International Journal of Heat and Technology
Vol. 42, No. 5, October, 2024, pp. 1507-1516
Journal homepage: http://iieta.org/journals/ijht

# Intelligent Monitoring of Thermodynamic Parameters in Compressor Operations and Development of a Fault Prediction Model Using Deep Learning

Litao Sun[1,2,3,4*], Longxue Cheng[1], Xianxia Liang[1], Longfei Yue[1], Yupeng Li[1]

[1] Department of Electrical Engineering, Hebei Institute of Mechanical and Electrical Technology, Xingtai 054000, China
[2] International College, Krirk University, Bangkok 10220, Thailand
[3] Hebei Technical Innovation Center for Intelligent Sensing and Advanced Control of Mechanical and Electrical Equipment, Xingtai 054000, China
[4] Xingtai Technical Innovation Center for Intelligent Sensing and Control of Mechanical and Electrical Equipment, Xingtai 054000, China

Corresponding Author Email: LT-SUN@hotmail.com



https://doi.org/10.18280/ijht.420503

**Received:** 13 April 2024
**Revised:** 26 August 2024
**Accepted:** 12 September 2024
**Available online:** 31 October 2024

***Keywords:***
*compressor, fault prediction, thermodynamic model, intelligent monitoring, deep learning, sparrow search algorithm (SSA), long short-term memory (LSTM)*

**ABSTRACT**

Compressors, as essential industrial equipment, are widely utilized in air conditioning, refrigeration, energy, and chemical sectors. The operational stability of compressors directly impacts system efficiency and safety. Due to the complex thermodynamic processes and variable operating conditions involved in compressor operations, accurately monitoring their status and predicting potential faults are crucial for improving equipment reliability and optimizing maintenance strategies. Traditional compressor fault prediction methods usually rely on thermodynamic models and statistical analysis. While some progress has been made, existing methods often face limitations when addressing complex nonlinear, multivariable, and time-varying characteristics. Recently, machine learning and deep learning-based fault prediction methods have gained significant attention, but challenges remain in real-world applications, including data quality, model accuracy, and computational efficiency. To address these issues, this paper proposes an intelligent monitoring and fault prediction approach for compressors based on deep learning. First, a thermodynamic model of the compressor operation process is constructed, enabling real-time acquisition of key operational parameters. Subsequently, a fault prediction model is developed by integrating the sparrow search algorithm (SSA) with the long short-term memory (LSTM) model. By performing time series analysis on compressor operational data, the model achieves accurate fault prediction and early warning. This approach effectively enhances prediction accuracy and robustness, offering strong practical application value.

## 1. INTRODUCTION

With the continuous advancement of industrialization, compressors play a crucial role in various mechanical equipment and are widely used in fields such as air conditioning, refrigeration, petrochemicals, and energy [1-4]. As a high-efficiency power device, the stable operation of compressors directly impacts system efficiency and safety. Therefore, accurately monitoring the operational status of compressors and predicting their faults in a timely manner has become an important research topic in related fields [5-7]. During compressor operation, changes in internal environments and external loads can impact performance, further affecting thermodynamic parameters of the system, such as pressure, temperature, and flow rate [8, 9]. Consequently, accurately obtaining and analyzing thermodynamic parameters during compressor operation has become a critical approach to improving compressor operational efficiency and reliability, reducing energy consumption, and minimizing fault occurrences.

Currently, research on compressor fault prediction and health monitoring has made certain progress, with many researchers attempting to predict and diagnose compressor faults based on traditional thermodynamic models, statistical methods, and machine learning techniques [10-13]. By real-time monitoring and analyzing compressor operational data in combination with various fault modes, researchers have proposed multiple predictive algorithms aimed at improving the accuracy of fault detection and early warning capabilities [14, 15]. These studies not only contribute to extending equipment lifespan and reducing maintenance costs but also enhance production safety and system reliability to a certain extent. Thus, constructing an efficient and accurate compressor fault prediction and monitoring model holds significant application value and practical significance.

However, most existing research is based on traditional thermodynamic models and statistical analysis methods, often relying on manually set rules and feature selection, making it challenging to address the complex, nonlinear, and time-varying nature of compressor operations [16-19]. Even studies using machine learning and deep learning methods often face issues in balancing data quality, model complexity, and prediction accuracy [20, 21]. Current fault prediction models still exhibit deficiencies in handling multivariable and multifactor influences, such as overfitting, low computational efficiency, and poor model robustness, which to some extent restricts their promotion and application in actual engineering.

To address the above issues, this paper proposes a new deep learning-based method for intelligent monitoring and fault prediction of compressor operational status. First, a thermodynamic model of compressor operation based on thermodynamic principles is constructed, and an intelligent detection method is designed to monitor key operational parameters of the compressor in real-time, providing accurate status assessment. Secondly, this paper proposes a new compressor fault prediction method based on the combination of the SSA and the LSTM model, achieving early fault prediction by processing complex time series data. Through this integrated technical framework combining deep learning and thermodynamic models, compressor fault prediction accuracy, timeliness, and robustness are effectively improved. The research in this paper not only provides an innovative solution for compressor fault prediction but also establishes a new technological foundation for the intelligent operation and maintenance and health management of industrial equipment.

## 2. THERMODYNAMIC MODEL CONSTRUCTION AND INTELLIGENT PARAMETER DETECTION FOR COMPRESSOR OPERATION

Figure 1 presents the schematic of the intelligent detection for compressor thermodynamic parameters. In constructing the thermodynamic model of compressor operation for intelligent parameter detection, a series of reasonable assumptions about the working medium's thermodynamic characteristics and operating conditions are necessary. These assumptions aim to simplify system complexity while ensuring the model's operability and computational efficiency in practical applications.

(1) It is assumed that the working medium within the compressor system remains in a uniform state, meaning that thermodynamic parameters such as temperature and pressure are consistent at all points within the system.

(2) The flow of the working medium within the cylinder is assumed to be single-phase, implying that the flow is uniform and continuous, disregarding multiphase flow or irregularities in flow.

(3) When constructing the thermodynamic model, it is assumed that gas state parameters at all points within the compressor cylinder are identical, meaning the gas inside the cylinder remains in a homogeneous isothermal and isobaric state.

(4) To simplify the analysis of gas state changes, pressure variations in the intake and exhaust pipes of the compressor are assumed negligible, with pressure considered as a constant value.

(5) Focusing on the gas state changes inside the cylinder, only the internal energy of the gas in the cylinder is considered, while the influence of gas kinetic and potential energy is ignored.

Based on the law of mass conservation, assuming no leakage of the working medium, the change in mass entering and leaving the control volume of the compressor equals the mass increment of the working medium within the control volume. Specifically, by monitoring the flow rates at the intake and exhaust ports and combining with the state parameters of the working medium, the mass increment of the working medium within the compressor at each stage can be calculated, thus providing foundational data for subsequent energy analysis. Let $L$ represent the mass of the working medium in the cylinder, $L_t$ the mass of discharged medium, and $L_f$ the mass of intake medium, then:

$$dL = dL_T - dL_f \tag{1}$$

According to the first law of thermodynamics, the energy changes in an open system can be described by the energy conservation equation. For a compressor, the energy changes during the compression, expansion, intake, and exhaust processes all need to be modeled individually. By establishing differential equations for each stage, the changes in gas state parameters over time can be described, accurately reflecting the combined effects of internal energy, external power input, heat exchange, and other factors on the working medium in each process. Let $W$ represent the heat added from the external environment to the system, $s$ represent time, $Q$ represent the work done by the working medium on the external environment, $g_f$ the specific enthalpy of the working medium in the exhaust valve chamber, $g_t$ the specific enthalpy in the intake valve chamber, and $i$ the specific internal energy of the working medium in the cylinder. Then, the thermodynamic process in the open system is expressed as:

$$\frac{dW}{ds} - \frac{dQ}{ds} = \frac{dL_f}{ds} g_f - \frac{dL_t}{ds} g_t + \frac{d}{ds}(L \cdot i) \tag{2}$$

Since

$$g = Z_o \cdot S \tag{3}$$

$$i = Z_n \cdot S \tag{4}$$

$$j = Z_o / Z_n \tag{5}$$

Assuming that the temperature of the working medium in the cylinder is represented by $S$, the temperature of the working medium in the exhaust valve chamber by $S_f$, and the temperature of the working medium in the intake valve chamber by $S_t$, with constant-volume specific heat represented by $Z_n$, constant-pressure specific heat by $Z_o$, and adiabatic coefficient by $j$, Eq. (2) can be rewritten as:

$$\frac{dW}{ds} - \frac{dQ}{ds} = \frac{dL_f}{ds} jZ_n S_{fn} - \frac{dL_t}{ds} jZ_n S_{tn} + LZ_n \frac{dS}{ds} + Z_n S \frac{dL}{ds} \tag{6}$$

Assuming the cylinder pressure is represented by $PO$, cylinder volume by $VN$, compression factor by $ZC$, the amount of gas substance by $L$, the gas constant by $E$, and the gas temperature by $S$. Then:

$$dQ = OdN \tag{7}$$

$$ON = CLES \tag{8}$$

Then Formula (6) can be written as:

$$
\begin{aligned}
&LZ_n \frac{dS}{ds} + \frac{CLES}{N}\frac{dN}{ds} + \frac{dL_f}{ds} jZ_n S_{fn} \\
&-\frac{dL_t}{ds} jZ_n S_{tn} - \frac{dW}{ds} + Z_n S \frac{dL}{ds} = 0
\end{aligned} \tag{9}
$$

During the intake process, the gas enters the compressor from the environment, and changes in temperature and pressure need to consider the state change of the gas flow. During compression, the gas volume decreases, and pressure and temperature increase. In the exhaust process, the compressed gas is discharged, with gas expansion and heat exchange considered. Expansion may occur when the compressor is shut down or in special operating conditions, where the gas energy gradually releases. By modeling each of these processes and integrating them into an overall thermodynamic model, a thermodynamic process model that can reflect the real-time operational state of the compressor is ultimately constructed. For the intake process ($dL/ds{=}dL_t/ds$, $dL_f/ds{=}0$), we have:

$$
LZ_n \frac{dS}{ds} + \frac{CLES}{N} \cdot \frac{dN}{ds} + Z_n S \frac{dL}{ds} - jZ_n S_t \frac{dL_t}{ds} - \frac{dW}{ds} = 0 \tag{10}
$$

For the exhaust process ($dL/ds{=}{-}dL_f ds$, $dL_t/ds{=}0$), we have:

$$
LZ_n \frac{dS}{ds} + \frac{CLES}{N} \cdot \frac{dN}{ds} + jZ_n S_f \frac{dL}{ds} + Z_n S \frac{dL}{ds} - \frac{dW}{ds} = 0 \tag{11}
$$

For the compression and expansion processes ($dL/ds{=}dL_t/ds$ ${=}dL_f/ds{=}0$), we have:

$$
LZ_n \frac{dS}{ds} + \frac{CLES}{N} \cdot \frac{dN}{ds} - \frac{dW}{ds} = 0 \tag{12}
$$

To enable intelligent detection of thermodynamic parameters during compressor operation, this study designs a system capable of real-time monitoring and analysis of the state within and around the compressor cylinder. For fundamental thermodynamic parameters such as the working medium's mass in the cylinder, cylinder volume, cylinder pressure, and temperature, high-precision sensors and flow meters are installed to acquire real-time data. Pressure sensors monitor changes in cylinder pressure, temperature sensors measure cylinder temperature, and flow meters measure the mass flow rate during intake and exhaust. Utilizing these real-time data, combined with thermodynamic equations, enables calculation of the working medium's mass and specific internal energy within the cylinder. Additionally, based on these fundamental parameters, the specific enthalpy and specific internal energy of the medium in the cylinder can be derived, achieving real-time assessment of the gas state within the cylinder. The coordinated operation of temperature, pressure, and flow sensors forms a comprehensive real-time monitoring system that supplies data support for the thermodynamic process model of the compressor.

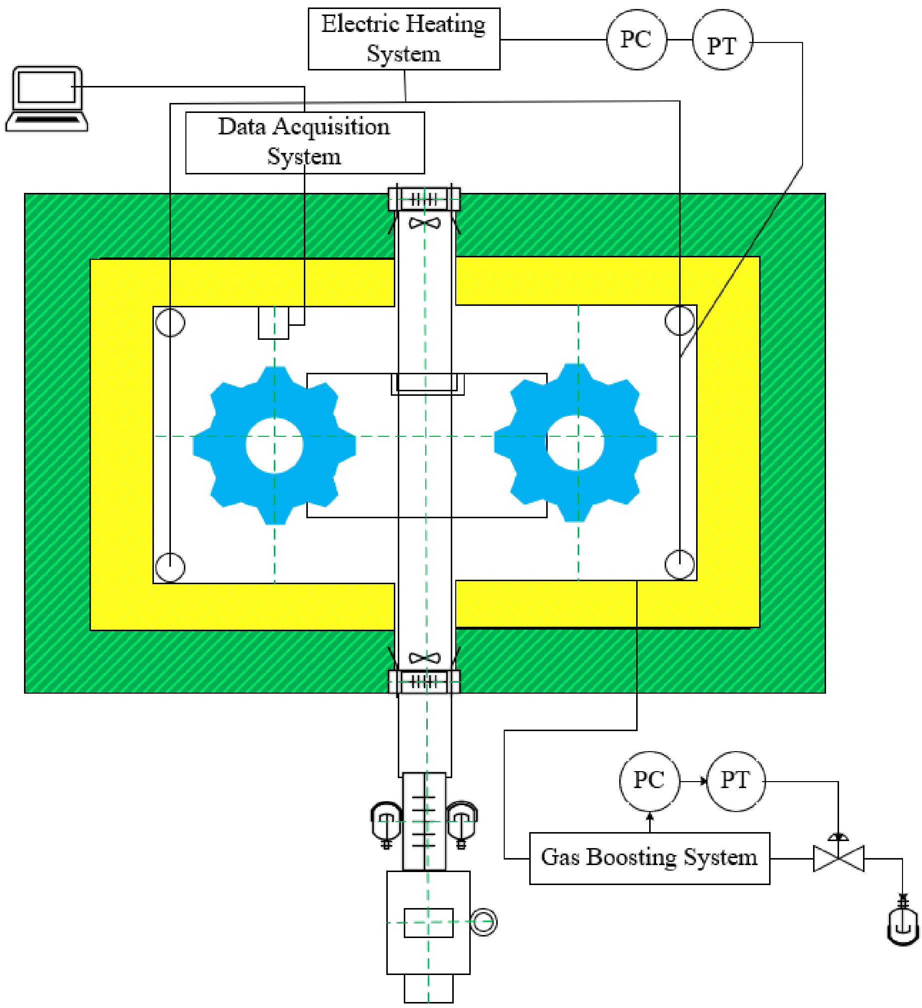


**Figure 1.** Schematic of intelligent detection for compressor

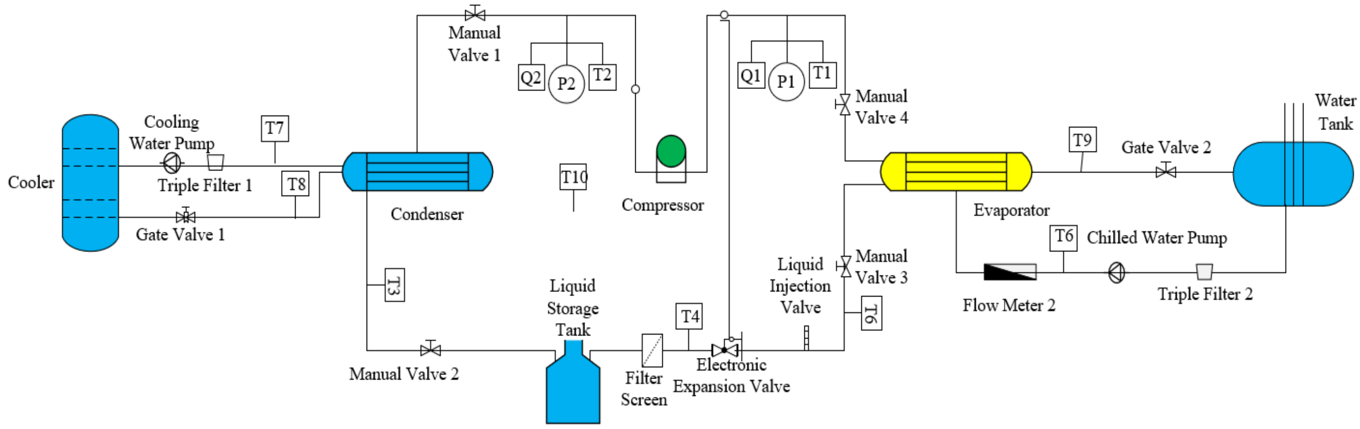


**Figure 2.** Schematic of the compressor refrigeration system

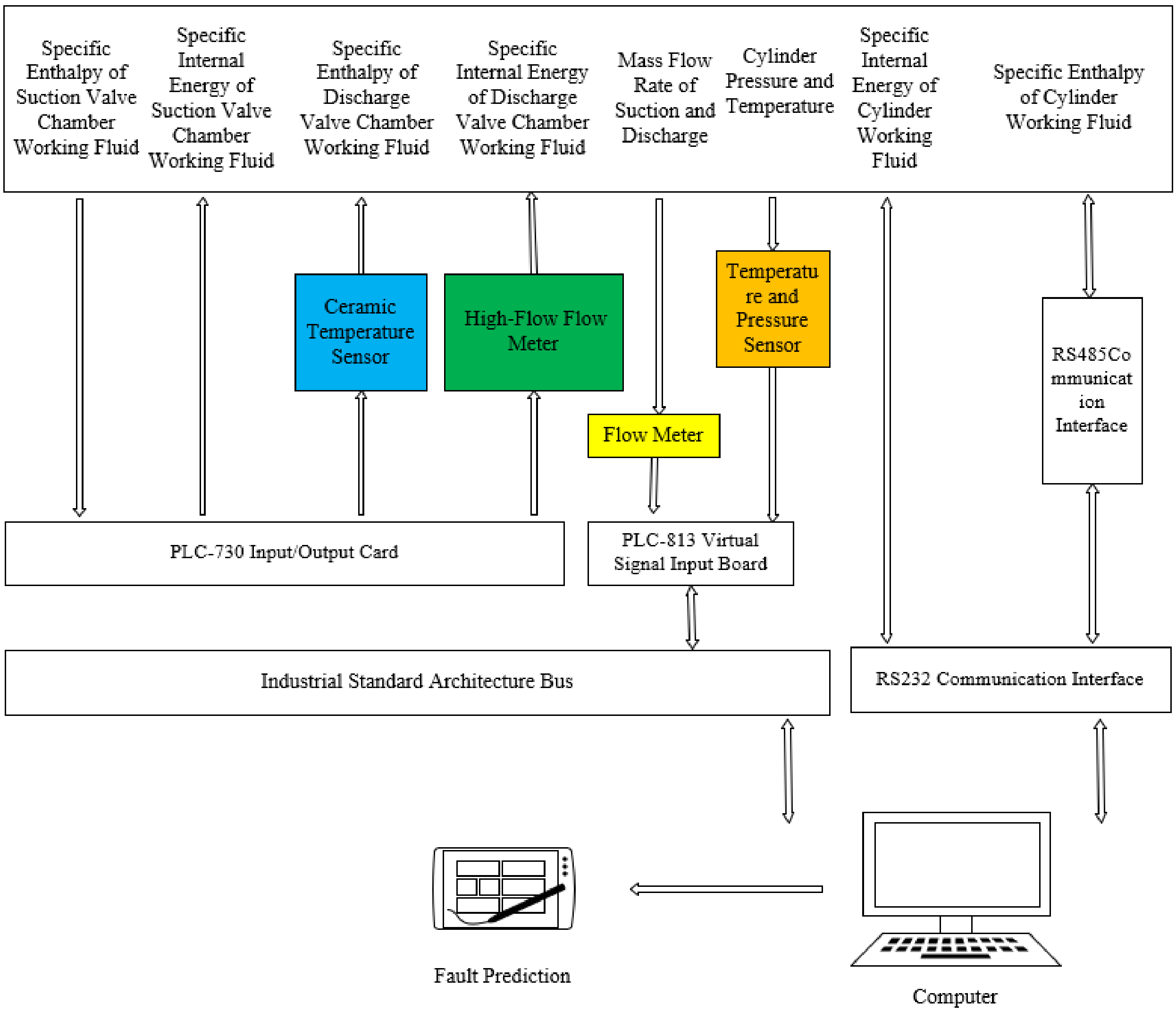


**Figure 3.** Framework of the compressor thermodynamic parameter monitoring and control system

In practical application scenarios like the refrigeration system illustrated in Figure 2, precise intelligent detection of thermodynamic parameters during intake and exhaust is essential. To monitor parameters such as the specific enthalpy and temperature of the working medium in the intake and exhaust valve chambers, high-precision sensors must be installed at the intake and exhaust ports. Specific enthalpy and temperature of the working medium in the intake and exhaust valve chambers can be directly measured by sensors, and calculations using flow data further determine the thermodynamic properties of the working medium during the intake and exhaust processes. Using the first law of thermodynamics and accounting for external power input and the work done by the medium on the surroundings, the real-time data enables calculation of energy changes at each stage, thus allowing assessment of the compressor's overall operational efficiency and fault status.

Figure 3 presents the framework of the thermodynamic parameter monitoring and control system for compressors. Using intelligent algorithms, this study compares these thermodynamic parameters with historical operating data and fault patterns to predict and identify potential anomalies or fault risks. This intelligent monitoring system not only achieves precise monitoring of the compressor's operational process but also dynamically adjusts operational strategies based on real-time thermodynamic parameters, enhancing the compressor's operational efficiency and reliability.

## 3. CONSTRUCTION OF THE COMPRESSOR FAULT PREDICTION MODEL BASED ON SSA-LSTM MODEL

In the operation of compressors, multiple parameters such as pressure, temperature, and flow are involved, and these parameters exhibit complex dynamic patterns over time due to influences from the mechanical structure and process conditions. Traditional fault prediction methods often struggle to fully uncover deeper patterns within high-dimensional, nonlinear data. Therefore, this paper adopts the SSA-LSTM model for compressor fault prediction. The SSA has a global search capability that allows it to find optimal solutions within a large hyperparameter space. Meanwhile, the LSTM network effectively retains long-term dependencies when handling time-series data. Combining these two methods enables the SSA-LSTM model to adaptively extract essential features from multi-dimensional time-series data for compressors, while the LSTM's memory mechanism captures long-term temporal trends within the data, providing higher accuracy in fault prediction. Additionally, compressor fault prediction requires a model that can maintain high predictive accuracy in variable operating environments and with incomplete sensor data. SSA not only efficiently adjusts LSTM's hyperparameters but also adapts to various changes and interference factors that may occur during compressor operation. LSTM handles data irregularities and missing data, ensuring the model's stability in practical applications. The integration of SSA and LSTM enables the SSA-LSTM model to adapt to various dynamic changes in the compressor's operating process and to perform real-time fault diagnosis and prediction, providing a scientific basis for preventive maintenance and fault management of equipment.

Specifically, the SSA is employed to optimize the parameters of the LSTM model, enhancing the accuracy and reliability of compressor fault prediction. SSA is a swarm intelligence optimization algorithm that simulates the foraging behavior of sparrows. By modeling the collaborative and competitive behavior mechanisms among sparrows during foraging, the algorithm seeks the optimal solution within the search space. In this model, the "leader sparrow" guides the group toward optimal food sources in an unknown environment, while the "follower sparrows" adjust their positions according to the leader's position. This strategy balances global and local search, enabling SSA to effectively avoid local optima and enhancing the global search capability of the optimization process.

Let $s$ denote the current iteration count, $IT_{MAX}$ represents the maximum number of iterations, and $A_{u,k}$ be the position of the $u$-th sparrow in the $k$-th dimension. $B \in (0, 1]$ is a random number, with alert and safety values represented by $E_2$ and $TS$, respectively. Let $W$ be a random number following a normal distribution, $M$ be a matrix with one row and $f$ columns of all ones, and $f$ denotes the dimensionality of the compressor fault prediction problem. The position update formula for the discoverers is as follows:

$$A_{u,k}^{s+1} = \begin{cases} A_{u,k}^{s} \cdot \exp\left(\dfrac{-u}{\beta \cdot IT_{MAX}}\right)\left(E_2 < TS\right) \\ A_{u,k}^{s} + W \cdot M\left(E_2 \geq TS\right) \end{cases} \tag{13}$$

Assume that the current optimal position occupied by the discoverers is $A_O$ and the current global worst position is $A_{WO}$. Let $X^{+}$ be a constant controlling the magnitude of individual position updates. Then the position update formula for the joiners is as follows:

$$A_{u,k}^{s+1} = \begin{cases} W \cdot \exp\left(\dfrac{A_{WO}^{s} - A_{u,k}^{s}}{u^2}\right)\left(u > \dfrac{v}{2}\right) \\ A_O^{s+1} + \left|A_{u,k}^{s} - A_O^{s+1}\right| X^{+} M \quad (otherwise) \end{cases} \tag{14}$$

When aware of danger, the sparrow population exhibits anti-predation behavior. Suppose the step control parameter is $\alpha$, the current global optimal position is $A_{BE}$, and $J \in [-1, 1]$ is a random number. Let $d_u$ be the fitness value of the current sparrow individual, with $d_h$ and $d_q$ representing the current global best and worst fitness values, respectively. A very small constant is denoted by $\gamma$, and the corresponding mathematical expression is as follows:

$$A_{u,k}^{s+1} = \begin{cases} A_{BE}^{s} + \alpha \cdot \left|A_{u,k}^{s} - A_{BE}^{s+1}\right|\left(d_u > d_h\right) \\ A_{u,k}^{s} + J \cdot \left(\dfrac{\left|A_{u,k}^{s} - A_{WO}^{s}\right|}{\left(d_u - d_q\right) + \gamma}\right) \quad \left(d_u = d_h\right) \end{cases} \tag{15}$$

In the compressor fault prediction model, the LSTM neural network is the core component, used for processing complex time-series data from the compressor operation process, extracting the long-term dependency features from the data to achieve accurate fault prediction. The basic structure of LSTM includes the forget gate, input gate, and output gate. These three gating mechanisms are responsible for determining the "memory" and "forgetting" processes within the neural network. Through these gating mechanisms, the LSTM network can selectively "remember" important historical information related to faults while "forgetting" redundant information unrelated to fault prediction, thereby significantly improving prediction accuracy. In the specific task of compressor fault prediction, the time-memory capability of LSTM is particularly important. The operating state of the compressor often includes parameters with complex dependencies, such as temperature, pressure, and vibration, and the dynamic changes of these parameters over a long period are crucial for fault prediction.

Assume the previous cell state is $z_{s-1}$, and the connection between the previous hidden state $g_{s-1}$ and the current input $a_s$ is represented by $|g_{s-1}, a_s|$. The weight matrix and bias term of the forget gate are represented by $q_d$ and $y_d$, respectively. Sigmoid is the activation function, and the forget gate expression is as follows:

$$d_s = sigmoid\left(q_d \cdot \left|g_{s-1}, a_s\right| + y_d\right) \tag{16}$$

Assuming the current cell state is $z_s$, the input gate expression is:

$$u_s = sigmoid\left(q_u \cdot |g_{s-1}, a_s| + y_u\right) \quad (17)$$

The candidate cell state $z'_s$ is calculated using the tanh function, with the calculation formula as:

$$z_s^{'} = \tanh\left(Q_{zg} g_{s-1} + Q_{za} a_s + y_z\right) \quad (18)$$

The forget gate $d_s$ and the input gate $u_s$ control the size of the updated cell state $z_s$, with the calculation formula:

$$z_s = d_s * z_{s-1} + u_s * z_s^{'} \quad (19)$$

Assuming the current hidden state is $g_s$, the output gate expression is:

$$p_s = sigmoid\left(Q_{pg} g_{s-1} + Q_{pa} a_u + y_p\right) \quad (20)$$

The calculation of the hidden state $g_s$ is determined by $p_s$ and $z_s$:

$$g_s = p_s * \tanh\left(z_s\right) \quad (21)$$

Through its detailed internal structure, the LSTM neural network can capture the deep-level associations of these parameters over time, thus learning the latent patterns in the data. In the compressor operation data, the occurrence of certain faults may require prediction based on historical data spanning hours or even days, and the LSTM, with its "long short-term memory" capability, can maintain stable learning performance over such extended time spans.

In the compressor fault prediction model, the basic principle of the SSA-LSTM model is to optimize the hyperparameters of the LSTM model using the SSA to improve the accuracy and stability of compressor fault prediction. The LSTM itself, as a powerful time-series data processing model, can effectively capture the long-term dependency relationships in the compressor operation process. However, the performance of LSTM largely depends on the selection of its hyperparameters, such as learning rate, hidden layer size, and the number of iterations, and the reasonable setting of these hyperparameters directly affects the model's training results and prediction accuracy. SSA, as a swarm intelligence-based optimization algorithm, simulates the foraging behavior of sparrows to perform a global search in the hyperparameter space and automatically finds the optimal combination of hyperparameters. By using SSA to optimize the LSTM model, it can be ensured that the model maintains high training efficiency and prediction accuracy when processing compressor operation data. Especially when dealing with complex time-series data and multiple variables, the optimized LSTM can better capture potential fault patterns and trends. Figure 4 shows the compressor fault prediction process based on the SSA-LSTM model.

Specifically, in this paper, the Sparrow Search Algorithm sets the maximum number of iterations to 100 and the population size to 50, with 20% of the individuals designated as "discoverers," responsible for exploring a broader hyperparameter space. This setup allows SSA to effectively search for the optimal solution across multiple hyperparameter dimensions, including learning rate, number of iterations, and the number of neurons in the two hidden layers. After 80 iterations, SSA quickly converges, finding the optimal combination of hyperparameters, with a learning rate of 0.0016 and the best number of iterations as 83. This hyperparameter combination provides the LSTM network with an efficient training framework, enabling the model to accurately identify and predict compressor faults.

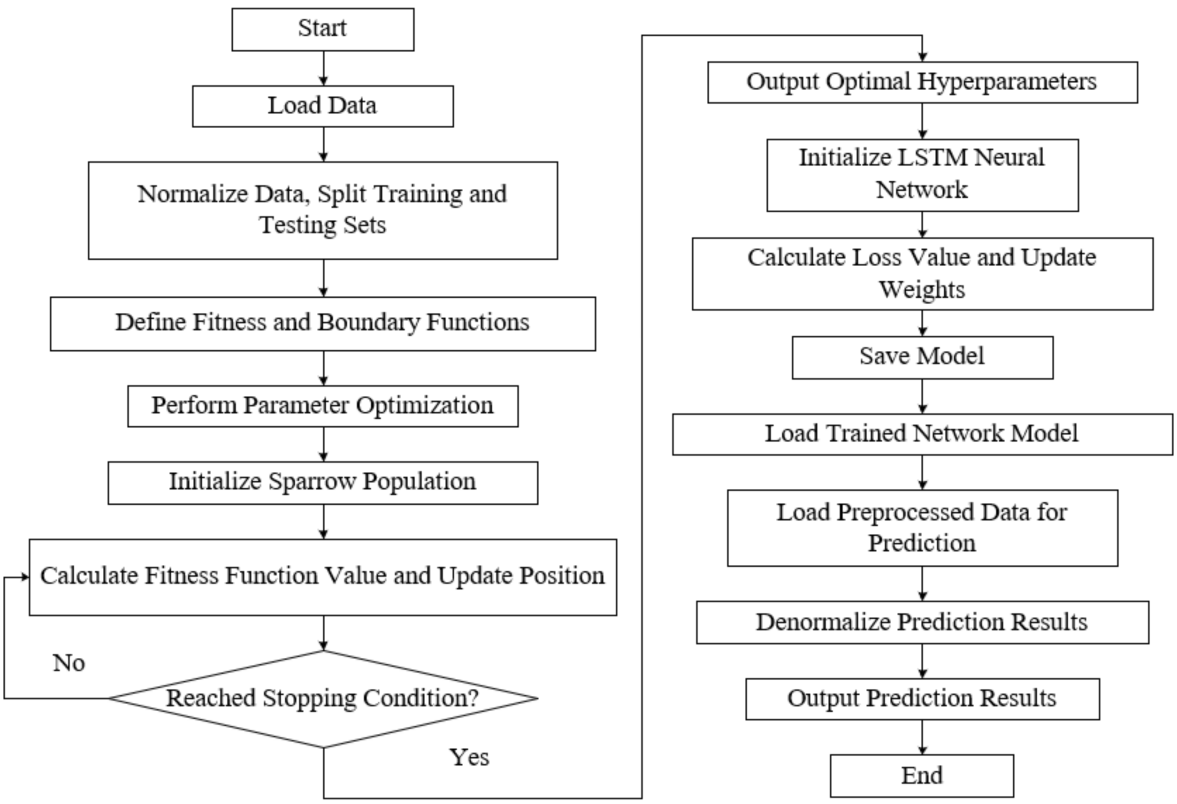


**Figure 4.** Compressor fault prediction process based on SSA-LSTM model

## 4. EXPERIMENTAL RESULTS AND ANALYSIS

Table 1 presents the relationship between compression ratio and volumetric efficiency, cooling capacity, power, and COP. Under varying compression ratios, the operational efficiency of the compressor shows significant changes. As the compression ratio decreases (from 7.32 down to 2.31), both volumetric efficiency and cooling capacity increase significantly, while power consumption decreases, leading to a gradual increase in the COP. For instance, when the compression ratio drops from 7.32 to 2.31, cooling capacity increases from 1125 W to 2123 W, power consumption decreases from 913 W to 645 W, and the COP rises from 1.25 to 3.32. This indicates that at lower compression ratios, the compressor achieves more efficient energy conversion, enhancing cooling performance while reducing power consumption. This data provides a foundation for subsequent fault prediction, especially as fluctuations in volumetric efficiency, power, cooling capacity, and COP under different operating conditions can help identify potential anomalies or faults.

Table 2 provides the relationship between condensing temperature and the compressor performance parameters: volumetric efficiency, cooling capacity, power, and COP. From the data, it is evident that as the condensing temperature increases, the volumetric efficiency, cooling capacity, and COP generally decrease, while power demand shows an upward trend. Specifically, when the condensing temperature rises from 18.56℃ to 23.89℃, volumetric efficiency decreases from 0.87 to 0.68, cooling capacity reduces from 912 W to 765 W, and power consumption increases from 421 W to 468 W. This trend indicates that at higher condensing temperatures, the operational efficiency of the compressor decreases significantly, energy consumption rises, and the COP declines from 2.23 to 1.75. This change reflects the significant impact of condensing temperature on compressor performance, as higher condensing temperatures lead to reduced system efficiency and increased energy waste, providing potential indicators for fault prediction.

Table 3 shows the relationship between evaporating temperature and key performance parameters of the compressor, including volumetric efficiency, cooling capacity, power, and COP. Observations reveal that as the evaporating temperature rises, the compressor's volumetric efficiency, cooling capacity, and COP generally increase, while power consumption demonstrates a more complex variation. Specifically, as the evaporating temperature increases from -9.78℃ to -4.23℃, volumetric efficiency rises from 0.63 to 0.83, and cooling capacity increases from 489 W to 556 W. Power consumption fluctuates but shows an overall upward trend. Simultaneously, COP rises from 1.23 to 2.36, indicating that as the evaporating temperature increases, the compressor's energy efficiency improves, enabling it to deliver higher cooling capacity with less energy consumption. This suggests that a moderate increase in evaporating temperature can significantly enhance the overall operational efficiency of the compressor, reflecting the thermodynamic optimization of the system as the evaporating temperature changes.

In conjunction with the fault prediction method based on the LSTM and SSA proposed in this paper, the data in Tables 1-3 provide essential time-series features for the precise analysis of compressor operational status. The LSTM model can identify potential fault risks from the relationships between evaporating temperature and other key parameters. For instance, if the evaporating temperature increases significantly but the compressor's volumetric efficiency and COP do not improve as expected and instead show a decline, this may signal internal thermodynamic issues within the device, such as insufficient refrigerant, overheating, or internal leakage.

**Table 1.** Relationship data between compression ratio, volumetric efficiency, cooling capacity, power, and COP

| Compression Ratio | Volumetric Efficiency | Cooling Capacity (W) | Power (W) | *cop* |
|---|---|---|---|---|
| 7.32 | 0.72 | 1125 | 913 | 1.25 |
| 6.58 | 0.73 | 1326 | 889 | 1.35 |
| 5.42 | 0.74 | 1452 | 856 | 1.56 |
| 4.12 | 0.77 | 1521 | 823 | 1.78 |
| 3.45 | 0.81 | 1623 | 789 | 2.12 |
| 3.36 | 0.83 | 1745 | 754 | 2.23 |
| 2.89 | 0.81 | 1856 | 732 | 2.56 |
| 2.64 | 0.85 | 1952 | 689 | 2.78 |
| 2.38 | 0.88 | 2125 | 662 | 3.14 |
| 2.31 | 0.87 | 2123 | 645 | 3.32 |

**Table 2.** Relationship data between volumetric efficiency, cooling capacity, power, and COP with condensing temperature

| Condensing Temperature (℃) | Volumetric Efficiency | Cooling Capacity (W) | Power (W) | *cop* |
|---|---|---|---|---|
| 18.56 | 0.87 | 912 | 421 | 2.23 |
| 21.23 | 0.86 | 923 | 424 | 2.24 |
| 21.54 | 0.84 | 889 | 428 | 2.15 |
| 22.36 | 0.82 | 867 | 421 | 1.89 |
| 22.15 | 0.81 | 865 | 436 | 1.85 |
| 21.25 | 0.77 | 832 | 438 | 1.78 |
| 22.36 | 0.76 | 826 | 439 | 1.76 |
| 22.36 | 0.73 | 824 | 448 | 1.74 |
| 23.54 | 0.71 | 789 | 462 | 1.71 |
| 23.89 | 0.68 | 765 | 468 | 1.75 |

**Table 3.** Relationship data between volumetric efficiency, cooling capacity, power, and COP with evaporating temperature

| Evaporating Temperature (℃) | Volumetric Efficiency | Cooling Capacity (W) | Power (W) | *cop* |
|---|---|---|---|---|
| -9.78 | 0.63 | 489 | 478 | 1.23 |
| -9.36 | 0.65 | 482 | 489 | 1.35 |
| -8.87 | 0.68 | 512 | 512 | 1.56 |
| -8.25 | 0.71 | 523 | 523 | 1.58 |
| -7.54 | 0.72 | 524 | 532 | 1.68 |
| -7.12 | 0.74 | 534 | 524 | 1.87 |
| -6.28 | 0.77 | 538 | 541 | 1.78 |
| -5.78 | 0.81 | 521 | 526 | 1.89 |
| -5.23 | 0.82 | 548 | 535 | 2.21 |
| -4.23 | 0.83 | 556 | 524 | 2.36 |

Based on the time-series data provided in Figures 5-7, the data illustrate the variation in compressor outlet temperature as state collection counts vary across different compressor operating conditions. In Time Series 1, Time Series 2, and Time Series 3, the fluctuations and trends between the actual and predicted values are consistent, demonstrating regularity in compressor operation across different conditions. By analyzing long-term dependencies in time-series data, the LSTM model can recognize normal and abnormal modes of compressor operation under varying conditions. For example, in some periods, if the condensing or evaporating temperature shows large fluctuations but the volumetric efficiency and cooling capacity fail to increase as expected and instead decrease, this could indicate internal compressor issues, such as poor cooling or refrigerant insufficiency. The SSA further optimizes the LSTM model's parameters, adaptively adjusting weights and learning rates to improve fault prediction accuracy.

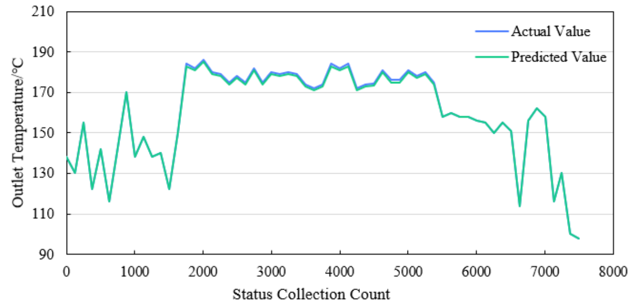


**Figure 5.** Comparison of actual and predicted compressor outlet temperatures in normal operation (Time Series 1)

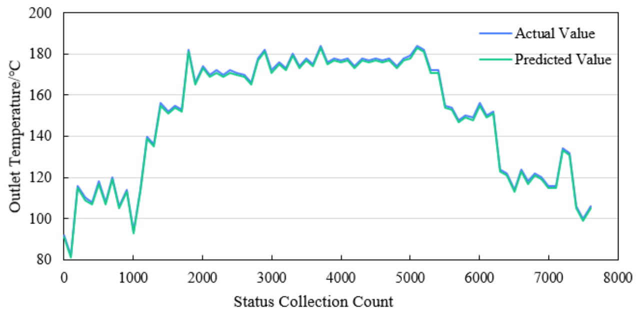


**Figure 6.** Comparison of actual and predicted compressor outlet temperatures in normal operation (Time Series 2)

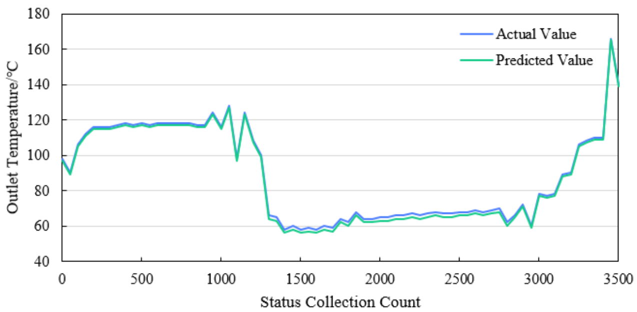


**Figure 7.** Comparison of actual and predicted compressor outlet temperatures in normal operation (Time Series 3)

Through this data, we observe that, within specific time intervals, the compressor's performance exhibits varied trends as the state collection count changes. For instance, in Time Series 1, volumetric efficiency and cooling capacity fluctuate over time, with power and COP values showing correlations to condensing and evaporating temperatures. In Time Series 2, an increase in evaporating temperature results in cooling capacity and power fluctuations, while volumetric efficiency and COP improve during certain periods, reflecting the compressor's adaptability to different thermal environments. In Time Series 3, the compressor demonstrates more complex dynamic changes over time, particularly a sudden increase in power under high load, which could indicate a precursor to potential faults. Analysis of such complex time-series data provides valuable insights for fault prediction. Possible fault outcomes include compressor overload, internal component failures (e.g., compressor damage, leakage, or overheating), and performance degradation due to instability in the control system. This intelligent prediction method enables early fault detection and location, offering decision support for maintenance personnel, thereby reducing downtime and repair costs.

## 5. CONCLUSION

This paper proposed an innovative approach for intelligent monitoring and fault prediction of compressor operational status based on deep learning, integrating thermodynamic principles with advanced machine learning models to provide a smart solution for compressor fault prediction and health management. First, a thermodynamics-based model of the compressor operation process was established, which can accurately describe the compressor's thermodynamic characteristics under various conditions, offering a scientific basis for monitoring and evaluating key operational parameters. Based on this model, an intelligent detection method was designed to monitor key parameters such as volumetric efficiency, cooling capacity, power, and COP in real time, providing data support for compressor status evaluation and fault prediction. Additionally, this study innovatively combined SSA with LSTM model, proposing a new fault prediction method for compressors. This method processed complex time-series data to identify potential fault risks in advance. Experimental results show that compressor parameters such as volumetric efficiency, cooling capacity, power, and COP exhibit distinct fluctuating patterns under varying condensing temperatures, evaporating temperatures, and compression ratios. By training the deep learning model, it effectively captured the temporal variations and internal correlations of these parameters, achieving high accuracy in fault prediction. Through comparative analysis of actual and predicted values, the proposed method can accurately predict potential faults during the compressor's normal operation phase, thereby supporting subsequent maintenance decisions.

This research presented a novel technical framework for compressor fault prediction and health management, with significant research value. By combining thermodynamic modeling with deep learning, this approach surpasses the limitations of traditional mechanical fault diagnosis methods, offering a new intelligent monitoring and early warning tool for compressors and similar industrial equipment. The integration of SSA with the LSTM model leverages time-series data generated during compressor operation, improving fault prediction accuracy and timeliness, and significantly enhancing equipment reliability and safety.

However, this study also has certain limitations. First, although the proposed model can handle various types of time-series data, its generalization capability and adaptability require further verification in practical applications, particularly when applied to different brands and models of compressors, which may require additional adjustments and training. Second, while the thermodynamic model describes the basic operational patterns of compressors, it may have limitations in handling complex dynamic load changes, environmental variations, and system fault modes.

Additionally, the deep learning methods employed rely on extensive historical data, which could pose challenges for data collection and processing in practical deployment. Future research directions could focus on: (1) exploring fault prediction methods adaptable to various industrial equipment; (2) further optimizing deep learning models to improve robustness in complex environments; and (3) developing more efficient online learning algorithms to achieve real-time monitoring and prediction, addressing the needs of industrial equipment for dynamic change and fault prediction in sudden failure scenarios.

## ACKNOWLEDGMENT

This paper was supported by Hebei Province Higher School Science and Technology Research Youth Fund Project, "Deep Learning-based Compressor Condition Monitoring and Fault Diagnosis Artificial Intelligence Expert System Research and Development" (Grant No.: QN2022098).

## REFERENCES

[1] Jaatinen-Värri, A., Honkatukia, J., Uusitalo, A., Turunen-Saaresti, T. (2024). Centrifugal compressor design for high-temperature heat pumps. Applied Thermal Engineering, 239: 122087. https://doi.org/10.1016/j.applthermaleng.2023.122087

[2] Uusitalo, A., Jaatinen-Värri, A., Turunen-Saaresti, T. (2024). Centrifugal compressor design analysis for large-scale transcritical carbon dioxide heat pumps. Applied Thermal Engineering, 257: 124355. https://doi.org/10.1016/j.applthermaleng.2024.124355

[3] Olympios, A.V., Song, J., Ziolkowski, A., Shanmugam, V.S., Markides, C.N. (2024). Data-driven compressor performance maps and cost correlations for small-scale heat-pumping applications. Energy, 291: 130171. https://doi.org/10.1016/j.energy.2023.130171

[4] Uusitalo, A., Jaatinen-Värri, A., Turunen-Saaresti, T., Honkatukia, J., Tiainen, J. (2024). Centrifugal compressor design and cycle analysis of large-scale high temperature heat pumps using hydrocarbons. Applied Thermal Engineering, 247: 123035. https://doi.org/10.1016/j.applthermaleng.2024.123035

[5] Scherba, V.E. (2022). Procedure for estimating the heating time of working chamber walls in a piston compressor when implementing regenerative heat exchange. Chemical and Petroleum Engineering, 58(3): 293-300. https://doi.org/10.1007/s10556-022-01090-4

[6] Fan, Z.F., Li, H.K., Cao, H.W., Dong, J.N. (2022). Research on running status monitoring and rotating blade crack detection of large-scale centrifugal compressor based on blade tip timing technique. IEEE Transactions on Instrumentation and Measurement, 72: 3501011. https://doi.org/10.1109/TIM.2022.3231270

[7] Ceviz, M.A., Afshari, F., Ceylan, M., Muratçobanoğlu, B., Mandev, E., Gelen, G. (2023). Experimental study to evaluate effect of source temperature on COP and compressor status in water-to-air heat pumps. Heat Transfer Research, 54(16): 51-66. https://doi.org/10.1615/HeatTransRes.2023048436

[8] Zheng, Y.P., Ahn, H.J. (2024). Surge monitoring system for a small maglev centrifugal compressor. Transactions of the Korean Society of Mechanical Engineers A, 48(7): 485-490. http://doi.org/10.3795/KSME-A.2024.48.7.485

[9] Lv, Q., Yu, X.L., Ma, H.H., Ye, J.C., Wu, W.F., Wang, X.L. (2021). Applications of machine learning to reciprocating compressor fault diagnosis: A review. Processes, 9(6): 909. https://doi.org/10.3390/pr9060909

[10] Wang, H.Y., Chen, J.W., Zhu, X.J., Song, L.M., Dong, F. (2023). Early warning of reciprocating compressor valve fault based on deep learning network and multi-source information fusion. Transactions of the Institute of Measurement and Control, 45(4): 777-789. https://doi.org/10.1177/01423312221110896

[11] Guo, F.Y., Zhang, Y.C., Wang, Y., Ren, P.J., Wang, P. (2021). Fault diagnosis of reciprocating compressor valve based on transfer learning convolutional neural network. Mathematical Problems in Engineering, 2021(1): 8891424. https://doi.org/10.1155/2021/8891424

[12] Gao, Y., Zhang, L., Zhou, J.W., Wei, B.J., Yan, Z.C. (2023). Research on reliability of centrifugal compressor unit based on dynamic Bayesian network of fault tree mapping. Journal of Mechanical Science and Technology, 37(5): 2667-2677. https://doi.org/10.1007/s12206-023-0440-7

[13] Nambiar, A., Aravinth, S., Sugumaran, V., Ramteke, S. M., Marian, M. (2024). Prediction of air compressor faults with feature fusion and machine learning. Knowledge-Based Systems, 304: 112519. https://doi.org/10.1016/j.knosys.2024.112519

[14] Aravinth, S., Sugumaran, V. (2023). Prediction of air compressor condition using vibration signals and machine learning algorithms. Journal of Vibration and Control, 29(5-6): 1342-1351. https://doi.org/10.1177/10775463211062330

[15] Jiang, X.M., Tang, W.J., Zhao, H.X., Cheng, X.Y. (2022). Toward smart condition monitoring of rotatory machines: An optimized probabilistic signal reconstruction methodology for fault prediction with multisource uncertainties. IEEE Access, 10: 60862-60875. https://doi.org/10.1109/ACCESS.2022.3180888

[16] Xu, Q.H., Gao, P.J., Wang, J.L., Zhang, J., Ip, A., Zhang, C. (2024). AKGNN-PC: An assembly knowledge graph neural network model with predictive value calibration module for refrigeration compressor performance prediction with assembly error propagation and data imbalance scenarios. Advanced Engineering Informatics, 60: 102403. https://doi.org/10.1016/j.aei.2024.102403

[17] Wang, Y.F., Ren, P., Xiong, W., Peng, X.Y. (2024). Strain analysis and non-destructive monitoring of the two-stage hydraulic-driven piston compressor for hydrogen storage. Journal of Energy Storage, 94: 112494. https://doi.org/10.1016/j.est.2024.112494

[18] Song, D., Xu, F.Y., Ma, T.C. (2022). Crack damage monitoring for compressor blades based on acoustic emission with novel feature and hybridized feature selection. Structural Health Monitoring, 21(6): 2641-2656. https://doi.org/10.1177/14759217211068107

[19] Song, D., Ma, T.C., Shen, J.X., Xu, F.Y. (2023). Multiobjective-based acoustic sensor configuration for structural health monitoring of compressor blade. IEEE Sensors Journal, 23(13): 14737-14745. https://doi.org/10.1109/JSEN.2023.3277339

[20] Peng, Z.Q., Wang, Q.B., Liu, Z.R., He, R.J. (2024).

Remaining useful life prediction for aircraft engines under high-pressure compressor degradation faults based on FC-AMSLSTM. Aerospace, 11(4): 293. https://doi.org/10.3390/aerospace11040293

[21] Jeon, S.H., Yoo, S., Yoo, Y.S., Lee, I.W. (2024). ML- and LSTM-Based radiator predictive maintenance for energy saving in compressed air systems. Energies, 17(6): 1428. https://doi.org/10.3390/en17061428