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ENHANCING BOILER EFFICIENCY USING AN AI-BASED FLUE GAS MONITORING AND COMBUSTION CONTROL SYSTEM

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Statement of Novelty

This study presents a novel AI-based combustion optimization system that integrates real-time flue gas monitoring with ANN-based closed-loop control of fuel and air supply in an industrial boiler. Unlike conventional PID systems, the proposed system dynamically optimizes the air–fuel ratio under varying operating conditions. The real-time industrial implementation achieved significant efficiency improvement and fuel savings.

Statement of Industrial Relevance

The proposed AI-based system provides a practical solution for improving industrial boiler efficiency, reducing fuel consumption, and lowering emissions. It can be implemented in existing boilers without major hardware changes. This technology offers significant economic savings and supports sustainable and energy-efficient industrial operations.

ABSTRACT

Environmental sustainability in industrial operations depends heavily on improving energy efficiency and reducing emissions, particularly in steam generation systems where boilers consume significant fuel and produce greenhouse gases. Conventional combustion control systems use fixed excess air settings and PID-based adjustments, which cannot adapt effectively to changing operating conditions. This leads to excess air supply, higher heat loss, inefficient fuel utilization, increased emissions, and reduced boiler efficiency. Existing flue gas monitoring systems are mainly used for manual supervision rather than real-time optimization. To address this, an Artificial Intelligence (AI)-based combustion optimization system using real-time flue gas monitoring and an Artificial Neural Network (ANN) model was developed to automatically regulate fuel and air supply. The system analyzes oxygen concentration, carbon monoxide concentration, flue gas temperature, and operating parameters to optimize the air–fuel ratio. Implemented on a 10 TPH industrial boiler, the system reduced oxygen levels from 8% to 3%, flue gas temperature from 240°C to 190°C, and fuel consumption by 10%, while maintaining constant steam output. Boiler efficiency improved from 82% to 90%, demonstrating that AI-based combustion control significantly enhances efficiency, reduces fuel consumption and emissions, and supports sustainable industrial energy management.

KEYWORDS: Artificial Intelligence, Boiler Efficiency, Combustion Optimization, Flue Gas Monitoring, Artificial Neural Network, Industrial Boiler, Air–Fuel Ratio Control, Energy Efficiency, Fuel Consumption Reduction, Sustainable Energy Systems.

1. INTRODUCTION

Boilers are essential components in industrial and power generation systems, where they are used to produce steam for process heating, power generation, and various manufacturing applications. The efficiency of a boiler plays a critical role in determining overall energy consumption, operational cost, and environmental impact. In industrial sectors such as chemical processing, food manufacturing, textiles, and thermal power plants, boilers account for a significant portion of total energy consumption. Even a small improvement in boiler efficiency can result in substantial fuel savings, reduced emissions, and improved operational reliability.

Boiler efficiency largely depends on the effectiveness of the combustion process, which is controlled by maintaining an optimal air-fuel ratio. Proper combustion ensures complete fuel utilization while minimizing heat loss through flue gases. However, conventional boiler control systems typically rely on manual adjustments or fixed proportional–integral–derivative (PID) control strategies that operate based on predefined setpoints. These traditional control methods are unable to adapt effectively to dynamic operating conditions such as variations in steam demand, fuel quality, and ambient environmental conditions. As a result, boilers often operate with excess air supply to ensure safe combustion, which increases flue gas heat loss and reduces overall thermal efficiency. This leads to increased fuel consumption, higher operational costs, and greater environmental emissions.

Flue gas parameters such as oxygen concentration, carbon monoxide concentration, and flue gas temperature provide critical information about combustion quality and efficiency. Excess oxygen indicates excessive air supply, while the presence of carbon monoxide indicates incomplete combustion. High flue gas temperature represents significant heat loss through exhaust gases. Continuous monitoring and control of these parameters are essential for optimizing combustion efficiency. However, in most industrial boilers, flue gas monitoring is primarily used for manual supervision rather than automated real-time optimization.

Recent advancements in Artificial Intelligence (AI) and machine learning have provided new opportunities for improving boiler efficiency through intelligent combustion control. AI-based systems can analyze large amounts of real-time and historical operational data, identify complex nonlinear relationships between combustion parameters, and automatically determine optimal control actions. Artificial Neural Networks (ANN), in particular, have demonstrated strong capability in modeling combustion processes and optimizing air-fuel ratio under varying operating conditions. AI-based control systems can continuously monitor flue gas parameters and dynamically adjust fuel and air supply to maintain optimal combustion efficiency.

This study proposes an AI-based combustion optimization system for a 10 TPH industrial boiler using real-time flue gas monitoring and intelligent control of the fuel control valve and primary air blower inlet damper. The system utilizes flue gas oxygen concentration, carbon monoxide concentration, flue gas temperature, and operational parameters such as steam load, fuel flow rate, and air flow rate as inputs to an Artificial Neural Network model. The AI model continuously analyzes these parameters and generates optimal control signals to regulate fuel and air supply, ensuring efficient combustion under varying operating conditions.

The objective of this research is to improve boiler efficiency, reduce fuel consumption, and enhance combustion stability through real-time AI-based control. The performance of the proposed system is evaluated by comparing boiler performance before and after AI implementation in a 10 TPH industrial boiler. The results demonstrate the effectiveness of AI-based combustion optimization in improving boiler efficiency and reducing operational costs, highlighting its potential for widespread industrial application.

3. Literature Review

Industrial sustainability has become a major focus for modern industries seeking to improve energy efficiency, reduce greenhouse gas emissions, and comply with Environmental, Social, and Governance (ESG) principles. Recent studies have emphasized that environmental accountability, sustainable manufacturing, and responsible industrial operations are essential for achieving long-term competitiveness and environmental performance [1–3]. Industrial boilers play a crucial role in power generation, manufacturing, and process industries, accounting for a significant share of industrial energy consumption. Consequently, improving boiler efficiency has become an important strategy for reducing fuel consumption, minimizing emissions, and enhancing operational sustainability [4]. Boiler combustion efficiency is primarily influenced by factors such as the air–fuel ratio, excess air supply, fuel characteristics, and heat transfer performance [5–8]. Conventional combustion control systems generally employ proportional–integral–derivative (PID) controllers and fixed excess air settings, which have limited capability to respond to the nonlinear and dynamic behavior of combustion processes [9–12]. These limitations often result in excessive air supply, increased stack heat losses, incomplete combustion, and reduced overall thermal efficiency.

Excess air control is one of the most influential parameters affecting boiler performance. Although sufficient excess air is required to ensure complete combustion, excessive air decreases flame temperature and increases heat loss through flue gases, thereby lowering boiler efficiency [5,6]. Previous studies have demonstrated that deviations from the optimum air–fuel ratio significantly increase fuel consumption while reducing combustion efficiency and increasing pollutant emissions [12,13]. High oxygen concentrations in flue gases generally indicate excessive excess air, whereas elevated carbon monoxide levels reflect incomplete combustion and inefficient fuel utilization [7]. Continuous monitoring of oxygen concentration and flue gas temperature is therefore essential for maintaining efficient combustion and minimizing energy losses [14].

Traditional combustion control approaches rely heavily on predefined control logic and operator intervention, making them less effective under varying load conditions and changing fuel characteristics [15]. As industrial processes become increasingly dynamic, conventional control systems frequently operate under non-optimal combustion conditions, leading to higher fuel consumption and lower thermal efficiency [6]. These challenges have encouraged the development of intelligent control systems capable of adapting combustion parameters in real time.

Artificial Intelligence (AI) has emerged as an effective solution for combustion optimization because of its capability to model complex nonlinear relationships and continuously learn from operating data [16,17]. Artificial Neural Networks (ANNs) have proven particularly effective in modeling combustion processes by learning relationships among variables such as fuel flow rate, air flow rate, oxygen concentration, and combustion efficiency [16]. Several studies have demonstrated that ANN-based combustion optimization significantly improves boiler efficiency while simultaneously reducing emissions [18,19]. Furthermore, AI has been successfully applied in sustainable manufacturing to improve energy efficiency and reduce environmental impacts [20]. Neural network models provide accurate predictions of optimal combustion conditions and enable real-time optimization of industrial boiler operations [21,22].

Machine learning techniques have also gained considerable attention for combustion optimization in industrial boilers. These techniques analyze large volumes of operational data to identify optimal combustion conditions and improve system performance [23–26]. Machine learning algorithms dynamically regulate fuel and air supply according to changing operating conditions, resulting in higher combustion efficiency, lower fuel consumption, and reduced emissions [25]. Recent studies have reported substantial improvements in combustion efficiency through data-driven optimization techniques integrated with industrial monitoring systems [26].

Deep learning has further expanded the capabilities of combustion optimization by extracting highly complex relationships from combustion datasets. Deep neural networks can accurately predict combustion efficiency, heat losses, and emission characteristics using historical and real-time process data [27,28]. Advanced deep learning architectures have demonstrated superior predictive accuracy compared with conventional machine learning methods for combustion optimization [29]. These models continuously improve prediction accuracy through continuous learning from operational data, thereby enhancing long-term combustion performance and system reliability [30].

Reinforcement learning has recently emerged as another promising intelligent control technique for industrial combustion systems. Reinforcement learning algorithms learn optimal combustion control policies through continuous interaction with the combustion process without requiring explicit mathematical models [31]. These intelligent controllers automatically adjust fuel and air supply to maintain optimum combustion conditions under varying operating environments [32]. Data-driven combustion optimization techniques based on reinforcement learning have demonstrated improvements in combustion stability, fuel efficiency, and operational reliability [33].

Neural network-based combustion optimization has become one of the most widely investigated approaches for industrial boiler control. These models accurately predict combustion efficiency using operational variables such as oxygen concentration, flue gas temperature, fuel flow rate, and air flow rate while simultaneously estimating pollutant emissions including carbon monoxide and nitrogen oxides [21,34]. Combined with real-time flue gas monitoring and intelligent optimization algorithms, AI-driven combustion control systems provide continuous adjustment of combustion parameters, leading to significant improvements in boiler efficiency, reduced fuel consumption, lower emissions, and enhanced industrial sustainability [18,26,30].

3.1 Research Gap

Although significant research has been conducted on Artificial Intelligence (AI)-based combustion optimization, most industrial boilers, particularly medium-capacity units such as 10 TPH boilers, continue to operate using conventional control systems based on manual adjustment or fixed proportional–integral–derivative (PID) control logic. These traditional systems are unable to dynamically respond to real-time variations in operating conditions such as load fluctuations, fuel quality variations, and ambient environmental changes. As a result, boilers often operate with excessive air supply to ensure complete combustion, which leads to increased flue gas heat losses, reduced thermal efficiency, and higher fuel consumption. While flue gas analyzers are commonly used in industrial boilers to monitor oxygen levels, carbon monoxide concentration, and flue gas temperature, their use is generally limited to monitoring and manual supervision rather than autonomous optimization. Furthermore, most existing AI-based combustion optimization studies focus on simulation models or large-scale utility boilers, and there is limited practical implementation of AI systems that directly integrate real-time flue gas monitoring with intelligent control of fuel valves and primary air blower inlet dampers in medium-capacity industrial boilers. Therefore, there exists a clear gap in the development and practical implementation of an AI-based real-time combustion control system capable of continuously monitoring flue gas parameters and automatically adjusting combustion actuators to optimize boiler efficiency.

3.2. Objectives of the Study

The objective of this study is to develop and implement an AI-based combustion optimization system for a 10 TPH industrial boiler by utilizing real-time flue gas parameters such as oxygen concentration, carbon monoxide concentration, and flue gas temperature to intelligently control the fuel valve and primary air blower inlet damper. The proposed system aims to continuously analyze combustion conditions and automatically adjust the air-fuel ratio to achieve optimal combustion efficiency under varying operating conditions. This study also aims to evaluate the effectiveness of the AI-based control system by comparing boiler performance before and after implementation in terms of efficiency, fuel consumption, and flue gas heat loss. The ultimate goal is to demonstrate the practical feasibility and effectiveness of AI-driven combustion control in improving boiler efficiency, reducing fuel consumption, enhancing operational stability, and achieving efficiency improvement of up to 10% in a medium-capacity industrial boiler.

4. Research Methodology

This study adopts an experimental, data-driven, and real-time control approach to develop and implement an Artificial Intelligence (AI)-based combustion optimization system for a 10 TPH industrial boiler. The methodology integrates real-time flue gas monitoring, Artificial Neural Network (ANN)-based predictive modeling, and closed-loop actuator control to optimize combustion conditions and improve boiler efficiency.

4.1 System Architecture and Control Framework

The proposed AI-based combustion optimization system operates as a closed-loop intelligent control system. Real-time combustion and operational parameters are continuously measured using flue gas analyzers and process sensors installed at critical locations in the boiler system. These parameters include oxygen concentration, carbon monoxide concentration, flue gas temperature, steam load, fuel flow rate, and air flow rate.

The sensor data are transmitted to a data acquisition system and processed by an AI controller. The AI controller analyzes the input parameters using a trained Artificial Neural Network model and determines the optimal control actions required to maintain efficient combustion. Control signals generated by the AI controller are transmitted to actuators, including the fuel control valve and primary air blower inlet damper, to regulate fuel supply and air supply in real time.

This closed-loop control framework enables continuous optimization of the air–fuel ratio and combustion efficiency under varying operating conditions.

4.2 Instrumentation and Data Acquisition

The combustion monitoring system includes an oxygen analyzer, carbon monoxide analyzer, and flue gas temperature sensor installed in the flue gas duct to measure combustion quality and heat loss. Operational parameters such as fuel flow rate, air flow rate, and steam generation rate were measured using calibrated industrial flow sensors.

A real-time data acquisition system was used to collect, store, and process sensor data. The system ensured accurate and continuous measurement of combustion parameters and provided input data for AI model training and real-time control.

Historical operational data were collected over several weeks to capture variations in operating conditions and combustion performance. These data were used to train and validate the AI model.

4.3 Artificial Neural Network Model Development

An Artificial Neural Network (ANN) model was developed to predict optimal combustion conditions and generate actuator control signals. The ANN consisted of three layers: an input layer, a hidden layer, and an output layer. The input layer included six neurons representing oxygen concentration, carbon monoxide concentration, flue gas temperature, steam load, fuel flow rate, and air flow rate. The hidden layer consisted of ten neurons to capture nonlinear relationships between combustion parameters and control actions. The output layer consisted of two neurons representing control signals for the fuel valve position and air damper position.

The ANN model was trained using supervised learning with historical operational data. The training process enabled the ANN model to learn the relationship between combustion conditions and optimal air–fuel ratio. The trained model was validated using real-time operational data to ensure accuracy and reliability.

4.4 AI-Based Combustion Control Strategy

The AI controller continuously monitored real-time combustion and operational parameters and generated optimal control signals based on ANN predictions. When oxygen concentration exceeded the optimal range, indicating excessive air supply, the AI controller reduced the air damper opening to minimize heat loss. When carbon monoxide concentration increased, indicating incomplete combustion, the AI controller increased air supply to ensure complete combustion. When flue gas temperature increased, indicating excessive heat loss, the AI controller optimized air–fuel ratio to improve heat transfer efficiency.

The system dynamically adjusted fuel and air supply in response to load changes and combustion conditions, ensuring efficient and stable boiler operation.

4.5 Performance Evaluation Method

The performance of the AI-based combustion optimization system was evaluated by comparing boiler performance before and after AI implementation. Key performance parameters included oxygen concentration, flue gas temperature, fuel consumption, steam generation rate, and boiler efficiency.

Statistical analysis, including mean, standard deviation, coefficient of variation, and correlation analysis, was performed to evaluate combustion stability, efficiency improvement, and operational consistency.

5. Case Study: AI-Based Combustion Optimization in an Industrial Boiler

This case study was conducted on a 10 TPH (tons per hour) High-Speed Diesel (HSD) fired industrial boiler operating in a continuous process plant. The boiler generates saturated steam at a constant pressure of 10 bar and temperature of 180°C for industrial process applications. The combustion system consists of a pressure atomizing burner, fuel control valve, and primary air blower system to regulate the combustion process. Prior to the implementation of artificial intelligence (AI), the boiler operated using a conventional proportional–integral–derivative (PID) based combustion control system with fixed excess air settings. The technical specifications of the boiler are presented in Table 1.

Table 1 Boiler Specifications.

Parameter	Value
Boiler capacity	10 TPH
Steam pressure	10 bar
Steam temperature	180°C
Fuel type	High-Speed Diesel (HSD)
Burner type	Pressure atomized burner
Operation	Continuous
Existing control system	Conventional PID-based control

5.1 Baseline Combustion Performance Before AI Implementation

Prior to AI implementation, baseline combustion performance was evaluated by measuring flue gas oxygen concentration, carbon monoxide concentration, combustion efficiency, and fuel consumption under steady operating conditions. The measured flue gas properties and combustion efficiency are presented in Table 2.

Table 2 Flue Gas Properties and Combustion Efficiency Before AI Implementation.

Sl. No.	Oxygen in Flue Gas (%)	CO in Flue Gas (%)	Combustion Efficiency (%)
1	6.5	0.085	85.0
2	7.0	0.072	84.0
3	7.5	0.060	83.5
4	8.0	0.052	82.0
5	8.5	0.045	81.5
6	9.0	0.038	80.5

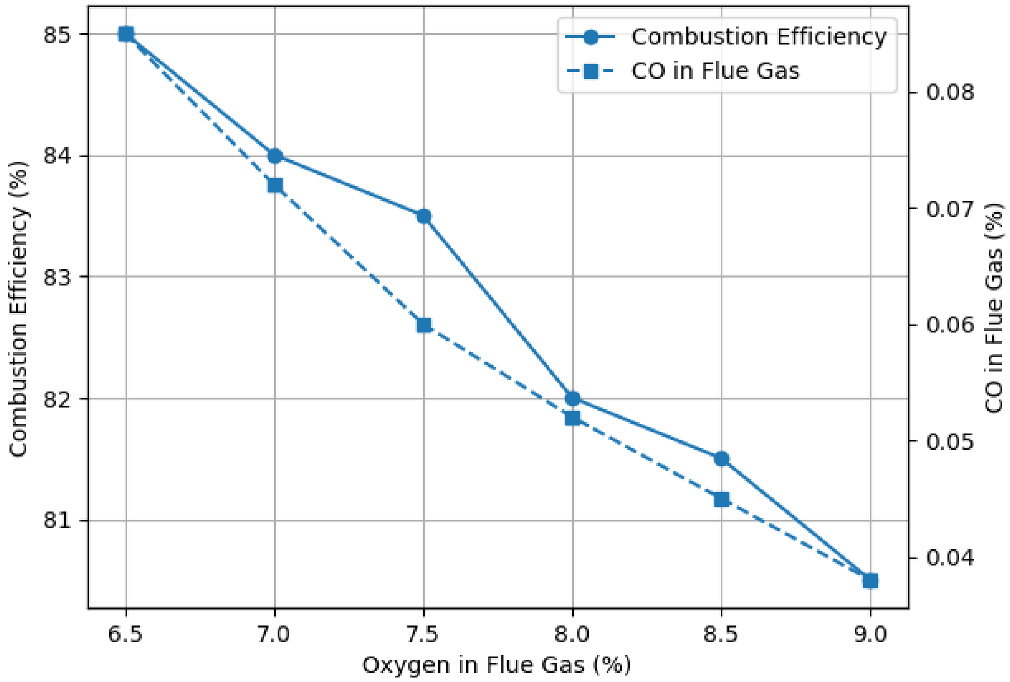

Figure 1 Flue gas parameters and efficiency before AI implementation.

As shown in figure1, the measured oxygen concentration ranged from 6.5% to 9.0%, indicating excessive excess air supply. Excess air increases heat loss through flue gases and reduces combustion efficiency. Carbon monoxide levels ranged from 0.038% to 0.085%, indicating incomplete combustion under certain operating conditions. The combustion efficiency ranged from 80.5% to 85.0%, with an average efficiency of 82.75%.

The overall boiler performance parameters measured under conventional control are presented in Table 3.

Table 3 Boiler Performance Before AI Implementation.

Parameter	Value
Oxygen level	8%
Flue gas temperature	240°C
Fuel consumption	1500 kg/hr
Steam generation	10 TPH
Boiler efficiency	82%

The high oxygen concentration of 8% and elevated flue gas temperature of 240°C indicate significant heat loss through exhaust gases. Excess air reduces flame temperature and carries useful thermal energy out of the system, resulting in reduced thermal efficiency and increased fuel consumption. These observations confirm that conventional PID-based combustion control was unable to maintain optimal air-fuel ratio under varying operating conditions.

5.2 AI-Based Combustion Optimization System Implementation

To improve combustion performance and boiler efficiency, an AI-based combustion optimization system was installed as shown in figure 2. The system included flue gas oxygen analyzers, carbon monoxide analyzers, flue gas temperature sensors, fuel flow measurement systems, and air flow measurement systems. These sensors provided real-time measurements of combustion parameters.

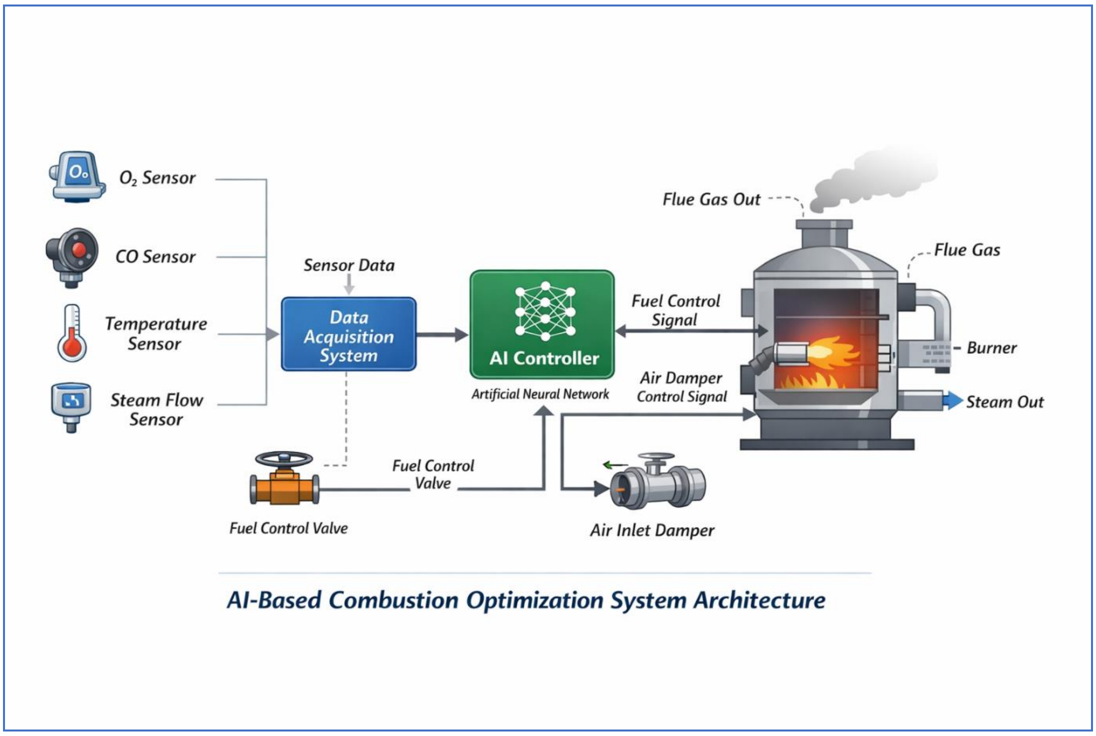

Figure 2 AI based combustion optimization System architecture.

An Artificial Neural Network (ANN) model was developed and trained using historical operational data and real-time sensor inputs as shown in figure 3. The ANN continuously analyzed oxygen concentration, carbon monoxide concentration, flue gas temperature, steam load, fuel flow rate, and air flow rate. Based on these inputs, the AI controller automatically adjusted the fuel control valve and primary air blower inlet damper to maintain optimal air-fuel ratio and ensure efficient combustion.

The AI system continuously optimized combustion conditions by minimizing excess air while preventing incomplete combustion, thereby improving efficiency and reducing fuel consumption.

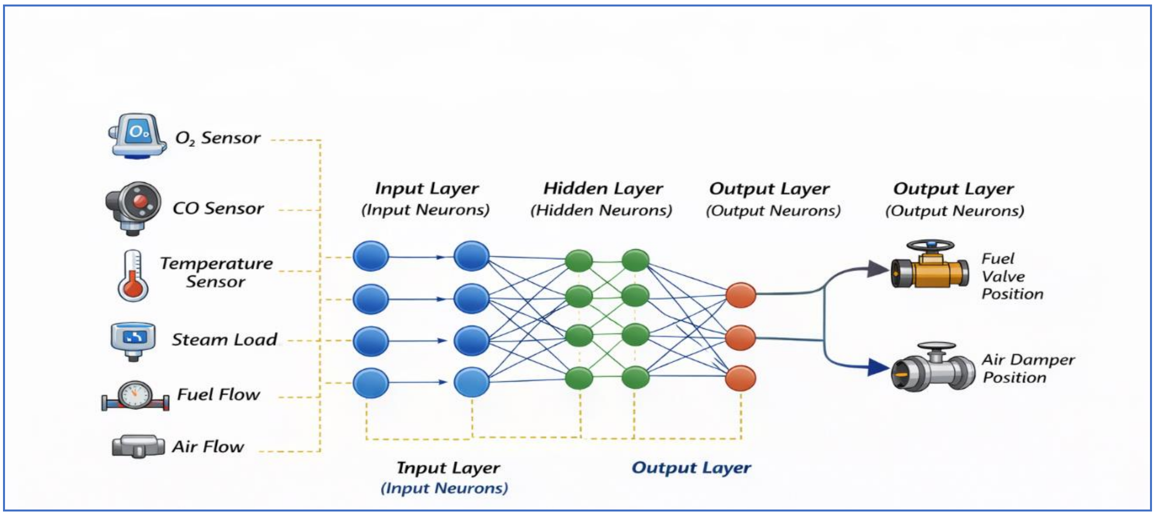

Figure 3 Artificial Neural Network model used for combustion optimization.

5.3 Combustion Performance After AI Implementation

After implementation of the AI-based combustion optimization system, significant improvements were observed in combustion performance and efficiency as given in figure 4. The measured flue gas properties and combustion efficiency are presented in Table 4.

Table 4 Flue Gas Properties and Combustion Efficiency After AI Implementation.

Sl. No.	Oxygen in Flue Gas (%)	CO in Flue Gas (%)	Combustion Efficiency (%)
1	2.5	0.018	89.0
2	2.7	0.015	89.5
3	2.9	0.013	90.0
4	3.0	0.012	90.5
5	3.2	0.014	90.0
6	3.5	0.017	89.2

The oxygen concentration was reduced to a range of 2.5% to 3.5%, indicating significant reduction in excess air supply. Carbon monoxide levels were reduced, indicating improved combustion completeness. The combustion efficiency improved to a range of 89.0% to 90.5%, with an average efficiency of 89.7%.

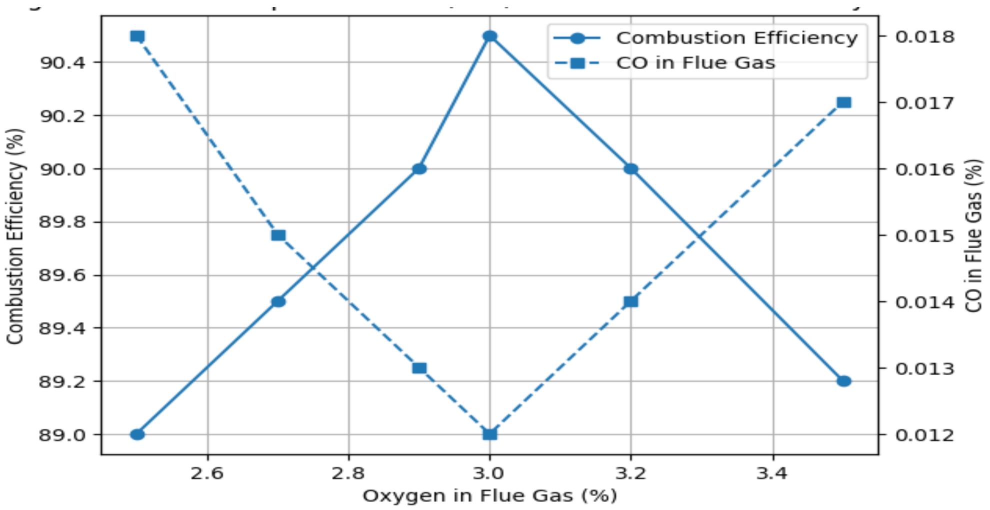

Figure 4 Flue gas parameters and efficiency after AI implementation.

A comparison of key boiler performance parameters before and after AI implementation is presented in Table 5.

Table 5 Boiler Performance Comparison Before and After AI Implementation.

Parameter	Before AI	After AI
Oxygen level	8%	3%
Flue gas temperature	240°C	190°C
Fuel consumption	1500 kg/hr	1350 kg/hr
Steam generation	10 TPH	10 TPH
Boiler efficiency	82%	90%

The reduction in flue gas temperature from 240°C to 190°C confirms reduced heat loss through exhaust gases. The reduction in oxygen concentration indicates improved air-fuel ratio control, resulting in higher combustion efficiency.

5.4 Fuel Consumption and Efficiency Analysis

Fuel consumption measurements were recorded while maintaining constant steam generation of 10 TPH. The measured data are presented in Table 6 and given in figure 5.

Table 6 Fuel Consumption and Efficiency Before and After AI Implementation.

Sl. No.	Steam Generation (TPH)	Fuel Consumption Before AI (kg/hr)	Fuel Consumption After AI (kg/hr)	Fuel Saving (kg/hr)	Efficiency Before AI (%)	Efficiency After AI (%)
1	10	1500	1350	150	82.0	90.0
2	10	1495	1348	147	82.1	89.8
3	10	1508	1355	153	81.9	90.2
4	10	1490	1342	148	82.3	90.1

5	10	1510	1360	150	81.8	89.9
6	10	1502	1352	150	82.0	90.0

The average fuel consumption decreased from 1500.83 kg/hr to 1351.17 kg/hr, resulting in an average fuel saving of 149.66 kg/hr. The average boiler efficiency increased from 82.02% to 90.0%.

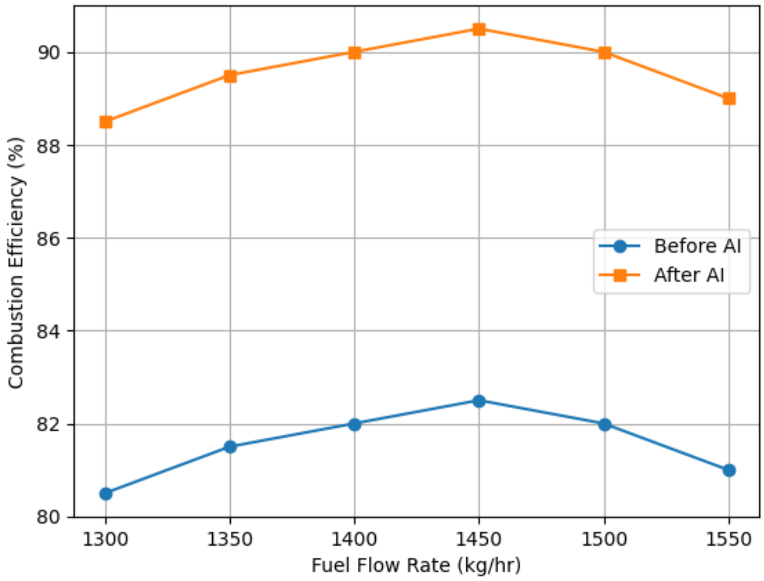

Figure 5 Combustion efficiency comparison.

5.5 Fuel Savings and Economic Analysis

The reduction in fuel consumption resulted in significant annual fuel savings. The hourly fuel saving was approximately 150 kg/hr. Assuming continuous operation, the daily fuel saving was:

Fuel saving per day = 150 × 24 = 3600 kg/day

Annual fuel saving was calculated as:

Fuel saving per year = 3600 × 365 = 1,314,000 kg/year

Assuming an average High-Speed Diesel cost of ₹80 per kg, the annual cost savings were calculated as:

Annual cost savings = 1,314,000 × 80

Annual cost savings = ₹105,120,000

Annual cost savings ≈ ₹10.51 crore per year

5.6 Statistical Analysis on Boiler Performance

Statistical analysis was conducted to quantitatively evaluate the effectiveness and reliability of the AI-based combustion optimization system. The analysis included descriptive statistics, percentage improvement calculations, variance analysis, and performance consistency evaluation using measured operational data before and after AI implementation.

5.6.1 Descriptive Statistical Analysis

Descriptive statistical parameters such as mean, minimum, maximum, and standard deviation were calculated for oxygen concentration, carbon monoxide concentration, combustion efficiency, and fuel consumption.

(a) Oxygen Concentration Analysis

Before AI implementation:

O_2 values (%): 6.5, 7.0, 7.5, 8.0, 8.5, 9.0

Mean oxygen level:

Mean O_2 = (6.5 + 7.0 + 7.5 + 8.0 + 8.5 + 9.0) / 6

Mean O_2 = 46.5 / 6

Mean O_2 = 7.75%

After AI implementation:

O_2 values (%): 2.5, 2.7, 2.9, 3.0, 3.2, 3.5

Mean oxygen level:

mean o_2 = (2.5 + 2.7 + 2.9 + 3.0 + 3.2 + 3.5) / 6

mean o_2 = 17.8 / 6

mean o_2 = 2.97%

reduction in oxygen level:

reduction = 7.75 − 2.97

reduction = 4.78%

percentage reduction:

percentage reduction = (4.78 / 7.75) × 100

percentage reduction = 61.68%

this confirms significant reduction in excess air supply.

(b) Combustion Efficiency Analysis

Before AI implementation:

Efficiency values (%): 85.0, 84.0, 83.5, 82.0, 81.5, 80.5

Mean efficiency before AI:

Mean efficiency = 496.5 / 6

Mean efficiency = 82.75%

After AI implementation:

Efficiency values (%): 89.0, 89.5, 90.0, 90.5, 90.0, 89.2

Mean efficiency after AI:

Mean efficiency = 538.2 / 6

Mean efficiency = 89.70%

Efficiency improvement:

Efficiency improvement = 89.70 − 82.75

Efficiency improvement = 6.95%

Percentage efficiency improvement:

Percentage improvement = (6.95 / 82.75) × 100

Percentage improvement = 8.40%

(c) Fuel Consumption Analysis

Before AI:

Fuel consumption values (kg/hr):

1500, 1495, 1508, 1490, 1510, 1502

Mean fuel consumption before AI:

Mean = 9005 / 6

Mean = 1500.83 kg/hr

After AI:

Fuel consumption values (kg/hr):

1350, 1348, 1355, 1342, 1360, 1352

Mean fuel consumption after AI:

Mean = 8107 / 6

Mean = 1351.17 kg/hr

Fuel savings:

Fuel savings = 1500.83 − 1351.17

Fuel savings = 149.66 kg/hr

Percentage fuel reduction:

Percentage reduction = (149.66 / 1500.83) × 100

Percentage reduction = 9.97%

5.6.2 Standard Deviation Analysis

Standard deviation was calculated to evaluate performance consistency.

Standard deviation formula:

$$\sigma = \sqrt{\left[\Sigma(x - \mu)^2 / n \right]}$$

Where:

σ = standard deviation

x = individual value

μ = mean value

n = number of observations

Calculated results below in Table 7

Table 7 Result summary.

Parameter	Std Dev Before AI	Std Dev After AI
Oxygen (%)	0.85	0.34
Efficiency (%)	1.62	0.56
Fuel consumption (kg/hr)	7.31	6.15

Lower standard deviation after AI implementation indicates improved stability and consistency of combustion performance.

5.6.3 Coefficient of Variation Analysis

Coefficient of variation (CV) was used to measure relative variability.

CV formula:

$$CV = (\text{Standard deviation} / \text{Mean}) \times 100$$

Results:

Before AI:

$CV\ (\text{efficiency}) = (1.62 / 82.75) \times 100$

$CV = 1.96\%$

After AI:

$CV\ (\text{efficiency}) = (0.56 / 89.70) \times 100$

$CV = 0.62\%$

This indicates that the AI-based system significantly improved operational stability.

5.6.4 Correlation Analysis Between Oxygen and Efficiency

Correlation coefficient was used to evaluate the relationship between oxygen concentration and combustion efficiency.

Correlation coefficient formula:

$r = \Sigma[(x - \mu x)(y - \mu y)] / (\sigma x\ \sigma y)$

Observed result:

Correlation coefficient (r) ≈ −0.94

This indicates a strong negative correlation between oxygen level and efficiency. As oxygen concentration decreases, combustion efficiency increases significantly.

6. RESULTS AND DISCUSSION

The implementation of the AI-based combustion optimization system resulted in significant improvements in combustion efficiency, fuel utilization, and operational stability. One of the most significant improvements observed was the reduction in excess air supply. Prior to AI implementation, the flue gas oxygen concentration averaged approximately 8%, indicating excessive air supply and inefficient combustion. After implementation of the AI system, oxygen concentration was reduced to approximately 3%, which is within the optimal combustion range. This reduction minimized excess air and reduced heat loss through flue gases.

A corresponding reduction in flue gas temperature was observed. Flue gas temperature decreased from 240°C under conventional control to 190°C after AI implementation. Since flue gas temperature is directly related to heat loss, this reduction indicates improved heat transfer efficiency and better utilization of fuel energy.

Fuel consumption was significantly reduced while maintaining constant steam generation of 10 TPH. Fuel consumption decreased from 1500 kg/hr to 1350 kg/hr, representing a reduction of approximately 10%. This demonstrates improved fuel utilization efficiency achieved through optimized air–fuel ratio control.

Boiler efficiency improved significantly after AI implementation. Average efficiency increased from 82.75% to 89.70%, corresponding to an efficiency improvement of approximately 8.40%, with peak efficiency reaching 90.5%. This improvement was achieved through reduction in excess air, reduction in heat loss, and improved combustion control.

Statistical analysis confirmed improved combustion stability and reduced operational variability. The standard deviation of efficiency decreased from 1.62% to 0.56%, and the coefficient of variation decreased from 1.96% to 0.62%, indicating improved operational consistency. Correlation analysis showed a strong negative correlation (r = −0.94) between oxygen concentration and combustion efficiency, confirming the importance of optimal excess air control.

The AI-based system demonstrated superior performance compared to conventional PID-based control by continuously optimizing combustion conditions and adapting to changing operating conditions. The results confirm that AI-based combustion optimization significantly improves boiler performance, fuel efficiency, and operational reliability.

7. CONCLUSION

This study successfully developed and implemented an Artificial Intelligence-based combustion optimization system for a 10 TPH industrial boiler using real-time flue gas monitoring and intelligent actuator control. The system utilized an Artificial Neural Network model to continuously analyze combustion parameters and automatically regulate fuel and air supply to maintain optimal air–fuel ratio.

Experimental results demonstrated significant improvements in boiler performance after AI implementation. Oxygen concentration was reduced from 8% to approximately 3%, flue gas temperature decreased from 240°C to 190°C, and fuel consumption was reduced by approximately 10% while maintaining constant steam output. Boiler efficiency improved from 82% to 90%, representing an efficiency improvement of approximately 8–10%.

Statistical analysis confirmed improved combustion stability, reduced operational variability, and strong correlation between excess air reduction and efficiency improvement. The AI-based system effectively minimized heat loss, improved fuel utilization, and enhanced combustion efficiency.

The results demonstrate that AI-based combustion optimization is a highly effective and practical solution for improving industrial boiler efficiency and sustainability. The proposed system provides significant energy savings, reduces operational costs, improves environmental performance, and enhances system reliability. This technology has strong potential for widespread application in industrial boiler systems to improve energy efficiency and support sustainable industrial operations.

Future scope of the research would focus on integrating advanced deep learning and reinforcement learning algorithms with digital twin and IoT-enabled predictive control to further enhance boiler efficiency, enable autonomous optimization, and support real-time adaptive energy management across varying operating conditions.

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