Computer Prediction Model for Equipment Maintenance Using Cloud Computing and Secure Data-sharing

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Abstract. With the popularization of automation in the industrial field, productivity has been greatly improved. However, manufacturing corporations are facing a data tsunami which brings new challenges to predictive maintenance (PdM). In recent years, many approaches and architecture for predictive maintenance have been proposed to solve some of these problems to varying degrees. This paper introduces a general framework based on the Internet of Things, cloud computing and big data analytics for PdM of industrial equipment. In this framework, smart sensors are installed on the device to obtain electrical data, which is then encrypted and uploaded to the cloud platform to predict the health condition by deep learning methods. Several working instances including feature selection, feature fusion, and Remaining Useful Life (RUL) prediction are provided. The effectiveness of the proposed methods is demonstrated by real-world cases.

Keywords: Predictive maintenance; cloud computing; Internet of Things; deep learning.

1. Introduction

In order to realize the fourth industrial revolution as soon as possible, many developed countries treat computer technology as their national strategic goal [1]. For instance, the United States focuses on the improvement of IT technologies and puts forward the concept of the Industrial Internet [2]. Germany proposes the concept of Industry 4.0 involving both physical and cyber manufacturing systems [3]. Industrial equipment maintenance is an important domain in the manufacturing system. According to [4], equipment idling and sudden shutdowns account for the largest number of production problems. Due to these problems, manufacturing systems have been made vulnerable to economic losses and susceptible to consequential effects. Therefore, manufacturing enterprises are realizing that there is a critical need for proper maintenance of industrial equipment [5].

Maintenance strategies widely adopted by manufacturing enterprises are grouped into three categories, namely Run-to-failure (R2F), preventive maintenance (PvM), and predictive maintenance...
(PdM) [6]. R2F is the simplest maintenance strategy used when machine parts are malfunctioned. However, suspension of production line, repair of industrial equipment, and adjustment of production facilities will add direct costs to the manufacturing process. PvM is a regular check method to carry out maintenance work. This strategy is not very efficient since it will bring more manpower and time cost. Among the three categories, PdM using machine learning (ML) algorithms to determine when maintenance activities are necessary, is the most effective strategy for anomaly detection to minimize operating costs, make reliable predictions, and improve equipment conditions [7]. However, there exist two flaws in PdM strategy. For one thing, there is a lack of general architecture for PdM optimization. Traditionally, companies need to purchase physical devices to monitor industrial equipment and calculate evaluation metrics, which may increase operating costs. Particularly, it is difficult for manufacturing companies to cope with elastic computing power. For another, while ML algorithms are applied to PdM, their performance and reliability are often limited by the quality of data representation. Specifically, data with redundant attributes and a lack of temporal information generates poor PdM performances. To deal with these defects, this paper first introduces a general framework based on cloud computing for PdM problem. Then, a Long Short-Term Memory (LSTM) network is proposed to predict the Remaining Useful Life (RUL) of the industrial equipment and a manual attribute selection method for three-phase electrical equipment is provided to improve the performance of the LSTM. The contributions of this paper are listed as follows: 1) Establish a general framework for PdM based on cloud computing and big data analytics. 2) Propose an LSTM model to predict the RUL of industrial equipment and a manual attribute selection method for three-phase electrical equipment. 3) Verify the effectiveness of the proposed methods with real-world cases. The results show that our approach is promising.

The rest of this paper is organized as follows. Section II gives a literature review about cloud computing and commonly used ML algorithms in PdM works along with different feature extraction methods. Section III describes system architecture and proposed methods. Application and comparison analysis are presented in Section IV. Finally, conclusion and future work are discussed in Section V.

2. Literature Review

2.1. Benefits of Cloud Computing Techniques

Cloud computing is a model for providing computing services by building cloud centers. According to the types of users, cloud computing can be divided into public cloud, private cloud, and hybrid cloud. According to the needs of users, cloud computing can be divided into Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS).

The service model of cloud computing is to build a supercomputer to process and store data and treat it as a service. The main advantages of cloud computing are ubiquitous accessibility, easy scalability, and mobility. Fila, R., El Khaili, M., and Mestari, M. [8] propose a cloud-based architecture for PdM and use a multi-user leasing model. A database about gears is used since gear is used in several core fields such as aeronautics, electronics, medicine, nuclear, finance, weather, and automotive. In this study, 16 related attributes and 3 damage modes are well discussed. In order to evaluate the performance of the architecture services, four evaluation methods, i.e., response time, availability, cost and reputation are provided. The experimental results show that cloud computing architecture can be as a new method for autonomous data mining and cognitive learning algorithm. Yang, F. N. and Lin, H. Y. [9] also propose an architecture based on cloud platform for PdM. In this paper, due to the advantages of strong expansibility and high-cost performance of public cloud, Microsoft Azure HDInsight's Microsoft R Server is adopted. For better data storage and processing, Hadoop and Apache Spark are deployed in the cloud node respectively. In the new framework, Apriori algorithm and Random Forests are used as the main algorithms for PdM. In the experiment, 388,744 samples of gear boxes and 14 characteristics were analyzed, and good experimental results were obtained. This study provides a new approach to the goal of providing PdM service by using cloud computing technologies. Wang, J., Zhang, L., Duan, L., and GAO, R. X. [10] propose a PdM model based on cloud and mobile agent. In this new model, a low-
cost cloud computing node is deployed to perform computation-related services in PdM. In addition, the cloud node also deploys mobile agents related components for data sharing and interaction. In order to verify the proposed new model, this paper uses a motor test system to conduct experiments. The motor current is collected at the sampling rate of 2 kHz, and the data lasting for 10 seconds is sampled as a data set. The current envelope is used as the main feature of data because it clearly shows the difference between a healthy motor and a faulty motor. This paper demonstrates that the deployment of mobile agents in the cloud effectively increases the flexibility and adaptability of the system, reduces raw data transmission, and responds instantly to dynamic changes in operations and tasks.

As mentioned above, cloud platform has the advantages of supporting elastic computing, on-demand service, cost-effective business model, and high security. Therefore, this paper adopts cloud computing architecture to solve the PdM problem of industrial equipment.

2.2. Commonly Used Machine Learning Algorithms in PdM

With the progress in data analytics, various ML algorithms are employed in the PdM works. These algorithms can be grouped into four main categories, i.e., Supporting Vector Machines (SVM), K-Means, and Artificial Neural Network (ANN).

SVM is a well-known supervised ML technique due to its high precision that can perform pattern recognition, classification, and regression analysis [11]. Falamarzi, A., Moridpour, S., Nazem, M., and Cheraghi, S. [12] used SVM model to predict the fault of tram. 250 km of railway and 25 different train railway lines are measured in this research, and two types of track of straight and curve are studied. The results show that the SVM is good at curve railway. Lasisi, A and Attoh-Okine, N. [13] propose a new architecture based on SVM for PdM. In this architecture, the combination of high dimensional track parameters is transformed into a low dimensional form, which is used as a track defect predictor. In this paper, one-mile track is used as the data, 31 features and 31 parameters are studied. By using True Positive Rate and False Positive Rate as the measurement of prediction performance, SVM is found to be the most effective technology and can better predict defects. These findings provide insights into predictive maintenance based on geometric degradation. In spite of the promising results, the SVM lacks temporal dependency consideration while making the decision on performing the maintenance activity or not.

K-Means is also a commonly used clustering algorithm based on Euclidean distance. K-Means is a classical unsupervised ML algorithm for clustering tasks due to its good performance and easy-to-understand expression. Bekar, E. T., Nyqvist, P., and Skoogh, A. [14] used the K-Means to perform PdM on bottleneck machines used to create engine components. Before prediction, they also proposed that intelligent methods based on cross-industry standard process to obtain qualified structured data. Four databases about bottleneck machines are used for analysis and prediction. K-Means is used to cluster data points to understand the outliers in the outlier clustering. In the last two different machine data is divided into three different categories. This paper increases the possibility of using machine learning algorithms in the real industry. Another case for machine health condition predicting in the next two weeks is proposed by Amihai, I. et al. [15]. This method classifies the vibration data by K-Means and achieves 87.33% accuracy. In ablation experiments, the entity embeddings and full connection layer are removed respectively to test the result. The overall accuracy is still over 85%. Although K-Means is easy to understand and implement, it has some drawbacks. Firstly, it is difficult to determine the number of clusters. Secondly, K-Means is order sensitive, in other words, data order will cause changes in the final results.

ANN is one of the most widely employed ML algorithms inspired by biological neurons and has been applied in many PdM works on grounds of its robustness and real-time performance. [11], [16]. Scalabrini Sampaio, G. et al. [17] proposed training the neural network to predict the time of equipment failure. They built a model to simulate the vibration of the motor and the collected data is structured to make the training effect better. In this study, they used the method of K times cross validation to train and test. They achieved good results. In addition, compared with other machine learning algorithms, they found that ANN has better performance on a dataset of cooling fun of motor vibration. A PdM
A method based on a wind turbine test rig is proposed by Biswal, S. and Sabareesh, G.R. [18]. The bench type wind turbine test-bed system is designed to obtain the vibration characteristics of the bearing, gearbox, shaft, and other key parts in health and fault conditions. The main failure states are the root crack of gear and the axial crack of the roller bearing inner ring. ANN is used as the prediction model, and its accuracy is 92.6%.

Although ANN is a powerful predictive algorithm, it requires expert knowledge on hyper-parameter tuning. Moreover, previous ANN research on PdM lacks the combination of temporal dependency and attribute selection to the final results. In this paper, LSTM is employed to predict the RUL of industrial equipment. Meanwhile, a manual feature extraction method is proposed to improve the LSTM performance.

3. Methods

3.1. System Architecture

Industry 4.0, our next generation of industry, is aimed at realizing intelligent manufacturing. The fourth industrial revolution holds the promise of improved productivity, better quality and less breakdown [19]. In the context of Industry 4.0, manufacturing technologies are transformed and upgraded by the IoT, cloud computing and big data analytics [20] [21].

The IoT refers to an inter-networking world where different objects can be embedded with wireless sensors or other smart digital devices so that they are networked and connected for the purpose of collecting and exchanging information [22]. Cloud computing is a general term that refers to delivering computational services to the Internet. An ideal cloud platform should have five characteristics: almost endless resource pooling, on-demand self-service, broad network access, rapid elasticity, and measured service. This allows real-time response even during peak business hours, which can solve the problem of software and hardware performance bottlenecks [23]. With an aggressive push toward the cloud platform and IoT technologies, data is becoming more and more accessible and ubiquitous, resulting in the issue of a huge flood of data [24]. Because big data has the characteristics of Volume, Velocity, Variety, and Value, manufacturing sectors have a growing demand for big data analysis. Fig. 1 shows the framework of the proposed methods.

To solve the PdM problem of the industrial equipment, this research establishes a general framework based on IoT technologies, cloud computing, and deep learning. Firstly, raw data is consistently collected by the electrical sensor attached to the industrial equipment and then uploaded to the cloud platform after encrypted utilizing SHA-256 [25]. Then, a universal method is applied to select the necessary features of the processed data. After feature selection, data is uploaded to the cloud platform to be analyzed by a specific algorithm. Finally, the results are well presented on a web browser or a cell phone.

3.2. Manual Feature Selection Method

This section proposes a manual attribute selection method for three-phase industrial equipment. There are 28 attributes defined and presented in Table 1.

Line voltage can be expressed by phase voltage, therefore, if $U_A$, $U_B$, and $U_C$ are known, $U_{AB}$, $U_{BC}$, and $U_{CA}$, can be removed. Note that:

$$P_A = \frac{1}{\sqrt{3}} \cdot U_A \cdot I_A \cdot \cos \varphi_A$$

(1)

$$P_B = \frac{1}{\sqrt{3}} \cdot U_B \cdot I_B \cdot \cos \varphi_B$$

(2)

$$P_C = \frac{1}{\sqrt{3}} \cdot U_C \cdot I_C \cdot \cos \varphi_C$$

(3)

$$P = P_A + P_B + P_C$$

(4)
If $I_A, I_B, I_C, \cos \varphi_A, \cos \varphi_B,$ and $\cos \varphi_C$ are selected $U_A, U_B,$ and $U_C,$ $P_A, P_B, P_C$ and $P$ can be calculated according to Equation (1) to (4). Note that:

$$Q = Q_A + Q_B + Q_C$$ (5)  

$$S^2 = P^2 + Q^2$$ (6)  

If $Q_A, Q_B,$ and $Q_C$ are known, $S_A, S_B,$ and $S_C$ can be also calculated. Additionally, because $f_A, f_B,$ and $f_C$ are related to the sources, they should not be removed.

![Framework of the proposed method](image)

Fig 1. Framework of the proposed method.

Table 1. Attributes collected from the industrial equipment.

| Category       | Feature                     |
|----------------|-----------------------------|
| Current        | *A phase current            |
|                | *B phase current            |
|                | *C phase current            |
| Voltage        | *A phase voltage            |
|                | *A phase voltage            |
|                | *A phase voltage            |
|                | AB phase voltage            |
|                | BC phase voltage            |
|                | CA phase voltage            |
| Power          | A phase active power        |
|                | B phase active power        |
|                | C phase active power        |
|                | Total active power          |
|                | *A phase reactive power     |
|                | *B phase reactive power     |
|                | *C phase reactive power     |
|                | Total reactive power        |
|                | A phase active power        |
|                | B phase active power        |
|                | C phase active power        |
|                | Total apparent power        |
To sum up, the proposed method manually selects 15 out of 28 attributes marked by asterisks in table 1 according to electrical knowledge. It can be further extended to a larger electrical attribute space.

### 3.3. Health Prediction by LSTM

This part consists of three main units, i.e., feature fusion, Long Short-Term Memory (LSTM) network and the Full Connected (FC) layers.

The proposed model considers both real-time and historical data for RUL prediction as the current health condition of the industrial equipment is affected by the previous. The fused feature $F$ is formulated as:

$$F = \psi(f_1 \cdot f_2 \cdot \ldots \cdot f_C)$$

$$∀f_i \in R^{D_{\times}T}, i \in \{1,2,\ldots,C\}$$

$$F \in R^{D_{\times}T}, D = \sum_{i=1}^{C} d_i$$

Where $C$ stands for attribute categories (i.e., current, voltage, power factor, and frequency); $d_i$ is the dimension of each category; $T$ is the time sequence; and $\psi(\cdot)$ is fusion operation. In the proposed manual selection method: $|C| = 5$, and $d_1 = d_2 = \ldots = d_C = 3$.

The LSTM conducts $F$ to extract features and the FC takes these features as input to predict the RUL defined as:

$$RUL = \frac{\text{Time to failure} - \text{Current time}}{\text{Time to failure}}$$

LSTM is a special kind of Recurrent Neural Network (RNN) and mainly to solve the gradient vanishing and gradient explosion problems in the long sequence training. In short, LSTM can perform better in longer sequences than regular RNN. LSTM has two transfer states that is hidden state $h^t$ and cell state $c^t$. Among them, the $c^t$ passed down changes very slowly. Usually, the output $c^{t+1}$ is $c^{t-1}$ the passed from the previous state plus some values. However, the $h^t$ passed down changes very quickly. $h^{t-1}$ and $h^{t-1}$ have a big difference.

LSTM has three gates (i.e., forget gate, input gate, and output gate) to control which information will be removed and carried at current node. Besides, LSTM will get four states by using current input $x^t$ and $h^{t-1}$ passed down from the previous state. Note that:

$$z = \tanh (W \cdot [x^t, h^{t-1}])$$

$$z^i = \sigma (W^i \cdot [x^t, h^{t-1}])$$

$$z^f = \sigma (W^f \cdot [x^t, h^{t-1}])$$

$$z^o = \sigma (W^o \cdot [x^t, h^{t-1}])$$

| Power factor          | *A power factor | *B power factor | *C power factor | Total power factor |
|-----------------------|-----------------|-----------------|-----------------|-------------------|
| Frequency             | *A phase frequency | *B phase frequency | *C phase frequency |                  |
Among them, \( z^t \), \( z' \), and \( z^0 \) are gated by multiplying the splicing vector by the weight matrix, which is converted to a value between 0 and 1 with a sigmoid activation function. However, \( z \) will be an input data by multiplying the splicing vector by the weight matrix, which is converted to a value between -1 and 1 by a tanh activation function. There are three phases in the LSTM. The first phase is forgetting stage. This phase is mainly the input of the previous node to selectively. In other words, this phase will remember what is important and forget what is not important. Specifically, the \( z^f \) obtained by calculation is used as a forget gate to control what needs to be left and what needs to be forgotten in the last state \( c^{t-1} \). Second one is the memory stage. This stage will selectively remember the input from this current stage. The current input is represented by the \( z^t \). The \( z^t \) control how many new information to left. The \( c^t \) can be got by adding the results from the previous two phases. Note that:

\[
c^t = z^f \ast c^{t-1} + z^i \ast z
\]  

(15)

The third phase is output stage. This stage will decide what will be treated as the output of the current stage \( (h^t) \) by using \( z^0 \) to control. Besides, this stage will scale up and down for \( c^t \) by a tanh activation function. Note that:

\[
h^t = z^0 \ast \tanh(c^t)
\]  

(16)

In the last, the \( y^t \) will be got by using \( h^t \). Note that:

\[
y^t = \sigma(W' \cdot h^t)
\]  

(17)

The * is element-wise multiplication and the + is matrix addition. Therefore, the prediction of the RUL can be calculated as:

\[
RUL = w^2 \cdot \sigma(w^1 \cdot LSTM(F) + b^1) + b^2
\]  

(18)

Where \( w^1, w^2, b^1, \) and \( b^2 \) are parameters of the FC layers.

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**Fig 2.** Network architecture. Given a sequence of electrical record, the target is to estimate the health condition (RUL) at current time.
4. Experiments

4.1. Implementation Details
Data of a turn-milling center in an aircraft manufacturing cooperation is utilized to support the experiments in this paper. There are a total of 34394 records and 28 attributes presented in Table 1. The available data consists of ten maintenance cycles collected by R2F policy. In the first eight maintenance cycles, anomalies occurred during the working condition. In the last two, random anomalies were captured when the equipment was in the off-working condition. The PdM performances of LSTM and other ML algorithms (i.e., SVM, K-Means) are achieved by ten-fold cross validation with the accuracy rate (ACR).

\[
\text{ACR}[] \% = \text{Percentage of correct classified samples}
\]  

(19)

If both idea RUL as in (10) and the prediction are below or above the alarm threshold\(\xi\), the current health condition is considered correct based on the confusion matrix. Specifically, \(\xi\) is set to 0.3 in real production process. The details of each maintenance cycle are presented in Table 2.

| MC | Records |
|----|---------|
| 1  | 1558    |
| 2  | 126     |
| 3  | 1714    |
| 4  | 1447    |
| 5  | 4415    |
| 6  | 2810    |
| 7  | 1063    |
| 8  | 3756    |
| 9  | 6289    |
| 10 | 10916   |

Table 2. Details of Each Maintenance Cycle (MC).

In this paper, network parameters are randomly initialized and the hyper parameter \(T\) is set to 8. The dimension of hidden state \(\hat{h}^t\) and cell state \(c^t\) is set 16. The LSTM is trained 120 epochs and the Adam optimizer is selected to adjust the learning rate dynamically. The batch size is set to 64 and the experiments are all implemented in Python 3.7 and run on a work station with GeForce RTX 2080Ti.

4.2. Experimental Results
Classical ML algorithms (i.e., SVM and K-Means) are employed to compare with the LSTM. The general computation costs of these competitors are summarized in Table 3, where \(N\) the total number of the records, \(D\) is the feature dimension, and \(M\) is the dimension of hidden state \(\hat{h}^t\) and cell state \(c^t\) in the LSTM.

| Method   | Time complexity          |
|----------|--------------------------|
| SVM      | \(O(N^3)\)               |
| K-Means  | \(O(N \log N)\)          |
| LSTM     | \(O(4T(DM + D^2 + D))\) |

Table 3. General Computational Costs of the Competitors.
In this experiment, Gaussian kernel is employed in the SVM; the cluster number of K-Means is set to $k = 2$; $M$ and $T$ in the LSTM are set to 16 and 8 respectively. ACR achieved through ten-fold cross validation is used as the metric.

Table 4. Comparison with Other ML Algorithm in Terms of ACR [%].

| Method   | ACR        |
|----------|------------|
| SVM      | 49.85 ± 3.21 |
| K-Means  | 70.56 ± 1.48 |
| LSTM     | 72.81 ± 1.47 |

The comparison results in Table 4 shows that LSTM dominates SVM and K-Means in terms of ACR. The reason why the LSTM can get a good performance is that it can use the previous data to help current prediction and adjustment.

5. Conclusion
Since increasing attention has been given to predictive maintenance of industrial equipment, intelligent maintenance is now regarded as a key future perspective in both academia and industry. In this paper, a general framework and a feature selection method are presented for the predictive maintenance of industrial equipment. The framework is based on IoT, cloud computing and deep learning. The advantages of the proposed method are demonstrated compared with the traditional ML algorithm.

The future work will mainly concentrate on two aspects. Firstly, it might be interesting to employ generation models combined with expert knowledge for feature extraction. Secondly, it is worth searching for a more effective FCNN to improve the performance of the RUL prediction component.

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