PREDICTING FURNACE GAS TEMPERATURE IN COAL-FIRED POWER PLANTS BASED ON MACHINE LEARNING MODELS

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ABSTRACT

The contemporary variability in coal properties has led to unpredictability in the performance of coal power plants, particularly with regard to furnace gas temperature. This thesis presents on predicting furnace gas temperature in coal-fired power plants based on machine learning models. The study focuses on three popular techniques: decision tree, artificial neural network (ANN), and linear regression. The aim is to identify the most accurate and reliable model for temperature prediction in such power plant settings. Historical data of furnace gas temperatures and corresponding operational parameters were collected from a coal-fired power plant to conduct the analysis. The dataset was preprocessed and divided into training and testing sets. Three different machine learning models were developed and evaluated using these datasets. The results demonstrate that the decision tree model achieved the highest accuracy of 89.26% in predicting furnace gas temperature. The ANN model followed closely with an accuracy of 88.95%, indicating its strong performance as well. On the other hand, the linear regression model achieved an accuracy of 68.5%, suggesting its relatively lower predictive capability in this specific context. The findings of this comparative analysis contribute to the field of predictive modeling in coal-fired power plants. The decision tree model can serve as a valuable tool for power plant operators and engineers in accurately estimating furnace gas temperature, facilitating efficient plant operations and maintenance.

Keyword: Coal, Power plant, Furnace Machine Learning, ANN, Decision Tree, Hyperparameter Optimization

I. INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools for optimizing various industrial processes, including those in the energy sector. Coal-fired power plants, being a significant source of electricity generation, can greatly benefit from the application of AI and ML techniques. These advanced technologies offer opportunities to enhance efficiency, reduce emissions, and improve overall operational performance. AI and ML techniques can be utilized in several aspects of coal-fired power plants, including process optimization, predictive maintenance, and emissions control. By leveraging data-driven models and intelligent algorithms, these technologies enable power plant operators to make informed decisions, optimize resource allocation, and improve plant performance.

One of the key areas where AI and ML techniques are employed in coal-fired power plants is the prediction and control of furnace gas temperature. Accurate estimation of furnace gas temperature is crucial for ensuring efficient combustion, minimizing pollutant emissions, and preventing equipment damage. Traditionally, temperature prediction in power plants has relied on empirical models and simplistic control strategies. However, with the advancements in AI and ML, more sophisticated and data-driven approaches can be adopted.

AI and ML techniques, such as Decision Trees, Artificial Neural Networks (ANNs), and Regression models, offer the capability to analyze complex relationships and patterns within the vast amounts of operational data collected from coal-fired power plants. These models can learn from historical data, including temperature measurements, fuel characteristics, air flow rates, and other process parameters, to predict furnace gas temperature accurately.

Coal-fired power plants are among the world's most prevalent power generation technologies today. This is because they are relatively inexpensive to build and operate, and coal is abundant and widely available. Coal-fired power plants generate electricity by burning coal to produce steam. The steam is then used to turn a turbine, generating electricity. The basic operation of a coal-fired power plant can be broken down into four main stages: fuel preparation, combustion, steam generation, and electricity generation. The process flow of a typical coal-fired power plant as in Figure 1 below.

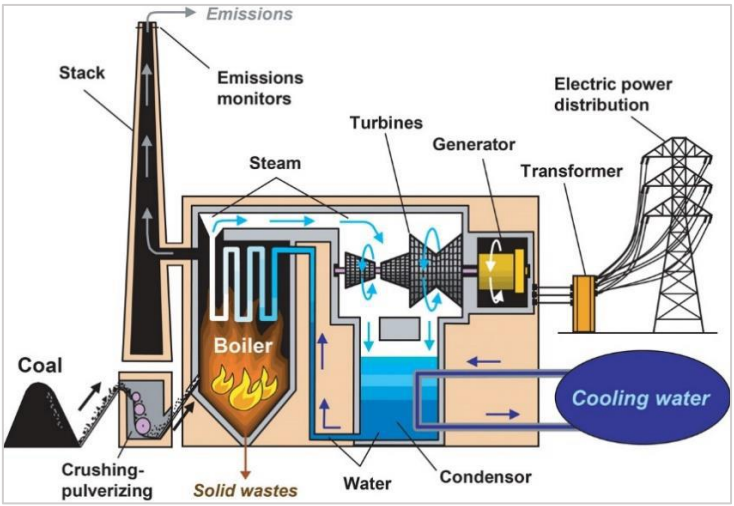

Figure 1. Process flow of a typical coal fired power plant

However, the performance and efficiency of these power plants are greatly affected by the properties of the coal being used. Coal with varying properties can lead to issues such as slagging, fouling, and reduced boiler efficiency, which can result in unplanned outages and increased operational costs. To address these challenges, developing a prediction model for a coal-fired power plant that takes

into account the properties of the coal being used can be a valuable tool for plant operators. This model can use machine learning algorithms to analyze historical data of the plant and predict future performance based on the properties of the incoming coal.

By comparing and evaluating the performance of these AI and ML techniques, power plant operators can determine the most accurate and reliable method for predicting furnace gas temperature. This knowledge allows for better control and optimization of combustion processes, leading to improved efficiency, reduced emissions, and enhanced overall operational performance.

This paper aims to conduct a comparative analysis of Decision Trees, Artificial Neural Networks, and Regression models for predicting furnace gas temperature in coal-fired power plants. By evaluating their performance, we seek to provide valuable insights and recommendations for the implementation of AI and ML techniques in the energy sector.

II. LITERATURE REVIEW

A. Background Of Coal Fired Power Plant Operation

Coal-fired power plants have been a major source of electricity generation for decades. In a typical coal-fired power plant, coal is burned to produce steam, which drives a turbine connected to a generator. The heat produced during combustion is transferred to water to create high-pressure steam, which is then directed to the turbine blades. The steam causes the turbine to rotate, generating electricity. However, the efficient operation of a coal-fired power plant is influenced by a variety of factors, including coal properties, fuel preparation, and combustion control. The whole process can be described in Figure 2 below.

Coal handling and preparation plant (CHPP) is an essential component in the coal-fired power plant operation. The primary function of the CHPP is to prepare the coal for combustion and remove any impurities to ensure efficient and safe operation of the plant. The CHPP typically receives the coal from the mine through a conveyor belt system and processes it to remove any rocks, dirt, or other debris that may have been mixed in during transportation. The coal is then crushed to a specific size, depending on the plant's specifications, before being transported via conveyor belt to the boiler for combustion. The CHPP is a critical component in the coal-fired power plant operation as it directly impacts the plant's efficiency, reliability, and safety (Zhao & Lin, 2011). Any malfunction in the CHPP can lead to a reduction in power generation or even a shutdown of the entire plant. Therefore, the proper maintenance and management of the CHPP are essential to ensure the continued operation of the plant.

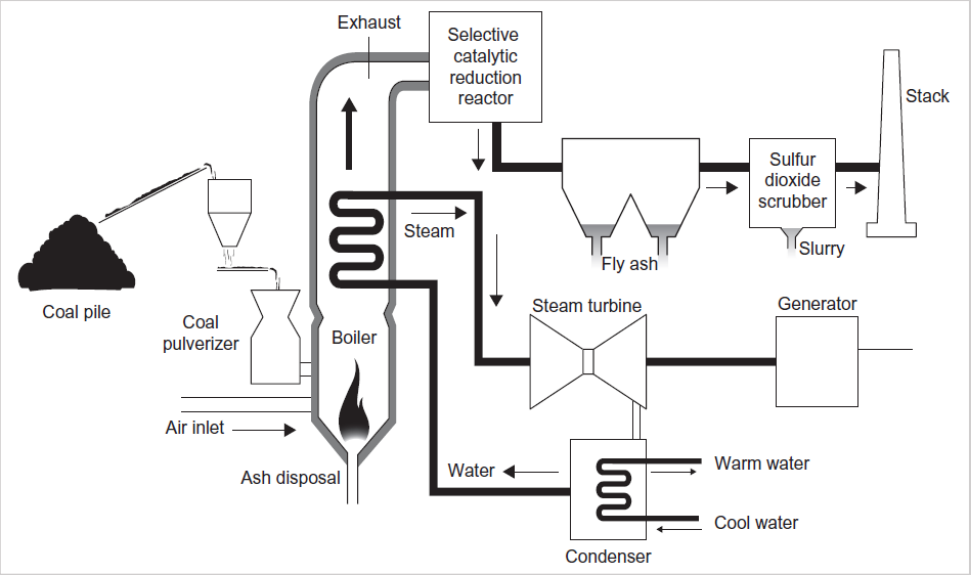

Figure 2 Schematic of a pulverized coal-fired power station.

Next, the coal that has been processed will go through combustion. Coal combustion is a process where coal is burned in a furnace to release energy, which is then used to generate steam. The steam produced from the combustion of coal is then directed to a turbine, which converts the steam energy into mechanical energy that drives a generator to produce electricity (Khaleel et al., 2022). This process is known as a steam turbine cycle and is commonly used in coal-fired power plants.

B. Machine Learning In The Power Generation Industry

As Artificial Intelligence (AI) applications are inspired by the thinking and behaviour of humans and animals to solve problems, machine learning is inspired by the concept of "learning from experience". The algorithm builds statistical hypotheses in the form of mathematical expressions from available data. The hypothesis is then applied to perform prediction or decision making tasks (Lepenioti et al., 2020).

The power generation industry has been increasingly adopting machine learning and artificial intelligence to improve power plant operations' efficiency and reliability. Machine learning techniques, such as neural networks, support vector machines, and decision trees, are able to learn from historical data and make predictions about future events. By applying machine learning algorithms to the vast amounts of data generated by power plants, operators are able to detect anomalies, predict equipment failures, and optimize plant performance. Machine learning can be divided into two: classification and regression. There are fundamentally several established machine learning methods to choose from to solve classification and regression problems.

Choosing the suitable model depends on the objective of its use and the type of data. In the power generation industry, such situations include the prediction of flue gas emissions (Adams et al., 2020), the prediction of overall power plant performance (Hundi & Shahsavari, 2020), and leakage detection in certain areas of concern in power plants (Khalid et al., 2020). Besides modeling numerical data, machine learning, specifically deep learning, also caters to image recognition or object detection. This includes crack detection in pipelines or reactors of nuclear power plants (Chen & Jahanshahi, 2018) and remote sensing of plant emissions through satellite images (Zhang & Deng, 2019).

Several models have been developed to predict power plant performance. These models include empirical models, physical models, and hybrid models. Empirical models are based on a statistical analysis of data collected from the power plant's operating conditions, and they correlate power plant performance with input variables such as coal properties, ambient conditions, and operational parameters (Haddadin et al., n.d.). These models are easy to develop and require minimal computational resources, but they lack physical insights and may not be able to capture complex interactions between different variables. On the other hand, physical models are based on fundamental principles of thermodynamics, fluid mechanics, and heat transfer. They incorporate detailed information about the power plant's design and operating conditions and accurately simulate the power plant's behavior under various scenarios (Kumar et al., 2019). However, physical models require detailed knowledge of the power plant's geometry, material properties, and operational parameters, and they can be computationally expensive. Hybrid models attempt to combine empirical and physical models' strengths by incorporating statistical correlations and fundamental principles. These models can capture complex interactions between variables and provide accurate predictions of power plant performance, while also being computationally efficient (Zhou et al., 2021). However, hybrid models require careful calibration and validation, and they may be sensitive to errors in the input data.

C. Artificial Neural Network and Decision Tree

Artificial Neural Networks (ANNs) have revolutionized the field of machine learning and artificial intelligence. Inspired by the structure and functionality of the human brain, ANNs are powerful computational models capable of learning from data, recognizing patterns, and making predictions. ANNs have found widespread applications in various domains, including image and speech recognition, natural language processing, financial analysis, and predictive modeling.

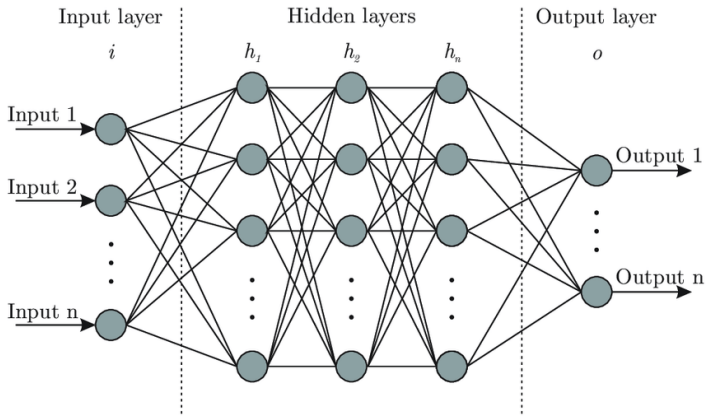

Figure 3 Sample of artificial neural network architecture

The core concept behind ANNs is to mimic the behavior of biological neural networks, which consist of interconnected neurons transmitting information through synapses as in figure 3. Similarly, ANNs comprise interconnected artificial neurons, known as nodes or units, organized into layers. The nodes receive input signals, perform computations, and pass the output signals to subsequent layers. The strength of connections, known as weights, determines the influence of each input on the output (Montesinos López Osval Antonio and Montesinos López, 2022). Through a process called training or learning, ANNs adjust these weights based on observed data to improve their predictive accuracy.

ANNs have been extensively used to predict power plant efficiency, a key performance indicator reflecting the conversion of fuel into electricity. Researchers have developed ANN models that consider various input variables, such as fuel characteristics, environmental conditions, operating parameters, and equipment performance data (Smrekar et al., 2009). These models have demonstrated high accuracy in predicting power plant efficiency, aiding in optimization efforts and energy conservation measures. Heat rate, which represents the amount of fuel required to produce a unit of electricity, is another important parameter in power plant performance assessment. ANNs have been employed to model the complex relationships between heat rate and factors such as steam temperature, pressure, feedwater flow rate, and ambient conditions (Arferiandi et al., 2021). ANN-based heat rate prediction models have shown promising results in capturing non-linear dependencies and achieving accurate predictions, supporting operational efficiency improvements.

Regression analysis is a commonly used statistical technique to predict the performance of coal-fired power plants. It involves developing mathematical models that relate the power plant's output variables, such as power output and efficiency, to input variables, such as coal properties, ambient conditions, and operational parameters. For prediction problems with regression type, DT is one of the suitable models to be used as it offers high accuracy, versatility, and computational efficiency, and it is also robust towards uncertainties (Liu et al., 2013). For over 20 years, DT has been greatly applied

because of these qualities in dealing with large datasets, as it is used to recognize the patterns and extract the features for predictive modeling (Myles et al., 2004). Abided by its name, DT resembles the structure of a tree with many branches and nodes. As illustrated in Figure 4, the starting point of the tree is called the root node, which denotes the first ranked attribute. The arrows pointing out of each node are the branches. Apart from the root node, if a node has branches pointing towards and out of it, it is called an internal node, but if a node has only a branch pointing towards it, it is called a leaf. These leaves carry the end results of a DT model (Song & Lu, 2015). Following this concept, DT can be applied to both classification and regression problems, and for this project, it is used for the latter to handle real, numerical numbers. The idea is to determine the target value and patterns in various branches. Following the root node, each consecutive node directly carries probability and attribute value without the need to perform separate procedures such as group distance calculation and mapping to a higher dimensional space. This simultaneously reduces computation time compared to other machine learning models. According to (Navin & Vadivu, 2015), a few major advantages of DT are that it indirectly performs feature selection, it can handle nonlinearity in data well, and with simple structure and minimal jargon, it is easy to understand and interpret.

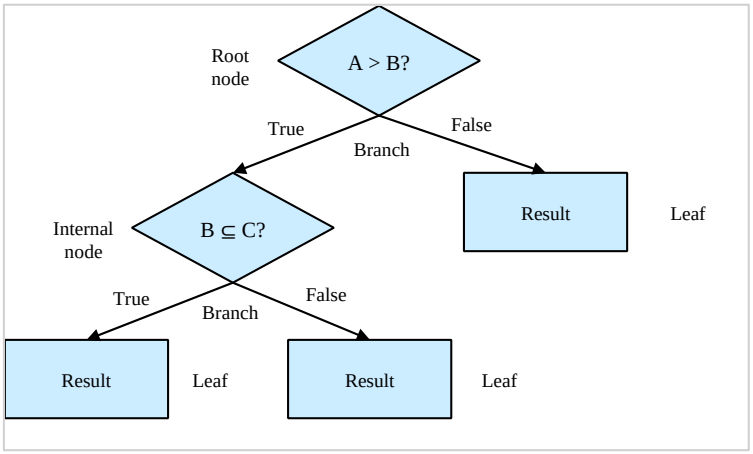

Figure 4 The concept of decision tree

III. RESEARCH MODEL AND RESEARCH QUESTIONS

The motivation behind developing a prediction model for a coal fired power plant in correlation with its coal properties is to provide plant operators with a tool that allows them to optimize the performance of the plant while minimizing the potential for unplanned downtime and maintenance costs. The incoming coal properties can significantly impact the performance of the power plant, and if the plant operators can predict and plan for these impacts, they can adjust the control settings to ensure that the plant continues to operate at optimal efficiency. By developing a prediction model that incorporates the coal properties as a significant parameter, the plant operators can be more proactive in their approach

to plant management, and ultimately improve the overall performance of the power plant. The objective of the research can be summarised as follows:

1. To identify the significant parameters that affect the performance of the plant.

2. To find the best machine learning model that can predict the furnace gas temperature on coal properties and coal-fired power plant operation factors.

3. To improve the performance of the machine learning models developed with hyperparameter optimization.

IV. METHODOLOGY : DATA COLLECTION AND MODEL DEVELOPMENT

The research begins with the Input Phase, where the Problem Statement is identified, and the objectives, scope, and potential impact of the study are determined. This sets the foundation for the subsequent stages.The model development phase commences with data extraction from two sources: pi datalink and coal properties data. The collected data undergoes data pre-processing, where it is cleaned, organized, and prepared for analysis. Data integration ensures that the combined dataset is ready for further processing.

Handling missing data is then addressed to ensure the integrity of the dataset. Following this, features selection is performed to identify the most relevant variables for the analysis, streamlining the subsequent stages. The core of the model development phase involves creating three predictive models: linear regression, neural network, and decision tree. These models are constructed to analyse the data and make predictions based on the selected features.

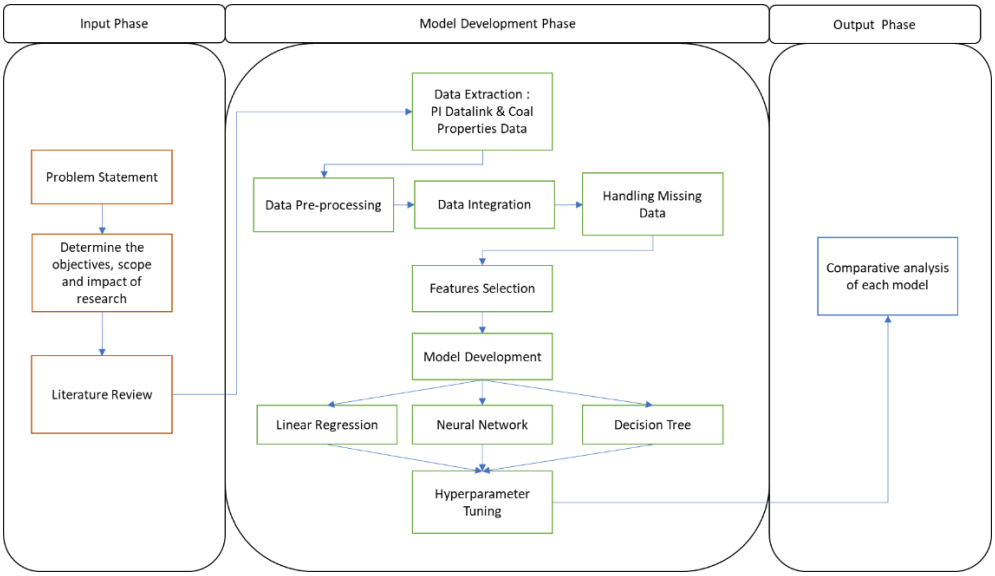

Figure 5 Overall workflow of the research study

In order to improve model performance, hyperparameter tuning is used to fine-tune the model parameters, maximizing their accuracy and efficiency. In the Output Phase, the results from each model are evaluated through Comparative Analysis. This assessment allows for a comprehensive understanding of the strengths and weaknesses of each model, leading to its conclusions. The overall workflows could be simplified in the diagram in Figure 5. A comprehensive feature selection process has been undertaken, reducing the initial set of 100 attributes to a refined subset of 23 attributes.

Table 1 Estimated lower and upper limits of normal parameter condition for the training

Parameters	ID for model	Range	Unit
To forecast and optimize: Furnace gas temperature	FGT	1200 – 1400	°C
Pulverizer outlet temperature	PULVOUTTEMP	55 – 75	°C
Economizer outlet gas temperature	ECOOUTTEMP	375 – 425	°C
Primary superheater inlet steam temperature	PSHINSTMTEMP	395 – 420	°C
Secondary superheater inlet steam temperature	SSHINSTMTEMP	475 – 500	°C
Reheater inlet steam temperature	RHINSTMTEMP	365 – 380	°C
Coal properties: Gross calorific value	COALGCV	4747 – 5997	kCal/kg
Hardgrove grindability index	COALHGI	12.4 – 54	–

Ash	COALASH	0.5 – 5.4	%
Controllable settings: Average coal feed rate	COALFEEDRATE	58 – 90	t/h
Total coal flow	TOTALCOALFLOW	300 – 450	t/h
Pulverizer classifier vane speed	PULVCLSFSPEED	55 – 70	rpm
Pulverizer grinding pressure	PULVGRPRES	6 – 12	MPag
Pulverizer primary air temperature	PULVPRIMAIRTEMP	150 – 270	°C
Overfire air inlet damper	OFAINDMPR	40 – 85	%
Overfire air flow	OFAAIRFLOW	110 – 250	t/h
Economizer inlet temperature	ECOINTEMP	270 – 300	°C
Forced draft (FD) fan damper	FDFDMPR	50 – 70	%
Centrifugal Induced draft (CID) fan damper	CIDFDMPR	70 – 90	%
Flue gas bypass damper	BYPASSDMPR	40 – 100	%
Primary superheater spray water control valve	PSHSPRYWTRCV	0 – 40	%
Primary superheater spray water flow	PSHSPRYWTRFLOW	0 – 50	t/h
Secondary superheater spray water control valve	SSHSPRYWTRCV	20 – 50	%
Secondary superheater spray water flow	SSHSPRYWTRFLOW	30 – 100	t/h
Reheater spray water control valve	RHSPRYWTRCV	0 – 20	%
Reheater spray water flow	RHSPRYWTRFLOW	0 – 20	t/h

In this research study, the development of machine learning models was conducted using the powerful and versatile MATLAB platform. MATLAB's comprehensive set of tools and functions provided a robust environment for model development, data preprocessing, and performance evaluation. Leveraging the Regression Learner app and Neural Network Design tools within MATLAB, we sought to explore regression algorithms and systematically analyze their effectiveness in predicting continuous target variables.

V. RESULTS & DISCUSSION

To optimize an Artificial Neural Network (ANN) using Bayesian Optimization (BayesOpt) within MATLAB, our discussion revolves around a comprehensive understanding of the optimization process and the relevant parameters involved. The purpose of this optimization is to elucidate the iterative optimization approach for tuning two critical hyperparameters of the ANN: the number of hidden layers and the learning rate as in table 2 below.

Table 2 Bayesian optimization result for ANN model

Optimizer	Default Parameter	Bayesian Optimization
Number of hidden layers	10	1
Learning rate	0.01	0.27735
Root Mean Squared Error (RMSE)	65.87	10.9654
R-squared	0.9613	0.9873
Mean Squared Error (MSE)	4340	120.24
Mean Absolute Error (MAE)	56.7843	7.1356

The iterative approach, as depicted in the table, enables the exploration of the hyperparameter space, with the ultimate goal of identifying the optimal configuration that minimizes the objective (e.g., loss or error) of the ANN. Monitoring the convergence of the objective value and the observed and estimated best performance metrics is essential for determining when to terminate the optimization process and select the most suitable hyperparameters for the ANN model. The result of the best optimization value is shown in table 2.

The comparison table illustrates the substantial enhancements achieved through Bayesian Optimization for a neural network model compared to its default parameters. The optimization process led to a remarkable refinement in the model's architecture and performance. Notably, the number of hidden layers was reduced from 10 to 1, simplifying the structure. Additionally, the learning rate increased from 0.01 to 0.27735, potentially enabling faster convergence during training. These alterations resulted in significant improvements across performance metrics: the RMSE dropped from 65.87 to 10.9654, the R-squared increased from 0.9613 to 0.9873, and both MSE and MAE substantially decreased from 4340 to 120.24 and 56.7843 to 7.1356, respectively. Overall, the Bayesian Optimization process successfully fine-tuned the neural network model, greatly enhancing its predictive accuracy and efficiency across multiple evaluation criteria.

We also utilized a default linear regression model to predict the gas temperature of a furnace. Hyperparameter tuning is less common for linear regression compared to more complex machine learning models like neural networks. This is because linear regression is a relatively simple and interpretable algorithm with fewer hyperparameters to tune. However, there are situations where changing the model type to include interactions and robust linear regression can be beneficial. In this

study, we also experimented with models that incorporate interaction terms and robust linear regression, and the results are summarized in the table 3 below.

Table 3. Comparison between different type of linear regression model.

	Linear regression	Robust linear	Interactions linear
Root Mean Squared Error (RMSE)	211.67	212.52	160.17
R-squared	0.23	0.22	0.56
Mean Squared Error (MSE)	44804	45163	25654
Mean Absolute Error (MAE)	171.75	169.71	122.69

The table showcases the comparative performance metrics of three distinct linear regression models: Linear Regression, Robust Linear, and Interactions Linear. The Interactions Linear model stands out with notably superior performance across all metrics. It demonstrates the lowest RMSE at 160.17, signifying more accurate predictions, and the highest R-squared value of 0.56, indicating a better fit to the data compared to the other models. Moreover, the Interactions Linear model also displays the lowest MSE at 25654 and the smallest MAE of 122.69, further solidifying its superior predictive capability and reduced error margins. In contrast, both the conventional Linear Regression and Robust Linear models exhibit slightly higher errors and lower accuracy in prediction when compared to the Interactions Linear model across all the evaluated metrics.

A decision tree model was trained and evaluated with the default parameters, and the following performance metrics were obtained as in table 4. The model's hyperparameters were optimized to further enhance its predictive capabilities. The hyperparameters that were tuned include the ensemble method, number of learners, minimum leaf size, and number of predictors as in Figure 6. The ensemble method was chosen from the options of bagging and LSBoost, and bagging was selected as the optimal

method. The number of learners ranged from 10 to 500, while the learning rate varied from 0.001 to 1. The minimum leaf size ranged from 1 to 49501. The search parameters are summarized in Table 4.8.

Table 4 Default and optimized Hyperparameter for decision tree model

Optimizer	Bayesian Optimization	Default Parameter
Ensemble method	Bag	Bag
Number of Learners	48	30
Minimum leaf size	1	8
Root Mean Squared Error (RMSE)	4.8571	6.8976
R-squared	1	1
Mean Squared Error (MSE)	23.5914	47.577
Mean Absolute Error (MAE)	1.8623	2.5367

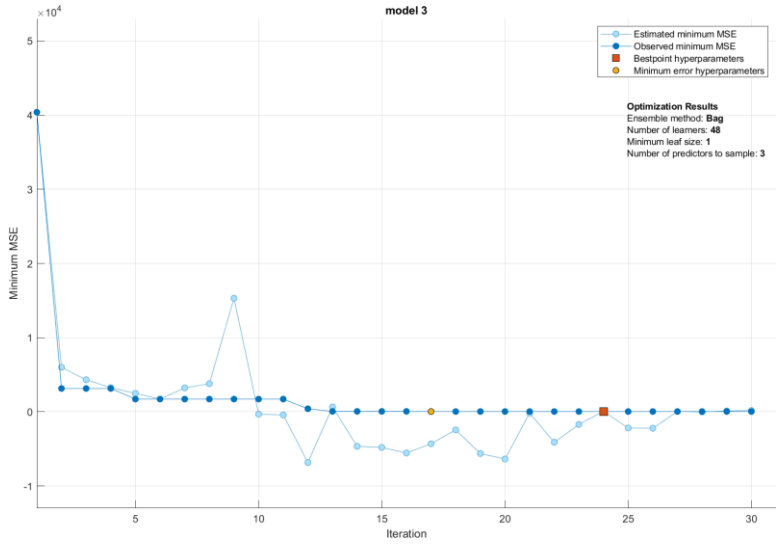

Figure 6 Hyperparameter tuning optimization with decision tree algorithm result

To optimize these hyperparameters, a Bayesian optimization technique was employed. Bayesian optimization is a method that iteratively explores the hyperparameter search space by evaluating different combinations of hyperparameters and selecting the set that maximizes the model's performance. We can see the progress of the optimization in Figure 6 on the number of iteration to find the lowest error.

The optimization process involved 30 iterations, with the primary goal of reducing RMSE through hyperparameter tuning. Notably, at the 17th iteration, the optimization process yielded its most favorable outcome, with a minimum RMSE of 4.8571. This indicates that the Decision Tree model, configured with the hyperparameters determined at this iteration, achieved the highest level of accuracy in predicting the target variable. The results demonstrated an exceptional goodness of fit, as evidenced by an R-squared value of 1.00, suggesting that the model explained all the variance in the data. This indicates a perfect fit of the Decision Tree model to the observed data. The RMSE value of 4.8571 signifies the root of the average squared differences between predicted and actual values and serves as an indicator of prediction accuracy. The relatively low RMSE and other favorable metrics, such as the MSE and MAE, obtained through the hyperparameter optimization process indicate that the Decision Tree model is well-suited for the specific task under consideration. Overall, the decision tree model with an optimizable ensemble approach demonstrated strong predictive capabilities for estimating the furnace gas temperature as shown in table 4.

To test the accuracy of a model built using decision tree, artificial neural network (ANN), or regression, you can compare the predicted values with the actual values from the test dataset. One common metric to evaluate the performance of a regression model is the percentage difference between the predicted and actual values, which can be calculated using the following formula:

Percentage Difference = (|Actual Value - Predicted Value| / Actual Value) * 100

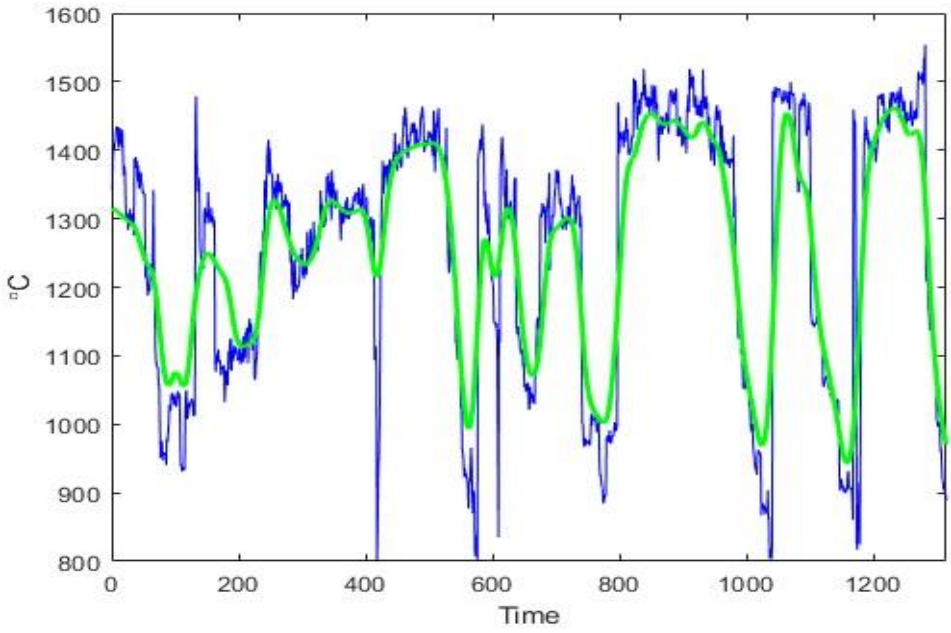

Figure 7 Predicted vs actual graph of the furnace gas temperature from the Decision Tree model.

Table 5 Accuracy of each algorithm after hyperparameter tuning

Algorithm	Hyperparameter Tuning	Accuracy (100 - % diff)	RMSE	MSE	MAE	R-squared
Decision Tree	Bayesian Optimization	89.26	4.8571	23.5914	1.8623	1.00
Artificial Neural Network	Bayesian Optimization	88.21	10.9654	120.24	7.1356	0.9873
Linear Regression	Interaction Linear	68.5	160.17	25654	122.69	0.56

The accuracy values provided represent the performance of different models in predicting furnace gas temperature shown in Table 4.10. The artificial neural network (ANN) model achieved an accuracy of 88.95% (difference) in predicting the furnace gas temperature. ANN is a machine learning model inspired by the human brain's neural network. It consists of interconnected layers of artificial neurons, also known as nodes, and can learn complex patterns in the data. The accuracy achieved by the ANN model indicates that it was effective in capturing the underlying patterns in the furnace gas temperature data.

The linear regression model achieved an accuracy of 68.5% (difference) in predicting the furnace gas temperature. Linear regression is a simple and widely used algorithm for predicting continuous values. It establishes a linear relationship between the input features and the target variable. The lower accuracy of the linear regression model suggests that it may not have captured the complex non-linear relationships present in the furnace gas temperature data as effectively as the other models.

Decision Tree model achieved an accuracy of 89.26% (difference) in predicting furnace gas temperature. Decision trees are a popular algorithm for both classification and regression tasks. They work by recursively partitioning the data based on different feature values and creating a tree-like structure to make predictions. The high accuracy suggests that the decision tree model performed well in capturing the patterns and relationships in the furnace gas temperature data.

VI. CONCLUSION

The comparative analysis of Decision Tree algorithm has the highest accuracy for the furnace gas temperature model, with a percentage difference of 89.26%. The Artificial Neural Network follows closely with an accuracy of 88.95%. On the other hand, Linear Regression has a significantly lower accuracy of 68.5%. The Decision Tree algorithm demonstrates the highest level of accuracy in predicting furnace gas temperature compared to the other two models. This indicates that the decision tree's ability to create a hierarchical structure of rules and conditions based on the available data has proven effective in capturing the patterns and relationships within the furnace gas temperature dataset.

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