Sensor Failure Identification in Industrial Big Data

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***Abstract*—With the rise of information and sensor technologies, sensors play an increasingly significant role in modern production systems. The reliability, safety, and productivity of a production system may largely depend on sensor performance. However, there has been a lack of unsupervised methods for sensor anomaly identification under the environment of industrial big data. This paper proposed an approach to detect sensor failure for industrial big data in an unsupervised manner with the help of random forest and long short-term memory neural networks. The data used in this research are time-series data collected from a gas turbine with 107 sensors. The dataset includes sensor data with 700,000 timestamps in recent years. In this research, random forest regression was first applied to identify the relationship among those sensor values. Afterward, a long short-term memory network is established to predict the values of the target sensor at the current time step. Then, sensor failures can be identified according to the difference between the predicted and actual sensor values. The conducted experiments show promising results that the approach successfully identifies the sensor failure in a completely unsupervised manner.**

Keywords-sensor failure identification; industrial big data; random forest regression; long short-term memory neural network

I. Introduction

Modern production systems are increasingly becoming more complex and di-verse to fulfill various production requirements. For industrial equipment, various sensors with ever-higher accuracy and reliability are required for condition monitoring [1]. The data collected from those sensors are not only significant to identify the state of production and surrounding environment, but also vital for operation management and decision making [2]. Simultaneously, sensor failure could significantly compromise the performance and safety of a system and lead to damage to property, environment, and even casualties. For this reason, sensor failure identification is essential and vital for industrial equipment.

In this research, our motivation is to help an energy company to find a solution for sensor failure identification. The company maintains a lot of large-scale machinery with complex networks of sensors. Those sensors are pivotal in deter-mining the machinery's health and maintenance schedule. The company recently noticed that they are conducting unnecessary maintenance caused by sensor failures. The unnecessary maintenance of large-scale machinery could be both costly and wasteful. Thus, the company wants to find a solution to detect potential sensor failure and verify the results of sensor warning. The data provided by the company and used during our research are collected from a gas turbine. The data includes a record of 107 sensors with 700,000 timestamps in recent years.

One of the challenges in this research is that data collected from multiple sensors hold different physical meanings and vary in different scales, which makes the acquisition of relevant information from data a difficult task. Actually, this challenge is also a common dilemma in many practical applications, especially in the scenarios that hundreds of parameters are collected together and formed into long time-series [3]. Another challenge is that sensor failures are usually not recorded during production, which means a lack of labels that could indicate the ground truth of the collected data. Thus, the solution for sensor failure identification shall also have the capability to deal with the unsupervised environment in this case.

To address the above challenges, this paper proposes an unsupervised method to identify sensor failure based on the combination of random forest regression (RFR) and long short-term memory neural network (LSTM). The proposed approach, RFR-LSTM, has the capability to identify sensor failure for industrial big time-series data in a completely unsupervised manner.

The rest of this paper is organized as follows: Section 2 explains the theoretical background, which includes feature importance, RFR, and LSTM. Section 3 details the proposed RFR-LSTM method for sensor failure identification. Section 4 illustrates the experiments conducted in this work together with the numerical results and discussion. Conclusion and future work are summarized in the last section of this paper.

II. Theoretical Background

A. *Feature importance*

As mentioned above, one challenge in this research is to acquire relevant information from the available data. To be more specific, we need to discover the relationship between the data collected from 107 sensors and identify which sensors could be used to verify each other. The target machinery has an abundance of sensors located over a relatively large area. It, therefore, stands to reason that not all sensors will be useful in predicting the values of a sensor x (where x is any arbitrary sensor value). Therefore, to be able to verify a sensor value x, we need to identify which other sensor values are required. To achieve this purpose, we introduce the concept of feature importance in our research. The feature importance is defined as "discriminative power in distinguishing a target of interest from other individuals [4]." Feature importance, as the name implies, represents the importance of a feature y in predicting feature x. If we change the order of the data for feature y, the prediction error will increase for feature x. Feature importance can be used to describe the relationship between each pair of parameters in our database.

B. *Random forest regression (RFR)*

One of the most popular methods to calculate feature importance methods is random forest. The method can be used for both classification and regression. The name, random forest, comes from the algorithm using a forest of decision trees. Random forest uses a modified version of bootstrap aggregation, also known as Bagging. It can be used to reduce the variance, in cases where the variance is high, which is the case with decision trees [5]. Bagging, as the term suggests, is the process of placing sub-samples of the data into bags with replacement. In order to avoid overfitting, random forest reduces the correlation between the sub-models as much as possible. Rather than allowing the bagging to happen from the entire dataset, random forest's improved technique only allows the bagging to happen from a randomly chosen subset of the data, that is selected at each time-step.

RFR works by taking the average real-valued output from the decision trees. The importance score of each feature can be calculated through recording the improvement in the split-criterion at each split and in every tree [6]. For this rea-son, as proposed in [7], RFR can also be applied as a means to distinguish relevant from irrelevant variables in variable selection approaches. It means that by calculating the feature importance, one may be able to determine which features are important in predicting each other.

In our case, the original size of features is 107 parameters, which are collected from multiple sensors mounted on different areas. We consider that sensors located closely or indicating similar physical meanings are relevant to each other. However, the relationship is difficult to be identified from the physical model directly. For this reason, we introduced RFR here to acquire the feature importance of all the 107 parameters to each sensor.

C. *Long short-term memory network (LSTM)*

LSTM is a special type of recurrent neural network (RNN) proposed in 1997 to address the problem of insufficient, decaying error backflow in RNN training [8]. In LSTM neural networks, memory cells are employed as independent activation functions and identity functions with fixed weights, which are connected to themselves [9]. Compared with traditional RNN, LSTM neural network applies memory cells with forget gates to establish connections between inputs and out-puts [10]. These forget gates could effectively keep information in the cell states. For this reason, LSTM has the capability to capture nonlinear dynamics from long time-series data. More detailed description of the theory to leverage LSTM for time-series sensor data prediction can be found in our previous work [9].

III. SENSOR FAILURE IDENTIFICATION BASED ON RFR-LSTM

As mentioned in the introduction, the main challenge in our research is to identify which sensors are relevant and can subsequently be applied to validate each other. To resolve this issue, we applied RFR to acquire the feature importance of all the sensors first. Then, we select the top 10 relevant sensor values as the key indicators to verify the target sensor. The main idea is to predict the current value of each sensor through an LSTM neural network, in which the inputs are the values from the ten most relevant sensor values, and the output are the predicted values of the target sensor. The difference between the actual and predicted sensor value can be leveraged to identify the potential sensor failure. Fig. 1 illustrates the process of the proposed method for sensor failure identification.

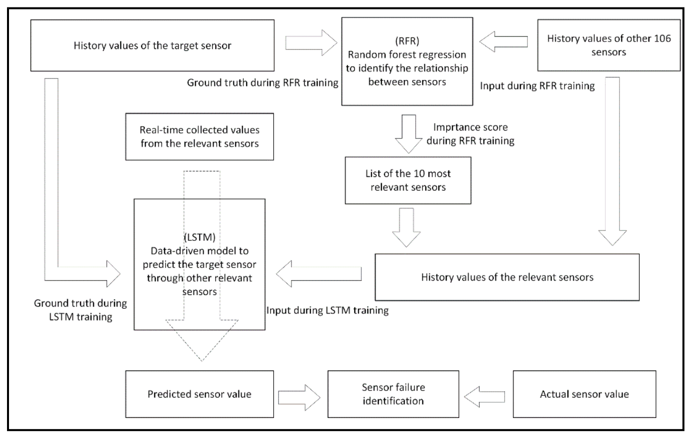

Figure 1. The process of sensor failure identification based on RFR-LSTM

IV. EXPERIMENTS AND NUMERICAL RESULTS

A. *Dataset preparation*

During the experiment, to improve the performance of data-driven model and avoid potential inconvenience, we first applied standard normalization to adjust the sensor data measured on different scales to a notionally common scale, and formatted them into sequences with three steps in each sample. As shown in Table 1, S1(t) represents the current value of Sensor 1, while S1(t-1) and S1(t-2) mean the value of Sensor 1 in the previous one and two timestamps, respectively. The same goes for other sensors.

During the experiment, we randomly selected 90% of the samples (630,000 samples) as training data. The rest 10% of samples (70,000 samples) are used to test the prediction result.

TABLE I. SENSOR DATA AFTER NORMALIZATION AND REORGANIZATION

S1(t-2)	S2(t-2)	S1(t-1)	S2(t-1)	S1(t)	S2(t)
0.15	0.49	0.2	0.5	0.21	0.52
0.2	0.5	0.21	0.52	0.21	0.48
0.21	0.52	0.21	0.48	0.2	0.5

B. Training process

During the training process, the applied random forest is composed of 100 decision trees. We consider the number of trees is large enough for accuracy with acceptable computational complexity since the total number of sensors in the database is 107. We selected mean squared error (MSE) as the criterion for evaluating the quality of a split during the RFR training process due to its broad applicability [11]. The selected criterion can help to calculate the importance score of each sensor. We consider the top 10 features with the highest importance as the relevant sensor values and will subsequently use them to predict the value of the target sensor through LSTM. Table 2 shows the selected parameters for RFR training.

TABLE II. PARAMETERS APPLIED FOR THE TRAINING OF RANDOM FOREST REGRESSION

Training parameters	Values
Measuring criterion	Mean Squared Error
Number of decision trees	100
Number of features chosen	10 highest importance

After the relevant sensors are identified through RFR, we applied LSTM to predict the value of the target sensor. The applied LSTM neural network in our re-search is composed of 50 neurons, and one fully connected layer in the output for prediction. Mean absolute error and Adam are selected as the loss function and optimizer with the learning rate as 0.001.

C. Numerical results and discussion

Fig. 2 shows the training loss with epoch for feature importance identification during RFR training. The training process converges around the 200th epoch, with the Mean Square Error (MSE) dropping to 0.0008.

Fig. 3 illustrates the mean absolute percentage error (MAPE) with epoch during LSTM training process. The training error after 200 epochs around 0.3%, which is acceptable as the prediction error for sensor failure identification.

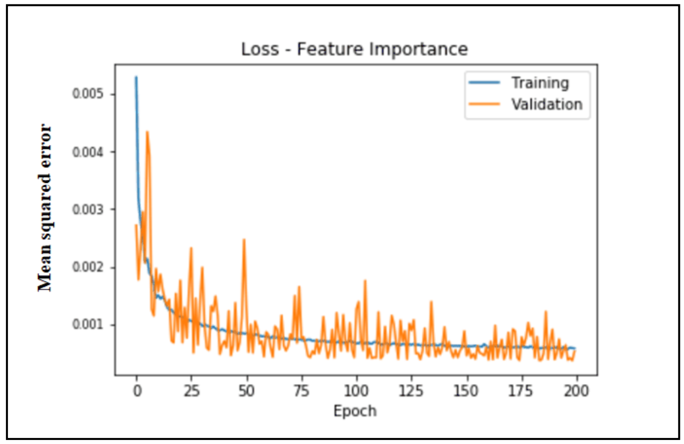

Figure 2. Loss with epoch during RFR training

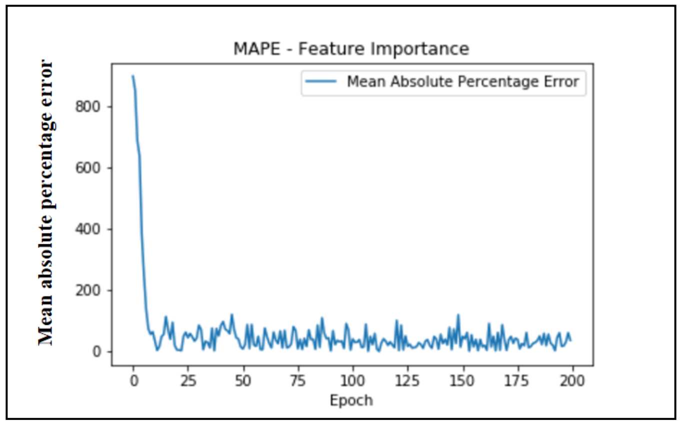

Figure 3. Mean absolute percentage error of LSTM training for prediction

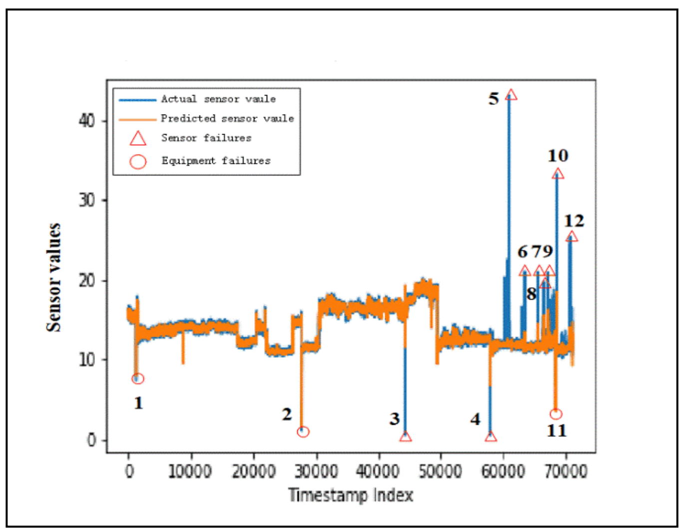

Figure 4. Identified sensor failures according to the difference between the predicted and actual sen-sor values

Fig. 4 shows the final testing result of the training LSTM neural network. After LSTM outputs the predicted sensor value, the difference between the predicted and actual sensor values can be leveraged to identify potential sensor failures. As shown in Figure 4, we can notice that the target sensor changes gradually and smoothly during most of the sampling time. We also find 12 singular points (la-belled as 1-12 in Figure 4) in the testing samples, in which 3 (labelled as 1, 2, and 11 in Figure 4) of the singular points can be predicted by the proposed RFR-LSTM method. The trained data-driven model is established to map the rule of how the target sensor changes with the other relevant sensors instead of the equipment. Thus, we consider these three singular points may indicate potential failures or anomaly of the equipment since both the actual and predicted sensor values vary differently from normal working conditions. Besides, we consider the rest 9 singular points (3-10, and 12) are caused by sensor failures due to the large difference between the predicted and actual sensor values, which means the tar-get sensor is changing irregularly and inconsistent with other sensors. However, due to the lack of expert or historical data with labels, it is difficult to validate the proposed method and its predication results quantitatively, which might be the main limitation of this study.

V. CONCLUSION AND FUTURE WORK

This paper proposed a novel approach to detect sensor failure in a completely unsupervised manner for industrial big time-series data. The proposed RFR-LSTM method can identify the relationship among sensors and subsequently predict sensor values through other relevant sensors. By comparing the difference between the predicted and actual sensor values, sensor failures can be identified. The industry data applied in our research is collected without labels, which makes it challenging to validate the accuracy in the experiment. Future work may focus on the validation of the proposed method in labeled industry data or experimental data.

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