Detection and Diagnostic with Random Forest and FMEA to Improve the Maintenance Management System in Steam Boiler of Power Plant

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ABSTRACT

IIoT and connected devices can continue to use smart equipment and improve access to data. While the data collected by sensors has been an invaluable asset to companies, the ability to understand and use this data to drive new insights. The development of CM technology and CMMS in power generation systems provides a validated set of operation and maintenance data with abundant event data. Maintenance decision-making is primarily based on equipment reliability and performance-based features for diagnosing equipment failure. The most critical asset and often reduces the reliability and availability of a CFSPP with the most frequency of disturbances is the steam boiler. As a departure from the idea of creating a integration concept, this article will focus on analyzing equipment health conditions and finding causes of failure of the tools, utilizing data for diagnostic purposes. Real-case used in this research are steam boilers, which are important assets in power plant generation. The online sensor and FMEA module data will be combined to realize the concept of anomaly diagnosis which is driven by hybrid data. Hoping that accurate diagnosis results can be obtained and be used to analyze the causes of failure and decrease in equipment performance resulting by a decrease of energy efficiency performance. The analytical approaches are carried out to have the goal of generating detection models and diagnostic insights of event data based on operational data and FMEA.

Keywords: Detection, Diagnostics, Random Forest, FMEA, CMMS, Maintenance

1. INTRODUCTION

Industry 4.0 involves direct collaboration in the technological revolution where machines and managers must make decisions that involve a huge amount of data and customization in the manufacturing process. Predicting when assets require maintenance is a major challenge in this context. The ability to perform predictive maintenance can help improve machine downtime, cost, control, and production quality (Zonta et al., 2020). Maintenance management is now becoming more automated and knowledge-based, with decision support systems playing a key role with help of new technology of Cyber-physical production systems (CPPS) shifting maintenance management from descriptive to prescriptive approaches (Ansari et al., 2019). The integration of Industrial Internet of Things (IIoT) with digital twin technology and Computerized Maintenance Management Systems (CMMS) can enable organizations to collect and analyze real-time data to optimize their operations, reduce downtime, and improve safety. The use of FMEA (Failure Mode and Effects Analysis) can further enhance this strategy by providing a prioritized list of potential failure modes, which can guide maintenance efforts and reduce the likelihood of downtime or equipment failure (Nemeth et al., 2018).

The concept of data analysis on power plant operating sensors itself has taken various machine learning (ML) techniques to detect failures and emission prediction reduction in power plant equipment such as BPNN, SVM, Random Forest and various other algorithms (Dhini et al., 2017; Li et al., 2020; H. Wang et al., 2019). By integrating this detection method as a benchmark for diagnosis with failure events using FMEA (Bhattacharjee et al., 2020), the implementation of preventive maintenance which also towards prescriptive is no longer impossible.

Although the potential for commercial success of IoT has been extensively researched, the same cannot be said for IIoT, particularly within the engineering sciences. Currently, IIoT research is in its early stages (Onu & Mbohwa, 2021), and there is a lack of theoretical understanding when it comes to the acceptance and use of IIoT technology. Additionally, there is a gap in the literature when it comes to examining

IIoT applications, prospects, and reviews, as these areas have been largely overlooked in existing research. Digital transformation faces numerous obstacles, whereas the various taxonomies and lists of these barriers have been proposed. Extensive literature (Jones et al., 2021) reviews on the subject have yielded several categorizations of these barriers, often ranked in terms of their level of significance or the difficulty of overcoming them.

To reduce the gap for these technologies, this paper approach is to analyze integration between the documents provided by industry which become legacy of the industry with data sensor analysis in hope of implementing the prescriptive maintenance reference model. This paper will talk about the analysis of operational data sensors using ML Random Forest and documents of FMEA provided by the Power plant Industry. This analysis specifically targets steam boilers, which have emerged as one of the most crucial components in coal-fired steam power plants due to their high downtime rates compared to other equipment in such power plants (Mohanty et al., 2020).

2. EQUIPMENT MONITORING TECHNOLOGY

One application of IIoT technology is the use of digital twins. CMMS can be integrated with digital twins to provide a comprehensive view of equipment performance. This integration can enable data-driven analysis and decision-making, as well as proactive maintenance and repair. FMEA, which also could be provided in CMMS, can be used to analyze data generated by digital twins and sensors to identify potential failure modes of equipment which also define the right way to measure the strategy of pro-active and corrective maintenance (Errandonea et al., 2020). By combining FMEA with CMMS and digital twins, organizations can create a comprehensive maintenance strategy that prioritizes preventive maintenance based on criticality.

2.1. Intersection of IIoT and Digital Twin in Industry

The IIoT is revolutionizing the way organizations manage their assets and operations. By connecting devices, machines, and sensors to the internet, IIoT technology can collect and analyze real-time data that can be used to optimize operations, reduce costs, and improve safety. Meanwhile, Digital Twin technology involves creating a virtual replica of physical equipment, machines, or systems to model, monitor, and optimize their behavior and performance. This integration enables industrial processes to be monitored and optimized in real-time which can be achieved by collecting real-time data from IIoT devices fed into Digital Twins to simulate the behavior of the physical equipment and machinery, enables companies to identify potential problems and optimize their processes to improve efficiency, reduce downtime, and minimize maintenance costs.

Industries have been using the Digital Twin (DT) paradigm for years to decrease the risks associated with their assets and enhance traceability, maintenance, and analysis to improve the asset's overall life cycle. This technology also can be applied to a single asset and its performance, or to more complicated systems such as production or services, where multiple components with varying behaviors are involved (Hlady et al., 2018; Shubenkova et al., 2018). IIoT can be used as a container in data analysis where data can be recorded and analyzed directly to detect the type of matching patterns associated with failures in the field.

2.2. Integration of CMMS and FMEA

CMMS are designed to help organizations manage their maintenance operations more effectively. They can be used to schedule and track preventive maintenance tasks, manage work orders, and track inventory. CMMS is designed to help businesses streamline their maintenance processes, reduce equipment downtime, and optimize maintenance costs. It typically includes features such as predictive maintenance, preventive maintenance, and reactive maintenance.

While FMEA is a method used to identify and prioritize potential failure modes of a system or process. FMEA is a systematic approach that evaluates, measures, and minimizes potential risks related to different aspects of a design. It involves a risk assessment process that identifies which features or failure modes could impact the quality of the product as perceived by the customer, regardless of their position in the supply chain. The main objective of FMEA is to determine how these risks can be mitigated (Kent, 2016).

The incorporation of CMMS and FMEA in power plants can provide numerous benefits, such as enhanced equipment reliability, reduced downtime, and increased safety for workers and the community nearby. By adopting a proactive approach to maintenance management and utilizing FMEA data to guide maintenance schedules and equipment replacement decisions, power plants can reduce the likelihood of unforeseen downtime and expensive equipment failures. This can lead to considerable cost savings over time while guaranteeing the plant operates safely and efficiently. Consequently, the intersection of CMMS and FMEA is a vital research and development field for power plant operators, holding great potential to significantly impact the entire industry. FMEA will also become a reference determining the root causes of failure starting from causes and effects to how to solve these problems. Root caused Failure Analysis (RCFA) will be a benefactor in determining proactive and corrective maintenance strategies.

2.3. Combination of IIoT and CMMS

The process typically involves collecting data from various sources, analyzing it to identify potential issues, using FMEA in CMMS database to further analyze these issues and identify potential failure modes, and then taking proactive and corrective action to address any identified issues. Figure

1 shows the concept mapping of how to combine analysis online sensor data and FMEA.

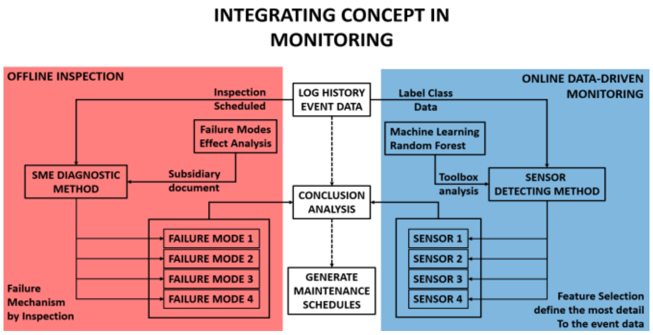

Figure 1. Mapping concept of combination in data sensor and FMEA

This integration of failure learning combines sensor data recorded online and FMEA document data that is used officially by the relevant industry as a reference in maintenance. In generating a maintenance strategy in CMMS, Knowledge-based maintenance (KBM) learning starts from FMEA which provides details of failure modes related to event conditions stored in the history log. these incidents are inspected in person for the appropriate type of failure. List of potential Failure Mode is found by field expertise which provides an overview of the types of failure mechanism and how to deal with them with proactive and corrective maintenance. Whereas in the data analysis approach, data stored online will be analyzed with a detection algorithm to find out which sensors provide various patterns. This pattern can be matched with the failure event conditions so that information can be drawn as a basis for failure analysis, starting from the location, type of equipment, and various other information related to failure conditions.

2.4. Feature Importance in CART ensemble RFC

Decision Tree or tree-based models are algorithms that divide a dataset using a tree-like structure. The concept behind decision trees is to split the data based on certain conditions, which are represented as branches in the tree. There are several algorithms for decision trees, including ID3, which is based on entropy values, and classification and regression trees (CART), which is based on Gini values.

Decision tree using the impurity method or CART is a decision tree algorithm, in addition to ID3, which explains the generation of binary decision trees (Breiman et al., 2017). The formula for finding impurity values in the CART algorithm is shown in Eq. (1).

$$Gini(D) = 1 - \sum_{i=1}^{m} P_i^{\,2} \qquad (1)$$

Where P_i is the probability value of a tuple D belonging to a certain class, and m is the total number of class labels. The Gini index considers binary separation for each attribute. Binary separation requires calculating the weighted sum of the impurity of each partition produced. The value of the Gini index is shown in Eq. (2).

$$Gini_A(D) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2) \qquad (2)$$

Random forest classifier (RFC) is a type of ML algorithm used for classification tasks. It is a collection of decision trees that work together to make predictions by taking a vote from all the decision trees in the forest (Breiman, 2001). The selection of the feature to initiate the split at a particular node is typically based on the increase in purity in the resulting nodes. Purity refers to the degree of class homogeneity at a specific node, which, for example, can be measured by the proportion of cases versus controls. A node with a higher proportion of one class is considered to be purer (Musolf et al., 2022). Each decision tree is trained on a random subset of the input features and samples from the training data. This randomization helps to reduce overfitting and increase the accuracy of the classifier. When making a prediction, each decision tree in the forest independently classifies the input, and the final prediction is based on the majority vote of all the decision trees. RFC is commonly used in various fields such as finance, medicine, and engineering for tasks such as fraud detection, disease diagnosis, and image classification.

There are various methods for calculating feature importance in random forest (RF), and one of them is the Gini importance. At each node, the Gini index, which measures node purity, is assigned to each feature to determine which feature to use for splitting. These Gini indices can be averaged across all nodes and trees to determine the Gini importance of a feature in the analysis.

Feature importance is determined by the reduction in node impurity, which is weighted by the probability of reaching that node. The probability of reaching a node can be calculated by dividing the number of samples that reach that node by the total number of samples. A higher value of feature importance indicates that the feature has a greater impact on the analysis. The importance of a feature is determined by calculating the total reduction in the criterion (which has been normalized) that results from the inclusion of that feature. It is also known as the Gini importance. To determine feature importance in each decision tree, the Gini Importance is calculated by computing the importance of each node in the tree. This method assumes that only binary trees, which have two child nodes, can be used to calculate the importance of a node, as shown in Eq. (3).

$$ni_j = w_j C_j - w_{left(j)} C_{left(j)} - w_{right(j)} C_{right(j)} \qquad (3)$$

Where ni_j is the importance of node j, while w_j is weighted number of samples reaching node j, and C_j is the impurity value of node j. The right and left on this equation stand for the child node on node j from the right split and left split respectively. The importance for each feature on a decision tree is then calculated which is shown in Eq. (4).

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k} \quad (4)$$

Where fi_i is the importance of feature i and ni_j is the importance of node j. To obtain a normalized importance value for a feature between 0 and 1, divide the feature's importance value (fi_i) by the sum of all feature importance values. The final feature importance value at the Random Forest level is calculated by taking the average of the feature importance values across all the trees. This is achieved by calculating the sum of the feature's importance value for each tree and then dividing it by the total number of trees.

3. Detection and Diagnosis using FMEA and RFC

To understand and analyze the existing problems, a literature review related to failures occurring in steam boilers and how to diagnose these failures based on steam boiler parameter data was conducted. A diagnosis will be made and connected to the failure modes described in the FMEA document, so a literature review on the FMEA document implemented by the industry is required.

3.1. Failure Event Selection

Generating a dataset for classification and labeling failure modes can be a challenging task when the system is not well understood. This challenge becomes more complex in situations where there are multiple failure modes and the root cause of the failure is not clear. In such situations, expert knowledge of the system can be useful in analyzing data from real systems. Event history logs can also be helpful in determining the possible failure modes of components. However, in the case of the Boiler, the logs only provide the name of the failed component without specifying the failure mode. The frequency of failures due to leakage is the highest among all the components with more than 480 hours throughout 2019 and 2020 in the steam boiler system, as shown in Figure 2.

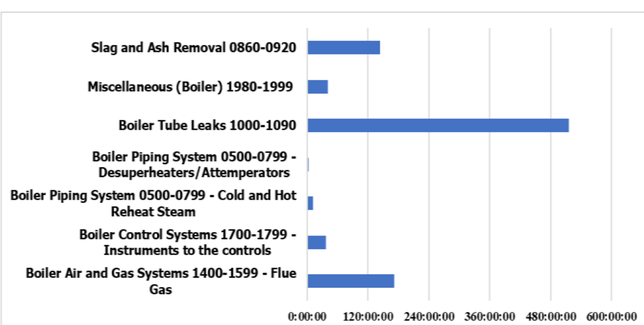

Figure 2. Total hours of event in Boiler

It can be inferred from the general trend that boiler leakages are the most frequent occurrence. The event data obtained is the ground truth data from the translation of historical data obtained from the REOC, which is used to provide information on the occurrence of leak failures in each segment. The event data will serve as a distinguishing label between different types of incidents. From the obtained data, there are three types of failure incidents that occurred throughout the data. Figure 1 shows the list of event incident related to leakage in boiler with scattered plot sensor value of boiler furnace pressure.

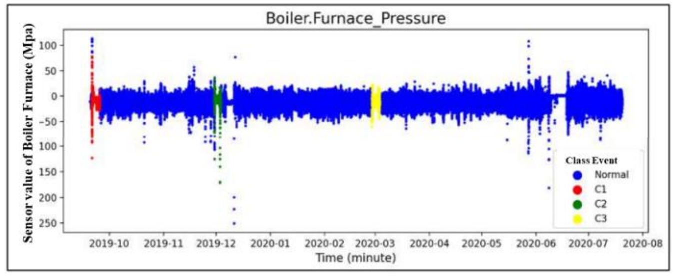

Figure 3. Scatterplot of Sensor of boiler furnace Pressure with 3 events leakage.

There are 3 events of leakage in boiler amounting to 17286 minutes (288 hours) with status of performance as derating and outage in unit #5 in October 2019 through march 2020. These events become ground truth label in data analysis. The 3 labels class of event mentioned in Table 1.

Table 1 Log History of Failure Event

Label	Event Description
Normal	Normal State / Not in described event failure
C1	Leakage in Secondary Superheater Zone
C2	Leakage in Convection Pass Wall
C3	Leakage in HCP Primary Superheater

3.2. Sensor Operational in Steam Boiler

The sensor data obtained is data from the operating sensors taken from coal-fired steam power plant Unit #5, which has a total of 437760 rows and 42 sensor columns. Out of the 42 operating sensors taken, there are 15 selected sensors referenced in various studies on the use of sensors for boiler pipe leakage using model-based detection (Y. Wang & Yin, 2017; Yin & Wang, 2015) and coordinated by the subject matter expert (SME) from the related power generation industry to determine the occurrence of leakage failure in the steam boiler. Table 2 shows the list of sensors provided and taken into analysis.

Table 2. List of sensors for analysis

No.	Name of sensor
1	Boiler Furnace Pressure
2	Boiler Steam Drum Pressure
3	Boiler Total Coal Flow
4	Booster Boiler Feed Pump-Turbine (BFPT)-A Outlet Pressure

5	Booster Boiler Feed Pump-Turbine (BFPT)-B Outlet Pressure
6	Economizer Inlet Flue Gas Temperature
7	Economizer Outlet Flue Gas Temperature
8	Primary Superheater (PSH) Inlet Steam Side A Temperature
9	Primary Superheater (PSH) Inlet Steam Side B Temp.
10	Primary Superheater (PSH) Outlet Steam Side A Temp.
11	Primary Superheater (PSH) Outlet Steam Side B Temp.
12	Secondary Superheater (SSH) Inlet Steam Side A Temp.
13	Secondary Superheater (SSH) Inlet Steam Side B Temp.
14	Riser to Steam Drum Side A Water Temperature
15	Riser to Steam Drum Side B Water Temperature

This sensor will indicate the detection of location and each part of equipment which will be detected with ML algorithm method.

3.3. Failure Mode Analysis Offline Monitoring

The FMEA document utilized in the industry under observation is a compilation of the failures and their causal analysis. However, it fails to provide a comprehensive explanation of the consequences of these failures, necessitating more detailed information on the failure modes and the methods of controlling them through the SME. The SME provide in-depth information regarding failure types, based on the inspection outcomes, and the appropriate proactive and reactive measures to be taken to address them. The FMEA document includes instructions on how to observe and manage the failures, as it is designed exclusively for inspection purposes.

The inspection process is conducted based on various condition monitoring standards, which can be implemented while the machine is either in operation or shutdown mode. List of FMEA module focusing on provided damage status and offload plan is shown in Table 3. The failures list has been limited based on the described event of failure incidents and the extent of the resulting damages.

Table 3. FMEA document focusing on related information

Failure Location	Failure Modes	Damage Status	Offload Plan
Downcomer	Mechanical Fatigue	Incipient	VT=>MT/PT
	Welding Flaws	Event-Based	QA/QC, Strict adherence to procedures
Secondary Superheater Tube and Header: Inlet Bank	Fly Ash Erosion	Active	CFD Modeling w/flow modification
	Rubbing/ Fretting	Active	VT=>UT (Meter or Weld Gauge)
	Soot blower Erosion	Incipient	VT =>UT or EMAT (Tubing only)
	Low-Temperature Creep	Incipient	VT=>Hydrostatic Testing, MT
	Chemical Cleaning Damage	Event-Based	QA/QC, UT => tube sampling
	Mechanical Fatigue	Incipient	VT=>MT/PT
	Welding Flaws	Event-Based	QA/QC, Strict adherence to procedures
Convection Pass Front Wall: Tubing	Long-Term Overheating/ Creep	Incipient	UT => Tube sampling
	Mechanical Fatigue	Active	VT=>MT/PT
	Welding Flaws	Event-Based	QA/QC, Strict adherence to procedures

There are multiple types of mechanical fatigue failures that can occur, whether in an active or incipient state. During an inspection, various conditions are reviewed with a offload-plan for the equipment to provide information on the appropriate failure mode in accordance with the monitoring procedure.

3.4. Proposed Model for Maintenance Decision Analytic

This research is directed towards conducting diagnostic analysis of the selected boiler operation sensor values to gain insights into failure events. To diagnose the occurrence of boiler leakage failure events, ML methods will be used to determine which selected boiler operation sensors influence the failure.

The resulting ML output in the form of a list of operation sensors will be analyzed to determine the location and mechanism of the failure event. this list of sensors will also be recommended to SME and re-researched at the R&D department at the specified Power Plant later. Figure 4. Illustrates the concept of how acquired sensor data will be processed and the obtained information stored into the database.

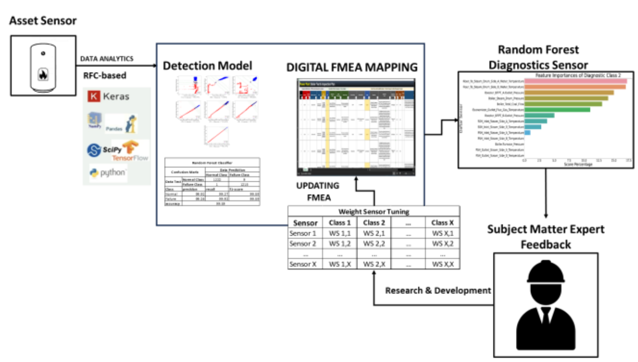

Figure 4. Processed sensor data into digital FMEA

While this step will be conducted by concerned staff and technicians. This paper will contribute the analysis of obtained sensor data through the list of feature importance random forest output of list sensor to estimate the type of failure mode based on the previously designed FMEA.

Figure 5 illustrates the research flow chart for creating diagnostic models on the data. The result will be used to give recommendation relating of how to update FMEA based on sensor diagnostic to subject matter expert whether result of the list data sensor could be compatible to failure modes or not.

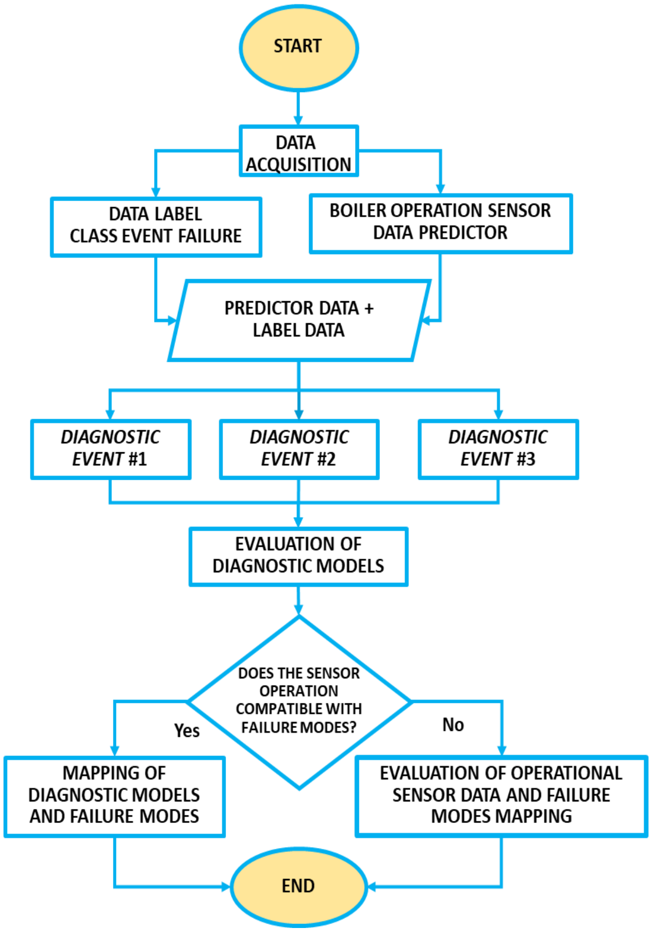

Figure 5. Flowchart of diagnostics Steam Boiler Data.

4. Research Results and Discussion

The study starts by performing a descriptive analysis of the data using the Exploratory Data Analysis (EDA) method, where only statistical values, histograms, and box plots are included. Next, a diagnostic analysis is carried out utilizing a classification ML algorithm. The preprocessed data is utilized to train the random forest ML algorithm, which provides diagnostic insights. These diagnostic insights will serve as the foundation for mapping the failure modes of FMEA.

4.1. Exploratory Data Analysis and Data Preprocessing

The statistical method is applied to determine whether the readings of a sensor are normal or provide an understanding of how to group the operational data of sensors into labeled categories, such as normal class and event occurrences. The statistical values of 15 sensors used in a boiler are presented in Table 4.

Table 4. Statistical analysis and blank values on sensor data

No	Data Sensor	mean	Min	50%	max	Null
1	Boiler.Furnace Pressure	-10.99	-250.34	-11.30	113.36	0
2	Boiler Steam Drum Pressure	153.66	0.08	173.49	185.33	0
3	Boiler Total Coal Flow	226.75	0.00	255.00	332.84	0
4	Booster BFPT A.Outlet Pressure	19.69	3.99	21.40	23.02	0
5	Booster BFPT B.Outlet Pressure	19.66	2.66	21.19	22.59	0
6	Economizer Inlet Flue Gas Temperature	419.00	419.00	419.00	419.00	0
7	Economizer Outlet Flue Gas Temperature	352.09	30.33	381.60	430.81	0
8	PSH Inlet Steam Side A Temperature	373.59	37.33	398.68	451.87	0
9	PSH Inlet Steam Side B Temperature	377.56	34.01	402.45	561.37	0
10	PSH Outlet Steam Side A Temperature	344.75	38.19	369.79	424.58	0
11	PSH Outlet Steam Side B Temperature	341.10	35.91	365.19	433.97	0
12	Riser To Steam Drum Side A Water Temperature	327.11	34.45	353.05	358.31	0
13	Riser To Steam Drum Side B Water Temperature	326.49	33.83	352.64	357.77	0
14	SSH Inlet Steam Side A Temperature	374.67	36.35	399.70	464.43	0
15	SSH Inlet Steam Side B Temperature	374.74	36.46	399.68	474.01	0

All of the sensor data in Table 4 have complete records with 437760 data samples and no null values. The statistical analysis shows that the Economizer Inlet Flue Gas Temperature sensor has consistent mean, median, min, and max values of 419, indicating that there is no significant difference in its readings across different events. Sensor values that do not have this difference will be removed from the sensor list because their values do not provide insight into further analysis.

The diagnostic analysis of the data involves using labels derived from the ground truth, and involves adjusting the data for events classified as class 1, 2, and 3. The technique to remove noise is done by first removing the failure event label, then detecting outliers in the normal label data using the interquartile range rule and removing those outliers. Afterwards, the event label data is merged back into the blue normal label data. A scatterplot visualization of the boiler furnace pressure sensor data that has been processed to remove noise and standardized using the ground truth label is depicted in Figure 5.

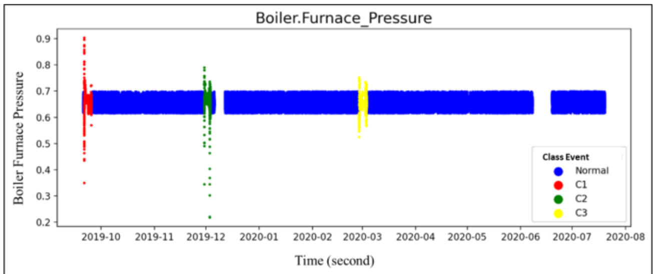

Figure 6. Scatterplot furnace pressure preprocessed data.

4.2. Detection Model Build

In creating the Data detection model, all 14 operating sensors were used to create the next diagnostic model. The diagnostic model is designed to detect leak failure events based on anomaly values in the sensors and classify them into normal class, class 1, class 2, and class 3. The model score resulting from the event class diagnosis with the RFC model is shown in Table 5.

Table 5. Confusion Matrix of Detection RFC

Confusion Matrix		Data Test			
		Normal Class	C1	C2	C3
Data Prediction	Normal Class	983	0	0	0
	C1	10	931	4	38
	C2	0	130	823	30
	C3	0	45	72	866
Summary		Normal Class	C1	C2	C3
Precision		98.99%	84.18%	91.55%	92.72%
Recall		100.00%	94.71%	83.72%	88.10%
F1-Score		99.49%	89.13%	87.46%	90.35%
Accuracy		91.63%			

The detection model created using the RFC algorithm with Gini criterion has an accuracy of 91.63%. However, it has a weakness in detecting class 1, as the precision of the model for class 1 is only 84.18%. Out of 1191 test data samples for class 1, 931 were correctly classified as class 1, while 130 were misclassified as class 2 and 45 were misclassified as class 3. The model's lowest sensitivity was found for class 2, where out of 983 data samples predicted for class 2, 823 were correctly detected, 130 data samples labeled as class 1 were detected as class 2, and 30 data samples labeled as class 3 were detected as class 2. The model's low sensitivity for class 2, which is only 83.72%, resulted in the F1 score for class 2 being the lowest at 86.23%.

4.3. Diagnostic Model Build

The ML model generated will provide insights in selecting sensors that have an impact on boiler leak failure. Each event will undergo diagnostic analysis to determine the type of failure mode that can be predicted, based on which sensors influence the boiler leak failure event. There are three failure events, resulting in three diagnostic results to determine which sensors will be used in the FMEA mapping for each event. The diagnostic outcomes for each event category are presented as follows:

4.3.1. Boiler leakage in the Secondary Superheater Zone.

The class 0 or normal class data has 351,437 data samples and the class 1 data has 6,117 data samples. The ratio of class 1 to class 0 data is close to 1:99, which requires sample adjustment. The sample adjustment method used is random under sampling (RUS). The diagnostic results of the RFC presented the feature importance values on the random forest model for each boiler operational sensor for class 1 label, as shown in Table 6.

Table 6. Top 5 feature importance value on class 1.

No.	Steam Boiler Sensor	Percentage	Cumulative
1	Booster BFPT A Outlet Pressure	28.17%	28.17%
2	Booster BFPT B Outlet Pressure	19.09%	47.26%
3	Boiler Total Coal Flow	11.98%	59.24%
4	Riser To Steam Drum Side B Water Temperature	10.88%	70.12%
5	Boiler Steam Drum Pressure	8.90%	79.02%

From the diagnostic results of class 1 event on the operation sensors, it is found that the sensors that have the most influence on the occurrence of boiler leakage in the secondary superheater zone are the pressure sensors of booster BFPT output pumps A and B, followed by the total coal flow sensor, the water temperature sensor in the riser to steam drum section B, the pressure sensor in the steam drum, and the subsequent sensors with top 5 cumulative percentage amounting to 79,02%.

4.3.2. Boiler leakage in the Convection Pass Wall Zone.

Class 0 data or normal class has 351437 data samples and Class 2 data has 4915 data samples. With the same conditions as class 1, the comparison of the amount of data for class 2 and class 0 which is close to 1: 99 requires a sample adjustment. The sample adjustment method used is RUS. From classes that have been balanced, the number of normal class samples is 4915 data. The diagnostic results of the RFC presented the feature importance values on the random forest model for each boiler operational sensor for class 2 label, as shown in Table 7.

Table 7. Top 5 feature importance value on class 2.

No.	Steam Boiler Sensor	Percentage	Cumulative
1	Riser To Steam Drum Side-A Water_Temperature	17.23%	17.23%
2	Riser To Steam Drum Side-B Water Temperature	17.00%	34.23%
3	Booster BFPT-A Outlet Pressure	15.00%	49.24%
4	Boiler Steam Drum Pressure	14.05%	63.29%
5	Boiler Total Coal Flow	13.04%	76.33%

Based on the diagnostic results of the class 2 incident on the operation sensor, it was found that the sensor that most influenced the occurrence of boiler leakage in the convection pass wall zone was the temperature sensor on the riser to steam drum Side-A and B, followed by the value of the Booster BFPT-A outlet pressure sensor, the steam drum pressure, and the next sensor with top 5 cumulative percentage amounting to 76,33%.

4.3.3. Boiler leakage in the High Convection Pass PSH Zone.

Class 0 data or normal class has 351437 data samples and Class 3 data has 6254 data samples. Under the same conditions as before, the comparison of the number of class 3 and class 0 data which is close to 1: 99 requires a sample adjustment. The sample adjustment method used is RUS. From classes that have been balanced, the number of normal class samples is 6254 data. The diagnostic results of the RFC presented the feature importance values on the random forest model for each boiler operational sensor for class 3 label, as shown in Table 8.

Table 8. Top 5 feature importance value on class 2.

No.	Steam Boiler Sensor	Percentage	Cumulative
1	Riser To Steam Drum Side-B Water Temperature	17.13%	17.13%
2	Riser To Steam Drum Side-A Water Temperature	15.34%	32.47%
3	Boiler Steam Drum Pressure	13.13%	45.60%
4	Booster BFPT-A Outlet Pressure	13.00%	58.60%
5	Boiler Total Coal Flow	12.12%	70.72%

According to the diagnostic analysis result of the Class-3 incident on the operation sensor, it was found that the temperature sensors on the riser to steam drum sides A and B had the greatest impact on the occurrence of boiler leakage in the Header zone of the convection pass wall. Subsequently, the steam drum pressure, the outlet pressure sensor value of Booster BFPT A, the total coal flow rate of the boiler, and the following sensors were also found to have an influence. Top 5 cumulative percentage amounting to 76,33%.

4.4. Diagnostic Discussion with FMEA and Recommendation Mapping

The diagnostic results show that the most influential sensors on boiler leakage incidents are temperature sensors for the riser to steam drum and steam drum pressure sensors, among others. The FMEA mapping based on inspection and SME validation indicates that the leakage incidents are caused by mechanical fatigue in the SSH, CPW, and HCP PSH areas. The inspection and repair priority for the SSH and CPW areas are categorized as IPI B, which requires repairs to be done within 24 hours to 6 days. The HCP PSH area also falls under IPI B. Specific sensors are needed to differentiate failure incidents in the Downcomer and Riser to Steam Drum areas. FMEA and Recommendation mapping is presented in Table 9.

Sensor Data-Driven Analysis		Failure Mode	Recommendation	
Sensor ID	Event Data		Corrective	Proactive
SSH Inlet Super Heater Side A & Side B	Boiler leakage in the Secondary Superheater Zone	Mechanical Fatigue	Fixed/ restored the thickness on the SSH location pipeline	Schedule inspections and look for the root cause of leak failures
Riser to Steam Drum	Boiler leakage in the Convection Pass Wall Zone.	Mechanical Fatigue	Repair / restore the thickness of the CPW location pipe	Schedule inspections and look for the root cause of leak failures
Riser to Steam Drum	Boiler leakage in the High Convection Pass PSH Zone	Mechanical Fatigue	Repair / restore the thickness of the HCP location pipe	Schedule inspections and look for the root cause of leak failures

5. Conclusion And Recommendation

5.1. Conclusion

The analysis of operation parameter sensor data and event data correlation with FMEA has led to the development of a more advanced prescriptive analysis diagnosis model from a conventional model.

A. The operation sensor data contains various anomalous values that can be separated using the interquartile range, but it cannot be validated due to the lack of support from manually recorded event data. Therefore, other approaches are needed in the analysis for this diagnosis purpose.

B. The diagnostic model for the boiler operation data, which includes 15 sensor data sets and ground truth data for each event, has a high level of accuracy approaching 100% when using various data approaches. However, for the model that includes failure event data as a whole, it cannot be perfectly distinguished based on the precision value of the classification model because the failure data from each class has similar characteristics, so the model as a grouping of each class still needs to be considered.

C. In the operational sensor data, failure modes can only be identified by referring to the FMEA TBM module and adjusting with the level of inspection priority (IPI). Since the IPI level for each recorded leakage failure event is more than 6 hours and all failure events result in outage status, the designated IPI level is close to level A, which indicates that the type of failure must be immediately addressed and requires significant repair time, namely mechanical fatigue for all failure events.

5.2. Recommendation

Before the era of Industry 4.0, physical assets in power plants mostly used conventional sensors that were only related to operational maneuvers, operational safety, and heat-balance calculations. However, the data from these old sensors did not fully support the acquisition of specific data related to the condition of steam boiler equipment, which was suspected to frequently experience damage and malfunctions. Even though advanced prescriptive analysis algorithms were used, if the available data was insufficient, the decision-making analysis results could not be optimized. Based on the imperfect diagnostic model test results, several factors need improvement, including:

a. The addition of sensors to some important locations of boiler equipment with high-frequency disruptions, to detect failures with the highest failure rates, and to adapt to smart sensor technology on IoT in the industry.

b. Improvement of data acquisition technology in the PI system to obtain accurate sensor data values without missing values or values that do not match the actual sensor values, which can cause discrepancies between failure types and the received sensor data.

c. More accurate event record data on the timing, duration, and type of disruptions, to explain the equipment's condition.

d. The model used in this research is still in the development stage and needs further development in future research.

e. The FMEA TBM module used in this research is not the appropriate module, which should be the CBM module. However, CBM activities are still under development in the industry, and the CBM module is not yet available.

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NOMENCLATURE

MT	magnetic particle
PT	dye penetrant
RT	x-ray
EC	eddy current
VT	borescope
VT	visual tube / attachment
VT	visual header / pipa > 4"
UT	ultrasonic thickness/accoustic

REFERENCES

Ansari, F., Glawar, R., & Nemeth, T. (2019). PriMa: a prescriptive maintenance model for cyber-physical production systems. *International Journal of Computer Integrated Manufacturing*, *32*(4–5), 482–503. https://doi.org/10.1080/0951192X.2019.1571236

Bhattacharjee, P., Dey, V., & Mandal, U. K. (2020). Risk assessment by failure mode and effects analysis (FMEA) using an interval number based logistic regression model. *Safety Science*, *132*. https://doi.org/10.1016/j.ssci.2020.104967

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324/METRICS

Breiman, L., Friedman, J., Olshen, R., & Stone, C. (2017). Classification And Regression Trees. In *Classification and Regression Trees*. https://doi.org/10.1201/9781315139470

Dhini, A., Kusumoputro, B., & Surjandari, I. (2017). Neural network based system for detecting and diagnosing faults in steam turbine of thermal power plant. *Proceedings - 2017 IEEE 8th International Conference on Awareness Science and Technology, ICAST 2017*, *2018-Janua*, 149–154. https://doi.org/10.1109/ICAwST.2017.8256435

Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital Twin for maintenance: A literature review. *Computers in Industry*, *123*. https://doi.org/10.1016/j.compind.2020.103316

Hlady, J., Glanzer, M., & Fugate, L. (2018). Automated creation of the pipeline digital twin during construction - Improvement to construction quality and pipeline integrity. *Proceedings of the Biennial International Pipeline Conference, IPC*, *2*. https://doi.org/10.1115/IPC2018-78146

Jones, M. D., Hutcheson, S., & Camba, J. D. (2021). Past, present, and future barriers to digital transformation in manufacturing: A review. *Journal of Manufacturing Systems*, *60*, 936–948. https://doi.org/10.1016/J.JMSY.2021.03.006

Kent, R. (2016). Design quality management. In *Quality Management in Plastics Processing* (pp. 227–262).

Elsevier. https://doi.org/10.1016/B978-0-08-102082-1.50008-3

Li, M., Deng, W., Xiahou, K., Ji, T., & Wu, Q. (2020). A data-driven method for fault detection and isolation of the integrated energy-based district heating system. *IEEE Access*, *8*, 23787–23801. https://doi.org/10.1109/ACCESS.2020.2970273

Mohanty, J. K., Dash, P. R., & Pradhan, P. K. (2020). FMECA analysis and condition monitoring of critical equipments in super thermal power plant. *International Journal of System Assurance Engineering and Management*, *11*(3), 583–599. https://doi.org/10.1007/s13198-020-00945-4

Musolf, A. M., Holzinger, E. R., Malley, J. D., & Bailey-Wilson, J. E. (2022). What makes a good prediction? Feature importance and beginning to open the black box of machine learning in genetics. *Human Genetics*, *141*(9), 1515–1528. https://doi.org/10.1007/s00439-021-02402-z

Nemeth, T., Ansari, F., Sihn, W., Haslhofer, B., & Schindler, A. (2018). PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning. *Procedia CIRP*, *72*, 1039–1044. https://doi.org/10.1016/j.procir.2018.03.280

Onu, P., & Mbohwa, C. (2021). Reimagining the future: Techno innovation advancement in manufacturing. *Materials Today: Proceedings*, *44*, 1953–1959. https://doi.org/10.1016/J.MATPR.2020.12.100

Shubenkova, K., Valiev, A., Mukhametdinov, E., Shepelev, V., Tsiulin, S., & Reinau, K. H. (2018). Possibility of Digital Twins Technology for Improving Efficiency of the Branded Service System. *Proceedings - 2018 Global Smart Industry Conference, GloSIC 2018*. https://doi.org/10.1109/GloSIC.2018.8570075

Wang, H., Peng, M.-J., Wesley Hines, J., Zheng, G.-Y., Liu, Y.-K., & Upadhyaya, B. R. (2019). A hybrid fault diagnosis methodology with support vector machine and improved particle swarm optimization for nuclear power plants. *ISA Transactions*, *95*, 358–371. https://doi.org/10.1016/j.isatra.2019.05.016

Wang, Y., & Yin, X.-L. (2017). A Method of Diagnosing Boiler Four-Tube Leakage Rate: Proceedings of the International Conference on Environmental Science and Sustainable EnergyEd.by ZhaoYang Dong. In *ESSE 2017*. https://doi.org/10.1515/9783110540048-053

Yin, X., & Wang, Y. (2015). Research on Fuzzy Diagnosis Method of Boiler Steam and Water Pipe Leakage. In *Mechanical Engineering and Control Systems* (pp. 75–78). WORLD SCIENTIFIC. https://doi.org/doi:10.1142/9789814740616_0017

Zonta, T., da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers and Industrial Engineering*, *150*. https://doi.org/10.1016/j.cie.2020.106889

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