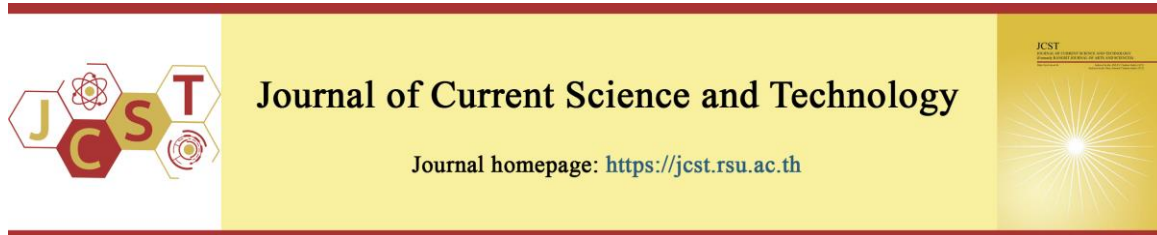


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Proactive Maintenance Strategy for Boiler Feed Pumps in Power Plant Industries Using Long Short-Term Memory Autoencoder-Based Anomaly Detection

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Abstract

The boiler feed pump (BFP) plays a crucial role in power plants. As part of a prognostic and health management strategy, deep learning frameworks are currently being developed for anomaly detection to improve reliability. This study proposes a data-driven proactive maintenance framework based on anomaly detection using data from the supervisory control and data acquisition (SCADA) system. This research applied an anomaly detection framework built on a long short-term memory autoencoder (LSTM-AE) to monitor several critical operating parameters, including vibration, bearing temperature, lube oil temperature, and motor winding temperature, in a coal-fired steam power plant in Indonesia. Data collected in 2023 and 2024 were used to train and validate the models. The applied LSTM-AE demonstrated strong reconstruction performance for both training and validation datasets, indicating its ability to learn and reproduce the dominant temporal patterns of normal SCADA behavior. The model was able to highlight deviations from learned normal behavior, which were interpreted as early-stage anomalies. These anomaly indications were subsequently verified through field inspection, which revealed mechanical wear in several critical components, including slight pump shaft bending, excessive clearance in the impeller hub bush, impeller wear ring, balance disc, and balance seat. Although a quantitative comparison with conventional fixed-threshold or statistical baseline methods was not conducted in this study, the results demonstrate the practical feasibility of applying LSTM-AE-based anomaly detection for industrial condition monitoring using SCADA data. The proposed framework shows potential to support proactive maintenance activities, such as inspection prioritization and maintenance scheduling.

Keywords: LSTM, autoencoder, boiler feed pump, SCADA, machine learning, power plant, proactive maintenance

1. Introduction

A boiler feed pump (BFP) is a specialized pump designed to supply feedwater to the steam drum or boiler. This pump operates at variable speeds to match feedwater demand according to the megawatt (MW) load generated by the generator (Khamfoy et al., 2025). As the plant load increases, the demand for steam also rises, requiring a higher feedwater flow from the BFP. Conversely, when the load decreases, the feedwater requirement is reduced accordingly. In

many existing power plants, equipment monitoring within the SCADA system is still based primarily on fixed-threshold alarms configured from predefined limit values. Conventional fixed-threshold methods rely on static operating assumptions and predefined alarm limits. While simple to implement, these methods may be insensitive to gradual or borderline degradation under variable operating conditions, particularly when vibration levels remain below predefined alarm and trip thresholds. Under such sub-

alarm conditions, conventional SCADA-based monitoring classifies equipment behavior as normal and does not trigger any warning. In contrast, data-driven approaches such as Long Short-Term Memory Autoencoder (LSTM-AE) models can learn complex nonlinear relationships and temporal dependencies directly from multivariate time-series data. By modeling normal operating behavior through reconstruction, LSTM-AE frameworks are able to highlight subtle and gradual deviations from learned normal behavior under real operating conditions, including variable-speed and non-stationary regimes. This capability makes deep learning-based anomaly detection a promising complementary tool to fixed-threshold monitoring for identifying abnormal behavior under sub-alarm operating conditions in industrial systems such as BFPs, rather than a direct replacement for conventional protection systems. Condition monitoring in power plants has attracted sustained research interest for more than a decade (Fast, 2010; Kim et al., 2014), and deep-learning approaches have accelerated this development in recent years (Lachekhab et al., 2024; Lee et al., 2024). A crucial objective in this effort is identifying equipment abnormalities, which plays a crucial role in condition-based maintenance and can help minimize the substantial expenses associated with unexpected operational interruptions.

There are two main categories of anomaly detection frameworks: model-driven and data-driven

methods (Swiercz & Mroczkowska, 2020). The data-driven approach is particularly significant in this context. It enhances information retrieval and decision-making accuracy by utilizing historical Condition Monitoring (CM) data (L'Heureux et al., 2017). Among data-driven approaches, signal processing and analysis techniques have gained widespread adoption. Machine learning (ML) algorithms show promise in effectively detecting such anomalies due to their ability to learn from past patterns. This learning capability makes ML techniques more adept at identifying anomalies, as they are trained to recognize data that deviates from previously observed behaviors (Aquize et al., 2017; Brady et al., 2018; Lachekhab et al., 2024; Lee et al., 2024; Shrestha et al., 2024). This paper presents a study on BFP fault diagnostics based on real industrial data. The contribution of this study is that the data used for fault diagnostics are acquired while the BFP was still in operation. There was no interruption to the steam generation process during data acquisition. The data were collected by the SCADA system, streamed online from several sensors installed on the BFP, and stored on a hard disk for further analysis. This contrasts with studies that rely on laboratory test-bench data or on inspection data acquired only while the boiler is shut down. This study utilizes real industrial SCADA data from a coal-fired power plant to develop and validate an LSTM-AE-based anomaly detection framework.

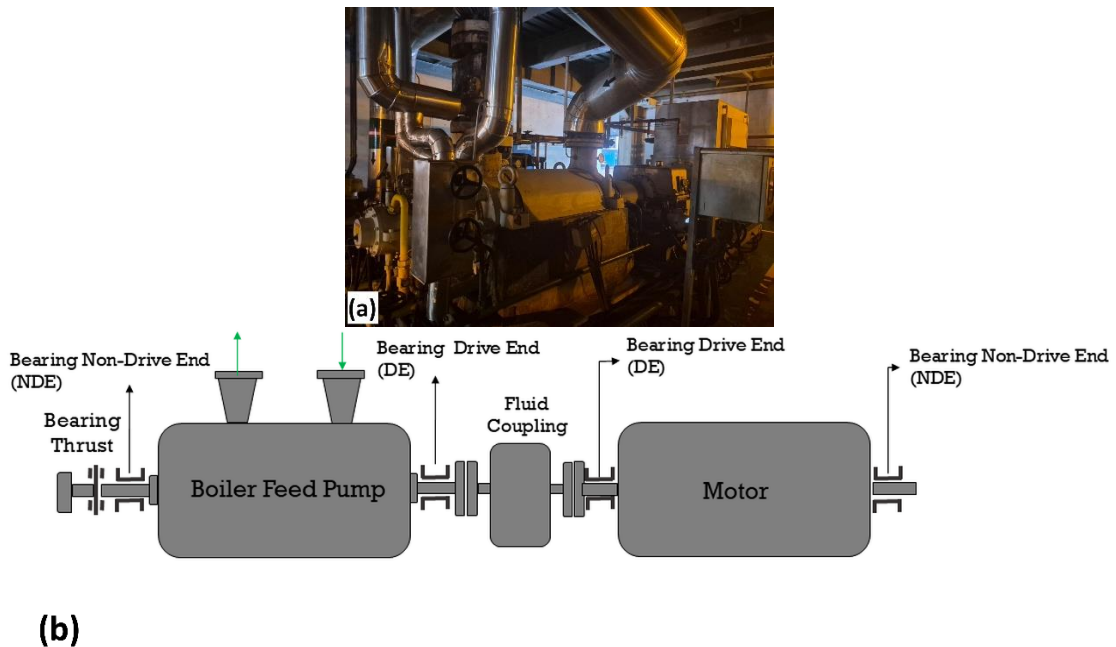


Figure 1 (a) Photograph of the boiler feed pump (BFP), (b) configuration scheme of boiler feed pump

Table 1 Design specifications of the boiler feed pump

Capacity	Head	Speed	Shaft Power	Efficiency
263 m ³ /h	1527 m	2900 rpm	1310 kW	77%

Figure 1 shows the configuration of a BFP, consisting of a motor and pump connected by a fluid coupling. Meanwhile, Table 1 shows the BFP's specifications, including capacity, head, speed, shaft power, and efficiency.

Prior research combined the Autoencoder approach for feature extraction, model generalization through data reduction, and the LSTM model (Ergen & Kozat, 2020; Pariaman et al., 2021) to address the issue of gradient reduction over extended periods and long sequences. The capability of the LSTM-AE model to handle multi-output, time series, and long-term dependence problems is another advantage (Hu et al., 2020). A combination model of LSTM and autoencoder has been employed in several studies to determine the condition of power plant equipment (Pariaman et al., 2021; Wisyaldin et al., 2020a, 2020b).

2. Objectives

This study aims to develop and validate a data-driven anomaly detection framework for BFPs operating under variable-speed conditions in coal-fired power plants. The primary focus is to investigate the feasibility and practical applicability of an LSTM-AE-based approach for industrial condition monitoring and proactive maintenance support. The specific objectives are:

- To develop an LSTM-AE-based anomaly detection model using multivariate SCADA time-series data from BFP systems.
- To evaluate the model's ability to accurately reconstruct normal operating behavior and quantify reconstruction performance using Mean Squared Error (MSE) and coefficient of determination (R^2).
- To analyze the temporal evolution of detected anomaly indications using SCADA trend data.
- To verify detected anomalies through SCADA trend analysis and field inspection results, and assess their relevance for proactive maintenance decision-making.

These objectives are addressed using an LSTM-AE framework, where the LSTM component captures temporal dependencies in multivariate SCADA time-series data, and the autoencoder structure learns normal operating patterns through reconstruction. Deviations between reconstructed and actual signals are subsequently used to identify

anomaly indications that may reflect abnormal operating behavior relevant to condition monitoring and proactive maintenance. It should be noted that this study does not include a quantitative performance comparison with conventional fixed-threshold or statistical baseline methods. Instead, it is intended as an industrial case study and proof-of-concept to demonstrate the feasibility and practical relevance of applying LSTM-AE-based anomaly detection to SCADA data from BFP systems under real operating conditions, particularly in sub-alarm vibration regimes.

3. Materials and Methods

3.1 Data Preparation

This Research used data from Teluk Balikpapan coal-fired power plant, Indonesia which have capacity 2×110 MW. This data included:

- 15 sensor data points extracted from the SCADA
- Operation and maintenance records obtained from the Computerized Maintenance Management System (CMMS)

Table 2 presents fifteen sensor variables of the BFP system obtained from the SCADA data series. The data were downloaded from the Engineering Work Station (EWS) of the SCADA system, covering the period from October 1, 2023, to March 31, 2024, with a data sampling interval of five minutes. In total, twenty-eight sensors are installed on the BFP; however, this study focuses on fifteen key variables that are critical for monitoring pump performance.

3.2 Long Short-Term Memory

Long Short-Term Memory (LSTM) is a form of recurrent neural network (RNN) that is effective for modeling sequential input and capturing temporal dependencies. However, unlike typical RNNs, LSTMs may memorize and retain data for extended periods of time (Syamsuddin et al., 2024). LSTM methods are frequently used to detect anomalies (Shrestha et al., 2024; Tong et al., 2022). A deep learning model called LSTM is typically used with time series data. LSTM-based deep learning is able to mimic highly complex functional forms and is even capable of establishing simple patterns within a large amount of highly nonlinear data. Deep learning helps sift through unnoticed and hidden relationships within data and then make the most of that data. Deep learning therefore offers representational capabilities that conventional machine learning techniques cannot readily provide. It is possible to address long-term

dependencies through the strategic design of LSTM (Zhang et al., 2019). LSTM is well suited to noisy, non-stationary signals such as SCADA time series, because it can learn to filter out irrelevant fluctuations. It is therefore appropriate for anomaly detection in the present study.

As shown in Figure 2, the LSTM cell is mainly composed of 3 gates, namely forget, input, and output gates. Sigmoid (g) is used to activate the gate, and the cell state and gate input are transformed by the hyperbolic tangent ($\tanh$) function. The weights of neurons and biases are denoted by w and b , respectively. The LSTM gate can be expressed by the following equations (Syamsuddin et al., 2024; Tong et al., 2022; Ye et al., 2015).

$$\text{Forget gate: } f_t = g(w_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$\text{Input gate: } i_t = g(w_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\text{State update: } \bar{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t C_t \quad (4)$$

$$\text{Output gate: } o_t = g(w_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h = o_t \tanh(C_t) \quad (6)$$

Table 2 Key variables used as model features of the boiler feed pump

No	Sensor	Unit	Tag ID
1	Speed	RPM	10LAC30CS101
2	Current	Ampere	10LAC30AP001XQ01
3	Shaft vibration at the driving-end bearing in the x-direction	mm/s	10LAC30CY101
4	Shaft vibration at the non-driving-end bearing in the x-direction	mm/s	10LAC30CY103
5	Shaft vibration at the driving-end bearing in the y- direction	mm/s	10LAC30CY102
6	Shaft vibration at the non-driving-end bearing in the y- direction	mm/s	10LAC30CY104
7	Temperature of the non-driving-end bearing	°C	10LAC30CT113
8	Temperature of the driving-end bearing	°C	10LAC30CT114
9	Temperature of the thrust bearing	°C	10LAC30CT115
10	Lube oil temperature at the cooler outlet	°C	10LAC40CT116
11	Lube oil temperature at the cooler inlet	°C	10LAC40CT116
12	Temperature of the non driving-end motor bearing	°C	10LAC30CT101
13	Temperature of the driving-end motor bearing	°C	10LAC30CT102
14	Axial displacement	mm	10LAC30CY105
15	Temperature of the winding motor	°C	10LAC30CT103

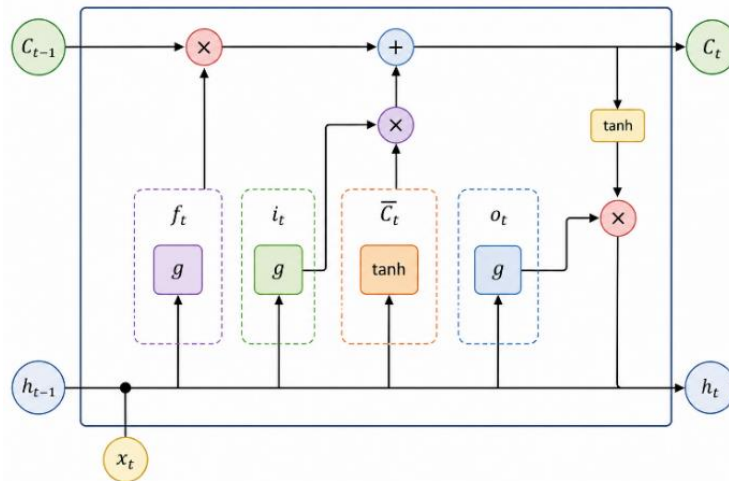


Figure 2 The LSTM cell: Adapted from Zhang et al. (2019)

3.3 Autoencoder

In order to provide a reconstructed input that is close to the original input, autoencoders compress data into a meaningful representation through encoding (lower dimensionality) and then decode that representation. Autoencoders are popular for processing large-scale data since they are easy to train and do not require complicated computations (Provotar et al., 2019; Que et al., 2019). It is acknowledged that the characteristics of the final model are essential as they constitute the raw material for the machine learning systems. It can be said that the classification of the proposed machine learning algorithms is particularly data or feature centric. The accessibility of ‘good features’ should result in building decent predictive models even for naive estimators. As a result, it is evident that proper data processing before adopting machine learning techniques is essential for extracting a desirable representation. Data dimensionality reduction techniques used to mitigate the above-stated problems include the autoencoder (AE). They learn how to do all these things by themselves without supervision in order to represent the inputs appropriately. This process is referred to as coding, or data reduction, and is useful in machine learning because it reduces computational overhead (Ye et al., 2015). As depicted in Figure 3, the input layer is on the left, the hidden layer in the centre, and the output layer on the right.

For instance, if the input is $X = (x_1, x_2, x_3, \dots, x_n)$ and $x_i \in [0,1]$ AE maps X to an implicit layer, denoted as $H = (h_1, h_2, h_3, \dots, h_s)$ and $h_i \in [0,1]$ this process is called encoding. The output from the hidden layer is defined as follows (Ye et al., 2015):

$$H = g(w_1 \cdot X + b_1) \quad (7)$$

the implicit variable Z forms the output layer with the same structure as X of the input layer, and the output H from the hidden layer is referred to as the implicit variable. Another name for it is decoding. In the following equation, the output is the output layer.

$$Z = g(w_2 \cdot H + b_2) \quad (8)$$

The implicit variable, which is the hidden layer's output H , reconstructs the Z of the output layer in a structural form akin to the X of the input layer. The parameters w_i and b_i denote the weight matrices and bias vectors of the neural network layers. These parameters are not manually defined; instead, they are automatically learned during the training process using backpropagation and gradient-based optimization. Their values are iteratively updated to minimize the reconstruction error between the input data and the reconstructed output of the LSTM-AE model. Decoding is then performed by entering the output layer into the given formula.

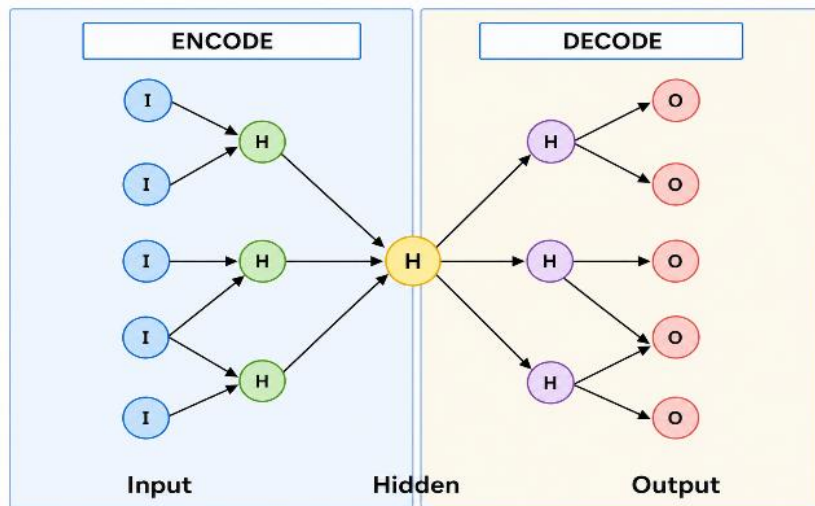


Figure 3 Autoencoder: Adapted from Zhang et al. (2019)

3.4 LSTM-AE-Assisted Time-Series Data Pattern Reconstruction

Building upon the LSTM architecture described in Section 3.2 and the autoencoder principles presented in Section 3.3, this study employs a LSTM-AE to reconstruct normal SCADA time-series behavior for anomaly detection. The principle of LSTM-AE-based reconstruction is illustrated in Figure 4, adapted from Pariaman et al. (2021).

The LSTM-AE reconstructs normal operating behavior from time-series data by integrating temporal modeling and representation learning (Maleki et al., 2021). Anomalies are identified using statistical upper and lower bounds derived from the reconstruction error, which are computed based on its mean and standard deviation, as defined by the following equations.

$$\bar{x} = \sum_{i=1}^w \frac{1}{w} x_i \quad (9)$$

$$\text{std} = \sqrt{\frac{\sum_{i=1}^w (x_i - \bar{x})^2}{w-1}} \quad (10)$$

$$SE = \frac{\text{std}}{\sqrt{w}} \quad (11)$$

with

$$UL = \bar{x} + kSE \quad (12)$$

$$LL = \bar{x} - kSE \quad (13)$$

with

w : specified time window

$\bar{x}$: average of the last (w) values

std : standard deviation

UL : upper limit

LL : lower limit

k : threshold multiplier

A multiplier of $k = 3$ is shown in Figure 5 for illustration, following the 3σ convention widely used in statistical process control. In the present study, k was tuned per sensor group; the selected values are reported in Section 4.4.

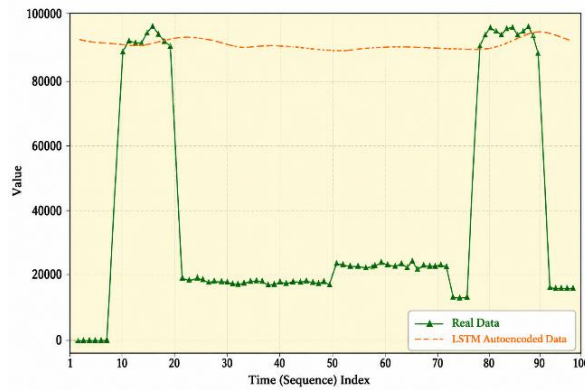


Figure 4 Illustration of the LSTM Autoencoder application: Adapted from Pariaman et al. (2021)

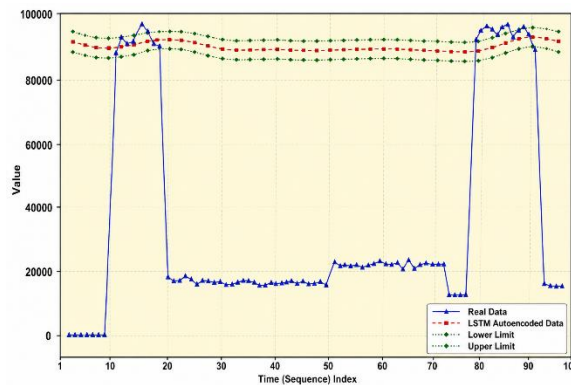


Figure 5 The application of the LSTM-AE and the upper and lower bounds: Adapted from Pariaman et al. (2021)

In implementing the anomaly detection framework for the BFP, the proposed approach marks data points in red when they exceed the upper bound, indicating potential anomalies (Moleda et al., 2020). The value of the threshold multiplier k is simulated based on the detected anomalies to obtain a representative sigma value that reflects the actual operating conditions of the power plant and the range of each sensor (Orabi et al., 2024; Panza et al., 2023). A sigma value that is too small will make the model overly sensitive, resulting in excessive anomaly detection, whereas a value that is too large will make the model less responsive to actual anomalies. Several sigma magnitudes are simulated and validated using historical operational data and expert discussions at the power plant to establish an optimal value as a best-practice implementation.

For model training, the LSTM-AE was implemented using a per-sensor univariate configuration, where each SCADA sensor signal was modeled independently. The time-series data were segmented into fixed-length sequences of 72 time steps, corresponding to a 6-hour operational window given the 5-minute sampling interval. Prior to training, all input features were normalized using Min–Max scaling to ensure consistent value ranges and stable model convergence. The dataset was divided into training (80%) and validation (20%) subsets to evaluate reconstruction performance and generalization capability. The model was trained using the Adam optimizer for 20 epochs with a batch

size of 128, minimizing the reconstruction loss measured by Mean Squared Error (MSE). This training configuration was selected to balance reconstruction accuracy and generalization performance under normal operating conditions.

4. Results and Discussion

4.1 Data Preprocessing

Figure 6 presents the raw mining data that have been collected, as illustrated in the plot below. The data were collected from the EWS of the SCADA system, with a data sampling interval of five minutes. The raw mining data was obtained from the 15 key sensor variables mentioned in Table 2.

To facilitate data analysis, a descriptive statistical analysis was performed on the SCADA sensor data of the BFP, as presented in Table 3.

Based on the plotted time series data and statistical analysis in Table 3, there are operating conditions where the pump speed, current, and axial displacement values are recorded as zero, indicating periods when the pump was not in operation. Therefore, data cleansing and filtering are required. An exploratory data analysis (EDA) is subsequently performed to extract data corresponding to normal operating conditions, excluding any null values. The speed data are filtered to include only values above 2000 rpm, as the pump typically operates within a range of 2000 to 2900 rpm depending on the unit loading conditions. Figure 7 shows the data series plot after performing EDA.

Table 3 Descriptive statistics of the data series before exploratory data analysis

Sensor Name	Count	Mean	Std	Min	25%	50%	75%	Max
AXIAL_DISP	235665	0.40	0.60	−2.16	0.42	0.61	0.68	1.35
CURRENT	235665	81.54	37.71	0.00	80.93	90.40	99.91	314.49
SPEED	235665	2,083.58	984.61	−1,007.75	2,372.00	2,488.16	2563.10	2773.75
SHAFT_VIB_DE_X	235665	2.02	0.94	0.00	1.72	2.12	2.62	12.84
SHAFT_VIB_DE_Y	235665	1.99	0.85	0.00	1.92	2.32	2.53	5.79
SHAFT_VIB_NDE_X	235665	2.25	1.26	0.00	1.82	2.61	3.29	13.02
SHAFT_VIB_NDE_Y	235665	1.47	0.65	−0.02	1.29	1.79	1.88	7.71
TEMP_DE_BEAR	235665	43.46	0.83	0.00	43.71	44.32	44.73	72.22
TEMP_LUBE_OIL_INLET	235665	36.73	1.89	0.00	36.76	37.26	37.74	39.78
TEMP_LUBE_OIL_OUTLET	235665	40.35	3.16	0.00	40.92	41.43	41.91	44.95
TEMP_NDE_BEAR	235665	40.76	1.81	0.00	40.16	41.05	42.06	71.74
TEMP_THRST_BEAR	235665	48.38	3.89	0.00	49.23	50.20	52.11	68.11
TEMP_MTR_NDE_BEAR	235665	51.77	5.75	0.00	54.39	55.20	55.35	59.60
WIND_TEMP1	235665	59.22	3.42	0.00	58.17	60.55	62.88	80.89
TEMP_MTR_DE_BEAR	235665	57.94	9.95	0.00	60.90	62.15	62.56	882.49

BFP 1B

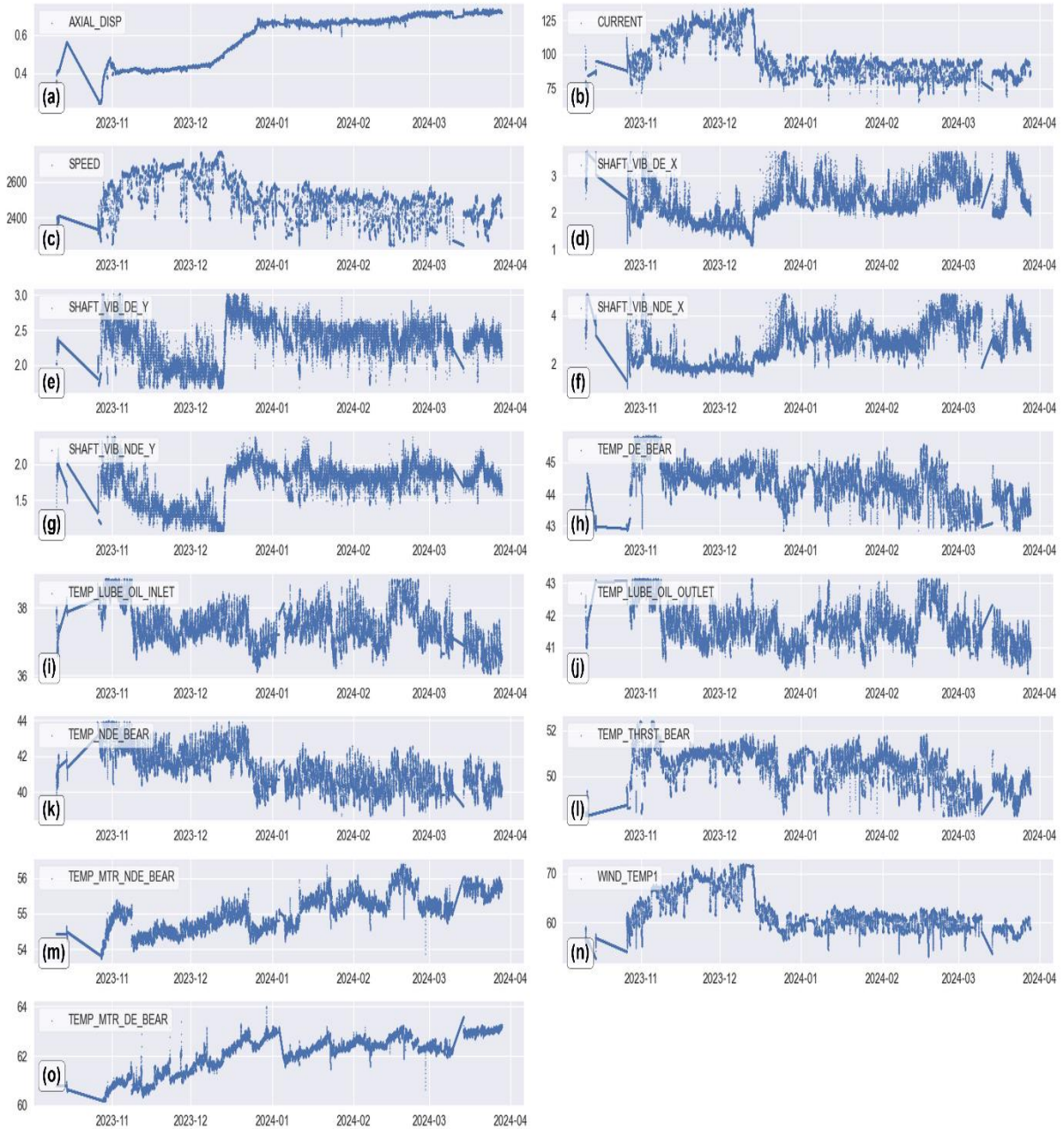


Figure 6 Raw SCADA time-series data before exploratory data analysis for the fifteen monitored boiler feed pump sensor variables: (a) Axial_Displacement, (b) Current, (c) Speed, (d) Shaft_Vibration_DE_X, (e) Shaft_Vibration_De_Y, (f) Shaft_Vibration_NDE_X, (g) Shaft_Vibration_NDE_Y, (h) Temperature_DE_Bear, (i) Temperature_Lube_Oil_Inlet, (j) Temperature_Lube_Oil_Outlet, (k) Temperature_NDE_Bear, (l) Temperature_Thrust_Bear, (m) Temperature_MTR_NDE_Bear, (n) Wind_Temperature1, and (o) Temperature_MTR_De_Bear

BFP 1B

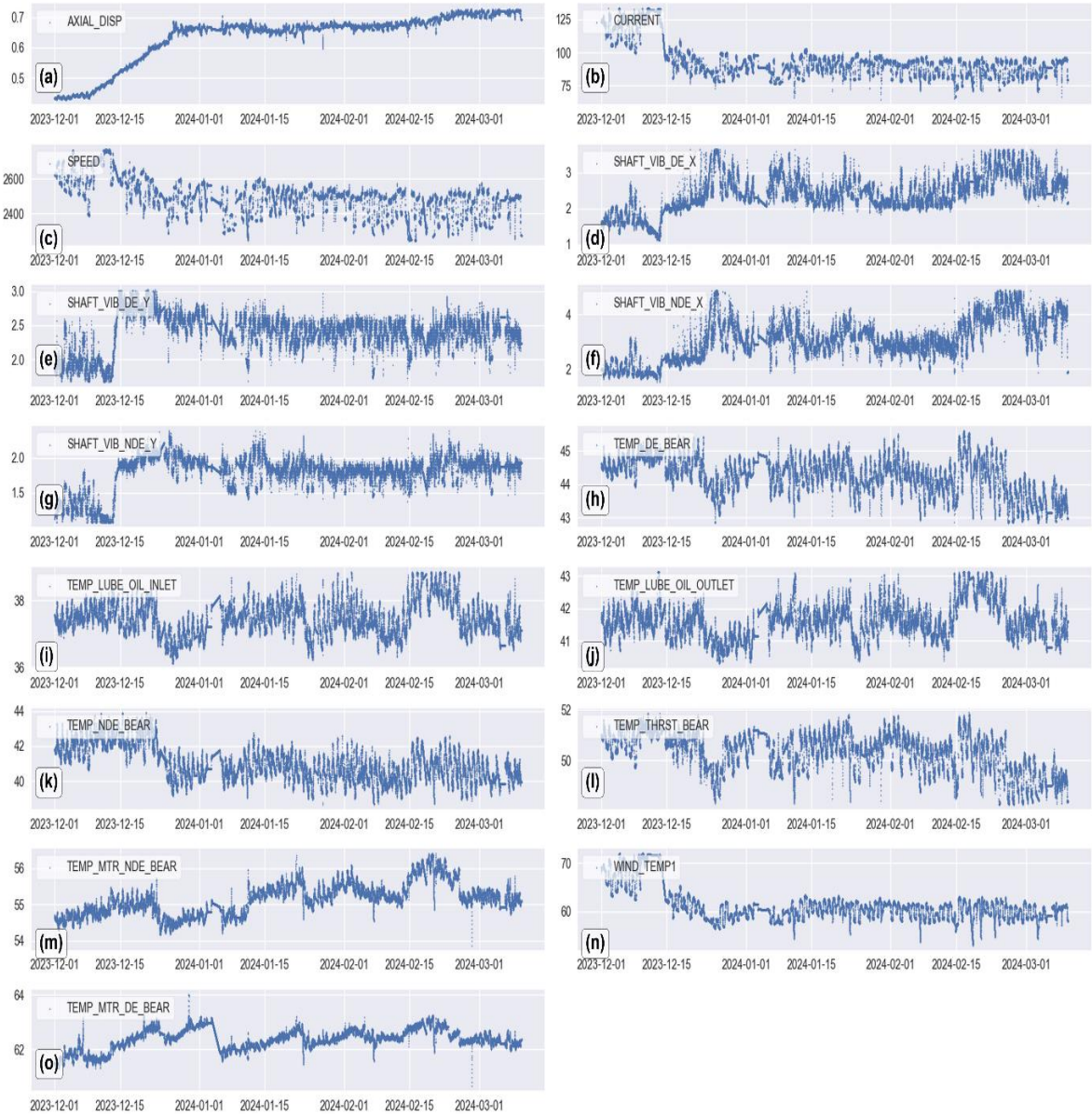


Figure 7 Cleaned and filtered SCADA time-series data after exploratory data analysis for the fifteen monitored boiler feed pump sensor variables: (a) Axial_Disp, (b) Current, (c) Speed, (d) Shaft_Vib_DE_X, (e) Shaft_Vib_DE_Y, (f) Shaft_Vib_NDE_X, (g) Shaft_Vib_NDE_Y, (h) Temp_DE_Bear, (i) Temp_Lube_Oil_Inlet, (j) Temp_Lube_Oil_Outlet, (k) Temp_NDE_Bear, (l) Temp_Thrst_Bear, (m) Temp_MTR_NDE_Bear, (n) Wind_Temp1, and (o) Temp_MTR_DE_Bear

Table 4 Descriptive statistical analysis of the data series after exploratory data analysis

Sensor	count	Mean	Std	min	25%	50%	75%	Max
AXIAL_DISP	28799	0.64	0.08	0.43	0.64	0.67	0.68	0.73
CURRENT	28799	93.20	12.94	64.39	85.21	91.15	95.55	133.40
SPEED	28799	2,492.16	101.36	2,246.04	2,452.37	2,495.65	2,539.68	2,770.35
SHAFT_VIB_DE_X	28799	2.43	0.49	1.10	2.13	2.40	2.74	3.66
SHAFT_VIB_DE_Y	28799	2.40	0.26	1.67	2.27	2.44	2.57	3.02
SHAFT_VIB_NDE_X	28799	3.08	0.73	1.53	2.58	3.04	3.57	4.91
SHAFT_VIB_NDE_Y	28799	1.79	0.24	1.11	1.73	1.85	1.94	2.39
TEMP_DE_BEAR	28799	44.52	0.54	42.85	43.30	44.29	44.66	45.39
TEMP_LUBE_OIL_INLET	28799	37.49	1.37	36.11	37.13	37.45	38.08	38.37
TEMP_LUBE_OIL_OUTLET	28799	41.63	0.49	40.31	41.23	41.69	41.96	43.14
TEMP_NDE_BEAR	28799	40.98	0.98	38.67	40.23	40.85	41.63	43.90
TEMP_THRST_BEAR	28799	50.31	0.75	48.27	49.74	50.45	50.92	51.87
TEMP_MTR_NDE_BEAR	28799	55.15	0.49	53.87	54.81	55.15	55.41	56.40
WIND_TEMP1	28799	61.28	3.45	52.13	59.12	60.61	61.94	64.91
TEMP_MTR_DE_BEAR	28799	62.37	0.37	60.64	62.17	62.38	62.62	64.01

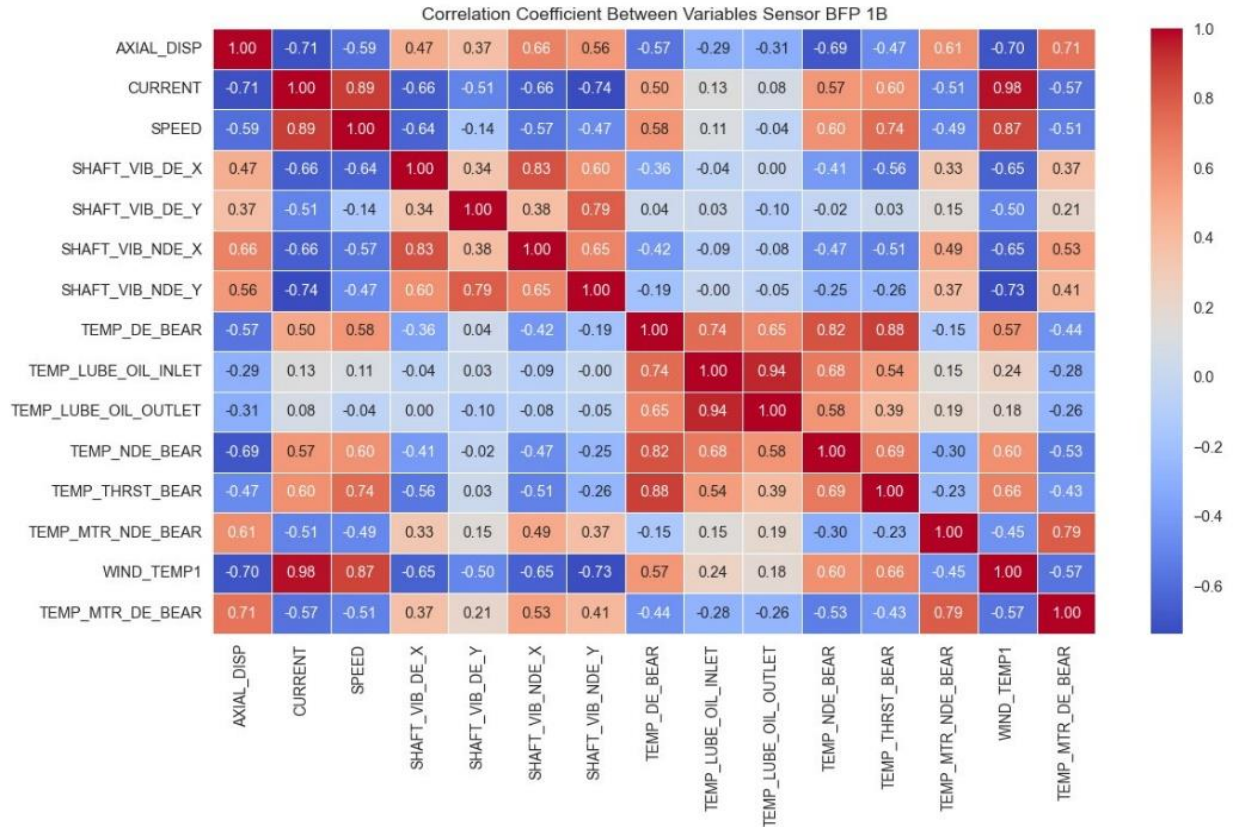


Figure 8 Sensor correlation heatmap

To facilitate data analysis, a descriptive statistical analysis was performed on the SCADA sensor data of the BFP after exploratory data analysis (EDA), as presented in Table 4.

As shown in Figure 8, which presents the sensor correlation heatmap, a strong relationship is observed between pump speed and motor current, which is also accompanied by an increase in winding temperature as the speed rises. This correlation pattern

confirms the operational validity and consistency of the sensor data, indicating that the measurements accurately reflect real system behavior under varying load and speed conditions. As an additional explanation of the statistical data quality, correlation values approaching +1 (e.g., $r > 0.8$) indicate a strong positive linear relationship between sensors, meaning that when one variable increases, the other tends to increase as well (Karamanou et al., 2022). Conversely, correlation values approaching -1 (e.g., $r < -0.8$), indicate a strong negative linear relationship, where an increase in one variable corresponds to a decrease in the other.

4.2 Model Training and Development

The trained LSTM-AE demonstrated stable learning behavior and successfully captured the normal operational patterns of the BFP using historical SCADA data. The model achieved low reconstruction error across all monitored variables, indicating effective convergence and accurate reproduction of normal time-series behavior. Model performance was further evaluated using unseen normal data, where the reconstructed signals closely followed the actual sensor measurements. These results confirm the model's ability to generalize beyond the training data and provide a reliable baseline for reconstruction-based anomaly detection in subsequent analyses.

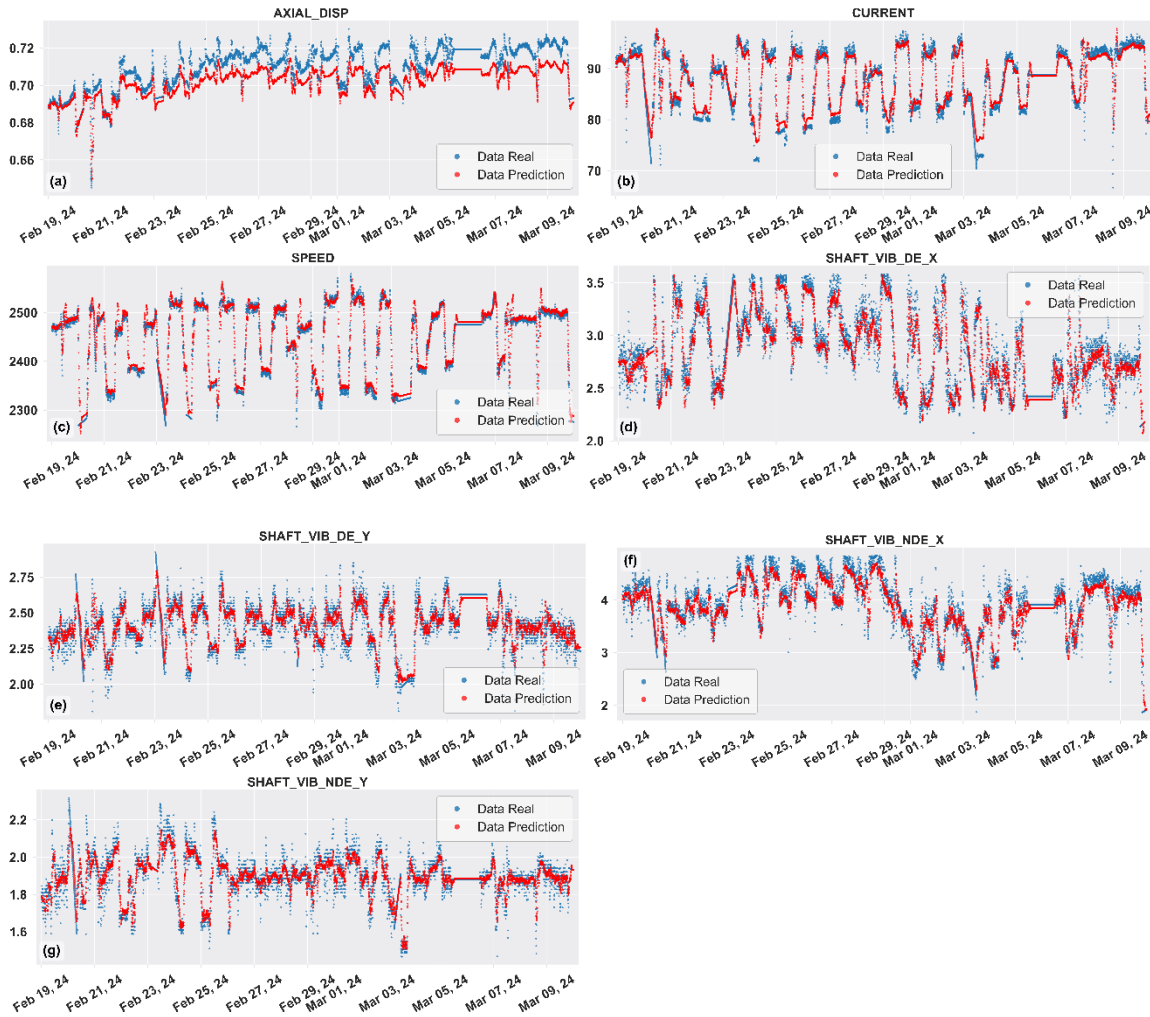


Figure 9 Reconstruction results of the LSTM-AE model for the monitored boiler feed pump sensor variables (part 1 of 2): (a) Axial_Dis, (b) Current, (c) Speed, (d) Shaft_Vib_DE_X, (e) Shaft_Vib_DE_Y, (f) Shaft_Vib_NDE_X, and (g) Shaft_Vib_NDE_Y

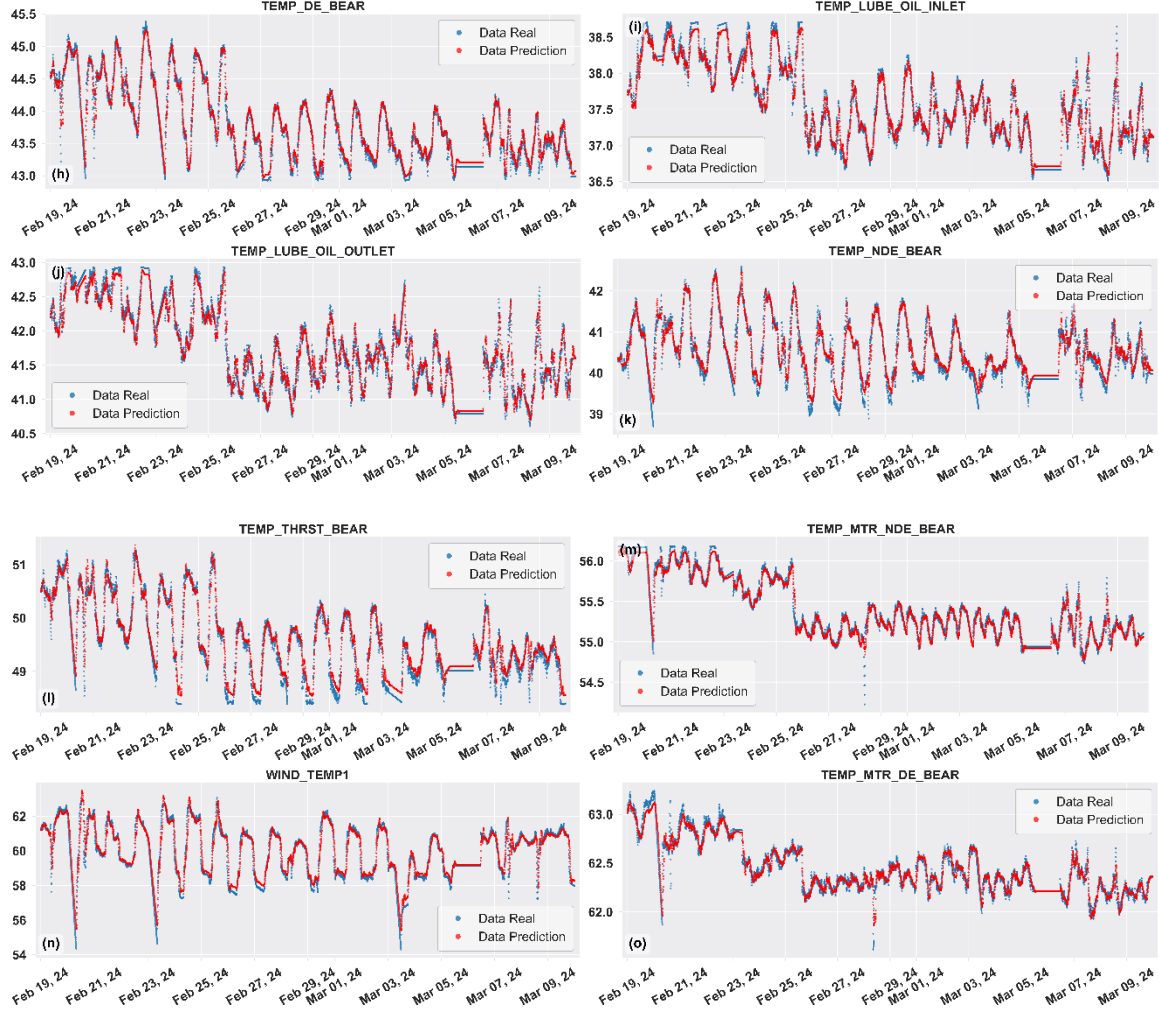


Figure 10 Reconstruction results of the LSTM-AE model for the monitored boiler feed pump sensor variables (part 2 of 2): (h) Temp_De_Bear, (i) Temp_Lube_Oil_Inlet, (j) Temp_Lube_Oil_Outlet, (k) Temp_Nde_Bear, (l) Temp_Thrst_Bear, (m) Temp_Mtr_Nde_Bear, (n) Wind_Temp1, and (o) Temp_Mtr_De_Bear

Figures 9-10 present the comparison between the real sensor readings and the reconstructed data generated by the LSTM-AE model for each of the fifteen monitored variables. The red lines represent the reconstructed signals, while the blue points indicate the actual sensor data obtained from the SCADA. Overall, the reconstruction plots demonstrate that the model effectively learns and reproduces the temporal behavior of the system under normal operating conditions. Most of the variables, such as SPEED, CURRENT, and temperature sensors (TEMP_DE_BEAR, TEMP_THRST_BEAR, TEMP_LUBE_OIL_IN/OUTLET), show very close alignment between the real and reconstructed signals, indicating low reconstruction error. This reflects the model's strong

capability in capturing the underlying nonlinear temporal dependencies among multiple sensor variables. Slight deviations observed in certain vibration sensors (SHAFT_VIB_DE_X, SHAFT_VIB_NDE_Y) suggest periods of dynamic operational transitions, likely due to load or speed changes during pump operation. These deviations are valuable as they can serve as early indicators of potential anomalies when the reconstruction error exceeds the defined threshold. In general, the reconstructed results validate the model's robustness in learning normal patterns and provide a solid foundation for detecting abnormal conditions in subsequent anomaly detection stages.

4.3 Reconstruction Error Analysis

To quantify the model's reconstruction performance, the Mean Squared Error (MSE) was employed as the primary metric (Lachekhab et al., 2024). The MSE measures the average squared difference between the actual and reconstructed sensor values, reflecting how well the model can reproduce the input data (Lee et al., 2024). During the training process, the model's validation loss, also computed using MSE, was continuously monitored on a separate validation dataset containing normal operation data that were not used in training. A low and stable validation loss indicates that the LSTM-AE generalizes effectively to unseen normal data and is not overfitted to the training samples. This consistency between training and validation loss confirms that the model successfully captured the normal temporal and nonlinear patterns of the BFP system.

Figure 11 illustrates the training and validation loss curves of the LSTM-AE model. These curves provide insight into the model's learning behavior during training, whether it learns effectively, underfits, or overfits. The blue line represents the training loss, indicating the model's reconstruction error on the training dataset, while the green line represents the validation loss, measuring the error on unseen data to evaluate generalization capability. The x-axis denotes the number of epochs, and the y-axis shows the loss value, where a smaller value indicates better performance. At the beginning of training, both losses are high, but they gradually decrease as the model learns. The convergence of the two curves at low loss values with a small gap indicates that the model has learned well and generalizes effectively to unseen data.

To further assess the reconstruction performance of the model, the MSE was computed for

each sensor variable, as presented in Table 5. The MSE quantifies the average squared difference between the real and reconstructed signals, where lower values indicate better reconstruction accuracy and thus more precise learning of normal operating behavior. Across all sensor variables, the MSE values remain consistently low, confirming that the LSTM-AE effectively captured the normal operational patterns of the BFP system. These findings demonstrate that the model is capable of distinguishing normal and abnormal conditions based on deviations in reconstruction error observed in subsequent analyses. Table 5 summarizes the training and validation performance metrics of the LSTM-AE model for each sensor variable of the BFP. Overall, the model demonstrates strong reconstruction capability, indicated by low MSE values and high coefficients of determination (R^2) for both training and validation datasets. The majority of the sensors achieved Train R^2 and Val R^2 values above 0.95, suggesting that the model successfully captured the underlying operational behavior of the system. CURRENT, SPEED and the temperature-related sensors show close agreement between training and validation results (Val $R^2 \geq 0.94$), indicating good generalization. Larger training-validation gaps are observed for AXIAL_DISP (1.00 $\rightarrow$ 0.87) and for the vibration channels, most notably SHAFT_VIB_DE_X (0.95 $\rightarrow$ 0.70). These gaps are attributed to the higher stochastic variability of vibration signals under changing load, and they mean that reconstruction-error thresholds for the vibration channels must be interpreted with correspondingly greater caution. Overall, these results validate that the LSTM-AE effectively learned the normal operational patterns of the BFP and can reliably serve as a baseline model for anomaly detection and proactive maintenance implementation.

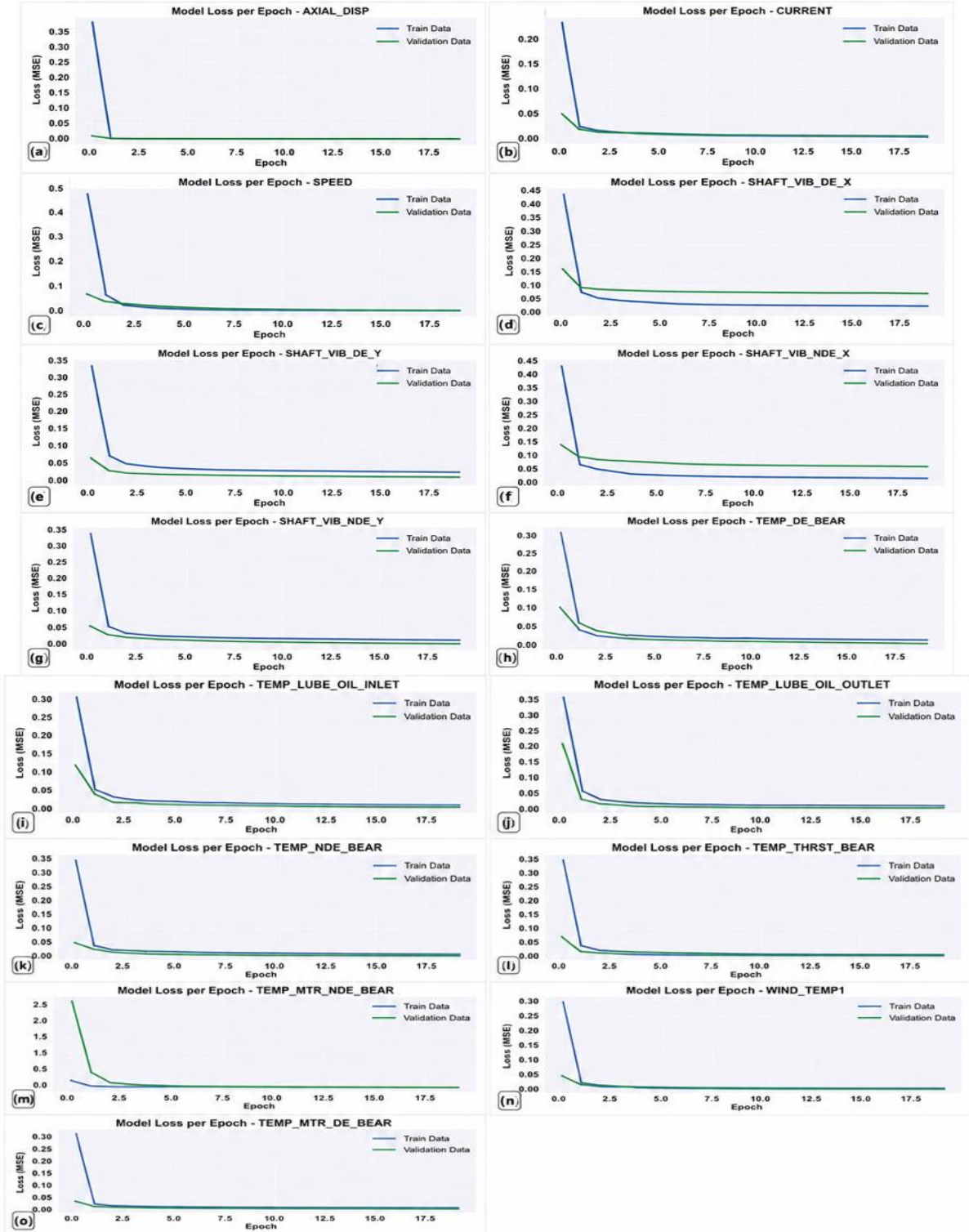


Figure 11 Training and validation loss curves of the LSTM-AE model for the fifteen monitored boiler feed pump (BFP) sensor variables: (a) Axial_Disp, (b) Current, (c) Speed, (d) Shaft_Vib_DE_X, (e) Shaft_Vib_DE_Y, (f) Shaft_Vib_NDE_X, (g) Shaft_Vib_NDE_Y, (h) Temp_DE_Bear, (i) Temp_Lube_Oil_Inlet, (j) Temp_Lube_Oil_Outlet, (k) Temp_NDE_Bear, (l) Temp_Thrst_Bear, (m) Temp_MTR_NDE_Bear, (n) Wind_Temp1, and (o) Temp_MTR_DE_Bear

Table 5 Model training and validation performance for boiler feed pump sensor variables

Sensor	Train MSE	Train R ²	Val MSE	Val R ²
AXIAL DISP	0.00	1.00	0.00	0.87
CURRENT	0.01	0.99	0.01	0.98
SPEED	0.01	0.99	0.01	0.98
SHAFT VIB DE X	0.05	0.95	0.08	0.70
SHAFT VIB DE Y	0.05	0.95	0.04	0.89
SHAFT VIB NDE X	0.06	0.94	0.09	0.85
SHAFT VIB NDE Y	0.03	0.97	0.05	0.81
TEMP DE BEAR	0.02	0.98	0.03	0.99
TEMP LUBE OIL INLET	0.02	0.98	0.02	0.97
TEMP LUBE OIL OUTLET	0.02	0.98	0.01	0.97
TEMP NDE BEAR	0.02	0.98	0.01	0.99
TEMP THRST BEAR	0.02	0.98	0.03	0.99
TEMP MTR NDE BEAR	0.01	0.99	0.01	0.96
WIND TEMPI	0.00	1.00	0.00	0.99
TEMP MTR DE BEAR	0.01	0.99	0.01	0.94

Table 6 Selected threshold multipliers (k) and operational data ranges for boiler feed pump sensor variables

No	Sensor	Threshold multiplier, k	Range data series	Normal operation
1	Vibration	6	min 1.1 max 4.9	0 - 7.1 mm/s
2	Temperature of pump bearing	10	min 42 max 46	42 – 60 °C
3	Temperature of motor bearing	14	min 53 max 64	42 – 65 °C
4	Temperature at the oil cooler inlet and outlet	14	min 36 max 43	32 - 45 °C
5	Axial	8	min 0.6 max 1.4	-2 - 2 mm
6	Temperature of winding motor	10	min 52 max 72	50 - 75 °C

4.4 Anomaly Threshold Determination

An anomaly threshold was statistically determined from the reconstruction-error distribution of the training data, defined as the mean plus k times the standard error of the moving window (Eq. 12). Several values of the threshold multiplier k were simulated to identify a representative threshold reflecting the plant's operational characteristics. Smaller k values produce a more sensitive model, while larger k values reduce false alarms but lower sensitivity. The chosen threshold was validated using historical maintenance logs and expert feedback from plant engineers.

The validation confirmed that the model accurately distinguishes between normal and abnormal conditions, providing a reliable foundation for proactive maintenance and real-time anomaly detection in power plant operations.

Table 6 presents the sigma thresholds and operational data ranges for six key sensors used in the anomaly detection framework of the BFP system.

In this study, a σ -based threshold on the LSTM-AE reconstruction error was adopted as a simple and interpretable decision rule consistent with common industrial SCADA practices, where

statistical limits are often preferred for transparency and ease of implementation. The anomaly detection capability in the proposed framework primarily stems from the LSTM-AE's ability to learn normal temporal behavior, while the σ -based threshold serves only as a decision boundary on the reconstruction error derived from healthy training data, rather than as the core detection mechanism. The threshold was calibrated in a fully data-driven manner using the distribution of reconstruction errors observed during normal operation, rather than relying on fixed engineering limits. To ensure practical relevance, the selected threshold was further assessed using SCADA trend inspection, historical maintenance records, and expert feedback from plant engineers. This qualitative validation was used to confirm that the resulting anomaly indications were physically meaningful and did not generate spurious alarms during clearly stable operating periods. Although more advanced thresholding strategies (e.g., percentile-based thresholds, adaptive or dynamic thresholds) may further improve detection robustness and false-alarm control, a systematic quantitative comparison of alternative thresholding methods was not conducted in this study due to the absence of continuous ground-

truth labels and the presence of only a single verified degradation event. This limitation is explicitly acknowledged, and alternative thresholding strategies are identified as important future work.

4.5 Anomaly Detection Result using LSTM-AE

From a theoretical perspective, the effectiveness of the proposed LSTM-AE model is attributed to its ability to capture both temporal dependencies and nonlinear feature representations. The LSTM component models sequential patterns in multivariate SCADA data by retaining long-term operational dependencies, which are essential for distinguishing gradual degradation trends from normal transient fluctuations. Meanwhile, the autoencoder learns a compact latent representation of normal operating behavior. When the pump condition deviates from this learned pattern, the reconstruction error increases, serving as a quantitative indicator of abnormal behavior. This mechanism explains why early-stage mechanical degradation, particularly in vibration signals, can be detected before reaching conventional alarm limits, making it more sensitive to subtle and progressive degradation patterns.

Based on the implemented algorithm and the established threshold limits, the following figures illustrate the detected anomalies in the BFP during its operational period. Figure 12 shows the anomaly detection results obtained from the four vibration sensors using the LSTM-AE model. The signal pattern shows several anomaly points that exceed the predefined threshold, indicating potential deviations from the normal operating condition.

From the anomaly detection results, several anomaly points were identified where the vibration values exceeded the upper threshold limit. These anomalies were observed primarily in the DE and NDE bearing sensors, which is consistent with the behavior expected during early-stage degradation.

The results of the anomaly detection on the pump bearing temperature, motor bearing temperature, lube oil temperature, axial displacement, and motor winding temperature show no evidence of abnormal patterns, as illustrated in Figures 13 to 17. This indicates that the equipment operated under normal conditions throughout the monitoring period.

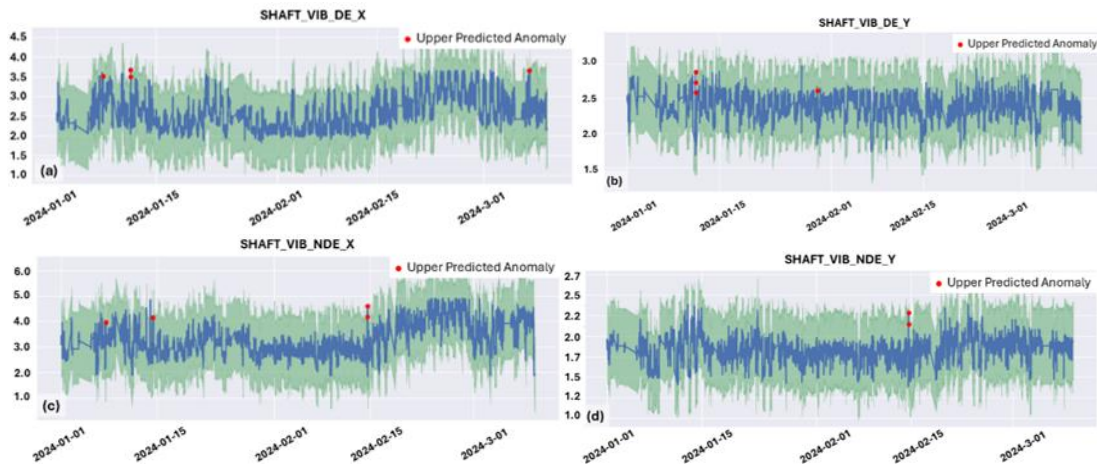


Figure 12 Anomaly detection results for the boiler feed pump vibration sensors using the LSTM-AE model: (a) Shaft_Vib_DE_X, (b) Shaft_Vib_DE_Y, (c) Shaft_Vib_NDE_X, and (d) Shaft_Vib_NDE_Y

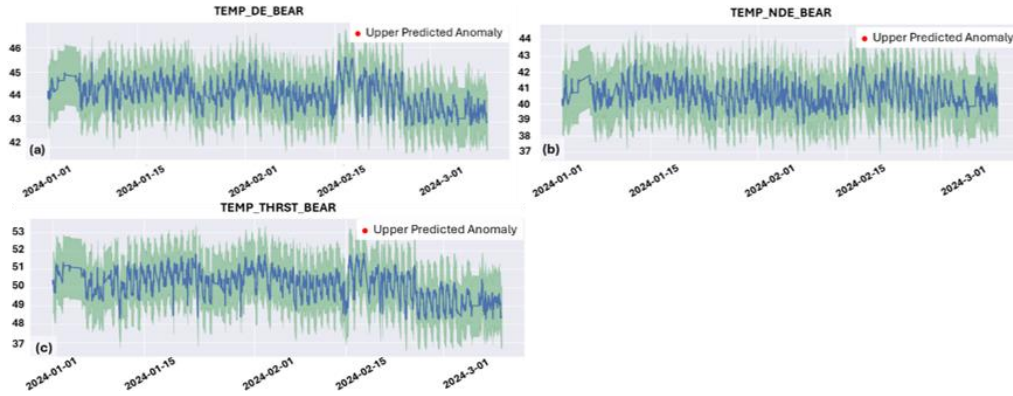


Figure 13 Anomaly detection results for the boiler feed pump bearing temperature sensors using the LSTM-AE model: (a) Temp_DE_Bear, (b) Temp_NDE_Bear, and (c) Temp_Thrst_Bear. No anomaly was detected

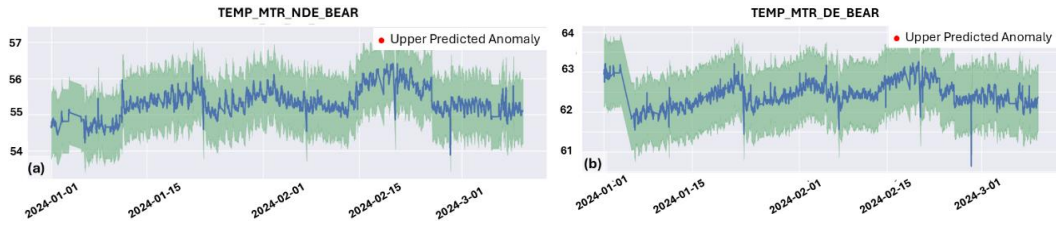


Figure 14 Anomaly detection results for the motor bearing temperature sensors using the LSTM-AE model: (a) Temp_MTR_NDE_Bear and (b) Temp_MTR_DE_Bear. No anomaly was detected

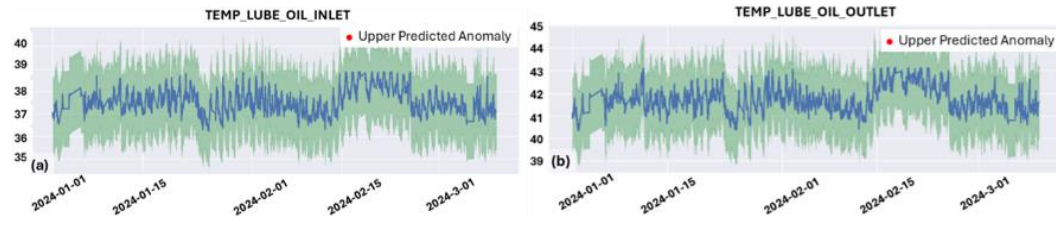


Figure 15 Anomaly detection results for the lube oil temperature sensors using the LSTM-AE model: (a) Temp Lube Oil Inlet and (b) Temp Lube Oil Outlet. No anomaly was detected

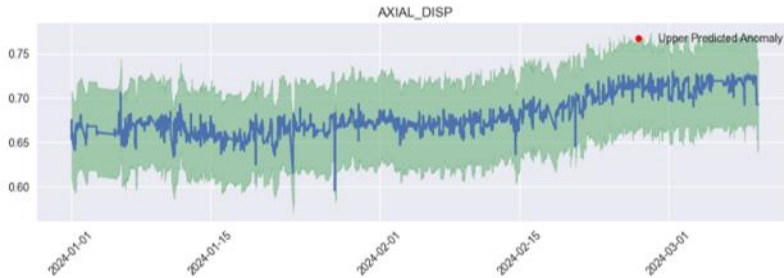


Figure 16 Detection of anomalies from the axial displacement sensor. No anomaly was detected

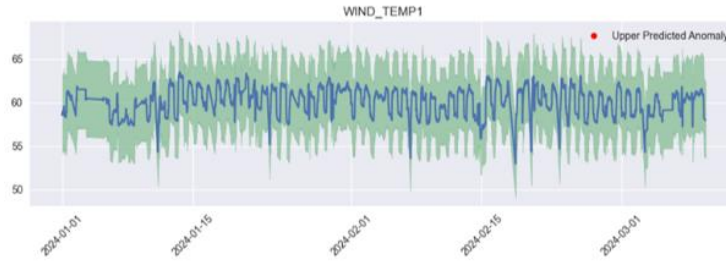


Figure 17 Detection of anomalies from the winding temperature sensor. No anomaly was detected

4.6 Analysis and Interpretation of the Anomaly Detection Results

This subsection interprets the detected anomalies in relation to conventional threshold-based monitoring and to the field inspection findings. In the studied plant, the operational vibration alarm and trip thresholds for the BFP are 6.8 mm/s and 7.1 mm/s RMS, respectively. During the entire monitoring period and at all timestamps corresponding to the 14 anomaly events reported in Tables 7 and 8, all shaft vibration measurements remained below both the alarm and trip limits. According to the plant's SCADA logic, these operating conditions would therefore be classified as normal, and neither a vibration alarm nor a trip would have been triggered. Nevertheless, the proposed LSTM-AE model consistently highlighted gradual and persistent deviations from learned normal behavior under these sub-alarm operating conditions. These anomaly indications were subsequently verified through field inspection, which revealed mechanical degradation. This empirical observation indicates that, for this specific case study, fixed-threshold monitoring based on the plant's operational alarm and trip limits did not generate any alarm-based warning prior to inspection, whereas the proposed LSTM-AE model provided additional anomaly indications under operating conditions that were still classified as normal by the conventional monitoring system.

The anomaly events reported in Tables 7 and 8 represent the complete set of upper-anomaly indications generated by the proposed LSTM-AE model for the analyzed monitoring period, rather than selected examples from a larger pool of detections. No anomaly indications were observed during clearly stable operating periods, indicating that the model did not generate spurious detections under normal conditions. Based on the anomaly detection results, it was observed that the anomalies occurred primarily in the pump vibration signals, as illustrated in Figure 12. To further assess the equipment condition, a detailed analysis was performed by examining the event

timestamps, magnitude variations, and temporal patterns across several observation intervals. This approach provides a more comprehensive understanding of the vibration behavior and its potential implications. The summarized vibration anomaly events, derived from the detection results shown in Figure 12, are presented in Table 7.

Based on the data presented in Table 7, verification and evaluation were conducted using historical SCADA records to examine the observed vibration patterns, as summarized in Table 8. For example, anomaly event No. 2 of the Vib DEX sensor (Table 8) detected on January 11, 2024, at 09:35 (UTC+8) corresponds to a gradual increase in vibration amplitude from approximately 2.2 mm/s to 3.5 mm/s over a 40-minute period. This sustained increase indicates the onset of abnormal vibration behavior rather than a transient fluctuation. Similarly, anomaly event No. 4 of the Vib NDEX sensor occurred on February 14, 2024, at 15:10 (UTC+8), where the vibration level increased progressively from 2.0 mm/s to 4.6 mm/s within the same operational period. Comparable gradual increases were also observed in the Vib DEY sensor (events No. 1–3), where vibration amplitudes rose consistently from 1.6 mm/s to approximately 2.8 mm/s within a short time window. These representative examples demonstrate that the detected anomalies are supported by clear SCADA trend behavior, characterized by gradual and sustained vibration increases across multiple sensor locations.

This verification confirms that the anomaly detection results reflect actual degradation processes in the BFP. Some anomalies were also associated with sudden vibration increases. For example, anomaly event No. 1 of the Vib DEX sensor on January 7, 2024, exhibited a rapid vibration rise from 2.4 mm/s to 3.5 mm/s within 5 minutes, with a simultaneous increase observed in the Vib NDEX sensor. These sudden changes further validate the anomaly detection results.

Table 7 Vibration anomaly detection results and event times

Sensor	Time	Value (mm/s)
SHAFT_VIB_DE_X	7 January 2024, 12:20 (UTC+8)	3.5
SHAFT_VIB_DE_X	11 January 2024, 9:35 (UTC+8)	3.5
SHAFT_VIB_DE_X	11 January 2024, 9:40 (UTC+8)	3.6
SHAFT_VIB_DE_X	7 March 2024, 11:40 (UTC+8)	3.6
SHAFT_VIB_DE_Y	11 January 2024, 9:20 (UTC+8)	2.5
SHAFT_VIB_DE_Y	11 January 2024, 9:25 (UTC+8)	2.7
SHAFT_VIB_DE_Y	11 January 2024, 9:30 (UTC+8)	2.8
SHAFT_VIB_DE_Y	29 January 2024, 20:40 (UTC+8)	2.6
SHAFT_VIB_NDE_X	7 January 2024, 12:20 (UTC+8)	3.9
SHAFT_VIB_NDE_X	14 January 2024, 8:25 (UTC+8)	4.1
SHAFT_VIB_NDE_X	14 February 2024, 15:05 (UTC+8)	4.1
SHAFT_VIB_NDE_X	14 February 2024, 15:10 (UTC+8)	4.6
SHAFT_VIB_NDE_Y	14 February 2024, 15:05 (UTC+8)	2.1
SHAFT_VIB_NDE_Y	14 February 2024, 15:10 (UTC+8)	2.2

Table 8 Verification and evaluation of detected vibration anomalies based on SCADA historical data

Sensor	Upper Anomaly	Event Description	Event Time
Vib DEX	4 times	1 Vibration increased on January 7, 2024 from 12:15 to 12:20 (UTC+8) (2.4 mm/s to 3.5 mm/s)	January 7, 2024 at 12:20 (UTC+8)
		2 Vibration gradually increased on January 11, 2024 from 08:55 to 09:35 (UTC+8) (2.2 → 3.5 mm/s).	January 11, 2024 at 09:35 (UTC+8)
		3 Vibration gradually increased on January 11, 2024 from 08:55 to 09:40 (UTC+8) (2.2 → 3.6 mm/s).	January 11, 2024 at 09:40 (UTC+8)
		4 Vibration increased on March 7, 2024 from 11:35 to 11:40 (UTC+8) (2.6 → 3.6 mm/s).	March 7, 2024 at 11:40 (UTC+8)
Vib DEY	4 times	1 Vibration gradually increased on January 11, 2024 from 08:50 to 09:20 (UTC+8) (1.6 → 2.5 mm/s).	January 11, 2024 at 09:20 (UTC+8)
		2 Vibration gradually increased on January 11, 2024 from 08:50 to 09:25 (UTC+8) (1.6 → 2.7 mm/s).	January 11, 2024 at 09:25 (UTC+8)
		3 Vibration gradually increased on January 11, 2024 from 08:50 to 09:30 (UTC+8) (1.6 → 2.8 mm/s).	January 11, 2024 at 09:30 (UTC+8)
		4 Vibration gradually increased on January 29, 2024 from 20:20 to 20:40 (UTC+8) (1.9 → 2.6 mm/s)	January 29, 2024 at 20:40 (UTC+8)
Vib NDEX	4 times	1 Vibration increased on January 7, 2024, from 12:15 to 12:20 (UTC+8) (2.2 → 3.9 mm/s)	January 7, 2024 at 12:20 (UTC+8)
		2 Vibration gradually increased on January 14, 2024, from 08:05 to 08:25 (UTC+8) (2.3 → 4.1 mm/s).	January 14, 2024 at 08:25 (UTC+8)
		3 Vibration gradually increased on February 14, 2024, from 14:30 to 15:05 (UTC+8) (2.0 → 4.1 mm/s)	February 14, 2024 at 15:05 (UTC+8)
		4 Vibration gradually increased on February 14, 2024, from 14:30 to 15:10 (UTC+8) (2.0 → 4.6 mm/s).	February 14, 2024 at 15:10 (UTC+8)
Vib NDEY	2 times	1 Vibration gradually increased on February 14, 2024, from 14:45 to 15:05 (UTC+8) (1.5 → 2.1 mm/s).	February 14, 2024 at 15:05 (UTC+8)
		2 Vibration gradually increased on February 14, 2024, from 14:45 to 15:10 (UTC+8) (1.5 → 2.2 mm/s).	February 14, 2024 at 15:10 (UTC+8)



Figure 18 Field inspection results of boiler feed pump components following the LSTM-AE-based anomaly detection: (a) slight shaft pump bending, (b) hub bush impeller over clearance, (c) impeller wear ring over clearance, (d) balance disc over clearance, and (e) balance seat over clearance

Based on Table 8, it can be observed that the LSTM-based anomaly detection model successfully captured both gradual and sudden increases in vibration amplitude over specific time periods. This behavior indicates early signs of pump degradation. Subsequent field inspection of the BFP revealed mechanical wear in several critical components, including slight pump shaft bending, excessive clearance in the impeller hub bush, excessive clearance in the impeller wear ring, and excessive clearance in the balance disc and seat, which further confirms the model's anomaly detection results. The inspected components can be seen in Figure 18.

The predominance of vibration-related anomalies is consistent with mechanical degradation mechanisms in rotating machinery, where early faults such as shaft bending, increased clearance, and wear typically manifest in vibration signals before thermal effects become evident.

Although the proposed framework demonstrated consistent detection under real operating conditions, its performance depends on threshold selection and sensor data quality; the absence of labeled fault data limits quantitative false-alarm evaluation, but validation through SCADA trend analysis and field inspection provides practical confidence in the detected anomalies. From an application perspective, the LSTM-AE framework can be integrated into existing SCADA-based monitoring systems as an early warning tool to support proactive maintenance and reduce unplanned downtime.

5. Conclusion

This study demonstrates the feasibility of applying a deep learning-based proactive maintenance framework for boiler feed pumps (BFP) using a Long Short-Term Memory Autoencoder (LSTM-AE) and multivariate Supervisory Control and Data Acquisition (SCADA) data. The LSTM-AE model demonstrated strong reconstruction capability across multiple boiler feed pump sensors, effectively learning normal operating behavior and providing a reliable basis for reconstruction-based anomaly detection. The results indicate that the proposed framework is capable of identifying early-stage abnormal behavior, thereby supporting proactive maintenance decision-making and contributing to improved operational reliability in coal-fired power plant environments.

Despite the promising results, this study has several limitations that should be acknowledged. First, the performance of the proposed anomaly

detection framework depends on the quality and reliability of SCADA sensor data. Noise, sensor drift, or calibration errors may affect reconstruction accuracy and anomaly sensitivity. Second, the k -based statistical thresholding approach, while transparent and practical for industrial implementation, is sensitive to threshold selection and assumes relatively stable statistical behavior. Although the threshold multipliers were tuned using historical data and expert validation, adaptive or probabilistic thresholding methods may provide improved robustness. Third, this study focuses on a single LSTM-AE model without comparison to other anomaly detection techniques. Comparative evaluation with alternative models is left for future work. These limitations highlight opportunities for further improvement and extension of the proposed framework. Future work will focus on extending the proposed framework toward real-time deployment within SCADA environments, enabling continuous online anomaly monitoring of boiler feed pumps. In addition, comparative studies involving alternative anomaly detection models may be conducted to evaluate detection performance, robustness, and false alarm rates. Further research may also investigate sensor health monitoring and data quality assessment to ensure reliable anomaly detection under long-term industrial operating conditions.

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7. CRediT Statement

Habib Muhajir: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Visualization, Writing – Original Draft

Achmad Widodo: Conceptualization, Methodology, Validation, Writing – Review & Editing, Supervision

Toni Prahasto: Methodology, Validation, Writing – Review & Editing, Supervision

8. Abbreviations

Abbreviation	Full Term
AE	Autoencoder
BFP	Boiler Feed Pump
CM	Condition Monitoring
CMMS	Computerized Maintenance Management System

Abbreviation	Full Term
DE / NDE	Drive End / Non-Drive End
EDA	Exploratory Data Analysis
EWS	Engineering Work Station
LSTM	Long Short-Term Memory
LSTM-AE	Long Short-Term Memory Autoencoder
ML	Machine Learning
MSE	Mean Squared Error
MW	Megawatt
RMS	Root Mean Square
RNN	Recurrent Neural Network
RPM	Revolutions Per Minute
SCADA	Supervisory Control and Data Acquisition

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