Fault analysis of industrial robots based on self-organised critical theory

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Abstract: Industrial robots, as a structurally sophisticated mechatronics system, have a high cost of routine maintenance and repair. Repairs after fault require the corresponding manpower and material resources, and have hysteresis. If the fault can be predicted in a timely and accurate manner, the maintenance process can be carried out in advance, and the hidden dangers can be eliminated to fundamentally solve the fault problem. Based on the self-organised critical theory (SOC theory), this article draws lessons from its self-organisation evolution model and uses the self-organised criticality of industrial robot fault to establish an autoregressive moving average model (ARMA model) for industrial robots. According to the analysis of residual value and the explanation for the faults of industrial robots, find ways and means to prevent and reduce faults.

1 Introduction

With the continuous increase of raw materials, labour costs, and customer demand for products, industrial production has increasingly emphasised automation. As a direct executor, industrial robots play a decisive role in the overall automation of industrial manufacturing. Due to the increasing degree of integration and complexity of industrial robot systems, the fault of individual robots components often causes chain reaction, resulting in the failure of the task process or even the entire system cannot run and even paralysed. Moreover, the maintainability of the industrial robot system is not high, and the maintenance and knowledge accumulation based on experience alone cannot keep up with the increase in the complexity of the industrial robots system. Luh et al. used artificial neural networks to generate faults and filter them, fault alarm concentration, and artificial immune rules to implement fault diagnosis for robot systems [1]. Michal Zajac proposed a particle filter-based method that combines negative likelihood tests to solve fault detection tasks [2]. Ikbal Eski et al. used two types of neural network prediction models here to analyse the robot joints noise and vibration. The results show that the model of RNN type can be used to predict the vibration of industrial robots [3]. There are many related researches on robot faults, but still have some problems such as how to explain the causes of faults and how to effectively achieve fault diagnosis, prediction, and other issues.

Therefore, this paper draws lessons from the self-organised critical theory and self-organisation evolution model, discusses the feasibility of explaining the faults related to industrial robots by self-organised critical theory, analyses the characteristics and connections of industrial robots fault from internal, and then finds an effective way to ensure the normal working efficiency of the industrial robots.

2 Self-organised criticality of faults in industrial robots

SOC theory is an important branch of complexity science [4, 5]. It can use a simple power-law distribution to link seemingly unrelated phenomena and it also can explain the physical mechanism of these phenomena. The so-called ‘self-organisation’ means that the formation of the state is mainly caused by the interaction between the organisations within the system. The so-called ‘critical state’ means that the system is in a special sensitive state, and tiny local changes can be continuously amplified and extended to the entire system. The self-organised critical theory can be clearly and vividly elaborated on the basic principles using the ‘sand pile model’ [6–8].

The fault process of industrial robots is similar to that of ‘sand collapse accident’, and its fault performance will naturally develop to the self-organised critical state. When the system is in a critical state, there are more interactions between the components inside the system, even a small interference event can cause a series of chain reaction in the system and eventually lead to the collapse of the system. Then, using the self-organised critical theory to explain the inherent mechanism of industrial robots fault from the overall behaviour will find a new perspective for us to solve the problem of fault.

3 Judgment basis for self-organised criticality of faults in industrial robots

With the continuous evolution of the system, the industrial robots fault system that shows a self-organised criticality phenomenon will produce a series of ‘accidents’ of different sizes. The statistical law of the quantities related to these accidents is presented as a power-law relation.

\[ N(S) = S^{-\tau} \]  

(1)

In (1), \( N(S) \) is the number of occurrences of a fault event occurring on the scale \( S \), and \( S \) is the component of the robot involved in the fault.

If both sides of the equation take the logarithm, the equation is changed to

\[ \log N(S) = - \tau \log S \]  

(2)

Equation (2) indicates that when the power-law distribution occurs, \( \log N(S) \) and \( \log S \) approximate a straight line in double logarithmic coordinates.

Therefore, using double logarithmic coordinate to judge the scale and frequency of the accidents studied, if the law relation is approximately linear, it indicates that the researched industrial robot fault has a power law distribution, which proves that the system has self-organised criticality.

4 Validation of self-organised criticality data for industrial robots fault

Components involved in robots fault and partial data of fault frequency shown in Table 1, and the result is shown in Fig. 1.
It can be seen from Fig. 1 that the relation between the fault components and the number of faults in the double logarithmic coordinates is approximately linear, and it can be considered that the faults of industrial robots have self-organised criticality.

5 Fault analysis of industrial robots

The fault of an industrial robot is usually starts from one component of the system. However, due to improper or untimely treatment measures and the comprehensive effect of other reasons, the fault of this component may cause a series of associated components fault, resulting in failure of the task process. The failure of the task process of industrial robots is the non-linear process [9–11] of the interaction of various components in the industrial robot system. Therefore, by the self-organised critical theory explained the whole process of the failure, eliminated hidden danger timely can prepare for the prevention and reduction of robot faults.

This paper, by WKD5938/WKD5937 dynamic signal test and analysis system collected and analysed the vibration signal [12, 13] of IRB120 M2004 model six-axis industrial robot. The equipment is shown in Fig. 2 below:

Take 1-axis of industrial robot as an example to briefly explain the analysis process:

(i) Collect vibration signals of the stationary and moving of industrial robot 1-axis under the normal condition of different position, intercept signal within 0–20 s and filtering, oscillograph are shown in Figs. 3 and 4 below.

(ii) By statistical methods obtained the threshold [14, 15] range of vibration signals in normal state of industrial robots. That is to say, the industrial robots are in normal and fault of critical state, then the small disturbance will be amplified and extended to the whole system, and that we said ‘self-organised critical state’.

(iii) Select the vibration signal of 1-axis in the fault state and filter it, as shown in Fig. 5 below. Eventually, getting the threshold range of vibration signal in the fault state of industrial robot.

| Fault components | 2 | 3 | 5 | 7 | 8 | 11 | 12 | 15 | 16 | 18 |
|-------------------|---|---|---|---|---|----|----|----|----|----|
| frequency         | 49| 34| 20| 14| 12| 10 | 8  | 7  | 6  | 6  |

Fig. 1 Power-law relation of the fault in the double logarithmic coordinate

Fig. 2 Experimental equipment

Fig. 3 Vibration signal of industrial robot 1-axis in static state

Fig. 4 Vibration signal of industrial robot 1-axis in motion state

Table 1 Partial data of the fault
(iv) Further analyse vibration signals of 1-axis under normal and fault conditions, and obtain radial displacement under normal and fault conditions, as shown in Figs. 6 and 7 below.

(v) By the pose transformation [16, 17] matrix obtaining the 6-axis matrix relative to the base; Continue to collect and analyse vibration signals and displacement changes of other remaining axes; Substituting relevant data into the matrix to obtained the final displacement change. Comparing this value with the precision value of the industrial robot to judge whether the robot has exceeded the precision range. If it is greater than the standard value, the fault of industrial robot can be determined preliminarily.

6 Summary

Previously, most of the researches on industrial robots fault are from the environmental factors, equipment defects, human operation errors, improper protection and other external aspects to analyse the causes and put forward corresponding measures. Now, have the self-organised criticality of industrial robots fault allows us to analyse and explain the causes of fault in industrial robots from the internal mechanism of fault occurrence, providing an effective tool for us to find the overall behaviours characteristics of industrial robots fault. Based on the research here, the main work in the next step is continue to collection and analysis data of industrial robots other axes, theory combined with practice, using the experiment verify the feasibility and accuracy of the fault prediction methods for industrial robots, so as to further perfect the theory basis.

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8 References

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