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# MULTI-OBJECTIVE OPTIMIZATION OF BOILER COMBUSTION EFFICIENCY AND EMISSIONS USING GENETIC ALGORITHM AND RECURRENT NEURAL NETWORK IN 660-MW COAL-FIRED POWER PLANT

**Mohamad Arwan Efendy**
Master's Candidates in Mechanical Engineering*
**Ahmad Syihan Auzani**
*Corresponding author*
Doctoral*
E-mail: auzani@ui.ac.id
**Sholahudin**
Doctoral*
*Department of Mechanical Engineering
Universitas Indonesia
Lingkar str., Pondok Cina, Kecamatan Beji, Depok,
West Java, Indonesia, 16424

***Indonesia has demonstrated a firm commitment to achieving Net Zero Emissions (NZE) by 2060. The implementation of diverse strategies, such as the application of biomass co-firing technology in coal-based steam power plants, demonstrates this commitment. This study focuses on the 660 MW supercritical coal-fired boiler as the object of investigation. The key problem addressed in this research is the unstable combustion performance due to the dynamic and nonlinear interactions among operational variables under biomass co-firing conditions. These fluctuations can negatively impact boiler efficiency, $CO_2$ emissions, and the plant's capability factor. The study proposes a dynamic multi-objective optimization framework using a Recurrent Neural Network (RNN), Response Surface Methodology (RSM), and a Multi-Objective Genetic Algorithm (MOGA) to enhance performance reliability and support Indonesia's transition to cleaner energy sources.***

***The findings indicate that the RNN model exhibited superior prediction accuracy compared to the RSM, with a Root Mean Square Error (RMSE) value of 0.1523% for boiler efficiency, 1.6993% for $CO_2$ emissions, and 0.5284% for the capability factor. The MOGA optimization exhibited an enhancement in boiler efficiency from 86.6793% to 87.32%, a reduction in $CO_2$ emissions from 114.213 mg/Nm$^3$ to 53.972 mg/Nm$^3$, and an augmentation in the capability factor from 87.9% to 89.32%. Furthermore, coal consumption is reduced to 51,524 tons per hour, which can generate operational cost savings of IDR 1.34 billion per day.***

***The RNN and MOGA-based approaches have been demonstrated to be more effective than RSM for optimizing boiler combustion. This method is important for developing a strategy to improve the efficiency of the combustion process in boilers in coal-fired power plants. It will also help support the transition to clean energy and achieve the NZE 2060 target***

***Keywords: boiler efficiency, co-firing, artificial neural network, genetic algorithm, net zero emission***

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## 1. Introduction

Coal-fired power plants remain a predominant source of global electricity generation, accounting for approximately 36% of the world's electricity output as of 2022 [1]. Despite accelerated global efforts to transition toward renewable energy sources, coal-fired generation continues to constitute a critical component of the energy portfolio in numerous economies, particularly within developing nations such as Indonesia [2, 3]. However, burning coal is closely connected to high carbon dioxide ($CO_2$) emissions, which greatly increase greenhouse gas levels and worsen global climate change.

In this situation, making boiler systems in coal-fired power plants more efficient is a crucial way to significantly lower both coal use and $CO_2$ emissions without needing to spend a lot of money on major infrastructure changes. Augmenting boiler efficiency not only mitigates environmental externalities but simultaneously enhances the economic viability of power plant operations by reducing fuel costs. However, optimizing combustion processes is profoundly challenging, primarily due to the nonlinear, multifactorial dynamics governing the relationships among operational parameters, such as fuel quality, air and fuel flow rates, load fluctuations, and system constraints [4, 5].

Conventional optimization and control methodologies, typically relying on linear models and rule-based approaches, have demonstrated limited efficacy in managing the intricate, interdependent behaviors characteristic of large-scale combustion systems [6]. Recent advancements in artificial intelligence and machine learning technologies, including Artificial Neural Networks and Genetic Algorithms, have shown considerable promise in overcoming these limitations by facilitating predictive modelling and adaptive optimization under complex, nonlinear conditions [7, 8]. Particularly, Recurrent Neural Network, by virtue of their inherent ability to capture temporal dependencies and dynamic system behaviors, offer superior predictive performance compared to traditional static models [9]. Moreover, the application of multi-objective genetic algorithms enables the simultaneous optimization of multiple conflicting objectives, such as maximizing boiler efficiency while minimizing $CO_2$ emissions, thereby yielding Pareto-optimal solutions that are critical for practical decision-making in industrial contexts [10].

Considering the persisting reliance on coal-fired power generation within the global energy landscape, coupled with the urgent imperatives of environmental sustainability and operational efficiency, the scientific exploration and development of intelligent, data-driven, multi-objective optimization frameworks for boiler combustion are of paramount importance. Advancing such frameworks is essential not only for achieving immediate gains in operational performance but also for supporting broader initiatives aimed at carbon neutrality and energy transition.

Therefore, research devoted to the development of advanced multi-objective optimization models based on genetic algorithms and recurrent neural networks for enhancing combustion performance in coal-fired boilers remains highly relevant, both from a scientific and practical standpoint.

## 2. Literature review and problem statement

The paper [10] presents research on combustion optimization of a coal-fired boiler using neural networks and Nelder-Mead optimization, achieving a 15% reduction in NOx emissions and a 0.57% improvement in unit heat rate. It is shown that AI-based models can enhance performance under steady full-load conditions. However, unresolved issues remain regarding model adaptability to dynamic operational changes and fuel variability, critical for supercritical plant stability. The reason for this may be the static nature of the optimization approach and the absence of predictive multi-variable dynamic models. A way to overcome these difficulties can be through hybrid multi-objective optimization using genetic algorithms, response surface methodology, and recurrent neural networks. This approach was not fully explored in [10], where optimization focused only on static conditions. All this suggests that it is advisable to conduct a study on dynamic combustion optimization to ensure sustained efficiency and emission control under real operational variability in supercritical coal-fired power plants.

The paper [11] presents a review of the physical and chemical properties of biomass combustion ashes and their implications for boiler performance. It is shown that co-firing biomass with coal can significantly affect boiler operation due to the distinct composition of biomass ash, which often contains higher concentrations of alkali metals, chlorine, and other volatile elements compared to coal ash. These properties promote slagging, fouling, corrosion, and deposition on heat transfer surfaces, leading to reduced thermal efficiency, increased maintenance needs, and potential damage to boiler components. However, unresolved issues remain regarding the prediction and real-time management of these impacts, particularly under variable biomass ratios and operating conditions. The reason for this may be the highly variable nature of biomass fuels and the original design of boilers optimized for coal combustion. A way to overcome these difficulties can be through dynamic optimization and adaptive control strategies that continuously adjust combustion parameters to mitigate ash-related problems. This highlights the necessity to develop advanced predictive and optimization frameworks capable of maintaining stable and efficient boiler operation during biomass co-firing.

The paper [12] presents the results of research on biomass cofiring in coal-fired power plants to reduce greenhouse gas emissions. It is shown that cofiring with oil palm empty fruit bunch pellets can lower emissions while utilizing existing infrastructure. But there were unresolved issues related to the impact of dynamic biomass properties such as moisture, calorific value, and ash content on combustion stability, efficiency, and equipment durability. The reason for this may be objective difficulties associated with the high variability of biomass, which challenges the combustion process originally optimized for uniform coal fuels, leading to risks of incomplete combustion, fouling, and efficiency loss. A way to overcome these difficulties can be the development of adaptive combustion control and predictive adjustment strategies. This approach was used in [12], however, fuel variability and its operational effects were not fully addressed. All this suggests that it is advisable to conduct a study on dynamic combustion optimization to sustain power plant performance under variable biomass cofiring conditions.

The paper [5] presents the results of research on the impact of coal blending and biomass co-firing on supercritical power plant performance. It is shown that blending and co-firing can reduce emissions while maintaining power generation efficiency under controlled conditions. But there were unresolved issues related to the effects of dynamic variations in fuel properties on combustion stability and plant efficiency. The reason for this may be objective difficulties associated with fluctuating heating values and ash content, which disrupt combustion and heat transfer, leading to efficiency loss. A way to overcome these difficulties can be through dynamic adjustment of combustion and operational parameters. This approach was used in [5], however, steady-state assumptions limited the ability to address real-time fuel variability impacts. All this suggests that it is advisable to conduct a study on adaptive strategies to maintain stable power plant performance under variable fuel conditions.

The paper [13] presents the results of research on the carbon mitigation and economic effects of biomass co-firing combined with carbon capture in coal-fired power plants. It is shown that integrating 5–20% biomass with monoethanolamine-based capture can significantly reduce lifecycle $CO_2$ emissions. But there were unresolved issues related to efficiency decline and higher operational costs due to dynamic variations in biomass properties. The reason for this may be the lower heating value of biomass, increased slagging, corrosion risks, and retrofit costs. A way to overcome these difficulties can be adaptive combustion management and flexible carbon capture integration. This approach was used in [13], however, the study primarily analyzed steady-state scenarios and did not fully address operational variability and its real-time impacts on performance. All this suggests that it is advisable to conduct a study on dynamic performance optimization strategies for biomass-cofired and carbon capture-integrated power plants to ensure consistent efficiency, lower emissions, and enhanced economic feasibility.

The paper [14] reviews the thermo-chemical characteristics of coal and biomass co-firing in industrial boilers. It is shown that co-firing reduces $NO_x$ and $SO_x$ emissions but introduces challenges such as lower combustion efficiency, slagging, and ignition variability due to biomass properties. However, unresolved issues remain regarding the dynamic impact of biomass fluctuations on combustion stability and heat transfer. The reason for this may be biomass variability and design limitations of coal-optimized boilers. A way to overcome these difficulties can be advanced optimization techniques that adapt to real-time fuel changes. This approach was not fully explored in [14], which focused mainly on experimental observations. All this suggests that it is advisable to conduct a study on dynamic multi-objective optimization to improve efficiency and emissions control in biomass co-firing systems.

The paper [15] presents the results of research on the energy and environmental performance of biomass combustion and co-firing in pulverized fuel and fluidized bed boilers. It is shown that co-firing can reduce carbon emissions and maintain high efficiency, especially in fluidized bed systems. But there were unresolved issues related to fuel variability, instability at partial loads, and increased auxiliary energy use, affecting net efficiency. The reason for this may be difficulties from fluctuations in calorific value, moisture, and ash content, combined with boiler designs optimized for coal. A way to overcome these difficulties can be real-time monitoring and adaptive combustion optimization. This approach was used in [15], however, the study relied on steady-state conditions and did not fully address real-time variability. All this suggests that it is advisable to conduct a study on dynamic optimization to ensure stable and efficient biomass co-firing under variable conditions.

The paper [16] presents research on an online combustion optimization framework for coal-fired boilers using deep learning and multi-objective evolutionary algorithms. It is shown that the integration of CIPSODM-LSTM modeling and DMS-D/MOEA optimization improves thermal efficiency and reduces $NO_x$ emissions. However, unresolved issues remain in adapting the optimization to real-time dynamic changes and varying load conditions. The reason for this may be challenges in modeling dynamic combustion behavior and the computational cost of real-time optimization. A way to overcome these difficulties can be through faster hybrid predictive and adaptive optimization frameworks. This approach was developed in [16], however, it focused on offline validation without fully addressing dynamic scalability. All this suggests that it is advisable to conduct a study on real-time dynamic optimization to sustain power plant performance under variable operating conditions.

The paper [17] presents research on optimizing thermal efficiency in a 660 MW supercritical coal-fired power plant using ANN and LSSVM models. It is shown that these models can predict performance based on operational variations under single-fuel coal conditions. However, unresolved issues remain regarding their adaptability to fuel composition changes such as biomass co-firing and dynamic temporal behavior. The reason for this may be the models' static nature and training based only on coal combustion data. A way to overcome these difficulties can be through the use of recurrent neural networks for dynamic prediction under co-firing scenarios. This approach was not explored in [17], where static models were applied. All this suggests that it is advisable to conduct a study on RNN-based dynamic optimization frameworks for supercritical plants operating under co-firing conditions.

This research proposes a dynamic optimization approach using real-time operational data from a 660 MW supercritical coal-fired power plant to address the performance challenges introduced by biomass co-firing. Although machine learning-based optimization has improved combustion processes, applications specifically targeting the variability and instability caused by biomass co-firing remain limited. Literature reviews reveal that existing models, developed mainly for coal-only operations, lack the adaptability needed for real-time dynamic changes in fuel properties. This gap is critical, as biomass co-firing affects combustion stability, thermal efficiency, and emissions, requiring fast and responsive control strategies. Current static or steady-state models are inadequate to maintain optimal performance under these conditions. Therefore, this study proposes a dynamic multi-objective optimization framework using a Multi-Objective Genetic Algorithm (MOGA), Response Surface Methodology (RSM), and Recurrent Neural Networks (RNN) to dynamically predict and optimize combustion parameters. The study is expected to fill the research gap by improving efficiency, reducing $NO_x$ emissions, and enhancing operational adaptability during biomass co-firing in supercritical boilers.

## 3. The aim and objectives of the study

The aim of this study is to develop a comprehensive optimization approach for improving boiler combustion performance in a 660-MW coal-fired power plant using real-time operational data. This approach integrates predictive modeling through response surface methodology and recurrent neural network, followed by multi-objective optimization using the genetic algorithm, and final decision analysis using the TOPSIS method. The proposed framework aims to increase boiler efficiency, reduce $CO_2$ emissions, and enhance the capability factor, thereby supporting cleaner and more sustainable power generation in line with Indonesia's Net Zero Emissions 2060 target.

To achieve this aim, the following objectives are achieved:

– to evaluate the relationship between operational factors and response using statistical analysis and modeling to confirm their effectiveness as predictors and ensure scientific validity;

– to optimize multiple objectives using the multi-objective genetic algorithm;

– to identify the implications of the optimal scenario based on the decision-making method of order preference technique-based on the similarity to the ideal solution for boiler operation parameters.

## 4. Materials and methods

### 4. 1. Object and hypothesis of the study

This study examines the supercritical boiler combustion system at a 660 MW coal-fired power station in Indonesia as a paradigm for the energy transition toward net zero emissions by 2060. The combustion performance was assessed based on the boiler efficiency, $CO_2$ emissions, and capacity factor using actual operational data. A significant relationship between operational parameters and combustion performance is hypothesized. The recurrent neural network predictive model addresses nonlinear and temporal interactions and is compared with traditional methods like response surface methodology. Optimization is conducted with a multi-objective genetic algorithm to identify the most efficient, low-emission, and stable operational situations. It is possible to assess the optimization outcomes utilizing the order preference method, which determines the solution nearest to the optimal condition. The suggested approach promotes a data-driven, reliable, and environmentally sustainable strategy for optimizing boiler combustion.

### 4. 2. Data collection

The data gathering for this study was based on the operational parameters of a supercritical 660-MW coal-fired power plant. The data were acquired from the distributed control system records concerning the operating parameters, performance test outcomes for evaluation, and emission data from the continuous emission monitoring system. Data gathering occurred from January to December 2021, before the tuning of boiler combustion. The dataset (Table 1) used in this investigation has 223 data points for each observed parameter. The primary input parameters consisted of four factors: load, total coal flow, total air flow, and coal heating value. The examined response factors include the boiler efficiency, carbon dioxide ($CO_2$) flue gas emissions, and capability factor.

This study employed many instrumentation and control systems to acquire dependable operating data from a supercritical 660-MW coal-fired power plant.

Fig. 1 illustrates the data collection process implemented in this study.

Table 1

Parameter data set boiler optimization

| Parameter | Unit | Category | Min | Max | Average |
|---|---|---|---|---|---|
| Load | MW | Factor (X3) | 321.61 | 648.69 | 589.18 |
| Total coal flow | Ton/h | Factor (X1) | 206.75 | 412.99 | 362.75 |
| Total air flow | Ton/h | Factor (X2) | 1881.87 | 3058.07 | 2701.11 |
| Kalori Batubara | Kcal/kg | Factor (X4) | 3261 | 4908 | 4154.55 |
| Boiler efficiency | % | Response (Y1) | 79.4946 | 86.6793 | 84.81628 |
| $CO_2$ | mg/Nm$^3$ | Response (Y2) | 54.3384 | 130.224 | 109.1646 |
| Capability factor | % | Response (Y3) | 62.89 | 87.9 | 81.19 |

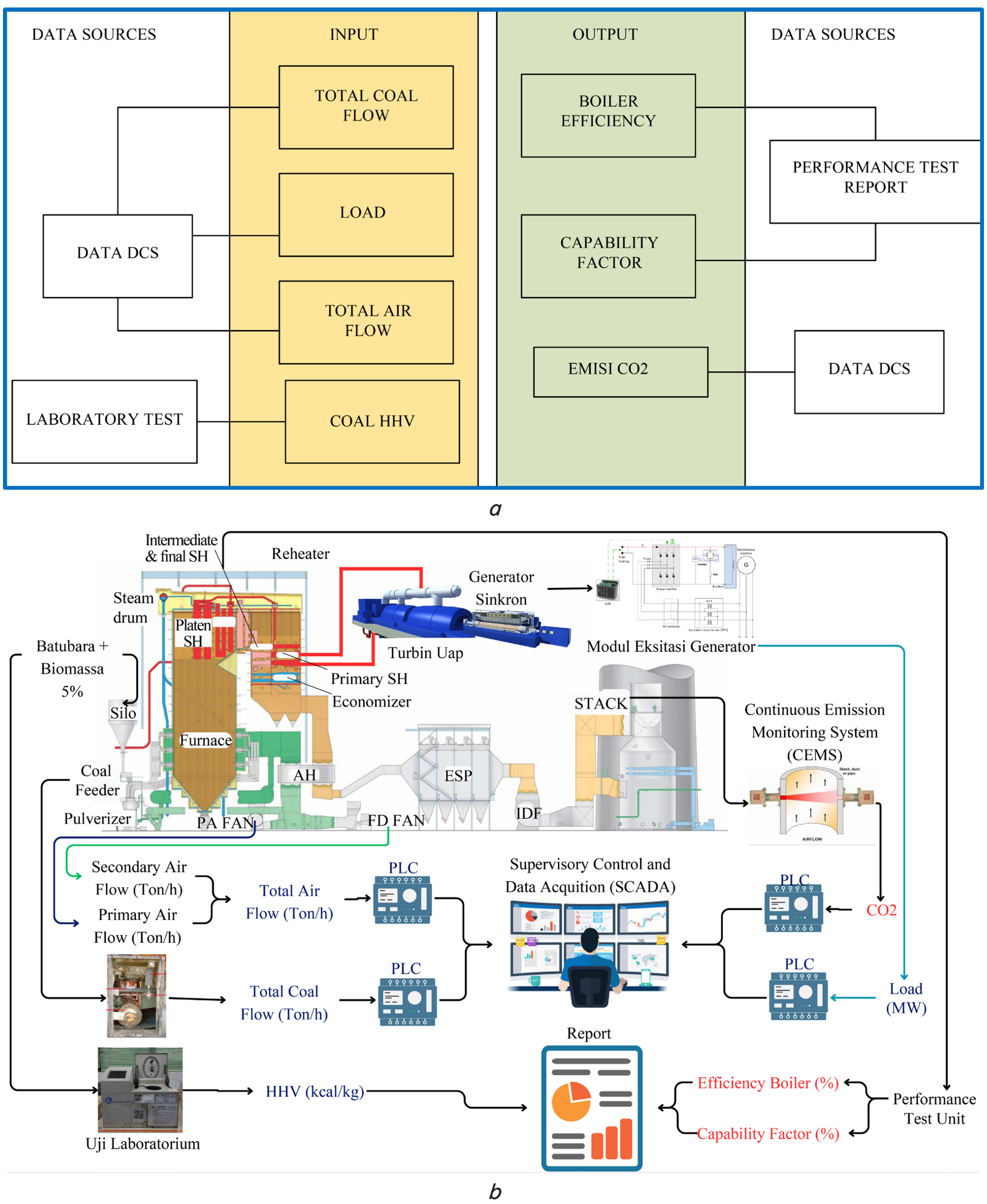



Fig. 1. Variable structure and instrumentation scheme:
*a* – input & output data flow and sources; *b* – data acquisition process flow in a 660-MW coal-fired power plant

The operational parameters were measured using various accurate instruments. The coal flow was measured using a gravimetric feeder or belt weighing system connected to the DCS, providing real-time mass flow data (tons/hour). The generator load is measured through a Power Meter with CT and PT sensors. The total air flow was measured using a Venturi flow meter based on the pressure difference. The higher heating value of coal was determined using a bomb calorimeter (kcal/kg). The boiler efficiency was determined utilizing the heat loss method, which considered the flue gas temperature, fuel flow, and oxygen concentration, as measured by a thermocouple and an oxygen analyzer. The ratio of real energy to the unit's maximal capacity determines the capability factor. A non-dispersive infrared gas analyzer quantifies $CO_2$ emissions and presents them in mg/nm as a metric of combustion efficiency and environmental effect.

### 4. 3. Predictive modeling

#### 4. 3. 1. Response surface methodology

Response surface methodology is a statistical and mathematical technique employed to model, analyze, and enhance the relationship between dependent response variables and many independent input factors. Response surface methodology, introduced by Box and Wilson in 1951, has been extensively utilized in engineering, biotechnology, and industry for optimization [18]. The objective of RSM is to determine combinations of input factors that maximize response variables [19].

Mathematically, the relationship between input variables $X_1$, $X_2$, $X_k$ and the response variable $Y$ is expressed as follows

$$Y = f\left(X_1, X_2, \ldots, X_k\right) + \epsilon, \tag{1}$$

where $f(X)$ describes the relationship and $\epsilon$ represents the residual error. This relationship is typically modeled using polynomial approximations: linear (first order) or quadratic (second order) [20].

*First order polynomial model.* This model assesses the main effects of input variables without considering interactions or quadratic effects [21]

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \epsilon, \tag{2}$$

where $\beta_0$ is the intercept and $\beta_i$ are regression coefficients.

*Second order polynomial model (quadratic).* Used for capturing non-linear relationships, this model includes quadratic effects and interactions [19]

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ij} X_i^2 + \sum_{i<1}^{k-1} \beta_{ij} X_i X_j + \varepsilon_{er}. \tag{3}$$

The RSM is crucial for processes affected by multiple variables, and analysis of variance helps determine the influence of these variables on the response. Tools like Design-Expert 13 assist in developing regression equations and analyzing causal relationships. The model's quality was evaluated using statistical parameters such as the p-value and adjusted $R^2$ [22, 23].

#### 4. 3. 2. Recurrent neural network modeling

In this study, the recurrent neural network model was built using MATLAB R2015a software with a Multilayer Perceptron (MLP) configuration. MLP is a feedforward network configuration consisting of three layers: an input layer, a hidden layer, and an output layer. The proposed model is effective in handling problems involving nonlinear relationships between inputs and outputs [24, 25]. Recurrent neural networks are a type of artificial neural network specifically designed for sequential or time-series data. Unlike feedforward networks that treat inputs as independent, RNNs incorporate an internal memory mechanism by reintegrating the hidden state from the previous time step into the network. This architecture enables recurrent neural networks to identify temporal relationships and patterns in dynamic data sequences. This study developed a recurrent neural network model employing the Bayesian regularization technique, as illustrated in Fig. 2, which includes four input variables. The network architecture had 10 hidden neurons, a time delay of 2, and three output variables.

Fig. 2 demonstrates that the recurrent neural network architecture differs from static artificial neural network models by including feedback from the hidden layer within the network. This feedback mechanism enables the model to include temporal correlations, enhancing its learning process and facilitating the discovery of complex and dynamic patterns in the data more efficiently.

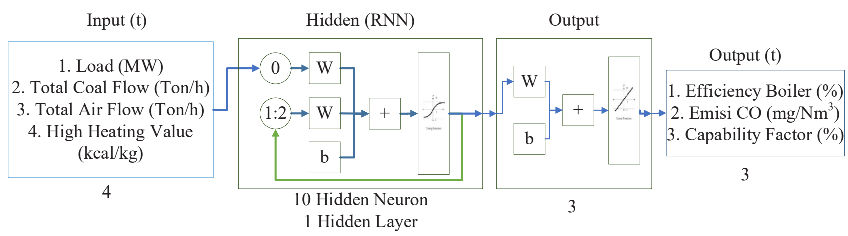



Fig. 2. Recurrent neural network

### 4. 4. Optimization method

#### 4. 4. 1. Multi-objective genetic algorithm

The Multi-objective genetic algorithm is a genetic algorithm is used to optimize several objectives simultaneously by considering the trade-off between objectives that are often conflicting. Multi-objective genetic algorithm classifies solutions in the Pareto front using the concept of Pareto dominance, where solution $X_1$ is dominant to $X_2$ if:

$$f_i\left(x_1\right) \leq f_i\left(x_1\right), \tag{4}$$

$$\forall_i \in \{1,2,\ldots,m\} \text{ and } \exists_i \in \{1,2,\ldots,m\}$$
$$\text{such that } f_i\left(x_1\right) < f_i\left(x_2\right). \tag{5}$$

Pareto-optimal solutions, which are indisputable in their superiority, jointly form the Pareto front. The multi-objective genetic algorithm uses selection, crossover, and mutation processes to produce numerous optimal solutions while maintaining solution diversity within the Pareto front. The principal advantage of the multi-objective genetic algorithm is its ability to produce Pareto-optimal solutions while comprehensively examining the solution space. This method presents problems such as elevated computational costs and the risk of convergence on poor solutions, which may hinder the attainment of the ideal solution.

#### 4. 4. 2. Technique for order preference based on similarity to ideal solution

The technique for order preference by similarity to ideal option is a multi-criteria decision-making approach that identifies the optimal option by evaluating its closeness to the ideal solution and its remoteness from the least favorable answer. This method effectively addresses trade-offs between conflicting objectives, such as enhancing boiler efficiency while minimizing CO emissions. In multi-objective optimization, TOPSIS ranks Pareto-optimal solutions and selects the most balanced alternatives according to performance weights. The computational efficiency and capacity to incorporate decision-makers' preferences render it appropriate for optimization in engineering, industry, and power plants.

**4. 5. Flow chart of research**

The study methodology is organized and illustrated in a flowchart (Fig. 3) to enhance the combustion performance of the 660-MW coal-fired power plant boiler. The process starts with problem identification and goal development, which is followed by literature evaluation serving as the theoretical foundation. Operational data are collected, processed, and standardized to guarantee uniformity. The statistical significance of the input variables relative to the output is evaluated; if deemed insignificant, the data undergoes reprocessing. The modeling phase employs two methodologies: response surface methodology (model A) and recurrent neural network (model B).

Subsequently, the refined findings are integrated into a multi-objective optimization framework employing the multi-objective genetic algorithm, which iteratively evaluates the efficacy of the solutions via selection, crossover, and mutation until a stable result is achieved. The final results are examined, and the best way to operate is found using the TOPSIS method, which helps make accurate predictions, better decisions, and increases boiler combustion efficiency in a coal-fired power plant.

## 5. Comprehensive results of predictive modeling and multi-objective optimization for boiler performance enhancement

**5. 1. Result of statistical analysis and predictive modeling of operational parameters**

**5. 1. 1. Statistical analysis results**

The relationship between operational factors and the responses was evaluated using statistical analysis and predictive modeling. The statistical performance indicators, including the coefficient of determination ($R^2$) for boiler efficiency, $CO_2$ emissions, and capability factor, are summarized in Table 2.

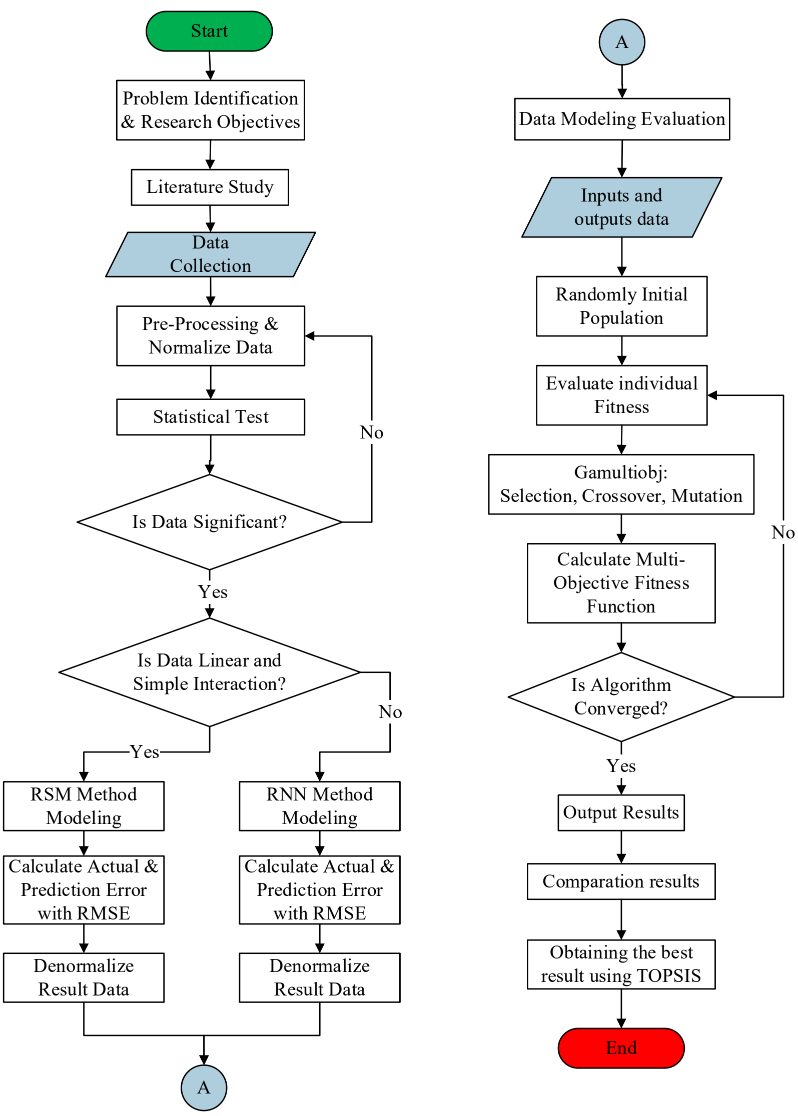



Fig. 3. Flow chart of research

Table 2

Coefficient of determination ($R^2$)

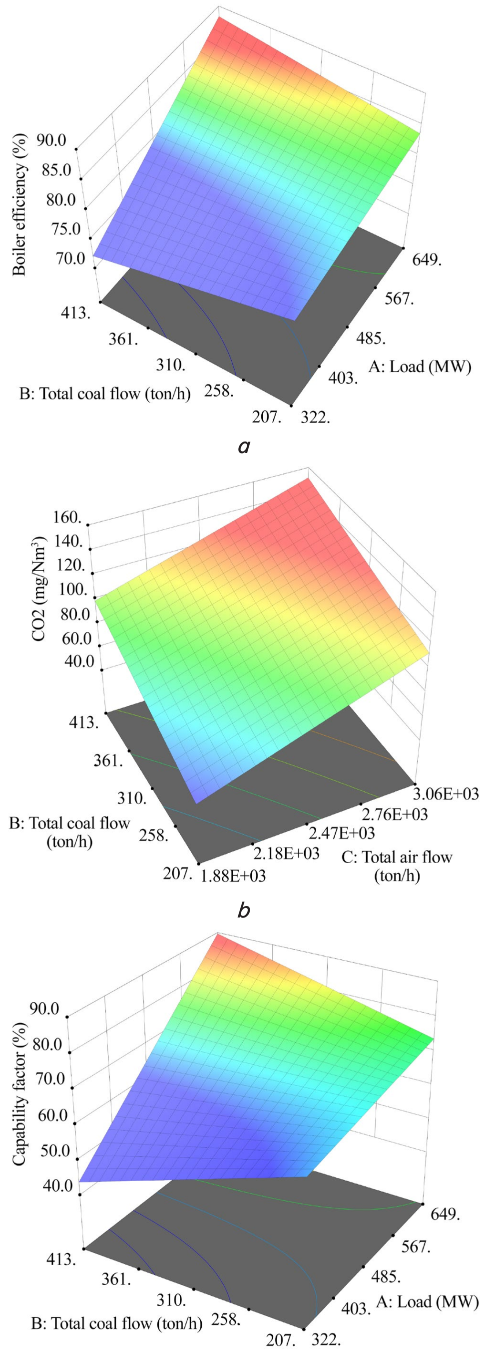
| FIT STATISTIC | Boiler efficiency (%) | $CO_2$ (mg/Nm$^3$) | Capability factor (%) |
|---|---|---|---|
| Std. Dev. | 0.147 | 7.110 | 0.7446 |
| Mean | 84.820 | 109.160 | 81.19 |
| C.V. % | 0.174 | 6.510 | 0.9171 |
| $R^2$ | 0.995 | 0.763 | 0.9897 |
| Adjusted $R^2$ | 0.995 | 0.752 | 0.9892 |
| Predicted $R^2$ | 0.994 | 0.734 | 0.9801 |
| Adeq recision | 219.635 | 42.032 | 193.6796 |

Table 2 demonstrates elevated model accuracy for boiler efficiency ($R^2 = 0.995$) and capability factor ($R^2 = 0.9897$), alongside a moderate but acceptable value for $CO_2$ emissions ($R^2 = 0.763$). The adequate precision values for all responses exceed typical thresholds, demonstrating appropriate model consistency for design exploration and subsequent optimization.

**5. 1. 2. Response surface method modelling results**

The correlation between input factors and responses is illustrated through the 3D contour plots presented in Fig. 4, which visualize how variations in operational parameters affect each output. These plots provide insights into the interaction effects between variables on boiler efficiency, $CO_2$ emissions, and capability factor.

The correlation between input factors and replies is delineated by mathematical equations derived from the statistical analysis results presented in Table 2, executed using Design Expert software. This regression model quantitatively delineates the impact of each operational parameter on the output, thus establishing a dependable foundation for future optimization and predictive processes.




*a* *b* *c*

Fig. 4. 3D contour response surface of: *a* – boiler efficiency; *b* – $CO_2$; *c* – capability factor

The resulting mathematical formulas are presented in equation (6) for boiler efficiency, equation (7) for $CO_2$ emissions, and equation (8) for the capability factor:

$$\begin{aligned}\mathbf{Y_1} = {} & (92.10719)+(0.037781*X_1)+\\ & +(0.070137*X_2)+(-0.029456*X_3)+\\ & +(-0.000803*X_4)+(0.00018*X_1*X_2)+\\ & +(6.14\text{E-}06*X_1*X_3)+(-01.9\text{E-}05*X_1*X_4)+\\ & +(-2.3\text{E-}05*X_2*X_3)+(-2.6\text{E-}05*X_2*X_4)+\\ & +(7.84\text{E-}06*X_3*X_4),\end{aligned} \tag{6}$$

$$\begin{aligned}\mathbf{Y_2} = {} & (-469.49001)+(0.8148*\mathrm{X}_1)+\\ & +(-4.83907*\mathrm{X}_2)+(0.762455*\mathrm{X}_3)+\\ & +(0.070422*\mathrm{X}_4)+(-0.000416*\mathrm{X}_1*\mathrm{X}_2)+\\ & +(-0.000056*\mathrm{X}_1*\mathrm{X}_3)+(-0.000159*\mathrm{X}_1*\mathrm{X}_4)+\\ & +(-0.000033*\mathrm{X}_2*\mathrm{X}_3)+\\ & +(0.001305*\mathrm{X}_2*\mathrm{X}_4)+(-0.000166*\mathrm{X}_3*\mathrm{X}_4),\end{aligned} \tag{7}$$

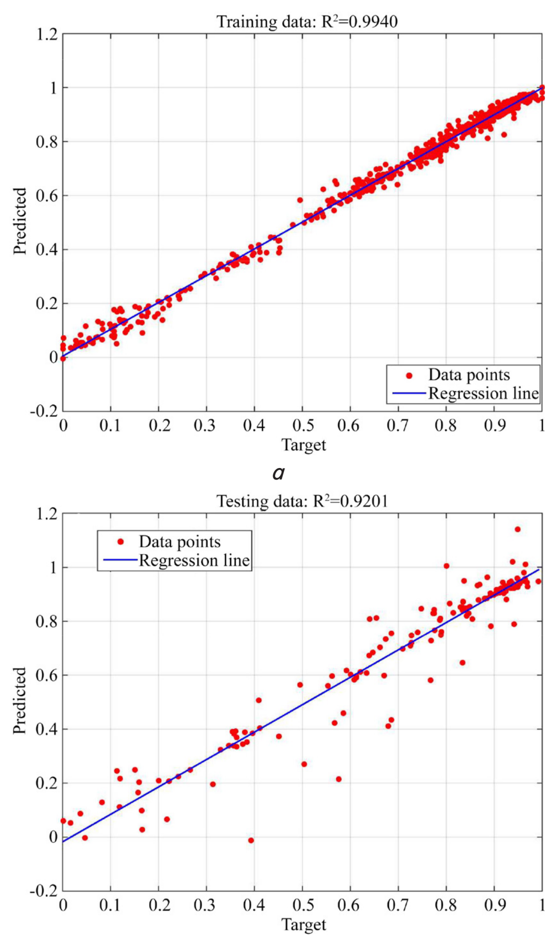
$$\begin{aligned}\mathbf{Y_3} = {} & (50.46732)+(-0.181766*\mathrm{X}_1)+\\ & +(0.07451*\mathrm{X}_2)+(-0.000635*\mathrm{X}_3)+\\ & +(0.013393*\mathrm{X}_4)+(0.000564*\mathrm{X}_1*\mathrm{X}_2)+\\ & +(0.000109*\mathrm{X1}*\mathrm{X3})+(-0.000044*\mathrm{X1}*\mathrm{X4})+\\ & +(-0.000191*\mathrm{X}_2*\mathrm{X}_3)+(2.6\text{E-}05*\mathrm{X}_2*\mathrm{X}_4)+\\ & +(1.44\text{E-}06*\mathrm{X}_3*\mathrm{X}_4),\end{aligned} \tag{8}$$

where $X_1$ – load; $X_2$ – total coal flow; $X_3$ – total air flow; $X_4$ – HHV; $Y_1$ – boiler efficiency; $Y_2$ – $CO_2$; $Y_3$ – capability factor.

Equations (6)–(8) define the quantitative relationship between the operational input variables and the three response parameters: boiler efficiency, $CO_2$ emissions, and capability factor. The inclusion of multiple interaction terms indicates the presence of nonlinear and combined effects among variables. These regression models enable the prediction of system performance across a wide range of operating conditions and are used as the basis for multi-objective optimization in the following section.

**5. 1. 3. Recurrent neural network modeling results**

The regression plots in Fig. 5 show how the predicted values compare to the actual values for both the training and testing datasets using the recurrent neural network model.




*a* *b*

Fig. 5. Regression plots of: *a* – training data; *b* – testing data

Fig. 5 displays the regression plots for the RNN model, illustrating the relationship between the predicted and target values. Subfigure *a* shows the regression for the training dataset with a coefficient of determination ($R^2$) of 0.9940, while subfigure *b* presents the regression for the testing dataset with an $R^2$ of 0.9201.

**5. 2. Result of multi-objective optimization using genetic algorithm**

Multi-objective genetic algorithm optimization was conducted to maximize boiler efficiency and capability factor while minimizing $CO_2$ emissions. The comparison of optimization outcomes between the RSM-based model (Model A) and the RNN-based model (Model B) is illustrated.

The optimization results obtained from the multi-objective genetic algorithm (MOGA) using Model A (RSM) and Model B (RNN) for boiler efficiency, $CO_2$ emissions, and capability factor are summarized in Table 3.

Both models generated feasible optimization ranges, with Model B (RNN) exhibiting enhanced prediction accuracy seen by consistently reduced RMSE values. These results offer a quantitative foundation for choosing the ideal operational situation in the following section.

**5. 3. Implications of optimal boiler performance scenario using TOPSIS decision**

The optimization results based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method are presented in Table 4.

Model B (RNN) was selected as the optimal solution by the TOPSIS method, as it outperformed Model A in all three criteria: higher efficiency, lower emissions, and greater operational capability.

The operational parameter optimization results obtained using MOGA and TOPSIS methodologies are shown in Table 5.

The TOPSIS approach determined the most effective operating state utilizing Model B (RNN), which attained better boiler efficiency and capability factor, alongside markedly reduced $CO_2$ emissions relative to the current condition. These parameters delineate the chosen scenario for implementation.

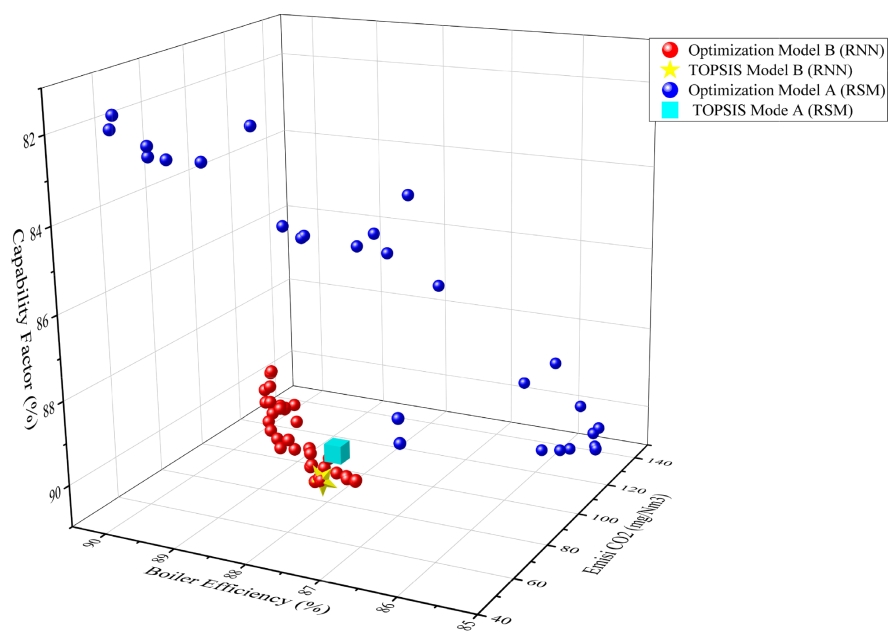



Fig. 6. Comparison results of multi-objective genetic algorithm optimization with Model A (RSM) and Model B (RNN)

Table 3

Optimization results of MOGA Model A (RSM) and Model B (RNN)

| RESULT | Model A (RSM) | | | Model B (RNN) | | |
|---|---|---|---|---|---|---|
| | Boiler efficiency (%) | $CO_2$ (mg/Nm$^3$) | Capability factor (%) | Boiler efficiency (%) | $CO_2$ (mg/Nm$^3$) | Capability factor (%) |
| Min | 85.43 | 50.00 | 81.67 | 87.03 | 53.97 | 87.54 |
| Max | 90.00 | 140.04 | 90.89 | 88.60 | 77.49 | 89.51 |
| Average | 87.64 | 88.87 | 86.34 | 87.95 | 65.11 | 88.85 |
| RMSE (%) | 0.703 | 6.357 | 1.091 | 0.152 | 1.699 | 0.528 |

Table 4

Results of technique for ordering preference by similarity to ideal solution

| Method | Boiler efficiency (%) | CO (mg/Nm$^3$) | Capability factor (%) |
|---|---|---|---|
| Model A (RSM) | 87.005 | 59.999 | 88.420 |
| Model B (RNN) | 87.323 | 53.972 | 89.320 |

Table 5

Parameters of the optimization results with TOPSIS (Model B)

| Condition | Load (MW) | Coal flow (Ton/h) | Total air flow (Ton/h) | HHV (Kcal/Kg) | Boiler efficiency (%) | $CO_2$ (mg/Nm$^3$) | Capability factor (%) |
|---|---|---|---|---|---|---|---|
| Existing | 648.69 | 380.989 | 2805.04 | 4151 | 86.6793 | 114.213 | 87.9 |
| | 646.25 | 399.299 | 2930.87 | 3999 | 86.4307 | 122.947 | 87.57 |
| Optimization results | 647.637 | 329.465 | 2704.757 | 4132.716 | 87.323 | 53.972 | 89.320 |

## 6. Discussion of the results of multi-objective optimization of boiler efficiency, $CO_2$ emissions, and capability factor using recurrent neural network

Statistical analysis and predictive modeling indicate that load, total coal flow, and calorific value are the main factors affecting boiler efficiency, $CO_2$ emissions, and capability factor. Regression analysis (6)–(8) and coefficient of determination (Table 2) show that load strongly influences boiler efficiency and capability factor, while total coal flow and total air flow predominantly affect $CO_2$ emissions. Although the RSM model performed satisfactorily, the RNN model (Model B) significantly outperformed Model A, achieving lower RMSE values of 0.1523% for boiler efficiency, 1.6993% for $CO_2$ emissions, and 0.5284% for capability factor (Table 3). Fig. 4 presents 3D contour plots where boiler efficiency (Fig. 4, *a*) increases with higher load and optimal coal flow, $CO_2$ emissions (Fig. 4, *b*) decrease with a balanced air-to-fuel ratio, and capability factor (Fig. 4, *c*) rises with increased load, indicating the need for precise operational control.

Fig. 5 shows the regression plots where the RNN model achieved excellent fitting for both training ($R^2 = 0.9940$, Fig. 5, *a*) and testing datasets ($R^2 = 0.9201$, Fig. 5, *b*), validating its predictive robustness. Fig. 6 depicts the 3D correlation among boiler efficiency, $CO_2$ emissions, and capability factor, where Model B (red points) exhibits tighter clustering and superior optimization compared to Model A (blue points), with ideal points identified by TOPSIS using a yellow star and cyan cube, respectively. Table 3 confirms that Model B consistently achieved lower RMSE across all outputs, while Table 4 shows that Model B optimized results with a boiler efficiency of 87.323%, $CO_2$ emissions of 53.972 mg/nm$^3$, and a capability factor of 89.32%, outperforming Model A. The final optimization using TOPSIS (Table 5) enhanced boiler efficiency, reduced $CO_2$ emissions, and improved capability factor, while reducing coal consumption by 51.5 to 69.8 tons per hour. This improvement results in daily savings of IDR 643 million to IDR 1.34 billion and supports Indonesia's Net Zero Emissions 2060 commitment. Overall, the integrated multi-objective optimization framework utilizing the RNN approach demonstrates superior technical, environmental, and economic advantages over the RSM method for supercritical coal-fired power plant operations.

While previous studies have advanced combustion optimization and emission reduction, the present study introduces significant improvements. Unlike the research on [11], where the focus was on the physical and chemical characteristics of biomass ash affecting boiler operations without proposing dynamic predictive models, this study develops a real-time predictive and optimization framework using recurrent neural networks and multi-objective genetic algorithm. In contrast to [12], who optimized biomass supply logistics but did not model dynamic operational variability at the boiler level, this study addresses operational instability caused by biomass co-firing through adaptive dynamic modeling. Unlike [5], where the impact of coal blending and biomass co-firing was evaluated under steady-state assumptions, this research integrates real-time dynamic data to optimize combustion across fluctuating loads. Compared to [13], which combined biomass co-firing with carbon capture but only analyzed steady-state performance impacts, this study enables operational flexibility through multi-objective optimization and decision analysis using the TOPSIS method. Additionally, unlike [14], where challenges in co-firing were highlighted but real-time optimization strategies were not explored, the proposed RNN-MOGA-TOPSIS framework dynamically adjusts operational parameters, achieving superior predictive accuracy (Table 3) and robust performance improvements (Fig. 5, 6), while contributing to Indonesia's Net Zero Emissions 2060 initiative. This study effectively addresses the research gaps, specifically the lack of dynamic, multi-objective optimization frameworks that can adapt to operational unpredictability in supercritical coal-fired boilers. This study integrates a recurrent neural network model (Model B) trained on real plant data with a multi-objective genetic algorithm and a decision-making process utilizing TOPSIS, therefore addressing the shortcomings of prior static and single-objective methodologies. The RNN model (Model B) provides considerable benefits compared to conventional regression or static machine learning models by effectively capturing intricate nonlinear and temporal relationships among operational parameters, resulting in markedly reduced RMSE values across all performance metrics (Table 3) and exhibiting enhanced generalization capability (Fig. 5). In contrast to previous studies that mostly focused on predictions under steady-state conditions or restricted aims, the dynamic characteristics of RNN facilitate real-time predictions amid varying load, fuel quality, and airflow conditions, hence improving practical applicability. The implementation of the TOPSIS for the selection of the final scenario signifies a methodological enhancement not employed in prior comparable studies. TOPSIS methodically assesses and ranks optimization outcomes according to their closeness to the optimal solution, so ensuring that the chosen operational circumstances attain the most favorable equilibrium among all objectives. The efficacy of this integrated framework is substantiated by the enhanced optimized performance demonstrated in Table 4 and the close clustering of optimal solutions illustrated in Fig. 6, leading to increased boiler efficiency, reduced $CO_2$ emissions, and an augmented capability factor relative to Model A. Furthermore, the enhanced operation results in significant coal conservation and emission reductions, closely matching with the strategic objectives of sustainable energy production and bolstering Indonesia's commitment to achieving Net Zero Emissions by 2060. The work effectively addresses the existing scientific gap by offering a flexible, dynamic, and comprehensive multi-objective optimization approach that was previously absent in combustion performance research.

This suggested research demonstrates notable advancements in maximizing boiler efficiency, $CO_2$ emissions, and capability variables. However, some limits must be recognized to accurately delineate its scope of use. This investigation was conducted on a 660 MW steam power plant. Secondly, operational data were gathered under optimal and standard operating conditions over the course of one year. Consequently, this model may not adequately account for fluctuations during transient operations, including start-up, shutdown, or emergency scenarios. The dataset indicates co-firing situations with a sawdust biomass blend of 5–10%, and an increased biomass proportion or alternative biomass types may contribute further combustion variability not accounted for by the existing model. This method assumes that all equipment works normally and does not consider issues like wear and tear or breakdowns, which could affect the model's predictions and optimization outcomes. Identifying these limits is essential to inform the practical implementation of this paradigm and to underscore areas for future study aimed at improving resilience in varied and demanding operational environments.

Despite the encouraging outcomes, several limitations must be acknowledged. Although the RNN model demonstrated good accuracy, its performance may decline under conditions far outside the training range, such as biomass co-firing levels above 10% or unstable load variations. The multi-objective genetic algorithm also demands substantial computational resources, limiting its real-time applicability unless further optimized. The model's reliance on continuous, accurate operational data makes it sensitive to sensor errors and missing data. Additionally, the study did not account for combustion kinetics or secondary pollutant formation ($NO_x$, $SO_x$), which could affect environmental assessments. Therefore, while the framework performs well under ideal conditions, caution is necessary for deployment in dynamic real-world settings. Future research should expand operational data to cover transient conditions, adopt advanced architectures like LSTM or GRU to improve temporal learning, and pursue real-time deployment in distributed control systems. Hybrid models integrating physics-based approaches could enhance resilience, while including additional emissions objectives would provide a more comprehensive sustainability evaluation, crucial for supporting the transition toward carbon-neutral power generation.

## 7. Conclusions

1. Statistical Analysis and Modeling: A robust association exists between operational variables and boiler performance, evidenced by high $R^2$ values for efficiency (0.995) and capability factor (0.9897). Despite the variability in $CO_2$ emission projections ($R^2 = 0.763$), the model retains its reliability. The proposed RNN outperforms RSM in terms of its ability to capture nonlinear and dynamic patterns.

2. Multi-Objective Optimization (MOGA): The RNN+MOGA model attained optimal performance, exhibiting a boiler efficiency of 87.95%, minimal $CO_2$ emissions of 65.11 mg/nm$^3$, and a peak capability factor of 88.85%. The RNN demonstrated superior accuracy and reliability in the pursuit of optimal solutions relative to RSM.

3. Assessment of the Optimal Scenario: The optimal outcome from the RNN achieved an efficiency of 87.32%, reduces $CO_2$ emissions to 53.97 mg/nm$^3$, and enhanced the capability factor to 89.32%. Coal use declined to 51,524 tons per hour, potentially reducing operational expenses by much to IDR 1.34 billion per day. The proposed method has demonstrated enhancements in technical performance, environmental sustainability, and economic efficiency improvement.

## Conflict of interest

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

Data cannot be made available for reasons disclosed in the data availability statement.

## Use of artificial intelligence

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


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