Performance degradation assessment methodology of harmonic reducer by using low-frequency time series data and genetic programming

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Abstract. The harmonic reducer, as an important transmission component in the industrial robot, determines the positioning accuracy, carrying capacity, and service life of the industrial robot. However, the performance and reliability of harmonic reducer will gradually decline or even fail under long-time and high-intensity operations. The sudden stop and failure of the industrial robot will directly affect production efficiency. In this paper, a data-driven method for performance degradation assessment (PDA) of the harmonic reducer is studied. An accelerated degradation test rig was set up to collect the run-to-failure datasets of harmonic reducer, including process data, such as torque and speed, and non-process data, such as vibration signals, which were captured under a low sampling frequency. Firstly, a sliding window-based kurtosis and root mean square (RMS) are applied to non-process data, which can detect the incipient failure time (IFT) of harmonic reducer. Subsequently, a data-level fusion of process data is conducted based on genetic programming to construct a monotonic health index for degradation assessment and trend analysis. The experimental study shows that the proposed method is effective to realize the PDA of harmonic reducer.

1. Introduction
Constructing an intelligent factory is an important theme of industry 4.0 [1, 2]. In recent years, industrial robots are prominent marks of the intelligent factory, which has been widely used in various fields. Because of its small size, light weight, high transmission efficiency, and strong carrying capacity, the harmonic reducer is widely used in the joint parts of industrial robots, such as arms, wrists, and hands. The harmonic reducer, as a key transmission component in the industrial robot, plays a significant role in determining the positioning accuracy, carrying capacity, and service life of the industrial robot. Due to the high intensity of industrial operation, the performance of harmonic reducer will gradually degrade and even fail during the operation period. The typical failure modes of harmonic reducer on the industrial robot are flex-spline fracture, tooth surface wear, and flexible bearing fracture. The performance degradation of the harmonic reducer will directly affect the working efficiency and motion precision of the industrial robot. Thus, guaranteeing the reliability of the harmonic reducer is a prerequisite for ensuring the efficient work of industrial robots.

The performance degradation assessment (PDA) is an emerging technology and dedicated to prognostics and diagnostics. The main strategy of PDA is to construct health indicators based on the measured signals, which can be used to initially detect an incipient failure and subsequently evaluate
the degradation degree of the machine [3]. The PDA technology has flourished in the application of bearings and gears in rotating machinery based on the data-driven method [4-6]. For example, Zhang et al. fused multiple features in the time and frequency domain to construct health indices based on spectral regression [7]. Bin et al. explore the relationship between information exergy index and machine degradation severity by using clustering methodology for bearing PDA [8]. However, in the literature, the research on the PDA of the harmonic reducer based on data-driven methodology is seldom reported. The working principle, working environment, and physical structure of harmonic reducer are different from the bearings and gears of rotating machines [9]. Thus, new data collection schemes and PDA methodology should be proposed to tailor for harmonic reducer. Currently, the studies of harmonic reducer mainly focus on structure optimization [10], failure mechanism [11], and lubrication optimization [12] based on the simulations and experiments. Although many accelerated degradation experiments of harmonic reducer under different environments have been conducted by scholars [13-15], they are mainly utilized to investigate the failure mechanism of harmonic reducer. For example, Ma et al. used simulations and experiments to research the relationship between torque and time-varying stiffness of the harmonic reducer [16]. Xiong et al. proposed a universal static analysis model that can facilitate the calculation of the ball load distribution of flex-splines in harmonic reducers [17]. Li et al. built a reliability model for harmonic reducer by considering many uncertainties such as manufacturing errors and operation conditions [18]. Liu et al. proposed a double speed loops control methodology to solve the problem of mechanical resonance of harmonic reducer [19]. More works on the mechanism research of harmonic reducer can be found in the Literatures [20, 21].

Based on this, in this paper, a data-driven PDA method of the harmonic reducer is proposed. Firstly, a test rig was designed to collect run-to-failure datasets and multi-source sensor data including process data and non-process data was collected under a low sampling frequency. A sliding window-based kurtosis and root mean square (RMS) are both used to determine the IFT of harmonic reducer. After that, the process signals are fused into a health index for degradation assessment and trending analysis based on genetic programming. Finally, the collected datasets are used to validate the proposed method and the comparison results show the superiority of the proposed health indicators.

2. Proposed methodology for PDA of the harmonic reducer

The PDA of the harmonic reducer has two steps: determining the IFT and evaluating the degradation degree. The two steps are implemented by using health indicators. The organization of this section is summarized as follows: the first part of this section reports a method to detect IFT by using low-frequency vibration data. The second part proposes a data-level fusion method of process data, such as temperature and torque, to construct a HI for degradation assessment based on genetic programming. The workflow for the PDA of the harmonic reducer is given in the last part.

2.1. Non-process data-based IFT detection

Based on the previous study of gears and bearings, the non-process data, such as vibration and acoustic signals, is more sensitive to IFT compared to process data, such as temperature and torque, because plentiful fault information is reflected in the system vibration. Kurtosis and RMS, as two statistical-based health indicators, have been widely used in the PDA of gears and bearings. In general, kurtosis is more sensitive to IFT than RMS in most cases. In this paper, because the sampling frequency of vibration data is low, a sliding window-based kurtosis and RMS are both used to determine the IFT of harmonic reducer.

The calculation formulas of kurtosis and RMS are given as follows:

\[
\text{Kurtosis} = \frac{1/n \sum_{i=1}^{n} (x_i - \bar{x})^4}{\left( \frac{1/n \sum_{i=1}^{n} (x_i - \bar{x})^2}{2} \right)^2} - 3 
\]
where \( n \) is the number of samples, which can be understood as the length of the window. \( x_i \) is the \( i^{th} \) sample and \( \bar{x} \) is the mean value.

As shown in Figure 1, before using the sliding window method, the length of the window and sliding length should be set at first, which are denoted as \( L_w \) and \( L_s \) respectively. The actual IFT can be obtained by the conversion of \( L_w \) and \( L_s \). For example, if the sampling frequency is set to 1 Hz, then the IFT detected by the sliding window-based kurtosis is \( T \). The actual IFT is denoted as \( T' \) and \( T' \) can be calculated as follows:

\[
T' = L_s \times T + L_w
\]

Once the IFT is determined, the assessment of degradation degree and trending analysis can be started.

**Figure 1.** Sliding window method for IFT detection of harmonic reducer.

**Figure 2.** Individuals evolved from GP

\[
I_1 = \left( (X_1 - X_2) \times X_3 \right) + \log(X_4)
\]

### 2.2. Data-level fusion of process data based on genetic programming for degradation assessment

To construct a suitable health indicator for degradation assessment, process data is fused based on genetic programming. Due to the mechanism of irreversible degradation, a health indicator for degradation assessment is expected to have a monotonic trend. Process data, such as temperature and torque, is more sensitive to the evolution of degradation. Process data in the time domain can show an obvious degradation trend by using simple fitting technology while non-process data do not have this feature in the time domain as plotted in Figure 1. Thus, a data-level fusion of process data is conducted based on genetic programming to obtain a health indicator for the assessment of degradation conditions and levels.

#### 2.2.1. Genetic programming

Genetic programming (GP) originates from the genetic algorithm (GA), which was first developed by Koza et al. [22]. Similar to GA, GP also belongs to the evolutionary algorithm. However, different from the GA and other machine learning algorithms that have black-box properties, GP is a kind of expression programming, which means that GP can give the explicit relationship between the input individuals and the new individuals evolved by GP. An example of the new individual \( I_1 \) is shown in Figure 2. Herein, the mathematical expression of \( I_1 \) can be built by the tree structure. In this paper, \( I_1 \) can be understood as the health indicator with the highest fitness value. \( X_1, X_2, X_3, \) and \( X_4 \) are the normalized sensor data and used as input of GP.

The workflow of GP for health indicator construction is summarized in Figure 3. Herein, the terminal set refers to the input, which will be used for building up the leaves of a tree plotted in Figure 3.
2. In this paper, the terminal set is the sensor data to be fused. The function set is a set of operational symbols, such as addition, subtraction, multiplication, and division. The genetic operators refer to crossover, mutation, and reproduction. The termination criterion can be decided based on the fitness value or the number of iterations. The most important issue in GP is to design a suitable fitness function for choosing the best individual. The design of the fitness function is discussed thoroughly in the next subsection.

![Workflow of GP for health indicator construction.](image)

Figure 3. Workflow of GP for health indicator construction.

![Incipient failure detection and Evaluation of degradation condition.](image)

Figure 4. Proposed methodology for PDA of harmonic reducer.

2.2.2. Fitness function. Another objective of this paper is to develop a health indicator for the evaluation of degradation conditions and levels. Monotonic degradation trends of health indicators are critically important for degradation assessment. Based on this, the merit of evaluating the monotonicity of health indicators is used as the fitness function of GP [23]. The quantitative expression of monotonicity is given as follows:
where $x$ refers to a health indicator; $n$ is the length of the health indicator. $d/dx$ is the derivative of health indicator, which is a discrete sequence. Thus, the monotonicity of health indicators is measured by the absolute disparity between the number of positive derivatives and the number of negative derivatives. The monotonicity property in (4) ranges from 0 to 1. If the fitness value is equal to 1, then the health index developed from GP is monotone completely. The objective is to obtain a health indicator with the highest fitness value for degradation assessment. The workflow of the proposed methodology for the PDA of the harmonic reducer is summarized in Figure 4.

3. Case study
In this section, a test rig was set up to gather the run-to-failure datasets of harmonic reducer. Then the collected signals are used to verify the effectiveness of the proposed method.

3.1. Test rig
The accelerated life test of the harmonic reducer is shown in Figure 5, which mainly includes a motor, a harmonic reducer, a magnetic powder brake, multiple sensors, etc. All parts of the test platform were placed on the isolation platform to isolate external interference. The ambient temperature was kept at about 20 °C to eliminate the interference of environmental factors on the test. The performance parameters of the harmonic reducer tested in the test rig are shown in Table 1.

To obtain the run-to-failure datasets of harmonic reducer, several groups of accelerated life tests were designed and carried out. The experimental parameter settings are shown in Table 2. The harmonic reducer was continuously operated from the brand-new state to complete failure. The load was selected as the output torque, which was easy to control and set to three or four times of the rated torque. As observed in Table 2, the life span of harmonic reducer varies greatly between samples under the same operating environment, which further shows the importance of health monitoring and degradation assessment. For convenience, each sample point is recorded as an observation epoch. The time units of an observation epoch are 30 s or 1s depending on the sampling frequency.

![Figure 5. Accelerated life test rig (1- Magnetic powder brake, 2- Torque and speed sensor of output terminal, 3- Tested harmonic reducer, 4- Accelerometer, 5- Torque and speed sensor of input terminal, 6- Drive motor).](image)

| Table 1. Harmonic reducer performance parameters. |
|-----------------------------------------------|
| Reduction ratio | Rated torque (N.m) | Maximum allowable moment (N.m) | Maximum allowable torque (N.m) | Maximum input speed (r/min) | Design life (h) |
|-----------------|--------------------|-----------------------------|-----------------------------|---------------------|---------------|
| 51              | 32                 | 69                          | 121                         | 6000                | 10000         |


Table 2. Accelerated life test of harmonic reducer.

| Nomenclature     | Load (N.m) | Sampling Frequency (Hz) | Total observation epoch | Running time (h) | Failure mode          |
|------------------|------------|-------------------------|-------------------------|------------------|-----------------------|
| Harmonic reducer_1 | 96         | 1/30                    | 1186                    | 9.9              | flexible bearing fracture |
| Harmonic reducer_2 | 96         | 1/30                    | 4876                    | 40.6             | flex-spline fracture   |
| Harmonic reducer_3 | 128        | 1                       | 35284                   | 9.8              | flex-spline fracture   |
| Harmonic reducer_4 | 128        | 1                       | 72106                   | 20               | flex-spline fracture   |
| Harmonic reducer_5 | 128        | 1                       | 20493                   | 5.7              | flex-spline fracture   |

The collected raw sensor data of harmonic reducer_1 is shown in Figure 6. In this paper, the kurtosis and RMS are calculated by using the x-axis vibration data to detect IFT. The temperature, input speed, and input torque are used as input of GP because they have more obvious degradation trends intuitively.

![Figure 6. Raw sensor data of harmonic reducer_1.](image)

3.2. Incipient failure detection of the harmonic reducers

Take the first run-to-failure as an example, the \( L_u \) and \( L_r \) are set to 240 and 10 observation epochs respectively. The kurtosis and RMS of harmonic reducer_1 are shown in Figure 7 and Figure 8 respectively. After conversion by the \( L_u \) and \( L_r \), the IFT of harmonic reducer_1 is around 1080 observation epochs. By using the same method, the IFT of harmonic reducer_2 to harmonic reducer_5 can be determined, which are at 4780 observation epochs, 33780 observation epochs, 70240 observation epochs, and 19360 observation epochs respectively.

3.3. Degradation assessment of the harmonic reducers

Subsequently, the observation epochs after the IFT of temperature, input speed, and input torque are used as input of GP. The function set of GP consists of + (plus), – (minus), × (times), / (divide), √ (sqrt), and log (log). The population size and the iterations are both set to 50. Firstly, the data of the
harmonic reducer_1 are used as training data and the rest are used for the test. The generated tree structure and its corresponding health indicator with the highest fitness function of harmonic reducer_1 are plotted in Figure 9 and Figure 10. Then, the developed tree structure is applied to other harmonic reducers, which are shown in Figure 11. It can be concluded that the method can construct monotonic health indicators for the degradation assessment of harmonic reducers.

Figure 7. Kurtosis of harmonic reducer_1.

Figure 8. RMS of harmonic reducer_1.

Figure 9 Tree structure developed from harmonic reducer_1.

Figure 10. Generated health indicator for harmonic reducer_1.

Figure 11. Health indicators for the degradation assessment of harmonic reducers: (a) health indicator for Harmonic reducer_2; (b) health indicator for Harmonic reducer_3; (c) health indicator for Harmonic reducer_4; (d) health indicator for Harmonic reducer_5.

3.4. Comparison analysis

Finally, the designed health indicators are compared with some statistical health indicators, such as spectral kurtosis, smooth index, mean, and variance, for PDA of harmonic reducer. Spectral kurtosis, smooth index, mean, and variance are applied to the PDA of harmonic reducer_4, which are shown in Figure 12. Then, some merits [23], including monotonicity and trendability, are used to evaluate the performance of some benchmarks and the proposed health indicator. The results are summarized in Table 3. It can be concluded from Table 3 that the proposed health indicator is more suitable for PDA.
of harmonic reducer and it has better comprehensive performance than other benchmarks in monotonicity and trendability.

**Figure 12.** Statistical health indicators for the degradation assessment of harmonic reducer_4: (a) spectral kurtosis; (b) smooth index; (c) mean; (d) variance.

**Table 3.** Comparison results between statistical health indicators and proposed health indicators in monotonicity and trendability.

| Health indicator | Spectral kurtosis | Smooth index | Mean | Variance | Proposed health indicator |
|------------------|-------------------|--------------|------|----------|---------------------------|
| Monotonicity     | 0.03              | 0.05         | 0.01 | 0.20     | 0.21                      |
| Trendability     | 0.22              | 0.40         | 0.29 | 0.76     | 0.98                      |
| Sum              | 0.25              | 0.45         | 0.3  | 0.96     | 1.19                      |

**4. Conclusions**

In this paper, a data-driven methodology of PDA for the harmonic reducer is proposed. A test rig was established to collect the condition data during the degradation of the harmonic reducer, which is used to verify the effectiveness of the proposed methodology. In further studies, more experiments that increase the sampling frequency and sensor types will be conducted and designed to collect the run-to-failure dataset. Based on this, more data-driven technologies, such as signal processing and machine learning algorithms, can be introduced to classify the fault type and monitor the health condition of harmonic reducer.

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