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Original Article

Monitoring and Prediction of Boiler Refractory Failure by Remote Refractory Failure Detection and Temperature Pressure Monitoring System an Artificial Intelligence-based System Using Machine Learning

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***Abstract** - Energy management is a crucial issue nowadays because the global energy demand is increasing day by day, and there are limited resources of energy available worldwide. The study utilized Internet of Things (IoT) devices to investigate cracks and hot spots of failed structures to understand and address the problem. Refractory materials constitute an integral element in industries involving high-temperature applications, such as furnaces, kilns, and reactors. Mechanical failure of these refractories in the said applications could result in large-scale disasters, including personnel hazards, costly downtime, and economic inefficiency in operations. This work constitutes research into the integration of various techniques in IoT applied to the early detection of refractory material failure. We have made the Smart system, which helps small-scale industries to identify energy loss and early detection of any fault in refractory. The system is based on the concept of artificial intelligence machine learning. It detects any fault in the boiler furnace, and we can also identify any significant heat/energy loss in the furnace. We used an artificial intelligence-based supervised machine learning algorithm and Python program to detect defects in refractory materials. The supervised data was collected over 21 months from the Thermax boiler furnace. This expert system will also reduce the inspection of periodic and frequent boiler plant shutdowns due to periodic checking and inspections. This smart system also avoids major boiler-exploding incidents and accidents in small-scale industrial plants.*

***Keywords** - Industry Innovation & Infrastructure, Energy loss, Refractory failure, Artificial intelligence based supervised Machine Learning, Energy management using the Internet of Things.*

1. Introduction

Refractories represent heat-resistant ceramic materials that line furnaces, kilns, converters, and other high-temperature vessels. The most common types of refractory materials are castable, flexible and relatively easy to apply- and shaped products, in the form of bricks, for example. In all, about 40% of consumed refractory materials are castable [1]. Modern materials make castable popular because they can have low porosity and be highly resistant to corrosion and heat. The more traditional types of castable, containing a higher amount of calcium aluminate, are much more porous and less durable. [3] Adding materials such as magnesia or silicon carbide may improve properties such as thermal shock and wear resistance. Refractory linings may be installed on-site or pre-fabricated into complex shapes. These materials withstand extreme temperatures and conditions and are subject to degradation over time, which could lead to operational failure under some circumstances. Traditional maintenance strategies, reliant on inspection and repair, may not be satisfactory in preventing such failures. IoT technology offers a solution in which refractory issues can be continuously monitored in real-time and identified early. This indicates the ability to improve industrial operations before problems could lead to significant failures. This paper discusses the process and methods of IoT system implementation using machine learning prediction features for early fault detection in refractory systems [6].

In this paper, we discuss our experiment with the possible ways of increasing the accuracy by applying various machine learning algorithms. Then, we developed a model for predictive refractory failure based on time series data. We then compare the performance of the following algorithms: Linear Regression, Logistic Regression, and Support Vector Machine. Our experiments show that Linear Regression got an average prediction accuracy of 90%, beating all the other algorithms. [7] That indicates that our approach is highly effective in predicting potential refractory failures.

2. Deficiency of Existing System, Scope and Gaps for Innovative Research Idea

The research aims to create better refractory materials; however, the current developments are pretty expensive and far beyond the reach of small-scale industries. The periodic inspection and maintenance of these materials and boiler plants require much time and, quite frequently, are done by ceasing operations one or two days, negatively affecting profitability and productivity for smaller operations. Convenient methods are still being developed to replace these inspections or to avoid plant shutdowns.

3. Energy Consumption Pattern and Losses in Induction Furnace

Figure 1 shows in detail how the total energy put into an induction furnace is expended and lost as it operates. The total supply of energy, which is symbolized as 100%, is the entire measure of energy that is supplied to the furnace so that it operates; this total energy, approximately 80%, is utilized to a productive extent towards the main utilization of the furnace, e.g., melting metals and the provision of necessary temperatures. This amount is termed "useful energy" since it is directly in proportion to the operation of the furnace.

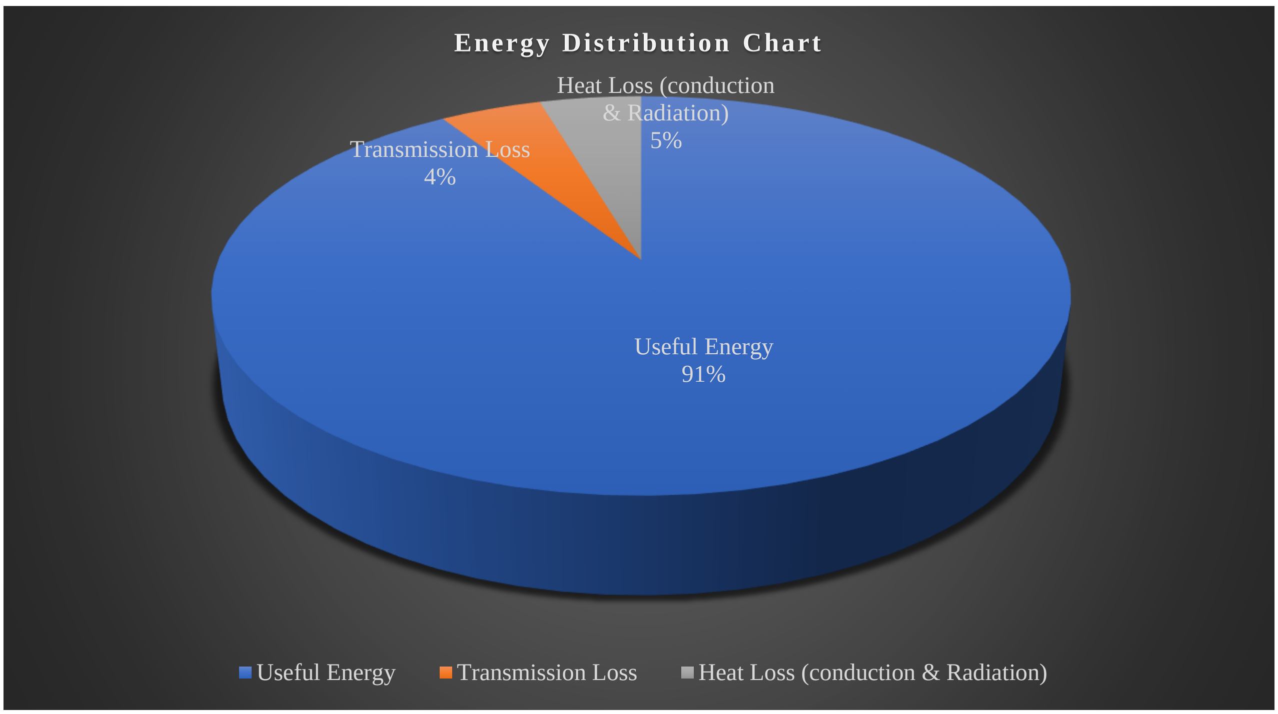


Fig. 1 Energy consumption pattern and losses in induction furnace

3.1. Energy Distribution

Total Energy Input = 100%

Category	Percentage (%)
Useful energy output	80%
Transmission loss	3–5%
Heat loss (conduction & radiation)	3–4%
Total losses (approximate)	6–9%

But all the energy is not utilized effectively. Approximately 3-5% of energy is lost as it is transmitted. This transmission loss occurs when energy is being passed through wires or cables, and some of it does not reach the furnace effectively. Moreover, an additional 3-4% of the energy is lost in the form of heat through conduction and radiation through the insulation lining of the furnace or the refractory.

The furnace loses heat by two major processes: conduction, where heat travels through the insulating material, and radiation, where heat energy is released in the form of infrared rays. While the induction furnace supplies 100% of the energy, only roughly 80% is utilized for its intended application. The rest of the energy is wasted through transmission inefficiencies and heat dissipation via the insulation of the furnace.

4. IoT Components of a Remote Refractory fault detection and Temperature monitoring system for Early fault Detection of refractory

IoT-based remote refractory fault detection and temperature monitoring systems would generally consist of sensors, a data acquisition unit, remote data connectivity modules, cloud-based data storage and analysis, and user interfaces for real-time monitoring, as shown in Figure 2. Edge computing, machine learning, and actuators can be added optionally to push the system's capabilities to the next level for predictive maintenance and fault detection. This combined system assists in detecting potential problems ahead of time, avoiding expensive failures and prolonging the life of the furnace refractory lining [34, 35].

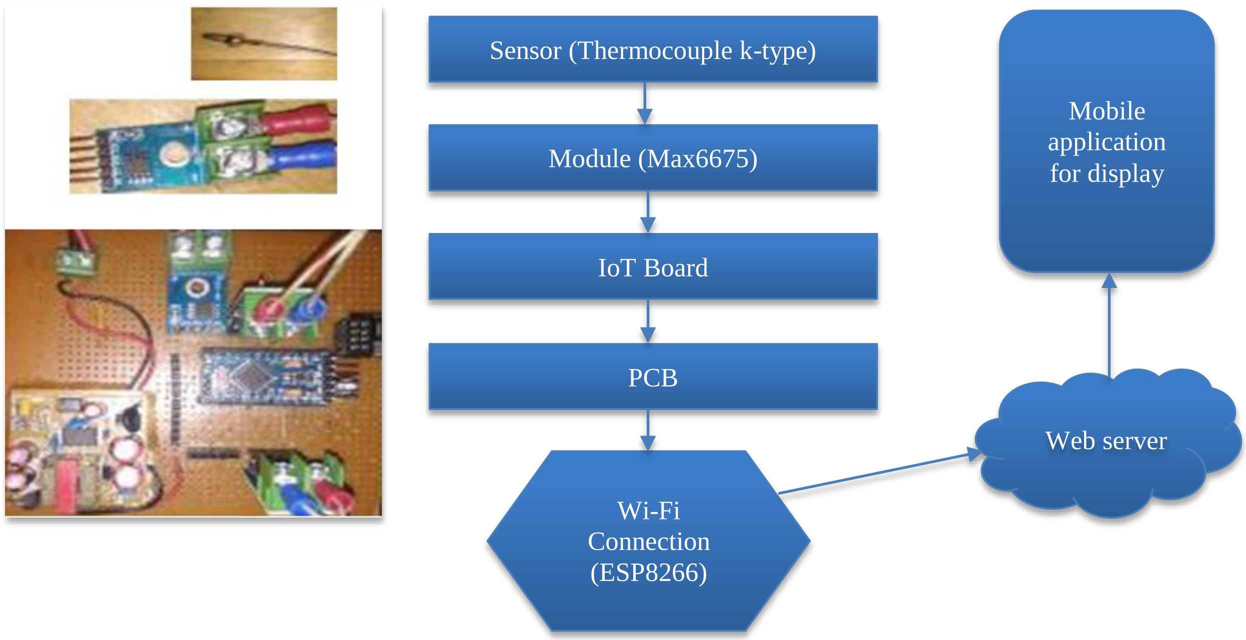


Fig. 2 IoT components of a remote refractory fault detection and temperature monitoring system for early fault detection of refractory

5. Methodology

This work aims to develop a prediction model that can predict possible failure of refractory in a high-temperature mechanical wear rupture. We initially adopted a time-series modeling approach because the failure occurred over five years. We identified a model for the compounded failure dataset extracted from the computer failure database repository [17]. The data is a collection of failures recorded over a given period of approximately 21 months. From the data set, we were experienced to visualize the time stamps of the specific refractory failed (output), without the sources of the failure (input). Therefore, we have no option but to apply a time series as each failure was recorded at a regular interval at different points over time [11]. We defined and identified our problem as a multiclassification problem, which requires some prediction to enable us to identify specific components like refractories that will fail in the future. We prepared and transformed our data, applied some supervised learning algorithms, and performed a comparison among them [13, 14]. We evaluated our algorithms and improved our results by selecting the best algorithm based on performance and accuracy. The skit-learn package in Python was deployed to provide an interface into several machine learning algorithms and useful convenience methods for data visualization, data sampling, and model tuning [15, 16]. However, we decided to diversify the methodology by deploying three different ML algorithms: Linear Regression, Logistic Regression, and Support Vector Machine.

5.1. Data Collection

A historical dataset on refractory failure for a period of 21 months starting from the year 2021–2023 was Collected [13]. The data was collected to provide failure specifics for I/O-related information and components in as much detail as possible so that data analysis might produce some useful findings. Data were collected and stored in networking and computational IoT systems [11].

5.2. Our proposed prediction Model is Divided into Three Steps

5.2.1. Data Pre-Processing Step

The dataset [13] constituted an output variable representing the month of failed refractory. We need to incorporate the input variables into the dataset to apply supervised machine learning algorithms. We obtained the input variables from the experimental observation using a remote refractory fault detection temperature pressure monitoring system where the data used was extracted from the same domain [11, 12]. To apply supervised machine learning algorithms, we need to incorporate the input variables into the dataset. We obtained the input variables from the study in [20], where the data used was extracted from the same domain. We deployed combinatorics analysis and allocated the possible combinations of sources of system component failure to the output variables [21, 22].

5.2.2. Training Step

When the appropriate design is chosen, parameter estimation is the following course of action: employing least squares, maximum likelihood, or method of moments. After estimation, validating the accuracy of a model becomes vital. Even though it is known that no model is exactly right, some may display greater accuracy than others. To illustrate, one would look at the model's residuals to examine their standard distribution and randomness, which aids in validating the model.

5.2.3. Prediction Step

In this step, the above model is used to produce forecasts for the future. To check if the residuals of the model, estimated by running the regression, really look like noise, that is, random and not showing any known trend.

6. Calibration of Artificial Intelligence based System

The setup compares the temperature readings of two devices, namely HTI IR-850 Infrared Thermometer versus Arduino System with a MAX6675 module and K-type thermocouple. The experiments are conducted in a controlled environment to ensure the temperature is always uniform. For accuracy, standard deviation, and standard error computation, both devices' readings are computed. After that, it will be deduced whether a performance difference exists between the devices using ANOVA. A program removes errors and noise due to deviation greater than +/-0.3 and errors more than +/-5.0% to correct any difference. The "best fitting value" is taken as an average of the differences between the readings of the two instruments for stabilized data that could help identify the most accurate temperature readings.

7. Refractory Failure Prediction using Machine Learning Model

This Predictive machine learning model employs regression algorithms and machine learning to forecast early refractory failure by predicting different variables that may impact refractory lifetime. Refractory failure generally occurs due to elevated temperatures and heat transfer pathways, so their anticipation is valuable in maintenance work to prevent loss of time for industrial processes [4, 5].

Problem Setup:

We have developed the predictive model to predict when refractory failures are likely to happen based on several inputs like- Temperature, Furnace area, Refractory material properties such as thermal conductivity, Material type, Insulator thickness, Amount of heat loss, Ambient temperature, Emissivity (thermal radiation emission ability) and Heat transfer mechanism (conduction, convection, and radiation)

By Utilizing previous observations of such variables as a source of previous data, the model attempts to forecast when the failures are likely to occur in upcoming situations [18,19].

Step-by-Step Procedure of the Predictive Model:[19]

1. Linear Regression Setup

The model suggests a linear association between two variables: x (predictor variable) and time period (in months). y (response variable): Temperature. The linear equation used to describe this relation is:

$$y=mx+cy = mx + cy=mx+c$$

Where m is the slope of the line (temperature changes with respect to time), c is the intercept (the temperature at the time).

2. Model Training

Randomly give values for the slope (m) and intercept (c). Based on these values, the model calculates temperature ($\hat{y}$) for any given time interval (x).

3. Model Evaluation

In order to verify the precision of the forecast, the model computes residual error (actual temperature minus predicted temperature) as a standard measurement named Mean Squared Error (MSE). It assists in learning the precision of the model to fit the data. MSE is computed by:

$$L=n1i=1\sum n(yi-yi\hat{})2$$

Where:
n denotes the observations.
yi refers to the actual temperature.
$\hat{y}$I represents the predicted temperature.
The smaller the MSE, the better the model.

4. Statistical Correction for Variables

The objective function calculates a more accurate error measure using the residual mean square (RMS) for the selected independent variables. A formula calculates the correction factor (CF) to adjust the performance of the model using the number of observations (N) and independent variables

$$(F): CF=(N-F-1)(RMS)+(F+1)$$

This adaptation helps refine the model to such an extent that it will not overfit or underfit the data.

The main goal of the model is to use machine learning regression algorithms to accurately forecast refractory failures. The model facilitates proactive interventions and efficient maintenance scheduling by estimating the time and circumstances under which a failure is likely to occur. By anticipating refractory failures, this technology serves as a predictive maintenance solution. Its deployment improves operational efficiency and reliability by facilitating appropriate scheduling and averting unscheduled downtimes in industrial processes.

8. Successful Implementation of IoT Based Remote Refractory Fault Detection and Temperature Monitoring System and Zone-Wise Data Collection

For industrial settings with high temperatures, deploying an Internet of Things (IoT) based remote refractory failure detection and temperature monitoring system with zone-wise data collecting is a breakthrough. The purpose of this system is to improve safety and operational efficiency by guaranteeing the early detection of defects in refractory materials used in furnaces, kilns, or comparable equipment. It uses various high-temperature sensors, including stress/strain sensors, infrared sensors, and thermocouples, to keep an eye on important parameters. These sensors are positioned strategically throughout the equipment's designated zones to ensure thorough coverage and in-depth analysis.

IoT gateways gather information from these sensors and safely send it to a cloud-based platform for analysis in real-time. Predictive maintenance and less downtime are made possible by sophisticated machine learning algorithms that analyze the data to find patterns suggesting possible problems. Additionally, zone-wise data visualization is made possible by the cloud platform, giving operators a user-friendly interface for tracking temperature changes and system health. Any irregularities automatically trigger alerts and messages, enabling prompt remedial action.

The prevention of refractory failures, optimal temperature maintenance, increased operating efficiency, and substantial cost savings through the implementation of data-driven maintenance programs are just a few advantages of this technology.

This system is a flexible tool for contemporary industrial operations since it can be accessed remotely, enabling personnel to keep an eye on machinery from any location. The effectiveness and ease of adoption of this system are dependent on several factors, including a user-friendly interface, dependable communication protocols, accurate data processing algorithms, and a strong sensor selection.

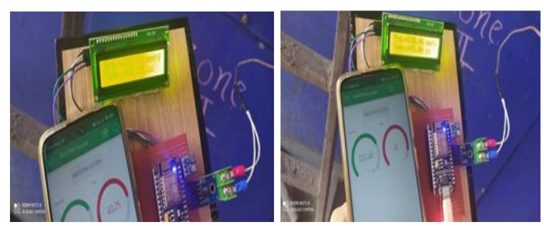


Fig. 3 Successful implementation of IoT-based system and zone-wise data collection

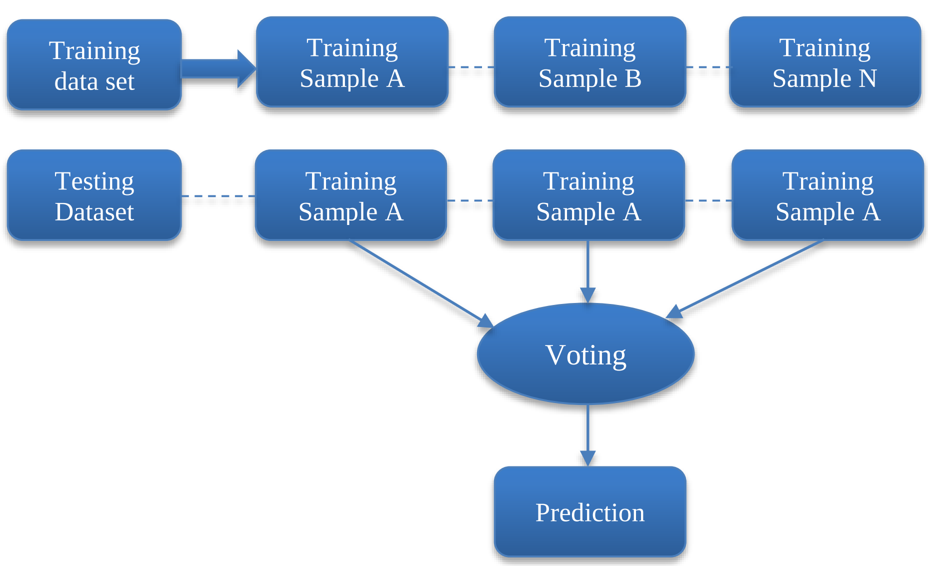


Fig. 4 Methodological flow diagram of predictive machine learning model

9. Methodological Flow Diagram of Predictive Machine Learning Model

The sequential steps required to create and implement a successful machine learning system are described in the methodological flow diagram for a predictive machine learning model. The first step in the process is data collection, which involves gathering pertinent information from multiple sources to make sure it accurately reflects the problem domain. The raw data is then cleaned and transformed during the data preprocessing step, addressing problems like duplicates, missing values, and inconsistencies [31]. In order to reduce dimensionality and increase model efficiency, feature selection is then carried out to determine the most important features that affect the target variable. With a focus on hyperparameter tuning, the best approach is selected during the model selection phase, taking into account the kind of problem (e.g., classification, regression, or clustering) [32, 33]. The preprocessed data is sent into the chosen algorithm during the model training phase, enabling it to discover patterns through iterative optimization methods. To ensure the model is effective, it is evaluated using measures like accuracy, precision, recall, or mean squared error after training. To enable real-time or batch processing predictions, the model is finally integrated into a production environment during the deployment phase. Performance is continuously monitored to ensure optimal performance. The iterative aspect of the process is shown by the flow diagram, which permits feedback loops for model improvement and refining at different phases.

10. Statistical Calculations: Regression Analysis for Zone 1

Regression analysis is a very powerful statistical modelling technique employed to investigate the relationship between two variables, which are usually referred to as independent variable (X) and dependent variable (Y). [23] Independent variable X here refers to the months (April 2022 to December 2023), and the dependent variable Y refers to the temperature in Zone 1. Regression analysis is done to predict Y's value from known values of X and to understand the patterns within the data [8, 9]. The data provided consists of temperature measurements for 21 months, beginning with April 2022 and continuing through December 2023 [10]. For each month, the measurement for both the independent variable (Month/Year, X) and dependent variable (Temperature, Y) is taken [8,10]. Preparation for regression analysis involves generating some additional columns as follows:

1. X−MxX - M_xX−Mx: Each value of X minus its mean, Mx.
2. Y−MyY - M_yY−My: Deviation of each Y value from its mean, My.
3. (X−Mx)2(X - M_x) ^2(X−Mx)2: Deviations of the X values squared.
4. (X−Mx) (Y−My) (X - M_x) (Y - M_y) (X−Mx) (Y−My): The deviations of the X and Y values multiplied together. We can see that with time, Zone-1 temperature seems to increase steadily, showing a likely linear relationship between temperature and months [23, 24].

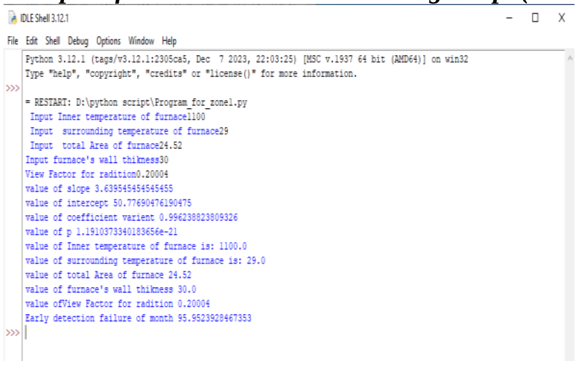
10.1. Statistical Calculations

Mean of X (MxM_x): The average of the months' values.
Mx=∑XN=1+2+⋯+2121=11M_x = \frac {\sum X} {N} = \frac {1 + 2 + \cdots + 21}{21} = 11Mx=N∑X=211+2+⋯+21=11
Hence, the mean of X is 11, which is the middle point of the time interval given.
Mean of Y (MyM_y): The average temperature for the 21 months.
My=∑YN=53.25+58.95+⋯+123.2521=88.75M_y = \frac{sum Y}{N} = \frac{53.25 + 58.95 + 123.25}{21} = 88.75My=N∑Y=2153.25+58.95+⋯+123.25=88.75
Therefore, the mean of Y is 88.75.
Sum of Squares (SS) and Sum of Products (SP)
Sum of Squares (SS): The total of the squared deviations of X, which is the measure of variability in the independent variable.
SS=∑(X−Mx)2SS = sum (X - M_x)^2SS=∑(X−Mx)2
the variation of X values is summated as Total SS is 770
Sum of Products (SP): The summation of the product of the deviation of X and Y.
SP=∑(X−Mx)(Y−My)SP = sum (X - M_x)(Y - M_y)SP=∑(X−Mx)(Y−My)
Here, the summation SP is 2802.45,
Regression Line Calculation
To calculate the linear relation between X and Y, we use the equation of the regression line:
Y=a+bXY = a + bXY=a+bX
Where:
b is the slope of the regression line, and it is calculated as:
b=SP/Sb = {SP}{SS}b=SSSP
Substituting the values for SP and SS:
nb=2802.45770=3.64b = 2802.45/770 = 3.64b=7702802.45=3.64
a is the y-intercept, which can be determined as:
na=My−bMxa = M_y - bM_xa=My−bMx
Thus, the regression equation Y=48.71+3.64XY = 48.71 + 3.64XY=48.71+3.64X suggests that for each month that passes, the temperature in Zone-1 increases by approximately 3.64 units. The constant term a=48.71a = 48.71a=48.71 represents the expected temperature when X=0X = 0X=0, which is purely theoretical, as the months in the data begin from X=1X = 1X=1. However, this intercept gives us an understanding of the base temperature from which changes are measured.

The positive slope (b=3.64b = 3.64b=3.64) indicates a direct relationship between time and temperature in this region. As the month's progresses, the temperature consistently rises, reflecting a warming trend in Zone 1 [25, 26].

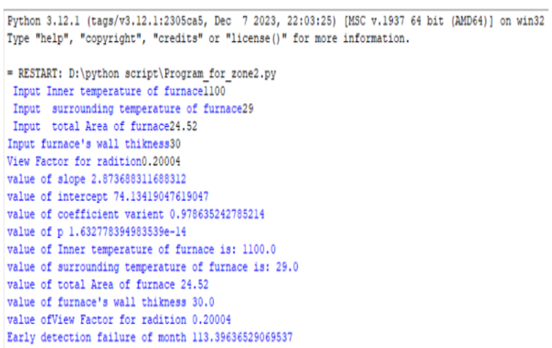
Thus, the regression analysis of the given data for Zone-1 demonstrates a strong linear relationship between the passage of time (months) and the temperature. The regression equation Y=48.71+3.64XY=48.71 + 3.64XY=48.71+3.64X accurately captures this relationship and can be used to predict temperatures for future months [27, 28]. The calculations for SS and SP also verify the strength of the correlation, as the sum of products is far greater than the sum of squares, which indicates a strong correlation. [28] We applied this same calculation to zone-2 and zone-3 using simultaneous data obtained from the company. This analysis can be valuable for making long-term temperature trend insights and making sound decisions in the realm of climate science or urban planning.

10.2. Output of Predictor Machine Learning Script (Zone-1)



```
IDLE Shell 3.12.1
File Edit Shell Debug Options Window Help
Python 3.12.1 (tags/v3.12.1:2305ca5, Dec  7 2023, 22:03:25) [MSC v.1937 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
= RESTART: D:\python script\Program_for_zone1.py
 Input Inner temperature of furnace1100
 Input  surrounding temperature of furnace29
 Input  total Area of furnace24.52
Input furnace's wall thikness30
View Factor for radition0.20004
value of slope 3.639545454545455
value of intercept 50.77690476190475
value of coefficient varient 0.996238823809326
value of p 1.1910373340183656e-21
value of Inner temperature of furnace is: 1100.0
value of surrounding temperature of furnace is: 29.0
value of total Area of furnace 24.52
value of furnace's wall thikness 30.0
value ofView Factor for radition 0.20004
Early detection failure of month 95.9523928467353
>>>
```

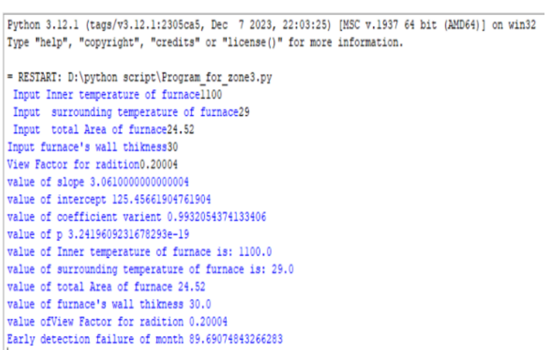
10.3. Output of Predictor Machine Learning Script (Zone-2)



```
Python 3.12.1 (tags/v3.12.1:2305ca5, Dec  7 2023, 22:03:25) [MSC v.1937 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.

= RESTART: D:\python script\Program_for_zone2.py
 Input Inner temperature of furnace1100
 Input  surrounding temperature of furnace29
 Input  total Area of furnace24.52
Input furnace's wall thikness30
View Factor for radition0.20004
value of slope 2.873688311688312
value of intercept 74.13419047619047
value of coefficient varient 0.978635242785214
value of p 1.632778394983539e-14
value of Inner temperature of furnace is: 1100.0
value of surrounding temperature of furnace is: 29.0
value of total Area of furnace 24.52
value of furnace's wall thikness 30.0
value ofView Factor for radition 0.20004
Early detection failure of month 113.39636529069537
```

10.4. Output of Predictor Machine Learning Script (Zone-3)



```
Python 3.12.1 (tags/v3.12.1:2305ca5, Dec  7 2023, 22:03:25) [MSC v.1937 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.

= RESTART: D:\python script\Program_for_zone3.py
 Input Inner temperature of furnace1100
 Input  surrounding temperature of furnace29
 Input  total Area of furnace24.52
Input furnace's wall thikness30
View Factor for radition0.20004
value of slope 3.0610000000000004
value of intercept 125.45661904761904
value of coefficient varient 0.9932054374133406
value of p 3.2419609231678293e-19
value of Inner temperature of furnace is: 1100.0
value of surrounding temperature of furnace is: 29.0
value of total Area of furnace 24.52
value of furnace's wall thikness 30.0
value ofView Factor for radition 0.20004
Early detection failure of month 89.69074843266283
```

11. Validation

For all three zones, predictions of failure were conducted by various means:

Zone-1: Failure was predicted at 106 months manually and 96 months based on statistical calculations using experimental data. By employing the experimental setup data with a Predictive model script predictor, the failure was predicted to be at about 96 months.

Zone-2: Failure was predicted by manual inspection at 125 months, statistical calculation provided an estimate of 114 months, and the Predictive model script prediction was approximately 114 months.

Zone-3: Failure was predicted manually at 98 months, statistical calculation estimated 90 months, and the Predictive model script estimated the failure at approximately 90 months. The Predictive model script-based predictions for all the zones were extremely close to the statistical calculation estimates.

S. No.	Manual inspection	Statistical calculation using experimental setup data	Using Predictive model
Zone-1	106 Months	96 Months	95.95(approximate 96 Months)
Zone-2	125 Months	114 Months	113.39(approximate 114 Months)
Zone-3	98 Months	90 Months	89.69(approximate 90 Months)

12. Results and Discussion

Two techniques were used to anticipate failure for every zone: manual inspection and the Remote Real-Time Failure Detection and Prognostics Monitoring System, or RRFDTPMS. Wood-fired fuel was used in every zone, and both systems recorded the mean temperature and the quantity of hotspots seen for analytical purposes [29, 30].

Zone-1: The RRFDTPMS predicted failure at 96 months, but the manual examination anticipated it at 106 months. The manual inspection revealed that the peak temperature was 449.77°C, although the RRFDTPMS averaged 400.16°C. Their individual hot spot number detection values were not significantly impacted by this temperature variance. Six hotspots were identified by both RRFDTPMS.

Zone-2: Manual examination yielded a forecast of 125 months, but RRFDTPMS predicted failure at 114 months. This zone's average temperature, as determined by RRFDTPMS, was 401.73°C, which was greater than Zone 1 but lower than the manual inspection's 449.77°C. Similar to Zone 1, six hotspots were detected by both systems.

Zone-3: Manual inspection projected 98 months of failure, but RRFDTPMS predicted 90 months. Both the manual inspection and RRFDTPMS recorded an average temperature of 449.77°C and 400.94°C, respectively. Interestingly, this zone had seven hotspots detected by RRFDTPMS, one more than the six found in Zones 1 and 2.

The data shows a common pattern throughout the three zones where the RRFDTPMS failure prediction was lower than the estimations from manual inspection. This suggests that RRFDTPMS might be offering a more cautious prediction model. The temperature readings also show a clear difference between the two approaches, with hand examination regularly registering higher average temperatures. This can result from possible restrictions or a calibration difference between the two systems. Six hotspots each in Zones 1 and 2 and seven in Zone 3 were among the rather uniform number of RRFDTPMS hotspots found in all zones. The shorter failure prediction timeframe in Zone 3 is responsible for the higher number of hotspots found there, highlighting the significance of hotspots in overall failure prognosis. In conclusion, it appears that RRFDTPMS predicts failures more promptly, which may allow for earlier intervention. The validity of field temperature monitoring is questioned by the higher temperature readings obtained via visual inspection, which also suggests that further calibration or research may be required. The same number of hotspots were discovered by both methods, confirming the usefulness of this indication in failure prediction.

13. Conclusion

The IoT-based remote refractory fault detection and temperature monitoring system showed a higher ability to forecast early refractory failures, according to a comparison between experimental data and manual examination. Interestingly, of the three zones found, the third zone was the most susceptible, with a higher likelihood of early failure compared to zones one and two. Its closeness to structural joints and openings-areas naturally prone to weakness—is the main cause of this increased danger. Its criticality was further highlighted by the third zone's noticeably higher frequency of hot spots. These results demonstrate how IoT-based approaches have revolutionized predictive maintenance, bringing about a change in industrial tactics. Organizations may proactively mitigate future failures, prevent catastrophic disruptions, significantly save maintenance costs, and maximize operational efficiency by utilizing real-time data and powerful predictive analytics. This innovation represents a paradigm shift in developing industrial management and maintenance techniques.

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