Stress Loading Analysis for Quayside Container Crane Draw Bar Based on VMD-Weibull Distribution

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Abstract. The load distribution characteristics of quayside container crane (QCC) draw bar system is of great significance for fatigue analysis, life assessment and reliability calculation of metal structures. In order to describe the load distribution characteristics accurately, a method for extracting the characteristic parameters based on the VMD-Weibull distribution was proposed. Firstly, use the Wiener filtering feature of VMD to perform filtering processing. Then use the cubic spline interpolation envelope method to reconstruct the data, and performs Weibull distribution modeling on the reconstructed data to extract the scale parameters and shape parameters. Compared with the maximum entropy probability density curve, the stress loading is consistent with the Weibull distribution. At last, evaluate the draw bar and predict the development trend of the draw bar performance.

1. Introduction
The quayside container crane (QCC) is a kind of intermittent operation machinery, which has the characteristics of short, repetitive, and periodic cycles [1]. The load distribution characteristics of the QCC draw bar system are of great engineering significance to the metal structure fatigue analysis, life assessment and reliability calculation. The lifting load of the QCC metal structure is relatively random, and the dynamic characteristics are also complex and non-linear. It is the most critical component that determines the crane's safety and dynamic performance [2]. The front girder of the QCC is mainly a member that bears moving loads, and the form of double draw bars is mostly used to improve its bearing capacity and reduce its weight. The QCC metal structure is mainly composed of a bridge frame, a gate frame and a draw bar system. The QCC draw bar system includes front draw bar and rear draw bar. The front draw bar used to support the front beam is articulated and foldable, which can adapt to the pitch of the front beam. The rear draw bar is fixed to balance the tension of the front and support rear beam. When the QCC is working, the draw bar system plays a supporting role. When the ship is docked, the front beam will be in a lifted condition. At this time, the draw bar system will be folded into the guide support along with the movement of the front beam, and it will be suspended and fixed on the trapezoidal frame by a safety hook [3]. In daily loading and unloading operations, when the load trolley pass through the front beam, the downward deflection of the front beam and the stress of the front draw bar will inevitably change. Therefore, the draw bar will bear a large alternating load during the work of the machine, which is prone to fatigue damage. And it is an very important fracture danger component (FCM component) [4].

Draw bar stress is not only an important parameter for the internal condition of the draw bar system, but also a core indicator for judging the safety status of the draw bar. At present, domestic and foreign researches on the QCC draw bar are mainly focused on the analysis of the stress of metal structural parts by using ANSYS simulation modeling to obtain the condition assessment and life prediction of structural parts. Yin Yinan and others proposed to predict the real-time stress of QCC using support
vector machine method, and established a real-time data prediction model of QCC stress based on SVR [5]. Li Jing and others proposed to use mathematical statistical analysis combined with the three-peak valley rain flow counting method to analyze the stress of the QCC, and obtained the distribution law of the load spectrum in line with the Weibull distribution to realize the compilation of the load spectrum [6]. Here the Weibull distribution model is used to evaluate the stress of the QCC draw bar, and the development trend of its performance is judged according to the evaluation result in order to make a reasonable response to it. At the same time, the maximum entropy probability density curve fitting of draw bar stress is compared and analyzed.

In summary, this paper studies the load distribution characteristics of the QCC draw bar, proposes a method for extracting characteristic distribution parameters based on Weibull distribution, and compares it with the maximum entropy probability density curve. First, the data is denoised, then the Weibull distribution is modeled on the denoised data, and its shape parameters and scale parameters are extracted. The data is solved for the maximum entropy probability density curve, and compared with the Weibull distribution curve, the tension of the draw bar is evaluated, and the development trend of the draw bar performance is predicted.

2. A Brief Description of the Relevant Techniques

2.1. Weibull Distribution

The probability density function of the Weibull distribution can be expressed as [7]:

\[
f(x) = \frac{\alpha}{\beta} \left( \frac{x - \gamma}{\beta} \right)^{\alpha-1} \exp\left\{-\left(\frac{x - \gamma}{\beta}\right)^\alpha\right\}
\]

(1)

Where \(\alpha\) is the shape parameter and \(\beta\) is the scale parameter and \(\gamma\) is the position parameter. The shape of the curve changes with the change of the shape parameter. The shape parameter determines the shape of the distribution density curve. The scale parameter \(\beta\) has no effect on the shape of the distribution. It can determine the value of the proportional constant include shrink or magnification by reducing or enlarging the abscissa.

According to the Weibull probability density function \(f(x)\), the distribution function of the variable can be solved as \(F(x_p)\), that is, the probability of \(x_i\) being less than a certain value \(x_p\) can be obtained as \(P(x_i < x_p)\). The Weibull distribution function of the variable can be obtained by integrating the following formula:

\[
F(x_p) = \int_0^{x_p} \frac{\alpha}{\beta} \left( \frac{x - \gamma}{\beta} \right)^{\alpha-1} \exp\left\{-\left(\frac{x - \gamma}{\beta}\right)^\alpha\right\} dx
\]

(2)

The integral represents the area enclosed by the curve between 0 and \(x_p\) and the abscissa, and is obtained by integration:

\[
F(x_p) = 1 - \exp\left\{-\left(\frac{x - \gamma}{\beta}\right)^\alpha\right\}
\]

(3)

The Weibull distribution function can be obtained by replacing \(x_p\) with any of the \(x\):

\[
F(x) = 1 - \exp\left\{-\left(\frac{x - \gamma}{\beta}\right)^\alpha\right\}
\]

(4)
2.2. Variational Mode Decomposition

Due to the complexity of the actual conditions of the QCC, the collected data components are also relatively complicated. The data of the other components are mixed in the load data of the draw bar. The Variational Mode Decomposition (VMD) method can effectively separate the components. This method assumes that the multi-component signal $f$ decomposes into a sum of AM-FM components, and the intrinsic mode function (IMF) is redefined as $u_k$ with the expression [8]:

$$ u_k(t) = A_k(t) \cos(\varphi_k(t)) $$

$$ \omega_k(t) = \varphi_k'(t) = d\varphi_k(t) / dt $$

where $A_k(t)$ is the instantaneous amplitude; $\varphi_k(t)$ is the instantaneous phase, and its derivative $\omega_k(t)$ is the instantaneous frequency; Both the envelope $A_k(t)$ and the instantaneous frequency $\omega_k(t)$ vary much slower than the phase $\varphi_k(t)$. The constraint variational model constructed by VMD is

$$ \min_{[u_k; \omega_k]} \left\{ \sum_t \left| \mathcal{F} \left[ \left( \sigma(t) + \frac{j}{\pi t} \right) u_k(t) \right] \exp(-j\omega_k(t)) \right|^2 \right\} $$

$$ s.t. \sum_k u_k(t) = f $$

where $\{u_k\} = \{u_1, \ldots, u_k\}$ are the mode components, $\{\omega_k\} = \{\omega_1, \ldots, \omega_k\}$ are their corresponding center frequencies, and $k$ is the number of decomposed IMFs, and $\sigma(t)$ is impulse function.

In order to solve the above constrained optimization problem, a quadratic penalty term and Lagrangian multiplier are introduced to convert it into an unconstrained problem as follows:

$$ L\{u_k; \omega_k, \lambda\} = \alpha \left\{ \sum_t \left| \mathcal{F} \left[ \left( \sigma(t) + \frac{j}{\pi t} \right) u_k(t) \right] \exp(-j\omega_k(t)) \right|^2 \right\} $$

$$ + \int \left( f(t) - \sum_k u_k(t) \right)^2 + \left( \lambda(t) \cdot f(t) - \sum u_k(t) \right) $$

where $\alpha$ is penalty parameter; $\lambda$ is Lagrangian multiplier.

Eq. (8) is solved by the direction alternating multiplier algorithm, so that $u_k$ and $\omega_k$ iteratively update, and finally the saddle point of Eq. (8) is the optimal solution. The components in the frequency domain are solved by Eq. (9), and the estimated center frequencies are updated by Eq. (10):

$$ \hat{u}_{k+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{k=1}^n \hat{u}_k(\omega) + \hat{\lambda}(\omega)/2}{1 + 2\alpha(\omega - \omega_k)^2} $$

$$ \omega_{k+1} = \frac{\int_{0}^{\infty} \omega |\hat{u}_k(\omega)|^2 d\omega}{\int_{0}^{\infty} |\hat{u}_k(\omega)|^2 d\omega} $$

2.3. Maximum Entropy Probability Density Curve

Assume that the information source delivers $n$ possible results $x = \{x_1, x_2, \ldots, x_n\}$ messages with probability $p = \{p_1, p_2, \ldots, p_n\}$, and the occurrence of each message sample is independent of each other. To determine the amount of information in a certain message sample, there are the following possible
values: \( \ln(1/p_i), \ln(1/p_j), \ldots, \ln(1/p_n) \). The amount of information requested should be a statistical average of these possible values [9]:

\[
H = -\sum_{i=1}^{n} p_i \ln(p_i) \tag{11}
\]

Among them, \( 0 \leq p_i \leq 1 \), \( \ln p_i < 0 \).

In order to find the \( p_i \) value when the system's information entropy value \( H \) is maximum, it is necessary to satisfy the constraint conditions:

\[
\sum_{i=1}^{n} p_i = 1 \tag{12}
\]

\[
\sum_{i=1}^{n} p_i g_j = E(g_j) = a_j \tag{13}
\]

Equation (12) is a normalization condition, and equation (13) is a moment constraint, where \( g_j (j = 1, 2, \ldots, m) \) is a statistical moment function of each order, and the highest order \( m \) is generally selected based on experience. \( E(g_j) \) represents the expected value of the statistical origin moments of each order actually observed, which is the known information we obtained from the sample data. Their expressions are as follows:

\[
g_j(x_i) = x_i^j \tag{14}
\]

\[
E(g_j(x)) = \sum_{i=1}^{n} p_i \cdot g_j(x_i) \tag{15}
\]

The Lagrange function can be made from the constraints (12), (13) and the objective function (11) as:

\[
L(p, u) = -\sum_{i=1}^{n} p_i \ln p_i + (\mu_0 + 1) \left( \sum_{i=1}^{n} p_i - 1 \right) + \sum_{j=1}^{m} \mu_j \left( \sum_{i=1}^{n} p_i g_j(x_i) - E(g_j(x)) \right) \tag{16}
\]

Where \( \mu_j (j = 1, 2, \ldots, m) \) is a Lagrangian multiplier, in fact \( (\mu_0 + 1) \) is a multiplier corresponding to \( \sum_{i=1}^{n} p_i = 1 \). To simplify the derivation here, write \( (\mu_0 + 1) \) instead of \( \mu_0 \). To find the value of \( p_i \), let \( \frac{\partial L}{\partial p_i} = 0 \) be obtained:

\[
-(\ln p_i + 1) + (\mu_0 + 1) + \sum_{j=1}^{m} \mu_j g_j(x_i) = 0 \tag{17}
\]

From Equation (17):

\[
p_i = \exp(\mu_0 + \mu_1 g_1(x_i) + \mu_2 g_2(x_i) + \cdots + \mu_m g_m(x_i)) \tag{18}
\]
3. Instance Analysis

3.1. Data Collection
The data collection of the draw bar structure uses the strain gauge electrical measurement method, using a resistance strain gauge as a sensitive element to measure the strain at a point on the component, and then determining the surface stress condition of the component based on the stress-strain relationship [10]. The resistance strain gauge senses the magnitude of the strain, converts it into a voltage, and then processes the electrical signal such as amplification and filtering to output a display signal according to the mechanical quantity. The data comes from QCC at an important container terminal. Real-time monitoring data of the QCC are collected through the independently developed network crane condition monitoring and evaluation system (NetCMAS). The characteristics of data processing of the NetCMAS system are processing signals while collecting.

3.2. Date Preprocessing
(1) Remove non-working condition. The data of a certain week is shown in Figure 1 (a)(b). According to the angle data, the non-working condition data when the beam is lifted is removed, and Figure 1 (c) is the data when the beam is laid flat condition.

(2) Detrending. The red circle shown in Figure 2 is the drift trend generated by the big car moves. This paper applies the VMD method, and the number of decomposition levels is set to 2. IMF1 shown in Figure 2 is the trend term. It can be seen from the decomposition effect diagram of VMD that the IMF1 component can better reflect the trend term of the data. The processed IMF2 component is reconstructed by the envelope method to obtain the tie rod load data.

![Figure 1. Data when lifting the beam in a week](image1)

![Figure 2. VMD detrending analysis](image2)

3.3. Model Comparison
The Weibull distribution fitting is performed on the collected data according to the above method, and one week of data is taken as a group of obtained Weibull distribution probability density curves as shown in Figure 3, and one week of data is taken as a group of obtained maximum entropy probability
density curves as shown in Figure 4. By modeling the Weibull distribution and fitting the maximum entropy probability density curve for the stress data of the QCC draw bar, it is found that the stress load of the QCC draw bar is relatively stable and follows the Weibull distribution law.

![Weibull probability density curve fitting](image1.png) ![Maximum entropy probability density curve fitting](image2.png)

**Figure 3.** Weibull distribution curve  **Figure 4.** Maximum entropy curve

By modeling the Weibull distribution and fitting the maximum entropy probability density of the 291 sets of QQC draw bar stress load data from 2009 to 2016, the scale parameter $\beta$ and shape parameter $\alpha$ trends obtained are shown in Figure 5. The changing trend of the Lagrange multiplier is shown in Figure 6. It can be seen from Figure 5 that the stress load of QCC draw bar is relatively consistent with the Weibull distribution law, and its scale parameters $\beta$ and shape parameters $\alpha$ have fluctuations within a certain range. It can be seen from Figure 6 that the load distribution of the QCC draw bar is relatively stable. The main reason for analysis is that the loading and unloading work of the QCC is not regular. The proportions of the work condition data and the non-work condition data in the load data are also different. It can be seen that when the shape parameter $\alpha \in [0.4, 0.7]$ and scale parameter $\beta \in [0.1, 2]$, the QCC can be regarded as in a healthy condition, and the development trend is also relatively good. Through the quantitative analysis of the stress data, the health condition of the QCC structure can be evaluated from the development trend of the parameters.

A total of 41 sets of data in 2017 were selected for verification analysis, and the draw bar in that year were actually in a healthy condition. The 41 sets of data were fitted with a Weibull distribution, and the scale parameters and shape parameters were obtained as shown in the Figure 7, which were in the given range. The quantitative analysis verified the reliability of the results.
Weibull parameters

Lagrange multiplier

Weibull parameters

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