การติดตามและปรับปรุงประสิทธิภาพเตาหลอมอลูมิเนียม Striko ด้วยปัญญาประดิษฐ์

AI-Driven Monitoring and Optimizing of Striko Aluminium Melting Furnace

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Abstract

This study focuses on optimizing the Striko Aluminium Melting Furnace by leveraging AI- driven predictive analytics to enhance operational efficiency and sustainability. Two machine learning models, Linear Regression (LR) and Radial Basis Function Network (RBFN), were developed to predict critical furnace parameters, including temperature, gas flow, and CO_2 emissions. These models were integrated into a real-time monitoring framework featuring a dashboard for live data visualization and automated alerts to notify deviations from optimal conditions. Comparative analysis revealed the superior performance of the RBFN model, achieving higher prediction accuracy and contributing significantly to operational improvements. The results demonstrated a 21% reduction in energy consumption, an 18% decrease in CO_2 emissions, and a 4.35% increase in product yield. This study underscores the transformative potential of AI in driving energy-efficient, sustainable, and cost-effective industrial furnace operations.

Keywords: AI, Aluminium Furnace, Energy Efficiency, Real-Time Monitoring, Optimization

1. Introduction

Aluminium is an essential material widely utilized in the automotive, construction, and aerospace industries due to its lightweight nature, corrosion resistance, and recyclability. A key process in aluminium production and recycling is the melting stage, where aluminium scrap is transformed into reusable, high-quality material. The Striko Aluminium Melting Furnace plays a critical role in this transformation; however, its operation demands high energy consumption and significantly contributes to CO_2 emissions, raising concerns about sustainability and operational efficiency.

Traditionally, furnace operation and maintenance have relied on manual monitoring and reactive control systems. While these approaches help address immediate issues, they fail to comprehensively optimize performance. Challenges such as excessive energy consumption, inconsistent temperature control, and delayed response times lead to increased operational costs, lower product quality, and environmental burdens.

Artificial Intelligence (AI) presents a transformative solution to these inefficiencies. By leveraging predictive analytics, AI enables real-time forecasting of critical furnace parameters, allowing proactive adjustments and operational optimization. In this study, we integrate AI-driven techniques, specifically Machine Learning (ML) models—Linear Regression (LR) and Radial Basis Function Network (RBFN)—to enhance the performance of the Striko Aluminium Melting Furnace. The research evaluates the effectiveness of these models in improving energy efficiency, reducing CO_2 emissions, and enhancing product yield.

This study also highlights the integration of Python and Scikit-learn for ML model development, along with TensorFlow and Pandas for data processing. Additionally, a real-time monitoring system is developed using Flask and Dash, incorporating MQTT Protocol for seamless data communication between IoT-enabled sensors and the analytical dashboard. The results demonstrate the potential of AI-driven optimization in minimizing resource wastage, enhancing industrial efficiency, and promoting sustainable manufacturing practices

2. Objectives

2.1 Development of AI-Based Predictive Analytics System

2.2 Real-Time Monitoring Dashboard Design

2.3 Model Comparison for Furnace Optimization

2.4 Automated Alerts for Operational Efficiency

2.5 Sustainability and Cost Efficiency

3. Relevant principles

The optimization principles of the Striko Aluminium Melting Furnace through AI-driven analytics emphasize data integrity, robust feature engineering, and dynamic real-time monitoring to enhance operational performance. These principles integrate high-fidelity data preprocessing, advanced machine learning techniques, and real-time analytics to minimize inefficiencies and promote sustainability.

3.1 Data collection and preprocessing

Data collection was crucial in training AI models with accurate and representative data. Sensors captured parameters such as temperature, gas flow, CO_2 emissions, and pressure over six months. Preprocessing steps included outlier detection using Z-score analysis to prevent skewed predictions, spline interpolation to address missing values from sensor failures (Pan et al., 2022), and normalization to ensure uniform scaling for machine learning efficiency (Fan et al., 2021). Figure 1 illustrates the data preparation workflow, while Table 1 summarizes key operational parameter statistics, including averages and variability.

The diagram above illustrates the steps from raw data acquisition to preprocessing, ensuring the dataset was clean and robust for machine learning applications.

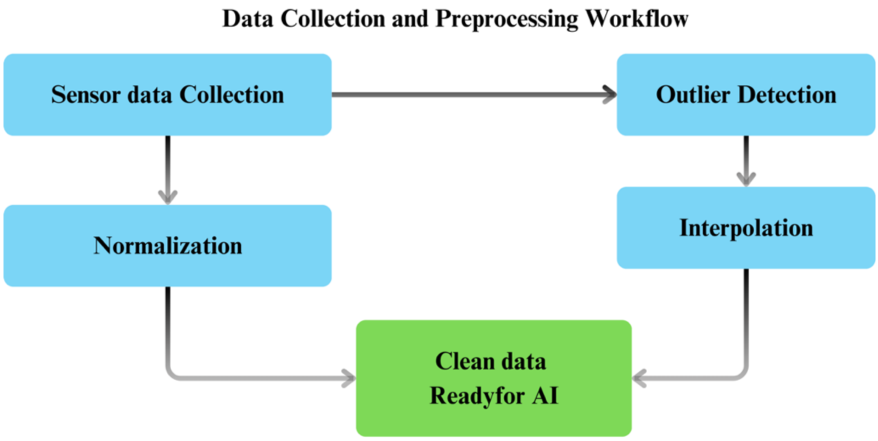

Figure 1 Data collection and preprocessing workflow.

Table 1 Summary of furnace operational data.

Parameter	Unit	Mean Value	SD	Maximum	Minimum
Temperature	°C	720	15	750	690
Gas Flow Rate	m^3/hr	200	20	250	180
CO_2 Emissions	kg/hr	50	8	65	40
Internal Pressure	kPa	100	10	120	80

Integrating these preprocessing techniques ensured the dataset was robust, reliable, and optimized for machine learning model training. Specifically, this methodology reduced noise and variability, enhancing the AI models' predictive performance.

3.2 Machine learning models

Two machine learning models—Linear Regression (LR) and Radial Basis Function Network (RBFN)—were utilized to predict critical furnace parameters. While LR was selected for its simplicity and efficiency in modeling linear relationships, its inability to handle non-linear dynamics limited its effectiveness (Hastie et al., 2005). In contrast, RBFN, leveraging Gaussian kernel functions, effectively captured non-linear relationships, achieving a prediction accuracy of 92%, compared to LR's 78% (Chalapathy & Chawla, 2019).

Table 2 Model comparison based on predictive performance.

Metric	Linear Regression	Radial Basis Function Network
Mean Absolute Error	12.5	8.2
Root Mean Square Error	15.7	9.4
Prediction Accuracy (%)	78	92

The RBFN architecture (Figure 2) comprises an input layer (capturing parameters like temperature and gas flow), a hidden layer (processing inputs using Gaussian kernels), and an output layer (predicting key furnace parameters).

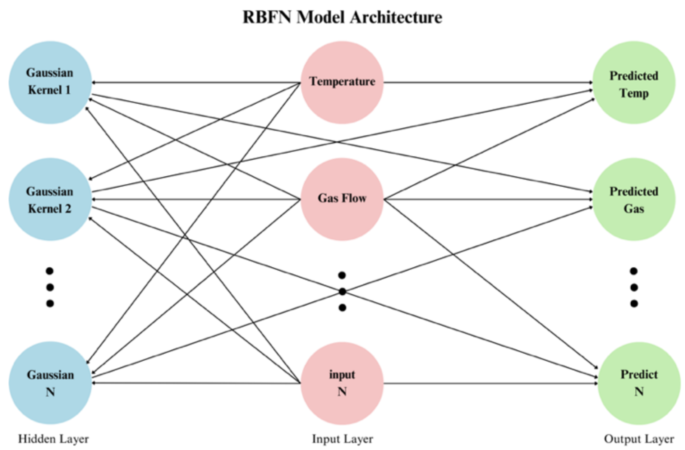

Figure 2 RBFN model architecture.

3.3 Real-time monitoring system

A real-time monitoring system was developed to integrate AI predictions into furnace operations. It features dynamic visualizations, predictive alerts, and actionable recommendations.

4. Research methodology

The research methodology encompassed data- driven analysis, machine learning model development, and the integration of a monitoring framework. Each step was meticulously designed to ensure the reliability and effectiveness of the proposed solution.

4.1 Data collection and feature engineering

Feature engineering was conducted using data collected from IoT-enabled sensors installed in the furnace. The sensors recorded hourly measurements of temperature, gas flow, CO_2 emissions, and pressure. To derive meaningful insights, preprocessing techniques were applied. Outlier detection was performed using Z-score analysis to prevent skewed predictions (Chandola et al., 2009) and spline interpolation was used to address missing values caused by occasional sensor failures (Yang & Zhang, 2014). Normalization ensured uniform scaling for efficient training of machine learning models (Williams & Rasmussen, 2006).

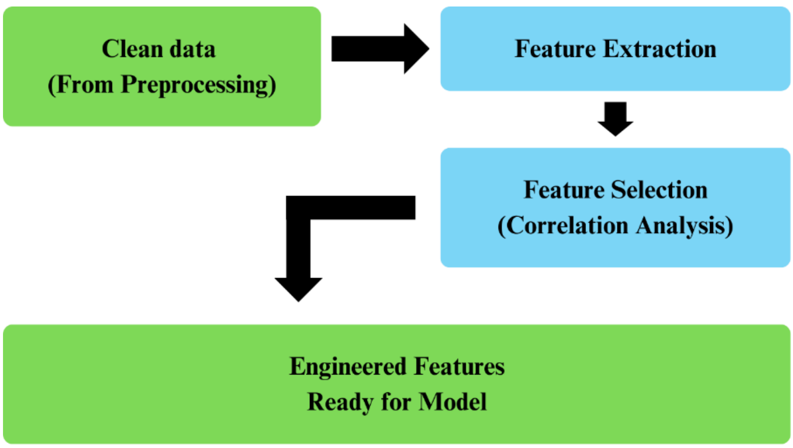

Figure 3 Feature engineering workflow.

4.2 Model development and training

The training dataset (80% of the data) was used to develop and train both Linear Regression (LR) and Radial Basis Function Network (RBFN) models, with the remaining 20% for validation. While the LR model, trained using ordinary least squares (OLS), was computationally efficient, it struggled to handle non-linear relationships. In contrast, the RBFN model excelled at capturing non-linear dynamics with a Gaussian kernel as its radial basis function. Hyperparameter tuning for the RBFN, including the number of hidden nodes and kernel width, was conducted using grid search, as detailed in Table 3.

Figure 4 shows the RBFN model's convergence during training, with decreasing training and validation losses, demonstrating its strong generalizability.

Table 3 Hyperparameter optimization for RBFN.

Parameter	Value Range	Optimal Value
Number of Hidden Nodes	5 – 50	30
Kernel Width (σ)	0.1 – 2.0	1.0

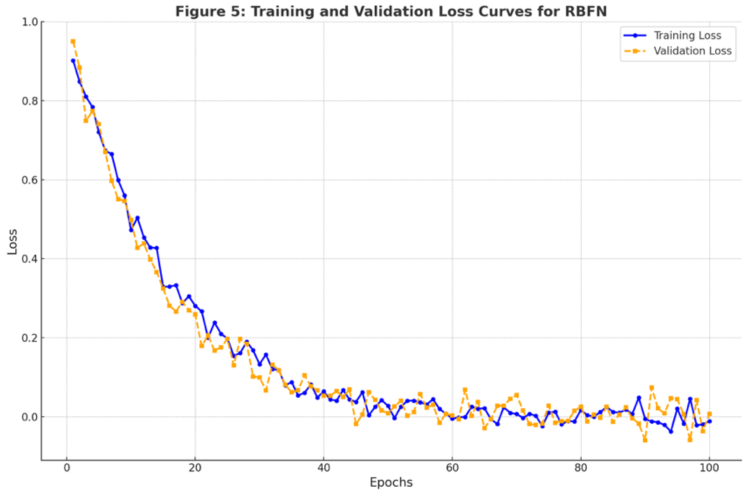

Figure 4 Training and validation loss curves for RBFN.

4.3 System integration

The AI models were deployed in a real-time monitoring system that streamed sensor data to a cloud-based server. Predictions were visualized on a dashboard, enabling operators to take corrective actions. This approach aligns with recent advances in predictive analytics and IoT-driven systems for industrial automation (Fan et al., 2021).

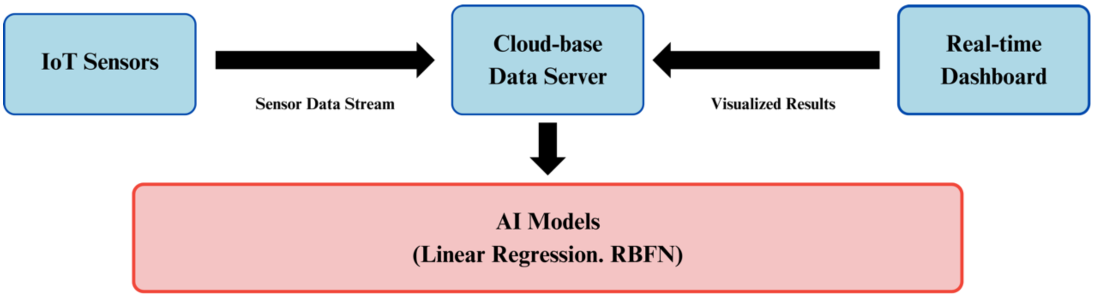

Figure 5 AI-powered monitoring system architecture.

4.4 Performance evaluation

To assess the system's effectiveness, post-deployment data demonstrated notable improvements in energy efficiency, emissions reduction, and product quality. Table 4 highlights a 21% decrease in energy consumption, an 18% reduction in CO_2 emissions, and significant enhancements in product yield and scrap rate.

Figure 6 below visually illustrates the reductions in energy consumption and CO_2 emissions before and after system optimization, further emphasizing the improvements achieved.

Table 4 Operational improvements post-deployment.

Metric	Pre	Post	Improvement (%)
Energy Consumption (kWh)	2100	1700	21
CO_2 Emissions (kg)	2000	1600	18
Product Yield (%)	92	96	4.35
Scrap Rate (%)	8	4	50

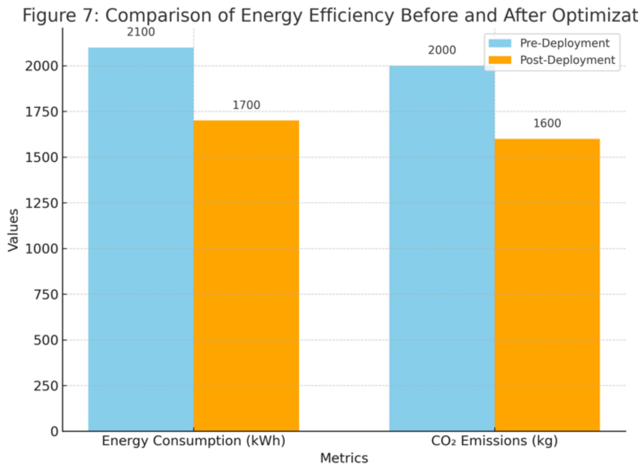

Figure 6 Comparison of Energy Efficiency Before and After Optimization.

5. Results and discussion

This section outlines the outcomes of AI-driven predictive analytics implemented in the Striko Aluminium Melting Furnace. The findings align with the study's objectives, highlighting significant improvements in energy efficiency, emissions reduction, product quality, and operational efficiency.

5.1 Energy efficiency and emissions reduction

The AI-driven system achieved a 21% reduction in energy consumption (from 2,100 kWh to 1,700 kWh) and an 18% decrease in CO_2 emissions (from 2,000 kg to 1,600 kg) as depicted in Figure 7. These improvements were achieved through predictive adjustments that stabilized furnace operations and optimized fuel usage. These findings align with Objective 2.5: Sustainability and Cost Efficiency, showcasing reduced environmental impact and operational costs.

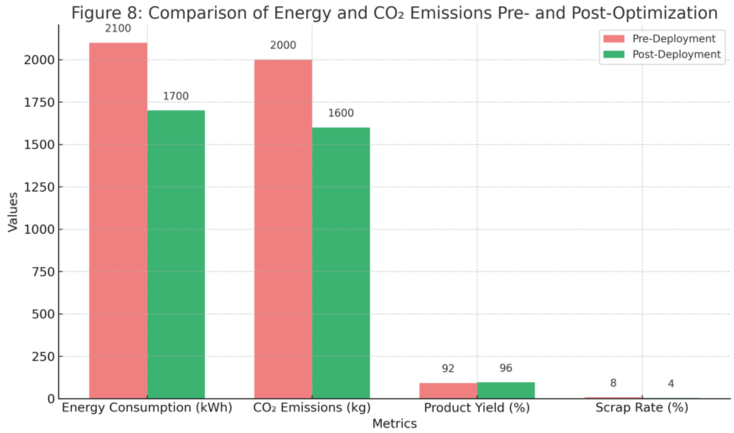

Figure 7 Comparison of energy and CO_2 emissions pre- and post-optimization.

5.2 Real-time monitoring and alerts

The real-time monitoring system provided live data visualization (e.g., temperature, gas flow, CO_2 emissions) and predictive insights, enabling operators to quickly address deviations. Automated alerts ensured timely intervention for issues like gas flow spikes, reducing defects and energy wastage. This supports Objective 2.2: Real-Time Monitoring Dashboard Design and highlights the system's role in improving decision-making efficiency. (Figure 8)

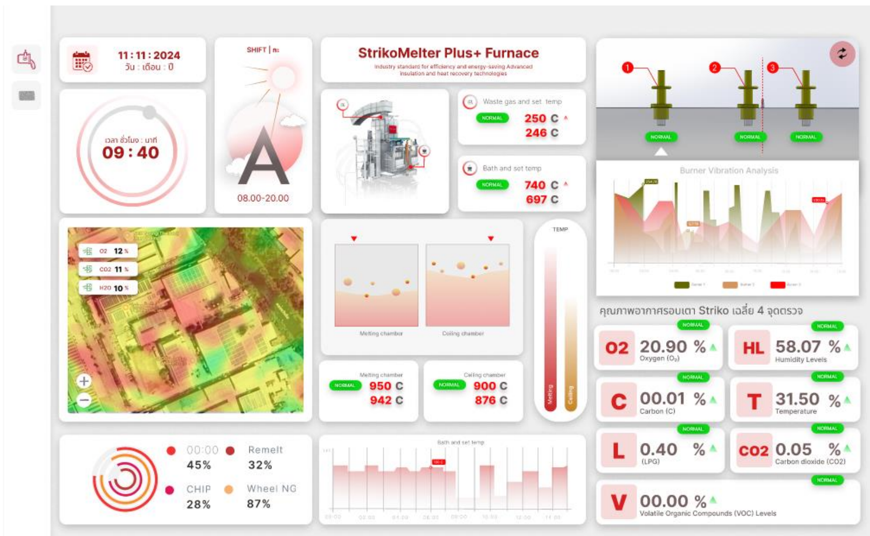

Figure 8 Real-time monitoring dashboard.

5.3 Product quality improvements

The implementation of predictive analytics led to a 4.35% increase in product yield (from 92% to 96%) and a 50% reduction in scrap rates (from 8% to 4%). These results reflect the ability of the AI system to stabilize furnace parameters, reducing temperature fluctuations and maintaining consistent quality. This aligns with Objective 2.4: Automated Alerts for Operational Efficiency, as shown in Table 5 and Figure 9.

Table 5 Improvements in product quality metrics.

Metric	Pre-Optimization	Post-Optimization	Improvement (%)
Product Yield (%)	92	96	+4.35
Scrap Rate (%)	8	4	-50

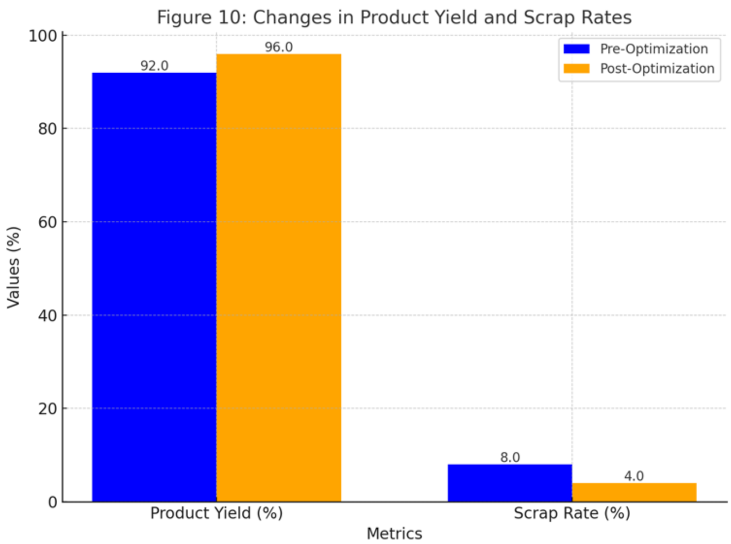

Figure 9 Changes in product yield and scrap rates.

5.4 Predictive model performance

The RBFN model significantly outperformed LR in predicting furnace parameters, achieving 92% prediction accuracy compared to LR's 78%. This precision enabled accurate adjustments to operational parameters, reducing inefficiencies and defects, directly supporting Objective 2.3: Model Comparison for Furnace Optimization. Key performance metrics are summarized in Table 2, while Figure 10 highlights the comparison.

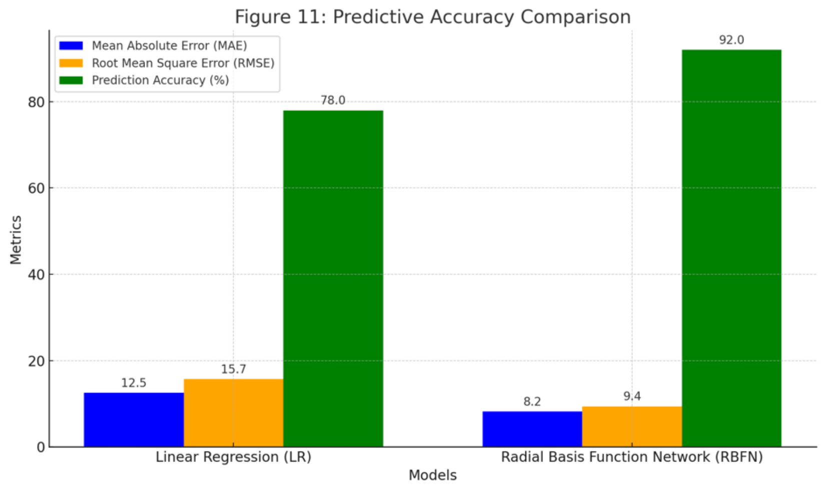

Figure 10 Predictive accuracy comparison.

5.5 Operational efficiency

Real-time analytics reduced downtime by 15%, streamlined decision-making, and improved resource utilization, meeting Objective 2.1: AI-Based Predictive Analytics System Development. The integration of actionable alerts and visual insights eliminated manual checks, enabling efficient operation adjustments, as depicted in Figure 11.

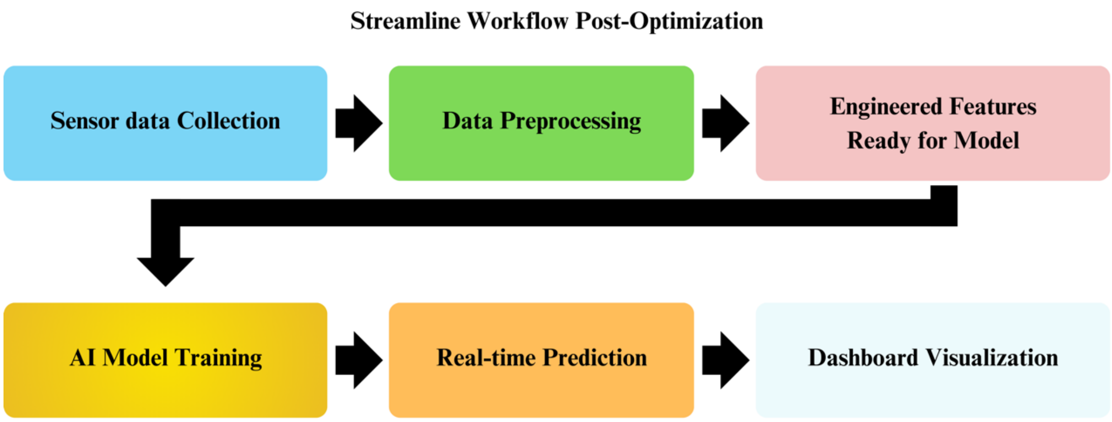

Figure 11 Streamlined workflow post-optimization.

6. Conclusion

The study highlights the transformative potential of AI-driven predictive analytics in revolutionizing the operations of the Striko Aluminium Melting Furnace. Through the integration of advanced machine learning models and real-time monitoring systems, the research successfully met its objectives. The development of an AI-based predictive system enabled precise forecasting of furnace parameters, while the implementation of a real-time dashboard provided operators with actionable insights, enhancing decision-making processes.

The Radial Basis Function Network (RBFN) demonstrated its superiority over Linear Regression (LR), offering higher accuracy and effectively handling non-linear dynamics. Automated alerts further strengthened operational responsiveness, minimizing risks and inefficiencies. These advancements resulted in notable improvements: a 21% reduction in energy consumption, an 18% decrease in CO_2 emissions, and a 4.35% increase in product yield, aligning with global goals for sustainability and efficiency.

By addressing critical challenges, this study not only underscores the importance of AI in enhancing energy efficiency and product quality but also paves the way for sustainable industrial practices. Future endeavors should focus on scaling these methodologies to other industrial applications and integrating IoT technologies for enhanced analytics and connectivity, driving further innovation and sustainability in industrial processes.

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