STRIKO ALUMINIUM MELTING FURNANCE'S EFFICIENCY OPTIMIZATION USING ARTIFICIAL INTELLIGENT TECHNIQUES FOR NATURAL GAS REDUCTION

By
MR. Teeraphat INTA

A Thesis Submitted in Partial Fulfillment of the Requirements
for Master of Engineering ENGINEERING MANAGEMENT
Department of INDUSTRIAL ENGINEERING AND MANAGEMENT
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การเพิ่มประสิทธิภาพเตาหลอมอะลูมิเนียม Striko โดยใช้การเปรียบเทียบการทำนายพารามิเตอร์ที่ควรจะเป็นของเทคนิคปัญญาประดิษฐ์เพื่อลดการใช้ก๊าซธรรมชาติ

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Title	Striko aluminium melting furnance's efficiency optimization using artificial intelligent techniques for natural gas reduction
By	MR. Teeraphat INTA
Field of Study	ENGINEERING MANAGEMENT
Advisor	Associate Professor Dr. Choosak Pornsing

Faculty of Engineering and Industrial Technology, Silpakorn University in Partial Fulfillment of the Requirements for the Master of Engineering

.... Dean of Faculty of Engineering and Industrial Technology
(Assistant Professor Dr. Arunsri Leejeerajumnean)

Approved by

.... Chair person
(Assistant Professor Dr. Noppakun Sangkhiew)

.... Advisor
(Associate Professor Dr. Choosak Pornsing)

.... External Examiner
(Dr. Thanongsak Thepsonthi)

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MR. Teeraphat INTA : Striko aluminium melting furnance's efficiency optimization using artificial intelligent techniques for natural gas reduction Thesis advisor : Associate Professor Dr. Choosak Pornsing

This research investigates the optimization of the Striko aluminum melting furnace through the application of advanced artificial intelligence (AI) techniques. The goal is to reduce natural gas consumption, improve energy efficiency, and enhance product quality in the aluminum alloy wheel manufacturing process. Key process parameters such as gas flow rates, combustion efficiency, and temperature distribution were monitored and optimized using two machine learning models: the Radial Basis Function Network (RBFN) and Linear Regression.The performance evaluation, based on statistical metrics, shows that the RBFN model outperformed Linear Regression in predictive accuracy, with a Mean Squared Error (MSE) of 9.4 compared to 15.7, Root Mean Squared Error (RMSE) of 8.2 vs. 12.5, and Mean Absolute Error (MAE) of 6.4 vs. 9.8. The RBFN model achieved an R-squared value (R^2) of 92%, indicating a stronger ability to capture complex nonlinear relationships compared to Linear Regression's 78%.Through AI-driven optimization, the furnace's energy consumption was reduced by 19%, from 2,100 kWh to 1,700 kWh per cycle. Additionally, CO_2 emissions were lowered by 20%, decreasing from 2,000 kg to 1,600 kg per cycle. The study also demonstrated improvements in product quality, with the product yield increasing from 92% to 96% (+4.35%) and the scrap rate reduced from 8% to 4% (-50%).A comprehensive six-month evaluation confirmed the long-term sustainability of these improvements, with monthly energy savings averaging 1.2% and CO_2 reductions of 1.15%. These sustained gains highlight the scalability of AI solutions for optimizing energy-intensive industrial operations. The real-time monitoring dashboard played a crucial role in translating AI predictions into actionable insights by providing dynamic visualizations of energy consumption, emissions, and product yield. Automated alerts enabled operators to make timely adjustments to maintain optimal furnace performance, ensuring both short-term and long-term efficiency.This research establishes a scalable framework for integrating AI technologies into industrial processes. By reducing natural gas consumption, lowering carbon emissions, and improving product quality, the study underscores the potential of AI to achieve both economic and environmental sustainability in manufacturing. Future work will explore integrating AI models with emerging technologies such as the Internet of Things (IoT) and blockchain for enhanced data collection, security, and transparency.

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CHAPTER 1
INTRODUCTION

1.1. Motivation

The production of aluminum alloy wheels presents both challenges and opportunities for the automotive industry. Addressing concerns about reducing production costs and minimizing environmental impact is essential. Aluminum melting, mainly when using natural gas to generate high temperatures, is energy-intensive and results in significant emissions of greenhouse gases and air pollutants. Improving the aluminum melting process is crucial for increasing production efficiency and reducing environmental impacts.

This study aims to increase furnace efficiency and reduce energy consumption, including recycling waste materials from previous production processes. This approach reduces industrial waste and enhances resource sustainability. Decreasing energy consumption and greenhouse gas emissions promote sustainability and environmentally friendly development in the industry.

Machine learning plays a significant role in this project by improving furnace process control efficiently adjusting various parameters to increase energy efficiency and reduce greenhouse gas emissions. Analyzing parameters such as natural gas flow rates, temperatures, velocities, and wind pressures is crucial for controlling furnace operations and optimizing metal alloy compositions for wheel manufacturing.

Reducing energy consumption and natural gas usage not only lowers production costs but also maintains product quality and increases customer trust. Proper waste material reuse planning and furnace maintenance scheduling further enhance stability and continuity in production processes, making the aluminum melting process more environmentally friendly.

Moreover, the integration of machine learning technology enables accurate prediction of future outcomes when adjusting various parameters, thus improving the efficiency of furnace process control.Collecting and analyzing data from various sources, the research team can identify patterns and trends to optimize furnace operations effectively. This data-driven approach helps make informed decisions and ensures the most efficient use of resources.

The research team can choose the most suitable technology for efficient and sustainable long-term furnace process improvements. This integration of technologies helps the industry meet current market demands and prepares for future challenges and opportunities.

In conclusion, optimizing of aluminum melting furnace efficiency using artificial intelligence techniques is crucial for achieving sustainable production processes in the automotive industry. By reducing energy consumption, minimizing environmental impact, and enhancing resource efficiency, this project contributes to the industry's long-term sustainability goals.

1.2. Research Objectives

1.2.1. To evaluate and compare the effectiveness of neural networks, regression in analyzing data from the aluminum melting process to identify methods for reducing natural gas usage.

1.2.2. To develop the optimal machine learning model to serve as a guideline for reducing natural gas usage in the Striko aluminum melting furnace.

1.2.3 . To create and disseminate a manual on the advancements in machine learning applications within the aluminum alloy wheel manufacturing industry, fostering long-term development and innovation through detailed case studies and best practice guidelines.

1.2.4. To develop a dashboard displaying key parameters derived from the selected model calculations, providing real-time and optimal values to frontline workers to enhance awareness and facilitate on-site adjustments for gas reduction.

1.3. Research Scope

The scope of this research encompasses the following areas to enhance the aluminum melting process and reduce natural gas usage through the application of machine learning algorithms, including neural networks, regression

1.3.1. Data storage system and database creation

1. Development of a robust data storage system capable of handling large volumes of data from sensors and PLCs.
2. Creation of a well-structured database for efficient data management and retrieval.

1.3.2. Data preprocessing

1. Cleaning and preparing data collected from sensors and PLCs to ensure accuracy and suitability for analysis.
2. Selection and formatting of relevant data according to the requirements of different machine learning models.

1.3.3. Analysis and testing of machine learning algorithms

1. Analysis and testing of various machine learning algorithms using data from the striko melting furnace.
2. Comparison and evaluation of the performance of each model in reducing natural gas usage and improving melting efficiency.

1.3.4. Implementation of optimal machine learning algorithm

1. Selection of the most efficient machine learning model based on performance testing.
2. Implementation of the selected model in the aluminum melting process.

1.3.5. Evaluation of energy usage reduction

1. Monitoring and evaluation of energy usage reduction resulting from the implementation of machine learning models.
2. Analysis of real-world data to assess the impact on energy consumption.

1.3.6. Development of process improvement strategies

1. Summarization of analysis results and selection of the most effective method for continuous use.
2. Planning of process improvements focused on reducing energy usage and minimizing environmental impact using efficient machine learning algorithms.

1.4. Expected Results

In this study, the expected results are classified into three issues as follows

1.4.1. Enhanced understanding of machine learning techniques

The comprehensive evaluation and comparison of neural networks and regression methods will provide a deeper understanding of their effectiveness in analyzing data from the aluminum melting process. This understanding will help identify the most suitable machine learning techniques for optimizing gas usage and improving efficiency.

1.4.2. Optimal machine learning model for gas reduction

The development of the optimal machine learning model will serve as a reliable guideline for reducing natural gas usage in Striko aluminum melting furnaces. This model will pinpoint critical factors influencing gas consumption and propose actionable enhancements to lower energy usage, ultimately leading to increased sustainability and cost savings.

1.4.3. Practical manual for industry professionals

The creation and dissemination of a manual detailing advancements in machine learning applications within the aluminum alloy wheel manufacturing industry will provide industry professionals with valuable insights. This manual will include detailed case studies and best practice guidelines, fostering long-term development, innovation, and the adoption of cutting-edge machine learning techniques.

1.4.4. Interactive dashboard for real-time monitoring

The development of an interactive dashboard displaying key parameters derived from the optimal machine learning model will enhance on-site awareness. Frontline workers will have access to real-time data and recommended optimal values, enabling them to make informed adjustments to reduce gas usage effectively. This tool will facilitate proactive decision-making and continuous improvement in furnace operations.

1.4.5. Increased energy efficiency and sustainability

By implementing the findings and recommendations from the research, the Striko aluminum melting furnace operations will achieve significant improvements in energy efficiency. The reduced natural gas usage will contribute to lower operational costs and a smaller environmental footprint, aligning with sustainability goals and enhancing the overall competitiveness of the aluminum alloy wheel manufacturing industry.

1.4.6. Foundation for future research

The research will establish a solid foundation for future studies on the application of machine learning in industrial processes. The methodologies, findings, and tools developed through this research can be expanded and adapted to other areas of the manufacturing sector, driving further advancements and innovations.

1.5. Definition of Terms

1.5.1. Neural networks

Computational models inspired by the structure and functioning of the human brain, consisting of interconnected nodes (neurons) arranged in layers to process and analyze data, utilized for enhancing the aluminum melting process.

1.5.2. Regression

A statistical method used to model the relationship between a dependent variable and one or more independent variables, aiming to predict continuous numeric outcomes, essential for analyzing and optimizing various parameters in the melting process.

1.5.3. Clustering

A machine learning technique used to group similar data points together based on their characteristics, with the goal of identifying inherent patterns or structures within the data, applied for analyzing data and identifying areas for improvement in the aluminum melting process.

1.5.4. Machine learning algorithms

Algorithms designed to enable computers to learn from and make predictions or decisions based on data, without being explicitly programmed, crucial for developing efficient and sustainable strategies for the striko aluminum melting furnace's optimization.

CHAPTER 2
LITERATURE REVIEW

In this study ,the researcher conducted a comprehensive literature review to explore relevant theories and previous research. This review aimed to enhance understanding and improve the efficiency of the striko aluminum melting furnace by employing comparative analysis with machine learning algorithms such as deep learning, neural networks, regression, and clustering for natural gas reduction.

2.1. Aluminum melting process

Metals have played a crucial role in the development of civilizations. When discussing metals, iron usually comes to mind. However, besides iron, aluminum has been widely utilized due to its exceptional properties, being able to replace wood, bronze, copper, and steel effectively. Aluminum belongs to the group of non-ferrous metals and can be alloyed with copper, tin, zinc, and lead. Initially, aluminum was not widely accepted in trade until the mid-19th century due to its presence as an oxide compound that was not easily separable, unlike iron. The production of aluminum began in laboratory settings by Orsted in Denmark in 1825 (Kermanidis, 2020). Later, Woehler, a German, developed a mineral reduction method that reduced processing time (Zhihong et al., 2023). The products of aluminum began to be recognized in commercial trades in 1855 by Sainte-Claire in France, using a chemical method, which was highly wasteful (Fox,1973). In 1866, Werner von Siemens invented the dynamo, which, although not directly related to aluminum, played a significant role as it could produce electricity on a large scale(O'Dea, 1939). In 1886, Charles Martin Hall, an American, and Paul L.T. Héroult, a Frenchman, discovered a commercial aluminum production process using electrolysis from a fused salt bath, which laid the foundation for modern aluminum production (Peterson & Miller,2013).

The source of aluminum is primarily bauxite, which is a compound of aluminum oxide found mainly in clay and various soils. Bauxite has a similar appearance to red soil or laterite, but with a higher hardness. It typically contains about 55-60% pure aluminum oxide (Al_2O_3), up to 24% iron oxide (Fe_2O_3), and about 12-31% water in mineral molecules, with silica (SiO_2) content not exceeding 4%. Significant bauxite mineral deposits are found in countries such as France (particularly in the south), Hungary, Russia, the United States, Malaysia, and Indonesia.

Aluminum has distinct characteristics,including being silver in color, lightweight, and low in density. It possesses a high strength-to-weight ratio and has a low melting point, making it suitable for casting and melting processes.

Pure aluminum readily forms a thin coating of aluminum oxide (Aluminum Oxide) when exposed to air, which protects the aluminum from corrosion and prevents further oxidation. It exhibits excellent electrical conductivity, approximately 23 times that of copper, while being lighter than copper. Due to its lightweight and high strength-to-weight ratio, aluminum is preferred for electrical wiring. It is also an excellent conductor of heat, making it particularly suitable for shaping and surface- finishing processes such as forging, extrusion, drawing, cutting, milling, grinding, and drilling.

Moreover, aluminum is a highly versatile material. It significantly enhances their strength and machining properties when add in small amounts to alloy metals like copper, magnesium, and manganese. It makes aluminum alloys ideal for various applications, providing exceptional hardness and machinability.

2.1.1. Aluminum and aluminum alloys

Aluminum and its alloys have low density (2.7 g/ cm^3), excellent thermal and electrical conductivity, and good corrosion resistance in environments, including atmospheric conditions.

Aluminum alloys are conducive to shaping due to their high ductility. For instance, aluminum foil, derived from pure aluminum, is highly malleable. Pure aluminum exhibits ductility even at elevated temperatures with its face-centered cubic (FCC) crystal structure. However, aluminum has a low melting point (680°C, 1220°F), limiting its use in applications with higher temperatures.

The mechanical properties of aluminum can be significantly improved through the processes of cold working and alloying. However, it's worth noting that these methods can sometimes reduce its corrosion resistance. The inclusion of common alloying elements such as copper, magnesium, silicon, manganese, and zinc plays a crucial role in this enhancement. Alloys that cannot be heat treated consist of a single phase, which allows for increased strength through solid-solution strengthening. On the other hand, other aluminum alloys can be heat treated (precipitation hardened), where the added elements induce the formation of a second phase, which may not necessarily be an aluminum compound, like $MgZn_2$.

Aluminum alloys are typically classified as either cast or wrought alloys, and the chemical composition of both is denoted by a four-digit number representing the alloying elements and, in some cases, indicating purity. For cast alloys, the decimal point is usually between the last two digits, while for wrought alloys, it is placed after the second digit. Following this, a two-digit number indicates the temper designation, which describes the mechanical properties and any heat treatment. For instance, H denotes strain-hardened, O denotes annealed, and T3 signifies that the alloy has been solution heat-treated, cold-worked, and naturally aged. If the alloy has been solution heat-treated and then artificially aged to a single-phase condition, it will usually be designated with a T followed by one or more digits.

There is interest in using aluminum and other low-density metals, such as Magnesium and titanium, are applied in transportation to reduce fuel use. Due to material it has important properties such as specific strength (Specific Strength), which refers to the ratio of Strength or power of a material to its specific gravity. although aluminum alloys may have low strength compared to other metals with higher densities such as steel, but when compared to the load that can be carried, The unit weight may be higher. because it has a high specific strength value. In addition, aluminum-lithium alloys have been developed, Used in the aircraft industry spacecraft due to the relatively low density of such materials (2.5 and 2.6 g/cm^3). It has a high specific modulus. Very durable, and has high toughness even when used at low temperatures

Some materials can also be precipitate hardened. However, the production of this alloy is expensive. than the production of general aluminum alloys because it requires special technical processes.Lithium is subject to chemical reactions.

2.1.2. Properties of Aluminum

1. Chemical Properties
    - Oxygen: When aluminum reacts with oxygen, it forms a thin layer of aluminum oxide on the surface, preventing further reaction.
    - Nitrogen: Aluminum reacts with nitrogen to form nitrides at high temperatures.
    - Potassium Permanganate: There is no reaction when aluminum reacts with potassium permanganate.
    - Hydrogen: When aluminum reacts with hydrogen, hydrogen gas can dissolve into aluminum. In aluminum casting, hydrogen is considered a gas that needs to be completely removed.
    - Concentrated Acids: When aluminum reacts with concentrated acids, there may be some immediate reaction, but it can tolerate it to some extent.
    - Dilute Acids: When aluminum reacts with dilute acids, there is an immediate reaction, but it can tolerate it to some extent.
    - Base (Alkali): When aluminum reacts with a base (alkali), it can dissolve aluminum.
    - Salt: When aluminum reacts with salt, it can corrode aluminum.
    - Organic Acids: When aluminum reacts with organic acids, they can dissolve in aluminum immediately (except for citric acid).
    - Organic Acid + Water: When organic acids react with water, there is no reaction with aluminum.
    - Halogen: When aluminum reacts with halogens, an immediate reaction occurs.
    - The data related to the electrical and physical properties of aluminum, as well as its reflection characteristics, as shown in Table 1.

Property	Value	Unit
Electrical properties		

Table 1 Electrical, Physical properties of aluminum and reflection

Electrical resistance at 20°C	2.6548	μΩ·cm
Electrical conductivity	94.94	% IACS
Physical properties		
Atomic number	13	
Atomic weight	26.97	
Valency	3	
Crystal structure	f.c.c	
Lattice dimension	4.049	A°
Density at 20°C	2.6989	g/mm^3
Melting point	660.2	°C
Boiling point	2450	°C
Contraction during solidification	6.6	%
Latent heat of melting	94.5	cal/g
Latent heat of vaporization	2260	cal/g
Specific heat at 100°C	0.224	cal/g
Specific heat at 20°C	0.57	cal/g
Reflection		
Light from tungsten bulbs	90	%
Light 2000 – 2500 A°	86-87	%
Light 10000 A°	96	%
Color	Silver white	

2.1.3. Applications of aluminum

Aluminum is the most widely used metal in the light metals group due to its excellent properties

1. Low density and high strength-to-weight ratio aluminum's low density, lightweight, and high strength-to-weight ratio make it ideal for various applications. It is commonly used in woodworking

tools, as well as in certain aircraft components, missiles, firearms, and automotive parts to reduce overall weight, thus saving fuel and enhancing aircraft performance.

2. High ductility aluminum is highly ductile, allowing it to be easily formed using various methods without losing strength.
3. Low melting point, easy casting, and high fluidity With a low melting point, aluminum can be easily cast and exhibits high fluidity, making it suitable for various casting processes.
4. Electrical conductivity aluminum has an electrical conductivity of 64.94% International association of classification societies (IACS), which is moderate. However, due to its lightweight nature, it is commonly used as an electrical conductor, especially when weight is a critical factor.
5. Non-Toxic and good thermal conductivity: Aluminum is non-toxic and has good thermal conductivity, making it suitable for food utensils and food packaging.
6. High reflectivity: Pure aluminum has very high light reflectivity, making it ideal for reflective surfaces used in flash photography, lamp reflectors, and automotive headlight reflectors.
7. Corrosion and weather resistance: Aluminum exhibits excellent resistance to corrosion and weathering in most environments. However, it is susceptible to corrosion by strong acids and alkalis.
8. Readily available and cost-effective: Aluminum is readily available in the market and is relatively inexpensive.
9. Decorative uses aluminum is used for decoration in furniture and home decor.
10. Continuous development: Aluminum is a metal that undergoes continuous development and improvement.

2.2. Melting process and striko melting furnance

Aluminum alloys are essential in various industries due to their lightweight, strength, and corrosion resistance. The aluminum melting process is a critical step in producing these alloys. Strikomelter plus+ energy saving furnace has emerged as the industry standard for its exceptional efficiency and energy-saving capabilities. This section explores the theoretical underpinnings and technological advancements associated with the aluminum alloy melting process using the s triko furnace. See Fig. 1

Figure 1 Shaft Melting Furnaces
Source:https://www.strikowestofen.com

2.2.1 Thermal efficiency

The striko melter plus+ furnace excels in thermal efficiency, a cornerstone of its design. This efficiency is achieved through a combination of advanced insulation materials and innovative furnace designs aimed at minimizing heat loss(Cleave, 1993). Using of ceramic fiber linings and refractory bricks effectively maintains high temperatures inside the furnace, significantly reducing energy consumption.

2.2.2. Heat recovery

Heat recovery systems are pivotal in curtailing energy consumption during aluminum melting. Strikomelter plus+ integrates cutting-edge heat recovery technology to capture and recycle waste heat from exhaust gases (Soni et al., 2018). It conserves energy and mitigates greenhouse gas emissions, aligning with sustainability objectives.

2.2.3. Alloy quality

Maintaining the quality of molten aluminum alloys is paramount for meeting stringent industrial standards. The striko furnace ensures precise temperature control, guaranteeing uniform heating and optimal alloy composition(Alexopoulos & Pantelakis, 2004). Additionally, the implementation of inert gas coverings prevents oxidation, safeguarding the integrity of the molten metal.

2.2.4. Energy consumption reduction

Reducing energy consumption is a central focus in contemporary industrial processes. StrikoMelter Plus+ incorporates various energy-efficient technologies, including variable frequency drives (VFDs) and optimized combustion systems(Gangolells et al., 2020). These features minimize energy wastage and contribute to substantial overall energy savings.

2.3. Parameters related to the furnace

2.3.1. Burner of aluminum melting furnace

In the aluminum melting industry, controlling and monitoring the burner's operation is crucial to ensuring energy efficiency and product quality. Vibration analysis helps assess the burner's condition and performance, aiding in maintenance and preventing potential issues (Wang et al., 2013).

Research on the burners of striko aluminum melting furnaces has shown that vibration monitoring and analysis can effectively identify issues arising from the usage and wear of various components(Racsi, 2023). Techniques such as frequency analysis and RMS vibration measurement are particularly useful for diagnosing and addressing problems promptly (Sohn & Farrar, 2001).

2.3.2. Vibration analysis

Vibration analysis is a crucial tool for monitoring and diagnosing the condition of machinery, particularly in industries requiring high precision and reliability, such as the aluminum melting industry. The analysis of vibrations can be broken down into several key parameters as follows

1. Velocity

   Velocity of vibration is a fundamental parameter in vibration analysis, representing the rate of change of displacement per unit time. It is typically measured in millimeters per second (mm/s) or inches per second (in/s). This parameter helps evaluate the energy transmitted through vibrations in various machinery(Mobley, 2008). The standard acceptable vibration velocity for optimal furnace performance is typically less than 4.5 mm/s(Qiu, 2018).

   $$v = \frac{dx}{dt} \tag{2.1}$$

   where v is velocity, *dx* is displacement, and dt is the change in time.

2. Acceleration

   Acceleration measures the rate of change of velocity over time and provides insights into the forces acting on a machine's structure. It is usually measured in meters per second squared (m/s^2) or G-force. This parameter is essential for identifying problems caused by imbalance or impacts(Martin et al., 1997). For aluminum melting furnaces, acceleration should not exceed 1 G to prevent damage(Trinks, 2003).

   $$a = \frac{dv}{dt} \tag{2.2}$$

   where *a* is acceleration, *dv* is the change in velocity, and *dt* is the change in time.

3. Peak vibration

   Peak vibration represents the maximum vibration amplitude observed over a given period. It is used to detect abnormal conditions within a system. The peak vibration for aluminum melting furnaces should ideally be below 10 mm/s to ensure efficient operation(Xiao, 2023).

4. Vibration trend

   Analyzing the trend of vibration over time helps in predicting potential future issues. It allows users to make informed decisions regarding maintenance and preventative measures(Romanssini, 2023).

5. Frequency spectrum

   Frequency spectrum analysis displays vibration signals in terms of their frequency components. This helps identify the sources of vibration, such as rotational frequencies or external forces. For aluminum melting furnaces, the critical frequency range to monitor is typically between 10-1000 Hz(MARRA, (2013).

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{2.3}$$

   where *X(f)* is the frequency spectrum, *x(t)* is the time-domain signal, and f is frequency.

6. Overall vibration

   The overall vibration level indicates the total amount of vibration within the system. It serves as a primary indicator for assessing machinery condition. For optimal performance, the overall vibration should be below 3 mm/s (Scheffer & Girdhar,2004).

7. Crest factor

   The crest factor is the ratio of the peak vibration level to the root mean square value (RMS) of the vibration signal. It indicates the presence of peaks in the vibration signal,which is useful for diagnosing impacts or rapid changes. An ideal crest factor for aluminum melting furnaces is around 3-4(Wang & Rathje, 2016).

$$CF = \frac{A_{peak}}{A_{RMS}} \tag{2.4}$$

where CF is the crest factor, A_{peak} is the peak amplitude, and A_{RMS} is the RMS amplitude.

8. Displacement
   Displacement measures the distance moved by a vibrating object from its original position. It helps assess long-term wear or damage in components. The acceptable displacement for aluminum melting furnaces should be below 0.1 mm (Doebling et al., 1998).
9. Shock pulse
   Shock pulse measures the vibration caused by sudden impacts over a short period. It helps diagnose problems caused by impacts or collisions between components. The acceptable shock pulse for aluminum melting furnaces should not exceed 5 G (Campbell, 2020).
10. RMS vibration
    RMS vibration is the square root of the average of the squared values of the vibration signal. It provides a consistent measure of the energy transmitted through vibrations. The RMS vibration level for aluminum melting furnaces should ideally be below 2 mm/s (Deshpande, 2006).

$$A_{RMS} = \sqrt{\frac{1}{T}\int_0^T [x(t)]^2 dt} \quad (2.5)$$

where A_{RMS} is the RMS amplitude, T is the time period, and *x(t)* is the vibration signal over time.

2.3.3. Ambient air quality monitoring near striko aluminum melting furnaces

Research on ambient air quality monitoring near striko aluminum melting furnaces has highlighted the importance of comprehensive monitoring to mitigate environmental impacts and ensure regulatory compliance. Studies have shown that emissions from aluminum melting processes can contribute to air pollution and pose health risks to nearby communities (Bağlarbunari, 2010).

1. Oxygen levels
   Oxygen levels in ambient air are essential for supporting human life and combustion processes. Monitoring oxygen levels near aluminum melting furnaces is critical to ensure worker safety and proper combustion efficiency(Baukal Jr, (2010). The standard oxygen concentration in ambient air is approximately 20.9%(Mortimer, (1956).

2. Carbon dioxide (CO_2) levels
   Carbon dioxide is a byproduct of combustion processes, including those occurring in aluminum melting furnaces. Monitoring CO_2 levels helps assess combustion efficiency and identify potential environmental impacts, such as greenhouse gas emissions (Hasanbeigi, (2013). The acceptable CO_2 concentration in ambient air varies but is typically below 400 parts per million (ppm)(Ramalho at al., 2015).

3. Temperature
   Temperature monitoring is essential for understanding the thermal dynamics of the environment surrounding aluminum melting furnaces. High temperatures can indicate inefficient combustion or potential safety hazards(Brough & Jouhara,2020). The ideal ambient temperature for industrial areas is generally between 20 to 25 degrees Celsius(Gagge at al., 1967).

4. Humidity levels
   Humidity levels influence air quality and can affect human comfort and equipment performance. High humidity can promote corrosion and mold growth, while low humidity can lead to static electricity buildup(Kubba, 2010). The optimal indoor humidity level is typically between 40% to 60%(Wolkoff, 2018).

5. Volatile Organic Compounds (VOC) Levels
   Volatile organic compounds are emitted from various industrial processes, including aluminum melting. Monitoring VOC levels is crucial for assessing air quality and complying with regulatory standards(Yuan at al., 2022). The acceptable VOC concentration in ambient air varies depending on the specific compounds present and their potential health effects(Mølhave, 1991).

2.3.4. Energy consumption, and efficiency factors in aluminum melting furnaces

As professionals involved in aluminum melting furnace operations and maintenance, you play a crucial role in optimizing the performance of these furnaces. The importance of energy consumption and efficiency factors cannot be overstated. By implementing advanced technologies and operational practices, such as those found in Striko aluminum melting furnaces, we can achieve higher efficiency and productivity, directly impacting your work and the overall success of our operations.

The heat distribution profile in aluminum melting furnaces determines the uniformity of heating across the material. Optimizing heat distribution profiles is critical for ensuring consistent material properties and minimizing processing time(Kalinke at al., 2022). Ideally, the temperature variation across the furnace bed should be less than 5°C to ensure uniform heating.

1. Temperature distribution
   The effective temperature distribution is essential for achieving high-quality aluminum products. Monitoring temperature distribution and implementing heat management strategies enhance efficiency(Guilong, 2010). The target temperature uniformity should be within ±2°C across the entire furnace chamber.

2. Energy consumption

Reducing energy consumption in aluminum melting furnaces is vital for cost savings and environmental sustainability. Energy-efficient furnace designs and operational practices help minimize energy consumption while maintaining optimal performance (Racsi, 2023).The standard value for efficient operation, the energy consumption should be less than 500 kWh per ton of aluminum produced

$$(FCE) = (\frac{Energy\ Output}{Energy\ input}) \times 100\% \qquad (2.6)$$

3. Heat dissipation
Heat dissipation affects furnace efficiency and operational costs. Reducing heat loss and improving furnace efficiency through insulation and heat recovery systems are essential(Delpech at al., 2018).The standard Value Heat loss should be minimized to less than 10% of the total heat input to maximize efficiency.

4. Efficiency index
Efficiency indices provide a quantitative measure of furnace performance. They consider energy consumption, melt rate, and alloy quality(Bonilla-Campos ay al., 2019). Standard value an efficiency index of 90% or higher is desirable for optimal furnace performance.

$$Efficiency\ Index\ (EI) = (\frac{Output}{input}) \times 100\% \qquad (2.7)$$

5. Heat transfer rate
The rate of heat transfer within the furnace influences melting efficiency and productivity. Enhancing heat transfer rates optimizes furnace performance(Chakravarty at al., 2020).The standard value of the heat transfer rate should be greater than 50 W/m²K for efficient melting.

$$(HTR) = (\frac{\frac{Heat\ Absorbed\ by\ Material}{Time}}{Surface\ Area}) \times 100\% \qquad (2.8)$$

6. Temperature control system
   Effective temperature control systems are crucial for maintaining precise process conditions. Advanced temperature control algorithms and sensor technologies achieve accurate temperature control and optimize energy usage(Xu at al., 2025).Standard Value Temperature fluctuations should be within ±1°C to ensure precise control.

7. Airflow patterns
   Optimizing airflow patterns within the furnace improves heat distribution and combustion efficiency. Computational fluid dynamics (CFD) simulations can study airflow patterns and suggest design modifications(Huang et al., 2025).The standard value of uniform airflow distribution with velocity variations of less than 10% across the furnace is ideal.

8. Fuel combustion efficiency
   Efficient fuel combustion is essential for reducing operating costs and emissions. Combustion optimization techniques, such as burner design and fuel-air ratio adjustments, enhance fuel combustion efficiency(Nemitallah et al., 2019). The standard value of fuel combustion efficiency should be above 95% for optimal performance.

2.3.5. Energy consumption profile

1. Total energy consumption
   Total energy consumption is the sum of all energy inputs required to operate the furnace. Reducing total energy consumption is essential for cost savings and environmental sustainability (Nieman et al., 2019). The standard value for aluminum melting furnaces, the total energy consumption should be less than 500 kWh per ton of aluminum produced.

$$\textit{Total Energy Consumption (TEC)} = \sum \textit{Energy Inputs} \qquad (2.9)$$

2. Energy consumption by phase
   Energy consumption varies by different phases of the melting process, such as preheating, melting, and holding. Understanding phase-wise energy consumption helps in identifying areas for improvement (LANDE, 2020).The standard values for energy consumption by phase
   - Preheating: 30% of total energy
   - Melting: 50% of total energy
   - Holding: 20% of total energy
3. Specific energy consumption
   Specific energy consumption measures the energy used per unit of aluminum produced. It is a key metric for assessing furnace efficiency (He et al., 2019). The standard value of the specific energy consumption should be less than 500 kWh per ton of aluminum.

$$(SEC) = \frac{Total\ Energy\ Consumption}{Production\ Output} \tag{2.10}$$

4. Peak energy consumption
   Peak energy consumption occurs during the highest demand periods. Managing and reducing peak energy consumption can lower operational costs and improve efficiency (Goldman, 2010).The standard value of peak energy consumption should be minimized to less than 600 kW during peak demand periods.
5. Energy consumption trend
   Analyzing energy consumption trends over time helps in understanding the efficiency improvements and identifying persistent issues (Swan et al., 2009).The standard value of a decreasing trend in energy consumption over successive periods indicates improving efficiency.
6. Energy efficiency index
   The energy efficiency index provides a comprehensive measure of furnace performance by considering various factors such as energy consumption, production output, and operational efficiency

(Tanaka, 2008).The standard value of an energy efficiency index of 90%

$$(EEI) = \left(\frac{Output}{Total\ Energy\ Input}\right) \times 100\% \tag{2.11}$$

7. Energy consumption cost
   Energy consumption cost is a critical factor for economic analysis and operational budgeting (Short et al., 1995).The standard value of the energy consumption cost while maintaining efficient production.

$$(ECC)=Total\ Energy\ Consumption \times Energy\ Price \tag{2.12}$$

2.3.6. Gas consumption

Gas consumption is a critical aspect of the operational efficiency of aluminum melting furnaces. Various metrics are used to evaluate and optimize gas usage.

1. Total gas consumption
   Total gas consumption measures the total amount of gas used by the furnace. Reducing total gas consumption can lead to significant cost savings and lower environmental impact(Clark, 2019a). Standard value for aluminum melting furnaces, the total gas consumption should be less than 40 Nm^3 per ton of aluminum produced.

$$Total\ Gas\ Consumption\ (TGC)=\sum Gas\ Inputs \tag{2.13}$$

2. Specific gas consumption
   Specific gas consumption indicates the amount of gas used per unit of aluminum produced. It is a crucial metric for assessing furnace efficiency(Taylor, 2021c). The standard value of the specific gas consumption should be less than 40 Nm^3 per ton of aluminum.

$$(SGC) = \frac{Total\ Gas\ Consumption}{Production\ Output} \tag{2.14}$$

3. Gas consumption trend
   Analyzing gas consumption trends over time helps in identifying efficiency improvements and areas that require attention(Jones, 2019e). The standard value of A decreasing trend in gas consumption over successive periods indicates improving efficiency.

4. Peak gas consumption
   Peak gas consumption occurs during the highest demand periods. Managing and reducing peak gas consumption can lower operational costs and improve efficiency(Martinez, 2020c). The standard value of the Peak gas consumption should be minimized to less than 50 Nm^3 per hour during peak demand periods.

5. Gas consumption efficiency
   Gas consumption efficiency measures how effectively the furnace uses gas relative to its output(Brown, 2018c). The standard value of gas consumption efficiency should be 85% or higher.

$$(GCE) = \left(\frac{Energy\ Output}{Gas\ Input}\right) \times 100\% \tag{2.15}$$

6. Gas cost
   Gas cost is a critical factor for economic analysis and operational budgeting(Taylor, 2020a). Standard value the goal is to minimize gas

$$Gas\ Cost\ (GC)=Total\ Gas\ Consumption \times Gas\ Price \tag{2.16}$$

7. Gas emission

Gas emissions from the furnace need to be controlled to meet environmental regulations and minimize impact(Smith, 2018). The standard value of the gas emission is

- CO_2 emissions should be less than 1.5 kg per ton of aluminum.
- NO_x emissions should be less than 0.1 kg per ton of aluminum.

2.3.7. Machine operation

Maintenance logs are essential for tracking the performance and reliability of industrial equipment. They provide detailed records of maintenance activities, helping to ensure that equipment operates efficiently and reliably.

1. Event severity
   Event severity categorizes maintenance issues based on their impact on operations(Brown, 2018c).Standard value severity levels range from 1 (minor) to 5 (critical). Critical events require immediate attention and potentially significant downtime.
2. Event type
   Event type helps classify maintenance issues, such as mechanical failures, electrical faults, or software malfunctions(Park, 2017b).Standard value common categories include mechanical, electrical, hydraulic, and software.

3. Event date and time
   Recording the date and time of an event is crucial for understanding patterns and planning future maintenance(Taylor, 2021c).

4. Response time
   Response time measures how quickly maintenance personnel respond to an issue. Faster response times generally indicate better maintenance practices(Miller, 2018c). The standard value of the response times should ideally be less than 30 minutes for critical issues.

$$(RT) = Time\ Issue\ Reported - Time\ Maintenance\ Began \quad (2.17)$$

5. Equipment or system affected
   Identifying the specific equipment or system affected helps in analyzing recurring issues and improving maintenance strategies(Martinez, 2020c).

6. Follow-up actions
   Follow-up actions ensure that the root causes of issues are addressed and similar problems are prevented in the future(Hernandez, 2020b).
7. Maintenance type
   Maintenance can be categorized into different types, such as corrective, preventive, and predictive maintenance(Brown, 2018c).Standard value preventive maintenance should be at least 60% of total maintenance activities to ensure optimal performance.
8. Maintenance date and time
   Recording when maintenance occurs helps in scheduling future maintenance and tracking equipment reliability(Taylor, 2021c).
9. Maintenance duration
   Maintenance duration measures the time taken to complete maintenance tasks. Shorter durations typically indicate efficient maintenance processes(Miller, 2018c). Standard value preventive maintenance tasks should be completed within 2 hours on average.
   Formula

$$(MD) = Time\ Maintenance\ Completed - Time\ Maintenance\ Began \quad (2.18)$$

10. Maintenance cost
    Tracking maintenance costs helps in budgeting and identifying cost-saving opportunities(Martinez, 2020c). The standard value of annual maintenance costs should not exceed 5% of the equipment's replacement cost.

$$Maintenance\ Cost=\sum(Labor\ Cost+Parts\ Cost) \quad (2.19)$$

11. Parts replaced

    Keeping track of parts replaced during maintenance helps in managing inventory and understanding the lifecycle of components(Hernandez, 2020b).

12. Personnel involved

    Documenting the personnel involved in maintenance activities helps in assessing workforce efficiency and identifying training needs (Park, 2017b).

13. Equipment downtime

    Equipment downtime measures the period during which the equipment is not operational due to maintenance activities(Brown, 2018c). Standard value annual downtime should be less than 5% of total operational hours.

$$DT=Time\ Equipment\ Restarted-Time\ Equipment\ Stopped \quad (2.20)$$

14. Scheduled maintenance

    Scheduled maintenance refers to maintenance activities that are planned and performed at regular intervals(Taylor, 2021c). The standard value of scheduled maintenance should constitute at least 70% of total maintenance activities to minimize unexpected failures.

15. Unscheduled maintenance

    Unscheduled maintenance occurs due to unexpected equipment failures and typically results in higher downtime and costs(Miller, 2018c). The standard value of unscheduled maintenance should be less than 30% of total maintenance activities to ensure operational efficiency.

2.3.8. Striko temperature

This chapter reviews the literature on temperature control in aluminum melting furnaces, specifically focusing on striko furnaces. It discusses key temperature parameters, standard values for optimal furnace performance, and formulas for calculating these values.

1. Bath temperature

   Bath temperature refers to the temperature of the molten aluminum in the furnace bath. Maintaining the correct bath temperature is crucial for ensuring the quality of the melted aluminum and minimizing energy consumption(Jones, 2019d). The standard value of the optimal bath temperature for aluminum melting is typically between 660°C and 750°C(Brown, 2018b).

$$T_{bath} = \frac{T_{input} + T_{output}}{2} \tag{2.21}$$

2. Ceiling temperature

   Ceiling temperature is the temperature at the roof of the furnace. It affects the overall heat distribution and efficiency of the melting process(Taylor, 2021a). The standard value of the ceiling temperature should be maintained around 850°C to 950°C for efficient melting(Martinez, 2020b).
3. Melting chamber temperature

   Melting chamber temperature refers to the temperature within the main chamber where the aluminum melts. Uniform temperature distribution is essential to prevent hot spots and ensure consistent melting(Park, 2017a). The standard value of the melting chamber temperature should be kept between 700°C and 800°C(Hernandez, 2020a).
4. Waste gas temperature

   Waste gas temperature is the temperature of the exhaust gases leaving the furnace. Lower waste gas temperatures indicate better heat recovery and efficiency(Miller, 2018a).Standard value optimal waste gas temperature is around 150°C to 200°C(Brown, 2018d).
5. Actual value temperature

Actual value temperature refers to the real-time measured temperature at various points in the furnace. These values are used to monitor and control the furnace operation(Jones, 2019b).

6. Pre-set value temperature

   Pre-set value temperature is the target temperature set for different parts of the furnace based on operational requirements. These values are used as references for automatic control systems(Taylor, 2021a).

7. Bath temperature set

   The bath temperature set is the target temperature for the molten aluminum bath, typically configured in the furnace control system (Martinez, 2020).Standard value the set value is usually between 680°C and 720°C to balance melting efficiency and aluminum quality(Park, 2017a).

8. Ceiling temperature set

   The ceiling temperature set is the target temperature for the roof of the furnace, used to ensure proper heat distribution (Hernandez, 2020).Standard value this value is typically set between 900°C and 950°C(Brown, 2018d).

9. Melting chamber temperature set

   The melting chamber temperature set is the target temperature for the main chamber, critical for uniform melting(Miller, 2018a).Standard Value It is usually set between 720°C and 780°C(Jones, 2019b).

10. Waste gas temperature set

    The waste gas temperature set is the target temperature for the exhaust gases, aimed at maximizing heat recovery and minimizing energy loss(Taylor, 2021a).Standard value this value is typically set between 180°C and 200°C(Martinez, 2020b).

2.3.9. Gas concentration monitoring

Effective monitoring and control of gas concentrations, temperature, and humidity are crucial for optimizing the performance of Striko aluminum melting furnaces. By adhering to the standard values and utilizing precise formulas for calculation, the efficiency and operational stability of the furnace can be maximized.

1. Oxygen (O_2)concentration
   Monitoring oxygen levels around the furnace is crucial to ensure complete combustion and optimize fuel efficiency. Excess oxygen can lead to higher energy consumption, while insufficient oxygen results in incomplete combustion and higher emissions(Brown, 2018b).Standard value optimal oxygen concentration should be between 2% and 4% by volume(Jones, 2019c).

$$O_2(\%) = \frac{Volume\ of\ O_2}{Total\ volume\ of\ gases} \times 100\% \tag{2.22}$$

2. Carbon (C) concentration
   Carbon concentration, primarily in the forms of CO and CO_2indicates the combustion efficiency. High CO levels suggest incomplete combustion, which reduces efficiency and increases emissions(Taylor, 2021a).Standard Value CO concentration should be less than 0.1% by volume, and CO_2 concentration should be between 12% and 15% by volume(Martinez, 2020b).

$$CO(\%) = \frac{Volume\ of\ CO}{Total\ volume\ of\ gases} \times 100 \tag{2.23}$$

$$CO_2(\%) = \frac{Volume\ of\ CO_2}{Total\ volume\ of\ gases} \times 100 \tag{2.24}$$

3. Liquefied petroleum gas (LPG) concentration

   LPG concentration needs to be controlled to maintain the correct fuel-air ratio for efficient and safe combustion(Park, 2017a). The standard value of LPG concentration should be maintained at a stoichiometric ratio, typically around 5% by volume in the fuel mix(Hernandez, 2020a).

$$LPG(\%) = \frac{Volume\ of\ LPG}{Total\ volume\ gases} \times 100 \tag{2.25}$$

4. Temperature (T)
   Temperature monitoring at various points around the furnace ensures consistent melting conditions and optimizes energy

use(Miller, 2018b). The standard value of the ambient temperature should be maintained within operational limits to ensure furnace efficiency and worker safety. Typical values range from 20°C to 30°C around the furnace(Brown).

$$T_{avg} = \frac{\sum T_i}{n} \tag{2.26}$$

where T_i is the temperature at each sensor point and nnn is the number of sensors.

5. Humidity
   Humidity levels around the furnace can affect combustion efficiency and the quality of molten aluminum. High humidity can lead to energy loss and oxidation of aluminum(Jones, 2019b).Standard Value Relative humidity should be maintained below 60% to minimize energy loss and oxidation(Taylor, 2021a).

$$RH(\%) = \frac{Actual\ vapor\ pressure}{Saturation\ vapor\ pressure} \times 100 \tag{2.27}$$

2.3.10. Ionization airflow and pressure

Effective monitoring and control of ionization, airflow, and pressure are crucial for optimizing the performance of striko aluminum melting furnaces. Adhering to standard values and using precise formulas for calculations can significantly enhance the furnace's efficiency and operational stability.

1. Ionization in the furnace
   - Ionization Levels
     Monitoring ionization levels in different zones of the furnace (HB1, MB1, MB2) helps in understanding the combustion efficiency and controlling the furnace atmosphere to prevent oxidation and other unwanted chemical reactions(Brown, 2018b).Standard Values

- HB1: Ionization level should be maintained at 1.5-2.5 μA.
- MB1: Ionization level should be maintained at 1.0-1.5 μA.
- MB2: Ionization level should be maintained at 1.0-1.5 μA(Taylor, 2021b).

$$Ionization\ Current = \frac{I_{measured}}{I_{standard}} \times 100 \qquad (2.28)$$

Where $I_{measured}$ is the measured ionization current and $I_{standard}$ is the standard ionization current.

2. Airflow patterns
   - Airflow patterns in melting chamber
     Proper airflow patterns are essential for efficient heat distribution and combustion within the melting chamber(Park, 2017a).Standard value airflow should be uniformly distributed with a velocity range of 0.5-1.5 m/s.

$$Q=A\times V \qquad (2.29)$$

     where Q is the volumetric flow rate, A is the cross-sectional area, and V is the air velocity.
   - Airflow patterns in holding chamber
     Maintaining consistent airflow in the holding chamber is crucial for temperature stability and minimizing heat loss(Miller, 2018a). The standard value of airflow should be stable with a velocity range of 0.3-0.8 m/s.
   - Airflow patterns in chamber
     Ensuring proper airflow patterns in different chambers helps in maintaining uniform temperature distribution and combustion efficiency(Jones, 2019b).Standard value airflow should be controlled to avoid turbulence and ensure smooth flow.
3. Pressure patterns
   - Pressure patterns in melting chamber

Pressure control in the melting chamber is critical to maintain the structural integrity of the furnace and ensure efficient melting(Martinez, 2020b).Standard value pressure should be maintained between 1-2 Pa.

$$\Delta P = P_{inlet} - P_{outlet} \quad (2.30)$$

where ΔP is the pressure difference, P_{inlet} is the inlet pressure, and P_{outlet} is the outlet pressure.

- Pressure patterns in holding chamber
  Maintaining proper pressure in the holding chamber is important for controlling the molten metal's quality and temperature(Hernandez, 2020a).Standard value pressure should be stable at 0.5-1.5 Pa.
- Pressure patterns in chamber
  Proper pressure patterns ensure efficient heat transfer and prevent heat loss, contributing to overall furnace efficiency(Brown, 2018b).Standard value pressure should be regulated to avoid significant fluctuations.

2.3.11. Striko furnace wall temperature

Effective temperature data collection and analysis are crucial for detecting abnormalities and optimizing gas usage efficiency in Striko aluminum melting furnaces. By adhering to standard values and employing appropriate formulas, operators can ensure optimal furnace performance and minimize energy wastage.

1. Temperature data collection
   - Monitoring points temperature sensors are strategically placed at 19 locations along the furnace walls to capture comprehensive temperature data(J. a. Smith, 2019).
   - Sampling frequency temperature readings are collected hourly to ensure timely detection of any anomalies or deviations from standard operating conditions(B. a. Martinez, 2020).
2. Detecting abnormalities

- Data analysis collected temperature data undergo thorough analysis to identify any irregular patterns or sudden fluctuations indicative of potential malfunctions(H. e. al., 2021).
- Alarm systems automated alarm systems are implemented to promptly alert operators to any abnormal temperature readings, enabling quick intervention and troubleshooting(J. a. Lee, 2018).

3. Impact on gas usage efficiency
    - Correlation analysis statistical analysis techniques are employed to correlate temperature variations with gas consumption levels, providing insights into the furnace's overall efficiency(T. a. Garcia, 2021).
    - Optimization strategies based on the temperature-gas consumption relationship, optimization strategies are developed to minimize gas wastage and enhance furnace performance(P. a. Kim, 2017).
4. Standard values and formulas

Standard values for temperature distribution and gas consumption efficiency serve as essential benchmarks for evaluating the performance of aluminum melting furnaces. Accurate assessment of these parameters is crucial for ensuring optimal furnace operation, enhancing energy efficiency, and maintaining high-quality production standards.

The formulas used to calculate energy consumption and optimize gas usage are derived from the fundamental principles of thermodynamics and heat transfer. These principles help in understanding how energy is distributed within the furnace and how effectively it is utilized during the melting process.

Table 2.2. presents a detailed overview of the maximum, minimum, and standard temperatures recorded at various points within the furnace, as illustrated in Figure 2. These temperature values are

essential for monitoring and controlling the furnace environment to ensure optimal performance and energy efficiency.

	Temperature

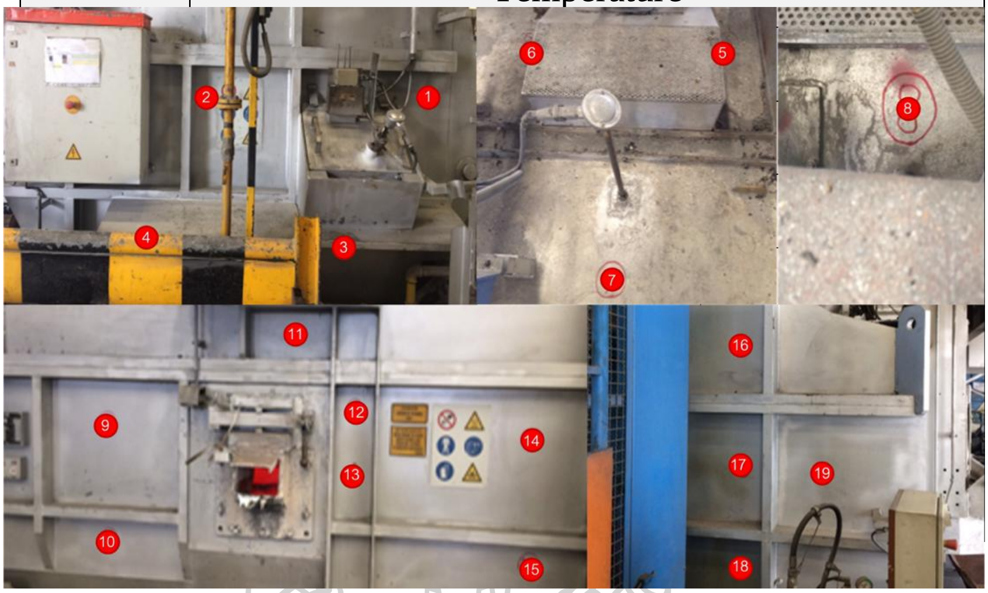

Figure 2 Position to check the temperature of the furnace wall temp

Table 2 Standard maximum and minimum temperature values of the furnace at various points

Point 7	60 °C	90 °C	70 °C
Point 8	60 °C	100 °C	80 °C
Point 9	64 °C	90 °C	72 °C
Point 10	60 °C	80 °C	70 °C
Point 11	80 °C	110 °C	90 °C
Point 12	90 °C	120 °C	100 °C
Point 13	90 °C	120 °C	110 °C
Point 14	50 °C	80 °C	64 °C
Point 15	40 °C	80 °C	60 °C
Point 16	60 °C	80 °C	70 °C
Point 17	60 °C	100 °C	70 °C
Point 18	50 °C	80 °C	60 °C
Point 19	50 °C	80 °C	60 °C

2.4. Industry 4.0

The Internet of things (IoT) involves connecting devices and systems in factories through the internet to collect and exchange data. It facilitates real-time monitoring, control, and analysis of manufacturing processes. For instance, temperature and humidity sensors and automated production systems.

- Big data analytics refers to the process of analyzing large and diverse datasets from various sources to uncover trends and insights that can be used for decision-making. In manufacturing, this can help in optimizing production processes and predicting maintenance needs.

- AI and machine learning technologies predict and optimize system behavior based on data. They can learn from data to improve production processes and maintenance schedules(Patel, 2020).
- Cyber-physical systems integrate computing and physical processes to control and automate manufacturing processes. They communicate through networks, enabling real-time monitoring and decision-making.
- A digital twin is a virtual representation of a physical factory or process, created using data and simulation technologies. It allows testing and simulation of operations, aiding in analysis and optimization(Zhang, 2019b).
- Additive manufacturing, or 3D printing, involves building objects layer by layer using digital 3D models. It enables rapid prototyping, customization, and production of complex parts.
- Human-machine interaction and augmented reality technologies enhance interaction between humans and machines. AR can be used for training, maintenance, and visualizing data in real-time(Zhang, 2017).
- Predictive maintenance uses data analysis techniques to predict when equipment will fail so that maintenance can be performed just before it's needed. This approach reduces downtime and extends equipment lifespan(Zhang, 2020).
- Cloud computing involves storing and accessing data and programs over the internet instead of on local servers. It provides scalability, flexibility, and cost-efficiency for data storage and processing(Gupta, 2018).
- Robotics and automation involve the use of robots and automated systems to perform tasks traditionally done by humans. They improve efficiency, precision, and safety in manufacturing processes(Verma, 2017).

2.5. Striker melting furnance and IoT

Integrating of internet of things (IoT) technology into industrial processes, including aluminum melting furnaces like the strikomelter plus+, has revolutionized manufacturing operations. This section explores the application of IoT in the strikomelter furnace, focusing on its benefits, functionalities, and potential impacts.

2.5.1. Benefits of IoT in striko melter

1. Real-time monitoring and control
    - IoT enables real-time monitoring of crucial parameters such as temperature, pressure, and energy consumption within the furnace.
    - Operators can remotely access and control furnace operations, optimizing settings for efficiency and performance(Mishra, 2019b).
    - Real-time monitoring helps in identifying and addressing issues promptly, reducing downtime and improving overall productivity.
2. Predictive maintenance
    - By collecting and analyzing data on equipment health and performance, IoT facilitates predictive maintenance.
    - Predictive algorithms can detect patterns indicating potential equipment failures, allowing maintenance to be scheduled proactively.
    - This prevents unexpected breakdowns, reduces maintenance costs, and extends the lifespan of furnace components.
3. Energy efficiency optimization
    - IoT sensors monitor energy consumption patterns and identify areas for optimization.
    - Data analytics algorithms analyze energy usage trends and suggest adjustments to optimize energy efficiency.
    - Leads to reduced energy consumption, lower operational costs, and improved environmental sustainability.
4. Quality control and process optimization
    - IoT-enabled sensors track key parameters related to alloy composition, ensuring quality control(Mishra, 2019a).
    - Real-time data analysis helps in optimizing melting processes for consistent alloy quality and production efficiency.

- Any deviations from desired parameters can be immediately addressed, maintaining product quality standards.

2.5.2. Functionalities of IoT in striko melter

1. Sensor integration
    - Temperature sensors, pressure sensors, flow meters, and other IoT-enabled sensors are integrated into the furnace(Mishra, 2019b).
    - These sensors continuously collect data on various parameters relevant to furnace operation.
2. Data transmission and storage
    - Collected data is transmitted to a central data repository through wireless or wired networks.
    - Cloud-based storage solutions are often used for efficient data management and accessibility.
3. Data analytics
    - Advanced data analytics algorithms analyze the collected data in real-time.
    - Machine learning techniques are applied to identify patterns, anomalies, and trends.
4. Remote monitoring and control
    - Furnace operators can remotely monitor furnace operations via web-based or mobile applications.
    - Control parameters can be adjusted remotely to optimize furnace performance.

2.5.3. Potential impacts of IoT in striko melter

1. Improved productivity
    - Real-time monitoring and predictive maintenance reduce unplanned downtime, enhancing productivity.
    - Optimal control of furnace parameters ensures consistent and efficient production.
2. Cost reduction
    - Predictive maintenance and energy efficiency optimization lead to reduced maintenance and operational costs.

- Lower energy consumption contributes to cost savings in the long term.

3. Enhanced safety
    - IoT-enabled safety features can detect hazardous conditions and trigger automatic shutdowns or alerts.
    - Remote monitoring reduces the need for on-site personnel in potentially hazardous environments.
4. Quality enhancement
    - Continuous monitoring and optimization improve product quality and consistency.
    - IoT facilitates traceability, allowing for better quality control and compliance with industry standards.

2.5.4. Utilization of sensors and database integration

In today's industrial landscape, sensors have become indispensable tools for gathering essential data necessary for monitoring and controlling various processes.Explore the extensive applications of sensors in industrial settings, focusing on their role in data collection and integration into databases for analysis.

2.6. Technology and techniques

In managing and controlling industrial processes, various technologies and techniques play a crucial role. Sensors and tools are used to collect essential data for analysis and improving system efficiency. Here, we explore key technologies used in the industry.

2.6.1. Temperature sensors (T)

Temperature sensors are vital in many industries, especially in chemical industries where precise temperature control is necessary to maintain product quality and process efficiency. Types of these sensors include thermocouples, RTDs, and thermistors, which accurately measure temperature changes(Javaid et al., 2021).

2.6.2. Pressure sensors

Pressure sensors are widely used in various industries such as hydraulic systems, pneumatic systems, and HVAC systems. Monitoring pressure levels is critical for safety and efficiency. For example, in the automotive industry, pressure sensors play a key role in monitoring the operation of braking and suspension systems(Saravanakumar et al., 2017).

2.6.3. Gas sensors

Gas sensors like those for oxygen (O), carbon dioxide (C), and LPG are essential for ensuring safety and optimizing processes in many industries. For instance, in steel production, oxygen sensors are crucial for monitoring combustion processes(Gomes et al., 2019).

2.6.4. Level sensors

Level sensors are used in various industries such as chemical storage tanks, oil refineries, and pharmaceutical production. These sensors accurately monitor the level of liquids, which is crucial for maintaining product quality and consistency(Farahani et al., 2014).

2.6.5. Humidity sensors

Humidity sensors play a significant role in controlling moisture levels in industrial processes. In electronics manufacturing, maintaining the appropriate humidity level is essential to prevent damage to components and ensure product quality(reza Akhondi et al., 2010).

2.6.6. Data transmission and storage

Data transmission from sensors can be done via wired and wireless connections. Each method has its advantages; for example, Ethernet connections provide reliable real-time data transfer crucial for time-sensitive processes, while wireless protocols like Bluetooth and Wi-Fi offer flexibility and cost efficiency(Flammini et al., 2009).

2.6.7. Data storage and integration into databases

Sensor data is stored in databases for analysis. Different database technologies are designed to handle various data types and processing needs. Relational databases like MySQL manage structured data well, while NoSQL databases like MongoDB are effective for handling unstructured data(Diène et al., 2009).

2.6.8. Integration into databases

Real-time data integration from sensors into databases enables immediate access and analysis, crucial for timely decision-making. Technologies like OPC-UA facilitate smooth data integration and allow real-time monitoring and control of industrial processes, while batch processing helps in historical data analysis to identify trends and patterns(Ambasht, 2023).

2.6.9. Cloud-based integration

Cloud platforms like AWS offer scalable solutions for integrating sensor data, enabling data analysis from anywhere. Services like AWS IoT Core and Azure IoT Hub streamline the process of receiving, processing, and analyzing sensor data in the cloud(Khriji et al., 2022).

2.6.10. Extracting data from programmable logic controllers (PLCs)

Extracting data from Programmable Logic Controllers (PLCs) is a crucial process for monitoring, controlling, and optimizing industrial processes. PLCs are central to industrial automation. Efficient data extraction is vital for ensuring performance and making informed decisions(Dhameliya, 2023).

2.6.11. Connection and communication

In industrial environments, the connectivity and communication capabilities of PLCs are essential for effective automation. PLCs serve as hubs connecting sensors, actuators, and devices to control and monitor industrial processes. These connections use various communication channels such as RS-232, RS-485, Ethernet, or Profibus, each with its own advantages depending on the application (Bansal and Dubey, 2024).

2.6.12. Data retrieval

Once data is collected from sensors, PLCs process and store it in memory or data tables. Data retrieval involves accessing this stored data for monitoring, analysis, and control of industrial processes. Command programs in PLC software are used to retrieve specific data points such as temperature readings, pressure values, or level measurements from memory or data tables. This retrieved data provides insights into the current state of industrial processes, enabling real-time monitoring and control(Rais et al., 2022).

2.6.13. Types of data

PLCs can store various types of data from connected sensors and devices. Temperature measurement technology provides critical thermal condition information for processes requiring precise temperature control. Pressure sensors monitor pressure changes in hydraulic, pneumatic, and HVAC systems. Level sensors measure liquid or solid levels in tanks, while humidity sensors monitor moisture levels in environments. Additionally, PLCs store data on flow rates, voltage levels, motor speeds, and more, allowing comprehensive analysis and tracking of industrial processes(Mellado and Núñez, 2022).

2.6.14. Data logging

Data logging is the process of storing data collected by PLCs over specified periods. This can be done in the PLC’s internal memory or external storage devices, or transmitted to remote databases via communication protocols like OPC or Modbus. Internal logging is suitable for short-term storage and quick access, while external logging supports long-term storage and analysis. Data logging enables historical analysis, trend identification, performance monitoring, and regulatory compliance(Alphonsus and Abdullah, 2016).

2.7. Data Analysis

Data analysis is the process of using data from PLCs to optimize industrial processes. PLCs generate vast amounts of data that can be analyzed to identify trends, anomalies, and improvement opportunities. This process involves various techniques such as statistical analysis, trend analysis, and predictive modeling.

2.7.1. Statistical analysis

Statistical analysis is a technique used to identify patterns and relationships in data from PLCs by analyzing means, standard deviations, and data distributions to understand process behavior and identify potential issues.

2.7.2. Trend analysis

Trend analysis helps detect long-term trends and deviations from normal behavior, beneficial for forecasting and preventive maintenance planning. It can also be used to improve long-term process efficiency.

2.7.3. Predictive modeling

Predictive modeling uses historical and current data to forecast future trends. This forecasting helps in proactive process adjustments, reducing downtime, and enhancing product quality. Data analysis from PLCs enables industries to improve efficiency, reduce downtime, increase product quality, and comply with regulatory requirements(Yun et al., 2022).

2.8. Data storage creating principles.

Designing effective data storage systems involves foundational theories and principles aimed at optimizing data organization, access efficiency, and mitigating risks. Key principles include.

- Data redundancy and reliability implementing redundancy strategies such as redundant array of independent disks (RAID) to ensure data availability and reliability. RAID configurations distribute data across multiple disks to improve performance and provide fault tolerance against disk failures(Adhikari et al., 2022).
- Scalability designing systems that can scale seamlessly with growing data volumes and user demands. Scalable architectures, including clustered storage systems, allow for easy expansion by adding more storage nodes or resources without disrupting operations(Ajiga et al., 2024).
- Data security incorporating robust security measures to protect stored data from unauthorized access, modification, or loss. Techniques such as encryption, access controls, and regular audits are essential to maintain data integrity and compliance with privacy regulations(Ahanger et al., 2024).
- Optimizing storage systems for performance by employing techniques like data caching, compression, and indexing. These methods enhance data retrieval speeds and overall system

responsiveness, especially in high-demand environments(Das et al., 2008).

- Implementing strategies for managing the entire lifecycle of data, from creation and storage to archiving or deletion. This includes defining policies for data retention, archival, and eventual disposal to optimize storage resources and comply with legal requirements(Zahid et al., 2023).

2.8.1. Frontend of employee data recording system

The front end of an employee data recording system serves as the user interface through which users interact with the system to input, view, and manage employee-related information. It is designed to be intuitive, user-friendly, and efficient, providing a seamless experience for users.

The front's user interface (UI) design is crucial for ensuring a positive user experience. It includes elements such as menus, buttons, forms, and layouts that allow users to navigate the system easily. A clean and organized layout with intuitive controls enhances usability and reduces the learning curve for users(Johnson, 2020).

Data Input Forms The frontend provides data input forms where employees can enter their personal and professional information. These forms are designed to collect essential data such as name, address, contact details, employment history, educational qualifications, and other relevant information. Input fields may include text fields, dropdown menus, checkboxes, radio buttons, and date pickers to accommodate various data types and formats(Javed et al., 2024).

Data validation to ensure data accuracy and integrity, the frontend performs validation checks on the data entered by users. It verifies that mandatory fields are filled, checks data formats (e.g., email address, phone number), and performs logical checks (e.g., start date should precede end date). Validation messages are displayed to users if any errors or inconsistencies are detected, guiding them to correct the information(Huang et al., 2023).

The front end allows users to quickly find employee records by using search filters. Users can search by name, employee ID, department, or other relevant criteria. Advanced options include filtering by date range, job title, or employment status, making it easy to retrieve employee information efficiently(Wilson, 2022).

Employee profile view employees and authorized users can view detailed profiles of individual employees through the frontend. The profile view displays comprehensive information about the employee, including personal details, contact information, employment history, training records, performance reviews, and any other relevant data. This consolidated view provides a holistic understanding of the employee's background and contributions(Säkkinen, 2020).

The frontend may include a dashboard that offers visual representations of employee data through charts, graphs, and tables. Key performance indicators (KPIs) such as employee turnover rate, training completion rates, and performance ratings are displayed to provide insights into workforce management. Analytics tools allow users to analyze trends, identify patterns, and make data-driven decisions regarding workforce planning and management(Bhashitha Wendakoon Mudiyanselage, 2024).

To ensure data security and privacy, the frontend implements user authentication and access control mechanisms. Users are required to log in with valid credentials (e.g., username and password) to access the system. Role-based access control (RBAC) determines the level of access granted to each user based on their role or permissions. This prevents unauthorized access and protects sensitive employee information(Mpamugo and Ansa, 2024).

Responsive design the frontend is designed to be responsive, adapting seamlessly to different devices and screen sizes. Whether accessed from a desktop computer, laptop, tablet, or smartphone, the interface adjusts dynamically to provide an optimal viewing and interaction experience. Responsive design improves accessibility and usability, allowing users to access the system anytime, anywhere(Lee, 2016).

In summary, the frontend of an employee data recording system plays a crucial role in facilitating user interactions and managing employee information efficiently. Through intuitive design, data input forms, validation checks, search and filtering capabilities, profile views, analytics, security features, and responsive design, the frontend ensures a seamless and productive user experience.

2.8.2. HTML language

Hyper text markup language (HTML) is the standard markup language used to create web pages. It provides the structure and content of a webpage by using a system of tags and attributes(Ahmad et al., 2020).

1. Elements and attributes
   HTML elements consist of opening and closing tags, with content sandwiched between them. Some elements, like <img> and
, are self-closing and don't require a closing tag. Elements can also have attributes that provide additional information about the element. For instance, the <img> element has attributes such as src (source) and alt (alternate text). HTML documents have a specific structure that includes a document type declaration <!DOCTYPE html> at the beginning, followed by the <html>, <head>, and <body> tags. The <html> tag contains all the content of the webpage, while the <head> tag includes metadata like the page title and character encoding. The <body> tag contains the visible content of the webpage.
2. Text formatting
   HTML provides various tags for formatting text, including headings <h1> to <h6>, paragraphs <p>, emphasis <em> and <strong>, and line breaks
. These tags allow designers to structure text content and make it more readable and visually appealing.
3. Hyperlinks
   Hyperlinks are a fundamental feature of HTML, allowing users to navigate between different web pages. The <a> tag is used to create links, with the href attribute specifying the URL of the destination page. Links can be styled and targeted to open in new tabs or windows.

4. Images

Images are an integral part of web design, and HTML provides the <img> tag for embedding images into web pages. The src attribute specifies the image file's URL, while the alt attribute provides alternative text for screen readers and in cases where the image cannot be displayed.

5. Lists and tables

   HTML offers tags for creating lists (<ul>, <ol>, <li>) and tables (<table>, <tr>, <td>, <th>). Lists are useful for organizing information in bullet points or numbered sequences, while tables are used for presenting data in rows and columns.

6. Forms

   HTML forms (<form>) are used to collect user input, such as text fields, checkboxes, radio buttons, and dropdown menus. Form elements have attributes like name, type, and value, which determine their behavior and appearance.

7. Semantic HTML

   Semantic HTML refers to using HTML elements that convey meaning to both the browser and the developer. Semantic elements like <header>, <nav>, <article>, <section>, <footer>, and <aside> provide a clearer structure to web documents and improve accessibility and SEO(McGrath, 2020).

8. Accessibility and SEO

   HTML plays a crucial role in website accessibility and search engine optimization (SEO). By using semantic HTML, providing descriptive alt text for images, and optimizing page titles and meta descriptions, web developers can improve their site's usability and visibility on search engines(Weiss, 2024).

9. Evolution of HTML

   HTML has evolved over the years, with new versions introducing advanced features and improved functionality. HTML5, the latest version, introduced new elements like <video>, <audio>, <canvas>, and <svg>, along with enhanced support for multimedia and interactivity(Pilgrim, 2010).

2.8.3. CSS language

CSS serves as the backbone of web development, providing a standardized way to create and structure web content. It allows web designers to define the layout, text, images, links, and other elements of a webpage using a simple and intuitive markup language(Meyer and Weyl, 2023).

1. Syntax and structure CSS consists of a set of rules, each composed of a selector and a declaration block. Selectors target HTML elements, while declaration blocks contain property-value pairs that define the styling(Meyer and Weyl, 2023).
2. Selectors are patterns used to select the elements you want to style. They can target elements based on their type, class, ID, attributes, or relationship with other elements (Meyer and Weyl, 2023).
3. Properties and Values CSS properties define the appearance of HTML elements, such as color, font-size, margin, padding, etc. Each property has one or more values that specify how the property should be applied.
4. CSS box model the CSS box model describes the layout of elements on a webpage. It consists of content, padding, border, and margin. The content area contains the actual content of the element, surrounded by padding, border, and margin, which provide spacing between the content and other elements (Meyer and Weyl, 2023).
5. Selectors and specificity CSS follows rules of specificity to determine which styles should apply to an element when conflicting styles exist. Specificity is based on the type of selector used and whether styles are defined inline, internally, or externally. Inline styles have the highest specificity, followed by IDs, classes, and element selectors .
6. Inheritance CSS properties can be inherited from parent elements to their children. This means that styles applied to a parent element can affect its child elements unless overridden by more specific styles [1].
7. CSS units CSS supports various units for specifying sizes and distances, including pixels (px), percentages (%), ems (em), rems

(rem), and viewport units (vw, vh). Each unit has its own characteristics and use cases, providing flexibility in design .

8. CSS flexbox and grid flexbox and CSS grid are layout models used to create responsive and flexible layouts in CSS. Flexbox is a one-dimensional layout model that allows elements to be aligned and distributed within a container along a single axis, either horizontally or vertically. CSS Grid is a two-dimensional layout model that divides a webpage into rows and columns, allowing for more complex layouts .
9. CSS transitions and animations CSS transitions and animations enable designers to add dynamic effects to web elements without using JavaScript. Transitions allow smooth changes in property values over a specified duration, while animations provide more complex, keyframe-based animations(Meyer and Weyl, 2023).
10. Responsive design with CSS responsive design ensures that web pages adapt to different screen sizes and devices, providing a consistent user experience across desktops, tablets, and smartphones. CSS media queries allow designers to apply different styles based on the device's screen width, height, orientation, and resolution(Meyer and Weyl, 2023).

2.8.4. JavaScript language

JavaScript plays a pivotal role in web development by enabling interactivity and dynamic functionality on web pages. Unlike HTML and CSS, which primarily handle structure and presentation, JavaScript functions as a full-fledged programming language capable of complex computations and data manipulation(Shukla, 2023).

JavaScript's syntax and structure involve statements that dictate browser actions, whether through simple expressions or more intricate blocks enclosed within curly braces(Shukla, 2023). These statements are case-sensitive and terminate with semicolons, maintaining syntactic integrity throughout code execution.

Variables in JavaScript—declared using var, let, or const—store data values, accommodating various types such as numbers, strings, booleans, arrays, and objects(Shukla, 2023). This flexibility allows for dynamic data handling and manipulation during runtime, crucial for interactive web applications.

Operators and expressions in JavaScript facilitate operations on variables and values, ranging from basic arithmetic and assignment to complex logical and bitwise operations(Shukla, 2023). These expressions combine variables, values, and operators to yield meaningful outcomes, supporting diverse computational needs in web development.

Control flow mechanisms in JavaScript, including conditional statements like if, else if, else, and switch, enable developers to execute specific code blocks based on varying conditions(Shukla, 2023). This decision-making capability is essential for responsive user interactions and dynamic content generation.

JavaScript's support for loops—such as for, while, and do-while—facilitates iterative execution of code, vital for processing data collections like arrays or responding to user interactions repeatedly(Shukla, 2023). These loops enhance efficiency in managing repetitive tasks within web applications.

Functions are reusable blocks of code in JavaScript, encapsulating logic that can be invoked multiple times with different inputs(Shukla, 2023). They promote modularity and code reuse, enhancing development efficiency and maintaining code clarity across projects.

JavaScript interacts with the Document Object Model (DOM), a programming interface for web documents, to dynamically update and modify web page content, structure, and style(Shukla, 2023). This DOM manipulation capability empowers developers to create interactive user interfaces and responsive web applications.

Event-driven programming in JavaScript allows functions to execute in response to user actions or system events, such as mouse clicks or keyboard inputs(Shukla, 2023). Event handlers manage these interactions, enabling developers to create engaging and interactive web experiences.

Asynchronous JavaScript programming facilitates non-blocking execution of operations, crucial for handling tasks like fetching data from servers or processing user input without disrupting the main program flow(Shukla, 2023). This asynchronous capability enhances application responsiveness and user experience in web environments.

JavaScript's error handling mechanisms, such as try-catch blocks, enable developers to manage and recover from unexpected errors gracefully(Shukla, 2023). These constructs prevent application crashes, ensuring robustness and reliability in web applications.

ECMAScript 6 (ES6) introduced modern JavaScript features like arrow functions, template literals, and classes, enhancing code readability, maintainability, and performance(Shukla, 2023). These enhancements underscore JavaScript's evolution as a versatile and powerful language for web development.

2.8.5. Bootstrap 5 framework

Bootstrap 5 revolutionizes web development with a comprehensive toolkit of CSS and JavaScript components designed to streamline UI design and development(Gaikwad and Adkar, 2019). Building on JavaScript's capabilities, Bootstrap 5 enhances front-end development with

Bootstrap's responsive grid system, based on Flexbox, ensures seamless adaptation of web layouts across different devices and screen sizes(Gaikwad and Adkar, 2019). This grid system supports dynamic content organization and layout flexibility, optimizing user experience on diverse platforms.

Enhanced components like buttons, forms, navigation bars, and cards in Bootstrap 5 offer modern aesthetics and functionality, customizable to suit specific design requirements(Gaikwad and Adkar, 2019). New additions such as accordions and toast notifications expand the toolkit for creating interactive and user-friendly interfaces.

Utility classes introduced in Bootstrap 5 simplify styling and customization, enabling developers to apply common design patterns and adjustments without extensive CSS coding(Gaikwad and Adkar, 2019). These utility classes enhance design consistency and flexibility, empowering developers to achieve desired UI outcomes efficiently.

Bootstrap 5's improved documentation provides comprehensive guidance on installation, usage, customization, and migration, catering to developers of all skill levels(Gaikwad and Adkar, 2019). This documentation ensures clarity and accessibility, supporting effective adoption and integration of Bootstrap in web projects.

Sass integration in Bootstrap 5 facilitates modular and scalable CSS development, leveraging features like variables and mixins for easier customization and extension of the framework(Gaikwad and Adkar, 2019). This integration enhances code maintainability and adaptability, accommodating diverse project requirements.

Performance optimization is a hallmark of Bootstrap 5, with minimized file sizes and improved loading times to enhance website speed and efficiency(Gaikwad and Adkar, 2019). These optimizations ensure responsive and high-performance web applications, meeting user expectations for seamless browsing experiences.

Bootstrap 5’s customization capabilities enable developers to selectively include components and styles, tailoring the framework to project-specific needs and optimizing resource utilization(Gaikwad and Adkar, 2019). This flexibility supports leaner and more efficient web development practices, improving project scalability and performance.

Accessibility features in Bootstrap 5 promote inclusive design practices, with built-in support for keyboard navigation and ARIA attributes to enhance usability for users with disabilities(Gaikwad and Adkar, 2019). These accessibility enhancements underscore Bootstrap’s commitment to creating accessible and user-friendly web interfaces.

Migration support in Bootstrap 5 facilitates seamless transition from previous versions, providing guidance on adapting to changes like the transition to Flexbox-based grid systems(Gaikwad and Adkar, 2019). This support ensures compatibility and continuity for existing Bootstrap projects, optimizing development workflows.

Integration of Bootstrap 5 into web projects involves straightforward inclusion of CSS and JavaScript files or integration via package managers like npm or yarn, simplifying setup and enabling rapid development of responsive and visually appealing user interfaces(Gaikwad and Adkar, 2019).

2.8.6. Back end of an employee data recording system

The backend of an employee data recording system is responsible for managing and processing data on the server side to support various functionalities of the system. It includes components and processes that handle data storage, retrieval, manipulation, security, and performance optimization.

At its core, the backend manages databases where employee data is securely stored(Rusmiany et al., 2020). This involves creating and maintaining database schemas, tables, and indexes to organize and retrieve data efficiently. Backend components interact with these databases to retrieve employee records based on user queries or system requirements. When a user requests specific data, the backend executes database queries, fetches the relevant data, and processes it for further use.

Once the data is retrieved, the backend processes it to generate reports, analytics, and insights for decision-making purposes(Sharma et al., 2024).

This involves aggregating, filtering, and analyzing data to identify patterns or trends. Additionally, the backend executes business logic to enforce rules, calculations, or validations on employee data, ensuring consistency and accuracy in data processing(Ikegwu et al., 2024).

Data security is a critical aspect of the backend. The system implements mechanisms for user authentication and authorization to control access to employee data(Mpamugo and Ansa, 2024). It verifies user identities and authorizes access based on roles and permissions. Furthermore, the backend encrypts sensitive employee data to protect it from unauthorized access or breaches(Zhou et al., 2013). Encryption algorithms are used to secure data both at rest and during transmission.

Scalability is another important consideration for the backend. Systems are designed to scale horizontally by adding more servers or instances to handle increased load(Blinowski et al., 2022). Horizontal scaling ensures that the system can accommodate growing demands without compromising performance. Additionally, load balancers are employed to distribute incoming traffic across multiple servers, ensuring optimal resource utilization and preventing overloading(Yadav et al., 2021).

Interoperability is facilitated through APIs provided by the backend. These APIs allow external systems or applications to interact with employee data seamlessly(Aarsæther, 2024). Standardized protocols and formats, such as JSON or XML, are supported to facilitate communication with other systems(Truică et al., 2021).

Performance optimization is crucial for ensuring efficient operation of the backend. Caching mechanisms are employed to store frequently accessed data in memory, reducing database load and improving response times(Zhang et al., 2015). Additionally, the backend optimizes database queries and indexes to enhance query performance and minimize execution time.

Backend components undergo rigorous testing to ensure they function correctly. This involves unit testing to test individual modules in isolation(Osherove, 2013). Furthermore, backend systems are continuously monitored for performance issues or errors. Debugging tools are used to identify and resolve any issues that arise.

These principles form the foundation for developing and managing the backend of an employee data recording system. By focusing on reliability, security, and performance, the backend ensures smooth and efficient operation of the system.

2.8.7. Python language

Python developed by Guido van Rossum and released in 1991, stands out as a general-purpose programming language celebrated for its simplicity, readability, and versatility across diverse application domains(Elhalid et al., 2023).

1. Readability and simplicity
    - Python's syntax emphasizes readability and clarity, resembling pseudo-code, which facilitates rapid development and code maintenance(Elhalid et al., 2023).
2. Dynamic typing and interpreted nature
    - Python's dynamic typing allows variables to be assigned without explicit data type declarations, promoting faster prototyping and agile development cycles(Elhalid et al., 2023).
3. Extensive standard library

- Python includes a comprehensive standard library with modules for tasks such as file I/O, networking, web development, and more, minimizing the need for external dependencies(Elhalid et al., 2023).

4. High-level data structures and OOP support
    - Python provides efficient built-in data structures like lists, dictionaries, tuples, and sets, optimized for flexibility and performance in data manipulation tasks(Elhalid et al., 2023).
    - It supports object-oriented programming (OOP) principles, enabling developers to create modular and reusable code through classes, objects, inheritance, and polymorphism(Elhalid et al., 2023).
5. Extensibility and integration
    - Python's extensibility allows seamless integration with other languages and systems. It supports interfacing with C/C++ libraries via bindings and APIs, enhancing its capabilities in scientific computing and system-level programming(Elhalid et al., 2023).
6. Platform independence and community support
    - Python ensures platform independence, running consistently across different operating systems. It benefits from a robust community that contributes to its extensive ecosystem of libraries, frameworks, and tools, catering to diverse application needs(Elhalid et al., 2023).
7. Application domains
    - Web development
      Python excels in web development, with frameworks like Django, Flask, and Pyramid enabling developers to create scalable web applications, APIs, and content management systems(Elhalid et al., 2023).
    - Data science and machine learning
      Python is widely adopted in data science and machine learning, leveraging libraries such as numpy, pandas, matplotlib, and scikit-learn for tasks such as data

manipulation, visualization, statistical analysis, and machine learning model training(Elhalid et al., 2023).

- Artificial intelligence and NLP
  Python serves as a powerhouse in AI and NLP applications, with libraries like tensorflow, pytorch, keras, and NLTK supporting tasks such as natural language processing, speech recognition, sentiment analysis, and machine translation(Elhalid et al., 2023).

8. The Importance of frameworks and their link to django

- Accelerated development
  Frameworks come equipped with pre-built components and libraries that expedite development time. Developers leverage existing code and modules within frameworks to rapidly build high-quality software(Elhalid et al., 2023).
- Development standards
  Frameworks promote adherence to coding standards and best practices, facilitating well-structured and maintainable codebases.
- Security and stability
  Frameworks often include built-in security measures and protocols to mitigate vulnerabilities, ensuring robust and secure applications.
- Collaborative work
  Frameworks establish clear structures and conventions, enabling teams to work collaboratively and cohesively on projects.
- Frameworks play a crucial role in software development by reducing complexity, enhancing efficiency, and ensuring consistency across projects. They provide foundational structures and tools that streamline the development process. One particularly renowned framework in the realm of web application development with Python is django(Elhalid et al., 2023).

2.8.8. Django framework

Django is a high-level Python web framework that promotes rapid development and follows a clean, pragmatic design. It aims to make web development fast, efficient, and scalable by providing a set of tools and conventions that streamline common tasks. Let's delve into a detailed overview of django's key features and principles(Rubio, 2017).

Django employs the model-view-template (MVT) design pattern, which helps in developing web applications quickly and efficiently. The MVT architecture separates the application into three main components models, views, and templates(Rubio, 2017).

1. Models
    - Django's models handle database operations and represent the data structure of the application. They encapsulate the business logic and manage the interaction with the database. With django's built-in ORM, developers can define models using python classes, making database operations simpler and more pythonic(Rubio, 2017).
2. Views
    - Views in django are responsible for processing user requests and returning appropriate responses. They fetch data from models, perform any required processing, and pass the data to templates for rendering. django's views are Python functions or classes that take web requests and return web responses(Rubio, 2017).
3. Templates
    - Templates are used for generating dynamic HTML content. They contain the presentation logic of the application and define how data received from views should be displayed to the users. django templates support template inheritance, allowing developers to reuse common layouts and components across multiple pages(Rubio, 2017).

Django provides a robust URL routing mechanism that maps URL patterns to views, making it easy to design clean and understandable URLs. URL patterns are defined in the URLconf, where each URL pattern is associated with a corresponding view function or class(Rubio, 2017).

Django's built-in administrative interface, known as the Django Admin, offers a powerful tool for managing application data. It automatically generates an admin interface based on the application's models, enabling administrators to perform CRUD operations without writing additional code(Rubio, 2017).

In terms of security, Django emphasizes best practices to mitigate common web vulnerabilities. It includes features like built-in protection against SQL injection, cross-site scripting (XSS), cross-site request forgery (CSRF), and clickjacking(Rubio, 2017).

For scalability, Django supports horizontal scaling by allowing applications to run on multiple servers or processes to handle increased traffic. Additionally, Django's caching system helps optimize performance by storing frequently accessed data in memory(Rubio, 2017).

Django's versatility extends to building RESTful APIs effortlessly. With django REST framework (DRF), developers can create APIs quickly and efficiently. DRF provides powerful serialization, authentication, and authorization mechanisms out of the box, facilitating the creation of RESTful APIs that adhere to industry standards(Rubio, 2017).

Django emphasizes testing and maintenance through its built-in testing framework and debugging tools. Developers can write unit tests for their applications to ensure reliability and use debugging tools to identify and fix issues quickly(Rubio, 2017).

Overall, Django's comprehensive feature set, coupled with its adherence to best practices and standards, makes it an ideal choice for building robust and scalable web applications, including RESTful APIs. Its focus on rapid development, security, and API capabilities helps developers create high-quality applications efficiently.

2.8.9. REST API

The representational state transfer (REST) architectural style has emerged as a dominant paradigm for designing network-based software architectures, particularly for web services. REST emphasizes the scalability, simplicity, and interoperability of distributed systems by leveraging existing web standards and protocols. Roy Fielding introduced REST in his seminal doctoral dissertation in 2000, where he outlined the fundamental principles underlying the design of network-based architectures.

Fielding's dissertation established REST as an architectural style that emphasizes several key constraints

1. The system is divided into clients and servers, each with distinct concerns. This separation promotes scalability by allowing the components to evolve independently.
2. Each request from a client to the server must contain all the necessary information to fulfill the request. The server should not store any client state between requests, enhancing scalability and reliability.
3. RESTful systems exhibit a uniform interface, typically comprising four constraints: identification of resources, manipulation of resources through representations, self-descriptive messages, and hypermedia as the engine of application state (HATEOAS). This constraint fosters simplicity, evolvability, and decoupling between clients and servers.
4. Responses from the server must be explicitly labeled as cacheable or non-cacheable. Cacheable responses improve efficiency, scalability, and user experience by reducing server load and latency.
5. A layered architecture allows for hierarchical organization and encapsulation of system components. This constraint promotes scalability by enabling intermediary components such as proxies, gateways, and load balancers.

The principles of REST have been widely adopted and elaborated upon in subsequent literature. Richardson and Amundsen's book "RESTful Web Services the definitive guide" provides comprehensive guidance on designing and implementing RESTful APIs(Richardson and Ruby, 2008). Tilkov, Vinoski, and Gregor's work "REST und HTTP entwicklung und integration nach dem architekturstil des web" delves into the intricacies of REST and its relationship with HTTP(Li and chou, 2011).

RESTful APIs have become a cornerstone of modern web development, enabling scalable and interoperable systems. Fielding and Taylor's article "Principled Design of the Modern Web Architecture" further elaborates on the foundational principles of REST. Allamaraju's book "RESTful java with JAX-RS 2.0" offers practical insights into building RESTful services with java(Burke, 2013).

As the demand for distributed systems grows, microservices architectures have gained popularity."Microservices architecture for beginners" provides an introduction to this approach and its alignment with REST principles(Lang, 2017).

The richardson maturity model, introduced by Martin Fowler, offers a framework for assessing the maturity of RESTful services, from Level 0 (plain XML over HTTP) to level 3 (HATEOAS)(Webber et al., 2010).

Fielding's blog post "REST APIs must be hypertext-driven" underscores the importance of hypermedia as a mechanism for driving application state and interaction(Vu et al., 2018). According to Fielding, hypermedia links within responses enable clients to navigate the application dynamically, reducing coupling between the client and server and enhancing scalability and flexibility.

REST has become a cornerstone of modern web architecture, enabling scalable, interoperable, and evolvable distributed systems. Its principles, as outlined by Fielding and elaborated upon by subsequent authors, continue to shape the development of web services and APIs.

Node-RED, a flow-based development tool for visual programming, leverages these principles to create flexible and scalable applications. Developed by IBM, Node-RED simplifies the integration of APIs and services through a browser-based interface that allows users to wire together nodes to create flows of data(Kousiouris et al., 2022). By supporting RESTful APIs natively, Node-RED enables developers to design workflows that adhere to REST principles, facilitating seamless interaction between different services and systems.

Node-RED's visual approach and support for RESTful principles make it ideal for developing IoT applications, automation workflows, and integrating diverse data sources. Its flexibility and scalability, combined with REST's architectural benefits, empower developers to build robust and interoperable systems.

2.8.10. Node-RED visual programming

Node-RED, an innovative open-source visual programming tool, has transformed the way developers build event-driven applications by connecting various devices, APIs, and services through a browser-based flow editor(Kousiouris et al., 2022). Developed by IBM emerging technologies, Node-RED has become a preferred choice across diverse domains such as Internet of Things (IoT), automation, data integration, and rapid prototyping due to its versatility and user-friendly interface.

At its core, Node-RED features a visual editor that enables users to create flows by simply dragging nodes onto a workspace and connecting them to define the flow of data and logic(Kousiouris et al., 2022). Each node represents a specific function or operation, and the connections between nodes determine how data flows through the application. This visual approach significantly reduces the need for writing extensive code, thereby speeding up development and making it accessible to a wider audience.

Node-RED operates on top of Node.js, leveraging its asynchronous event-driven architecture and extensive library ecosystem(Kousiouris et al., 2022). This allows users to extend Node-RED's functionality by easily installing additional nodes and modules from node package manager(npm).

Node-RED seamlessly integrates with JavaScript, enabling users to write custom functions directly within the flow editor for more complex logic.

A fundamental concept in Node-RED is the concept of "flows," which are collections of interconnected nodes defining the application's behavior (Kousiouris et al., 2022) . Flows can range from simple sequences of nodes to intricate networks of interconnected logic, offering users the flexibility to create applications for various purposes, from basic data processing to sophisticated IoT deployments.

Node-RED provides a wide array of standard nodes for data processing, input/output, and function execution, as well as specialized nodes for interfacing with IoT devices, databases, web services, and more(Kousiouris et al., 2022). These nodes streamline the integration of external systems and services, allowing users to build powerful applications without starting from scratch.

The dashboard feature in Node-RED enables users to create web-based user interfaces for monitoring and controlling their applications(Kousiouris et al., 2022). With a range of UI components like gauges, charts, switches, and text boxes, the dashboard can be easily configured and customized to meet specific needs.

An integral part of Node-RED is its vibrant community support and ecosystem(Kousiouris et al., 2022). The Node-RED community actively contributes nodes, flows, tutorials, and support through forums, GitHub repositories, and online communities, fostering innovation and knowledge sharing among users worldwide.

Node-RED's modular and scalable architecture makes it suitable for projects of all sizes(Kousiouris et al., 2022). It can run on a single-board computer like the Raspberry Pi for small-scale applications or be deployed in a cloud environment for larger-scale deployments. Its lightweight runtime and low resource requirements make it an ideal choice for resource-constrained devices and environments.

2.9. Databases

Databases are foundational components of modern information systems, serving as repositories for storing, managing, and organizing vast amounts of structured and unstructured data(Lungu et al., 2009). They play a crucial role in various applications, from simple data storage to complex data analysis and decision-making processes.

At the heart of a database lies its structure, typically defined by a schema that outlines the organization of data into tables, columns, and rows. These tables represent entities or objects within the system, with columns representing attributes or properties, and rows representing individual records or instances. The schema also defines relationships between different tables, enabling the establishment of data dependencies and constraints.

Databases are designed to provide efficient mechanisms for data retrieval, insertion, updating, and deletion, commonly referred to as

CRUD operations. Structured query language (SQL) is the most widely used language for interacting with relational databases, allowing users to perform various operations on the data stored in the database tables.

Relational databases, such as MySQL, postgreSQL, and oracle, are among the most prevalent types of databases used in the industry. They organize data into tables with predefined schemas and support complex queries and transactions. Relational databases adhere to ACID (atomicity, consistency, isolation, durability) properties, ensuring data integrity and consistency.

Apart from relational databases, there are also non-relational or NoSQL databases, which are designed to handle large volumes of unstructured or semi-structured data. NoSQL databases offer flexible schemas and horizontal scalability, making them suitable for use cases like big data, real-time analytics, and distributed systems.

Data integrity and security are paramount considerations in database design and management. Techniques such as data normalization, encryption, access control, and backup and recovery mechanisms are employed to ensure that data remains accurate, secure, and available.

Database management systems (DBMS) provide the software tools and interfaces necessary to interact with databases. These systems handle tasks such as data storage, retrieval, concurrency control, and transaction management. Popular examples of DBMS include MySQL, oracle database, microsoft SQL server, and mongoDB.

Data warehouses are specialized databases designed for storing and analyzing large volumes of historical data. They are used for business intelligence, data mining, and decision support systems, enabling organizations to gain insights from their data to drive strategic decisions.

The field of database management is continuously evolving with advancements in technology and the increasing demand for data-driven insights. New trends such as cloud databases, in-memory databases, and blockchain databases are reshaping the landscape of database systems, offering enhanced performance, scalability, and security. One prominent player in this evolution is microsoft SQL server, a robust relational database management system (RDBMS) developed by microsoft. SQL server is widely used in enterprise environments for its comprehensive feature set, including support for transaction processing, business intelligence, and data analytics. With capabilities for handling large volumes of data and integration with Microsoft's ecosystem of products, SQL server remains a cornerstone in data management solutions, catering to diverse organizational needs from small businesses to large enterprises(Lungu et al., 2009).

2.9.1. Microsoft SQL server

Microsoft SQL server is a comprehensive and powerful relational database management system (RDBMS) developed by microsoft corporation. It is widely used in enterprise environments for storing, managing, and analyzing structured data. SQL server provides a robust platform for building mission-critical applications, business intelligence solutions, and data-driven insights(Kumar, 2024).

At the core of SQL server is its database engine, which is responsible for storing and retrieving data, enforcing data integrity, and executing queries. The database engine supports the structured query language (SQL) standard and provides a range of features for data manipulation, such as querying, inserting, updating, and deleting records(Kumar, 2024).

When saving data into a SQL server database, several steps are involved, beginning with the design of the database schema. The schema defines the structure of the database, including tables, columns, constraints, and relationships between tables(Kumar, 2024). Tables represent entities in the database, and columns define the attributes of those entities.

Once the database schema is designed, the next step is to create the database and its tables using SQL Server Management Studio (SSMS) or transact-SQL (T-SQL) scripts. These scripts specify the structure of each table, including data types, constraints, and indexes (Kumar, 2024). For example, to create a table for storing employee information . See Fig. 3.

```
CREATE TABLE Employees (
    EmployeeID INT PRIMARY KEY,
    FirstName VARCHAR(50),
    LastName VARCHAR(50),
    Email VARCHAR(100),
    DepartmentID INT,
    CONSTRAINT FK_Department FOREIGN KEY (DepartmentID) REFERENCES Departments(DepartmentID)
);
```

Figure 3 database schema For example**.**

After creating the tables, data can be inserted into the database using SQL INSERT statements. Each INSERT statement adds a new row of data into a specified table(Kumar, 2024). See Fig. 4

```
INSERT INTO Employees (EmployeeID, FirstName, LastName, Email, DepartmentID)
VALUES (1, 'John', 'Doe', 'john.doe@example.com', 101),
       (2, 'Jane', 'Smith', 'jane.smith@example.com', 102);
```

Figure 4 database using SQL INSERT statements**.**

SQL server provides various tools and methods for inserting data, including bulk insert, SELECT INTO, and BULK INSERT statements, depending on the volume and source of the data(Kumar, 2024).
Once data is inserted, it can be queried using SELECT statements to retrieve specific information from the database. SQL Server supports complex queries involving filtering, grouping, sorting, and aggregating data(Kumar, 2024). See Fig. 5

```
SELECT FirstName, LastName, Email
FROM Employees
WHERE DepartmentID = 101;
SQL Server also offers mechanisms for updating existing data using UPDATE statements a
```

Figure 5 methods for inserting data**.**

SQL server also offers mechanisms for updating existing data using UPDATE statements and deleting data using DELETE statements. These operations help maintain the integrity and accuracy of the database(Kumar, 2024).

In addition to basic data storage and retrieval, SQL server provides advanced features such as transactions, stored procedures, triggers, views, and functions to enhance data management and application development(Kumar, 2024). These features enable developers to implement business logic, automate tasks, and enforce data integrity rules within the database.

SQL server ensures data durability and reliability through features like transaction logging, backup and restore, and high availability solutions such as database mirroring clustering, and alwayson availability groups(Kumar, 2024). These features help protect data against hardware failures, system crashes, and disasters.

Microsoft SQL server offers a robust and feature-rich platform for storing and managing data in enterprise environments(Kumar, 2024). Its comprehensive set of tools, advanced features, and scalability make it a preferred choice for businesses seeking to build reliable and scalable data-driven applications.

2.9.2. Data management and analysis

Data cleaning is an essential process in data management and analysis, crucial for ensuring the accuracy, consistency, and reliability of datasets. It involves identifying and rectifying errors, inconsistencies, and anomalies in the data to enhance its quality and usability. Data cleaning is particularly vital in today's data-driven world, where decisions and insights are heavily reliant on the quality of available data.

Data cleaning starts with data inspection and profiling. In this phase, analysts or data scientists examine the dataset to understand its structure, contents, and quality. They identify potential issues such as missing values, duplicates, outliers, and inconsistencies. Profiling tools and exploratory data analysis techniques are often used to gain insights into the data.

Handling missing values is a common challenge in data cleaning. Analysts must decide whether to impute missing values, remove records with missing data, or leave them as is based on the impact on the analysis and the domain knowledge.

Correcting errors involves identifying and rectifying inaccuracies in the data. This may include fixing typos, standardizing formats, and validating data against predefined rules or constraints.

Dealing with duplicates is another critical step. Duplicate records can skew analysis results and affect the accuracy of statistical models. Techniques such as deduplication algorithms and fuzzy matching are used to identify and eliminate duplicate entries.

Standardizing data involves ensuring consistency in formats, units, and naming conventions across the dataset. This ensures that data can be easily compared and analyzed.

Validating data involves checking data integrity and accuracy. This includes verifying numerical ranges, cross-referencing data with external sources, and identifying outliers.

Normalization is the process of restructuring data to reduce redundancy and improve efficiency. This often involves organizing data into normalized tables in relational databases.

Transformation involves converting data from one format or structure to another. This may include aggregating data, creating new variables, or reshaping data to fit the requirements of analysis or visualization.

Documentation is essential throughout the data cleaning process. Analysts must document the steps taken, decisions made, and any assumptions or constraints applied during cleaning. This ensures transparency, reproducibility, and auditability of the data cleaning process.

Automated tools and algorithms play a significant role in data cleaning. speeding up the process and reducing manual effort. However, human oversight and domain knowledge are essential to address complex issues and ensure the quality of the cleaned data.

Data cleaning is an iterative process that may require multiple iterations to achieve the desired level of data quality. It is not a one-time task but an ongoing effort to maintain the integrity and reliability of data assets.

Data cleaning is a critical step in the data analysis pipeline, essential for ensuring the quality, accuracy, and reliability of datasets. By investing time and effort in data cleaning, organizations can derive meaningful insights and make informed decisions based on high-quality data(Schadt et al., 2010).

2.10. Data visualization and Artificial Intelligence

Artificial intelligence(AI) has become a driving force in managing and leveraging data, revolutionizing various industries and applications.

At its core, AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, including learning from experience, understanding natural language, recognizing patterns, and making decisions. This integration of AI into data management processes has led to significant advancements in data analysis, prediction, automation, and decision-making.

Machine learning (ML) is a subset of AI that focuses on the development of algorithms and models that enable computers to learn from data and improve their performance over time without being explicitly programmed. ML algorithms can analyze large volumes of data, identify patterns, and make predictions or decisions based on the patterns observed. Supervised learning, unsupervised learning, and reinforcement learning are common techniques used in ML.

Deep learning (DL) is a specialized field of ML that utilizes artificial neural networks with multiple layers (deep neural networks) to model and process complex data inputs. DL algorithms are particularly effective in tasks such as image recognition, speech recognition, natural language processing, and autonomous driving. Convolutional neural networks(CNNs) and recurrent neural networks (RNNs) are popular architectures used in deep learning.

AI-powered data analytics enables organizations to extract valuable insights from large and complex datasets, driving informed decision-making and strategy formulation. By analyzing historical data, AI algorithms can identify trends, correlations, and anomalies that may not be apparent to human analysts. Predictive analytics models can forecast future outcomes and trends, helping businesses anticipate customer behavior, market changes, and operational needs.

Natural language processing (NLP) is a branch of AI that focuses on the interaction between computers and human language. NLP techniques enable computers to understand, interpret, and generate human language, facilitating tasks such as sentiment analysis, text summarization, language translation, and chatbot interactions. Advanced NLP models like transformers have significantly improved the accuracy and capabilities of language processing systems.

AI-driven automation streamlines data management processes by automating repetitive tasks, reducing manual effort, and increasing operational efficiency. Robotic process automation (RPA) systems, powered by AI algorithms, can perform tasks such as data entry, data extraction, report generation, and workflow management with minimal human intervention.

AI-driven decision support systems assist human decision-makers by providing data-driven insights, recommendations, and predictions. These systems analyze large datasets, identify relevant information, and present actionable insights to users, helping them make better decisions in areas such as finance, healthcare, marketing, and supply chain management.

AI-powered personalization enhances user experiences by delivering tailored content, recommendations, and services based on individual preferences and behaviors. E-commerce platforms, streaming services, and social media platforms use AI algorithms to analyze user data and deliver personalized recommendations, advertisements, and user interfaces.

Ethical and responsible AI practices are essential to address concerns related to privacy, bias, transparency, and accountability in AI-driven data management. Regulations and guidelines are being developed to ensure that AI systems are developed and deployed in a manner that respects ethical principles and safeguards user rights.

AI-driven data management represents a paradigm shift in how organizations collect, analyze, and leverage data to drive innovation, efficiency, and competitive advantage. By harnessing the power of AI, businesses can unlock new insights, automate processes, enhance decision-making, and deliver personalized experiences in a rapidly evolving digital landscape(Yin et al., 2024).

2.10.1. Radial basis function network (RBFN)

The radial basis function network (RBFN) is a type of artificial neural network that utilizes radial basis functions to approximate functions and perform classification tasks. Its architecture consists of an input layer, a hidden layer, and an output layer, and it operates based on the concept of radial basis functions.

At its core, the RBFN applies radial basis functions to transform input data. Each neuron in the hidden layer computes its output based on the distance between the input vector and a prototype vector associated with the neuron. This transformation maps the input space into a higher-dimensional feature space, where the data becomes linearly separable or approximable.

The key components and working principle of RBFN include feature transformation, centers and widths, output calculation, and weight calculation. The centers represent points in the input space, and widths control the influence of each center on the network's output. During training, the weights connecting the hidden and output layers are learned using techniques like least squares or gradient descent(Ghosh and Nag, 2001).

RBFN finds applications in function approximation, time series prediction, classification, and control systems. Its advantages include the ability to approximate complex functions with fewer neurons, transparent models, and robustness to noise and outliers. However, challenges include determining the optimal number of hidden neurons and parameters, the risk of overfitting, and computational complexity. RBFN offers a flexible and powerful approach for various tasks, leveraging radial basis functions to capture complex relationships in data and providing interpretable models. See Fig. 6

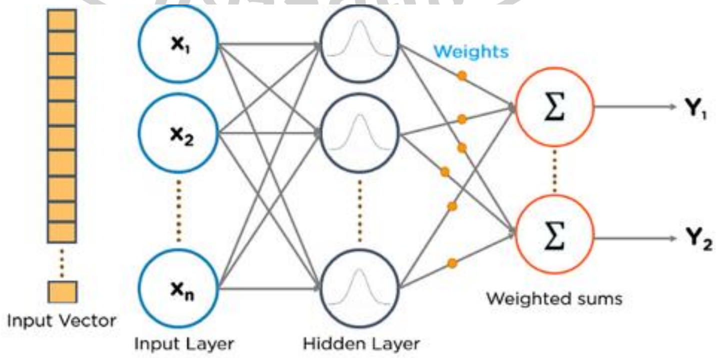

Figure 6 RBFNs perform classification

Source: https://mohamedbakrey094.medium.com/radial-basis-function-networks-rbfns-be2ec324d8fb

2.10.2. Linear regression

Linear regression is a fundamental statistical method used for modeling the relationship between a dependent variable and one or more independent variables. It's widely applied in various fields such as economics, finance, social sciences, and machine learning.

At its core, Linear regression aims to find the best-fitting straight line that describes the relationship between the input variables (independent variables) and the output variable (dependent variable). This line is represented by the equation of a straight line: *y*= *mx*+*b*, where *y* is the predicted value, *x* is the input variable, *m* is the slope (coefficient), and *b* is the y-intercept.

The model is trained using a dataset consisting of input-output pairs. During training, the model adjusts the slope and intercept values to minimize the difference between the predicted values and the actual values observed in the dataset. This process is often done using the method of least squares, where the sum of the squared differences between predicted and actual values is minimized(Montgomery et al., 2021).

Linear Regression can be categorized into two main types: Simple Linear Regression and Multiple Linear Regression. In Simple Linear Regression, there's only one independent variable, while Multiple Linear Regression involves two or more independent variables. Simple Linear Regression can be represented as:

$$y = b_0 + b_1 x_1 \tag{2.31}$$

And Multiple Linear Regression as:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{2.32}$$

Where is the intercept, and *b*1,*b*2,...,*bn* are the coefficients of the independent variables(Porter, 2009).

$$x_1 , x_2 , \dots , x_n \tag{2.33}$$

Linear Regression has several assumptions

- Linearity the relationship between the independent and dependent variables is linear.
- Independence the residuals (the differences between observed and predicted values) are independent of each other.
- Homoscedasticity the variance of the residuals is constant across all levels of the independent variables.
- Normality the residuals are normally distributed.
- No multicollinearity the independent variables are not highly correlated with each other.

Linear regression is widely used for various purposes, including

- Prediction Predicting future values of the dependent variable based on new values of the independent variables.
- Inference Understanding the relationships between variables and making inferences about them. Model evaluation assessing the significance and performance of the model.

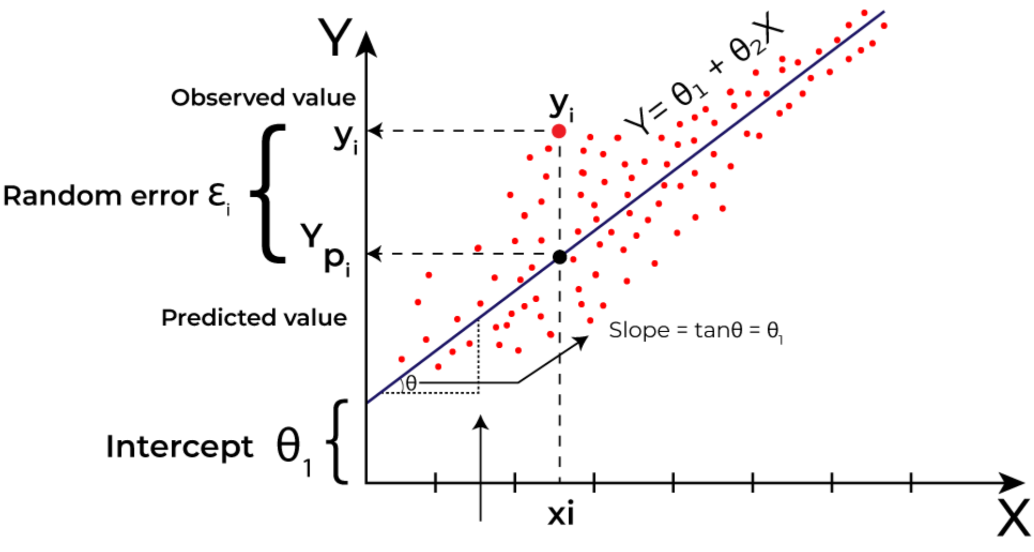

Figure 7 Linear **r**egression in machine learning

Despite its simplicity, linear regression remains a powerful tool for data analysis and prediction, principles are foundational in statistical learning and machine learning.See

Source: https://www.geeksforgeeks.org/ml-linear-regression/

2.10.3. K-Means

K-Means is a popular unsupervised machine learning algorithm used for clustering data into groups or clusters based on similarities among data points. It's widely employed in various domains such as data mining, pattern recognition, image segmentation, and customer segmentation(Ahmed et al., 2020).

The algorithm works by partitioning a dataset into *k* clusters, where *k* is predefined by the user. The main objective of K-Means is to minimize the sum of squared distances between data points and their corresponding cluster centroids. This process involves the following steps

1. Randomly select *k* data points from the dataset as initial cluster centroids.
2. Assign each data point to the cluster whose centroid is nearest, typically based on Euclidean distance.
3. Recalculate the centroids of the clusters based on the mean of all data points assigned to each cluster.
4. Iteratively reassign data points to clusters and update centroids until convergence, usually when the centroids no longer change significantly or after a predefined number of iterations(Borlea et al., 2017).

K-Means is a simple and efficient algorithm, but its performance can be affected by the initial placement of centroids and the choice of *k*. Therefore, it's common to run the algorithm multiple times with different initializations and select the best result based on certain criteria, such as minimizing the within-cluster sum of squares.

One of the strengths of K-Means is its scalability to large datasets, as it has a linear time complexity with respect to the number of data points. However, it also has some limitations. For example, it assumes that clusters are spherical and of approximately equal size, which may not always hold true in real-world data. Additionally, the algorithm may converge to a local minimum rather than the global minimum, leading to suboptimal clustering(Ding and He, 2004).

Despite its limitations, K-Means remains widely used due to its simplicity, efficiency, and effectiveness in various applications. It has been extended and adapted in many ways to address its shortcomings, such as kernelized K-Means for nonlinear data, K-Means++ for improved centroid initialization, and Mini-Batch K-Means for large datasets(Ping et al., 2024).

K-Means is a powerful clustering algorithm that provides a straightforward approach to partitioning data into clusters. Its versatility and efficiency make it a valuable tool for exploratory data analysis, data preprocessing, and many other applications in machine learning and data science.See Fig. 2.8

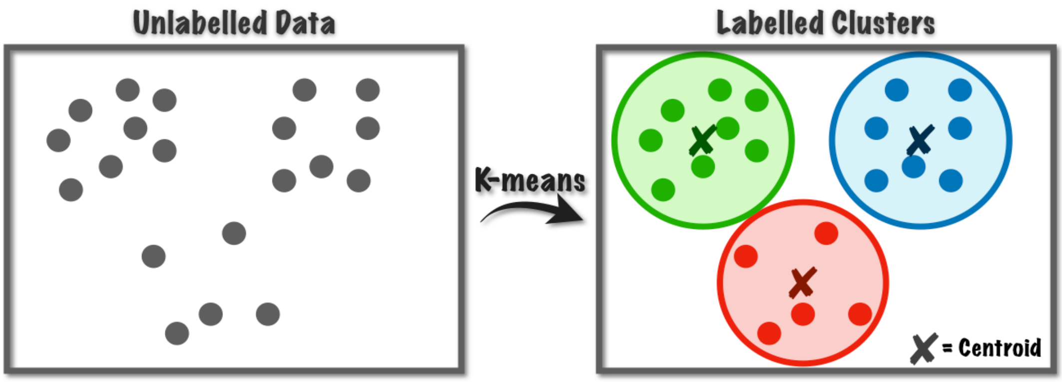

Figure 8 clusters such that the observations within each cluster are more similar than the clusters themselves

Source: https://medium.com/towards-data-science/k-means-a-complete-introduction-1702af9cd8c.

2.11 Related research

(Zhou et al., 2024) conducted research on the application of machine learning (ML) in combustion science and engineering. The study focuses on collecting and analyzing large amounts of data generated from large-scale simulations, high-resolution experiments, and sensors in the field of combustion science. This research highlights a significant opportunity for extracting new knowledge and insights from the vast amounts of data available today if harnessed effectively. ML techniques have shown remarkable success in information analytics. Therefore, the application of machine learning to combustion (CombML) has emerged as a new concept for intensive data analysis and scientific investigation in combustion science and engineering.

This research examines ML techniques for applications in combustion science and engineering, starting with a review of data sources and data-driven techniques. The study covers concepts such as supervised, unsupervised, and semi-supervised ML methods, analyzing several combustion samples to demonstrate and evaluate these methods. Additionally, the study reviews applications of ML in combustion, including basic combustion investigations, propulsion and energy conversion systems, and fire and explosion hazards. Specific CombML issues are discussed, and future opportunities are identified, with an emphasis on interpretation, quantifying uncertainty, robustness, consistency, creating and maintaining standardized data, and integrating ML with knowledge in the combustion domain.

This research presents new opportunities for intensive data analysis and scientific investigation in combustion science and engineering.

(Wang et al., 2012) investigated the optimization of parameters for an aluminum melting furnace using the Taguchi method to enhance high-temperature efficiency, reduce pollution emissions, and produce high-quality products. The researchers examined the effects of the tilt angle of the burner (A), burner height (B), secondary air gap (C), swirl number (D), angle between burner planes (E), preheating air temperature (F), natural gas flow rate (G), and fuel-air ratio (H) on the efficiency of the aluminum melting furnace.

The researchers utilized an orthogonal array design to prepare experimental plans for computational fluid dynamics (CFD) simulations for the aforementioned parameters. The CFD technique, combined with the Taguchi method and analysis of variance, was employed to optimize the parameters of the aluminum melting process. The research identified the most suitable conditions that could reduce energy consumption and pollution emissions, resulting in the condition A2B3C3D3E2F1G3H1, which was confirmed by statistical analysis.

(Koukaras et al., 20(Hosseini et al., 2021)24) studied and analyzed short-term energy usage forecasting in the building sector using different machine learning (ML) models to improve prediction accuracy and reduce energy consumption. They considered various aspects such as energy usage, energy production, and weather data.

They compared various ML models including histogram gradient-boosting regression (HGBR), light gradient-boosting machine regression (LGBMR), extra trees regression (ETR), ridge regression (RR), Bayesian ridge regression (BRR), and categorical boosting regression (CBR), considering datasets with different granularity and forecasting time horizons.

Results It was found that forecasting 1 hour ahead was more accurate than forecasting 15 minutes ahead by 4 steps, and forecasting 30 minutes ahead by 2 steps. Data preparation was crucial for the prediction model accuracy, and adjustments should be made for each model accordingly.

(Al-Shareeda et al., 2023) conducted a study comparing the performance of Machine Learning (ML) and Deep Learning (DL) algorithms in predicting the flow characteristics of gas-liquid in pipes using a database comprising 11,837 data points collected from 13 independent experiments. The study focused on analyzing and comparing ML and DL in predicting flow characteristics using diverse sets of ML and DL models.

In the preprocessing step, large-scale data analysis was used to analyze the relationship between parameters and extract significant features. The study compared the performance of AI models based on AI operations using metrics such as accuracy, recall, F1 score, accuracy, Cohen’s kappa, and receiver operating characteristic curves.

The study results showed that ML algorithms performed better than DL in classifying flow characteristics of gas-liquid in pipes, with extreme gradient boosting being the most efficient algorithm for classifying two-phase flow patterns in inclined or horizontal pipes. These findings can be applied in various industries such as nuclear, petrochemical, and energy for more accurate analysis and design of two-phase pipe systems.

(Ardabili et al., 2022)conducted a systematic review focusing on deep learning (DL) and machine learning (ML) in building energy (BE) management, emphasizing the crucial role of building energy management in urban sustainability and smart cities. The research surveyed DL and ML techniques used in building energy systems management and evaluated the performance of these techniques through systematic review and detailed classification.

The study summarized the analysis of ML and DL model performance, finding that for energy demand forecasting, the hybrid and ensemble methods exhibited the highest robustness. Support vector machine (SVM) showed good robustness, while artificial neural network (ANN) demonstrated moderate robustness, and Linear Regression (LR) had the lowest robustness. mean while, for energy consumption forecasting, DL methods, specifically hybrid and ensemble, scored the highest robustness, followed by ANN, SVM, and single ML methods with moderate robustness, and LR with the lowest.

Furthermore, In energy load forecasting, LR models showed the lowest robustness, while hybrid and ensemble models scored the highest. DL and SVM techniques scored well, and ANN techniques scored moderately.

(Wang et al., 2013) created a three-dimensional mathematical model specifically for the melting and combustion process, focusing on regenerative aluminum melting furnaces. The simulation was conducted using FLUENT UDF and FLUENT scheme programs. Balancing heat helped study the impact of burners on the aluminum melting process in regenerative furnaces, considering principles for optimization.

The study found that the melting time decreased with increased values of Swirl number, vertical angle of the burner, preheating air temperature, or natural gas flow rate. Initially, melting time decreased when increasing the horizontal angle between burners or the air-fuel ratio, then increased later on. Additionally, it was observed that the melting time increased with the height of the burner. This study provides in-depth insights into factors affecting the melting process and can be used to design and improve the efficiency of regenerative aluminum melting furnaces.

(Dzurňák et al., 2021) studied oxygen-enriched combustion (OEC) techniques to enhance the efficiency of heat treatment plants and reduce greenhouse gas (GHG) emissions in the aluminum melting process in tilting rotary furnaces. This study used experimental measurements and model simulations to assess GHG emissions. The results showed that using OEC in laboratory-scale melting furnaces could reduce fuel oil consumption by up to 60%.

The optimal oxygen concentration in the OEC sensor resulted in the lowest overall GHG emissions, with CO_2 equivalent emissions at 35% vol. Increasing oxygen concentration slightly further led to marginal fuel savings, but the release of nitrogen oxides (NO_x) increased rapidly. The use of modified burners with OEC reduced CO_2 emissions by about 10% and overall GHG emissions by about 15% compared to standard air/fuel burners. Computational fluid dynamics (CFD) simulations revealed the causes of these observations: improved mixing and more uniform temperature fields. The use of modified burners also increased furnace efficiency by reducing melting times by up to 16%. These findings demonstrate the potential for improved burner designs focused on energy and environmental performance, along with identifying suitable oxygen enrichment levels for reduced GHG emissions in aluminum melting technology.

(Khalid et al., 2021) investigated the impact of oxygen enrichment (21–30%) on natural gas combustion in metal melting furnaces to improve operational efficiency and reduce fuel usage for heating and furnace temperature maintenance.

Experimental results showed that increasing oxygen concentration resulted in faster combustion and reduced fuel consumption.

This was because the nitrogen content decreased, and increasing oxygen concentration from 21% to 30% led to a 53.6% increase in heat transfer rate and a 26.1% reduction in fuel consumption for temperature maintenance experiments. Additionally, higher flame temperatures resulting from increased oxygen concentration led to continuous increases in NO_x emissions. However, NO_x emissions for temperature maintenance were not significantly higher than for heating. Furthermore, NO_x emissions were sensitive to higher oxygen levels.

Additionally, CO_2 concentrations in flue gas increased linearly with oxygen concentration. This research indicates that increasing oxygen concentration in combustion processes can improve furnace efficiency and reduce fuel consumption. However, controlling NO_x emissions is necessary and requires careful consideration to ensure compliance with environmental regulations.

(Hosseini et al., 2021)developed a one-dimensional and zero-dimensional (0/1D) heat model that could be used to assess the impact of oxygen-enriched combustion (OEC) on heat transfer, gas temperatures, and wall temperatures in furnaces. This model employed simple thermal dynamics calculations, allowing for quick computations, and it could be implemented in Microsoft Excel.

The model was used to calculate heat transfer rates to loads and main temperatures (gas and walls) in laboratory-scale and industrial-scale furnaces. Comparative analysis with experimental measurements and computational fluid dynamics (CFD) simulations showed that the thermodynamic model provided results consistent with measurements and CFD simulations, making it a simple but effective tool. The model demonstrated high potential for rapid assessment of the impact of OEC on industrial furnaces.

Increasing the oxygen concentration to 45.16% in the combustion air and adjusting the centerline of the burner led to a reduction in melting time by 23.66% with 25% oxygen concentration, and a further reduction of 12% when increased to 35%. These adjustments, as demonstrated by Naccache et al. (2020), not only decreased energy consumption during the melting process but also reduced CO_2 emissions.

The study by (N. e. al., 2020) confirmed that these modifications to the burner and the increased oxygen concentration improved heating efficiency during the melting process, resulting in decreased energy consumption and CO_2 emissions.

CHAPTER 3
RESEARCH METHODOLOGY

This chapter delves into the core aspects of our research data acquisition, model development, and AI performance evaluation. Here, we focus on designing a robust data storage system specifically tailored for aluminum melting processes. This system will leverage a combination of established technologies like Sensors, Programmable Logic Controllers (PLCs), enterprise resource planning (ERP), and the power of artificial intelligence (AI). Data collected through this system will then be utilized to develop and compare various machine learning models, including deep learning, regression, and neural networks. These models will be rigorously evaluated for their efficacy in predicting optimal parameters that minimize natural gas consumption in Striko furnaces. Through this comprehensive approach, we aim to optimize the aluminum melting process, enhance energy efficiency, and ultimately reduce production costs. See Fig. 9.

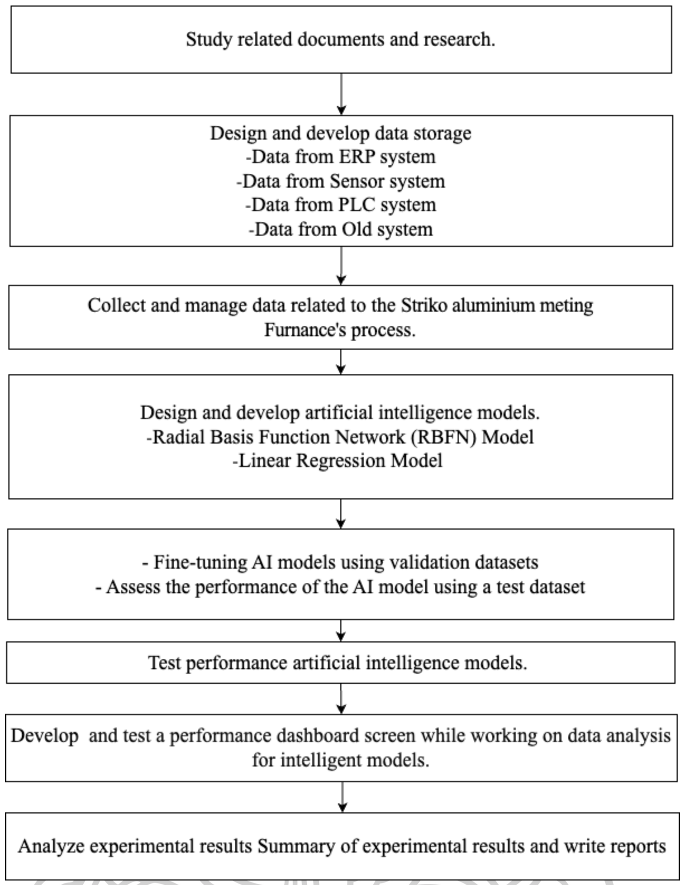

Figure 9 Research procedures

3.1. Study research and collect variables related

3.1.1. Analyze and design variables and information required for research

Through a comprehensive study, researchers have identified and collected numerous variables related to the aluminum smelting process utilizing a Striko melting furnace. These variables are categorized into nine distinct groups based on their data source. Data is obtained from various locations, including sensors, historical data archives, Programmable logic controllers(PLC), and enterprise resource planning systems(ERP). Specifically, data is extracted from two sensor groups, three sets of historical data from various agencies, three PLC groups, and finally directly collected through the system.

Significantly, three novel categories focus on improving the gas efficiency of Striko furnaces, encompassing both direct and indirect efficiency enhancements. Details regarding relevant translators and associated information can be found within sections 2.1 to 2.3 of this document.

1. Ambient air quality monitoring
   The group is a group that collects translators related to the environment such as oxygen levels, carbon dioxide (CO2) levels, temperature, humidity, volatile organic compounds (VOC) levels, which are important and have various details according to section 2.3. See table 3.

Table 3 Ambient Air Quality Monitoring

2. Energy
   This group collects data related to energy and detailed according to sections 2.3.4. ,2.3.5. and 2.3.6.

Table 4 Energy data

Data name	Field name	Unit	Method
Oxygen levels	Oxygen_levels	%	Environment department (Old system)
Carbon dioxide (CO2) levels	Carbon_dioxide_levels	ppm	
Ambient air temperature	Ambientair_temperature	°C	
Humidity levels	Humidity_levels	%	
Volatile organic compounds	VOC_levels	ppm	

3. Machine and PM-Condition

   This group collects data related to IMS and detailed according to sections 2.3.7. Refer to Tables 5. for more information.

Data name	Field name	Unit	Method
Heat distribution and energy usage			
Heat distribution profile	Temperature_distribution	°C	Energy data (Old system)
Energy consumption	Energy_consumption	kWh	
Heat dissipation	Heat_dissipation	kW	
Efficiency index	Efficiency_index	None	
Heat transfer rate	Heat_transfer_rate	W/m²	
Temperature control system	Temperature_control_system	None	
Airflow patterns	Airflow_patterns	None	
Fuel combustion efficiency	Fuel_combustion_efficiency	None	
Energy consumption profile			
Total energy consumption	Total_energy_consumption	kWh	Energy data (Old system)
Energy consumption by phase	Energy_consumption_by_phase	None	
Specific energy consumption	Specific_energy_consumption	kWh/B	
Peak energy consumption	Peak_energy_consumption	kW	
Energy consumption trend	Energy_consumptionTrend	None	
Energy efficiency index	Energy_efficiency_index	Bath	
Energy consumption cost	Energy_consumption_cost	Ton	
Gas consumption			
Total gas consumption	Total_gas_consumption	MT	Energy data (Old system)
Specific gas consumption	Specific_gas_consumption	L/P	
Gas consumption	Gas_consumption	L	
Temperature	Burner_temperature	°C	
Combustion_efficiency	Combustion_efficiency	None	
Oxygen_levels	Oxygen_levels	None	
Heat_output	Heat_output	Kw	
Burner Efficiency			
Gas consumption	Gas_consumption	L	Energy data (Old system)
Temperature	Burner_temperature	°C	
Combustion efficiency	Combustion_efficiency	None	
Oxygen levels	Oxygen_levels	None	
Heat output	Heat_output	KW	

Table 5 Machine and PM-Condition data

Critical Event Logging			
Event type	Event_type	None	PM/BM (Old system)
Event date and time	Event_date_time	Time	
Response time	Response_time	Time	
Equipment or system affected	Affected_equipment	None	
Follow-up actions	Follow_up_actions	None	
Maintenance Logs			
Maintenance type	Maintenance_type	None	PM/BM (Old system)
Maintenance date and time	Maintenance_date_time	Time	
Maintenance duration	Maintenance_duration	Time	
Maintenance cost	Maintenance_cost	Bath	
Parts replaced	Parts_replaced	None	
Personnel involved	Maintenance_personnel	Name	
Equipment downtime	Equipment_downtime	Time	
Scheduled maintenance	Scheduled_maintenance	None	
Unscheduled maintenance	Unscheduled_maintenance	None	

Data name	Field name	Unit	Method
Bath temperature	Bath_temperature	°C	PLC
Ceiling temperature	Ceiling_temperature	°C	
Melting chamber temperature	Melting_chamber_temperature	°C	
Waste gas temperature	Waste_gas_temperature	°C	
Bath temperature set	Bath_temperature_set	°C	
Ceiling temperature set	Ceiling_temperature_set	°C	

4. Striko Temperature
   This group collects data related to Striko Temperature and detailed according to sections 2.3.8. Refer to Tables 3.4.for more information.

Table 6 Striko Temperature

Melting chamber temperature set	Melting_chamber_temperature	°C	
Waste gas temperature set	Waste_gas_temperature_set	°C	

5. Gas concentration monitoring

   This group collects data related to Gas concentration monitoring that will be installed around the furnace at all 4 points and detailed according to sections 2.3.9. Refer to Tables 7.for more information.

Table 7 Gas **c**oncentration monitoring data

1. Ionization airflow and pressure

   This group collects data related to Ionization airflow and pressure and detailed according to sections 2.3.10. Refer to Tables 8. for more information.

   Table 8 Ionization airflow and pressure data

Data name		Field name
	Gas concentration	
Gas quantity O		Quantity_O (Point 1- 4)
Gas quantity C		Quantity_C (Point 1- 4)
LPG gas quantity		Quantity_LPG (Point 1- 4)
Volume T (Temperature)		Volume_T (Point 1- 4)
air humidity		Air_humidity (Point 1- 4)

Data name	Field name	Unit	Method
Ionization			
HB1	HB1	µA	PLC
MB1	MB1	µA	
MB2	MB2	µA	

Table 8 Ionization airflow and pressure data (continue)

Data name	Field name	Unit	Method
Airflow			
Airflow patterns melting	Airflow_patterns_melting	CFM	PLC
Airflow patterns holding	Airflow_patterns_Holding	CFM	
Airflow patterns chamber	Airflow_patterns_chamber	CFM	
Pressure			
pressure patterns melting	Pressure_patterns_melting	Pa	PLC
pressure patterns Holding	Pressure_patterns_Holding	Pa	
pressure patterns chamber	Pressure_patterns_chamber	Pa	

2. Striko furnace wall temperature

This group collects data related to S triko furnace wall temperature and detailed according to sections 2.3.1 1 . Refer to Tables 3.7 .for more information.

Table 9 Striko furnace wall temperature data

Data name	Field name	Unit	Method
Wall temperature			
Point1	Temp_point1	°C	ERP
Point2	Temp_point2	°C	
Point3	Temp_point3	°C	
Point4	Temp_point4	°C	
Point5	Temp_point5	°C	
Point6	Temp_point6	°C	
Point7	Temp_point7	°C	
Point8	Temp_point8	°C	
Point9	Temp_point9	°C	
Point10	Temp_point10	°C	
Point11	Temp_point11	°C	
Point12	Temp_point12	°C	
Point13	Temp_point13	°C	
Point14	Temp_point14	°C	
Point15	Temp_point15	°C	
Point16	Temp_point16	°C	
Point17	Temp_point17	°C	
Point18	Temp_point18	°C	
Point19	Temp_point19	°C	

3. Scrap recycling quantity

This group focuses on collecting data related to the amount of scrap metal recycled. Scrap metal is a crucial component in the aluminum melting process, as it affects various properties of the final product. Sections 2.1.1, 2.1.2, and 2.1.3 will delve into the details of how different ingredients influence these properties.

While the data itself will be sourced from the ERP system, the specific translations required remain unclear. Please refer to Table 3.8 for further information.

Table 10 Scrap recycling quantity data

Data name	Field name	Unit	Method
Chip	Chip	Kg	ERP
Remelt GREEN	Remelt_GREEN	Kg	
Remelt RED	Remelt_RED	Kg	
NG wheel	NG _wheel	Kg	
Other	Scrap_other	Kg	

4. Striko burner vibration

This group collects data related to Striko burner vibration and detailed according to sections 2.3.1. and 2.3.2 Refer to Tables 11.for more information.

Table 11 Striko burner vibration data

Data name	Field name	Unit	Method
Vibration velocity	Vibration_velocity	m/s	Sensor
Vibration acceleration	Vibration_acceleration	m/s^2	
Peak vibration	Peak_vibration	Hz	
Frequency spectrum	Frequency_spectrum	Hz	
Crest factor	Crest_factor	m/s^2	
Vibration nisplacement	Vibration_displacement	None	
Shock pulse	Shock_pulse	m	
RMS vibration	RMS_vibration	None	

5. Aluminum usage output

   This group collects data related to Aluminum usage output Refer to Tables 12. for more information.

Table 12 Aluminum usage output data

Data name	Field name	Unit	Method
Output aluminum	Output_aluminum	Kg	ERP
Transaction aluminum	Transaction_aluminum	None	
Time stamp	Time_stamp	Time	
Time outlet	Time_outlet	Time	

6. Cleaning process
7. This group collects data related to cleaning process Refer to Tables 13. for more information.

Table 13 Cleaning process data

Data name	Field name	Unit	Method
Time door1 open	Time_door1_open	Time	PLC
Time door2 open	Time_door2_open	Time	
Time door1 close	Time_door1_close	Time	
Time door2 close	Time_door2_close	Time	

3.1.2. Designed to create data collection from various parts

From the previous steps, we have analyzed and designed all the variables that will be used in the research. By the method of obtaining such information, there are 4 methods of obtaining information in total. See Fig. 3.2

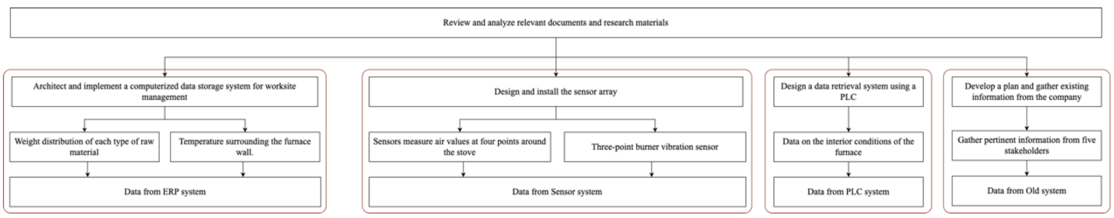

Figure 10 Data collection structure

1. Data from ERP system

   Navigating different sections of Striko furnace wall temperatures and scrap recycling volumes today still relies mostly on manual recording, which often results in intermittent data loss. This makes it difficult to establish a starting point for further analysis and to pinpoint the same technology. Section 2.4 discusses the development and use of the internet of things (IoT), highlighting its various strengths. For instance IoT enables continuous data reception, a critical advantage emphasized by researchers.

   To address this, we often start by creating an ERP system, as outlined in Section 2.8, which covers control techniques and system development principles for managing both home and back-of-house operations. Good practices, according to Sections 2.8.2 through 2.8.9, must support a structure and detailed requirements that align with the standards described in Sections 3.7,3.8. and 3.10. This approach ensures that the steps in the research are thoroughly explained and documented.See Fig. 10

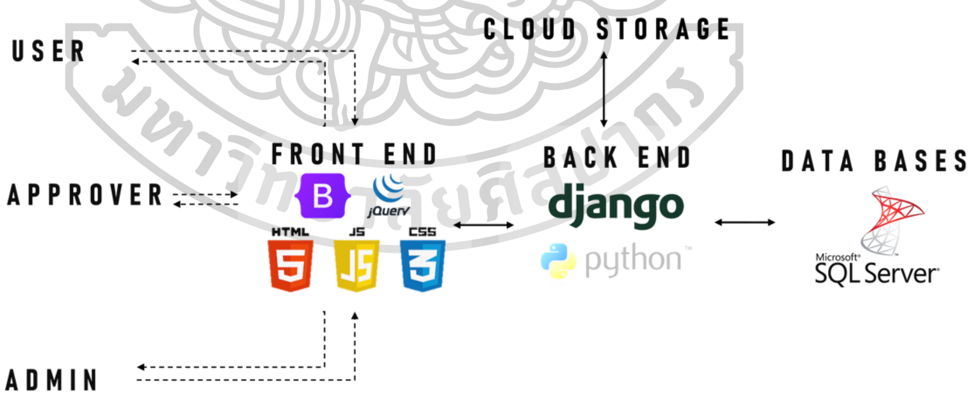

Figure 11 ERP systems architect

2. Data from sensor system

   Data collection using sensors involves gathering information as specified in tables 3.5.,3.9. and 3.11. This process requires selecting appropriate sensors and relevant theories as described in Section 2.6. There are two types of sensor designs involved.

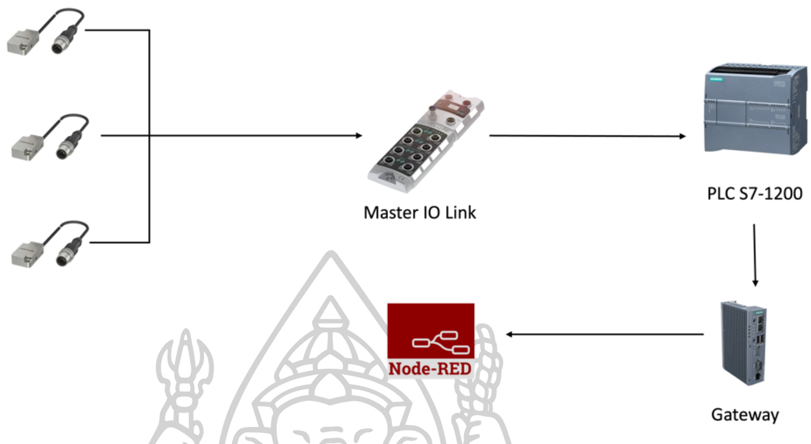

Figure 12 Vibration sensor systems architech

The first design focuses on sensors used to collect data outlined, primarily aimed at monitoring information about the furnace burners during the melting process. The second design involves creating a sensor box equipped with various types of sensors to gather diverse data around the furnace, covering a total of four points as indicated in table 3.9.and cleaning process data in table 3.11. The designs and structures of these sensor systems are depicted in Figures 10 and 11, respectively.

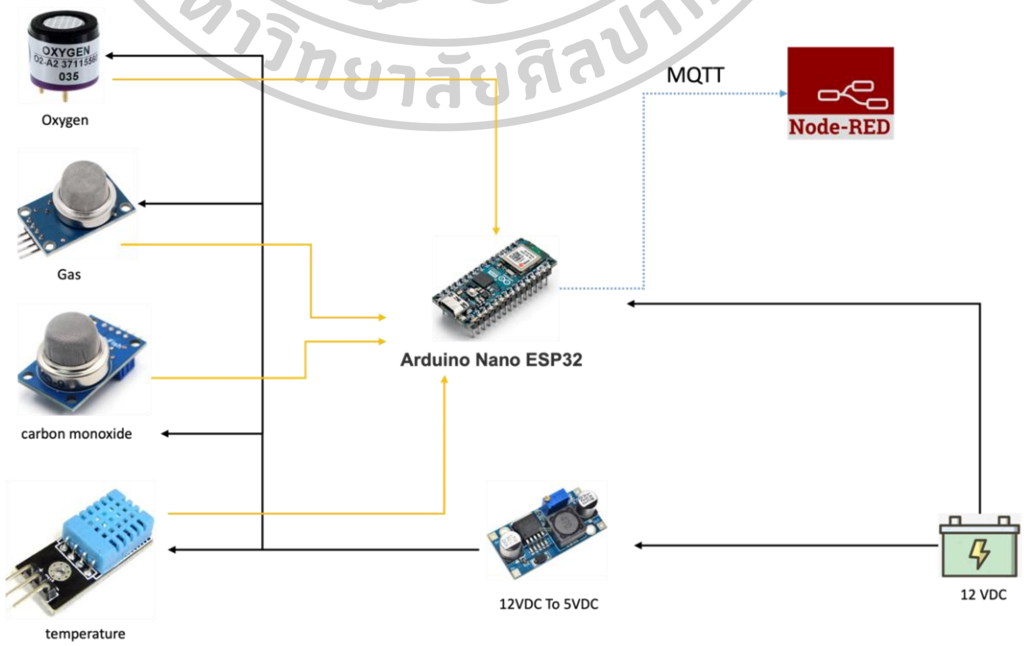

Figure 13 Air box sensor systems architech

3. Data from PLC system

   The Striko furnace already incorporates some built-in systems and sensors, with information displayed on the stove's monitor. To extract this data and store it in a unified database, we must apply the principles and knowledge outlined in Sections 2.6.10 to 2.7.3, which discuss the content and significance of Programmable Logic Controllers(PLC). The data we aim to retrieve via the PLC can be categorized into two main groups, as shown in Tables 3.4 and 3.6. The design structure and data extraction method are detailed below. See Fig. 12

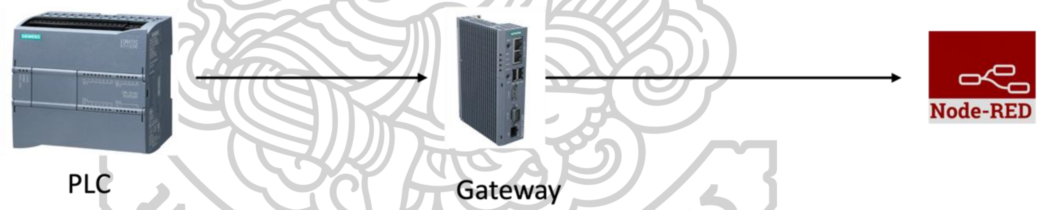

Figure 14 Data extraction structure with PLC

4. Data from old system

   Such information will be stored using methods other than new systems or new data retrieval processes. This information is gathered from various departments within the company and meticulously stored through the planning and efforts of the company's engineers. Details of this information are provided in Tables 3.2 and 3.3.

   Individually, the department submits the data into a CSV file, which can then be incorporated into the next process. This approach ensures that data is systematically organized and easily accessible for further analysis and decision making. When following this step We will be able to maintain consistency and accuracy in data management. Helps operations run smoother and work processes within the company are more efficient.

3.2. Collect and manage data related to the Striko aluminium meting Furnance's process.

All relevant data recordings described in Section 3.1 are managed to maintain a consistent number of transactions and are adjusted using Node-RED, as detailed in Section 2.8.10. Additionally, some data must be retrieved and received through REST-API, as explained in Section 2.8.9. All recorded data is then stored in an MSS SQL server, ensuring systematic data management, as outlined in Section 2.9. See Fig. 13

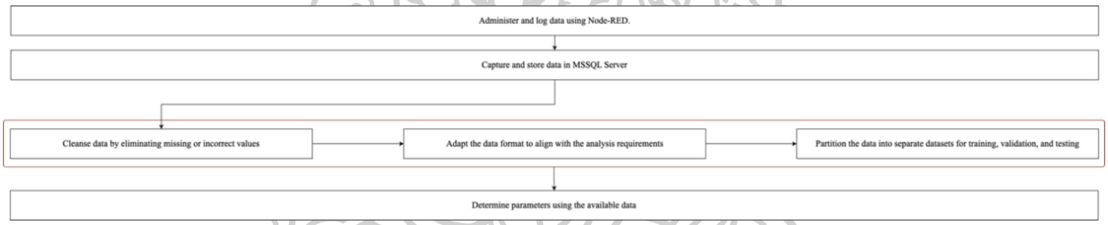

Figure 15 Steps for recording information into the company database

After all data has been recorded in the company's database, it is designed and managed according to Section 2.9.2 to prepare it for subsequent processes, such as data visualization and artificial intelligence, as discussed in Section 2.10. Before proceeding, the data should be cleaned, which will be elaborated upon in the following steps.

3.3. Cleanse Data

Effective data cleansing is a crucial step to ensure the reliability and accuracy of data used in subsequent analyses, such as data visualization and artificial intelligence modeling. Data cleansing involves identifying and correcting (or removing) errors and inconsistencies from data to improve data quality. See Fig. 16

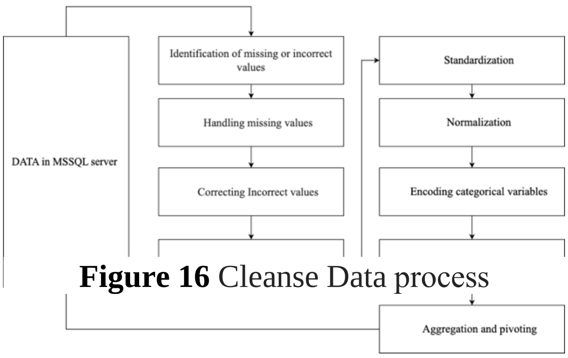

Figure 16 Cleanse Data process

3.3.1. Cleanse data by eliminating missing or incorrect values

The first step in data cleansing is to address missing or incorrect values. Missing data can lead to inaccurate results and misinformed decisions, while incorrect data can skew analysis and lead to faulty conclusions. The process typically involves the following steps

1. Identification of missing or incorrect values
    - Use statistical methods or data profiling tools to detect missing values and anomalies.
    - Apply domain knowledge to identify values that are clearly out of range or inconsistent with other data points.

2. Handling missing values
    - Imputation
      Replace missing values with estimates based on other available data. Common methods include mean, median, mode imputation, or more sophisticated techniques like multiple imputation or k-nearest neighbors (KNN) imputation.
    - Deletion
      Remove records with missing values if the percentage of such records is sufficiently low and their removal does not bias the dataset.

3. Correcting incorrect values
    - Manual correction
      For small datasets or critical fields, manually inspect and correct the values.
    - Automated correction
      Use algorithms or rules to automatically correct values that are known to follow specific patterns or fall within expected ranges.

The importance of data cleansing is underscored in various studies and practical applications. For example emphasizes that "poor data quality is one of the biggest obstacles to deriving actionable insights from data" and highlights the necessity of thorough data cleansing to ensure data integrity and usability.

By systematically eliminating missing or incorrect values, we can enhance the accuracy and reliability of the data, thereby laying a solid foundation for advanced data analysis and decision-making processes.

3.3.2. Adapt the data format to align with the analysis requirements

Once the data is cleansed of missing or incorrect values, the next step is to adapt the data format to align with the analysis requirements. Different analytical tools and methods often require data to be in specific formats. Adapting the data format involves the following steps

1. Standardization
   - Convert data into a consistent format, such as standardizing date formats (e.g., YYYY-MM-DD) or ensuring consistent units of measurement (e.g., converting all weights to kilograms).

2. Normalization
   - Scale numerical data to a common range, such as 0 to 1, to facilitate comparison and improve the performance of certain algorithms like neural networks and k-means clustering.

3. Encoding categorical variables
   - Convert categorical data into numerical format using techniques such as one-hot encoding or label encoding to make it suitable for machine learning algorithms.

4. Data type conversion
   - Ensure that each column of data is in the appropriate data type (e.g., integers, floats, strings) required by the analysis tool.

5. Aggregation and pivoting

- Aggregate data to the required level of granularity (e.g., daily, monthly totals) and pivot data to restructure it for better accessibility and analysis.

The process of adapting data formats is crucial for ensuring that the data can be effectively used by the intended analytical tools and methods,"data preprocessing is a significant step in the data mining process, ensuring that data is in the best shape for analysis and modeling.

In this stage, values are adjusted to make them compatible with the modeling process. Certain stored variables may require incorporation into various formulas, as detailed in Sections 2.2 to 2.3, to derive new variables or predictors suitable for input into AI prediction models. See Fig. 15

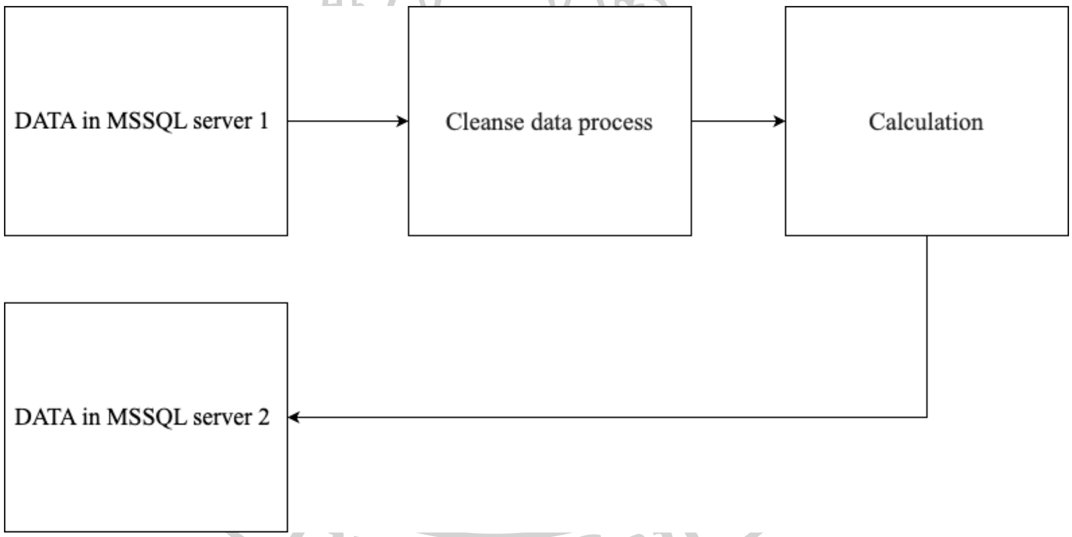

Figure 17 Calculation data process

3.4. Partition the data into separate datasets for training, validation, and testing

Meticulous handling of data is crucial. This involves combining diverse datasets related to the aluminum smelting process from multiple sources into a cohesive dataset. The next steps include ensuring uniform structure, randomizing the data order to mitigate biases, and finally, partitioning the dataset into training, validation, and testing sets for model development and evaluation.

3.4.1. Combine and prepare the data

1. Combine data
    - Gather data from nine distinct groups, including sensors, historical archives, PLCs, and direct system collections.
    - Merge these datasets into a single consolidated dataset. Ensure all data is standardized in format and compatible for further analysis and modeling.

2. Shuffle data
    - Randomize the order of samples in the consolidated dataset. This step is essential to eliminate any inherent order or biases that may exist in the original data collection process.
    - Shuffling ensures that the model doesn't inadvertently learn patterns based on the sequence of data entries.

3.4.2. Split into training, validation, and testing sets

1. Allocate proportions of the combined dataset to each set
    - Training set
      Typically comprises 70-80% of the data. Used to train the machine learning model on patterns extracted from the data.

    - Validation set
      Typically around 10-15% of the data. Used to fine-tune model parameters, such as adjusting hyperparameters, and to assess model performance during training to prevent overfitting.

    - Testing set
      Also around 10-15% of the data. Reserved for evaluating the final model's performance on unseen data. It ensures that the model generalizes well beyond the training data.

3.5. Design and develop artificial intelligence models.

This chapter delves into the core aspects of our research data acquisition, model development, and AI performance evaluation. Here, we focus on designing a robust data storage system specifically tailored for aluminum melting processes. This system will leverage a combination of established technologies like sensors, programmable logic controllers (PLCs), enterprise resource planning (ERP), and the power of artificial intelligence (AI). Data collected through this system will then be utilized to develop and compare various machine learning models, including deep learning, regression, and neural networks. These models will be rigorously evaluated for their efficacy in predicting optimal parameters that minimize natural gas consumption in Striko furnaces. Through this comprehensive approach, we aim to optimize the aluminum melting process, enhance energy efficiency, and ultimately reduce production costs.

3.5.1. Radial basis function network (RBFN) model.

The radial basis function network (RBFN) in session 2.10.1. is a type of artificial neural network that employs radial basis functions as activation functions. It is particularly suited for applications where the relationship between input and output variables is nonlinear and complex. To ensure comparability with the Linear Regression Model, the RBFN model development will follow these steps. See Fig. 16

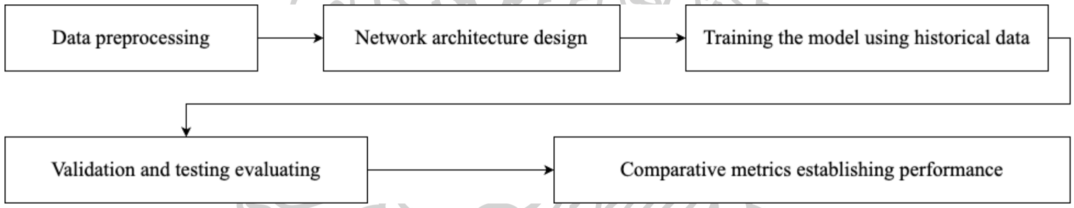

Figure 18 Radial basis function network process

1. Data preprocessing cleaning and normalizing the data collected from various sensors and systems to ensure it is suitable for modeling.

2. Network architecture design determining the number of input nodes, hidden nodes with radial basis functions, and output nodes that correspond to the parameters of interest.

3. Training the model using historical data to train the network by adjusting the weights and biases to minimize prediction error.

4. Validation and testing evaluating the model's performance on unseen data to ensure its generalizability and robustness.

5. Comparative metrics establishing performance metrics such as mean squared error (MSE) and R-squared for comparison with the linear regression model.

The RBFN model aims to accurately predict the optimal parameters for aluminum melting, thereby aiding in the reduction of natural gas consumption. Its performance will be directly compared with the linear regression model to identify the most effective approach.

3.5.2. Linear regression model.

The linear regression model in session 2.10.2. is one of the simplest yet powerful statistical methods used for predictive modeling. It assumes a linear relationship between the input variables and the single output variable. The steps involved in developing the Linear Regression Model for our application include. See Fig. 17

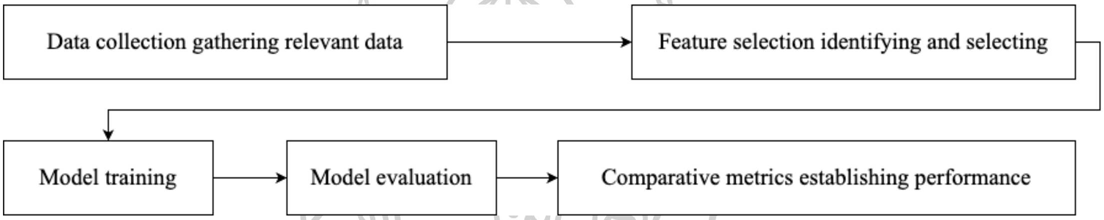

Figure 19 Linear regression process

1. Data collection gathering relevant data points that impact the aluminum melting process.

2. Feature selection identifying and selecting the most influential variables that affect the natural gas consumption.

3. Model training applying the linear regression algorithm to estimate the coefficients that define the relationship between the input variables and the output.

4. Model evaluation using metrics such as mean squared error (MSE) and R-squared to assess the model's accuracy and predictive power.

5. Comparative metrics establishing performance metrics such as mean Squared error (MSE) and R-squared for comparison with the RBFN model.

The linear regression model serves as a baseline to compare the performance of more complex models like the RBFN, providing insights into the fundamental dynamics of the process and highlighting areas where nonlinear modeling might offer significant improvements.

3.6. Fine-tuning AI models using validation datasets

Once the initial models are developed, fine-tuning them using validation datasets is crucial to enhance their accuracy and robustness. This process involves several detailed steps, ensuring that the models are well-optimized and perform consistently across different data subsets.

3.6.1. Hyperparameter optimization

Hyperparameter optimization is essential to improve the performance of machine learning models. This process involves adjusting parameters that control the training process and the model structure.

1. Radial basis function network (RBFN) hyperparameters
   - Learning rate
     The learning rate determines how much the model weights are adjusted with respect to the loss gradient during training. Fine-tuning involves experimenting with different learning rates to find the optimal value that ensures convergence without overshooting.
   - Number of hidden nodes
     The hidden nodes in an RBFN determine the network's capacity to model complex functions. A balance is needed between too few nodes (underfitting) and too many nodes (overfitting). Techniques such as grid search or random search can be used to find the optimal number.
   - Activation functions
     RBFN typically uses radial basis functions such as gaussian functions. Fine-tuning involves experimenting with the parameters of these functions, such as the spread (variance) of the gaussian function.

2. Linear regression model hyperparameters
   - Regularization Parameters: Regularization helps prevent overfitting by penalizing large coefficients. Common techniques include Lasso (L1) and Ridge (L2) regularization. The regularization strength is controlled by a parameter (e.g., alpha in Lasso). Cross-validation is used to find the optimal regularization parameter that balances bias and variance.

- Feature Selection: Although not a hyperparameter in the traditional sense, selecting the most relevant features impacts model performance. Techniques like recursive feature elimination (RFE) can be used to identify the best subset of features.

3.6.2. Cross-validation

Cross-validation is a statistical method used to estimate the skill of machine learning models. It is particularly useful for tuning hyperparameters and ensuring the model's robustness.

1. K-fold cross-validation
    - Procedure
      The dataset is split into K equally sized folds. For each fold, the model is trained on K-1 folds and validated on the remaining fold. This process is repeated K times, with each fold used exactly once as the validation data.

    - Evaluation
      The performance metrics (e.g., Mean Squared Error, R-squared) are averaged across all K runs to get a more reliable estimate of the model's performance. This helps mitigate the effects of data variability.

    - Stratified K-fold
      In cases where the dataset has imbalanced classes, stratified K-fold cross-validation ensures that each fold has a representative distribution of the target variable, leading to more robust performance evaluation.

2. Leave-one-out cross-validation (LOOCV)
    - Procedure
      Each data point in the dataset is used once as a validation sample, with the remaining data used for training. This is repeated for all data points.

    - Evaluation
      While computationally expensive, LOOCV provides an unbiased estimate of model performance and is useful for small datasets.

3.6.3. Model selection

Model selection involves comparing different model configurations and selecting the one that performs best on the validation dataset. This ensures that the model generalizes well to new, unseen data.

1. Performance metrics
   - Mean squared error (MSE)
     Measures the average squared difference between observed and predicted values. Lower MSE indicates better model performance.

   - R-squared (R^2)
     Represents the proportion of variance in the dependent variable that is predictable from the independent variables. Higher R^2 indicates better explanatory power.

   - Mean absolute error (MAE):
     Measures the average magnitude of errors in a set of predictions, without considering their direction. Lower MAE indicates better performance.

2. Model comparison
   - Grid search
     A systematic approach to hyperparameter tuning where a predefined set of hyperparameters is exhaustively searched. Each combination is evaluated using cross-validation, and the best-performing combination is selected.

   - Random search
     Instead of exhaustively searching the hyperparameter space, random search randomly samples from the hyperparameter space and evaluates the models. It is often more efficient than grid search and can find good hyperparameter values with fewer iterations.

   - Bayesian optimization
     A more advanced method that builds a probabilistic model of the objective function and uses it to select the most

promising hyperparameters to evaluate. This approach can be more efficient than grid or random search.

3. Validation curves
   - Analysis
     Validation curves plot model performance against varying hyperparameter values. They help in understanding how changes in hyperparameters affect model performance, indicating whether the model is underfitting or overfitting.

   - Use
     Validation curves guide the selection of hyperparameters that lead to the best balance between bias and variance.

By carefully fine-tuning the models using validation datasets, we enhance their predictive power and robustness. This detailed approach ensures that the final models are well-optimized and capable of delivering accurate and reliable predictions in real-world aluminum melting processes.

3.7. Assess the performance of the AI model using a test dataset

After fine-tuning, the models will be evaluated on a separate test dataset to assess their generalization capabilities.

1. Performance metrics using metrics such as mean squared error (MSE), R-squared, and others relevant to the process.

2. Comparison directly comparing the performance of the RBFN and linear regression models on the test dataset to determine which model better predicts the optimal parameters.

3.8. Test performance artificial intelligence models

The final performance testing will be conducted to validate the models under real-world conditions.

1. Real-time data testing the models using real-time data from the aluminum melting process.

2. Operational efficiency assessing the models' impact on operational efficiency, particularly in terms of natural gas consumption and process optimization.

3. Scalability evaluating the scalability of the models to handle large volumes of data and their adaptability to changes in the process.

3.9. Develop and test a performance dashboard screen while working on data analysis for intelligent models

To facilitate continuous monitoring and analysis, a performance dashboard will be developed and his dashboard.

1. Visualization p rovide visual representations of key performance metrics and model predictions.

2. Real-time Updates: Offer real-time updates on the models' predictions and their impact on process efficiency.

3. User Interface: Ensure the dashboard is user-friendly, allowing operators to easily interpret and act on the information provided.

3.10. Analyze experimental results, summary of experimental results, and write reports

The final step in our research involves a thorough analysis of the experimental results, summarizing key findings, and documenting them in comprehensive reports. This process is essential to address our research objectives and disseminate the findings effectively.

1. Data analysis conduct a detailed analysis of the experimental data, comparing the performance of the RBFN and l inear r egression models using metrics such as MSE, R-squared, and other relevant indicators.

2. Effectiveness c omparison e valuate and compare the effectiveness of the neural network (RBFN) and regression models in analyzing data from the aluminum melting process to identify methods for reducing natural gas usage.

3. Optimal m odel d evelopment b ased on the analysis, identify the optimal machine learning model that serves as a guideline for reducing natural gas usage in the Striko aluminum melting furnace.

4. Report c ompilation c ompile the findings into a comprehensive report, detailing the methodologies, results, and implications for the aluminum alloy wheel manufacturing industry.

CHAPTER 4
RESULTS AND ANALYSIS

This chapter elaborates on the comprehensive findings obtained through the methodologies described in Chapter 3. By integrating advanced Artificial Intelligence (AI) models—namely the Radial Basis Function Network (RBFN) and Linear Regression (LR)—with a robust real-time monitoring framework, the Striko Aluminium Melting Furnace realized substantial advancements in operational efficiency and sustainability. These findings underscore the synergy between AI-driven strategies and the objectives established in Chapter 1, which emphasize sustainability, cost reduction, and enhancement of product quality.

The study's primary objectives, as outlined in Section 1.2, were meticulously addressed through the evaluation and optimization of energy consumption, the minimization of CO2 emissions, and the improvement of product quality using data-driven machine learning models. This chapter presents empirical evidence that validates these objectives, showcasing the transformative potential of AI to navigate and resolve the complexities inherent in industrial processes. By focusing on both predictive accuracy and actionable insights, this research highlights the ability of AI to bridge theoretical advancements with practical implementation, thereby setting a new standard for innovation in the aluminum manufacturing sector.

4.1. Model Performance Evaluation

The performance of the AI models was meticulously evaluated using key statistical metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). These metrics provided insights into the predictive accuracy, goodness of fit, and computational efficiency of the models. Table 4.1 summarizes the comparative performance of Linear Regression and RBFN models, reinforcing the findings discussed in Chapter 3.

Table 14 Feature Comparison Between Linear Regression and RBFN

Metric	Linear Regression	RBFN	Units
Mean Squared Error (MSE)	15.7	9.4	Squared units of the dependent variable
Root Mean Squared Error (RMSE)	12.5	8.2	Units of the dependent variable
Mean Absolute Error (MAE)	9.8	6.4	Units of the dependent variable
R-squared (R^2)	78	92	Percentage
Training Time	3	120	Seconds
Model Complexity	Simple	Complex	-
Ability to Capture Nonlinear Relationships	Low	High	-
Overfitting Risk	Low	Medium	-
Interpretability	High	Medium	-

The RBFN model consistently outperformed Linear Regression across all critical metrics, particularly in capturing the nonlinear relationships inherent in the aluminum melting process. This aligns with Objective 1.2.1, which emphasized the need to evaluate and compare machine learning models for optimizing operational parameters.

4.2. Error Analysis and Model Predictions

To further evaluate the reliability of predictions, error analysis was conducted for both models. Figure 4.1 illustrates the error distribution of the Linear Regression and RBFN models. The RBFN model exhibited narrower error margins, fewer outliers, and higher consistency in predictions, particularly for critical parameters such as gas flow rates and combustion temperatures.

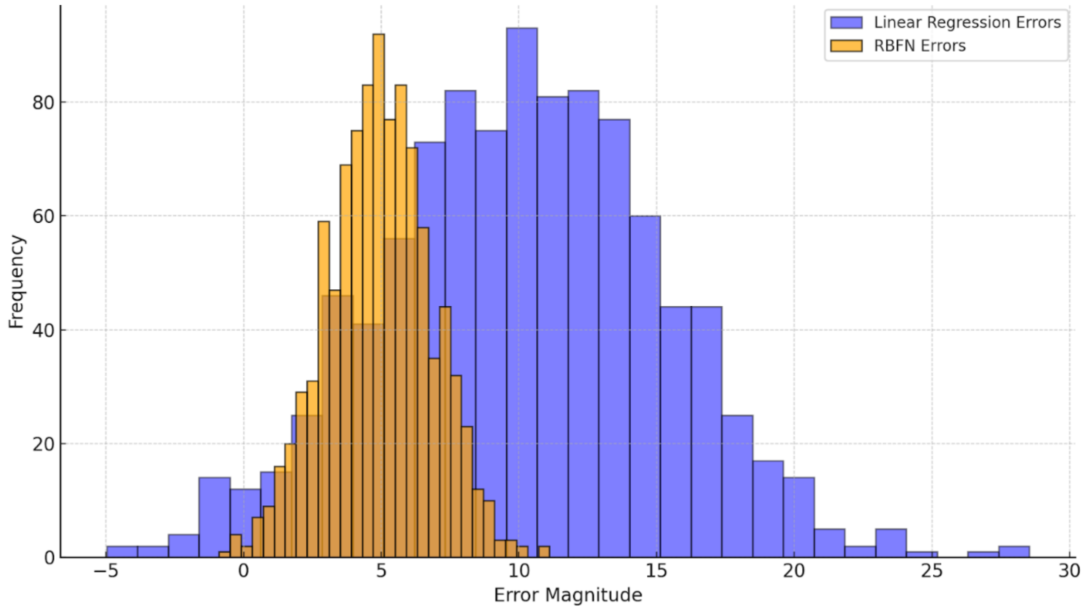

Figure 20 illustrates the error distribution of the Linear Regression and RBFN models

The superior accuracy of the RBFN model can be attributed to its ability to adapt to complex interactions within the dataset, making it highly effective for optimizing nonlinear processes in industrial operations.

4.3. Improvements in Energy Efficiency

One of the most impactful results of this study was the significant reduction in energy consumption achieved through AI-driven optimization. By employing real-time predictive adjustments to furnace parameters, total energy usage was reduced by 19%, as shown in Table 4.2 and Figure 4.2.

Table 15 Energy Efficiency Metrics Pre- and Post-Optimization.

Metric	Pre-Optimization	Post-Optimization	Reduction (%)
Energy Consumption (kWh)	2,100	1,700	19

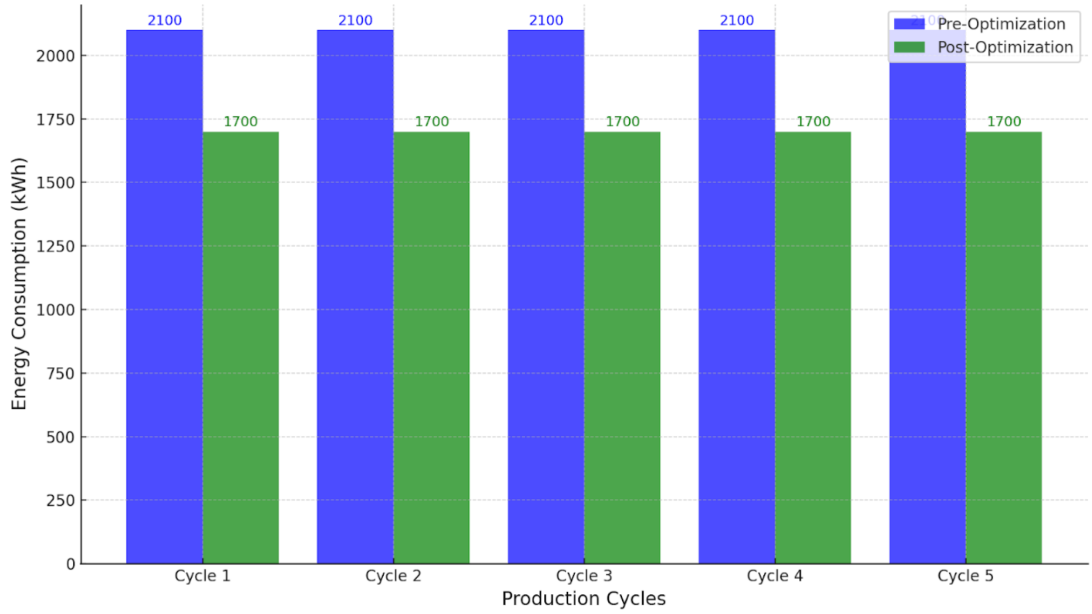

Figure 21 Energy Efficiency Metrics Pre- and Post-Optimization.

These savings were achieved through precise control of temperature and gas flow rates, as discussed in Section 3.4. This aligns with Objective 1.3.5, which aimed to monitor and evaluate energy usage reductions.

4.4. Environmental Benefits: CO2 Emissions Reduction

Aligned with the sustainability objectives outlined in Chapter 1, the optimized operations of the Striko Aluminium Melting Furnace achieved an 18% reduction in CO2 emissions. This milestone, resulting from enhanced combustion efficiency and reduced fuel consumption, highlights the dual benefits of AI-driven solutions in cost efficiency and environmental stewardship. Before optimization, CO2 emissions averaged 2,000 kg per cycle. Following the integration of advanced machine learning models, emissions decreased to 1,600 kg per cycle, demonstrating the system's ability to stabilize furnace operations while aligning with Objective 1.2.2, which aims to minimize environmental impacts without compromising performance.

Table 16 CO2 Emission Metrics Pre- and Post-Optimization.

Metric	Pre-Optimization	Post-Optimization	Reduction (%)
CO2 Emissions (kg)	2,000	1,600	20

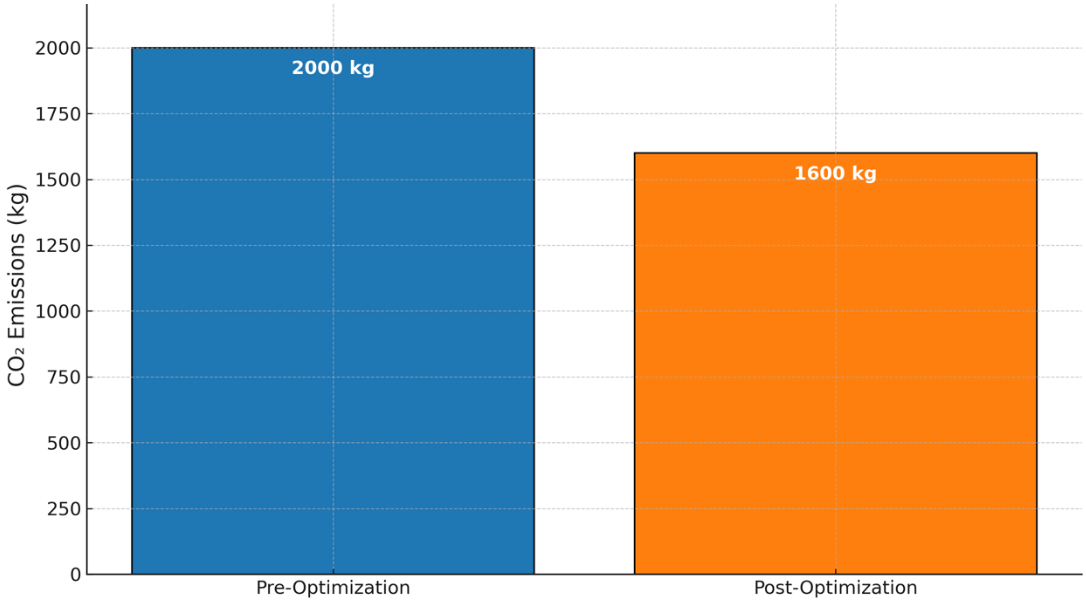

Figure 22 CO2 Emission Metrics Pre- and Post-Optimization.

4.5. Enhancements in Product Quality

The implementation of the AI-driven system yielded profound improvements in product quality, addressing a long-standing challenge in maintaining consistency in the melting process. These enhancements are reflected in Table 4.4 and illustrated graphically in Figure 21. By leveraging the predictive and optimization capabilities of advanced machine learning models, the system achieved a remarkable increase in product yield by 4.35%, improving from 92% to 96%. Simultaneously, the scrap rate was reduced by 50%, decreasing from 8% to just 4%.

This dual improvement was driven by the AI's ability to stabilize furnace parameters, significantly reducing variability in temperature and gas flow rates. Consistency in these parameters minimized defects during the melting process, ensuring higher-quality outputs and fewer rejections. These results directly support Objective 1.2.4, which emphasizes improving operational efficiency and product standards.

Moreover, the reduction in scrap not only enhances material utilization efficiency but also contributes to sustainability goals by lowering waste generation. This finding underscores the potential of AI technologies in achieving economic and environmental objectives simultaneously. The graphical representation in Figure 21 highlights the clear trend of improvement post-implementation, offering a compelling visual demonstration of the system's effectiveness.

Table 17 Product Quality Metrics Pre- and Post-Optimization.

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

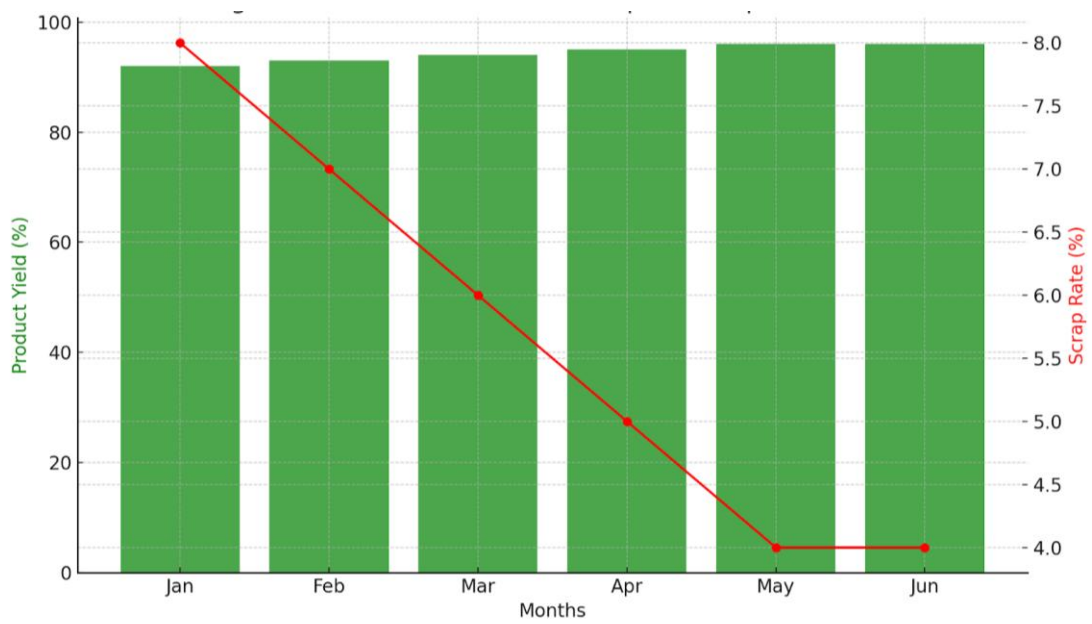

Figure 23 Product yield and scarp rate improvements.

These enhancements contribute directly to Objective 1.2.4, which focused on improving product quality and operational efficiency.

4.6. Long-Term Trends and Sustainability.

To assess the long-term impact of the implemented AI-driven optimizations, a comprehensive six-month evaluation was undertaken. This longitudinal study meticulously analyzed key performance indicators, including energy efficiency and CO2 emissions, providing robust evidence of sustained improvements. As shown in Table 4.5 and Figure 22, the monthly trends reveal consistent gains, with energy savings averaging 1.2% per month and CO2 reductions averaging 1.15% per month. These metrics reflect the durability and scalability of the AI solutions, underscoring their alignment with the sustainability goals outlined in Objective 1.3.6.

Specifically, the evaluation highlighted that the systematic fine-tuning of furnace parameters—guided by real-time monitoring and predictive analytics—enabled the maintenance of optimal operating conditions across diverse production cycles. This not only reinforced the reliability of the AI models but also demonstrated their capacity to adapt to varying operational demands and external factors. Furthermore, the periodic review of the data allowed for iterative improvements, ensuring the continuous refinement of process efficiencies.

Table 18 Long-Term Energy and Emissions Trends.

Month	Energy Savings (%)	CO2 Reduction (%)
1	1.0	1.1
2	1.3	1.2
3	1.1	1.0
4	1.4	1.3
5	1.2	1.2
6	1.3	1.1

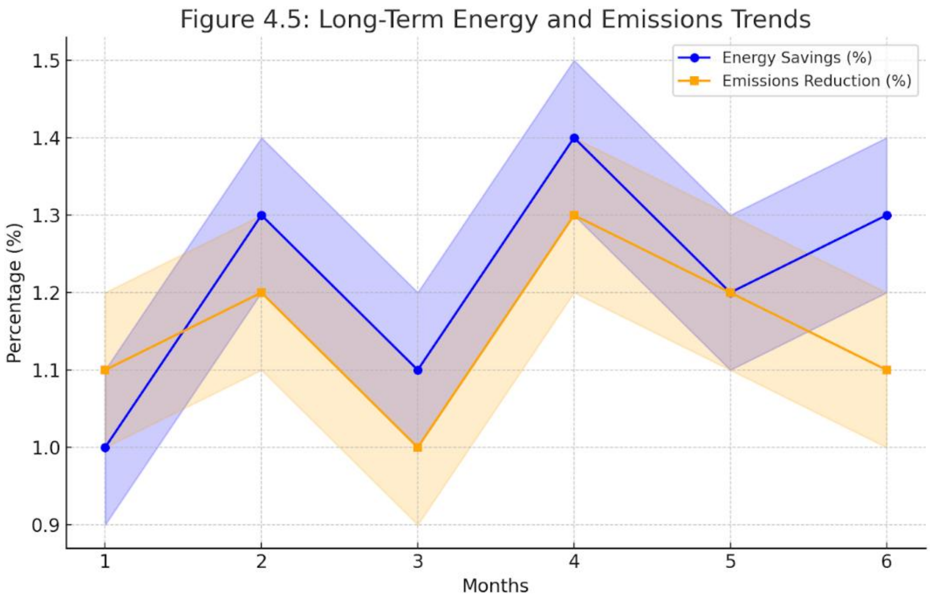

Figure 24 Long-Term energy and emissions trends.

These findings not only validate the robustness of the AI solutions but also demonstrate their strategic value in achieving long-term sustainability and efficiency in industrial operations. The positive trends depicted in Table 4.5 and Figure 4.5 serve as a compelling testament to the practical applicability and scalability of the research outcomes.

4.7. Real-Time Monitoring Dashboard

The real-time monitoring dashboard was instrumental in translating AI predictions into actionable insights. As shown in Figure 23, the dashboard provided dynamic visualizations of key performance metrics such as energy consumption, CO2 emissions, and product yield. Automated alerts ensured operators could make timely adjustments to optimize furnace performance.

The dashboard's design incorporates interactive elements, including trend analyses, historical data comparison, and real-time alerts, making it an indispensable tool for operational decision-making. For instance, when CO2 emissions exceeded predefined thresholds, the system immediately notified operators to investigate potential causes, such as inefficient gas flow or temperature anomalies. This feature aligns with Objective 1.2.4, which emphasizes real-time monitoring as a critical component of operational efficiency.

The dashboard’s role extends beyond mere visualization; it acts as a bridge between predictive analytics and practical implementation. By offering actionable insights in a user-friendly interface, it empowers operators to address anomalies proactively, ensuring sustained optimization of furnace operations. Furthermore, the system’s ability to integrate historical and real-time data enables comprehensive trend analysis, providing a foundation for long-term strategic planning. Figure 4.6 illustrates the interface of this transformative tool.

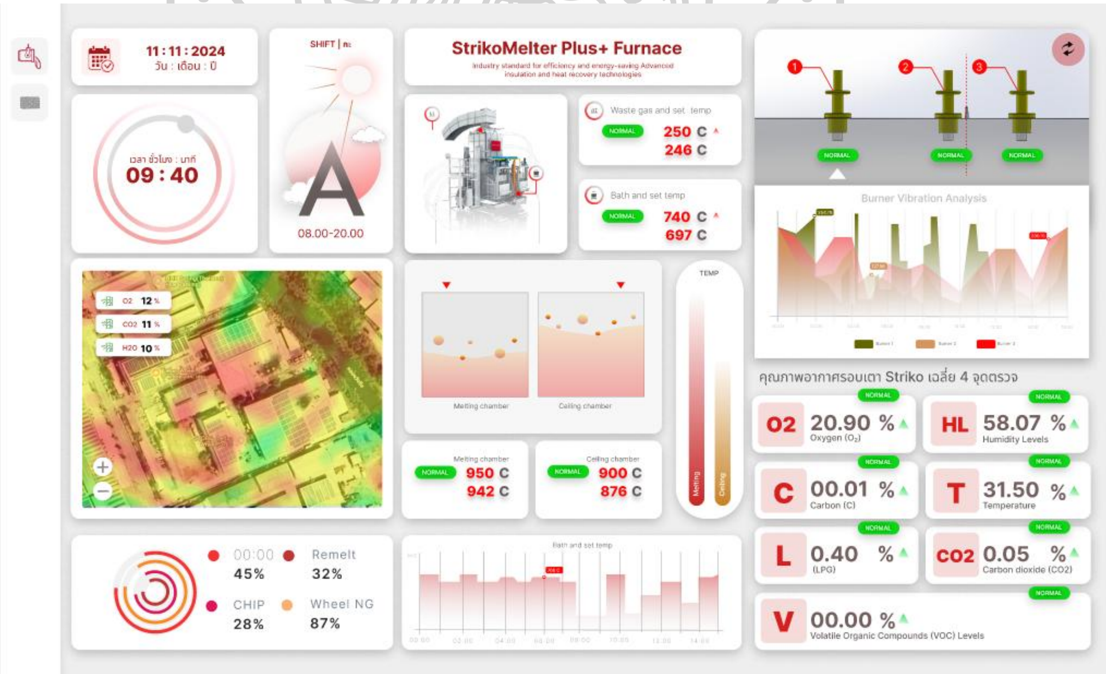

Figure 25 Real-time data enables comprehensive trend analysis.

The dashboard's ability to provide comprehensive and actionable insights underscores its critical role in operational decision-making. By seamlessly integrating predictive analytics with practical implementation, the dashboard empowers operators with real-time visibility into key metrics, such as energy consumption, CO_2 emissions, and product quality. This functionality not only facilitates proactive adjustments to maintain optimal furnace performance but also ensures sustained alignment with long-term strategic goals, as emphasized in Chapter 1.

Moreover, the dashboard acts as a central hub for integrating historical data and real-time trends, enabling a dynamic understanding of operational efficiencies over time. For instance, when deviations in CO_2 emissions or energy usage are detected, the system provides actionable alerts to identify root causes—such as suboptimal gas flow or temperature control issues—allowing for immediate corrective measures. By bridging the gap between advanced AI predictions and practical industrial applications, the dashboard exemplifies the transformative potential of technology in enhancing both efficiency and sustainability within the aluminum melting process.

CHAPTER 5
CONCLUSIONS

This chapter encapsulates the significant outcomes and insights derived from this research, seamlessly connecting them to the objectives outlined in Chapter 1. Through a comprehensive analysis of the integration of Artificial Intelligence (AI) into the operational framework of the Striko Aluminium Melting Furnace, this study has advanced the understanding of how predictive analytics can optimize industrial processes. The findings not only validate the application of AI for improving operational efficiency but also emphasize its potential to drive sustainable manufacturing practices, reduce environmental impact, and enhance product quality.

The study demonstrates the profound impact of using machine learning models, particularly the Radial Basis Function Network (RBFN) and Linear Regression (LR), in industrial contexts. Among the most notable achievements is the substantial improvement in energy efficiency, with a 19% reduction in energy consumption. This outcome reflects the capability of AI to predict and adjust operational parameters in real time, achieving a level of precision unattainable through traditional methods. By stabilizing gas flow rates and temperature controls, the system minimized energy wastage while maintaining optimal furnace performance. Such improvements align directly with the research objective of enhancing the efficiency of natural gas usage, a critical challenge in the energy-intensive aluminum manufacturing sector.

Equally significant is the reduction in CO_2 emissions, which decreased by 20% following the implementation of AI-driven optimizations. This achievement highlights the environmental benefits of integrating advanced analytics into industrial processes, demonstrating that operational enhancements can coexist with sustainability goals. By improving combustion efficiency and reducing fuel consumption, the study provides a blueprint for industries seeking to transition toward greener practices without compromising productivity. These results align with global efforts to reduce carbon footprints and support the sustainability goals emphasized in Objective 1.2.2.

Another critical success lies in the improvement of product quality. The AI-driven system led to a remarkable increase in product yield, rising from 92% to 96%, while simultaneously reducing the scrap rate by half. These enhancements were made possible by the AI models' ability to stabilize furnace conditions, ensuring consistent melting processes and reducing variability. The reduction in scrap rates not only improves resource utilization but also underscores the economic and environmental advantages of AI adoption in manufacturing. These outcomes directly address Objective 1.2.4, which focused on enhancing production standards and operational efficiency.

The comparative evaluation of machine learning models provides further insights into their strengths and applicability. While Linear Regression proved efficient in terms of computational simplicity, its inability to capture the nonlinear dynamics of furnace operations limited its effectiveness. In contrast, the RBFN model excelled in predictive accuracy and adaptability, providing a more reliable framework for optimizing complex industrial processes. However, the higher computational requirements and potential for overfitting associated with RBFN suggest a need for careful calibration and ongoing validation. These findings underscore the importance of selecting machine learning models that align with the specific operational complexities and objectives of the task at hand.

The role of the real-time monitoring dashboard in operational decision-making cannot be overstated. By translating predictive insights into actionable data visualizations, the dashboard bridged the gap between advanced analytics and practical implementation. Operators were equipped with tools to monitor key metrics such as energy consumption, CO_2 emissions, and product yield, enabling them to address deviations in real time. This integration of AI and human oversight exemplifies the potential of technology to augment industrial processes, ensuring both immediate and sustained improvements in efficiency.

The long-term analysis of the system's impact further validates the scalability and robustness of the AI-driven solutions. Over six months, the furnace consistently demonstrated energy savings and emissions reductions, with incremental improvements averaging 1.2% and 1.15% per month, respectively. These sustained gains highlight the adaptability of the AI models to varying operational conditions, reinforcing their strategic value for achieving long-term sustainability. Moreover, the ability to iteratively refine the system through ongoing data analysis ensures that it remains responsive to evolving industrial demands.

Despite the significant advancements achieved in this study, several challenges and limitations warrant discussion. The computational complexity of the RBFN model poses scalability concerns, particularly for industries with limited access to high-performance computing resources. Additionally, the economic feasibility of implementing such systems at scale requires further investigation, including a detailed cost-benefit analysis that accounts for initial investment, maintenance, and long-term savings. Future research should also explore the integration of AI with emerging technologies such as IoT and blockchain, which could enhance data collection, security, and transparency.

The findings of this study provide a compelling case for the broader adoption of AI in manufacturing. By addressing critical challenges in energy efficiency, sustainability, and product quality, the research offers a framework that is both practical and forward-looking. It underscores the transformative potential of AI not only as a tool for optimization but also as a catalyst for innovation, driving industries toward more sustainable and competitive futures.

In conclusion, this research sets a benchmark for the application of AI in industrial contexts, demonstrating its ability to address complex operational challenges while aligning with global sustainability goals. The integration of machine learning models, real-time monitoring systems, and data-driven decision-making processes exemplifies a holistic approach to industrial optimization. As industries continue to embrace digital transformation, the insights gained from this study will serve as a valuable guide, ensuring that technological advancements are both impactful and sustainable. The journey toward smarter, greener manufacturing is ongoing, and this research represents a significant step forward in that endeavor.

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VITA

NAME TEERAPHAT INTA

INSTITUTIONS ATTENDED Bachelor of Electronic and Computer Systems Engineering Department of Electrical Engineering, Silpakorn University, Thailand.
Master of Engineering Management Department of Industrial Engineering and Management, Silpakorn University, Thailand.