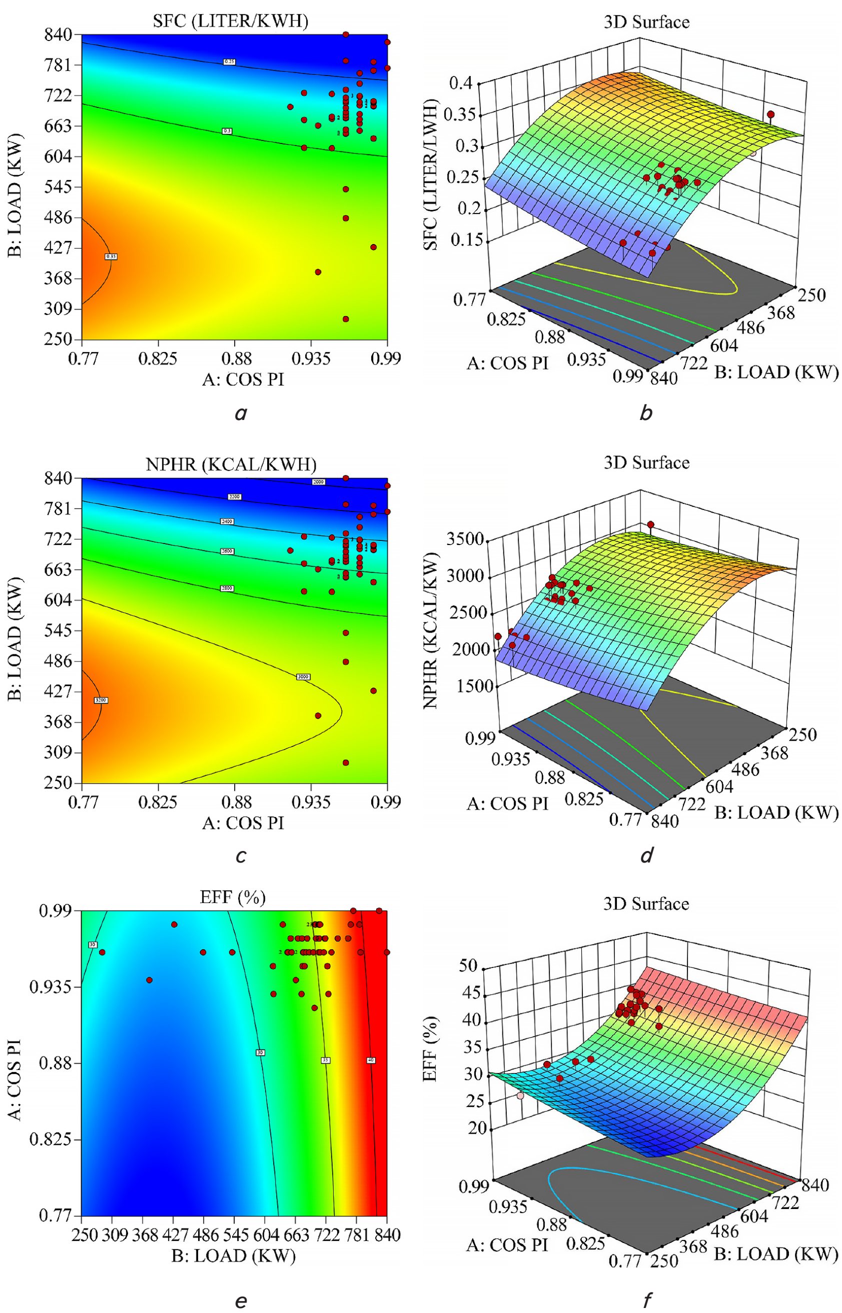

Fig. 4. Contour. 3D surface design expert: *a, b* — specific fuel consumption; *c, d* — net plant heat rate; *e, f* — efficiency

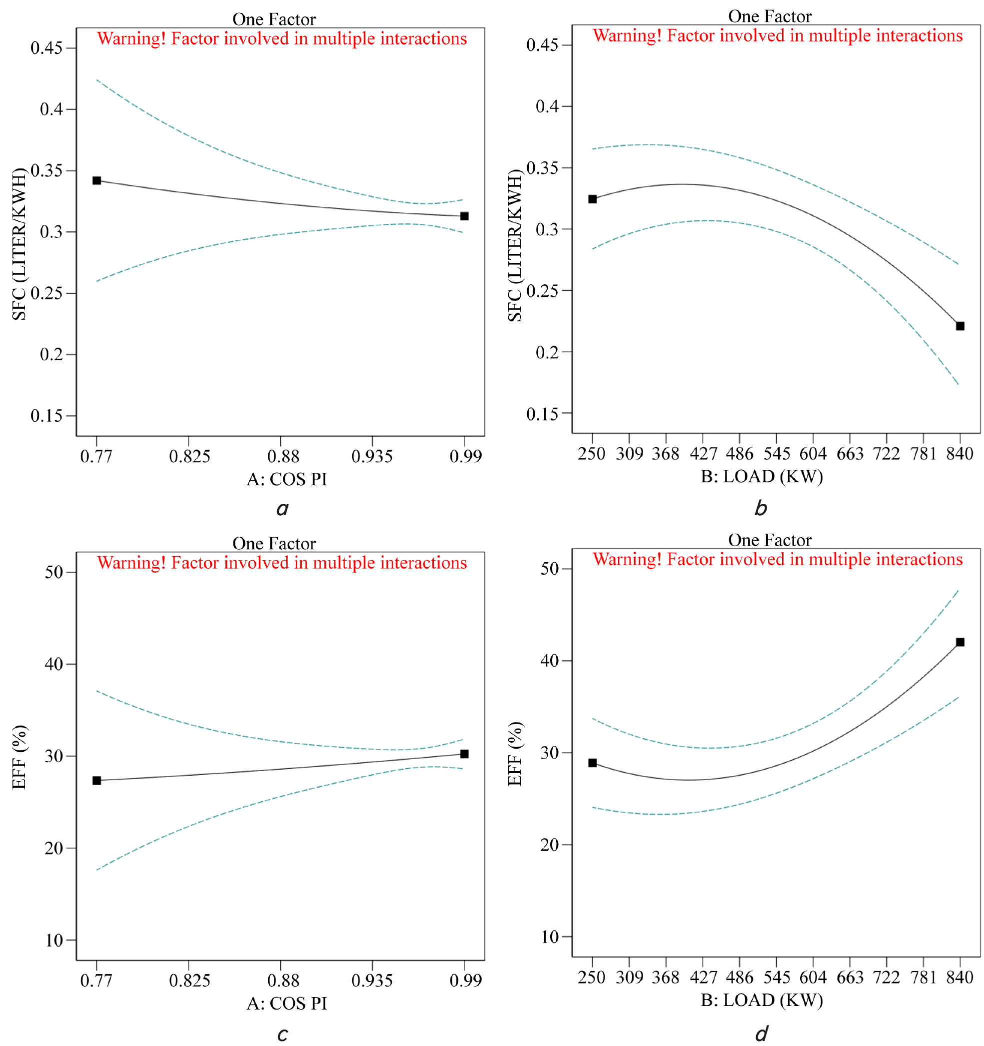

Fig. 5. Tradeoffs: *a, b* – specific fuel consumption; *c, d* – efficiency trade of parameter

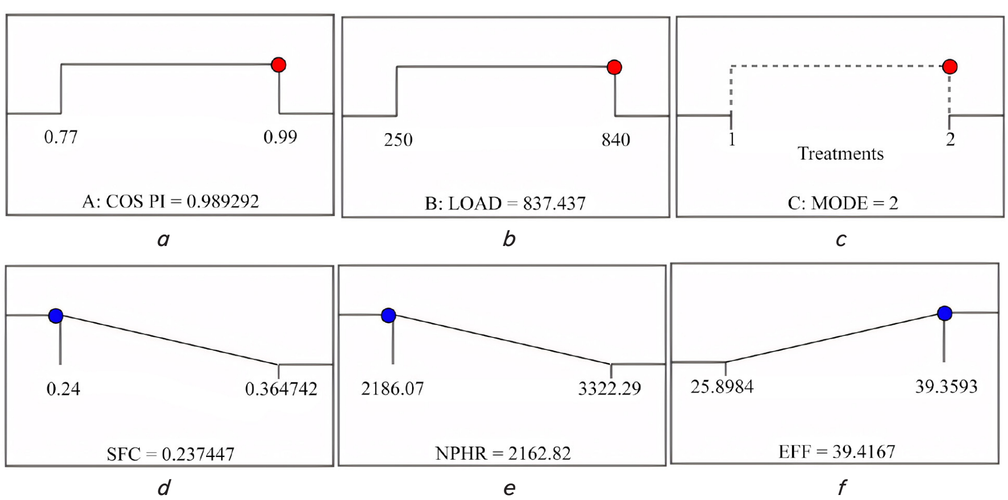

Fig. 6. Response surface method: *a* – best cos pi; *b* – best load; *c* – best mode; *d* – best output specific fuel consumption; *e* – best output net plant heat rate; *d* – best output efficiency

5. 3. Data normalization and ANN model preparation

Before ANN training, all datasets are normalized using min-max scaling to ensure consistent learning behavior across input ranges. Root mean square error (RMSE) is used to evaluate performance during training. The dataset is split into training, validation, and testing subsets. Based on trial-and-error, 20 neurons are selected for the baseload network and 32 for the load share network, ensuring best model convergence and minimum MSE.

Before performing ANN modeling on data with varying ranges, it is necessary to adjust the data using a common scale. This process is known as data normalization, which serves to minimize bias. It's the process of casting the data to the specific range, like between 0 and 1 or between –1 and +1. Normalization is required when there are big differences in the ranges of different features. This scaling method is useful when the data set does not contain outliers [39]. After normalization techniques evaluated root mean square error (RMSE) [40] calculations were conducted for each load mode, resulting in 20 neurons for the baseload mode and 32 neurons for the load share mode. Once the equation (16) computations were complete, the data was denormalized to return to the original scale

$$\frac{X - X_{\min}}{X_{\max} - X_{\min}} = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}}. \tag{16}$$

This formula represents the normalization process (min-max scaling), used to rescale values of X to the range of Y

$$X = \left(\frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} \right) \times \left(X_{\max} - X_{\min} \right) + X_{\min}. \tag{17}$$

This formula is the inverse of normalization, used to recover the original value of X after it was normalized to the Y scale.

5. 4. ANN model development and multi-objective optimization using MOGA

This subsection presents the training and validation of the ANN model using the Levenberg-Marquardt algorithm. Performance results show superior prediction accuracy compared to RSM. The trained ANN is then used as the fitness function within a multi-objective genetic algorithm (MOGA) to identify optimal parameter combinations. Pareto fronts show a clear trade-off between efficiency and fuel consumption, with ANN-MOGA producing more stable and uniformly distributed solutions than RSM.

Artificial neural networks (ANN) [24] are utilized to establish the relationship between three input variables and three output variables. Several steps are implemented for this analysis, including data collection, network development and configuration, weight and bias initialization, training, testing, and validation. The objective is to achieve maximum regression parameters (R^2) alongside minimal Mean Squared Error (MSE) [41] to accurately select the optimal number of neurons. A trial-and-error method is employed to determine the best design, focusing on architecture selection with the lowest error (root mean square error, RMSE) and the highest regression coefficient. Fig. 2 illustrates the architecture of the artificial neural network [42]. In this process, the difference between the model output and the desired data is referred to as the network error rate. Fig. 7 explains the base load mode, and Fig. 8 explains the share mode.

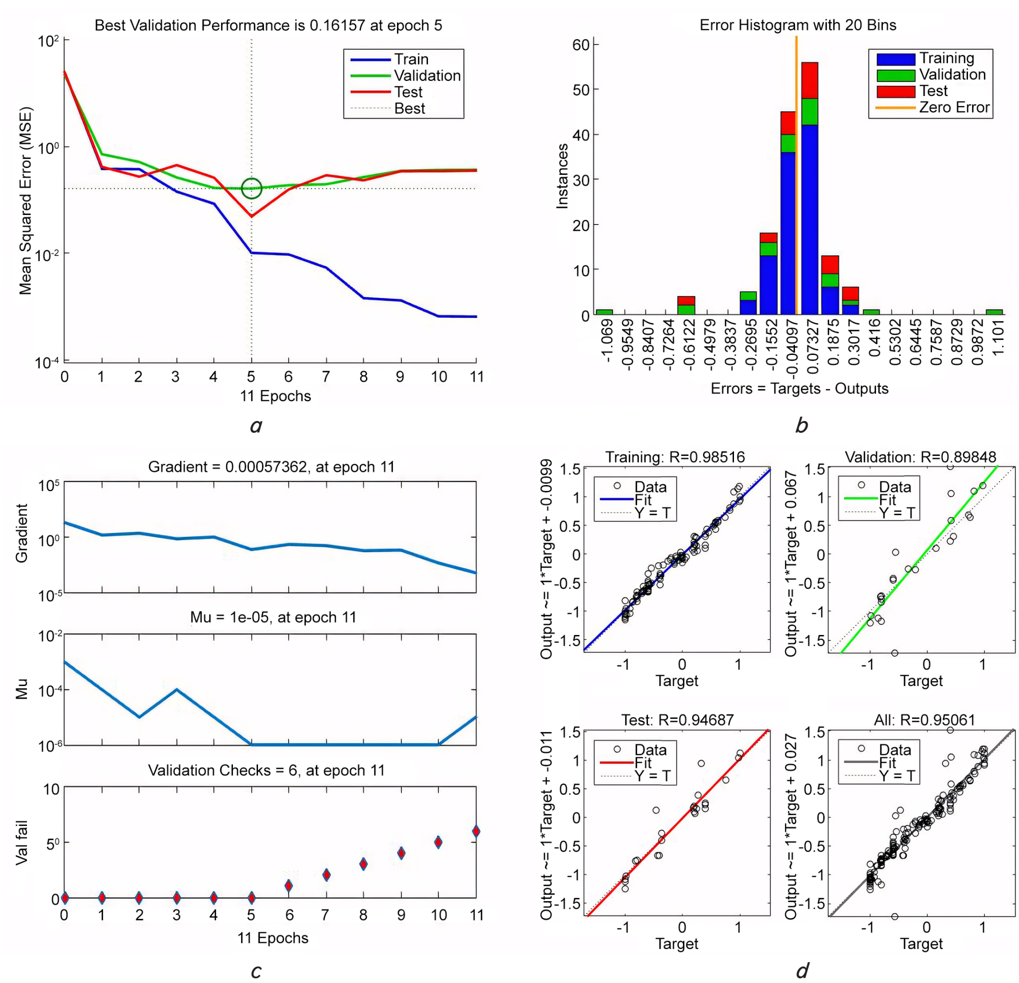

Fig. 7. Base load mode: *a* — artificial neural networks regression data result; *b* — error histogram for artificial neural networks; *c* — validation performance; *d* — training state

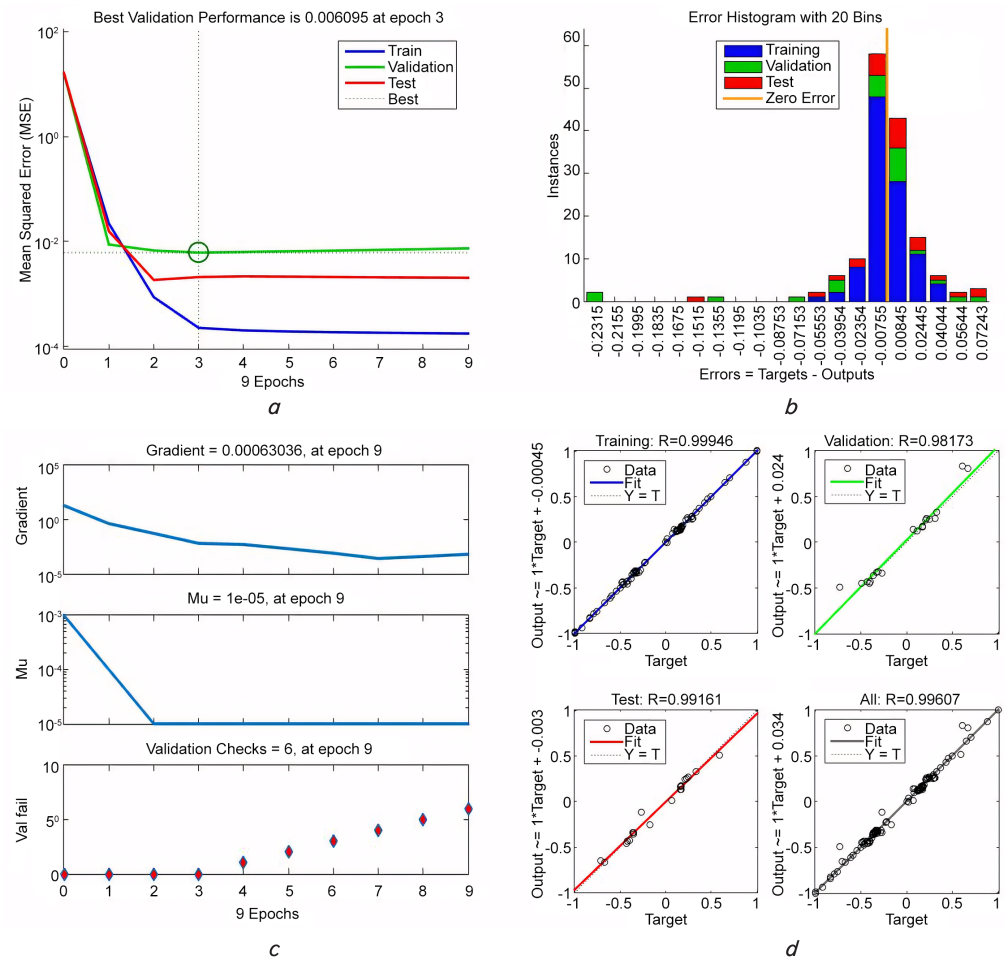

Fig. 8. Share mode: *a* — artificial neural networks regression data result; *b* — error histogram for artificial neural networks; *c* — validation performance; *d* — training state

Fig. 9 explains the 2D comparison of trendlines for ACTUAL, RSM, and ANN. In this study, the comparison results of the graphs indicate that calculations using RSM and ANN compared to actual values show a closer fit with the ANN method.

The comparison graphs in Fig. 9 clearly demonstrate the relative accuracy of RSM and ANN models in predicting the performance of B35-fueled diesel generators under both baseload and load share conditions. Across all three key performance indicators – specific fuel consumption (SFC), net plant heat rate (NPHR), and efficiency – the trendlines generated by the ANN model align more closely with actual measured values than those generated by RSM.

In baseload mode (Fig. 9, *a–c*), the ANN predictions consistently follow the actual data with lower deviation, especially in SFC and NPHR, where RSM exhibits a slight underestimation in mid-range runs. Efficiency values (Fig. 9, *c*) also show a smoother and more realistic trend with ANN, capturing the nonlinear progression of engine performance more accurately.

Under load share mode (Fig. 9, *d–f*), discrepancies between RSM and actual values become more pronounced, particularly for NPHR and efficiency (Fig. 9, *e*, *f*). ANN continues to provide a better fit in these scenarios, suggesting its robustness in modeling complex, non-linear systems under variable load and synchronization conditions.

These findings confirm that while both RSM and ANN are valuable tools for modeling engine performance, ANN offers superior predictive capability, especially under dynamic operational scenarios where interaction effects and non-linearities dominate. The enhanced alignment with actual values underscores ANN's potential for integration into real-time engine monitoring and control systems.

The artificial neural network (ANN) combined with the multi-objective genetic algorithm (MOGA) is then used to enhance the understanding of Pareto optimality as part of the theory and solution of multi-objective optimization problems [43]. The developed ANN model is also accurate in predicting the values of three objective functions: cos pi, load, and mode load, as well as three responses: SFC, NPHR, and Efficiency. Based on the obtained results, the functions developed through the ANN procedure are subsequently used as fitness characteristics in the optimization phase using ANN MOGA. Regarding population selection and optimization operations, the Pareto chart is chosen, as illustrated in Fig. 10. This Pareto frontier is achieved by solving the optimization model using the ANN MOGA Levenberg-Marquardt (LM) method.

The results depicted in Fig. 10 further validate the superiority of the ANN-assisted MOGA optimization over the RSM-based approach. The Pareto fronts for both baseload (Fig. 10, *a*) and load share conditions (Fig. 10, *b*) illustrate a clearer and more optimal trade-off curve in the ANN-MOGA configuration, with better convergence and distribution of non-dominated solutions across the efficiency axis. In contrast, the RSM-based optimization yields a more scattered and less uniform Pareto front, indicating reduced robustness in capturing the multi-dimensional trade-offs among performance objectives.

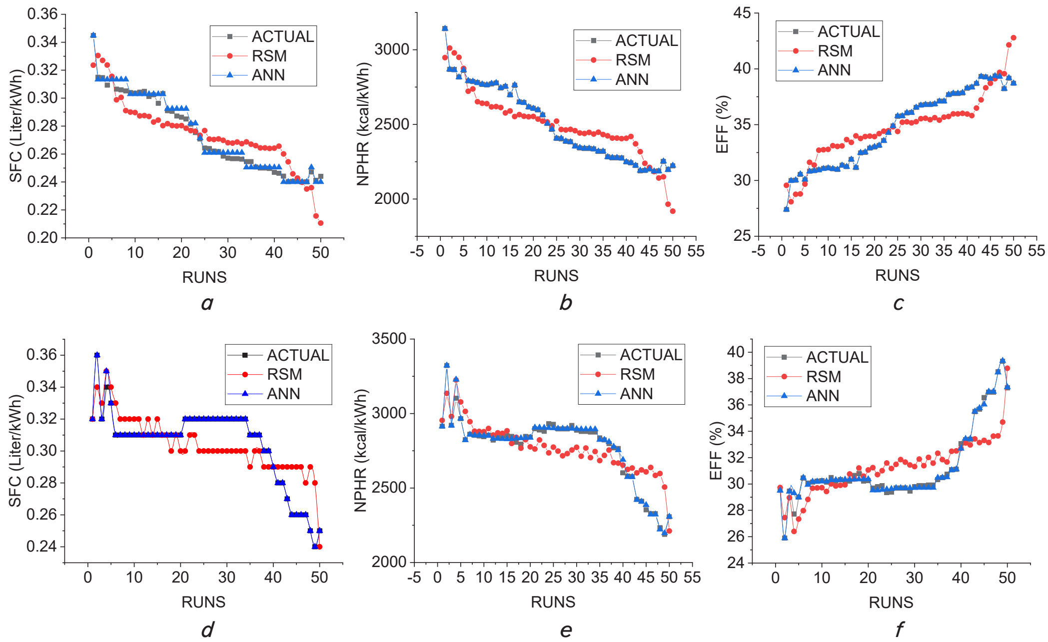

Fig. 9. Baseload: *a* – specific fuel consumption; *b* – net plant heat rate; *c* – efficiency; loadshare: *d* – specific fuel consumption; *e* – net plant heat rate; *f* – efficiency

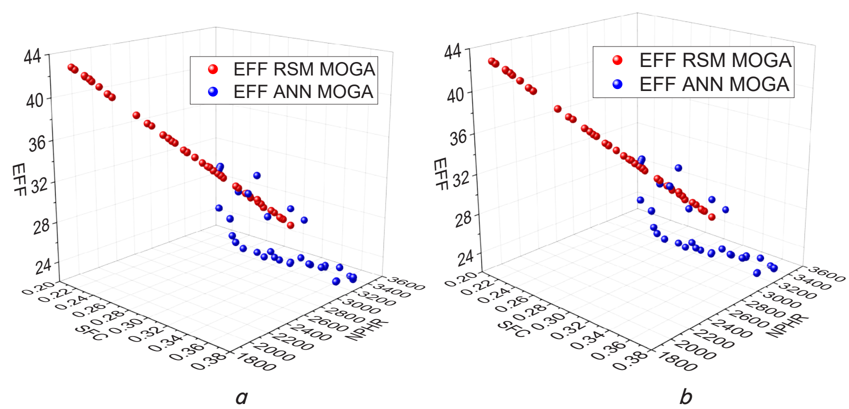

Fig. 10. Comparison of multi-objective genetic algorithm: response surface methodology vs. artificial neural network: *a* – baseload; *b* – loadshare

This observation confirms that the ANN-MOGA model provides a more stable and accurate mapping of complex, non-linear interactions among input variables, which directly affects the quality of Pareto-optimal solutions. The ability of ANN to generalize across a broad input space, combined with the exploration strength of MOGA and the fine-tuning capability of the Levenberg Marquardt method, ensures a balanced and high-quality solution set. These advantages make the proposed approach particularly suitable for real-world applications, where performance, efficiency, and operational stability must be jointly optimized under uncertain and variable conditions.

5. 5. Evaluation of optimization scenarios using TOPSIS

TOPSIS is applied to rank the optimized scenarios generated by RSM and ANN-MOGA models. The decision-making process considers three criteria – SFC, NPHR, and efficiency. Results show that the load share mode ($\cos \varphi = 0.97$, Load = 829 kW) optimized via ANN-MOGA yields the most balanced performance, achieving 0.24 L/kWh fuel consumption and 39.42% efficiency. This ranking confirms the ANN-MOGA scenario as the closest to the ideal solution under field constraints.

The application of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method in this study effectively ranked multiple optimization outcomes based on their proximity to the ideal solution. The method evaluated several operational scenarios derived from response surface methodology (RSM) and artificial neural network combined with multi-objective genetic algorithm (ANN-MOGA). Table 4 explain, base load condition ($\cos \varphi = 0.96$, load = 698 kW), the RSM model delivered the highest gross efficiency of 42.78%, with SFC of 0.21 L/kWh and NPHR of 1918.08 kcal/kWh. Meanwhile, under the load share condition ($\cos \varphi = 0.97$, load = 829 kW), the ANN-MOGA model achieved a gross efficiency of 39.42%, with SFC of 0.24 L/kWh and NPHR of 2164.94 kcal/kWh.

Using TOPSIS, the optimal solution was determined to be the ANN-MOGA load share mode, which balanced trade-offs between fuel consumption and efficiency, while closely aligning with the ideal solution criteria. This result highlights the strength of TOPSIS in providing a systematic and objective selection process among complex alternatives

Table 4

TOPSIS results

TOPSIS	Base load			Load share		
	SFC (Litre/kWh)	NPHR (kCal/kWh)	GROSS EFFICIENCY (%)	SFC (Litre/kWh)	NPHR (kCal/kWh)	GROSS EFFICIENCY (%)
RSM	0.21	1918.08	42.78	0.24	2198.17	38.93
RSM NN MOGA	0.24	2139.19	39.69	0.24	2164.94	39.42

6. Discussion of research results of optimization results for B35-fueled diesel generator systems

The experimental and modeling results presented in this study comprehensively address the research objectives through integrated empirical analysis, predictive modeling, and decision-support evaluation. The results assessing the influence of load, power factor, and operation mode was fulfilled through field data collection comprising 600 samples (Table 2). The results (Fig. 4, 5) confirm that high-load operation (620–649 kW) and power factor above 0.96 significantly reduce specific fuel consumption (SFC) to 0.30 L/kWh while improving gross efficiency to over 31%. Conversely, lower power factors in load share mode resulted in degraded performance, indicating the strong operational dependency of efficiency on parameter stability.

Predictive models were constructed using response surface methodology (RSM), validated through ANOVA as shown in Table 3 and visualized in Fig. 3 and Fig. 4. These second-order polynomial models accurately captured the relationship between operational parameters and output metrics (SFC, NPHR, efficiency), with Adjusted R^2 values consistently above 0.73. However, to address the nonlinear nature of generator behavior under field conditions, artificial neural networks (ANN) were implemented using normalized data, yielding significantly higher prediction fidelity, especially in load share conditions. This is evidenced in Fig. 7, 8, where regression performance and error histograms reveal superior fit of the ANN model.

The trained ANN model was used as the fitness function in a multi-objective genetic algorithm (MOGA) framework to generate Pareto-optimal solutions. As illustrated in Fig. 10, the ANN-MOGA optimization demonstrated better convergence and trade-off distribution between fuel consumption and efficiency compared to RSM. This configuration identified an optimal scenario in load share mode ($\cos\varphi = 0.97$, Load = 829 kW), achieving SFC of 0.24 l/kWh and gross efficiency of 39.42%, as shown in Table 4. The technique for order preference by similarity to ideal solution (TOPSIS) ranked this configuration as the closest to the ideal solution across all evaluation criteria (SFC, NPHR, and efficiency).

These results confirm that the operational limitations of B35-fueled generators namely increased SFC and performance derating can be effectively mitigated through multi-level optimization. Compared to prior studies that focused narrowly on emissions or lab-scale blends, this research provides a field-validated methodology combining RSM, ANN, MOGA, and TOPSIS within a decision-support framework. The contributions include not only accurate predictive tools but also actionable optimization strategies adaptable to other remote power systems employing national biodiesel mandates.

Nonetheless, some limitations must be acknowledged. The study is restricted to steady-state operation of a single generator type and does not cover emissions, transient behaviors, or electrical quality indicators such as harmonics or voltage stability. Furthermore, while the ANN model provides high accuracy, its black-box nature limits interpretability unless paired with explainable AI techniques. Future work should expand this framework by incorporating real-time adaptive controls, emissions modeling, and broader applicability to hybrid systems or multi-unit generator scenarios.

The experimental and modeling results presented in this study demonstrate that the operational performance of a 1000 kW diesel generator running on Biodiesel B35 can be significantly improved through the systematic adjustment of key operational parameters. Field data analysis confirmed that parameters such as load, power factor, and operation mode have a substantial impact on performance indicators including specific fuel consumption (SFC), net plant heat rate (NPHR), and thermal efficiency. High-load conditions and high-power factors were found to contribute positively to performance, particularly in base load mode, where SFC reached as low as 0.30 L/kWh and gross efficiency exceeded 31%. Predictive models developed using response surface methodology (RSM) captured these relationships with reasonable accuracy, validated by ANOVA and surface response analysis. However, artificial neural networks (ANN) offered superior performance in capturing nonlinear interactions, especially when combined with multi-objective genetic algorithm (MOGA) for optimization. The ANN-MOGA integration enabled the identification of Pareto-optimal configurations that balanced the trade-offs between minimizing fuel consumption and maximizing efficiency. The effectiveness of these solutions was confirmed through the application of the TOPSIS decision-making method, which ranked the ANN-MOGA-generated load share scenario ($\cos\varphi = 0.97$, Load = 829 kW) as the closest to the ideal solution.

The contribution of this study lies in its comprehensive, multi-method approach to solving practical challenges associated with B35 usage in remote-area diesel generators. Unlike previous works that focused narrowly on emissions or fuel blending effects, this study integrates empirical field data, hybrid modeling, and decision analysis to address the performance derating problem in operationally realistic settings. The combined use of RSM and ANN modeling each validated through extensive field testing adds robustness to the findings and fills a methodological gap in current literature.

In summary, the integrated methodology presented in this research demonstrates a feasible and replicable strategy for enhancing the operational efficiency of biodiesel-fueled generators in isolated power systems. The study contributes practical tools and validated models that can inform future deployment, especially in regions adopting national biodiesel mandates.

Nevertheless, the study has several limitations. It focuses solely on steady-state operations and considers only a single generator type, which may restrict the generalizability of the results. Other important factors, such as emissions, transient behavior, and power quality, were excluded from the analysis. Furthermore, the ANN model, despite its predictive strength, functions as a black box, making its internal logic difficult to interpret without additional explainability tools.

Future research should expand on this work by incorporating real-time monitoring and transient performance modeling, as well as integrating emissions and power quality indicators into the optimization framework. Applying the method to multiple engine types or hybrid energy systems, such as solar-diesel microgrids, could enhance its relevance for broader energy planning and policy. Additionally, embedding ANN-MOGA-based optimization into control systems could enable dynamic, real-time adjustment of generator parameters for improved efficiency and fuel economy. The framework proposed in this study thus provides a practical and replicable foundation for advancing the operational sustainability of biodiesel-powered generators in remote and off-grid environments.

7. Conclusion

1. Operational parameters load, power factor, and mode – were shown to significantly influence performance indicators such as specific fuel consumption (SFC), net plant heat rate (NPHR), and thermal efficiency. High-load operation and improved power factor contributed to lower SFC and higher thermal efficiency.

2. Predictive models developed using response surface methodology (RSM) effectively captured the nonlinear relationships among operational parameters. The RSM models achieved acceptable statistical accuracy and were validated through ANOVA and visual diagnostics.

3. Artificial neural network (ANN) models, trained using normalized data, outperformed RSM in prediction accuracy across all scenarios. The ANN architecture with 20 neurons (baseload) and 32 neurons (load share) provided the most reliable fit to the empirical data.

4. Multi-objective scenario generation using ANN as a surrogate model in the MOGA framework produced diverse Pareto-optimal solutions, highlighting trade-offs between fuel efficiency and consumption. The best configuration in the load share mode achieved 0.24 L/kWh and 39.42% efficiency.

5. The TOPSIS method successfully ranked the optimal scenarios based on proximity to ideal performance, confirming the ANN-MOGA solution in load share mode as the most balanced and practical option for real-world implementation.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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