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Anomaly detection for wind turbine pitch bearings via autoencoder enhanced nonlinear autoregressive model

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Abstract—The pitch bearing, as a safety-critical unit in wind turbines, is prone to damage. To prevent severe accidents, early anomaly detection for wind turbine pitch bearings is highly desirable. The two main challenges need to be solved: 1) non-stationary signals under the condition of slow rotating speed. 2) noise from electric and mechanical movement signals contaminating the measured vibration signals. To address these two challenges, a novel method, autoencoder (AE) enhanced nonlinear autoregressive (NAR) model, namely AE-NAR, has been proposed. Firstly, the autoencoder possesses the ability of global feature extraction and can be utilized for the processing of non-stationary signals. Secondly, the sparse representation of the NAR model with Bayesian Augmented Lagrangian can deal with the noise problem. The effectiveness of the model is first validated using open bearing datasets, then verified using real signals collected from industrial-scale wind turbine pitch bearings. The results show that the AE-NAR method can effectively detect the abnormal state of wind turbine pitch bearings.

Keywords—predictive maintenance, nonlinear autoregressive model, anomaly detection, condition monitoring, wind turbine

I. INTRODUCTION

Anomaly detection is to identify unique instances among all the instances that are significantly different to the normal pattern [1]. The anomaly detection based on vibration signals in the mechanical systems aims at finding early fault and it is a fundamental pattern recognition problem in a wide range of applications, such as wind turbines [2]. The sudden breakdowns can be prohibitively expensive due to lost productivity, and can even cause the significant safety risk, during the operation of wind turbines [3]. To avoid such unexpected breakdowns, the anomaly detection is essential to find the abnormal state of a wind turbine [4]. Once the anomaly is detected, the condition monitoring systems can subsequently infer fault type [5] and predict remaining useful life (RUL) [6], as shown in Fig. 1.

For anomaly detection, large amounts of data in healthy state is obtained but the data in abnormal state is rarely collected. This indicates that only little or insufficient for the purpose of fault detection and diagnosis. Furthermore, the early abnormal data may not be significantly different from the normal data, this further increase the difficulty of accurate fault detection. For the above two reasons, the purpose of anomaly detection in this paper is to design a abnormal state discriminator only based on the healthy state data. This abnormal state discriminator is a one-class classifier to fulfilling the task of detecting anomaly data.

Regarding the one-class classifier, there are two types of popular methods, statistical methods [7], [8] and deep learning methods [9]–[12]. The common practice of the statistical method for building one-class classifier is to learn certain data distribution of inliers and outliers. The deep learning method as a hot research topic in recent years, often encoder-decoder architectures to construct the classifier.

The autoregressive procedure can be used to produce the probability distribution underlying its latent representations [13]. The principal component analysis (PCA) method extracts the principal components of the data distribution, mapping training data into an infinite-dimensional feature space [14], [15].

The autoencoder based deep learning method was proposed to construct the model of normal behaviors and this method used a reconstruction loss to detect novelty [16], [17]. A novel research directly minimized the reconstruction error of the autoencoder to discriminate the outliers, with the gradient magnitude that makes the reconstruction error of normal samples more distinguished [12] . Pre-trained deep neural network and transfer learning are recently often used in detecting out-of-distribution samples [18], [19].

However, the anomaly detection for wind turbine pitch bearings have the following challenges:

- It is difficult to extract fault components from the collected vibration signal of wind turbine at early stage, which is non-stationary and weak under the condition of slow rotated speed.
- It is difficult to fully eliminate the influence of significant noise containing in the vibration signal during detection process.

To address this problem, a novel method, autoencoder (AE) enhanced nonlinear autoregressive (NAR), namely AE-NAR,
is proposed in this paper. The fault components in raw signals can be separated from significant noise through this method, which will be explained in the following theoretical process. This method can help detect abnormal conditions in a timely manner. In essence, the major work of this paper can be concluded as follows:

1) This paper proposes a type of anomaly detection method AE-NAR that can realize anomaly detection, especially for wind turbine pitch bearings.

2) This paper create a anomaly indicator that can help perceive slight anomaly, which specially considers the condition of signals with the characteristics of non-stationary and high noise ratio.

II. THEORETICAL PROCESS

A. Definition

Assume the raw signal is collected with dimension \( m_r \) and the length \( m_c \). The raw signal \( X \) can be specified as follows:

\[
X = [x_1, x_2, ..., x_{m_c}] \quad (1)
\]

where \( x_i \in R^{m_r} \) consists of the complete \( X \). It is assumed that the collected signal \( X \) is input into the autoencoder (AE) model \([20]\). AE includes the encoder and decoder operation, namely \( f_{\text{decoder}} \) and \( f_{\text{encoder}} \). The \( f_{\text{encoder}} \) represents encoder function that converts signals into low-dimensional space to obtain \( Z \):

\[
Z = [z_1, z_2, ..., z_{m_c}] \quad (2)
\]

where \( z_i \in R^n \) and the linear combination can obtain the \( Z \). The \( f_{\text{decoder}} \) is the inverse operation of \( f_{\text{encoder}} \). The relationships of them can be described as: \( z = f_{\text{encoder}}(x) \) and \( x = f_{\text{decoder}}(z) \).

Define \( J_{\text{decoder}} \) as Jacobi matrix, \( J_{\text{decoder}} = \frac{\partial f_{\text{decoder}}(z)}{\partial z} \). Given a data point \( x \), we can define the mathematical operator span on \( J_{\text{decoder}} \) as \( \Gamma \), representing the tangent space of \( f_{\text{decoder}} \) at \( x \), see Fig. 2. The definition is shown as follows:

\[
\Gamma = \text{span} \left( J_{\text{decoder}}(z) \right) = \text{span} \left( USV^T \right) \quad (3)
\]

where \( U \), \( S \) and \( V \) are calculated by Singular Value Decomposition (SVD). \( U = \begin{bmatrix} U^\parallel, & U^\perp \end{bmatrix} \) represents the tangent and orthogonal component, respectively. \( U^\parallel \) has the dimension \( (n_r, m_r) \) and \( U^\perp \) has the dimension \( (m_c - n_r, m_r) \).

Define the output of autoencoder (AE) during predicting process as \( Y \):

\[
Y = [y_1, y_2, ..., y_{m_c}] \quad (4)
\]

where \( m_c \) elements in \( Y \) are all a column vector with \( m_r \) row. Output of autoencoder \( y \) in (4) can be represented with \( x \) in (1) as follows:

\[
y = U^\top x = \begin{bmatrix} U^\top x \end{bmatrix} = \begin{bmatrix} y^\parallel \\ y^\perp \end{bmatrix} \quad (5)
\]

where \( y^\parallel \in R^{m_r} \) is the normal state component. \( y^\perp \in R^{m_c - m_r} \) is the noise, including anomaly state and background noise.

B. Detection model

The detection model involves the AE and NAR model. The AE model possess the ability of global feature extraction and the NAR model can realize real-time signal reconstruction, especially for the noise signal. The ability of global feature extraction of AE model is integrated into the NAR model to realize the final anomaly detection. The reconstruction error \( e_r \) is comprised of AE error and NAR error.

Denote that \( y \) as horizontal element of \( Y \) in (4), is a \( n \) row vector. Referring to \([21]\), The NAR model can be represented as follows:

\[
y = P\Theta + \Xi \quad (6)
\]

where \( \Theta \) denotes the model parameters and \( \Xi \) represents the stochastic error. If the elements in \( y \) is represented as \( y \), the \( P \) can be described as follows:

\[
P = \begin{bmatrix} y_M & \cdots & y_1 \end{bmatrix} = \begin{bmatrix} y_M & \cdots & y_1 \\ y_{M+1} & \cdots & y_2 \end{bmatrix} \cdots \begin{bmatrix} y_{M+N-1} & \cdots & y_N \end{bmatrix} \quad (7)
\]

where the \( M \) is related to the lag of the NAR model and \( N \) indicates the dimension of matrix \( P \). Subsequently, the process of determining the model parameters can be transformed into a \( l_1 \)-norm problem by utilizing Bayesian framework:

\[
\Theta = \arg \min_{\Theta \in \mathbb{R}^m} \left\{ \frac{1}{2} \| P\Theta - y \|^2 + \lambda \| \Theta \|_1 \right\} \quad (8)
\]

where \( \lambda \) is the penalty parameter. According to Augmented Lagrangian, the quadratic penalty can be transformed into a unconstrained optimization problem:

\[
\min_{\Theta \in \mathbb{R}^m} f_1(\Theta) + f_2(v) + \frac{\mu}{2} \| \Theta - v \|^2 \text{ s.t. } v - \Theta = 0 \quad (9)
\]
where \( f_1(\Theta) = \frac{1}{2} \| P \Theta - y \|_2^2 \) and \( f_2(v) = \lambda \| \Theta \|_1 \).

In order to calculate the coefficient matrix \( \Theta \), this paper refers to [21] to obtain the final iteration formulas:

\[
\hat{\Theta}_{k+1} = \left( P^T P + \mu I \right)^{-1} \left( P^T y + \mu (v_k + d_k) \right) \tag{10}
\]

\[
v_{k+1} = \max \left( 0, \left( \hat{\Theta}_{k+1} - d_k \right) - \mu/\lambda \right) \tag{11}
\]

\[
d_{k+1} = d_k - \left( \hat{\Theta}_{k+1} - v_{k+1} \right) \tag{12}
\]

where \( d, v, \) and \( \mu \) are the hyper-parameters, which can be tuned according to the real application.

Then, for \( i \)th dimension signal, the NAR error can be represented as follows:

\[
e_{\text{NAR},i} = P \Theta - y \tag{13}
\]

The complete NAR error can be represented:

\[
e_{\text{NAR}} = [e_{\text{NAR},1}, \ldots, e_{\text{NAR},m_r}]^T \tag{14}
\]

Regarding the AE model, the error is:

\[
e_{\text{AE}} = Y - X \tag{15}
\]

Finally, the \( e_r \) can be obtained:

\[
e_r = e_{\text{NAR}} + e_{\text{AE}} \tag{16}
\]

C. Indicator

The element \( x \) in \( X \) can be regarded as random variable. Referring to [22], the corresponding probability distribution of healthy state is shown below:

\[
P_x(x) = P_y(U^T x) = P_y(y^\parallel, y^\perp) \tag{17}
\]

\[
= P_{y\parallel}(y^\parallel) * P_{y\perp}(y^\perp)
\]

Referring to [22], we can know:

\[
P_{y\parallel}(y^\parallel) = \det S^{-1} * P_z(z) \tag{18}
\]

where \( S^{-1} \) is semi positive definite diagonal matrix of singular value decomposition of the \( J_{\text{encoder}} (z) \). \( z \) satisfies generalized Gaussian distribution (GGD), so the \( P_z(z) \), as distribution of \( z \), can be obtained through estimating GGD.

The intensity of \( y^\perp \) can be obtained by calculating the distance away from the center point of the hypersphere \( S^{m_r-n_r-1} \), so the distribution of \( y^\perp \) can be approximated as follows:

\[
P_{y\perp}(y^\perp) \approx \Gamma \left( \frac{m_r-n_r}{2} \right) / \left( 2^{\frac{m_r-n_r}{2}} \pi^{\frac{m_r-n_r}{2}} \right) \tag{19}
\]

We can define the energy matrix \( W \):

\[
W = \Gamma \left( \frac{m_r-n_r}{2} \right) \left( 2^{\frac{m_r-n_r}{2}} \pi^{\frac{m_r-n_r}{2}} \right) \tag{20}
\]

Combining to (17), (18), (19) and (20), we can obtain:

\[
P_z(x) \propto \det S^{-1} * P_z(z) * W * P_{y\parallel}(y^\parallel) \tag{21}
\]

According to [22], [23], noise \( y^\perp \in R^{m_r-n_r} \) can denote local coordinates related to the abnormal state and background noise. \( y^\perp \) also directly result in reconstruction error \( e_r \) during model construction. In addition, the logarithm does not change the function monotonicity. Thus, (21) can be edited as follows:

\[
P_z(x) \propto \log \left( \det S^{-1} * P_z(z) * W * P_{e_i}(e_i) \right) \tag{22}
\]

Probability distribution function \( P_z \) is related to signals in health state, which denotes that the collected signals are more likely health when obtaining larger \( P_z \).

Then we could divide the [22] into four components, which constructs the anomaly indicator \( I \).

\[
I = \log \det S^{-1} + \log P_z(z) + \log W + \log P_{e_i}(e_i) \tag{23}
\]

\[
= i_1 + i_2 + i_3 + i_4
\]
The indicator $I$ here can be used to detect the anomaly state. Along with normal state, the indicator will keep it at a fixed value. The indicator will drop dramatically when anomaly exists. Finally, we accumulate indicator $I$ over a period of time to judge the damaged condition of this phase. The accumulate indicator $I$ is named phase indicator $I_p$ here:

$$I_p = \int_a^b I dt$$  \hfill (24)

where the $a$ and $b$ are the beginning time and ending time of this phase. The length of $b - a$ will adjust the fault threshold accordingly.

III. EXPERIMENTS

A. Dataset Description

The degradation data of wind turbine pitch bearings is difficult to obtain because the damage may take place after ten years in the real industrial application. In addition, our method can adjust the threshold of indicator to change the sensitivity of anomaly detection. In other words, if the task of fault classification can be realized, the early anomaly detection can be realized by slightly adjusting the threshold of indicator, which is also the advantage of our method. Finally, the fault classification datasets are used to validate our method. A total of three datasets are used to validate the algorithm. Two datasets are related to the general bearing: dataset 1 is fixed speed; dataset 2 is variable speed. Another dataset 3 is collected from wind turbine pitch bearings. Their descriptions are shown as follow:

- Dataset 1 is collected from gearbox bearings, including five state types: health, ball fault, inner fault, outer fault and combined fault. The experimental data was generated on a physical platform with fixed rotated speed.
- Dataset 2 is acquired from ball bearings, including the same five state types as dataset 1. The experimental data was generated on a physical platform with variable rotated speed. The four types of operating rotational speed conditions are (a) increasing speed, (b) decreasing speed, (c) increasing then decreasing speed (d) decreasing then increasing speed.
- Dataset 3 is collected from an industrial-scale wind turbine pitch bearing, including only two state types: health and inner fault. The experimental data was generated on a real wind turbine pitch bearings with fixed rotated speed.

B. Anomaly Detection for Fault Classification Data

In this section, datasets of fault classification are tested for the anomaly detection without considering the specific fault types. The data of health state is regarded as the positive samples and the data of the other fault types are regarded as the negative samples, indicating the existence of anomaly. The training set only use few parts of positive samples. To keep the balance of the proportion of positive and negative samples, the content of the testing set is the combination of health samples and other fault type samples. Note that $I_p$ in (24) is used to solve the problems of maldistribution for green dots. A signal will be regarded as having anomaly when the phase indicator $I_p$ is exceed the 10% of the normal state in the experiments.

Considering the objectivity and diversity, the following measured indicators are used in this paper: accuracy, precision, recall, F1, FAR, FDR, AUC.

B1. Evaluation results of Dataset 1

Fig. 4 shows the result of several samples in dataset 1 under the condition of the fixed rotated speed. The green dots are
B2. Evaluation results of Dataset 2

Fig. 5 shows the result of several samples in dataset 2 under the condition of the variable rotated speed. The green dots are the detected anomaly ones that are judged by the indicator $I$ in (23). The large amounts of green dots may denote that the damage in dataset 2 is severe.

Tab. II shows the quantitative results for dataset 2. The precision and FDR can reach 100% in the health-inner. The weighted average of accuracy, precision, recall, F1, FDR, and AUC are all above 95%. The average value of FAR is very low, only 2%.

B3. Evaluation results of Dataset 3

Fig. 6 represents the short-time fourier transform of the signals collected from wind turbine pitch bearings. The fluctuated frequencies denotes that the signals in the wind turbine are truly non-stationary. Fig. 7 is only the result of one of the three sets, illustrating the effectiveness of our method.
In this paper, an autoencoder (AE) enhanced nonlinear autoregressive (NAR) model is proposed to realize the anomaly detection for wind turbine pitch bearings with slow rotated speed, which can well process the condition of non-stationary signals with large noise. Firstly, the NAR part can realize real-time signal reconstruction, especially for the noise signal. In addition, the ability of global feature extraction of AE model is integrated into the NAR model to realize the final anomaly detection. Finally, the subsequent phase indicator can comprehensively consider all the data in an certain window to give the ultimate judgement. The proposed method is verified at two datasets of general bearings and one dataset of real wind turbine pitch bearings. The validated results denote that the proposed method can detect the anomaly series in real industrial application.

### IV. Conclusion

In this paper, an autoencoder (AE) enhanced nonlinear autoregressive (NAR) model is proposed to realize the anomaly detection for wind turbine pitch bearings with slow rotated speed, which can well process the condition of non-stationary signals with large noise. Firstly, the NAR part can realize real-time signal reconstruction, especially for the noise signal. In addition, the ability of global feature extraction of AE model is integrated into the NAR model to realize the final anomaly detection. Finally, the subsequent phase indicator can comprehensively consider all the data in an certain window to give the ultimate judgement. The proposed method is verified at two datasets of general bearings and one dataset of real wind turbine pitch bearings. The validated results denote that the proposed method can detect the anomaly series in real industrial application.

### Table I: Detection Results of Dataset 1.

<table>
<thead>
<tr>
<th></th>
<th>accuracy</th>
<th>precision</th>
<th>recall</th>
<th>F1</th>
<th>FAR</th>
<th>FDR</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>health-ball</td>
<td>96.48%</td>
<td>0.96</td>
<td>0.96</td>
<td>0.96</td>
<td>0.04</td>
<td>0.97</td>
<td>0.93</td>
</tr>
<tr>
<td>health-inner</td>
<td>98.50%</td>
<td>1</td>
<td>0.98</td>
<td>0.98</td>
<td>0.02</td>
<td>1</td>
<td>0.98</td>
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<tr>
<td>health-outter</td>
<td>95.48%</td>
<td>0.96</td>
<td>0.95</td>
<td>0.95</td>
<td>0.05</td>
<td>0.97</td>
<td>0.92</td>
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<tr>
<td>health-combination</td>
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<td>0.95</td>
<td>0.06</td>
<td>0.97</td>
<td>0.91</td>
</tr>
<tr>
<td>weighted average</td>
<td>96.23%</td>
<td>0.97</td>
<td>0.95</td>
<td>0.96</td>
<td>0.04</td>
<td>0.97</td>
<td>0.93</td>
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### Table II: Detection Results of Dataset 2.

<table>
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<th></th>
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<th>precision</th>
<th>recall</th>
<th>F1</th>
<th>FAR</th>
<th>FDR</th>
<th>AUC</th>
</tr>
</thead>
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<tr>
<td>health-ball</td>
<td>97.49%</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
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<td>0.95</td>
</tr>
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<td>0.99</td>
<td>0.99</td>
<td>0.01</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>health-outter</td>
<td>96.49%</td>
<td>0.98</td>
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<tr>
<td>health-combination</td>
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<td>0.96</td>
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<tr>
<td>weighted average</td>
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<td>0.97</td>
<td>0.97</td>
<td>0.02</td>
<td>0.99</td>
<td>0.96</td>
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### References