Artificial Intelligence-Based Prediction of Molten Steel Temperature of Induction Furnace in Computational Fluid Dynamics (CFD) Environment

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Artificial Intelligence-Based Prediction of Molten Steel Temperature of Induction Furnace in Computational Fluid Dynamics (CFD) Environment

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THESIS ACCEPTANCE CERTIFICATE

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MASTER'S THESIS WORK

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S/No:	Code:	Title:	Core/Elective:	CH:	Grade:
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2.	PSE-852	Process Modelling and Simulation	Compulsory	3.0	A
3.	TEE-820	Process Intensification	Elective	3.0	A
4.	RM-898	Research Methodology	Additional	2.0	Q
5.	PSE-802	Optimization and Decision Analysis	Compulsory	3.0	A
6.	PSE-823	Advanced Process Dynamics and Control	Compulsory	3.0	B+
7.	CSE-801	Computational Fluid Dynamics	Elective	3.0	B+
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MASTER'S THESIS WORK

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Presented on: **14 Sep 2023** at: **1500 hrs in SCME (Seminar Hall)**

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Dedication

This thesis is dedicated to family, teachers and friends for their endless support, encouragement, love and honor.

Acknowledgment

All praise and eminence are due to "ALLAH," the undisputed architect of this world, who gave us the capacity for comprehension and sparked our curiosity about the planet as a whole. Warmest welcomes to the supreme ruler of this world and the hereafter, "Prophet Mohammed (PBUH)," a source of knowledge and benefits for all of humanity as well as for Uma.

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Hafiza Anza Hayat

Abstract

The efficient and precise control of molten steel temperature in an induction furnace is paramount in modern steelmaking processes. This master's thesis presents a novel approach to address this critical challenge that combines the power of Artificial Intelligence (AI) with Computational Fluid Dynamics (CFD) to predict and regulate the molten steel temperature accurately.

The primary objective of this study is to develop an AI-based predictive model that can anticipate the molten steel temperature in real-time, enhancing process control, optimizing energy consumption, and ultimately improving product quality. The research methodology encompasses four main stages: data collection and preprocessing, AI model selection, CFD simulation, and model validation.

The first phase focuses on creating a comprehensive CFD environment to simulate the induction furnace's thermal behavior, incorporating thermal boundary conditions and leveraging data augmentation techniques to generate a substantial dataset. In the second phase, several AI models are evaluated, and the most suitable one is selected based on performance metrics. The final phase entails training and validating the chosen AI model using the simulated data.

The thesis introduces an AI model to address the complexities and dynamics of the induction furnace environment. This model harnesses the power of machine learning algorithms, enabling it to capture intricate patterns and non-linear relationships in the data, leading to more accurate temperature predictions.

The study's results showcase the effectiveness and reliability of the proposed AI-based predictive model, demonstrating a notable improvement in temperature prediction accuracy compared to traditional methods. The thesis also explores real-world case studies, validating the model's applicability and efficiency in practical steelmaking scenarios.

In conclusion, this research successfully establishes a novel approach for predicting molten steel temperature in an induction furnace using AI within a CFD environment. The outcomes offer valuable insights into the steel industry, fostering more intelligent decision-making, reduced energy wastage, and enhanced process control. Additionally, this work sets a foundation for further exploration of AI integration in steelmaking processes and opens avenues for future research in related domains.

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Nomenclature

CFD	Computational Fluid Dynamics
FEM	Finite Element Method
AI	Artificial Intelligence
ANN	Artificial Neural Network
ML	Machine Learning
SL	Supervised Learning
UL	Unsupervised Learning
DNS	Direct Numerical Simulation
CNN	Convolutional Neural Network
BP	Back Propagation
LSTM	Long Short-Term Memory Network
DNN	Deep Neural Network
RNN	Recurrent Neural Network
SVM	Support Vector Machines
RF	Random Forest
MARS	Multivariate Adaptive Regression Splines
KNN	k-Nearest Neighbors
ODE	Ordinary Differential Equation
PDE	Partial Differential Equation
MSE	Mean Square Error
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
MISO	Multiple Input Single Output
LMA	Levenberg Marquardt Algorithm
SSE	Sum Squared Error
CEE	Cross Entropy Error
∇	Divergence
H	Magnetic Flux Intensity
D	Electric Flux Intensity
E	Electric Field
J	Conduction Current Density
A	Magnetic Vector Potential
t	time
T	Temperature
ρ^{charge}	Electric Charge Density
c	Specific Heat
k	Thermal Conductivity
Q	Heat Generated
i	Data Points
Y_m	Average of The Values
$Y_{i,pred}$	Predicted ANN Network
$Y_{i,CFD}$	CFD Modelling Output
$Q^{'}$	Number of Data Points

j	Current Density
j_e	External Current Density
ω	Frequency
ϵ_0	Free Space Reactive Permittivity
ϵ_r	Relative Permittivity
μ_0	Free Space Magnetic Permeability
μ_r	Relative Permeability
ν	Velocity Vector
μ	Dynamic Viscosity
F	Volumetric Force
$\sum$	Sum of All
net	Network

Chapter 1

Introduction

1.1. Motivation

Energy has always been a necessity for living but in the present age, it is inevitable to survive without it. It is the lifeline of industries being used as means of transport, agriculture, production plants and electrical energy [1-3]. In response to modernization in all sectors of life, renewable energy sources are depleting at a rapid rate due to its high consumption. In 2008, it was reported that the global consumption of petroleum-based fuel was 85.6 million barrels per day which is expected to reach 112.2 million barrels per day by 2035 through statistical analysis [4]. To bridge the gap, energy production should be increased relative to its consumption. Also, that focus should be made on energy efficient processes.

Iron-making stainless steel industries are one of the most energy-intensive industries where energy contributes to major proportion of operating and utilities cost [5, 6]. A country's economic standing thus depends on iron and steel making industries. These industries are also referred as sustainable industries as it is completely recyclable. Steel industries also pictures a country's competency in infrastructure development. About 5% of energy consumed globally is solemnly by iron and steel manufacturing sector [7-10].

Steel can be considered as a significant engineering material in terms of global economy as despite the COVID-19 pandemic situation recently observed, more than 1.9 billion tons of crude steel were produced in 2020 [11]. With the rapid advancement and heavily increasing market demands, iron and steel manufacturing sector can undoubtedly be termed as backbone of the modern society due to its innovative capabilities to keep up with the pace [12].

Over the past few decades, a significant growth is observed in steel production globally accounting 1700 million tons in 2017 alone. China being the biggest manufacturer of steel holds the responsibility of producing about half of the world's total steel production [13, 14]. Conventionally, oxygen steelmaking route was used for steel production but with development in technology world, focus has shifted towards electric route. The ratio of steel production in China from oxygen route to electric route is 53:47, highest being oxygen steelmaking route. India comes second and produces around 30% of its annual production by induction furnace due its recent popularity and advantages [15].

World steel association records average world per capita consumption of crude steel to be about 233 kgs. The highest being South Korea (1076 kgs) whereas, Pakistan's per capital of steel consumption (59 kgs) is even lower than the world average as well as from its regional country, India (76kgs). For a developing country like Pakistan, it is necessary to intensify its iron and steel manufacturing sector instead of playing a major share in importing steel [16]. Pakistan not only imports raw material but also the finished product which is not at all economical and fluctuations in exchange rate plays a big role in decreasing Pak Rupee worth. Therefore, Pakistan has brought its focus in this sector recently and in the year 2016-17, 18% of GDP was contributed by industrial sector which crosses agricultural sector by 2%.

It was observed that from 1996 to 2007, energy consumption increased by 1.44 quadrillion BTU having annual increasing rate of 3.38%. It is to be noted that the energy demand of industrial sectors is greater than agricultural sector hence moving towards industrialization would significantly increase country's overall energy consumption. The records of 2015 showed that the total amount of energy supplied was 93.91 million tons of oil equivalent that breaks down into energy consumed around 23.77% by industrial sector and only 0.98% by agricultural sector. Iron and steel-making plants are the focal point because of their major share about 13.45% in overall GDP of Pakistan and 64.4% GDP in industrial sector therefore, energy efficient process in the plant can remarkably lessen the energy consumption of the country [16].

The steel industry hence, concluded is a fundamental pillar of modern infrastructure, playing a pivotal role in various sectors, from construction to automotive and aerospace. Achieving consistent high-quality steel production is of paramount importance for the industry's competitiveness and sustainable growth. The molten steel temperature inside an induction furnace is a critical parameter that directly influences product quality, energy efficiency, and overall operational costs. Therefore, accurate and real-time prediction of this temperature is vital for optimizing the steelmaking process and ensuring the desired properties of the final product.

1.2. Research Problem

Furnace is basically a type of direct fired heat exchanger in which a heat source increases the temperature of the feed to a high degree. Induction furnace is a type of furnace in which heat source is electricity thus also known as electric furnace. The advantage of such a furnace is that it is a clean, energy efficient and easily controllable melting process in comparison to other metal melting methods. Induction furnaces are thus ideally used for melting and alloying of metals giving lowest melt losses possible [17].

The working principle of induction furnace is induction heating. Induction heating is gaining an upper hand over other conventional heating techniques such as flame, resistance heating or ovens. It is a non-contact, quick and efficient heating method. Lately, induction heating is being preferably used for industrial, medical and domestic purposes [18-20]. The working phenomena involves an ac source that delivers alternating voltage to an induction heating coil. The coil produces alternating magnetic field. The charge (feed metal to be melted) is placed inside the coil. As a result of magnetic field, the charge heats up because of either electromagnetic induction or joule’s effect [21].

The joule’s effect is the main heating mechanism in induction heating caused by opposition of eddy currents to magnetic field generated in the induction charge. Whereas, in electromagnetic induction, an alternating current is induced on placing the loop in an alternating magnetic field. The moment loop is short-circuited, the voltage causes the current to flow in a direction such that it opposes the change that caused it – Faraday's Lenz Law [22, 23].

Such complex pattern of induction heating couples the behavior of electromagnetic, thermal, and hydrodynamic forces. For such intricate systems, traditional analytical methods are unreliable to completely understand the working and thus, bring improvements in its efficiency. The research problems concerns prediction of temperature accurately inside the induction furnace for optimizing steel production process, ensuring product quality and minimizing energy consumption. Computational Fluid Dynamics (CFD) simulations have proven to be effective in analyzing such complexities. Furthermore, accurate forecasts without explicit equations are made possible by AI algorithms, which can make use of large datasets and extract complex patterns. AI has the ability to dramatically increase the precision and effectiveness of temperature prediction in induction furnaces when used in conjunction with CFD models, which offer thorough insights into fluid movement, heat transport, and other physical phenomena inside the furnace [24-26].

However, the successful integration of ANN with CFD in the context of temperature prediction for molten steel in an induction furnace poses several research challenges:

Data Fusion and Preprocessing: Combining data from CFD simulations with real-world industrial data to train the ANN accurately is challenging due to the inherent noise and uncertainties present in both types of data. Developing efficient data preprocessing techniques to handle these challenges is crucial for achieving reliable temperature predictions.

Model Architecture Selection: Designing an optimal ANN architecture that can effectively capture the complex and nonlinear relationships between process variables in the induction furnace and accurately predict temperature distribution is a critical research problem. Identifying the appropriate number of layers, nodes, and activation functions in the ANN to achieve the best performance poses a challenge.

Training and Optimization: Training an ANN using CFD and industrial data requires careful consideration of training algorithms and optimization techniques to achieve convergence and prevent overfitting. Exploring novel optimization strategies to enhance the efficiency and accuracy of the ANN model in predicting temperature is essential.

Generalization to Varying Operating Conditions: The induction furnace operates under various conditions, such as changes in steel composition, charging rates, and furnace geometry. Ensuring the ANN can generalize well to diverse operating conditions is a critical research problem to create a robust and versatile temperature prediction model.

Addressing these research challenges will lead to the development of an effective and reliable artificial intelligence-based temperature prediction model for molten steel in induction furnaces. This model can potentially revolutionize the steel manufacturing industry by optimizing energy consumption, enhancing product quality, and facilitating process automation.

1.3. Scope of The Study

The thesis investigates the application of Artificial Intelligence (AI), specifically Artificial Neural Networks (ANN), for temperature prediction of molten steel in an induction furnace using Computational Fluid Dynamics (CFD) simulations in the COMSOL Multiphysics environment. Key aspects include setting up a comprehensive CFD model, collecting and preprocessing relevant data from CFD simulations and real-world industrial processes, implementing an ANN-based model, training and validating the ANN, comparing the ANN predictions with conventional methods, and exploring optimization strategies to enhance the ANN's training process and improve prediction accuracy. The study will also compare the ANN predictions with empirical models, basic regression techniques, or other established methodologies to establish the effectiveness of the proposed AI-based approach. The scope also includes exploring and implementing optimization strategies, such as hyperparameter tuning and regularization, to achieve the best possible results.

It is important to note that the scope of this study may be limited to a specific type or size of the induction furnace, a particular steel composition, or a set of operating conditions. Researchers should acknowledge these limitations while drawing conclusions and discussing the potential applications of the developed AI-based temperature prediction model.

1.4. Contribution of The Thesis

This thesis develops an AI-based prediction model for estimating molten temperature in an induction furnace in a CFD environment, aiming to improve process control and optimization in industrial settings. Accurate temperature estimation leads to increased productivity, reduce energy consumption, and reduced production costs. This is done by integrating computational fluid dynamics (CFD) with an artificial neural network (ANN) which is an artificial intelligence (AI) based model for an induction furnace. The study encompasses the following key aspects:

- Exploring and analyzing historical temperature data and CFD simulation outputs to develop a data-driven AI model capable of predicting temperature distributions inside the furnace.
- Investigating methods to seamlessly integrate the AI-based predictive model with CFD simulations, thereby enhancing computational efficiency and enabling real-time predictions.
- Assessing the model's ability to adapt to variations in operating conditions, furnace geometries, and steel compositions to ensure generalizability across different industrial scenarios.

1.5. Thesis Outline

The introduction is given in chapter 1. The literature review on artificial intelligence and machine learning along with its applications in CFD is given in chapter 2. A review on previously held researches of temperature prediction in induction furnace is also addressed in chapter 2. Proposed researched methodology is depicted in chapter 3. The model development and its necessary conditions in CFD are described in chapter 4. Chapter 5 illustrates the selection and generation of ANN Model. Results and discussions are made on the overall thesis in chapter 6 followed by conclusions and future recommendation in chapter 7. Lastly, references are shown in chapter 8. The methodology of overall thesis is shown in Figure 1.

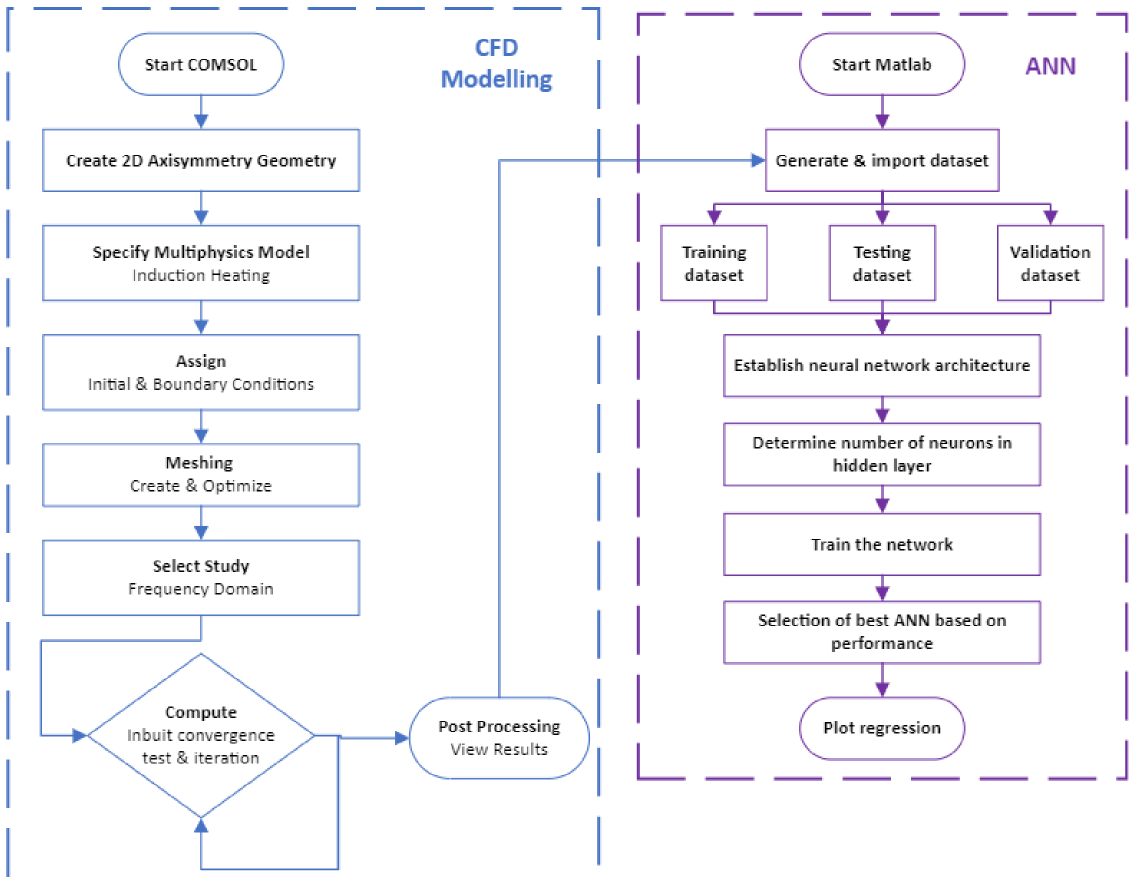

Figure 1: Schematic Methodology of Thesis

Chapter 2

Literature Review

2.1. Introduction to Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) are transformative technologies that have revolutionized various industries and are driving innovation in the modern world. AI refers to the development of computer systems that can perform tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, and making decisions. On the other hand, ML is a subset of AI that focuses on designing algorithms and models that enable computers to learn and improve from experience without being explicitly programmed.

AI has its roots in the 1950s, with pioneers like Alan Turing laying the groundwork for the field [27]. Since then, AI has evolved dramatically, driven by advancements in computing power, data availability, and algorithmic breakthroughs. Today, AI systems are integrated into everyday life, from voice assistants on smartphones to recommendation engines on streaming platforms.

Machine Learning, as a key component of AI, is based on the idea that machines can learn from data to improve their performance on a specific task. ML algorithms analyze vast amounts of data, recognize patterns, and make predictions or decisions based on the learned patterns. This data-driven approach has proven incredibly effective in diverse applications including chemical industries. The machine learning is primarily divided into [28]:

2.1.1. Supervised Learning (SL)

In this approach, the ML model is trained on labeled data, meaning the input data is paired with corresponding target outputs. The model learns to map inputs to outputs based on this labeled dataset, enabling it to make predictions on new, unseen data. SL is further categorized into classification and regression problems. The popular algorithms involved in SL are neural networks, linear/logistic regressions, decision tree, random forest etc. It is frequently used in predictive modelling. The steps of supervised learning are shown in Figure 2.

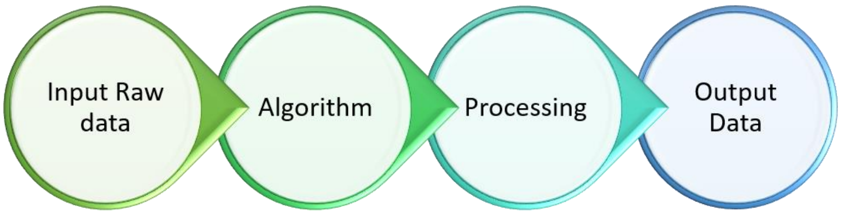

Figure 2: Supervised Learning

2.1.2. Unsupervised Learning (UL)

In unsupervised learning, the ML model works with unlabeled data, seeking to identify patterns and structures within the data without explicit guidance. Clustering and dimensionality reduction are common applications of unsupervised learning. The popular algorithms involved in UL are k-means clustering and association rule. It is commonly used in descriptive modelling. The steps of unsupervised learning are shown in Figure 3.

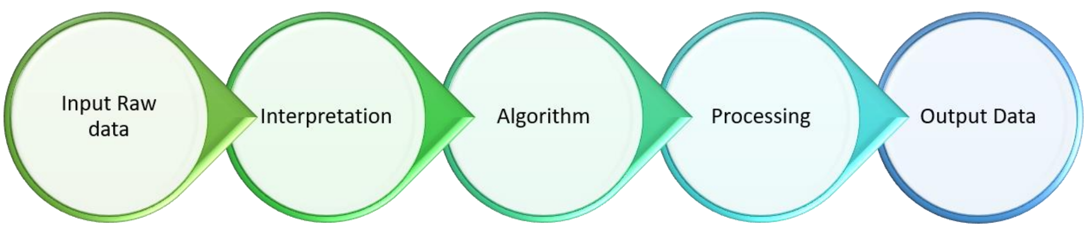

Figure 3: Unsupervised Learning

The rapid growth of AI and ML is fueled by the availability of big data, powerful computing resources, and open-source tools. Researchers and developers continuously push the boundaries of what AI can achieve, leading to groundbreaking applications that shape industries and human interaction with technology.

2.2. Applications of AI in Computational Fluid Dynamics (CFD)

CFD is a useful tool that makes precise predictions possible by numerically computing the Naiver-Stokes (N-S) equations. CFD has been extensively and consistently used over the years to simulate turbulent airflow, heat transfer and contaminant transport, as well as to simulate wind flow around buildings and track pollutants [29-31]. CFD still faces numerous obstacles, primarily in terms of accuracy and computational cost. The N-S equations must be numerically solved with space and time discretization in cases of realistic turbulent flow fields because analytical solutions are not possible. The direct numerical simulation (DNS) strategy is used to fully depict the flow phenomena [32].

While efforts are being made to enhance CFD techniques themselves with new turbulence models and algorithms, there has recently been interest in using new tools to support CFD simulation for increased accuracy [32, 33]. Artificial intelligence and data-driven models are gaining a lot of attention in a variety of applications thanks to digitization and the availability of large amounts of data. More specifically, deep learning and artificial neural networks (ANNs) have a lot to offer in terms of handling high-dimensional fields, universal non-linear approximation, and computational affordability.

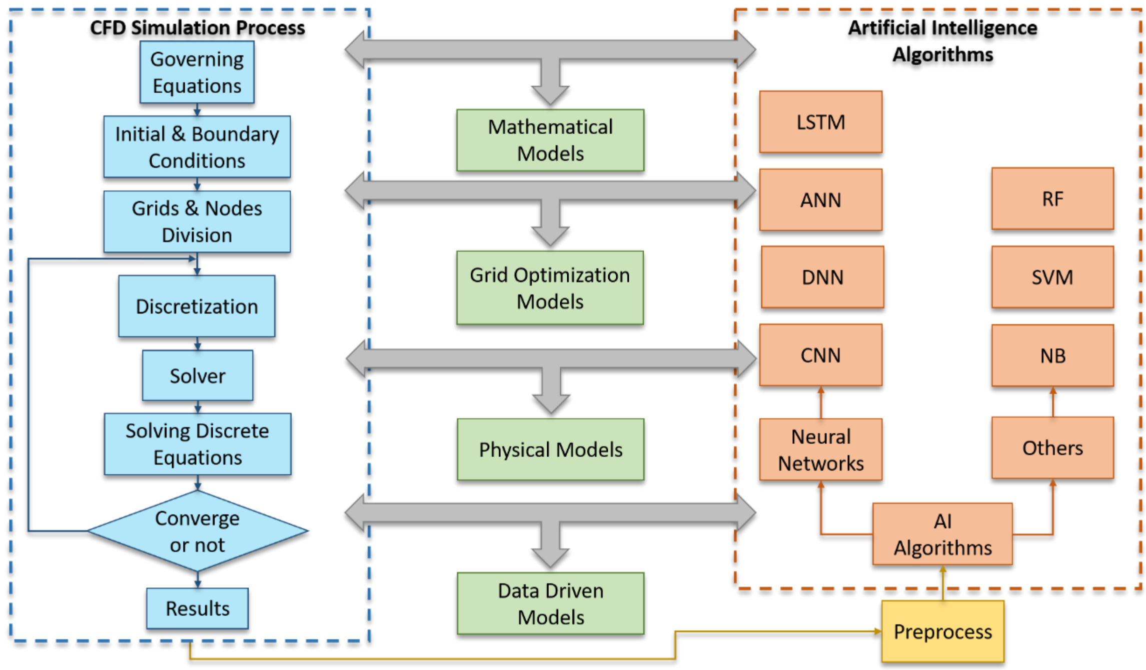

Figure 4: Integration of CFD and AI Based on Model Selection [34]

Figure 4 depicts the steps in the CFD simulation process, each of which has the potential to produce a significant amount of discretized equations and data. Four different types of models could be created by fusing these equations or data with AI algorithms namely [34]:

2.2.1. Mathematical Model

AI algorithms are typically used in mathematical models to solve the governing equations and optimize their numerical solutions, such as optimizing ordinary differential equation (ODE) by deep neural networks (DNN's). This kind of model is intended to look for more precise numerical answers to the equations and could significantly increase the accuracy of the results.

2.2.2. Grid Optimization Model

This model significantly decreases computation time. AI is incorporated in order to generate the domain grid or optimize the local grid more sensibly and effectively.

2.2.3. Physical Model

The physical model is used to assess the flow data and CFD modelling through the conjunction of machine learning (ML) and a CFD solver. By enhancing and modifying the parameters of the base model, physical model provides realistic calculations. As a result, a hybrid model that incorporates both data and physical mechanisms is produced.

2.2.4. Data Driven Model

Lastly, data driven models are frequently employed to predict results or verify the accuracy of a new model because it can build databases and evaluate the input-output relationships or data patterns.

In order to gain insight on actual working of AI and CFD together, let's take heat transfer as an example. In nature, daily life, and industry, heat transfer occurs frequently. In fields like energy, metallurgy, machinery, chemical engineering, and others, it has always been significant. Recent years have seen the emergence of numerous interdisciplinary fields, including multiphase heat transfer which is involved in the modelling of induction furnace in this thesis. The two most popular ways to study heat transfer are experiments and CFD calculations [35-37]. When there are too many experimental variables, the cost is high and the number of usable samples is constrained especially for non-linear partial differential equations (PDEs). In addition, it is challenging to calculate problems in the absence of obvious physical mechanisms. As a result, using AI to solve these issues has become very famous.

AI is used to produce various models based on the data obtained from experiments and calculations [38, 39]. Supervised learning (SL) is opted as a suitable method due to the physical relationship between the sample labels in the data set. Among the various SL algorithms, ANN is the most widely used and has been successfully applied in numerous works [40, 41]. As shown in Figure 5, three common techniques were used to train an ANN model: gradient descent, Newton's method, and Levenberg-Marquardt. The gradient descent is the least memory-intensive and slowest of them all. Levenberg-Marquardt is the quickest but uses the most memory, whereas Newton's method could effectively balance the two demands. The Leven-berg-Marquardt method could meet the demand for high precision because the parameter numbers in training data are restricted to < 100 in the case of heat transfer. Newton's method is appropriate for situations with greater than 100 parameters and a sizable amount of data. In general, gradient descent is not very common. Physical models, hybrid models, and data-driven models are typically classified according to the size of the data set [34].

The hybrid model falls between the physical model and the data-driven model in terms of database size requirements. Temperature, Reynolds number, and a few environmental factors could all be input parameters for these three models, whereas the output parameters comprises heat transfer coefficient, thermal efficiency, temperature differential, and heat load.

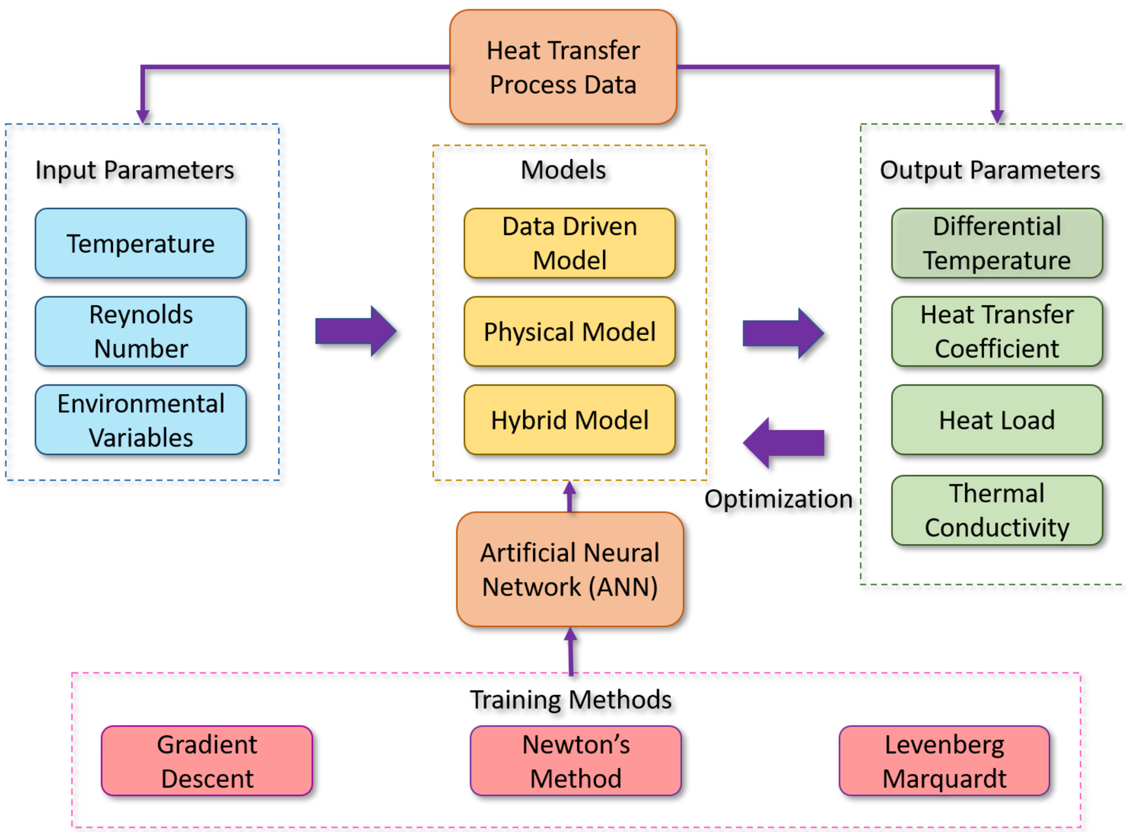

Figure 5: Application of AI in CFD Based on Heat Transfer [34]

In conclusion, the integration of AI with CFD has opened up new avenues for innovation and efficiency improvement in various engineering applications. In the context of predicting molten steel temperature in an induction furnace, AI-based CFD simulations offer accurate and efficient solutions, leading to enhanced process control, energy savings, and improved product quality. AI-driven CFD optimization can help identify the optimal furnace geometry, coil arrangement, and operating parameters to ensure precise temperature control and energy efficiency. CFD simulations are inherently influenced by uncertainties in boundary conditions, model parameters, and other inputs. AI methods, such as Bayesian inference and Monte Carlo simulations, can be applied to quantify these uncertainties and assess the reliability of CFD predictions. As AI technologies continue to advance, their synergistic relationship with CFD is likely to lead to further breakthroughs in the field of fluid dynamics and beyond.

2.3. Previous Studies on Molten Steel Temperature Prediction

The prediction of molten steel temperature in an induction furnace is a critical aspect of the steelmaking process, as it directly impacts the quality of the final product and the overall energy efficiency of the system. Over the years, researchers and engineers have extensively investigated various approaches to accurately forecast molten steel temperatures during the steelmaking process. This section provides an overview of some notable previous studies on molten steel temperature prediction, highlighting the methodologies and findings. Early attempts at predicting molten steel temperature often relied on empirical models based on experimental data. These models attempted to establish correlations between process parameters, such as power input, coil frequency, and charge material, and the resulting molten steel temperature. While these empirical models were simple to implement and provided some insights, their accuracy was limited due to the highly complex and non-linear nature of the induction heating process.

With the advancement of numerical methods, the Finite Element Method (FEM) gained popularity for simulating the induction heating process in induction furnaces. FEM enabled researchers to model the complex geometries of furnaces and account for the interactions between the magnetic field, heat transfer, and fluid flow. Using FEM, eddy current problem has been previously addressed. Considering if the current density, expressed in cylindrical coordinates, contains only an azimuthal component, the three-dimensional problem can be limited to a two-dimensional one on a meridional section by taking advantage of the cylindrical symmetry. They provided a mixed formulation in the proper weighted Sobolev spaces. By examining an equivalent weak formulation, the solution's existence and originality were demonstrated [42].

In order to estimate the temperature of the liquid steel inside the induction furnace, work has been done to measure temperature indirectly by determining the amount of energy put into the furnace, flow rate of cooling water, and the temperature at the outer wall lining of the induction furnace. The method for estimating temperature relies on taking into account the furnace's heat balance equation and using a number of parameters for the furnace throughout the process to estimate the furnace's heat losses. From this method, an estimate of temperature of molten steel can be done [43].

CFD emerged as a powerful tool for simulating fluid flow, heat transfer, and electromagnetic fields in induction furnaces. CFD simulations allowed for a detailed analysis of the complex physical phenomena involved in the steel melting process. Such that a study on thermal behavior of induction furnace has been carried out resulting favorable condition for copper melting by studying temperature distribution in the crucible. Their study revealed that copper-liner is used for prevention of heating of vessels by electromagnetic effect between coil and the vessel [44]. Further finite element method has been used for transient heat transfer analysis of induction furnace for suggesting an optimized heat transfer. The study also led to the analysis of ramming mass in the melting process and how its thickness and conductivity effects the melting rate. Lastly, composite walls are studied for furnace efficiency enhancement [24, 45].

The main aim of study targets melting of metal thus, temperature distribution in the melted charge due to which proper understanding on design and construction of induction furnace is required. A researcher used equivalent circuit and superposition method for this analysis [46]. Another used FEM approach to study performance during heating so that the capability of coil current and frequency to attain precise temperature may be studied [47]. The pinch effect also effects the molten steel produced by the electromagnetic force, which is directed toward the channel's center. It is observed that due to the skin and proximity effect, the electromagnetic force and joule heating are higher in the regions close to the induction coil. Thus, when molten steel flows through the channels, spiral recirculation would happen. Following its movement through the channels, the molten steel rises due to buoyancy. By using joule heating, it is possible to effectively make up for the heat loss of molten steel, and induction heating improves the uniformity of temperature [48].

Many researchers have done mathematical modelling to study induction heating phenomena by simplifying geometry of induction furnace to two-dimensional geometry. One study may target effect of electromagnetic power induced in crucible on heat transfer [49]. The other aims for investigation of operating conditions to enhance evaporation process claiming that molten steel temperature plays a vital role in influencing evaporation rate [50]. Another shifts its focus towards studying effect of frequency on molten steel thus, finding the most fitted inductor profile [51]. A few others targeted eddy current problem to solve non-linear heat transfer involving phase change [52].

Different papers used multiple styles of validation. Some built a laboratory scale induction furnace to experimentally study the results and compare them with numerical results [53]. Others compared temperature distribution obtained numerically with the macro etched section of solidified ingots. The comparison depicted that the dendritic grain structures obeyed the same direction as thermal flow which concluded that a uniform thermal field can be achieved by proper set of coils consequently, uniformity in ingots composition [54]. Another verified by comparison of three types of analysis including numerical, analytical and experimental. In this study, heat transfer in time dependent domain and radial temperature distribution of induction furnace for aluminum cylindrical disc was evaluated. The results illustrated that experimental and numerical methods gave a slope for temperature distribution lower than the analytical method with an error rate of 7% [55]. Another researcher hence, briefly explained the coupling of analytical and numerical method for model validation. He further used his developed technique for optimizing the induction heating and energy efficiency [56].

Induction furnaces are famous for melting of metals with no fuel requirement. Although, melting under thermal fatigue is an issue hence, a study has been done on estimating temperature and thermal stress distribution at refractory wall by ANSYS. The results of which were interpreted in S-log N curve [57]. Similarly, controlling temperature is another hindrance along with temperature distribution that significantly effects efficiency of the furnace. A PID control algorithm is devised to cater the controlling problem and its employment results illustrated that temperature control system is responsible for overshoot, response time and stability of the system [58].

The mock-ups of induction furnaces are made in COMSOL to study electromagnetic, hydrodynamic and thermal behavior and effects of various parameters on charge melting, temperature distribution and efficiency of the furnace are evaluated [44]. Moreover, case studies on quality of non-linear solutions has been made revealing that current iteration errors during time integration may not be accurate. Therefore, such studies suggested that fundamental balances (energy and material) and required smoothing at boundary should be used as additional parameters for quality assessment [59].

Recognizing the strengths and limitations of different approaches, researchers began developing hybrid models that combined empirical data, FEM, and CFD simulations. These hybrid models aimed to leverage the advantages of each technique to enhance the accuracy of temperature predictions. For instance, researchers integrated AI-based algorithms, such as neural networks, with CFD simulations to improve the accuracy of molten steel temperature forecasts. These hybrid models showed promising results and offered a good compromise between accuracy and computational efficiency. Such that reliable predictions have been made for end point temperature predictions using RBF neural network [60].

In conclusion, previous studies on molten steel temperature prediction have evolved significantly over the years, from simple empirical models to sophisticated AI-driven approaches. While early models provided valuable insights, the integration of advanced numerical methods, like CFD and FEM, significantly improved the understanding of the underlying physics. The latest machine learning and AI-based models have shown tremendous promise in accurately forecasting molten steel temperatures, making them crucial tools for enhancing steelmaking processes in induction furnaces. However, there is still room for further research and development, especially in optimizing the computational efficiency of AI-driven models without compromising their accuracy.

2.4. Comparison of Different AI Techniques for Temperature Prediction

The accurate prediction of molten steel temperature in an induction furnace is crucial for ensuring product quality and optimizing the steelmaking process. As Artificial Intelligence (AI) continues to advance, various AI techniques have been explored to improve temperature predictions in this domain. A comprehensive comparison of different AI techniques used for molten steel temperature prediction in an induction furnace, highlighting their strengths, limitations, and potential applications is given below.

2.4.1. Neural Networks

Neural networks, particularly Deep Learning architectures, have gained significant popularity for temperature prediction tasks due to their ability to learn complex relationships from large datasets. Convolutional neural networks (CNN) are well-suited for capturing spatial correlations in the temperature field within the induction furnace, while recurrent neural networks (RNN) can effectively model temporal dependencies in time-series data, making them useful for capturing dynamic changes in temperature over time. The back propagation (BP) neural networks are feedforward networks with multiple layers. They have high tolerance for distorted information and can effectively forecast molten steel temperature. The BP algorithm uses three layers architecture involving input layer, hidden layer and output layer. The input layers consist of the factors influencing steel temperature and the output layer comprises the end-point molten steel temperature under set operating conditions [61-63].

2.4.2. Support Vector Machines (SVM)

SVM is a popular supervised learning algorithm used for regression and classification tasks. SVM attempts to find the optimal hyperplane that best separates data points into different classes. In SVM regression, the basic concept is to draw patterns for a high-dimensional space by non-linear mapping and the perform linear regression in the concerned region. In the context of temperature prediction, SVM can be used to establish relationships between process parameters and molten steel temperature [64].

2.4.3. Random Forest

Random Forest (RF) is an ensemble learning technique that constructs multiple decision trees and combines their predictions to achieve a more accurate and stable result. The first algorithm for RF and its extension was proposed by [65, 66]. Random Forest can handle a mix of categorical and numerical features, making it versatile for temperature prediction tasks that involve diverse types of input data. RF feature importance analysis, aiding in understanding the influential process parameters on temperature.

2.4.4. Multivariate Adaptive Regression Splines

MARS (Multivariate Adaptive Regression Splines) is a regression technique that has been applied successfully in various prediction tasks, including temperature prediction. MARS is particularly useful when dealing with complex and non-linear relationships between input variables and the target variable, making it a potential candidate for molten steel temperature prediction in an induction furnace. This method was given by [67]. MARS builds a regression model using basis functions and splines. The model represents the relationship between the input variables (process parameters, furnace conditions, etc.) and the output variable (molten steel temperature) using a series of piecewise linear segments, known as splines. These splines connect specific regions of the input space, and the coefficients of these splines are learned during the model training process [68].

2.4.5. *k*-Nearest Neighbors

KNN is a non-parametric algorithm that makes predictions based on the similarity of data points in the feature space. It was first proposed by [69]. To apply KNN, historical data of the induction furnace operation is collected, including various process parameters (e.g., power input, stirring speed, coil frequency) and the corresponding molten steel temperatures. This dataset will serve as the training data for the KNN algorithm [70]. The parameter 'k' in KNN represents the number of nearest neighbors to consider when making a prediction. The value of 'k' affects the model's performance, and it is essential to choose an appropriate value through hyperparameter tuning.

Each AI technique has its unique strengths and limitations, making them suitable for different scenarios and applications in molten steel temperature prediction for an induction furnace. Neural networks excel in handling complex and high-dimensional data, Support Vector Machines are effective with smaller datasets and known process parameters, while Random Forest is versatile in handling diverse input data types. Depending on the specific requirements of the steelmaking process, the choice of AI technique should be carefully considered to achieve the most accurate and efficient temperature predictions [71]. A comparison of strengths and limitations of above-mentioned machine learning algorithms is shown in Table. Additionally, hybrid models that combine the strengths of multiple AI techniques may further enhance the overall predictive performance for this critical application.

Table 1: Comparison of Different AI Techniques and Application in Temperature Prediction

Method	Strengths	Limitations	Potential Applications
Neural Networks (NNs)	Excellent at handling complex, high-dimensional data. Can learn non-linear relationships and patterns in the data.	Requires a large training dataset. Prone to overfitting, especially with limited training data. High computational and memory requirements. Depends on training function	Neural networks are ideal for real-time temperature prediction tasks, where accuracy and responsiveness are critical, such as in process control and automation systems for induction furnaces.
Support Vector Machines (SVM)	Effective in handling small to medium-sized datasets. Robust against overfitting due to its structural risk minimization principle. Reduced generalization error.	May struggle with non-linear relationships. Depends on kernel selection. Limited ability to capture temporal or sequential patterns.	SVM can be valuable for predicting temperature based on known process parameters and historical data, making it useful for process optimization and parameter tuning in induction furnace operations.
Random Forest (RF)	Provides feature importance analysis, aiding in understanding the influential process parameters.	Slow performance. A complete change in model is observed over small change in training dataset	RF used in temperature prediction where feature importance analysis is essential for process optimization.

	Efficient for regression and classification problems.		
Multivariate Adaptive Regression Splines (MARS)	Automatic detection of variables relationship. Suitable for multiple target variable.	Not robust to overfitting. Complex algorithm. Not fit for noise and non-linear datasets.	MARS make it easier to interpret the relationship between input variables and the predicted molten steel temperature. The model can identify the most influential process parameters and indicate the regions of the input space where their effects are significant.
k-Nearest Neighbors (KNN)	A good choice for quick prototyping and baseline modeling. Easy interpretation. Space issues are improved by spatial trees.	KNN requires calculating distances between the new data point and all data points in the training set, making it computationally intensive for large datasets. Sensitive to noisy data. Determining of optimal k is crucial factor in accuracy of results.	KNN can help predict molten steel temperature based on historical data of induction furnace operation like power input, coil frequency or current in coils etc.

2.5. Gap Analysis and Research Opportunities

Previously studies have addressed the electromagnetic, hydrodynamic and thermal behavior in induction furnace separately. The modelling on coupling of aforementioned physics is limited. Even if the coupling procedure is followed, little attention is given to molten steel temperature prediction in induction furnace. The accurate temperature distribution is a complex task comprising of Multiphysics and is subjected to dynamic and real-time variations due to fluctuating process conditions. The temperature distribution plays crucial role in product quality, energy consumption and overall efficiency thus, this gap is analyzed in this thesis.

Research opportunities exist in developing AI models that can continuously learn and adapt to the changing operating conditions of the induction furnace in real-time. Combining AI techniques with CFD-based optimization could lead to efficient control strategies and energy-saving measures for the induction furnace. Such hybrid approaches would enable the AI model to optimize furnace parameters while considering the complex fluid dynamics and heat transfer phenomena within the furnace. Research can be undertaken to enhance the interpretability of AI-driven temperature prediction models. Explaining the AI models' decisions and providing insights into the factors influencing temperature predictions could increase their acceptance and adoption in real-world industrial settings.

Chapter 3

Research Methodology

3.1. Overview of Induction Furnace and CFD Modeling

3.1.1 Induction Furnace

The foundation of electromagnetic induction was laid by Michael Faraday in 1831 through an experiment conducted on his famous induction ring [72]. The first induction furnace was invented by Colby with a desire to melt platinum in non-carbonaceous environment however, this furnace could not be of commercial use. Later De Ferranti, using the same principle as Colby gave an induction furnace design in which he placed primary coils outside the secondary circuit that caused high level of magnetic leakage [73]. However, they both gave an incredible furnace design from a theoretical standpoint of a high efficiency furnace in which the metal charge can be under perfect temperature control. A few years later, Kjellin gave the first practical induction furnace design [74]. He placed primary coils within the secondary thereby, reducing magnetic leakage de. Since then, many improvements have been made in order to achieve currently practiced induction furnaces [75].

Furnace is basically a type of direct fired heat exchanger in which a heat source increases the temperature of the feed to a high degree. Induction furnace is a type of furnace in which heat source is electricity thus also known as electric furnace. The advantage of such a furnace is that it is a clean, energy efficient and easily controllable melting process in comparison to other metal melting methods. Induction furnaces are thus ideally used for melting and alloying of metals giving lowest melt losses possible [17].

The working principle of induction furnace is induction heating. Induction heating is gaining an upper hand over other conventional heating techniques such as flame, resistance heating or ovens. It is a non-contact, quick and efficient heating method. Lately, induction heating is being preferably used for industrial, medical and domestic purposes [18, 19]. The working phenomena involves an ac source that delivers alternating voltage to an induction heating coil. The coil produces alternating magnetic field. The charge (feed metal to be melted) is placed inside the coil. As a result of magnetic field, the charge heats up because of either electromagnetic induction or joule’s effect [21].

The joule’s effect is the main heating mechanism in induction heating caused by opposition of eddy currents to magnetic field generated in the induction charge. Whereas, in electromagnetic induction, an alternating current is induced on placing the loop in an alternating magnetic field. The moment loop is short-circuited, the voltage causes the current to flow in a direction such that it opposes the change that caused it – Faraday’s Lenz Law [22, 23].

Currently, induction heating technologies are rapidly evolving towards being highly reliable and efficient systems. The major pros of induction furnaces include [76]:

Rapid Heating: Due to high power densities, time taken to heat the load is prominently reduced and less heat is wasted in comparison to other techniques.

Efficient Working: High temperatures can be attained as only the induction target is to be heating thus minimizing heat losses to the surrounding hence the overall efficiency increases up to 90%.

Controlled Heating: Through the accurate design of coils, the heating location can be controlled thus, advanced techniques such as local heating and temperature profile can be applied to induction furnaces.

Safe and Environmentally Friendly: Induction furnace are known as clean and green furnaces as only the target heats up and the surrounding material remains intact due to lower temperature in other regions. They also don’t emit burnt fossil fuels hence, keeping the environment clean.

3.1.2. Computational Fluid Dynamics (CFD) Modelling

Numerical modelling is the fundamental reason of current advancement in induction heating processes. The current production demand does not allow trial and error in process design. Computational simulations can help access a problem in the process which is experimentally expensive, time consuming and probably impractical. Computer simulations help improvise and develop new techniques or processes and making them efficient in nature. Any new model can be developed from simple to complex numerical analysis. The main key is to select the appropriate theoretical model that perfectly fits the process to be modelled [22]. Uncertainty analysis can be done through numerical simulations and thus effects of different process parameters may be studied to increase the overall efficiency of the equipment or plant and reducing utilities consumption, heat losses and material wearing etc.

Process safety has always been a major concern hence, basic mechanisms are studied carefully and a number of experiments on laboratory scale are conducted before developing a commercial scale process still a bridge remains in safety which is covered by CFD tools [77]. These tools gain deeper understanding of the concerned physics of a process and suggest improvements making it more feasible, safe and environment friendly [78]. Simulations involving computational fluid dynamics (CFD) codes can give detailed information about heat transfer, mass transfer and fluid flow inside a processing equipment [79]. The numerical modelling of physics involved in this thesis is given below.

3.1.2.1.Mathematic Modelling of Electromagnetic Field

A brief overview of solving electromagnetic field in computational fluid dynamics environment involves solution of Maxwell's set of equations [80, 81].

Ampere's Law: $$\nabla \times H = J + \frac{\partial D}{\partial t} \qquad 3.1$$

Faraday's Law: $$\nabla \times E = -\frac{\partial B}{\partial t} \qquad 3.2$$

Gauss' Law: $$\nabla \cdot B = 0 \qquad 3.3$$

Gauss' Law: $\nabla \cdot \mathrm{D} = \rho^{charge}$ 3.4

Where E is the electric field, D is electric flux density, H is magnetic flux intensity, B is magnetic flux density, J is conduction current density and ρ^{charge} is electric charge density.

Maxwell equations is in complete correspondence with Maxwell laws of magnetism. The Equation 3.1 states that a magnetic field is always produced when there is a current flowing in the nearby surrounding. The equation shows that the curl of H is dependent upon two sources at a time i.e. conduction current density 'J' and electric charge density $'\rho^{\mathrm{charge}}'$.

The Equation 3.2 states that differential of magnetic flux density B always generates divergence in electric field E and induces current in nearby region. Whereas, the negative sign shows the direction of induced electric field.

The electromagnetic physics for induction heating inside an induction furnace can be explained by Equations 3.1 and 3.2. The alternating current is produced in the coils because of the influence of alternating voltage. The produced alternating current gives rise to alternating magnetic field having same frequency as the current in coils. The geometry of the coil, current inside coils, coupling of coil and workpiece greatly effects the strength of magnetic field. The magnetic field then generates eddy currents in the inductor. These eddy currents produce their own magnetic field in an opposite direction to the source magnetic field. In short, total magnetic field is a sum of source and induced magnetic fields inside an induction furnace.

Furthermore, the Equation 3.3 illustrates that divergence of magnetic flux density B is null which means that there is no source or sink from where magnetic fields lines generate leaving behind a perception that these lines are always in a continuous loop.

3.1.2.2.Mathematic Modelling of Heat Transfer

Generally, thermal process is dealt in time dependent domain and can be simply expressed by Fourier equation 3.5.

$$c\rho\frac{\partial T}{\partial t} + \nabla \cdot (-k\nabla T) = Q \qquad 3.5$$

Where T is temperature, ρ is metal's density, c is specific heat, k is thermal conductivity and Q is the heat generated. The heat source density due to rate of induced eddy currents is acquired by the solution of electromagnetic field. The above Equation 2.5 illustrated temperature distribution inside the induction furnace at any point across the geometry at any time under the influence of initial and boundary conditions.

The initial conditions are usually set to ambient cause they represent conditions at t=0 if not linked to any previous process whereas, the boundary conditions are responsible for thermal losses due to convection and radiation. For a symmetric geometry, Neuman boundary condition is applied at the axis. The Neuman boundary conditions states that no heat exchange occurs at the axis and is thus used for a properly insulated workpiece.

$$\frac{\partial T}{\partial n} = 0 \qquad 3.6$$

3.1.2.3.Finite Element Method

To get effective computational results, numerical methods like finite difference, finite volume, mutual impedance, finite element or boundary element methods are used. Each method has its pros and can be used as a stand alone or in combination with another. FEM gives element wise approximations of the governing equations. The area under study is further broken down into non-overlapping subareas thus minimizing energy at each node of each element. Most paper has referred FEM as a suitable method for electromagnetic applications due to its flexible geometry [82]. Space discretization is another significant aspect of FEM. The accuracy of the numerical method depends on careful meshing in the regions where the influence of rate of change of the unknown is huge. FEM solves electromagnetic problem along with temperature profiling across the geometry with respect to magnetic vector potential [83, 84].

3.2. Data Collection and Preprocessing

Data collection and preprocessing are crucial steps such as obtaining high-quality data and preparing it in a suitable format are essential for training and validating the ANN model effectively. Here's an outline of the data collection and preprocessing steps:

3.2.1. Data Collection

The data is firstly gathered from CFD simulations that is COMSOL modelling of the induction furnace. The CFD simulations should include information about the geometry, furnace dimensions, time, and temperature distribution inside the furnace during the steelmaking process. Ensure that the simulation data covers a wide range of operating conditions and scenarios to create a representative dataset. Secondly, the obtained detailed information about the induction furnace's physical dimensions, including its length, width, height, and other relevant geometry parameters. These parameters play a significant role in determining the temperature distribution inside the furnace and were validated with literature [85]. Record the simulation data with timestamps to capture the time-dependent behavior of temperature changes during the steelmaking process. The time-stamped data allows the model to consider temporal patterns and dynamics.

3.2.2. Data Preprocessing

First and foremost, check the CFD simulation data for missing values, outliers, and any inconsistencies. Handle missing values through imputation techniques, and remove or correct any outliers that could adversely affect the model's performance followed by combining the CFD simulation data with the corresponding furnace geometry and dimensions data ensuring that the timestamps align correctly with the corresponding temperature readings. After that scaling is done for the temperature and other numerical features to a common range. The last task in preprocessing is to divide the data into training and validation sets. The training set is used to train the ANN model, while the validation set is used to evaluate its performance and generalization capabilities.

By carefully collecting and preprocessing the CFD simulation data along with furnace geometry, dimensions, and time-stamped information, the dataset is prepared for training the ANN model to predict molten steel temperatures accurately. Proper data handling and preprocessing steps are essential to ensure the success of the thesis and the development of a robust and reliable temperature prediction model for induction furnaces.

3.3. Feature Selection and Engineering

The effective feature selection and engineering are crucial steps to improve the accuracy and generalization capability of the ANN model for predicting molten steel temperatures. Given the complex nature of the steelmaking process and the diversity of parameters involved, careful feature selection and engineering can significantly enhance the model's performance. By carefully choosing relevant features and crafting new informative ones, the model can effectively capture the intricate relationships between process parameters and temperature variations. The combined impact of feature selection and engineering will lead to a more interpretable, efficient, and reliable AI solution for temperature prediction, enhancing the steelmaking process's quality and efficiency. The selected features for ANN model are dimensions from width and height of furnace geometry moving across x-axis and y-axis at every minute for the total run time. So, time is another feature used as input variable whereas, temperature is the only output variable at the specified input features.

3.4. AI Model Selection and Justification

Molten steel temperature prediction in an induction furnace is a challenging task due to the dynamic and non-linear nature of the process. Accurate temperature prediction is essential for controlling the steelmaking process and avoiding defects in the final product. CFD simulations provide detailed insights into the flow and heat transfer phenomena inside the furnace, and integrating AI models can enhance the accuracy and efficiency of temperature predictions. In this work, ANN is selected as the AI model for its proven capabilities in handling complex non-linear relationships and its success in various predictive modeling tasks [86-88]. A few justifications for choosing ANN as the AI model for temperature prediction are:

3.4.1. Non-Linear Relationship

ANN excels at capturing complex non-linear relationships between input and output variables. In the context of molten steel temperature prediction, the temperature variations are affected by a multitude of factors, including induction power, geometry, material properties, and time. ANN's ability to approximate non-linear functions makes it well-suited for capturing these intricate dependencies.

3.4.2. Universal Function Approximator

The universal function approximation theorem states that a neural network with a sufficient number of neurons in its hidden layers can approximate any continuous function to arbitrary precision. Given the diverse and often unknown dynamics of induction furnace behavior, the flexibility of ANN to approximate complex functions is a significant advantage.

3.4.3. Feature Extraction and Engineering

ANN can effectively learn and extract relevant features from the input data during the training process. As predicting molten steel temperature relies on a multitude of parameters from CFD simulations, feature engineering can be a time-consuming task. ANN's ability to perform automatic feature extraction alleviates this burden and can reveal hidden patterns in the data.

3.4.4. Handling Noisy Data

Real-world data can be noisy and contain uncertainties. ANN is robust to noisy data and can learn to generalize from imperfect training samples. This is particularly important in industrial applications where variations in operating conditions and measurement errors are common.

3.4.5. Parallel Processing

ANN computations can be efficiently parallelized, making it suitable for handling large datasets and speeding up the training process. This scalability is advantageous in dealing with the vast amounts of data typically encountered in CFD simulations.

The choice of ANN as the AI model for molten steel temperature prediction in an induction furnace is justified based on its ability to handle complex non-linear relationships, perform feature extraction, and tolerate noisy data. The synergy between CFD simulations and ANN will enable accurate and efficient temperature predictions, which can significantly benefit the steel industry by improving product quality and optimizing the steelmaking process. The development and validation of the ANN-based model in this thesis will contribute to the advancement of AI applications in industrial processes.

3.5. Model Training and Validation

The model training and validation process plays a pivotal role in ensuring the accuracy and reliability of the developed ANN model. Model training involves feeding the ANN with a carefully curated dataset comprising CFD simulation outputs and corresponding molten steel temperatures. The ANN learns the underlying patterns and relationships between the input parameters and the target variable through an iterative optimization process, typically using backpropagation. To avoid overfitting and to evaluate the generalization capability of the model, a comprehensive validation strategy is employed. The dataset is split into training and validation sets, with the former used for training the ANN and the latter for assessing its performance. Various metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared, are computed to quantify the model's predictive accuracy. Additionally, techniques like k-fold cross-validation may be applied to obtain a more robust estimate of the model's performance. Through rigorous model training and validation, the thesis aims to demonstrate the ANN's capability to accurately predict molten steel temperatures in induction furnaces, thus contributing to enhanced process control and optimization in the steel industry. Further details on training and validation is given in Chapter 5.

3.6. Performance Metrics

The performance metrics used to evaluate the accuracy and effectiveness of the developed ANN model are crucial in assessing its predictive capabilities. Given the importance of precise temperature predictions in the steelmaking process, the following performance metrics are employed:

3.6.1. Mean Absolute Error (MAE)

The MAE is a commonly used metric that measures the average absolute difference between the predicted temperatures and the actual temperatures. It provides a straightforward indication of how well the model performs in terms of magnitude and direction, irrespective of positive or negative errors. A lower MAE indicates better accuracy, with zero implying a perfect prediction.

3.6.2. Root Mean Square Error (RMSE)

The RMSE is another widely used metric that measures the square root of the average of the squared differences between predicted and actual temperatures. RMSE penalizes larger errors more than MAE, making it sensitive to outliers. Like MAE, a lower RMSE value signifies better predictive performance.

3.6.3. R-squared (R^2) or Coefficient of Determination

R-squared evaluates the proportion of variance in the dependent variable (molten steel temperatures) that is explained by the model. It ranges from 0 to 1, where 1 indicates that the model perfectly captures the variance in the target variable. R-squared helps to understand how well the model fits the data and how much of the variability in temperature predictions can be attributed to the input parameters.

3.6.4. Scatter Plots and Residual Analysis

Visual inspection of scatter plots of predicted versus actual temperatures can reveal patterns, trends, and potential nonlinearities in the model's performance. Residual analysis, which involves plotting the differences between predicted and actual temperatures, can help identify systematic errors and model shortcomings.

The selection of appropriate performance metrics is essential to comprehensively evaluate the ANN-based molten steel temperature prediction model. By analyzing and interpreting these metrics, the thesis can ascertain the model's accuracy, robustness, and suitability for real-world application in the steel industry. The use of multiple metrics provides a comprehensive understanding of the model's strengths and limitations, ensuring that the developed AI solution meets the industry's quality and efficiency requirements. The mathematical equations for all three performance parameters: R^2, MSE and RMSE are shown below.

$$MSE = \frac{1}{Q'}\sum_{i=1}^{Q'}\left(Y_{i,pred} - Y_{i,CFD}\right)^2 \qquad 3.7$$

$$RMSE = \sqrt{\frac{1}{Q'}\sum_{i=1}^{Q'}\left(Y_{i,pred} - Y_{i,CFD}\right)^2} \qquad 3.8$$

$$R^2 = 1 - \frac{\sum_{i=1}^{Q'}\left(Y_{i,pred} - Y_{i,CFD}\right)}{\sum_{i=1}^{Q'}\left(Y_{i,pred} - Y_m\right)} \qquad 3.9$$

Where, Q' shows number of data points, $Y_{i,CFD}$ is CFD modelling output, $Y_{i,pred}$ is predicted ANN network, Y_m is the average of the values and i refers to data points [89].

Chapter 4

Induction Furnace Simulation and Data Generation

4.1. CFD Simulation Setup and Parameters

The overall process of induction heating is intricate, involving various thermal, electromagnetic, and hydrodynamic phenomena [90, 91]. The coil generates magnetic field that in return induces current in the metal charge. Through the application of joule heating, these induced currents heat up and melt the charge. The electrical properties of the charge alter as the temperature rises, changing the magnitude of induced currents and charge's temperature gradient. The geometry varies on melting i.e. the electromagnetic forces drive the charge away from the wall. The induced currents as well as related electromagnetic forces alter again due to changed geometry. Once the material is completely melted, the electromagnetic forces develop a stirring effect in the molten liquid, homogenizing the temperature in consequence of flow motion [92, 93].

To determine temperature distribution in charge, the governing equations must consider coupled phenomena among electromagnetic behavior, heat transfer and fluid flow. The numerical modelling involves two steps, calculating electromagnetic heating in frequency domain and using the results as input data for hydrodynamics and phase change heat transfer.

4.1.1. Geometry and Discretization

An induction furnace is modelled as 2D axisymmetric by COMSOL Multiphysics version 6.1 for silicon purification [83]. The workpiece under consideration is made up of an insulation layer of alumina around graphite crucible containing silicon as charge to be melted. The solenoid is made up of copper coils. To make simulations easier, the thermal model does not involve the coil [42, 83]. The geometrical sketch is shown in Figure 6 and its dimensions in Table 2.

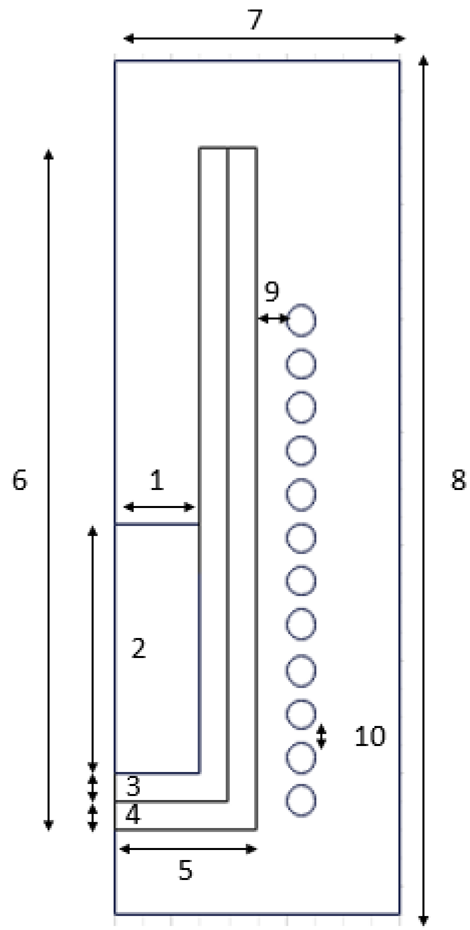

Figure 6: Sketch of The Geometry

Table 2: Dimensions of Geometry [85]

ID	Identification (ID) Type	Dimension
1.	Inner radius of the crucible	0.125 m
2.	Height of metal charge	0.45 m
3.	Width of crucible	0.05 m
4.	Width of insulation layer	0.05 m
5.	Outer radius of crucible	0.225 m
6.	Height of crucible	1.05 m
7.	Width of refractory wall	0.5 m
8.	Height of refractory wall	1.3 m
9.	Spacing between coil & crucible	0.025 m
10.	Spacing between coil turns	0.01 m
11.	Coil diameter	0.05 m
12.	Number of coils	12

The geometry was meshed by the use of the quadrilateral and triangular elements with proper refinement in the areas near charge and coil where high gradients of eddy currents are expected. The triangular meshing was used for the charge, crucible, insulating layer and coil domains whereas, quadrilateral meshing was used for refractory wall as shown in Figure 7. The curvature factor for triangular meshes were kept at 0.2 while for quadrilateral meshes, 0.3 was opted. Further details for meshing are given in Table 3. The physical properties of the materials are temperature dependent whereas, electromagnetic parameter in the coil are assumed constant [85].

Table 3: Mesh Statistics [85]

Mesh Statistics	**Values**
Number of Elements	31044
Elements Edge	1678
Elements Vertex	63
Mesh Vertices	20022
Triangular Elements	22373
Quadrilateral Elements	8672

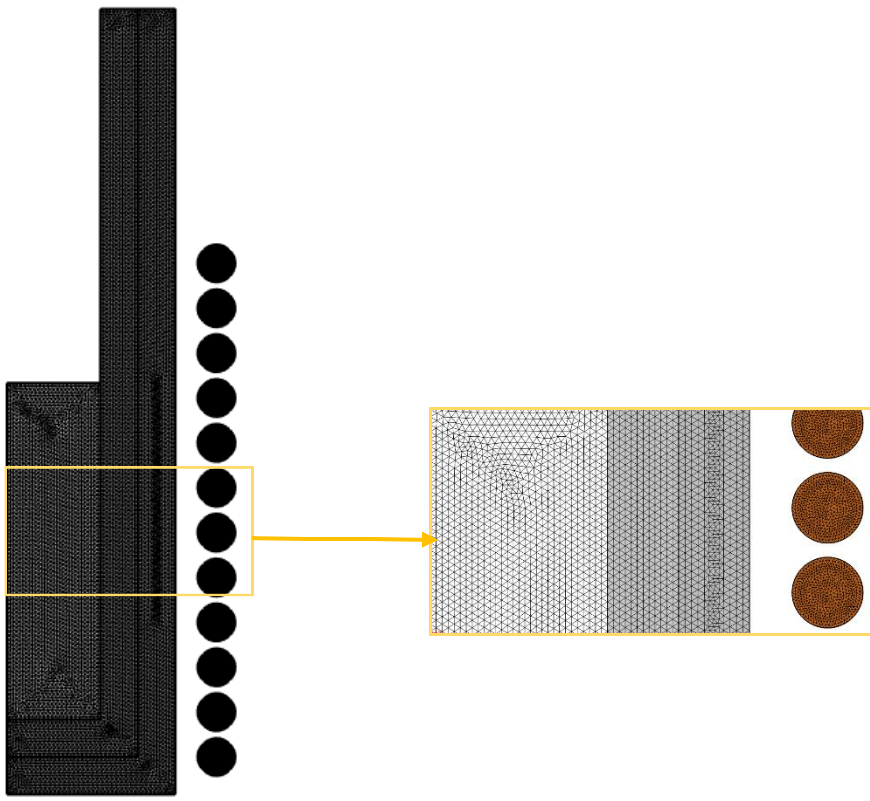

Figure 7: Meshing Details of The Geometry

4.1.2. Electromagnetic Model

Electromagnetic field generated by induction coil is governed by Maxwell equations solved in COMSOL Multiphysics as:

$$(j\omega\sigma - \omega^2\epsilon_0\epsilon_r)A + \nabla \times (\mu_0^{-1}\mu_r^{-1}) = J_e \qquad 4.1$$

$$B = \nabla \times A \qquad 4.2$$

Where A is the magnetic vector potential, B is the magnetic flux density, j is the current density, J_e is the external current density, ω is the frequency, ϵ_0 is the free space reactive permittivity, ϵ_r is the relative permittivity, μ_0 is the free space magnetic permeability and μ_r is the relative permeability [82, 94].

The electromagnetic model holds for entire computational domain. The coil was modelled as homogenized multiturn having current supplied at 2000 A that passes through 12 turns with a working frequency of 1000 Hz [85].

For an industrial furnace, electromagnetic field should not spread outwards thus field guides are added [59]. Hence in simulation, magnetic insulation is used as boundary condition. This condition implies that normal component of the magnetic field should be zero.

$$n \times A = 0 \qquad 4.3$$

4.1.3. Thermal Model

For the examination of thermal effects on electromagnetic field, it must be combined with the heat equation. The radial section of the workpiece serves as computational domain for thermal model [95]. Primarily, the metal charge exists in solid form but gradually melting takes place changing its state hence heat transfer equation with phase change should be considered [96]. Moreover, convective heat transfer is also involved as the electromagnetic and buoyancy forces impacts on molten metal. COMSOL Multiphysics uses Fourier equation to solve thermal domain.

$$\rho C_p \frac{\partial T}{\partial t} + \rho C_p \nu \cdot \nabla T = \nabla \cdot (k \nabla T) + Q \qquad 4.4$$

Where T is absolute temperature, t is time, ρ is density, C_p is specific heat capacity, k is thermal conductivity, ν is velocity vector and Q is the heat source.

The initial temperature is set at 30°C. The surface to surface radiation is used for free surfaces. The surface to ambient condition is used for outer wall surfaces. Whereas, periodic heat condition is used for convective cooling at exterior boundaries [85].

4.1.4. Hydrodynamic Model

For the development of a model close to realistic simulation, fluid flow must be considered hence involving convective heat transfer. The hydrodynamic domain is the molten region of the charge. This region is governed by Naiver-Stokes equation along with flow rate conservation [97].

$$\rho \frac{\partial \nu}{\partial t} + \rho \nu \cdot \nabla \nu = -\nabla p + \nabla \cdot [\mu(\nabla \nu + (\nabla \nu)^T)] + F \qquad 4.5$$

$$\nabla \cdot (\rho \nu) = 0 \qquad 4.6$$

Where ρ is density, ν is velocity vector, p is pressure, μ is dynamic viscosity and F is volumetric force.

It must be noted that density and viscosity are material properties dependent upon temperature. Boussinesq approximation is used to model fluid flow as the molten region is not large enough. It basically simplifies the Naiver-Stokes equation by taking a reference temperature hence, constant values for density and viscosity are used. The periodic condition is employed at exterior boundaries and no slip condition at free surfaces [85].

4.2. Thermal Boundary Conditions

A set of boundary conditions for each of the three fields thermal, flow, and electromagnetic were taken into consideration. The magnetic vector potential of value zero was used on the electromagnetic sub-model boundaries, whereas continuity was applied at all interfaces [50]. For fluid flow, no slip condition was employed to the walls and a static pressure of 0 Pa was used for exit. The gradients of zero were used for flow and thermal fields to create an axis. In hydrodynamic domain, the Dirichlet boundary condition was specified i.e. velocity is zero. Lastly, the initial temperature was set at 30°C [85]. The summary of initial and boundary conditions is shown in Table 4.

Table 4: Initial and Boundary Conditions [85]

Region	Boundary Condition		
	Electromagnetic	Flow	Thermal
Axis	A = 0	$\nabla v = 0$	$\nabla \mathrm{T} = 0$
Air Outlet	-	$P_{static} = 0$	$\varepsilon_{rad} = 1$
Free Surface	$A_L = A_R$	$\tau = 0$	$\varepsilon_{rad} = 0.2, T_L = T_R$
Initial Condition	-	$v = 0$	T = 30°C

4.3. Generation of Training and Testing Data

The temperature distribution across the furnace geometry was plotted as contour plots by COMSOL Multiphysics. The temperature distribution was further studied with 1D Plots in COMSOL. Data was exported from COMSOL to Excel at every point such that the temperature at each dimension from x and y axis at every minute for 150 minutes were taken under consideration. The dataset was generated in a way that by keeping x-dimension constant for 150 minutes and varying y-dimension, temperature was obtained. This was done for all x-dimensions across the geometry. The overall dataset includes x and y dimensions across furnace, time including every minute and its corresponding temperatures. The total dataset comprises of 153 inputs including x-dimensions, y-dimensions and time whereas, 151 outputs that is temperatures at 150 minutes. This gave rise to 99909 datasets for input only having a matrix of 653 rows and 153 columns. Similarly, 98603 datasets for output is generated having a matrix of 653 rows and 151 columns. Hence, the total generated data consist of 198512 data samples including 653 rows and 304 columns.

The overall generated data is divided into training and testing datasets as 70% of data was extracted for training while the remaining 30% was equally divided for testing and validation. This was done using a MATLAB code which separated the data in the excel file with a command of keeping every fifth row for testing so that a linear relationship may be developed. In short, COMSOL was linked with Excel for data generation and then Excel was integrated with MATLAB for data division and further AI processing.

Chapter 5

Artificial Intelligence Model Architecture

5.1. Overview of the Chosen AI Model

The Artificial Intelligence (AI) model chosen for above dataset is Artificial Neural Network (ANN). The ANN has emerged as powerful tool for solving complex problems in various domains, including process engineering, computational fluid dynamics (CFD), and metallurgy. In this thesis, an ANN-based model is employed for the prediction of molten steel temperature in an induction furnace, which is simulated using COMSOL Multiphysics software.

ANNs are a subset of machine learning algorithms inspired by the biological neural networks of the human brain. They excel in pattern recognition, classification, regression, and prediction tasks, making them versatile tools for data-driven decision-making and predictive modeling. The networks consist of huge amounts of interconnected elements that all functions simultaneously to solve the targeted problem. These networks are able to solve complex functions including non-linear patterns among various factors.

The major advantage of ANN is its ability of learning an existing relationship directly from the data. The network needs to be trained once and then it can be applied on unknows datasets to predict outcomes. Unlike conventional numerical methods, ANN does not demand following of a specific algorithm. In fact, ANN learn by example and discovers a pattern itself in the provided dataset. The indomitable characteristics of ANN is its ability to perform even if the is indefinite, non-linear or distorted and still give plausible results.

The origins of artificial neural networks can be traced back to the 1950s and 1960s, with the work of Warren McCulloch and Walter Pitts, who introduced the concept of a mathematical model of a neuron [98]. Later, the Perceptron algorithm developed by Frank Rosenblatt in 1957 laid the groundwork for single-layer feedforward neural networks [99, 100].

5.1.1. Multilayer Perceptron (MLP)

Multilayer perceptron (MLP) comprises of various processing units named neurons that are placed in multiple layers. An artificial neuron is illustrated in Figure 8. The neurons are interlinked with each other such that a neuron in one layer connects to all neurons in the upcoming layer. These networks are called feed-forward network as the data information only flows in a single direction at a time [101].

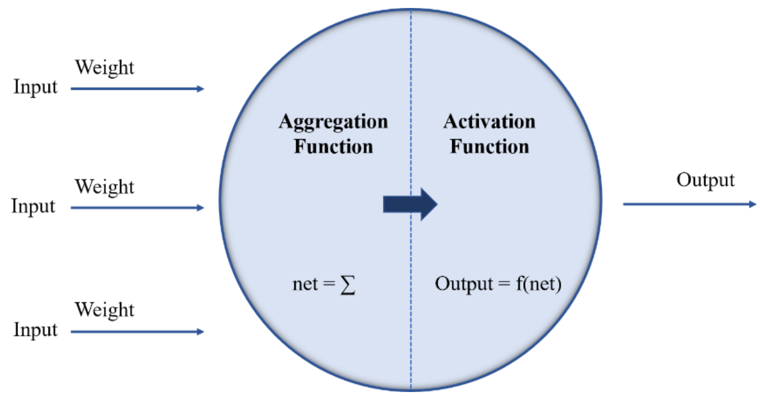

Figure 8: Structure of an Artificial Neuron [101]

To develop a perfect MLP model, firstly, the number of layers viz. input, hidden and output should be selected. Secondly, the number of neurons in hidden layer must be agreed. Also, that in MLP modelling, it is mandatory to choose activation function, error criteria and learning method. Usually, the activation function in hidden and output layer is symmetric sigmoid and it is set to one hence, termed as bias. The bias is a neuron that is permanently set to 1 and it connects with other neurons by a weight known as threshold. This threshold is the deciding criterion if the neuron falls on the required conditions so that precision may be attained. Theoretical advancements by Marvin Minsky and Seymour Papert in 1969, however, revealed the limitations of single-layer perceptron in solving non-linearly separable problems, leading to the “AI Winter” [102].

In the context of molten steel temperature prediction, ANNs can effectively capture the non-linearities and dependencies between various input parameters and the temperature output. Such a network is considered the best type for temperature prediction for several compelling reasons:

Non-Linear Modeling: The process of heating molten steel in an induction furnace involves complex and non-linear relationships between input parameters (e.g., furnace geometry, time) and the output (temperature). ANNs excel at capturing these intricate non-linearities, enabling them to model the system accurately, something traditional linear regression models may struggle with.

Universal Approximators: ANNs have been proven to be universal function approximators, meaning they can approximate any continuous function to arbitrary accuracy with the right architecture and training. This property allows ANNs to handle a wide range of input data and learn complex mappings effectively, making them suitable for the diverse and dynamic nature of molten steel temperature prediction.

Feature Learning: One of the key advantages of ANNs is their ability to automatically learn relevant features from raw data. In the context of molten steel temperature prediction, ANNs can identify essential patterns and correlations within the input parameters, reducing the need for handcrafted features and simplifying the modeling process.

Adaptability: The process of steelmaking is subject to various uncertainties, fluctuations, and changes in operating conditions. ANNs are highly adaptable and can learn from new data, making them robust in handling variations and changes in the process environment. This adaptability is crucial for real-world applications where conditions may not always match the training data.

Scalability: ANN models can be scaled to accommodate large datasets and can handle high-dimensional input spaces efficiently. This is advantageous when dealing with complex CFD simulations and a wide array of input variables involved in the induction furnace process.

Generalization: A well-trained ANN model can generalize its predictions to unseen data effectively. This is particularly important in the context of CFD simulations where accurate predictions at different time steps or under varying conditions are required. ANNs are capable of producing reliable predictions beyond the data points on which they were trained.

5.2. Model Architecture and Components

The architecture of an ANN refers to its overall structure and organization. An ANN is composed of several interconnected components that work together to process input data and produce output predictions. By adjusting the architecture and components of an ANN, researchers and engineers can build models tailored to specific tasks and datasets, making ANNs versatile and powerful tools in various fields of artificial intelligence and machine learning. Here are the main components and their roles in an ANN model:

5.2.1. Input Layer

The input layer is the first layer of the neural network and serves as the entry point for the input data. Each node (neuron) in the input layer corresponds to a feature or attribute of the input data. The number of nodes in the input layer is determined by the dimensionality of the input data.

5.2.2. Hidden Layers

Between the input and output layers, one or more hidden layers can exist in the ANN. Hidden layers are responsible for learning and representing complex patterns and relationships within the data. Each node in a hidden layer receives input from the previous layer and produces an output that is passed to the subsequent layer.

5.2.3. Neurons (Nodes)

Neurons are the fundamental processing units of an ANN. Each neuron takes a weighted sum of inputs from the previous layer and applies an activation function to produce an output. The activation function introduces non-linearity to the model, allowing the network to learn complex relationships in the data.

5.2.4. Weights and Biases

Weights and biases are learnable parameters in the neural network. Each connection between neurons is associated with a weight, which determines the strength of the connection. Biases are added to neurons to shift the output of the activation function. During the training process, the network learns the optimal values of weights and biases to minimize the prediction error.

5.2.5. Output Layer

The output layer is the final layer of the ANN, responsible for producing the model's predictions. The number of nodes in the output layer depends on the nature of the problem being solved. For regression tasks, there is typically one node in the output layer, whereas for classification tasks, the number of output nodes matches the number of classes.

In this study, ANN is used to predict temperature distribution along the furnace geometry. The input layer comprises of three variables (width, height, and time) and output layer of a single variable (temperature). Figure 9 shows the multilayer feed forward neural network architecture with multiple inputs and single output (MISO). Data consists of 99909 data sample from across the width and height of the furnace for the development of ANN model.

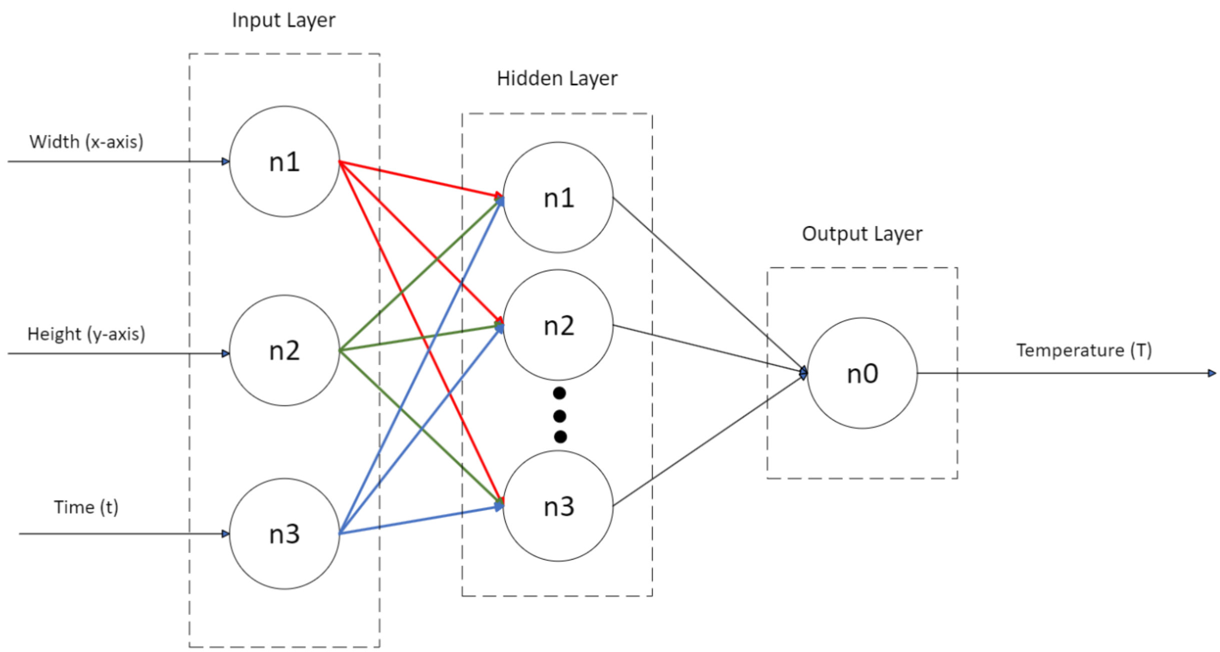

Figure 9: Architecture of Multiple Input and Single Output ANN (MISO)

The actual architecture of the neural network developed in MATLAB for data samples is shown in Figure 10. The architecture follows MISO structure having 153 inputs and its corresponding 151 outputs. The optimized neurons in hidden layer is set at 15.

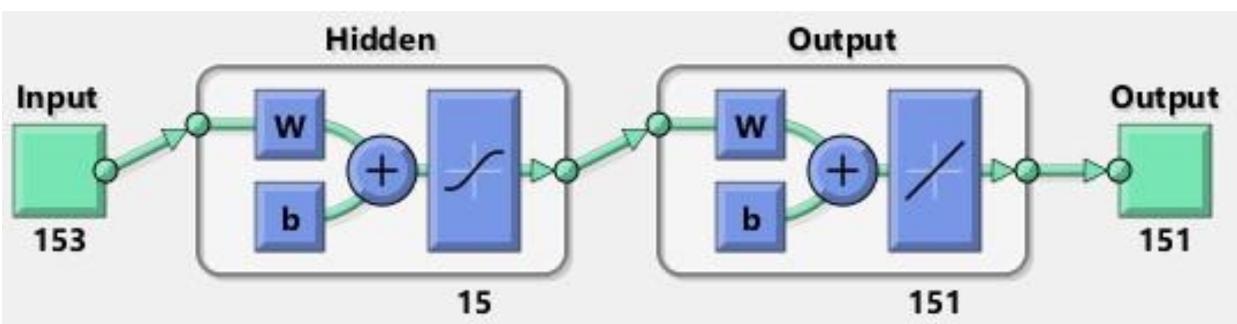

Figure 10: Proposed Architecture ANN Model

5.3. Training Procedure

5.3.1. Back Propagation Algorithm

In the 1980s, the field experienced a resurgence with the development of the backpropagation algorithm, which allowed for efficient training of multi-layer neural networks. The works of Geoffrey Hinton, David Rumelhart, and Ronald Williams played a pivotal role in popularizing the backpropagation algorithm, enabling the training of deep neural networks [103].

A correct setting of weights in the network is not known in advance, so initially a random value is given to them. In order to update the weights to proper values, the BP is commonly applied [101, 104]. Such a process is called training or learning. The BP is a generalization of the least mean squared algorithm that modifies the weights to minimize the mean squared error (MSE) between the target value and the actual outputs in hidden and output layer of the network.

The error function, which not only assesses how closely the network's predictions match the targets but also has a significant impact on the performance of the training algorithms, must be used in order to complete the neural network training. The degree of weight correction applied by the training algorithm at each epoch is evaluated based on the error value. There are two error functions that neural networks frequently employ [105]. The sum of squared differences between the values obtained and expected for each neuron in the output layer constitutes the sum-squared error (SSE), which is primarily used in regression problems. Additionally, the target value and the constructed logarithm of the error value on each neuron present in the output layer are combined by the cross-entropy error (CEE) function.

5.3.2. Levenberg Marquardt Algorithm

The LMA is the nonlinear optimization algorithm that quickly adjusts weights in ANN. Unfortunately, it does have some important shortcomings. The first is that this algorithm can only be used to train networks that are relatively small in size and have a single output neuron. The second is that since SSE is the only error function that defines LMA, it is mainly a best fit only for regression analysis.

The algorithm is a combination of two well-known optimization techniques, the Gauss-Newton method and the method of gradient descent. The Gauss-Newton method is widely used for solving least squares problems, but it can be sensitive to initial parameter values and may not converge efficiently for ill-conditioned problems. On the other hand, the method of gradient descent is more stable but slower in convergence.

The Levenberg-Marquardt algorithm strikes a balance between these two methods by introducing a damping factor, denoted as λ (lambda), which controls the step size during the optimization process. The algorithm iteratively updates the parameter values in the direction of the steepest descent (gradient descent) when the damping factor is large and in the direction of the Gauss-Newton approximation when the damping factor is small. This adaptive damping factor allows the algorithm to efficiently converge to a local minimum in the least squares' optimization problem. Equation 4 represents the mathematical form of LMA algorithm:

$$\Delta w = -(J^T J + \lambda I)^{-1} J^T E \qquad 5.1$$

where Δw is adaptation of weights, J is the partial derivatives matrix of case errors in connection with the weights, I denote the identity matrix, E is the vector of case errors, and λ is the damping factor [101].

The above algorithms are used for training the datasets generated by COMSOL where input parameters consist of width, height and time across the furnace geometry and targets that is outputs are corresponding predicted temperatures.

5.4. Hyperparameter Optimization

Hyperparameter Optimization refers to the process of finding the best combination of hyperparameters that yields the optimal performance of the neural network model for a given task. Hyperparameters are parameters that are set before the training process begins and determine the architecture and behavior of the neural network. Unlike the weights and biases of the model, which are learned during training, hyperparameters need to be set manually or through a search process. The goal is to strike a balance between overfitting (high variance) and underfitting (high bias) by selecting hyperparameters that generalize well to unseen data. Hyperparameter optimization is a critical step in building an effective neural network model as it directly influences the model's accuracy, convergence speed, and generalization capabilities. Careful optimization can lead to significant improvements in model performance and better utilization of computational resources.

The performance of an ANN model is evaluated on the basis of coefficient of determination (R^2), mean square error (MSE) and root mean square error (RMSE) of the training and validating dataset. The network is stopped whenever the RMSE values becomes constant producing a single figure that displays the network’s overall error.

Some common hyperparameters include number of hidden layers, number of neurons in hidden layer, learning rate, activation functions, batch size and number of training epochs. Hence, t is significant to optimize number of neurons in hidden layer so that over fitting or bad performance of neural network may be avoided to create an accurate ANN model. Therefore, number of neurons were optimized using hit and trial method between 1 and 20 to obtain minimum error functions. Levenberg-Marquart algorithm was used for the network. The results of which are shown in Table 5.

Table 5: ANN Modelling Results Obtained from Different Number of Neurons

Sr. No.	Number of Neurons in Hidden Layer	Training Set		Validation Set	
		MSE	R	MSE	R
1	3	595.2368	0.9980	447.2350	0.9985
2	6	96.1235	0.9996	68.3768	0.9997
3	9	107.4362	0.9996	69.4317	0.9997
4	12	26.1724	0.9999	43.8175	0.9998
5	15	12.5864	0.9999	14.1467	0.9999
6	20	18.8067	0.9999	21.8156	0.9999

On the basis of regression (R) that measures the correlation between inputs and targets, coefficient of determination (R^2), mean square root (MSE) and root mean square error (RMSE), a suitable network i.e. hidden layer with 15 number of neurons is opted. Most precise results are obtained on lower values of MSE and RMSE whereas R^2 close to 1 is preferred [89].

Chapter 6

Results and Discussion

6.1. CFD Modelling and Validation

Numerical results for electromagnetic heating are shown in figure. The electromagnetic force is only at the outer regions of the molten metal and it is directed towards the axis. High frequency of 1000 Hz is used to model induction heating. The contour plot of temperature inside the induction furnace is shown in Figure 11. The 3D diagram of induction furnace along with temperature distribution is shown in Figure 12. The contour plot shows that the temperature inside the charge rises up to 1600°C. The minimum temperature inside the charge was observed at 1327°C while the maximum temperature was 1703°C. This shows that the silicon metal is highly heated. The temperature specifically increased in inner crucible where it contacts with the charge due to low thermal conductivity and emissivity.

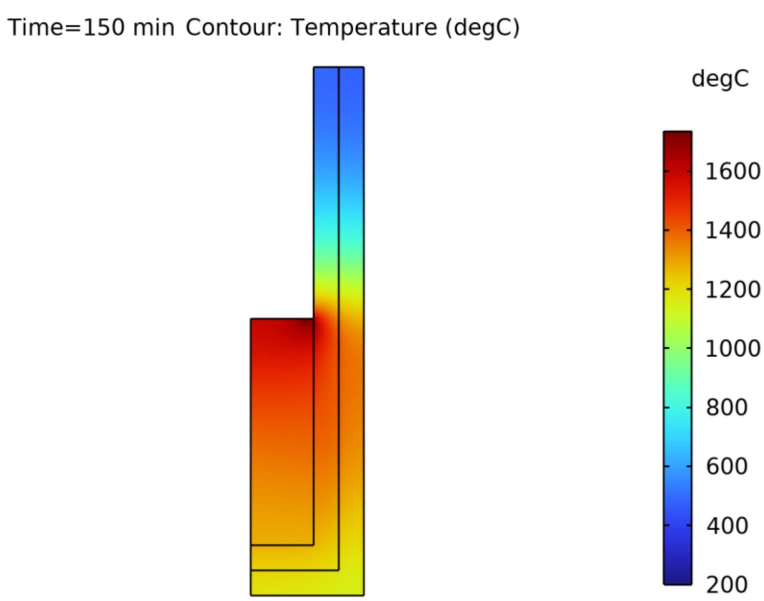

Figure 11: Temperature Contour Plots of Induction Furnace

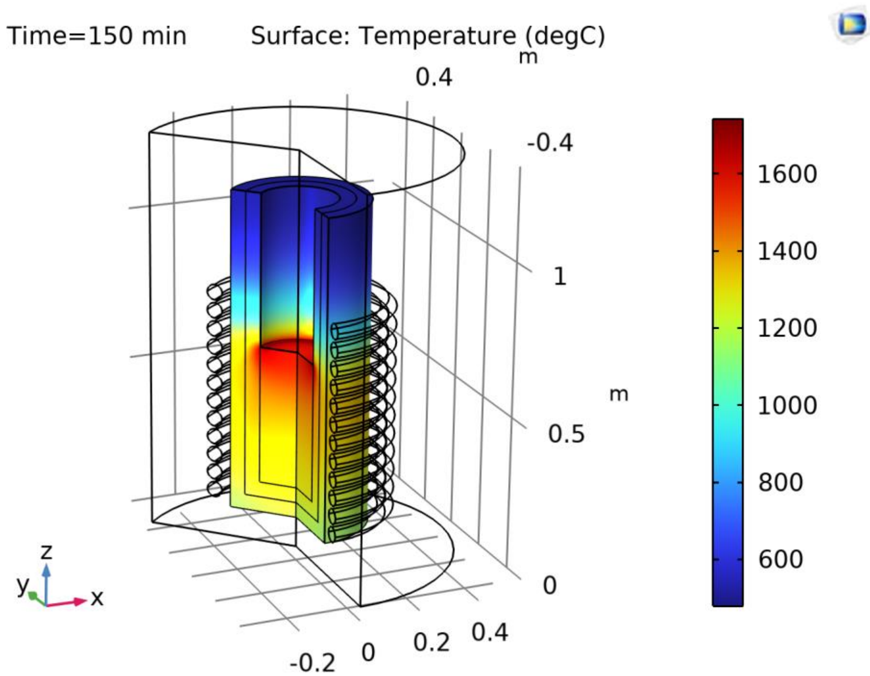

Figure 12: Three-Dimensional View of Induction Furnace

The comparison between COMSOL and literature results are shown in Table 6. In the literature, only the contour plot was shown so values are approximated from them. The literature followed was based on simulation of an industrial furnace and it showed agreement with experimental data. The comparison illustrates that the simulated results are confirming to literature data [85].

Table 6: Comparison of Modelling and Literature Results [85]

Layer	**Temperature (°C)**		
	Literature	**Simulation**	**%Error**
Alumina Insulation	1200	1138.6	5.39
Graphite Crucible	1500	1515.5	1.02
Silicon Metal Charge	1600	1702.9	6.04

6.2. Performance Evaluation of AI Model

The performance of the developed ANN model can be evaluated by regression plots. The data consists of 99909 data sample from across the width and height of the furnace for the development of ANN model. Regression performance of ANN model is shown in Figure

13. The dataset was divided into three categories; 70% for training (a), 15% for testing (b) and 15% for validation (c). The regression plots generated by ANN model depicts that the provided data was accurately trained achieving thus, testing and validation also provided precise results with the correlation factor (R) value of 0.99995.

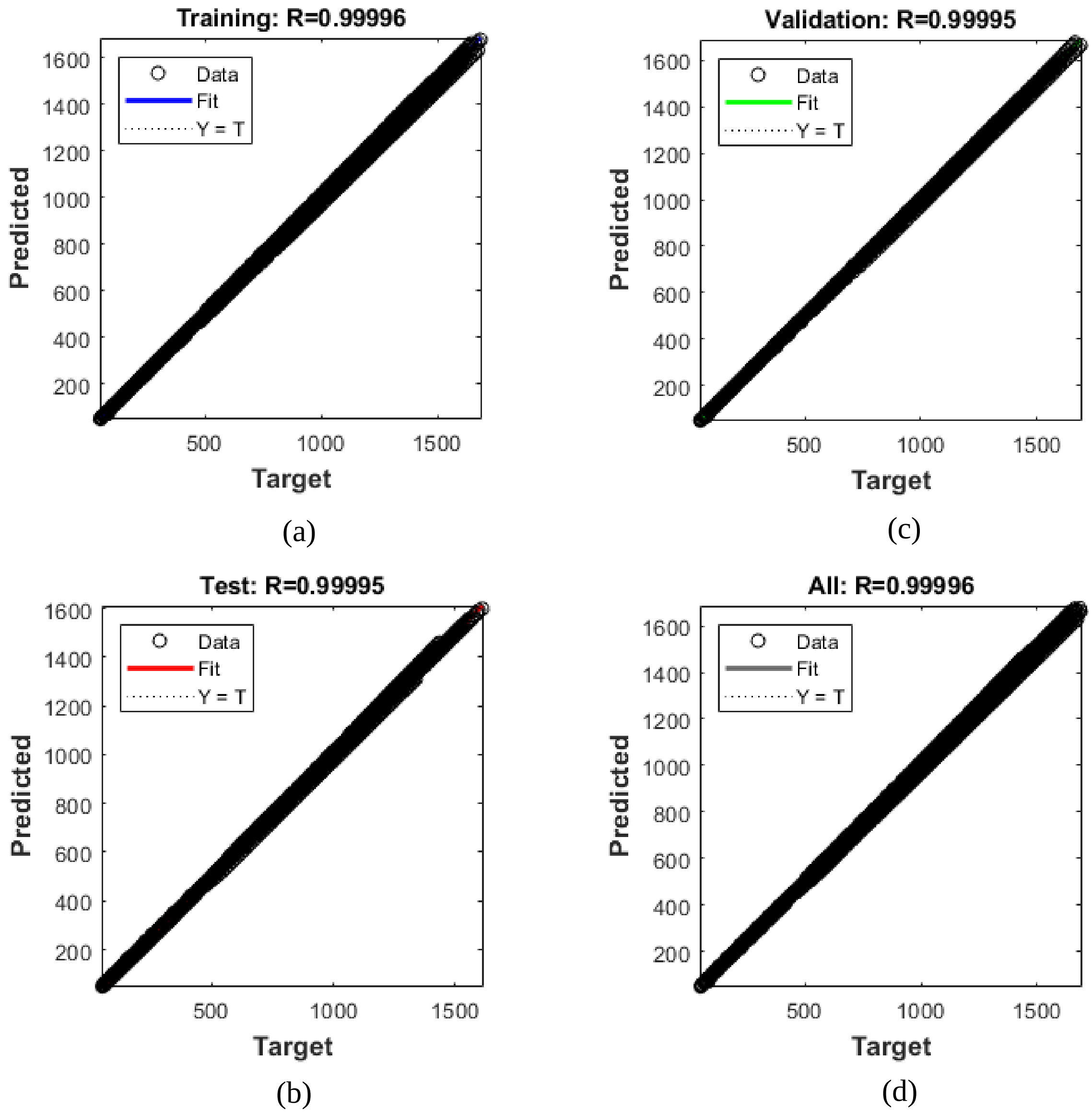

Figure 13: Regression Plots of ANN Model (a) Training Plot (b) Testing Plot (c) Validation Plot (d) Overall Plot

Performance evaluation of an ANN model based on regression plots with an R-squared value of 0.9999 is indicative of an exceptionally accurate and well-fitted model. The regression plot, showing the predicted molten steel temperatures plotted against the actual temperatures, exhibits a remarkably tight and linear relationship. The points on the plot align closely to a diagonal line, indicating that the model's predictions are highly consistent with the ground truth temperatures. The difference between the predicted and actual temperatures, known as the residuals, is minimal across the entire dataset. This indicates that the model's predictions are consistently close to the true values, with minimal errors. Such a high R^2 value suggests there is a low risk of overfitting, which occurs when a model performs exceptionally well on the training data but poorly on unseen data. The model's ability to generalize to new, unseen data is reassuring for real-world deployment. It also proposes that the model can effectively interpolate within the range of the training data and may even be capable of reliable extrapolation to predict temperatures outside the training data range.

6.3. Analysis of Model Accuracy and Robustness

Artificial neural network was trained using the data generated from COMSOL. 70% of dataset was used for training while the remaining 30% was equally divided between testing and validating datasets. A multi-input single output neural architecture was trained with Levenberg Marquardt training algorithm. The optimum architecture was developed by the hit and trial method of choosing the number of neurons in hidden layer. The number of neurons were selected on the basis of lowest MSE value and R closest to one hence, 15 number of neurons in hidden layer was selected. The input layer was fed with width and height data across the furnace for every minute for the total time of simulation that is 2.5 hours. Finally, output layer was used for prediction of temperature in correspondence to time, width and height respectively.

The above trained network is then used for testing and validation of the model. The ANN model was tested by providing only input dataset and attaining output dataset as targets achieved by the developed optimized network. The model showed strong predictive capabilities by its low MSE value i.e. 12.58 and correlation factor to be 0.9999. The resultant matrix was then compared with original results obtained by COMSOL Multiphysics.

The predicted temperature dataset from ANN model was close enough to COMSOL results and thus comparison graphs over different times such as 25 (a), 50 (b), 75 (c), 100 (d), 125 (e), and 150 (f) minutes were plotted as shown in Figure 14 and 15. By the graphs, it can be seen that ANN model is in good agreement with simulated results. There exists negligible or no error in the comparison plots thus it can be used as a reliable technique to predict temperatures across the induction furnace. The developed ANN model can also be used in industrial application for lowering energy consumption and improving furnace efficiency.

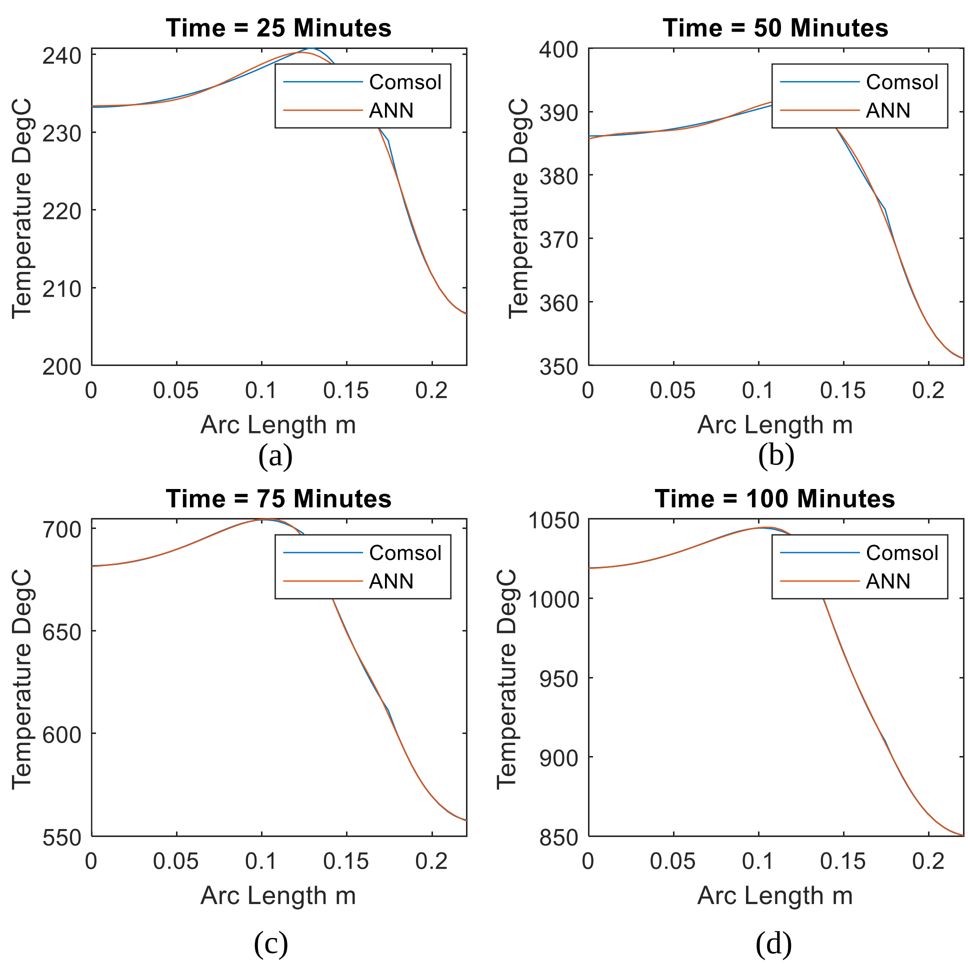

Figure 14: Comparison Plots of ANN and CFD Model (a) 25 Minutes (b) 50 Minutes (c) 75 Minutes (d) 100 Minutes

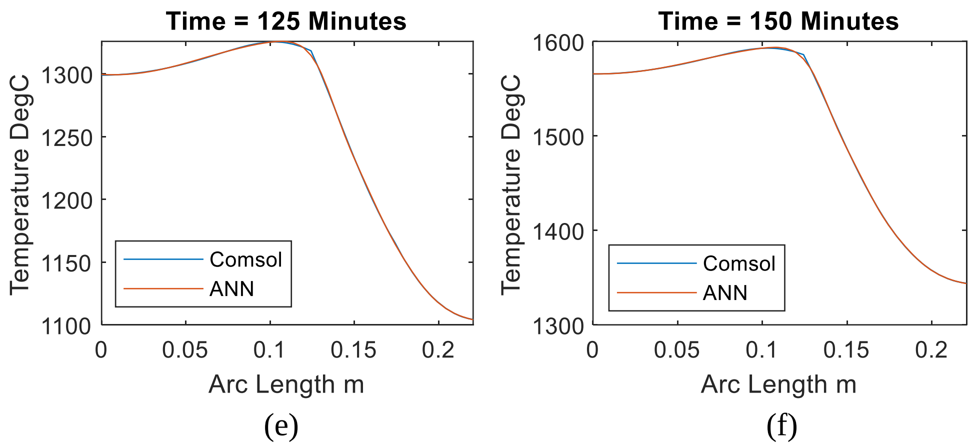

Figure 15: Comparison Plots of ANN and CFD Model (e) 125 Minutes (f) 150 Minutes

The analysis of model accuracy and robustness based on the comparison plots of predicted ANN temperatures and COMSOL resulted temperatures, with a slope of nearly 1, provides a strong indication of the model's excellent performance. Such a slope in the comparison plot signifies a perfect alignment between the predicted temperatures and the ground truth obtained from CFD simulations. This implies that the ANN model's predictions are almost identical to the actual temperatures, resulting in an accurate and reliable temperature prediction tool. The tight clustering of data points around the diagonal line indicates that the model exhibits minimal bias and variance, further confirming its robustness and ability to generalize well to different operating conditions within the steelmaking process. Such an analysis reinforces the confidence in the model's accuracy and applicability for predicting molten steel temperatures in induction furnaces, enabling enhanced process control, improved product quality, and increased efficiency in the steel industry.

6.4. Interpretation of Results

The CFD simulations provide valuable and detailed insights into the fluid flow and heat transfer phenomena inside the induction furnace. They serve as a reliable reference for molten steel temperatures, as CFD accurately simulates the physics governing the steelmaking process. The CFD results are essential for establishing the ground truth against which the ANN model's predictions are compared. Additionally, the CFD simulations offer a comprehensive understanding of the temperature distribution within the furnace, aiding in process optimization and identifying potential areas for improvement. Whereas, the ANN model serves as a powerful predictive tool capable of accurately forecasting molten steel temperatures. Through the training process, the model has learned the complex non-linear relationships between the input parameters, such as furnace dimensions, time, and temperature, enabling it to make precise temperature predictions. Its high accuracy, as evidenced by the comparison plots with the ground truth CFD temperatures, indicates that the model successfully captures the underlying patterns and dynamics of the steelmaking process. The ANN model's ability to generalize to new and unseen scenarios demonstrates its robustness and suitability for real-world applications in the steel industry.

The comparison between the ANN-predicted temperatures and the CFD results reinforces the accuracy and reliability of the AI model. The close alignment of data points along the diagonal line in the comparison plots signifies a near-perfect agreement between the predicted and actual temperatures. This indicates that the ANN model has successfully learned and effectively modeled the complex relationships between the input parameters and molten steel temperatures. The strong correlation between the ANN and CFD results validates the model's performance and enhances its credibility as a temperature prediction tool in the steelmaking process. The accurate temperature predictions provided by the ANN model allow for better process control and optimization. By utilizing the AI model's predictions, operators can make informed decisions to adjust furnace parameters, optimize energy consumption, and enhance product quality. The integration of ANN and CFD results empowers steel manufacturers with valuable insights that lead to cost-effective and efficient production processes.

Conclusion and Recommendations

Summary of Findings

This study aims to address the complexities and dynamics of the induction furnace environment. The developed model harnesses the power of machine learning algorithms, enabling it to capture intricate patterns and non-linear relationships in the data, leading to more accurate temperature predictions. Firstly, a two-dimensional Multiphysics model for induction furnace was developed by using COMSOL for predicting molten steel temperature. The results of which were then used for developing an ANN model. The hit and trial method were used to determine number of neurons in the hidden layer. The network comprised over 15 neurons and great performance with a correlation factor of 0.9999 was achieved. The results demonstrated that our AI-based approach outperformed traditional methods, offering more precise temperature forecasts.

Implications of the Study

The implications of this study are significant for the steel industry and the broader application of artificial intelligence (AI) in industrial processes. The successful development and validation of the Artificial Neural Network (ANN) model for molten steel temperature prediction offer numerous benefits. First, it enables steel manufacturers to achieve precise temperature control, leading to improved product quality and reduced defects. Second, the AI-driven temperature predictions contribute to energy efficiency and cost reduction by optimizing heating and cooling processes. Third, the study showcases the successful integration of AI with Computational Fluid Dynamics (CFD) simulations, demonstrating the synergy of these technologies in understanding and optimizing complex physical processes. This integration sets a precedent for similar applications in other manufacturing sectors, driving advancements in data-driven decision-making and process optimization. Overall, the study's implications extend to enhanced process efficiency, increased competitiveness, and the promotion of AI-driven innovations in industrial settings, making it a significant step towards the Industry 4.0 revolution.

Future Research Directions

Future research directions in the field of molten steel temperature prediction and AI-driven process optimization present exciting opportunities for further advancements. One potential direction is the exploration of advanced deep learning techniques, such as recurrent neural networks (RNNs) and attention mechanisms, to capture temporal dependencies and dynamic patterns in the steelmaking process. Additionally, integrating data from other sensors and sources, such as chemical composition data and environmental factors, could enhance the model's accuracy and broaden its applicability. Investigating the incorporation of uncertainty quantification techniques into the AI model would enable the estimation of prediction confidence intervals, providing valuable insights for decision-making under uncertainty. Furthermore, research efforts may focus on real-time deployment and edge computing solutions to ensure the ANN model's practicality in industrial settings. Lastly, extending the AI model's capabilities to predict other critical parameters in the steelmaking process, such as steel viscosity and flow characteristics, opens up new avenues for comprehensive process optimization and quality control. These future research directions have the potential to revolutionize the steel industry and pave the way for broader AI applications in other industrial domains.

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