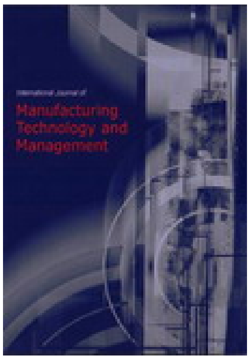

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Design of real-time monitoring method for production line equipment status based on cloud computing and internet of things technology

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Abstract: In order to solve the problems of low monitoring accuracy and long monitoring time in the traditional real-time monitoring method of production line equipment status, this paper designs the real-time monitoring method of production line equipment status based on cloud computing and internet of things technology. Based on the perception of the internet of things labels, collect production line equipment status data and real-time upload, extract time domain parameters of production line equipment status, build historical memory matrix, establish and train multiple state estimation model, design distributed processing cloud computing platform MapReduce framework, complete real-time monitoring of production line equipment status under this framework. The experimental results show that the real-time monitoring accuracy of production line equipment status by the proposed method is 98%, the monitoring time is within 7.25 s, and it has the application effect of high precision and low time consumption.

Keywords: cloud computing; internet of things technology; production line equipment; condition monitoring; radio frequency identification; RFID.

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1 Introduction

Throughout the development history of human society, every major industrial revolution or rapid development is led by the development and extensive application of production line equipment, and industry has occupied the leading position in the national economy (Deng et al., 2021; Zhu et al., 2022). With the continuous development of computer technology, industrial technology has gradually matured, and traditional production line equipment has been replaced by modernisation, automation and intelligence (Chu and Liu, 2019). Production line equipment is an important material foundation of industrial enterprises, and its operation status directly affects the overall production quality. If the production line equipment is in operation, its status, capacity, load and other dynamic information feedback is not timely, which will cause production line equipment failures and reduce the production efficiency of the workshop. Therefore, in order to ensure the stable operation of production line equipment, improve the safety and stability of the production process, many experts in relevant fields design real-time monitoring methods for the status of production line equipment (Fu et al., 2021).

Li et al. (2019) proposed a remote monitoring method for NC processing equipment based on the B/S architecture. Under the B/S architecture, this method collects multi-source signals from the sensors of NC processing equipment, transmits the collected signals to the NC system, reads the collected signals in combination with multithreading and socket protocols, and classifies the data of NC processing equipment according to the reading results, so as to achieve remote monitoring of the operation status of NC processing equipment. However, due to the large amount of data collected, the time domain parameters of the equipment status of the production line cannot be extracted and analysed, which increases the difficulty of data processing, and leads to certain errors in the status monitoring of the production line equipment, which affects the monitoring effect. Li et al. (2020) improved the auto association regression algorithm, established the generator set equipment status early warning model, designed the variable interval state matrix extraction method based on clustering, optimised the model parameters through the four fold cross validation learning mechanism, obtained the optimal equipment status monitoring model, and realised the generator set equipment status monitoring and early warning. However, in the actual process of real-time monitoring of the equipment state of the production line equipment, because the model is relatively complex and the calculation is difficult, the monitoring of the equipment state takes a long time, and the monitoring effect cannot meet the actual monitoring needs. Liu et al. (2021), based on the improved outlier and similarity editing algorithm, optimise the training set of the KNN regression algorithm to improve the operation efficiency, establish the normal behaviour model of the gearbox, monitor the state of the wind turbine gearbox, and realise the early warning of the gearbox failure. However, due to the complex multiple state of equipment operation, and the difficulty of data processing, there is a certain error between the monitoring results and the actual equipment status, and there is the problem of inaccurate monitoring. Chen et al. (2020) designed the core unit, combined BP neural network and particle swarm optimisation algorithm, built the fault diagnosis model of electronic transformer, and obtained the monitoring results. However, due to the complexity of the algorithm, it is necessary to identify the operation status data of multiple equipments at the same time, resulting in a long time for the real-time monitoring of the equipment status in the production line, which reduces the monitoring efficiency and cannot meet the application requirements of real-time monitoring.

Due to the traditional production line equipment status real-time monitoring method is low, long monitoring time, affect the production line equipment status real-time monitoring effect and work efficiency, so according to the problems existing in the above method, this paper puts forward the based on cloud computing and internet of things technology production line equipment status real-time monitoring method, the specific research route of this method is as follows:

1 The sensing tag based on the internet of things is designed. The sensing tag is built through RFID module, positioning module, attitude monitoring module and NB IoT module in the internet of things to obtain the status data of production line equipment and upload them in real time;

2 After obtaining the status data of the production line equipment, design the MapReduce framework of the distributed processing cloud computing platform, complete the reduce tasks and map tasks through the task tracker virtual machine, and calculate and process the real-time monitoring task of the production line equipment status, and output the processing results;

3 After output the processing result, extract the time domain parameters of the production line equipment status, including validity value, peak value, cliff coefficient, waveform coefficient, pulse coefficient and margin coefficient, and normalise the extracted time domain parameters;

4 Taking the extraction results of the processed production line equipment state as the basis, build the historical memory matrix, establish the multivariate state estimation model, obtain the predicted value of the current production line equipment status,

analyse the difference between the observed vector and the prediction vector, and monitor the current state of the production line equipment.

5 And through experiments, it is verified that the design method can quickly and accurately monitor the status of production line equipment in real time, laying a certain foundation for the safe operation of production line equipment.

2 Design of real-time monitoring method for production line equipment status

2.1 Design of perceptual labels for production line equipment based on internet of things technology

The internet of things technology refers to the information exchange through information sensing equipment according to the agreed protocol. The hierarchy of the Internet of Things is divided into three layers, namely, the perception layer, the network layer and the application layer from bottom to top. The sensing layer collects information data through barcode, QR code, radio frequency identification, smoke detector, speed sensor, camera and other devices (Liao et al., 2020). The physical communication interfaces are generally RS-485, RJ-45, WIFI, Bluetooth, Zigbee, etc.; The network layer transmits the collected information data through wired and wireless networks, playing a connecting role (Wang et al., 2021); The application layer transforms and analyses the obtained information, provides users with real-time monitoring scene and accurate management data through calculation, processing and knowledge mining, assists users in making scientific decisions, and realises the combination of data and business applications.

Therefore, based on the radio frequency identification (RFID) technology in the Internet of Things, this paper designs the perceptual tags of production line equipment. The monitored production line equipment is identified through RFID, the acquisition equipment is connected to read the attribute information of the monitored production line equipment, the A/D converter is used to convert the attribute information of the production line equipment into a specific data format, and the data information is transmitted to the application layer of the Internet of Things through wireless signals, where data analysis is completed (Chu et al., 2021). The construction of perceptual tags requires the establishment of four functional modules, namely, RFID module, positioning module, attitude monitoring module and narrow band internet of things (NB IoT) module.

1 RFID module

The RFID module can realise the coupling of the equipment ID of the production line and the acquisition parameters of each sensor by bridging the RFID radio frequency and the control part, use the radio frequency identification technology to read and write the starting signal of the register, build the connection between the radio frequency channel and the digital channel, and use the interrupt signal as the wake-up signal of the control unit to support the ultra-low power consumption operation of the related devices, and realise the radio frequency identification and control (Jeong et al., 2020).

2 Positioning module

Select the ATK-1218-BD Beidou positioning module, read the GPS data of the location after initialisation, and judge whether it is $GNRMC data. If the data meets, analyse it, and if not, repeat the reading (Wang, 2020).

3 Attitude monitoring module

The attitude monitoring module selects ADXL345 sensor to collect parameter data such as inclination and attitude of the production line equipment. Since the environment where the production line equipment is located will have vibration and mechanical noise, in order to reduce the impact of on-site vibration and mechanical noise on the accuracy of attitude parameter data acquisition, the attitude parameter data is preprocessed through Kalman filtering (Li, 2022).

First, initialise the ADXL345 sensor to enable the sensor to enter the self inspection mode. If the self inspection fails, an error message will be returned. If the self-inspection passes, the acceleration values of the current x, y and z axes will be read, and the accurate angle values of the x, y and z axes will be calculated according to the relationship between the tilt angle of each axis and the acceleration values, so as to monitor the attitude of the production line equipment. The relationship between the angle value α_1, β_1, ϑ_1 of the three axes of x, y, z and the acceleration value is as follows:

$$\begin{cases} \tan\alpha_1 = \dfrac{a_x}{\sqrt{\left(a_y^1 + q_z^1\right)}} \\ \tan\beta_1 = \dfrac{a_z}{\sqrt{\left(a_x^1 + q_y^1\right)}} \\ \tan\vartheta_1 = \dfrac{a_y}{\sqrt{\left(a_x^1 + q_z^1\right)}} \end{cases} \tag{1}$$

where a, q represents the sensor coefficient.

If the process noise variance is Q, the measurement noise variance is R, the state transition matrix is A, the observation matrix is H, and the time is k, the Kalman filtering result is:

$$P(k|k) = A(k-1|k-1) + Q + RH \tag{2}$$

4 NB IoT module

The parameter data of the production line equipment attitude obtained by sensing tags are uploaded to the Internet of Things application layer through the NB IoT module. Before uploading, the NB IoT module needs to be initialised to ensure that the module is successfully connected to the network and can complete the data upload task (Ding et al., 2020). Combined with the STM32 microcontroller to call the AT instruction of the module to complete the operation, the NB IoT module sends the corresponding return value to the STM32 microcontroller in real time to complete time synchronisation and realise the construction of the sensing tag.

There are many ways for the perceptual tag to be awakened. In case of abnormal vibration, the perceptual tag can be automatically awakened, or it can be awakened through handheld devices or monitoring platforms; Since the power consumption of the positioning module and the NB IoT module is relatively large, a time interval can be set to collect location information and upload data at a fixed time point when there is no exception. When there is an exception, it will be converted to real-time collection and upload, thus reducing the power consumption of the module.

2.2 Build a distributed processing cloud computing platform MapReduce framework

MapReduce is a model framework for cloud computing for massive data in large distributed processing cloud computing platforms. You can use the MapReduce framework to perform a large number of data operations. Therefore, all operations of the real-time monitoring method of production line equipment status in this paper are completed under the framework of the distributed processing cloud computing platform MapReduce.

The cloud computing platform MapReduce framework is characterised by virtualisation, multi-level services, elasticity, scalability, reliability, versatility and scale.

1. Virtualisation: using virtualisation technology can integrate heterogeneous computing resources and form resource pools for users to access.
2. Multilevel services: cloud computing platform provides three levels of services, namely infrastructure as a service, platform as a service and software as a service. IaaS is the lowest level service that directly provides computing, storage, network and other resources. Users have the greatest freedom to build their own platforms and software. PaaS is a higher level than IaaS, providing an off the shelf cloud platform, saving the work of the development platform. SaaS provides more convenient services. Users can directly use the software provided without any development.
3. Flexible and scalable: the cloud scale can be easily expanded without affecting the cloud services currently provided externally. The resources in the cloud are infinitely desirable for users, and can be automatically and quickly provided and recycled on demand.
4. Reliable and versatile: cloud computing technology provides a variety of fault tolerance mechanisms to ensure high reliability of services. Multiple copies of data are placed to prevent data loss due to hardware failure. Computing services stopped due to hardware failure can continue elsewhere through virtual machine migration. Virtualisation makes cloud computing resources transparent to users and can support applications in different industries at the same time (Shi and Gao, 2020).
5. Scale: the cloud computing platform does not require high hardware facilities. A large number of idle ordinary computers can be integrated into the resource pool through virtualisation technology. For users, it saves the hardware cost and daily management cost of the self built platform. For cloud service providers, the universality of cloud computing has greatly improved the utilisation of resources, and the scale has significantly increased the economic benefits.

In the MapReduce framework, the master-slave mode can be used to manage the real-time monitoring of production line equipment status. When complex tasks are divided into some simple jobs, the efficiency of cloud computing will be reduced. Therefore, master-slave mode can be used to transfer the real-time monitoring job of the production line equipment status to MapReduce, manage the job unit on the server to realise initialisation, creation, scheduling and task completion. When the real-time monitoring job of the production line equipment status is transferred to the MapReduce framework, the job will be divided into some system reads. Complete the reduce task and map task through the virtual machine of task tracker. After the map task is completed, reduce the task by shuffling, sorting, and merging. In the process of shuffling, key tasks appear randomly, possibly on one machine or many machines. The process of shuffling is to input the same key to the required reduce as required. Sort the key values according to the program requirements according to the different key values. After the 'shuffle' and 'sort' operations, the output <key, (list='')> will be sent to the reduce method of the Reduce task for processing, and finally the processed results will be obtained in HDFS.

2.3 Extract time domain parameters of production line equipment status

Time domain refers to the value and the relationship between the state signals of the production line equipment. The extraction of time domain parameters can obtain various dynamic parameters, usually including dimensionless and dimensionless quantities. Generally, after setting the specific time domain signal acquisition time, the time domain parameters of the equipment state of the production line equipment can be extracted with the specific time period as the acquisition unit. In order to improve the status of the production line equipment monitoring effect, through the Internet of things technology in the production line equipment operation environment layout data acquisition and transmission equipment, install a variety of sensors, effectively identify the production line equipment status signal, and through the real-time upload, the time domain parameters as equipment status monitoring judgement index, to measure the equipment status. Among them, the sensor includes piezoelectric vibration sensor, ultrasonic sensor, thermal sensor, liquid level sensor and so on. However, the dimensional parameters depend heavily on the historical data of the equipment operation, and will change with the change of external working conditions. Therefore, in the time domain parameters of the production line equipment state, the effective value, peak index, cliff coefficient, margin factor, deviation index and waveform factor are taken as the indicators to judge whether the production line equipment fails.

1 Valid values

Set the time history t of the vibration signal of the production line equipment as x(t) and the vibration cycle as T, then:

$$X_{rms} = \frac{\int_0^T x(t)dt}{T} \tag{3}$$

RMS, also known as root mean square value, is the average value of time. It can give a good judgement for faults such as surface wear of production line equipment with slow amplitude change over time. It reflects the vibration intensity and energy of production line equipment. For the surface vibration of normal production line equipment, the measured vibration signal changes little. For the surface damage of the production line equipment, the vibration signal property is not changed fundamentally, and only the vibration amplitude is larger. Therefore, the effective value parameters are used to judge the fault of the production line equipment, which ensures the feasibility, reduces the detection time and improves the monitoring efficiency.

2 Peak index

$$C_f = \frac{x_{max}}{X_{rms}} \tag{4}$$

The peak index reflects the maximum value of the vibration signal of the production line equipment at a certain time. If the peak index is too large, it usually indicates that there are local defects. When there is damage fault on the surface of production line equipment, the peak value index can judge it well.

3 Kurtosis coefficient

$$\alpha_4 = \int_0^T x(t)p(t)dx \tag{5}$$

where p(t) represents the probability density function of x(t).

Kurtosis coefficient is a dimensionless factor. The amplitude value of vibration signal of normal production line equipment is approximately subject to normal distribution, which indicates the regularity of vibration signal amplitude of production line equipment. It is sensitive to the local damage kurtosis coefficient of early production line equipment. After failure, the tail of probability density function of amplitude value increases, which can be reflected by kurtosis coefficient. When the fault develops to a certain stage, because its stability is not good enough, the kurtosis coefficient will decline. Because of this feature, we can use the kurtosis coefficient to analyse the development trend of equipment fault in the production line. For example, when the kurtosis coefficient starts to decrease from the maximum value, it can indicate that the equipment failure of the production line has extended to the middle and later stages.

4 Margin factor

$$L = \frac{X_{rms}}{X_r} \tag{6}$$

where X_r represents the square root amplitude.

The margin factor reflects a parameter index of the impact degree of the production line equipment, which can reflect the abrasion and surface damage faults of the production line equipment.

5 Deflection index

$$S_r = \frac{\sum_{i=1}^{N} |x_i|}{X_{rms}} \tag{7}$$

where x_i represents the vibration signal frequency.

Deflection index is a non-dimensional parameter, which reflects another index of the impact degree of the vibration signal of the production line equipment. It is not sensitive to the changes in speed and load, but is more sensitive to wear and surface damage failures of the production line equipment. Compared with kurtosis index, skewness has the characteristics of small value variation range.

6 Waveform factor

The waveform factor is used to judge the parameter indicators of the fault type of the production line equipment:

$$K = \frac{X_{rms}}{X_p} \tag{8}$$

where X_p represents the absolute average value.

Since the above indicators include dimensionless parameters and dimensional parameters, it is necessary to conduct normalisation processing. Set the original data as X, the minimum value of data as X_{min}, and the maximum value as X_{max}, then:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{9}$$

2.4 Real-time monitoring model of production line equipment condition based on multivariate state estimation

Multivariate state estimation technology (MSET) is a nonlinear modelling method, which has achieved good results in the application of various industrial equipment condition monitoring and other fields. As a non-parametric modelling method, MSET uses the similarity between the new observation state and the historical health state to judge the state of the production line equipment. It has high reliability and real-time, and has a certain impact on the condition monitoring of production line equipment.

First of all, the Hadoop data acquisition system in the production line equipment is used to derive the health history data. Different working conditions are distinguished by output power, season, time period and other factors. The typical data under different working conditions are completely selected to construct the history memory matrix. The history memory matrix is a typical representative of all healthy operating conditions in the production line equipment. The accuracy of the model depends entirely on the scientific and integrity of the history memory matrix. Then, the historical memory matrix is used to train the multivariate state estimation model. According to the state values of the current production line equipment, the predictive values of the current production line equipment state operation state can be obtained.

Therefore, according to the above extracted time-domain parameters of production line equipment status, this paper constructs a historical memory matrix, establishes a multivariate state estimation model, analyses the difference between observation vectors and prediction vectors under the framework of the distributed processing cloud computing platform MapReduce, and realises real-time monitoring of production line equipment status.

The construction of historical memory matrix D is the most critical step in establishing the multivariate state estimation model of production line equipment:

$$X = [x_1, x_2, \ldots, x_n] \tag{10}$$

The process history memory matrix is composed of multiple observations, and the number of observations is the dimension of the memory matrix. Suppose that n failures are detected in the equipment of a production line. The amount of historical health data exported by the data collection system is m. Then the observation vector of the production line equipment at the current time in the dataset:

$$X(t_m) = [x_1(t_1), x_2(t_2), \ldots, x_n(t_m)] \tag{11}$$

where $x_n(t_m)$ is the measured value of the relevant sensor at time t_m, Formula (10) is the observed value at a certain sampling time of the data, and all observation vectors in Formula (11) are represented by the historical memory matrix D:

$$D_{n*m} = [X(t_1), X(t_2), \ldots, X(t_m)] \tag{12}$$

The process memory matrix is used to establish a multivariate state model. For the real-time data collected at any time or the manually input observation vector X_{obs}, the Euclidean distance is used to calculate the similarity between each state vector in the process memory matrix and the input observation vector. Finally, the weight of each state vector in the process memory matrix is determined through the similarity. The prediction vector is the product of the weight vector and the selected process memory matrix, the weighted average calculates the prediction value X_{est} at this time:

$$X_{est} = D * W \tag{13}$$

where W represents the weight vector, which is calculated by the least square method, and its expression is:

$$W = (D^T * D) * (D^T * X_{obs}) \tag{14}$$

It can be seen from the above formula that W can be determined by the residual vector ε between X_{est} and X_{obs}, and its expression is:

$$\varepsilon = X_{est} - X_{obs} \tag{15}$$

The larger the residuals of the two, the abnormal fluctuations of the relevant parameters of the production line equipment will occur when the production line equipment is running in a sub-health or even fault state. The smaller the residuals, the healthier the production line equipment is running. Therefore, the status of the production line equipment can be judged by analysing the residual between the actual value and the predicted value. The residual reflects the status change information of the production line equipment to a certain extent.

3 Simulation experiment analysis

In order to verify the effectiveness of the real-time monitoring method for the status of production line equipment based on cloud computing and internet of things technology proposed in this paper, the production line equipment in a factory workshop is selected as the test object, and the methods in Li et al. (2019) and Li et al. (2020) are used as the comparison methods to conduct the test together with the methods in this paper. This test was run in the Win10 system equipped with i7 processor. The MATLAB 2016a simulation platform was used for testing. The real-time monitoring accuracy and monitoring time of the production line equipment status were selected as the experimental indicators. The higher the monitoring accuracy and the shorter the monitoring time, the better the monitoring effect of the monitoring method and the higher the monitoring efficiency.

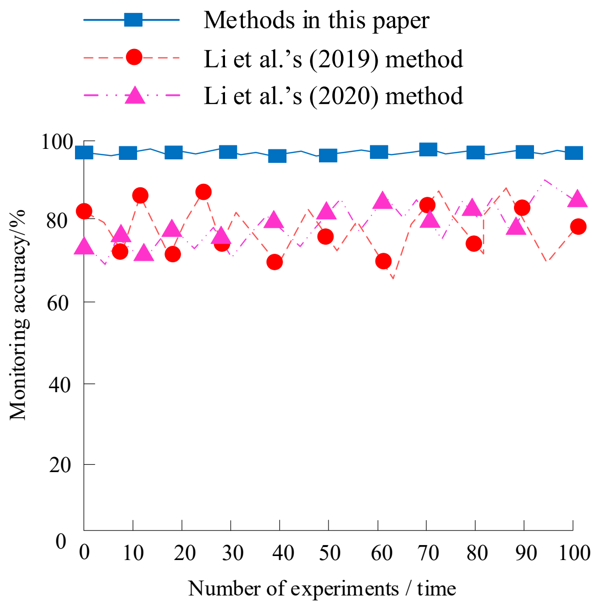
The production line equipment account information table is the basic account information of the production line equipment, as shown in Table 1.

Table 1 Equipment account information of production line

Serial no.	*Field name*	*Field description*	*Field type*	*Length*
1	id		varchar	64
2	sbmc	Equipment name	varchar	30
3	sbbh	Equipment no.	varchar	30
4	gghx	Specification and model	varchar	30
5	sccj	Manufacturer	varchar	30
6	scrq	Date of manufacture		
7	azrq	Install date		
8	azwz	Installation position	varchar	20
9	xjzq	Patrol inspection cycle (days)		10,0
10	sysm	Service life (years)		10,0
11	sbzt	Equipment status	varchar	20
12	bqmh	Tag no.	varchar	64
13	xjrq	Last patrol inspection date	varchar	
14	txbs	Reminder ID	varchar	10
15	gzts	Fault reminder identification	varchar	10
16	bftxbs	Scrap identification	varchar	10

The real-time monitoring method of production line equipment status based on cloud computing and Internet of Things technology, the Li et al.'s (2019) method and the Li et al.'s (2020) method proposed in this paper are used to compare and analyse the real-time monitoring accuracy of production line equipment status. The comparison results are shown in Figure 1.

Figure 1 Comparison results of real-time monitoring accuracy of production line equipment status by three methods (see online version for colours)



According to Figure 1, the accuracy of real-time monitoring of production line equipment using the Li et al.'s (2019) method is between 65% and 87%, and the highest accuracy is 87%; the accuracy of real-time monitoring of production line equipment using the Li et al.'s (2020) method is between 70% and 85%, and the highest accuracy is 85%; However, the accuracy of the real-time monitoring of the production line equipment status has always been more than 95%, the accuracy is relatively stable, the highest to 98%, much higher than the two methods, indicating that the application of this method is the highest accuracy of real-time monitoring of the production line equipment status, the best monitoring effect. This is due to the proposed method of using the historical memory matrix to train the multivariate state estimation model, which can improve the accuracy of real-time monitoring of production line equipment status and obtain high-precision production line equipment status data.

The method in this paper, the method in Li et al. (2019) and the method in Li et al. (2020) are used to compare and analyse the time used for real-time monitoring of equipment status in the production line. The comparison results are shown in Table 2.

According to Table 2, the real-time monitoring time of production line equipment status using the Li et al.'s (2019) method is 14.21~16.99 s; The real-time monitoring time of the equipment status of the production line using the Li et al.'s (2020) method is 22.11~26.81 s; The application of this method to the real-time monitoring of the equipment status of the production line is always kept within 7.25 s, which is the shortest time, indicating that this method has the highest efficiency in the real-time monitoring of the equipment status of the production line. This is due to the method proposed in this paper in state monitoring, in order to avoid the detection results change with the outside working conditions, the time domain parameters as equipment state monitoring indicators, using effective value parameters of production line equipment failure, can ensure feasibility at the same time, reduce the detection time, improve the monitoring efficiency.

Table 2 Comparison results of real-time monitoring time of production line equipment status by three methods (s)

Number of experiments (time)	*Methods in this paper*	*Li et al.'s (2019) method*	*Li et al.'s (2020) method*
10	5.21	14.21	22.11
20	5.26	14.32	23.85
30	5.63	14.80	24.12
40	5.98	15.85	24.95
50	6.12	15.99	25.42
60	6.85	16.42	25.84
70	7.25	16.99	26.81

It can be seen from the experimental test results that the real-time monitoring method of production line equipment status based on cloud computing and Internet of Things technology proposed in this paper can effectively improve the monitoring accuracy of the real-time monitoring of production line equipment status and reduce the monitoring time, indicating that the monitoring effect of the monitoring method is good and the monitoring efficiency is high.

4 Conclusions

Due to the traditional method takes a long time for the real-time monitoring of the production line equipment condition, and the monitoring accuracy is low, the actual monitoring effect is affected. In order to solve this problem, this paper studies the real-time monitoring method of the condition of the production line equipment together with cloud computing and Internet of Things technology. Through the Internet of things to establish awareness labels, obtain production line equipment status data, and according to the validity, peak, cliff coefficient parameters, the production line equipment state time domain parameters, on the basis of extraction results, build historical memory matrix, establish multivariate state estimation model, in the design of distributed processing cloud computing platform MapReduce framework, production line equipment state real-time monitoring. Through the simulation experiment, the accuracy of production line equipment status up to 98%, the monitoring time in 7.25 s, the real-time monitoring of the production line equipment condition, which can effectively improve the monitoring accuracy, reduce the monitoring time, has good practical application performance, can ensure the stable operation of the production line equipment, and improve the safety and stability of the production process.

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