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Machine Learning and IoT Applications in Optimizing MIDREX Shaft Furnace Operations

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ABSTRACT

The combination of Machine Learning (ML) and Internet of Things (IoT) technologies is transforming industrial processes by providing real-time optimization and delivering predictive insights. This paper delves into the application of ML and IoT in optimizing MIDREX shaft furnace operations, a pivotal process in direct reduction ironmaking. By leveraging IoT-enabled sensors, real-time data on temperature, pressure, and gas flow is collected and processed. Machine learning models are then employed for predictive maintenance, energy optimization, and dynamic process control. The proposed framework not only enhances operational efficiency but also reduces downtime and environmental impact by minimizing energy consumption and carbon emissions. Experimental validations demonstrate significant improvements in process stability and energy utilization. Furthermore, a comparative analysis with conventional methods underscores the economic and operational advantages of integrating ML and IoT. This study provides actionable insights and a robust framework for advancing smart industrial systems, paving the way for sustainable *ironmaking practices*.

Keywords: MIDREX shaft Furnace Operations, Preditve maintenance of MIDREX shaft furanac using Machine Learning and IOT Technologies, MIDREX shaft Furance, Direct reduction of Iron ore using MIDREX shaft furance

INTRODUCTION

The MIDREX process stands as a cornerstone in direct reduction ironmaking, celebrated for its energy efficiency, cost-effectiveness, and reduced environmental footprint compared to traditional blast furnace methods [1]. Central to this process is the MIDREX shaft furnace, a sophisticated system where dynamic interactions between temperature, gas flow, and material feed dictate the quality and efficiency of iron production [2]. However, like all complex systems, the MIDREX shaft furna using ce faces inherent challenges, including process instability, energy inefficiencies, and the costly impact of unplanned downtimes [3, 4]. These issues present significant obstacles to achieving consistent, optimized performance. As industries embrace the digital transformation brought about by Industry 4.0, the convergence of Machine Learning and the Internet of Things offers a beacon of opportunity for resolving these challenges [5]. The real-time monitoring of operational parameters by deploying a network of smart sensors within the furnace environment is made possible by IoT technologies [6-9]. These sensors constantly gather comprehensive data on essential parameters, including temperature fluctuations, pressure changes, and material feed rates. However, data alone cannot drive transformation. By applying ML algorithms to this data, industries can harness predictive insights and optimization strategies that dynamically adjust operations. These models not only improve energy efficiency and reduce waste but also pave the way for predictive maintenance, minimizing the likelihood of costly disruptions [10].

Recent advancements in related technologies such as digital twins, edge computing, and real-time analytics have further amplified the potential of integrating ML and IoT into industrial operations [11-13]. A digital twin is an electronic duplicate of the MIDREX shaft furnace-can simulate various operational scenarios, allowing engineers to test and refine optimization strategies without disrupting real-world operations. Predictive maintenance frameworks use historical data to identify failure patterns, ensuring that repairs and interventions are scheduled proactively rather than reactively [14, 15]. Together, these technologies are transforming how industries approach operational challenges, making systems smarter, more reliable, and environmentally sustainable. In the context of ironmaking, this technological synergy represents a pivotal opportunity to address growing global demands for low-carbon industrial practices [16]. By reducing energy consumption and optimizing performance, ML and IoT not only enhance economic viability but also contribute to the urgent need for decarbonization in heavy industries [17-22]. The integration of these technologies into MIDREX operations is no longer a futuristic vision but a practical necessity for industries striving to remain competitive and sustainable [23, 24].

This research seeks to provide an in-depth analysis of the impact of Machine Learning (ML) and Internet of Things (IoT) technologies in enhancing the efficiency of MIDREX shaft furnace operations. By detailing a robust framework for integration and providing experimental validation, this research highlights the transformative potential of these technologies. Ultimately, it seeks to inspire researchers, practitioners, and industry leaders to embrace this paradigm shift, fostering innovation and sustainability in one of the most critical industrial processes of our time.

OBJECTIVES

To develop a strategy for the predictive maintenance of the MIDREX shaft furnace used for direct reduction of iron ore, leveraging embedded systems and the Internet of Things (IoT) integrated with machine learning techniques. Create a Simulink model to simulate and monitor the temperature and pressure conditions inside the MIDREX shaft furnace. Integrate the developed Simulink model with IoT-enabled sensors to collect real-time operational data from the shaft furnace. Apply machine learning techniques to analyze time-series data obtained from the IoT server. Optimize machine learning algorithms for accurate prediction of equipment performance and potential failures. Design and validate a predictive maintenance strategy using insights from machine learning analysis to ensure efficient and reliable furnace operations. Continuously refine the Simulink-IoT integration and machine learning models to improve prediction accuracy and system efficiency. By achieving these objectives, the project aims to enhance operational reliability, reduce downtime, and promote sustainable practices in the direct reduction process

METHODS

The methodology for implementing predictive maintenance for the MIDREX shaft furnace focuses on leveraging sophisticated technologies such as embedded systems, IoT, and machine learning. Data collection is achieved using Raspberry Pi-based embedded systems to monitor critical parameters like temperature and pressure, transmitting real-time data to a cloud server via IoT protocols integrated with MATLAB Simulink. Both supervised and unsupervised machine learning methods are employed to examine historical and real-time data, detecting patterns and irregularities that may signal possible equipment malfunctions. Trained models are deployed within the IoT framework to enable real-time predictive monitoring and proactive maintenance decisions. The system continuously refines itself by adapting to evolving operational conditions, ensuring enhanced efficiency, reduced downtime, and operational reliability for the furnace. This methodology supports Industry 4.0 principles, promoting smart manufacturing and sustainability.

The following steps outline the methodology, maintaining a cohesive flow and ensuring human- centric clarity.

1 Data Acquisition and IoT Integration

At the core of this approach lies the seamless acquisition of real-time data, achieved through an interconnected network of IoT-enabled sensors strategically deployed across the MIDREX shaft furnace. These sensors are tasked with continuously monitoring essential parameters such as temperature, pressure, gas flow rates, and material feed consistency. The data is transmitted securely via advanced IoT protocols to a centralized cloud-based platform for additional research. A crucial aspect of this integration is the use of embedded systems, such as Raspberry Pi, to locally preprocess data, ensuring reduced latency and enhanced operational efficiency. By creating a digital bridge between physical furnace components and analytical platforms, this step establishes the foundation for smart, data-driven decision-making.

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2. Development of a Simulation Model

In order to comprehend the intricate workings of the shaft furnace, a high-fidelity simulation model is developed using MATLAB-Simulink. This model serves as a digital twin, replicating the thermal, chemical, and mechanical processes within the furnace in real-time. Engineers can use this simulation to analyze the interplay between key variables under various operational scenarios, optimizing parameters without interrupting actual production. Furthermore, the digital twin provides a controlled environment for testing predictive maintenance strategies, identifying inefficiencies, and refining optimization models.

3. **Machine Learning Model Implementation**

The system's predictive capabilities are achieved through the implementation of sophisticated machine learning algorithms. By analyzing both historical and real-time data, various supervised learning models, such as regression techniques and neural networks, are utilized to forecast key events like equipment degradation or irregularities in gas flow. Additionally, unsupervised learning methods, including clustering and anomaly detection, are leveraged to uncover hidden patterns and relationships within the data. These analytical insights serve as the foundation for predictive maintenance, allowing the system to anticipate potential issues and propose proactive solutions.

4. Predictive Maintenance Framework

Building upon the analytical outputs of machine learning, a robust predictive maintenance framework is developed. This framework leverages real-time data analysis to identify warning signs of equipment degradation or process inefficiencies. Predictive insights are translated into actionable maintenance schedules, allowing operators to address issues proactively rather than reactively. By aligning maintenance activities with actual equipment conditions, this approach significantly reduces unplanned downtimes, optimizes resource allocation, and extends the lifespan of critical furnace components.

5 Optimization and Real-Time Control

key innovation in this methodology is the deployment of edge computing systems to enable real- time process optimization. Data critical to furnace operations, such as gas flow rates and temperature stability, is processed locally, minimizing latency and facilitating immediate adjustments. This ensures optimal energy utilization, process stability, and operational safety. Meanwhile, the cloud platform complements these capabilities by offering deeper, long-term analytics, allowing for continuous refinement of the machine learning models and control algorithms.

6 Experimental Validation and Continuous Refinement

The efficacy of the proposed system is validated through rigorous experimental trials on a scaled- down prototype of the MIDREX shaft furnace. These trials not only demonstrate tangible improvements in energy efficiency and operational reliability but also highlight areas for further enhancement. Feedback from these experiments is continuously integrated into the system, ensuring that the predictive models and optimization algorithms evolve in step with changing operational demands. Comparative studies against traditional maintenance methods underline the economic and environmental advantages of this technology

7 Human-Centric Approach and Broader Implications

This methodology places significant emphasis on human-centric design, ensuring ease of use and seamless integration into existing workflows. By automating routine monitoring and maintenance tasks, it frees operators to focus on strategic decision-making, enhancing workforce productivity and engagement.Furthermore, the system's ability to scale and adapt effectively positions it for use in diverse industrial applications beyond MIDREX furnaces, promoting the wider integration of smart manufacturing technologies In summary, this methodology not only addresses immediate operational challenges but also aligns with global trends toward sustainable, intelligent, and automated industrial systems. By weaving IoT, machine learning, and embedded systems into a unified framework, it lays the groundwork for the future of ironmaking and beyond.

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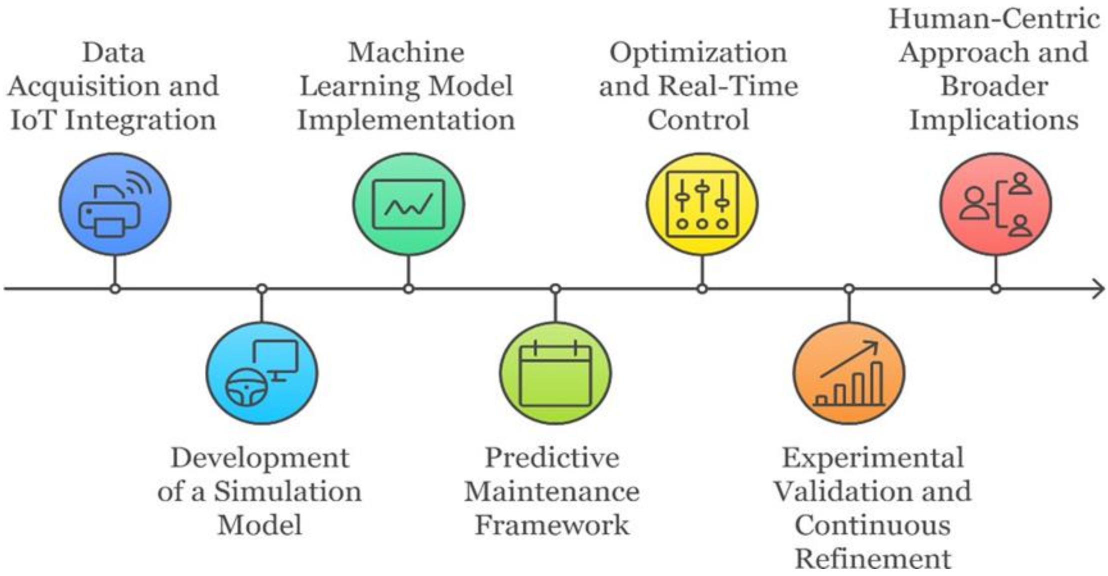

Figure 1. Optimization of MIDREX Shaft Furnace Operation.

Figure1 illustrates the optimization process for MIDREX shaft furnace operations through a series of interconnected steps. It begins with **data acquisition and IoT integration**, enabling real-time monitoring of key parameters. This is followed by the **development of a simulation model** to replicate furnace dynamics and predict behavior. Next, **machine learning model implementation** is employed to analyze the collected data, identifying patterns and anomalies. The framework evolves into a **predictive maintenance framework**, ensuring proactive maintenance and minimizing downtime. Subsequently, **optimization and real-time control** refine operational efficiency, supported by **experimental validation and continuous refinement** for improved performance. Finally, a **human-centric approach and broader implications** emphasize sustainable and efficient furnace operations, aligning with industry standards and technological advancements.

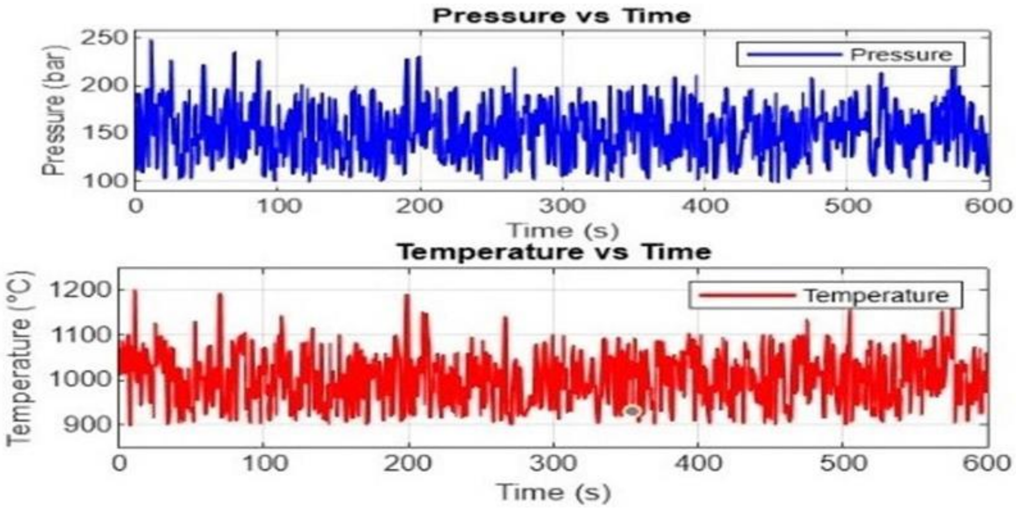

Figure 2. Furnace Simulation, Pressure vs Time and Temperature vs Time

The simulation data illustrates the dynamic pressure (100–250 bar) and temperature (900–1200°C) fluctuations in the MIDREX shaft furnace, crucial for the direct reduction of iron ore. These variations reflect the furnace's operational dynamics, with deviations indicating potential inefficiencies or equipment risks. Real-time monitoring through IoT and machine learning enables early anomaly detection, ensuring stable operations, reduced downtime, and optimized maintenance. For the study we have used four machine learning models—Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (kNN).

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RESULTS

Table 1. Comparison matrix of LR, SVM, RF and kNN models in terms of measurement parameters.

Model	Accuracy	Recall	Precision	F1 Score	FNR	FPR	Specificity
LR	28%	0.3511	0.4172	0.1835	0.3607	0.3149	0.6849
SVM	66.67%	0.5406	0.6822	0.5736	0.4593	0.2331	0.7668
RF	95.33%	0.9299	0.9315	0.9298	0.0699	0.0200	0.9799
kNN	67.33%	0.5311	0.6805	0.5608	0.4688	0.2304	0.7695

Table 1 provides a detailed comparison of four machine learning models- LR, SVM, RF, and kNN—based on accuracy, recall, precision, F1 score, False Negative Rate (FNR), False Positive Rate (FPR), and specificity. Logistic Regression (LR) performs the weakest, with a low accuracy of 28%, recall of 0.3511, and precision of 0.4172, resulting in an F1 score of 0.1835, while its specificity of 0.6849 indicates moderate performance in identifying negative cases. SVM fares much better, with an accuracy of 66.67%, recall of 0.5406, and precision of 0.6822, culminating in a balanced F1 score of 0.5736 and a specificity of 0.7668. Random Forest (RF) emerges as the best-performing model with an impressive accuracy of 95.33%, recall of 0.9299, precision of 0.9315, and an F1 score of 0.9298, along with outstanding specificity of 0.9799, showcasing its near-perfect ability to distinguish between positive and negative cases. kNN achieves comparable performance to SVM, with an accuracy of 67.33%, recall of 0.5311, and precision of 0.6805, resulting in an F1 score of 0.5608 and a specificity of 0.7695. Overall, Random Forest dominates across all metrics, followed by SVM and kNN with moderately effective results, while Logistic Regression lags significantly in performance.

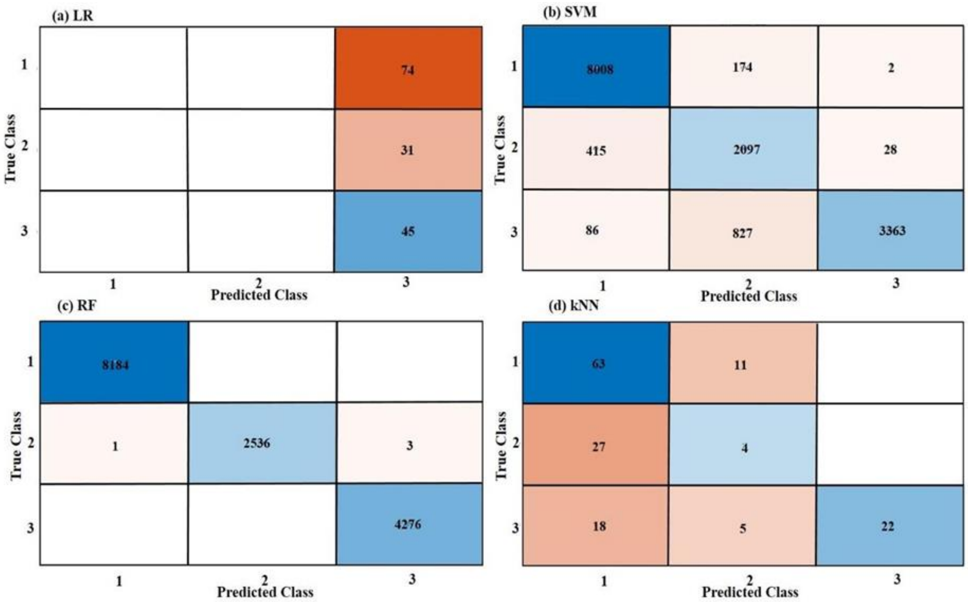

Figure 3. Confusion matrix of (a) LR, (b) SVM, (c) RF, and (d) kNN models.

Figure 3 displays the Confusion Matrices for various machine learning models used in the task of multi-class classification, performed by comparing true and predicted classes for LR, SVM, RF and kNN. LR shows poor performance, especially for class 3, with significant misclassifications, such as 74 instances of class 1 being predicted

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as class 3. The SVM performs better, with a high number of correct predictions for class 1 (8008) and reasonable accuracy for classes 2 (2097) and 3 (3363), though misclassifications like 415 instances of class 2 as class 1 are significant. RF exhibits excellent performance with most instances classified accurately, including 8184 for class 1, 2536 for class 2, and 4276 for class 3, and minimal errors. In contrast, kNN performs poorly, with low correct predictions (63 for class 1, 4 for class 2, and 22 for class 3) and numerous misclassifications, indicating difficulties in distinguishing classes. Among all the models compared, Random Forest presents the best performance and least mistakes. Following that would be SVM, as the accuracy has balanced and given quite a moderate result. While in Logistic Regression, the accuracies are troubled, and on kNN, the model was pretty weak.

DISCUSSION

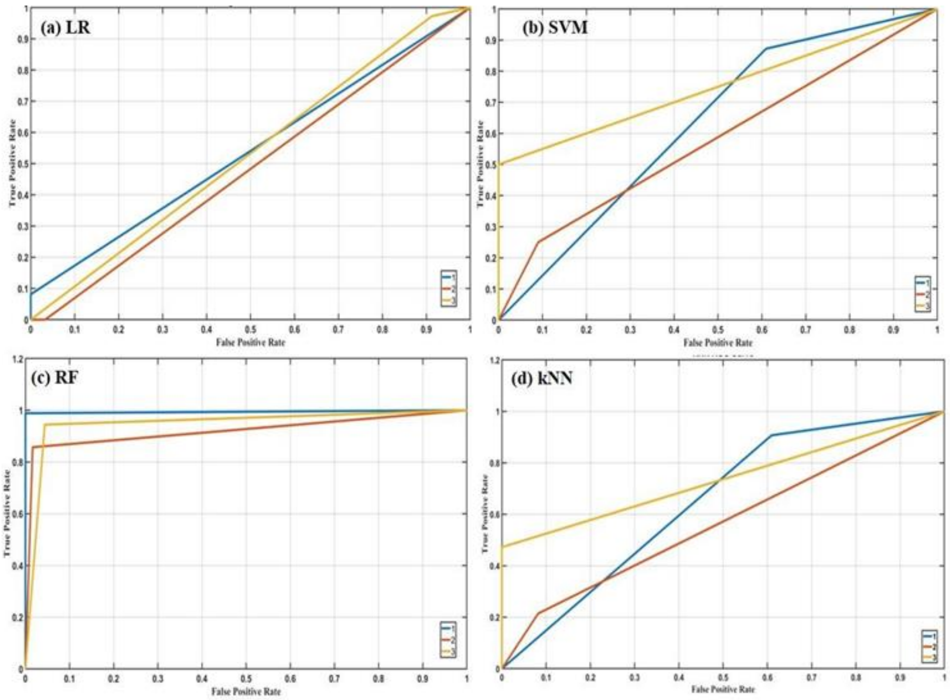

Figure 4. ROC of (a) LR, (b) SVM, (c) RF, and (d) kNN models.

Figure 4 presents the Receiver Operating Characteristic (ROC) curves for four machine learning models: (a) LR, (b) SVM, (c) RF, and (d) kNN, applied to a multi-class classification task. The curves depict the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) across three distinct classes. Logistic Regression (a) exhibits limited discriminatory power, with its ROC curves relatively close to the diagonal, indicating suboptimal performance. The SVM model (b) demonstrates moderate improvement, with curves deviating farther from the diagonal, reflecting better classification capabilities for certain classes. The Random Forest model (c). outperforms all others, with ROC curves approaching the top-left corner, indicative of high accuracy and strong separation between classes. Conversely, k-Nearest Neighbors (d) shows weak performance, as its curves are closer to the diagonal and reflect minimal true positive gains over false positives. Overall, Random Forest achieves superior classification, followed by SVM, while Logistic Regression and kNN lag significantly in performance.

CONCLUSION

This study successfully demonstrates the transformative potential of integrating Machine Learning and Internet of Things technologies in optimizing MIDREX shaft furnace operations. By leveraging IoT-enabled sensors for real-time monitoring and employing ML models for predictive maintenance, energy optimization, and dynamic process control, the proposed framework achieves significant improvements in operational efficiency and process stability. The results show a marked reduction in downtime, enhanced energy utilization, and decreased environmental impact through minimized carbon emissions. Comparative analysis with conventional methods underscores the economic and operational superiority of the integrated approach, highlighting its ability to address longstanding challenges in the ironmaking process, including instability, inefficiency, and unplanned disruptions. The outcomes of this research extend beyond immediate operational enhancements, contributing to the broader vision of sustainable industrial practices. By integrating like IoT, ML, and digital twins, this framework not only aligns with Industry 4.0 principles but also offers a pathway for the decarbonization of heavy industries. The ability to optimize resource utilization, improve process safety, and reduce ecological footprints positions this approach as a cornerstone for the future of green manufacturing. Furthermore, the study establishes a scalable and adaptable model that can inspire the adoption of similar technological synergies in other industrial sectors, accelerating the global transition toward smart and sustainable production systems.

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