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Anomaly Detection of Furnace Gas Valve Health Operation using Data Science in HSM, Tata Steel Ltd.

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Abstract: Hot strip Mill at Tata Steel Jamshedpur has three walking beam type reheating furnaces where the slabs are uniformly heated up to the target dropout temperature. The process automation architecture of the furnace consists of a combustion control system (Level1) and a math model-based process automation system (Level2). The Level2 system calculates the optimal set points for the combustion control system,and it linked with PI control of Level1 to control the furnace environment temperature through operating of furnace gas valve by mixing of air and gas.Burner places strategically place on furnace roof and walls to get evenly heated slabs. Heat is transferred to steel stock through mainly by means of convection and radiation from the burner gases and furnace walls.The percentage of valve open or close depend on the demand of temperature by furnace toheating ofslabs. The valveshealth condition monitoring is highly desirable for smooth running of furnaces and maintaining the uniform temperaturebecause in day-to-day operation, valve operating condition is deteriorating or throttle due to scale generation in reheating process. It is unpredictable to execute the maintenance and cleaning of valves on time and no system placed to identify the health of valve condition. Maintenance of valves is being done after failure or in caseof issue in furnace environment temperature.

Developed the system using Machine Learning approach to identify the early detection of health of gas valves conditioni.e., anomaly detection of gas valves operation in reheating furnaces.

This paper presents a method for finding anomalies and early warning ingas valve operation in furnaces by an application of Unsupervised Machine Learning – Isolation Forest. Our approach is to use historical data of each gas valve opening and gas consumption by each valveof respective zone of furnace.

Keywords: Furnaces, Slabs, Gas Valve, Temperature, Machine Learning, Isolation Forest, Anomaly Detection.

1. Introduction

Hot Strip Mill (HSM) at Tata Steel Jamshedpur is producing Hot Rolled Coil. In HSM, reheating furnaces is available to reheat the slab to achieve target drop out temperature for rolling after slabs is traversing from charging to discharging end with certain furnace speed based on mill pacing. Furnaces is main process safety critical equipment and running the furnaces in optimum control will be helpful in safety and better operational excellence and it improve the overall productivity of the furnaces with less gas consumption.

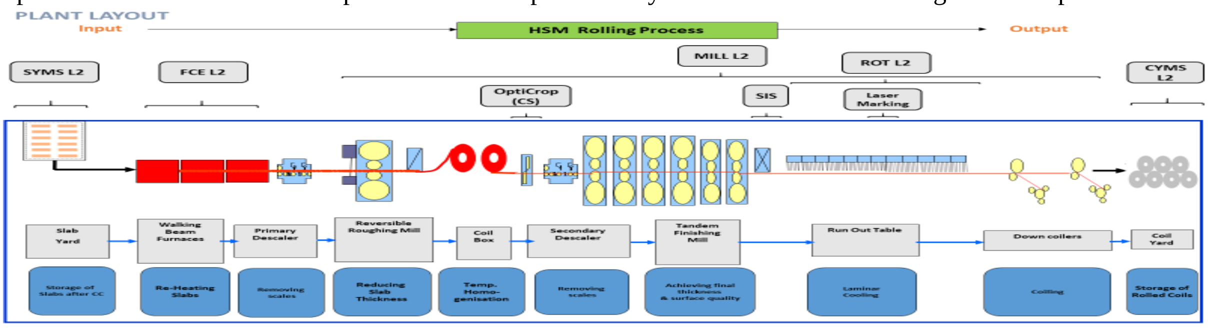

Figure 1: HSM, TSJ – Process of upstream to downstream.

Furnace Level-2 Model for Heating control of the Furnace to deliver the desire slab drop out temperature and improves the product quality, mill reliability and furnace efficiency.The process automation architecture of the furnace consists of a combustion control system (Level1) implemented in Honeywell Distributed Control

System and a math model-based process automation system (Level2). The Level2 system calculates the optimal set points for the combustion control system using mathematical models as slabs traverse from entry to exit of the furnace typically over a period of three hours to get discharged at a target drop out temperature.

Furnaces temperature profile is constructed to calculate heattransferred to steel stock through mainly by means of convection and radiation from the burner gases and furnace walls.The amount of gas burning with certain amount of oxygenis controlled by valves opening of each zone to maintain the furnace environment temperature based on Level-2 calculated setpoints of each zone.The Level1 system controls fuel and air supply from control valves to maintain the setpoints of each zone.

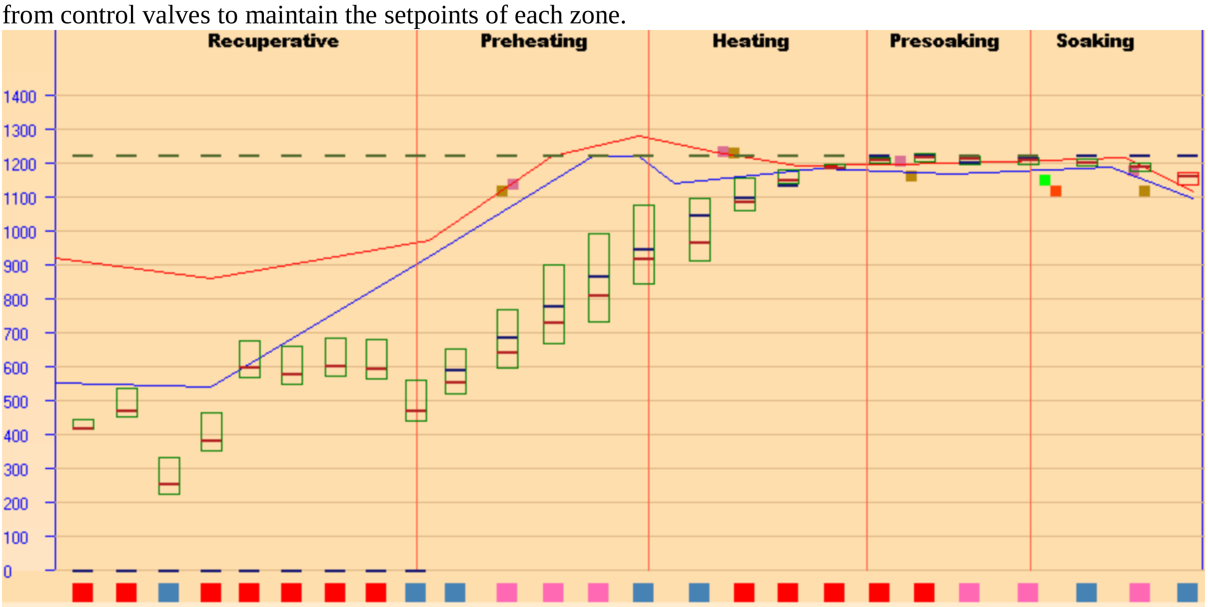

Figure 2:Furnace Environment Temperature Profile

In furnaces no direct measurement is possible to measure the temperature of product and only way to calculate the slab temperature from furnace environment temperature of each zonei.e., radiation curve andpre assumptions co-efficient fromLevel2using data from several instrumented slab trials.

The heat flow density to the slab is calculated using **Equation 1**from on-line model by means of a radiation temperature curve at top and bottom side ofthe slab. And with that in time, the entire temperature history of the slab is calculated,and these curves are derived using the thermocoupletemperatures along the furnace length.

$$q_1 = \varepsilon_1 \cdot \sigma \cdot \left(T_{rad1}^4 - T_{surf}^4\right) \qquad q_2 = \varepsilon_2 \cdot \sigma \cdot \left(T_{rad2}^4 - T_{surf}^4\right) \tag{1}$$

In **Equations 1**, q_1 and q_2 are the heat flow densities to the slab, derived using the empirical emissivityε_1 and $\varepsilon_2$in combination ith the related radiation temperatures T_{rad1} and T_{rad2}. The Stephan-Boltzmann constant isrepresented byσ. The slab surface temperatureis T_{surf} and above is applied for the top and bottom side of the slab.

It is highly desirable to maintain the furnace environment temperature from control valves of each zone of furnace and health of control valves require to monitor fromdata of valve opening or valve closing with respect to fuel flow supplyto each zone of furnace for proper combustion to maintain the furnace environment temperature.It is unpredictable to execute the maintenance and cleaning of valves on time and no system placed to identify the health of valve condition and maintenance of valves is only done only if breakdown in reheating furnaces and furnaces is not able to deliver the desired output to mill.

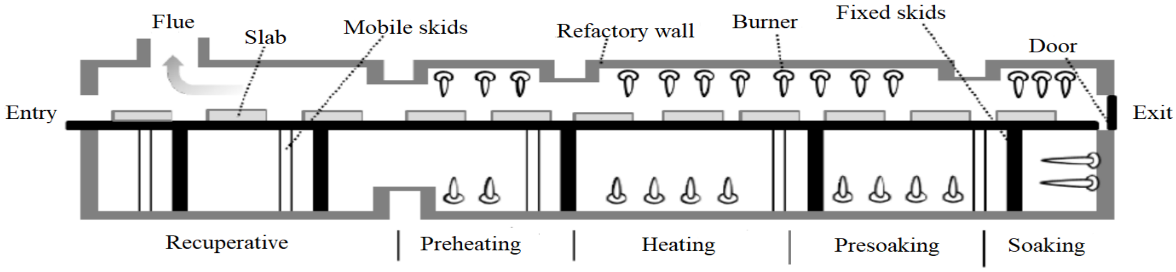

Figure 3: Typical Reheating Furnace

Figure 4:Scale Deposit on Buner

Developed an anomaly detection and early warning system using Machine Learning approach to identify and monitoring of valve health condition on real time basis based on past historical data of furnaces and anUnsupervised Machine Learning – Isolation Forest algorithm has applied on data to generate the alarm to process engineer to take corrective action for cleaning and checking of control valve health. This system helps to reheating process to maintain desired uniform drop out temperature of slab for rolling in downstream process of mill.

2. System Design and Description

2.1 Objective

To Detect Anomaly in Furnace Gas Valve operation using ML for gas valve health monitoring, and early detection of deviation in health of gas valve.

2.2Approach

Our approach is to use historical data of each control valve opening and gas consumption by each valve of respective zone of furnace and dataset has been prepared of each zone of furnaces and use Unsupervised Machine Learning – Isolation Forest to identify the Anomaly data points from given dataset. Anomaly detection is the methodology to identify an outlier datapoints that is significantly different pattern from majority of datapoints in dataset.

Dataset having very large volume and having complicated patterns hence it is very difficult to detect outlier or anomaly by just looking data. Due to this implement the anomaly detection application of Isolation Forest algorithm of Machine learning.

Isolation forest is a machine learning algorithm for anomaly detection, it is an unsupervised learning algorithm that identifies anomaly by isolating outliers in the data.Isolation Forest is based on the Decision Tree algorithm. It isolates the outliers by randomly selecting a feature from the given set of features and then randomly selecting a split value between the max and min values of that feature. This random partitioning of features will produce shorter paths in trees for the anomalous data points, thus distinguishing them from the rest of the data.

Figure 5:Process of Model Development

2.3Data Collection

In reheating furnaces, Total 10 number zones and heating is control by different control valve, which is firingthrough burnerstowards furnace environment by mixing of gas and oxygen. Delivery of gas and oxygen through burners is directly proportional to control valve opening. So past 6 months data has been collected from Level-2 process control system.

Zone	Zone Name	Side Burner	Top Burner
1	Upper Preheating Zone	-	24
2	Lower Preheating Zone	6	-
3	Upper Heating Zone	-	40
4	Lower Heating Zone	6	-
5	Upper Presoaking Zone	-	32
6	Lower Presoaking Zone	6	-
7	Upper Soaking Zone LS	-	16
8	Upper Soaking Zone RS	-	16
9	Lower Soaking Zone LS	5(Front)	-
10	Lower Soaking Zone RS	4(Front)	-

Table 1:Zone wise burner placement in Reheating Furnace

Section	Dimension (meters)
Length	42
Width	12
Height	2.3

Table 2:Dimension of Reheating Furnace

2.4Exploratory Data Analysis

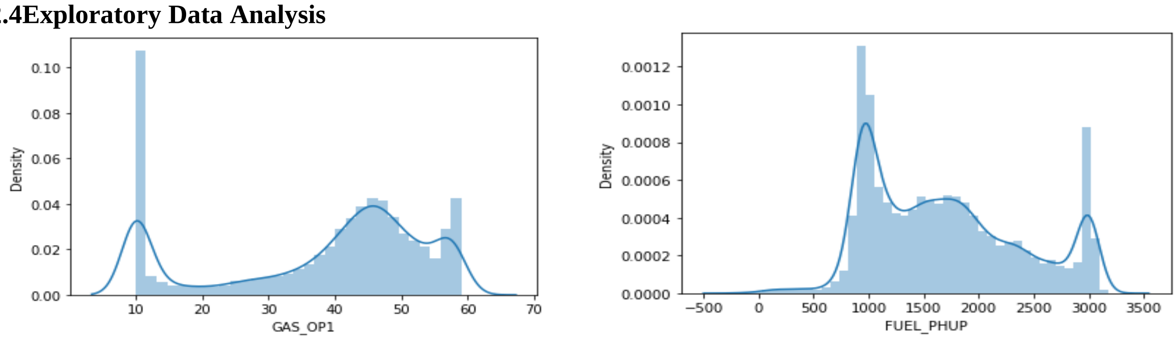

Figure 6:Distribution plot of Control valve opening and its gas.

With above distribution of control valve opening and gas supply through control valve to burner, it is identified there is spread in dataset and using this dataset our aim is to identify the anomaly data point of control valve opening with respect to gas by implementation of an application of Unsupervised Machine Learning – Isolation Forest.

2.5Model Development

For Isolation Forest model development, following four input arguments to the method. One parameter is compulsory and rest of three parameter is optional with default value.

Contamination: It is very sensitive parameter and determines assumption of outlier proportions in dataset. For this parameter we had discussion with furnace process engineer and assuming 2 % outliers for the development of model.

Number of estimators: Total number of trees will be generated by model. Its default value is 100.

Max Samples: Number of samples will be used for development of each tree.

Max features: Number of features to be train the tree from datasets. Its default is 1.

```
IsolationForest(behaviour='deprecated', bootstrap=False, contamination=0.1,
                max_features=1.0, max_samples='auto', n_estimators=50,
                n_jobs=None, random_state=None, verbose=0, warm_start=False)
```

Figure 7:Unsupervised Machine Learning – Isolation Forest method

```
random = df.iloc[:,2]
random2 = df['FCE_ID']

train = df[['GAS_OP1', 'GAS_OP2', 'GAS_OP3', 'GAS_OP4', 'GAS_OP5', 'GAS_OP6',
        'GAS_OP7', 'GAS_OP8', 'GAS_OP9', 'GAS_OP10','FUEL_PHUP','FUEL_PHLO'
        ,'FUEL_HUP','FUEL_HLO','FUEL_PSUP','FUEL_PSLO','FUEL_SRUP','FUEL_SLUP'
        ,'FUEL_SRLO','FUEL_SLLO']]

col = train.columns


for x in range(train.shape[1]):
    y = x
    z = 10+x
    X = train.iloc[:,[y,z]]

    anomaly_proportion = 0.020  # contamination
    clf_name = 'Anomaly Detection - Isolation Forest'
    clf = IForest(contamination=anomaly_proportion)
```

Figure 8:Isolation Forest Model of Anomaly detection of Control Valve Health.

After model development, require trainingtoAnomaly detection model with last 6 months dataset. For model training used below method.

```
clf.fit(X)
```

Figure 9:fit() method for model training.

Once the model has trained with fit() method and next step is to get the score of Anomaly data from dataset.If this modelidentifies the control valve of gas operation is Anomaly, then score 1 will be generated by model.

Anomaly score can find by using of predict() method of the developed model on dataset and add new attribute in data frame to display the score or represent the using graph.

```
isof_outliers = clf.predict(X)
isoF_outliers_values = X[clf.predict(X) == 1]

sns.scatterplot(data=isoF_outliers_values, x=isoF_outliers_values.iloc[:,0],
                y=isoF_outliers_values.iloc[:,1],color = "r")
plt.show()
```

Figure 10:predict() method for found out Anomaly score.

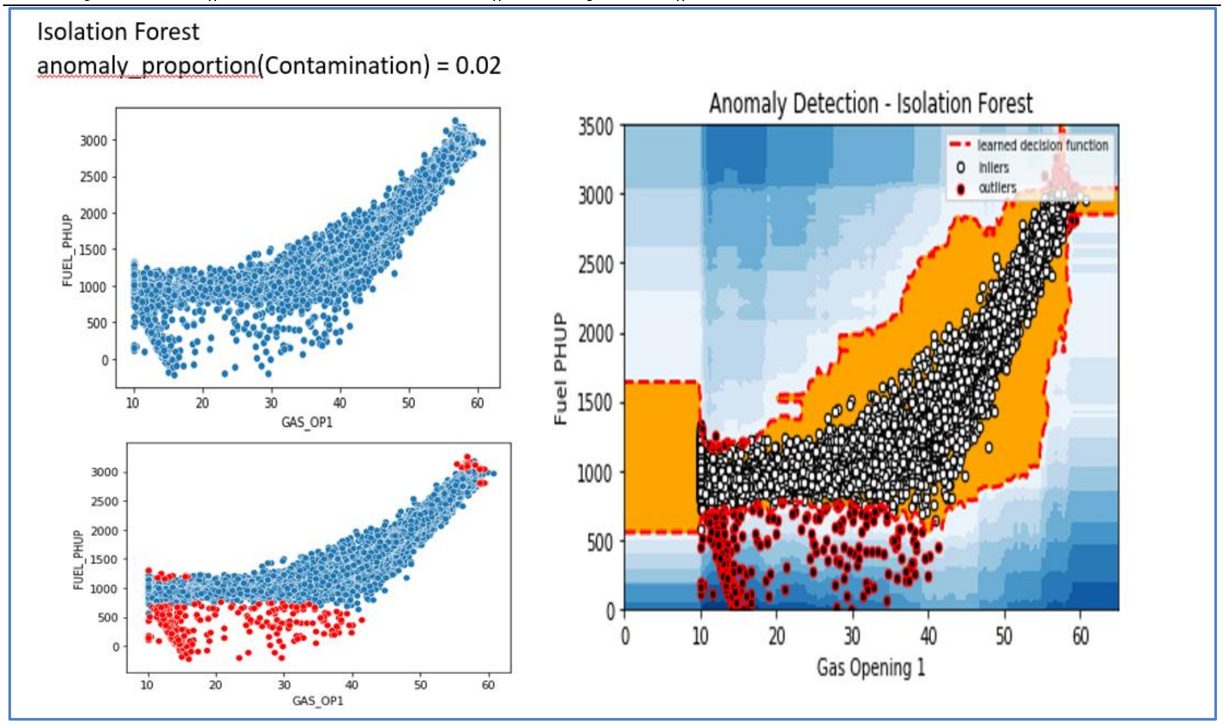

Figure 11:Graph of Anomaly Data Point.

In Above figure, Model decision of Anomaly from dataset by highlighted of red color line is shown as boundary and any data points beyond the boundary is called outlier or Anomaly data points for control valve gas operation and resultant to impact on reheating process of slabs in furnaces.

2.6Online implementation of model:

This developed model will be requiringdeploying on Level-2 process control system of furnace to identify the Anomaly of control valve gas operation in day-to-day operation or real time operation of furnace. To do this, following are pre-requisites for model deployment:Installation of Python software and package, Environment setup of model deployment, Connectivity to Level-2 process control and real time data of control valve gas operation, scheduling of model and model output will be sentto Level-2 process control system and early warning generate to process engineer on HMI for corrective action and preventive action.

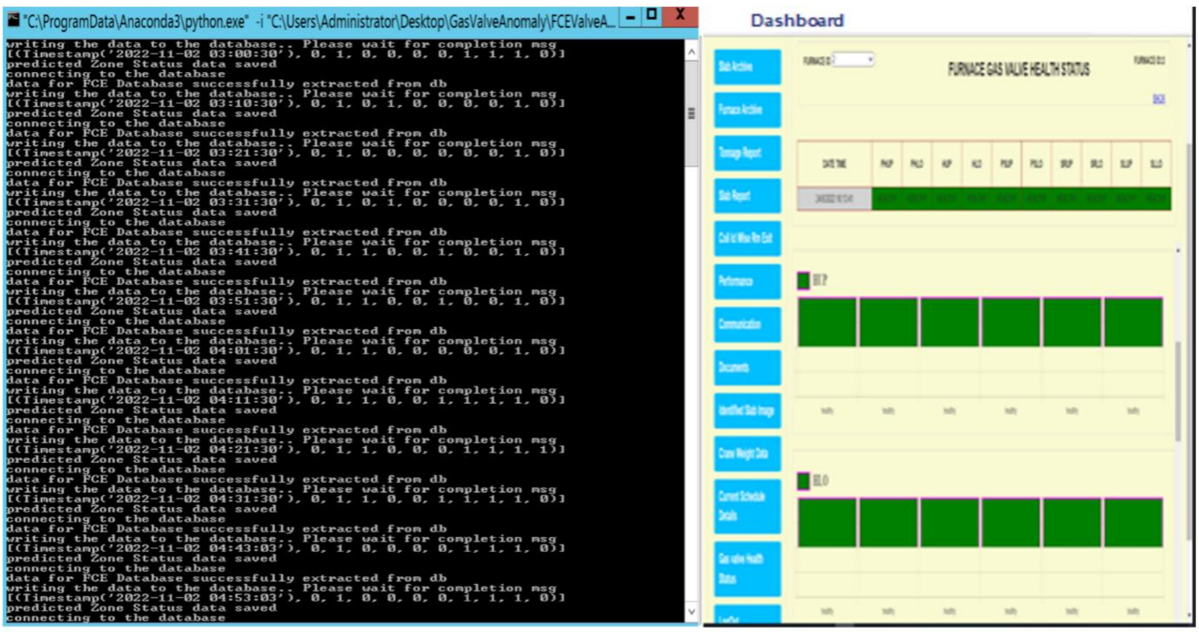

Figure 12:Model Deployment and Health of Control Valve Gas on HMI.

3. Benefits and Conclusion

To detect Anomaly in Furnace Gas Valve operation in real time operation of reheating furnaces. Early detection of deviation in health of control valve gas. It helps to process engineer to execute preventive maintenance before any major breakdown in furnace. Good health of control valve gas status is helpful to reduce the oxide scale formation and maintain the uniform temp of slab throughout slab length and meet expected slab drop out temperature at furnace exit to downstream process of mill for stable rolling.

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