2025 5th International Conference on Artificial Intelligence and Industrial Technology Applications (AIITA)

Early Warning Method for Equipment Time-Series Parameter Degradation Based on LSTM-KPI-ST

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***Abstract*—In practical industrial production scenarios, the operational parameters of equipment are customarily collected on a periodic basis, thereby forming time-series data. One significant challenge in monitoring these parameters is distinguishing between normal operational fluctuations and the subtle signs of gradual degradation that may be present within the time-series data. To address this issue, this paper puts forward the LSTM-KPI-ST algorithm, which integrates Long Short-Term Memory networks (LSTM) with Key Performance Indicators (KPI) assessments to predict the trends of parameter evolution. Additionally, it employs significance test (ST) to identify early indicators of degradation, enabling timely issuance of warning signals. This proposed algorithm enhances the detection of incipient faults by filtering out noise from regular operational variations, thus providing more reliable and accurate predictions. The effectiveness and reliability of this algorithm are substantiated through a case study focused on the early detection and warning of SF_6 gas leaks in electrical apparatus.**

Keywords— Time-series prediction; early degradation; warning; significance test

I. INTRODUCTION

In production operation settings, threshold-based methods [1] are typically employed to trigger alerts based on changes in key equipment parameters. Due to the cyclical and seasonal nature of environmental changes, certain parameters related to the environment, such as gas pressure within sealed containers and oil viscosity, exhibit cyclical fluctuation characteristics. These fluctuations significantly impact the operational performance of equipment, and if they remain within threshold limits, they do not trigger alarms. When slow degradation of parameters intertwines with these cyclical fluctuations, it becomes difficult to determine whether a warning is due to parameter degradation or normal environmental changes, making it challenging to assess the authenticity and validity of the warning. When a definitive alarm occurs, it indicates that degradation has been underway for some time and immediate maintenance is required. Early signs of degradation are often masked by normal cyclical fluctuations, affecting the accuracy of conventional alarm systems. Therefore, how to detect defects as early as possible and predict their trends is a critical issue in equipment condition assessment.

Equipment operational parameters are typically collected on a periodic basis and arranged in chronological order to form time series. Therefore, time series analysis methods are commonly used in equipment condition assessment, including techniques such as cyclical factor analysis, time series regression, time series modeling, and feature engineering [2]. In recent years, deep learning [3] has been widely applied in time series analysis, effectively predicting both the trend and seasonal components of time series data, achieving promising results. Specifically, Long Short-Term Memory networks (LSTM) [4][5], which address the long-term characteristics of equipment operation data, not only fit the dynamic models of time series processes but also solve the vanishing gradient problem. This enables the establishment of short-term correlation between current and future states, facilitating rolling predictions of future states [6].

Based on the aforementioned background, this paper proposes an early warning method for time series based on LSTM-KPI-ST. This method uses LSTM networks to predict future values of the time series and constructs a sequence of KPI that compare actual observations with predicted values [7][8]. It then applies ST to evaluate the effectiveness of these KPIs, thereby identifying early signs of degradation in the parameters and providing advance warnings [9]. In the case study analysis, this paper utilizes monitoring data from SF_6 gas to forecast trends of the gas state. By simulating leaks to mimic the degradation process of the gas, the LSTM-KPI-ST method successfully identified early signs of degradation, thereby validating the effectiveness and reliability of the proposed approach.

II. METHOD

The LSTM-KPI-ST method consists of three components: LSTM is responsible for forecasting the future trends of time series, KPI amplifies the trend elements within the time series, and ST identifies degradation signs and determines the alarm timing. The overall workflow of the method is shown in Figure 1. The crucial steps are described as follows.

A. Data Preprocessing

Raw measurement sequence M from specific equipment is influenced by randomness and measurement errors, introducing a certain level of uncertainty that requires preprocessing to obtain sequence X. Preprocessing mainly includes filling missing values, removing outliers, and data denoising, with Kalman filtering used for the latter.

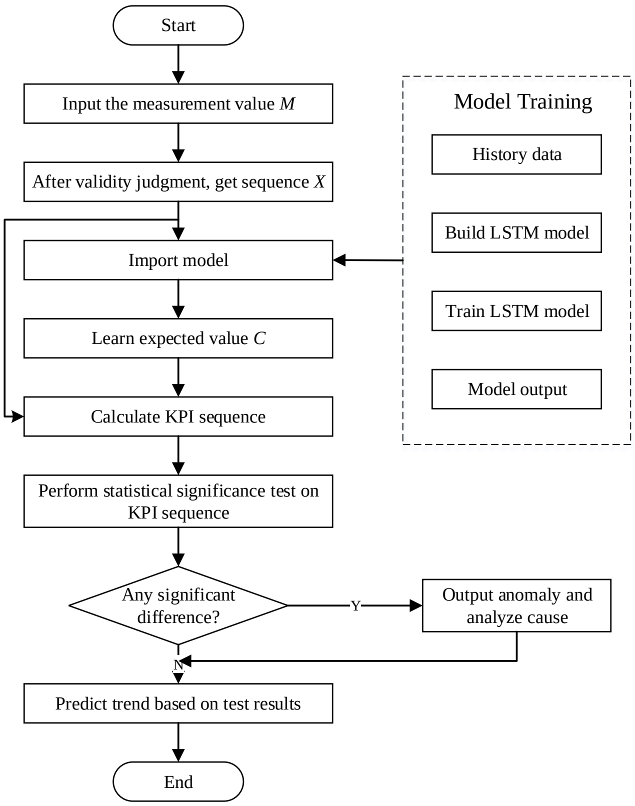


Figure 1. Flowchart of LSTM-KPI-ST.

B. Training the LSTM Model

The Conv-LSTM model, a variant of the LSTM model, is adopted. This model integrates the Convolutional Neural Network (CNN) and LSTM. Inheriting from the LSTM structure, Conv-LSTM can capture dependencies over long time spans, which is crucial when dealing with processes that have complex temporal dynamics. Additionally, Parameters in the convolutional layers are shared across the entire input, reducing the number of model parameters and aiding in better generalization. The CNN is designed to extract temporal features, while the LSTM is tasked with learning temporal dependencies, thus the Conv-LSTM model combines the advantages of both. Given the distinct individual characteristics among different devices, it is essential to train a dedicated LSTM model for each device separately.

C. Model Prediction

A data segment of length *T*, denoted as X_T, is fed into the trained LSTM model to generate a predicted value sequence *C* (characteristic parameters under normal conditions).

D. KPI Calculation

KPI is defined as the ratio of actual observed value *X* to the predicted value *C*. For observation X_t at time *t* and its corresponding prediction C_t, KPI_t at time *t* is calculated using formula (1) below, and KPI_t is added to the KPI sequence. As new observations are continuously added to *X* after a given time point, they are divided by the predictions obtained from running the algorithm at that time point. KPI is used to define the key deviation. If the state of the device is normal, the characteristic number should be close to "1"; if there is any defection, it will deviate from "1".

$$KPI_t = \frac{X_t}{C_t} \tag{1}$$

E. Significance test and anomaly detection

Although the validity of measurement data is assessed in step *A*, some deviations between measured and expected values are reasonable, leading to uncertainty propagation. Statistical methods are used to conduct significance testing on the KPI to determine if the observed deviations truly indicate a significant change, ensuring reliable alarms. Specific methods for significance testing can be parametric or non-parametric based on the characteristics of the sequence.

For trend testing of time series data, there are three scenarios:

- Null Hypothesis: The data has no trend; Alternative Hypothesis: The data has an increasing or decreasing trend.
- Null Hypothesis: The data has no decreasing trend; Alternative Hypothesis: The data has a decreasing trend.
- Null Hypothesis: The data has no increasing trend; Alternative Hypothesis:

The data has an increasing trend. Scenario 1 is a two-tailed test, while scenarios 2 and 3 are one-tailed tests.

Given the challenges in applying parametric tests to typical time series data, this paper outlines a non-parametric Cox-Stuart test process here.

Given a sequence $Y = \{y_1, y_2, \cdots, y_n\}$, pairs of values y_i and y_{i+d} are selected from it, where

$$d = \begin{cases} \frac{n}{2}, & n \text{ is even,} \\ \frac{n-1}{2}, & n \text{ is odd} \end{cases} \tag{2}$$

Let $e_i = y_{i+d} - y_i$, S^+ count the number of times e_i is positive and S^- count the number of times e_i is negative. When the sequence shows an upward trend, $S^+ > S^-$; the sequence is decreasing. When the sequence is approximately stable, both should be roughly equal, following a binomial distribution *B*(*d*, 0.5). Theoretically, without significant bias, KPI should exhibit minor fluctuations around "1". Calculate $p = cdf(K, 0.5)$, where *K* represents S^+ or S^-. Reject the null hypothesis when $p<0.01$, indicating a steady shift in the sequence.

F. Output Anomalies, Analyze Causes

Drawing on the outcomes of the significance test, we determine whether the sequence is abnormal. Once it is verified as abnormal, an alarm will be promptly triggered. Simultaneously, we will establish connections with other relevant systems to conduct a comprehensive analysis of the root causes.

III. CASE STUDY

In the electric apparatus industry, SF_6 gas is extensively used as an excellent electrical insulation and arc extinction medium, such as circuit breakers and gas insulation switchgear. During extended periods of operation, the seals of equipment may experience aging or damage. This can give rise to gas leakage, which in turn has the potential to compromise safe operation. Consequently, to safeguard equipment integrity and prevent substantial economic losses, substations carry out regular monitoring of SF_6 gas pressure. This practice allows for the assessment of equipment condition, and when necessary, triggers warnings. This aims to preempt issues such as degraded insulation performance resulting from gas leaks.

A. Data Overview

This case study is based on 8 months of monitoring samples from 130 measurement points in Substation A, numbered as measurement points 1 to 130. Among these 130 samples, some measurement points use sensors from brand A, while others use sensors from brand B. The collected data include the pressure of SF_6 gas and the temperature of the compartments. The LSTM-KPI-ST algorithm is applied for early assessment and prediction of SF_6 gas leakage deterioration in the equipment.

The SF_6 sensors incorporate a temperature compensation mechanism that converts the measured pressure at actual temperature to the standard pressure at 20°C. This compensation uses the Beattie-Bridgman formula：

$$P = (56.9 \times \rho \times T \times (1+B) - \rho^2 \times A) \times 10^{-6} \quad (3)$$

where $A = 74 \times (1 - 0.727 \times 10^{-3} \times \rho)$; $B = 2.51 \times 10^{-3} \times \rho \times (1 - 0.846 \times 10^{-3} \times \rho)$; P represents the pressure of SF_6, with the unit of *MPa*; ρ is the density of SF_6 with the unit of kg/m^3; and T stands for the absolute temperature with the unit of K.

Through observation and summarization of all the samples, the measurement data of SF_6 pressure - temperature data mainly show some key characteristics:

- There is a non-linear relationship between pressure and temperature.
- The pressure shows a certain periodicity and is affected by temperature, and the pressure-temperature relationship collected by different sensors (from different brands or different units of the same brand) varies to some extent.
- When observed on a daily basis, the pressure of SF_6 gas exhibits a relatively obvious day-night fluctuation phenomenon due to the influence of temperature, with a certain phase difference.

The above phenomena are primarily due to two reasons: firstly, different brands of sensors use varying temperature compensation methods, and there is considerable dispersion among sensors of the same brand; secondly, the rate at which pressure is affected during heating processes differs from that during cooling processes.

Ideally, if there is no leak, the measured pressure data should form a stable sequence. When a leak occurs, under ideal conditions, the rate of gas leakage would be proportional to the current pressure, leading to a gas pressure that follows an exponential distribution $P = P_0 e^{-\alpha t}$(where t is time, α is the leakage rate, and P_0 is the initial pressure). Since no leaks occurred during the entire observation period for all measurement points, simulated leak data samples were created with α=0.001 representing slow leaks, while α=0.01 representing fast leaks. Since the acquisition cycle is fixed (1 minute), time is represented by sequence points in relevant calculations.

B. Time-Series Prediction

Before the LSTM model is trained, the assessment of the validity of measurement values is crucial for laying the foundation for subsequent data processing. This involves verifying the reasonableness of the data, ensuring that values are non-negative (i.e., no negative pressures), falling within the specified range (0-0.75 *MPa* for pressure and -45 to 50°C for temperature), handling missing data by filling in gaps, and detecting and excluding outliers. Following this, preprocessing of the data includes compression, where high-frequency sampled raw data, which can be quite voluminous due to slow changes in pressure and temperature, is averaged on an hourly basis without losing significant features. Additionally, sequence length restructuring is performed; given that a seq2seq time series prediction algorithm is used, the data is restructured according to the selected stride and sequence length, preparing it for effective analysis.

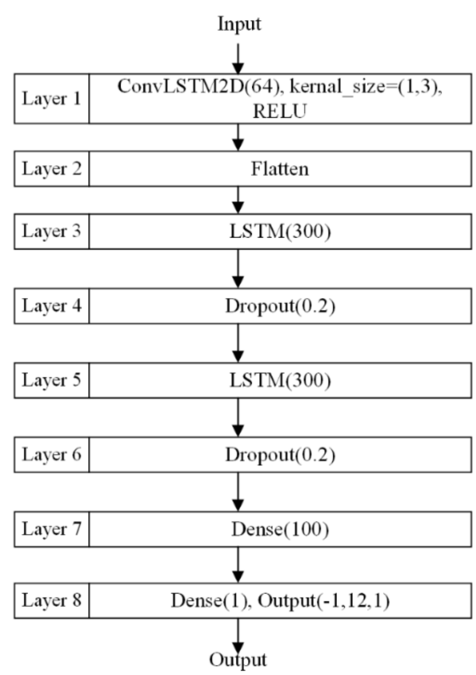


Figure 2. Network architecture.

The network architecture is illustrated in Figure 2, with hyperparameters set as follows: batch size = 16, epochs = 10, loss function = mean squared error (MSE), optimizer = Adam. The input sequence length is 24 hours, predicting the next 12 hours, with a sliding window step size of 12 hours for continuous rolling predictions.

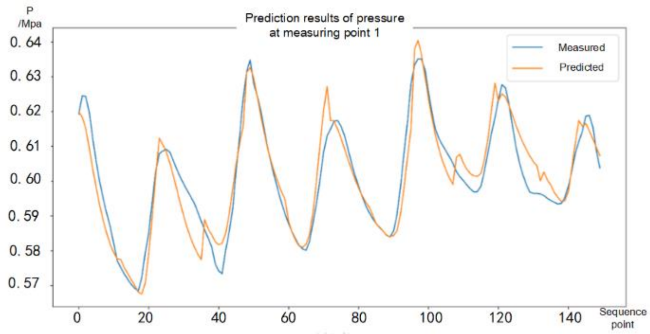
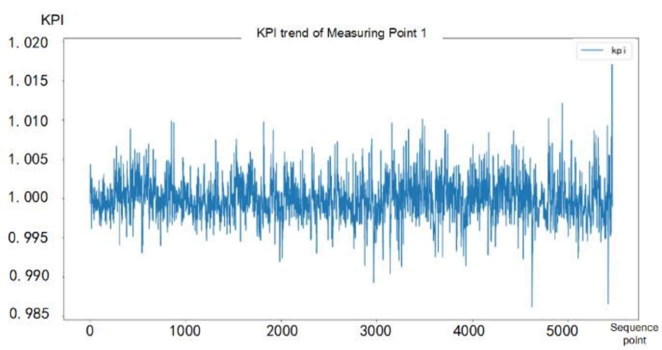


Figure 3. Prediction results of Measurement Point 1.

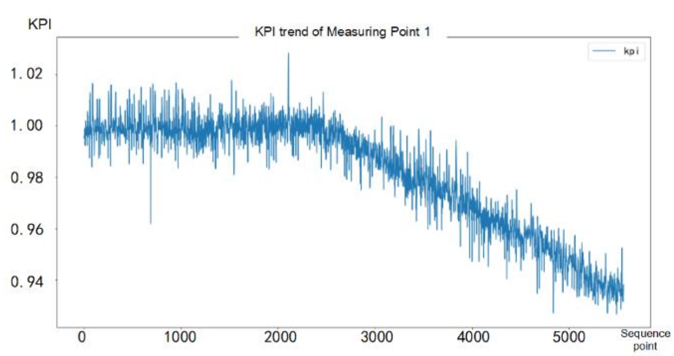
Taking measuring point 1 as an illustrative example, the prediction results are presented in Figure 3. The blue line depicts the measured data, and the orange line represents the predicted data. Specifically, for this case, the Mean Absolute Error (MAE) amounts to 0.032, the Mean Squared Error (MSE) is 0.002, and the coefficient of determination (R^2) reaches 0.79.

C. KPI Calculation

KPI is calculated following the formula (1) to obtain the KPI sequence. For instance, the KPI trend for measurement point 1 is depicted in Figure 4, where (a) shows the KPI trend for normal operating data, and (b) represents the KPI trend constructed with α=0.001 for defect data. The KPI of normal data fluctuates around 1, while that of defective data shows an obvious downward change. The KPI significantly indicates a degradation trend.



(a) KPI trend for normal operating data



(b) KPI trend constructed with α=0.001 for defect data

Figure 4. KPI results of point 1.

From Figure 4(b), it can be observed that during the non-leakage phase, there is already a slight downward trend in the pressure curve due to the decrease in ambient temperature, which causes the pressure to drop accordingly. During this phase, the KPI curve remains relatively stable, fluctuating around 1. Compared to the pressure curve, the KPI curve exhibits greater stability with smaller fluctuations, making it more sensitive to leakage defects. Consequently, the KPI curve can reflect leakage defects earlier than the pressure curve.

D. Leak Trend Recognition

This case employs Cox-Stuart test for significance test on the sequences, with the null hypothesis stating no decreasing trend in the data, and the alternative hypothesis suggesting a decrease. The test statistic $K = S^-$ is calculated, and $p = cdf(S^-, 0.5)$ is computed; if p<0.01, the null hypothesis is rejected, indicating a leak has occurred.

Traditional SF_6 gas leak alarm methods rely on threshold values. In this example, the alarm threshold is set at 0.4 MPa. Three warning criteria are analyzed to determine which method can detect leaks earlier: Criterion 1 is P < 0.4 MPa; Criterion 2 is KPI < 0.8; Criterion 3 is based on significance test. Taking Measurement Point 1 as an example, Figure 5 shows the timing of alarms triggered under each criterion.

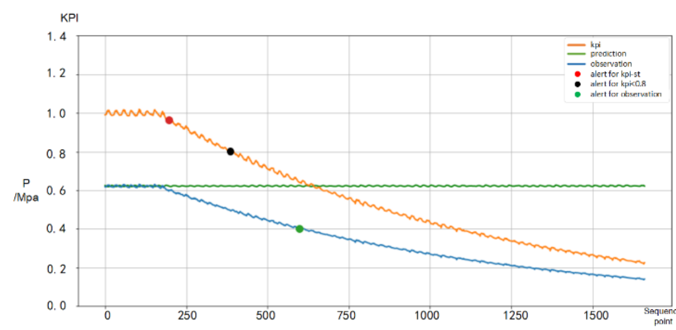
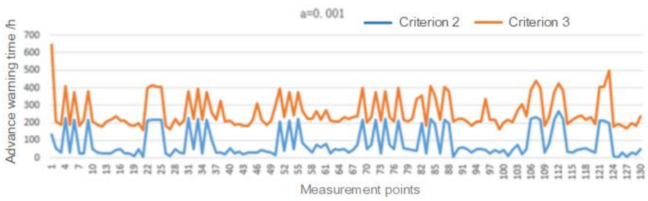


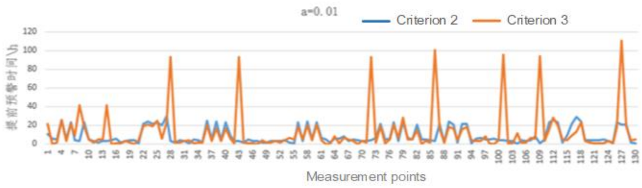
Figure 5. Alarm timing under Criterion 1,2 and 3.

In Figure 5, Blue line represents mixed simulated defect data (while α=0.001), green line indicates expected data (The state of no leakage), and orange line shows the KPI sequence. Red dots denote the warning positions for Criterion 3, green dots for Criterion 1, and black dots for Criterion 2. It is evident that the significance analysis method reacts most rapidly.

As illustrated in Figure 6, slow leaks (α=0.001, in subfigure (a)) and fast leaks (α=0.01, in subfigure (b)) were simulated for the 130 observation samples, calculating the warning lead time relative to the alarm time of the method using threshold (Criterion 1). For slow leaks, Criterion 2 warned on average 81.9 hours earlier than Criterion 1, and Criterion 3 warned 262.7 hours earlier. For fast leaks, Criterion 2 warned 8.8 hours earlier, and Criterion 3 warned 10 hours earlier. This demonstrates that the LSTM-KPI-ST method can effectively achieve early warning of SF_6 leaks.



(a) Slow leaks (α=0.001)



(b) Fast leaks (α=0.01)

Figure 6. Lead time for alarm of 130 measurement points.

In case of rapid leakage, the pressure threshold alarm can be triggered in a very short time. Criterion 2 and Criterion 3 do not seem to demonstrate absolute superiority in such situations. However, they can still provide an early warning 8 - 10 hours earlier than the pressure threshold alarm. During slow leakage, Criterion 3 can promptly issue an early warning upon the emergence of the degradation trend. On average, it anticipates the warning by 180 hours compared to Criterion 2. Therefore, it can be used to detect degradation trends in advance.

IV. Conclusion

To address the challenge of identifying and distinguishing between normal fluctuations and gradual degradation within collected equipment time-series parameters, this paper proposes the LSTM-KPI-ST algorithm. This method achieves trend prediction for equipment parameter time series and detects early changes in the trends. In the case study, slow and fast gas leaks were simulated on the observation data samples, resulting in accurate time series predictions and identification of leak trends, thereby validating the effectiveness of the method.

The principal strength of this approach resides in its utilization of KPI. The KPI method serves to magnify the crucial deviations within the time series, while the significance test is employed to discern the degradation trend. These characteristics empower the extraction of significant trends from noisy measurement data. This not only improves the timeliness and precision of warnings but also minimizes false alarms and missed detections. Additionally, parameter normalization is carried out to guarantee wide-ranging applicability. By leveraging these features, the LSTM-KPI-ST method provides a robust solution for early warning and condition assessment in equipment monitoring. This will be further validated through more cases in the future.

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