Failure Prediction of Circular Sawing Machines Based on Condition Evaluation and ARIMA Model

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Abstract. As the starting point of cutting, sawing is an important link in the production process. Circular saws have high precision and high sawing efficiency. Once a failure occurs, it will bring considerable losses. This paper presents a fault prediction method for circular saw based on state evaluation and ARIMA model. According to the mechanism of failure analysis, considering different parameter indicators for different failures, we first find out the components of the equipment involved in these parameters, and adopt the entropy weight method and trapezoid-triangular membership function model to determine the health status. The key mechanism of the components in poor condition is predicted using the ARIMA model, and the weighted method is used to predict the failure time.

1. Introduction

At present, the sawing industry in China has a good development situation, and it is gradually developing towards industrialization, scale, and intelligence. Circular sawing machines have high operating accuracy and efficiency. However, once a failure occurs, it will bring considerable losses.

 Scholars at home and abroad have done a lot of theory and research on the fault prediction model of CNC machines. The methods of fault prediction include prediction based on physical model, prediction based on statistical experience, and prediction based on data[1]. In literature[2], a method of covariance matrix matching evolutionary strategy is proposed to optimize the parameters of support vector machines, which can achieve more accurate short-term prediction than the previous methods using vector machines, and has been verified. In literature [3], a comprehensive architecture based on hidden Markov models is constructed, which is mainly suitable for trend estimation of changes in equipment health status. In literature [4], a new method is proposed, using five improved online support vector machines to achieve adaptive online state monitoring and fault prediction. In literature [5], a method for assessing the health status of transformers is proposed. Based on the big data cluster, the device status is divided into three categories: health, latent failure, and failure. The time series similarity analysis is used to predict that the equipment in the latent failure status needs to be converted into a fault status Time. In literature [6], a method based on ARMA model was proposed to predict the vibration data of rolling bearings. In literature [7], aiming at the difference in the characteristic frequencies of distributed faults and local faults, the ARMA prediction model in the time series analysis is constructed to predict the frequency spectrum of the fixed-axis gear vibration signal, and the gear fault is estimated by combining the obtained predicted value and the current value. This paper proposes a fault prediction method for circular saws based on state evaluation and ARIMA model.
2. Overview

2.1. Analysis of main failures of circular saw

According to the analysis, the faults of the circular saw machine are mainly divided into unstable operation or sudden stop of work; abnormal noises and large vibrations; poor flatness of cuts of processed products; and low processing efficiency.

1) Operation is unstable, or work stops suddenly

The main reason for this failure may be that the saw blade runs erratically due to too much spindle bearing clearance or bearing damage; the fasteners are loose; the current is too large or the voltage is unstable during cutting; the saw blade's fixing device is damaged or the supported ring deformation makes the saw blade have a large radial run out; the cutting material is not placed steadily; the single feed amount is out of range or the lateral feed speed is too fast.

2) There are abnormal noises and large vibrations

The cause of this failure may be the mismatch of the gaps between the transmission gears; the lubrication of the transmission link is not good; the blank is not clamped or there are iron filings on the saw teeth or the saw teeth are dull or broken; the motor power is unstable; the equipment bearing housing has an abrasion.

3) Poor flatness of cuts of processed products

The cause of this failure may be the tooth shape and the number of teeth is incorrect, or the saw teeth are not sharp enough; the feeding rack is unstable during cutting, resulting in inaccurate positioning or the machine assembly is not calibrated.

4) Low processing efficiency

Low processing efficiency is a holistic and systematic problem, which involves more problems. In addition to checking the cause of failure, pay attention to processing technology, saw blades, and processing materials.

Analysis of the above faults found that the main components found to be faulty are the main motor, transmission, circular saw power head, and feeding system, and the performance indicators need to be monitored separately, as shown in Figure 1 (These performance indicators are identified by numbers in the following diagrams).

The main motor is directly connected to the transmission mechanism to ensure stable transmission and efficient operation of the gearbox. If the motor fails, it will cause unstable transmission, gear operation failure, and incorrect sawing. The symptoms of general motor failure may appear as excessive current and voltage and high temperature, which may cause the motor coil to melt and destroy the motor. Therefore, the current, voltage, temperature and operating resistance of the main motor need to be monitored.

The transmission can drive the machine to run, including the automatic conveyance of blanks, the sawtooth feed and retract operation. The general reasons for the failure of the transmission include too large radial clearance of the bearing, too large gear mesh clearance. It is necessary to test the radial clearance of the bearing, the bearing pad pressing force, and the gear clearance.

The circular saw blade part is used to cut the blank. If the saw blade is bent or worn, the blank cutting will be uneven, and it is easy to increase the pressure on the moving blade. Here, we mainly measure the perpendicularity of the circular saw's extrusion direction to the center line of the main shaft, the bending degree of the circular saw and the radial vibration of the circular saw.

The feeding system uses AC servo to control high-precision ball screws, and the blank is transported to the feeding vise through the operation of the feed cylinder, which realizes automatic feeding and greatly reduces the participation of workers. The precise position of the transport is related to the quality of the product. So it is required to monitor the voltage and current of the AC servo feed motor, the perpendicularity of the blank cut facing the common axis.
2.2. Method Analysis

The health status of the device can be evaluated according to the use of the device and the efficiency of the cutting. In Figure 1, the relevant operating parameter indicators of the device have been listed, and the device status can be judged according to these indicators to establish a relevant evaluation model. Proceed as follows:

1). Standardize the parameters of the index. Different types of parameters make it difficult to conduct unified evaluation, so before this, the data must be standardized. In literature[8], the Banbanling and Shengbanling models are used, modify that as follows:

\[
x' = \begin{cases} 
\frac{x-x_l}{x_m-x_l}, & x_l \leq x < x_m \\
\frac{x-x_m}{x_u-x_m}, & x_m \leq x \leq x_u \\
0, & \text{other}
\end{cases}
\]  

(Among them, \(x_m\), \(x_u\), \(x_l\) represent the standard value, maximum value, and minimum value of the evaluation index. If there is no minimum value, record the value less than the standard value as 1. If there is no maximum value, record the value greater than the standard value as 1.)

2). Entropy weight method is applied to the index of evaluating the same component.

3). Establish membership model based on health level.

4). Bring the measured value into the membership model to get the health status of the component.

After the above 4 steps, the health status of the component has been evaluated. If only the health status is known, it can’t help to understand the future situation of the device, so it is proposed to predict the failure of the component whose healthy status is degraded. ARIMA called the differential moving average autoregressive model is a time series pre-analysis method, which is suitable for a time series in which an observation value is related to previous observation values and disturbances. The steps for evaluating using the ARIMA model are as follows:

1). Perform stationarity test, and perform differential or logarithmic operations on non-stationary sequences.

2). Find the value of the autocorrelation function and the partial autocorrelation function of the processed data to determine the order of the ARIMA model.

3). Perform parameter estimation, establish a model, and perform a white noise test on the residual sequence.

4). Make predictions through the established model.

2.3. Introduction to Related Theories

2.3.1. Entropy method. Suppose there are k indicators \(X_1, X_2, \ldots, X_k\), among them \(X_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\}\), assuming that the values normalized for each indicator are \(Y_1, Y_2, \ldots, Y_k\), then \(Y_{ij}\) represents the value of the j-th index of the i-th group of data after normalization.

The calculation formula of information entropy is
\[ E_j = \frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \]  
(Among them, \( p_{ij} = \frac{y_{ij}}{\sum_{i=0}^{n} y_{ij}} \). If there is \( p_{ij} = 0 \), then define \( \lim_{p_{ij} \to 0} p_{ij} \ln p_{ij} = 0 \).

Determine the weight coefficient of each indicator \( W_j : W_j = \frac{1 - E_j}{K \cdot \sum E_j} \) (3)

2.3.2. Establishing the evaluation membership function. This article divides the health status into 4 levels, namely health, general, degradation, and failure, and uses the normalized value to classify the membership function. The paper uses a trapezoid-triangular membership function model[9] to determine the membership of each evaluation index, see Figure 2.

![Figure 2. Trapezoid-triangle membership function model](image)

2.3.3. Comprehensive Evaluation. After normalizing the value of each evaluation index, substituting the membership function of each evaluation level to calculate the membership value, and then using a weighted method to obtain the membership value of each part as a whole belonging to each state level, and taking the highest membership level as the level Evaluation result. It is expressed as follows: Assume \( \bar{X}_{ij} \) represents the monitoring value of the \( i \)-th index for the \( j \)-th index, \( \beta_{js}^{(\ast)} \) indicates that the \( j \)-th index belongs to the membership function of the \( s \)-level evaluation index, \( W_j \) represents the weight coefficient occupied by the \( j \)-th index evaluation, and the detection value of the \( i \)-th group belongs to the \( s \)-level membership \( \alpha_i^s \) for:

\[ \alpha_i^s = \sum_{j=0}^{K_s} \beta_{js}^2 \left( \bar{X}_{ij} \right) \cdot W_j \]  

(4)

In the end, the overall evaluation level membership matrix of this part is:

\[ \alpha_i = [\alpha_i^1, \alpha_i^2, \alpha_i^3, \alpha_i^4] \]  

(5)

Assume

\[ \max_{1 \leq i \leq 4} \{ \alpha_i^s \} = \alpha_i^s^\ast \]  

(6)

The rating of this part is called \( s^\ast \) level.

2.3.4. Overview of the ARIMA model. The ARIMA (p, d, q) model is developed on the basis of the ARMA (p, q) model. The ARIMA (p, d, q) model is developed on the basis of the ARMA (p, q) model, and it can only deal with stationary time series. Non-stationary time series can be transformed into stationary time series through differential operations. The general of the ARMA (p, q) model can be expressed as Equation (7).

\[ Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \mu + \theta_1 \mu_{t-1} + \cdots + \theta_q \mu_{t-q} \]  

(7)

Where: \( p \) is the autoregressive order, \( \{\varphi_1, \varphi_2, \ldots, \varphi_p\} \) is called the autoregressive coefficient; \( q \) is the moving average order, \( \{\theta_1, \theta_2, \ldots, \theta_q\} \) is called the moving average coefficient; \( \mu_t \) is a series of white noise obeying the normal distribution; \( d \) is the number of differences when the time series reaches stationary.

2.3.5. Basic steps of ARIMA model establishment. The ARIMA model is suitable for stationary non-white noise sequences, so firstly perform a stationarity test, perform a difference or logarithmic operation on the non-stationary sequence, and obtain the autocorrelation function value and partial
autocorrelation function of the processed data to determine the Order, perform parameter estimation, establish a model, and perform a white noise test on the residual sequence. The model after the test is used to predict future changes.

According to the sample’s autocorrelation coefficient and the number of partial autocorrelation coefficient, it can determine the type of model. The construction of the model involves the order estimation and parameter estimation. The more parameters, the wider the model’s optional range, and the more accurate the model, but the more parameters increase the difficulty of estimation [10]. Common methods for ordering models include the FPE criterion, AIC criterion, and BIC criterion.

This paper uses the BIC criterion[11], which decision function is shown in equation (8):

$$F_{BIC}(p, q) = \ln \hat{\sigma}_k^2 + \frac{(p+q)\ln(n)}{n}$$  \hspace{1cm} (8)

After determining the model type and order, it needs to estimate the parameters in the model. The most commonly used methods for model parameter estimation include the least squares method, maximum likelihood estimation, moment estimation, etc. This paper uses the autoregressive approximation method, and its steps are as follows:

① According data sample \([Y_t, Y_{t-1}, \ldots, Y_n]\) to build an autoregressive (AR) model \(Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \mu_t\). Using the BIC order method to get the estimated order \(p\) and the autoregressive coefficients \(\hat{\varphi} = (\hat{\phi}_1, \hat{\phi}_2, \ldots, \hat{\phi}_p)\).

② Calculate the residual by equation (9)

$$\hat{\mu}_t = Y_t - (\hat{\phi}_1 Y_{t-1} + \hat{\phi}_2 Y_{t-2} + \cdots + \hat{\phi}_p Y_{t-p})$$  \hspace{1cm} (9)

get approximate ARMA \((p, q)\) model

\(Y_t = \hat{\phi}_1 Y_{t-1} + \hat{\phi}_2 Y_{t-2} + \cdots + \hat{\phi}_p Y_{t-p} + \hat{\mu}_t - \theta_1 \hat{\mu}_{t-1} - \cdots - \theta_q \hat{\mu}_{t-q}\)

③ Make \(Q(\varphi, \theta) = \sum_{t=p+q+1}^{n} (Y_t - \sum_{j=1}^{p} \phi_j Y_{t-j} - \sum_{j=1}^{q} \theta_j \hat{\mu}_{t-j})^2\), reach a minimum, \(\hat{\varphi}, \hat{\theta}\) is the least squares estimate of \(\varphi, \theta\). Definition:

\[
X = \begin{bmatrix} Y_{p+q+1} \\ Y_{p+q+2} \\ \vdots \\ Y_n \end{bmatrix}, \quad \hat{\varphi} = \begin{bmatrix} \hat{\phi}_{p+q} & \hat{\phi}_{p+q-1} & \cdots & \hat{\phi}_{p+1} \\ \hat{\phi}_{p+q} & \hat{\phi}_{p+q-1} & \cdots & \hat{\phi}_{p+1} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\phi}_{n-1} & \hat{\phi}_{n-2} & \cdots & \hat{\phi}_{n-q} \end{bmatrix} \quad \hat{\theta} = \begin{bmatrix} \hat{\theta}_{p+q} & \hat{\theta}_{p+q-1} & \cdots & \hat{\theta}_{p+1} \\ \hat{\theta}_{p+q} & \hat{\theta}_{p+q-1} & \cdots & \hat{\theta}_{p+1} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\theta}_{n-1} & \hat{\theta}_{n-2} & \cdots & \hat{\theta}_{n-q} \end{bmatrix}
\]

We get \(Q(\varphi, \theta) = |X - \varphi \cdot \hat{\theta}|^2 = |X - (Y, \hat{\varphi}, \hat{\theta})|^2\).

The solvable least squares estimate is

\[
(\hat{\varphi}, \hat{\theta}) = \left(\frac{Y^T}{U^T} \begin{bmatrix} \hat{Y} \end{bmatrix} \right)^{-1} \left(\frac{Y^T}{U^T} \begin{bmatrix} \hat{Y} \end{bmatrix} \right)^{-1} = \begin{bmatrix} \hat{Y} \end{bmatrix} \begin{bmatrix} \hat{Y}^T \hat{Y} & \hat{Y}^T \hat{U} & \hat{U}^T \hat{Y} \\ \hat{U}^T \hat{Y} & \hat{U}^T \hat{U} & \hat{U}^T \hat{U} \end{bmatrix}^{-1}
\]

The estimated residual variance is given by equation (10):

$$\hat{\sigma}^2 = \frac{1}{n-p-q} Q(\hat{\varphi}, \hat{\theta})$$  \hspace{1cm} (10)

3. Circular saw machine example analysis

This paper records 1000 groups of data in a certain period of time under normal operating conditions for weight calculation.

3.1. Performing a status evaluation

Table 1. Specification value of performance indexes

| Main motor | Transmission | Circular saw blade | Feeding system |
|------------|-------------|--------------------|---------------|
| A          | A2          | A3                 | A4            | B1           | B2           | B3           | C1           | C2           | C3           | D1           | D2           | D3           |
| Cap        | 33.0        | 402                | 60            | --           | 0.15         | 0.04         | 0.22         | 0.03         | 0.2          | 0.15         | 23.6         | 395          | 0.12         |
| Standard   | 28.9        | 380                | 40.5          | 2.6          | 0.078        | 0.029        | 0.12         | 0.015        | 0.12         | 0.08         | 20.5         | 375          | 0.07         |
| Lower      | 24.5        | 358                | 0.5           | 0.02         | 0.02         | --           | --           | --           | 0.025        | 18.9         | 350          | --           |

(Note: Part of the data in Table 2 is derived from industry indicators, and some of the data is obtained by analyzing and processing the obtained monitoring data. For example, the industry regulations for the insulation resistance value cannot be less than 0.5M ohm, and the standard value is obtained by averaging monitoring data.)
3.1.1. Calculate weight. Substitute data into equation (1) for Standardization, substitute data into equation (2) and (3) to calculate weight. The weight of each performance index is shown in Table 2.

Table 2. Weights of each evaluation index

| Component          | Main Motor | Transmission |
|--------------------|------------|--------------|
| A1                 | 0.2633     | 0.4406       |
| A2                 | 0.1853     | 0.1108       |
| A3                 | 0.3112     | 0.3243       |
| A4                 | 0.3645     |              |

In the results in Table 3, it is found that the transmission is in a degraded state. It is necessary to verify the prediction model. Record the 100 sets of data as follows. Table 3 shows the membership function of evaluation index.

Table 3. Membership function of evaluation index

| Status level | Membership function | Status level | Membership function |
|--------------|---------------------|--------------|---------------------|
| Health-1     | \( \beta_1(x) = \begin{cases} 1 & x \geq 0.8 \\ 5x - 3 & 0.6 < x < 0.8 \\ 0 & x \leq 0.6 \end{cases} \) Degradation-3 | Health-4 | \( \beta_3(x) = \begin{cases} 3 - 5x & 0.4 \leq x < 0.6 \\ 5x - 1 & 0.2 \leq x < 0.4 \\ 0 & 0 \leq x \leq 0.2 \end{cases} \) |
| General-2    | \( \beta_2(x) = \begin{cases} 4 - 5x & 0.6 \leq x < 0.8 \\ 5x - 2 & 0.4 \leq x < 0.6 \\ 0 & 0 \leq 0.4 \end{cases} \) Failure-4 | General | \( \beta_4(x) = \begin{cases} 2 - 5x & 0.2 \leq x < 0.4 \\ 1 & x \leq 0.2 \\ 0 & x \geq 0.4 \end{cases} \) |

3.1.2. Perform a health assessment. The health status of the component is divided into four states: health, general, degraded, and fault. The membership function is established by referring to the trapezoid-triangular membership function model. Show in Table 3.

Table 3. Membership function of evaluation index

| Status level | Membership function | Status level | Membership function |
|--------------|---------------------|--------------|---------------------|
| Health       | General             | Degenerate   | Malfunction         |
| Main motor   | 0.4486              | 0.3290       | 0.1802              |
|              | 0.1182              | 0.3676       | 0                   |
|              | 0.2929              | 0.3205       | 0                   |
|              | 0.3530              | 0.2821       | 0                   |
|              | 0.5383              | 0.3604       | 0.0801              |
| Transmission | 0.0389              | 0.3088       | 0.3281              |
|              | 0.0365              | 0.5020       | 0.4681              |
|              | 0.3617              | 0.4697       | 0.1685              |
|              | 0.0883              | 0.3927       | 0.5183              |
|              | 0                   | 0.7859       | 0.2141              |
| Circular saw | 0.4642              | 0.5358       | 0                   |
| blade        | 0.8850              | 0.1150       | 0                   |
|              | 0.7321              | 0.2679       | 0                   |
|              | 0.3823              | 0.6177       | 0                   |
|              | 0.5408              | 0.4592       | 0                   |
| Feeding      | 0.7763              | 0.1678       | 0.0559              |
| system       | 0.4679              | 0.3624       | 0.1650              |
|              | 0.6476              | 0.3524       | 0                   |
|              | 0.6028              | 0.1735       | 0.2237              |
|              | 0.6916              | 0.1294       | 0.1790              |

3.2. Forecast

In the results in Table 4, it is found that the transmission is in a degraded state. It is necessary to monitor the relevant indicators of the component and use these data to predict the fault using the ARIMA model. The device performs 10,000 cuts and counts the monitoring values every 100 times, recording 100 groups. The first 90 sets of data are used to build the model, and the last 10 sets of data are used to fit and verify the prediction model. Record the 100 sets of data as follows:
The above data can be seen from the observation in Figure 3. The performance shows a downward trend and does not have stability. It is subjected to a differential processing, and the processed data is tested for stability and white noise. The graph of autocorrelation coefficient ACF and partial autocorrelation coefficient PACF are drawn, as shown in Figure 4. The optimal model is determined according to the BIC standard value.

The calculated value is used to predict the b1 index using ARIMA (2,1,3), the b2 index is predicted using ARIMA (2,1,4), and the b3 index is predicted using ARIMA (1,1,1). As shown in Figure 4, it can be seen that the predicted trend is consistent with the actual.
It can be seen from Figure 5 that $B_1, B_2, B_3$ exceed the normal operating range at 89, 16, 32. And use the entropy weight to calculate the number of times the transmission will fail $n$:

$$n = 100 \times \sum_{i=1}^{3} A_i w_i = 100 \times (89 \times 0.3112 + 16 \times 0.3243 + 32 \times 0.3645) \approx 4400$$ (12)

Therefore, after 4400 times of this equipment, maintenance and overhaul of the transmission must be performed, and parts replaced if necessary.

4. Conclusion
The predecessor has done a lot of research on the aspect of fault prediction. The method proposed in this article is based on multiple evaluation indicators and experimental verification. It has certain reference value. What can be further improved later are:
1) When performing a comprehensive state evaluation, just average the measured data nearby and bring it into equation (1-4). There is a certain error and it is accidental.
2) The ARIMA model can be further optimized. After obtaining the passed model, multiple sets of known data can be used to introduce neural networks to further adjust parameters to optimize the model and make the prediction more accurate.

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