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## HEALTH INDEX EXTRACTING METHODOLOGY FOR DEGRADATION MODELLING AND PROGNOSIS OF MECHANICAL TRANSMISSIONS

### METODOLOGIA EKSTRAKЦИИ WSKAŹNIKA STANU TECHNICZNEGO DO MODELOWANIA I PROGNOZOWANIA DEGRADACJI PRZEKŁADNI MECHANICZNYCH

*Condition monitoring and prognosis is a key issue in ensuring stable and reliable operation of mechanical transmissions. Wear in a mechanical transmission, which leads to the production of wear particles followed by severe wear, is a slow degradation process that can be monitored by spectral analysis of oil, but the actual degree of degradation is often difficult to evaluate in practical applications due to the complexity of multiple oil spectra. To solve this problem, a health index extraction methodology is proposed to better characterize the degree of degradation compared to relying solely on spectral oil data, which leads to an accurate estimation of the failure time when the transmission no longer fulfils its function. The health index is extracted using a weighted average method with selection of degradation data with allocation steps for weight coefficients that lead to a reasonable mechanical transmission degradation model. First, the degradation data used as input are selected based on source entropy which can describe the information volume contained in each set of spectral oil data. Then, the weight coefficient of each set of degradation data is modelled by measuring the relative scale of the permutation entropy from the selected degradation data. Finally, the selected degradation data are fused, and the health index is extracted. The proposed methodology was verified using a case study involving a degradation dataset of multispectral oil data sampled from several power-shift steering transmissions.*

**Keywords:** health index, mechanical transmission, condition monitoring, spectral oil data, degradation modeling, remaining useful life.

*Monitorowanie i prognozowanie stanu to kluczowa kwestia dla zapewnienia stabilnej i niezawodnej pracy przekładni mechanicznych. Zużycie w przekładni mechanicznej, które prowadzi do wytwarzania cząsteczek zużycia a następnie ciężkiego zużycia, to proces powolnej degradacji, który może być monitorowany poprzez analizę widmową oleju, ale rzeczywisty stopień degradacji często trudno jest ocenić podczas praktycznego użytkowania z uwagi na złożoność wielu widm oleju. W celu rozwiązania powyższego problemu, zaproponowano metodologię ekstrakcji wskaźnika stanu technicznego, aby lepiej scharakteryzować stopień degradacji niż polegając wyłącznie na danych widmowych oleju; pozwala to na dokładne prognozowanie czasu uszkodzenia, gdy przekładnia przestanie spełniać swoją funkcję. Wskaźnik stanu technicznego ekstrahowany jest za pomocą metody średniej ważonej z wyborem danych o degradacji i etapami alokacji dla współczynników wagowych, dając w efekcie odpowiedni model degradacji przekładni mechanicznej. W pierwszym etapie, dane degradacji stosowane jako dane wejściowe wybierane są na podstawie entropii źródłowej, która może opisywać zakres informacji zawarty w każdym zbiorze danych widmowych oleju. Następnie współczynnik wagowy każdego zestawu danych nt. degradacji modelowany jest przez pomiar względnej skali entropii permutacji z wybranych danych degradacji. Na koniec, wybrane dane degradacji są integrowane i ekstrahowany jest wskaźnik stanu technicznego. Zaproponowana metodologia została zweryfikowana przy użyciu studium przypadku obejmującego zbiór wielowidmowych danych dotyczących degradacji oleju pobranego z kilku przekładni kierowniczych wspomaganych.*

**Słowa kluczowe:** wskaźnik stanu technicznego, przekładnia mechaniczna, monitorowanie stanu, dane widmowe oleju, modelowanie degradacji, pozostały okres użytkowania.

#### 1. Introduction

Failure caused by severe wear of friction couplings, which is the primary failure mode of mechanical transmissions, has an adverse influence on vehicle reliability that may have catastrophic consequences. Therefore, the wear in a mechanical transmission should be monitored regularly to avoid possible unscheduled maintenance, and proactive maintenance should be implemented in a timely manner to extend the period during which the transmission is in a healthy state. Currently, the condition monitoring (CM) and prognostics of a mechanical transmission, which uses CM data to evaluate the residual life before wear failure of friction couplings and provides a vital foun-

dition for condition-based maintenance, has attracted considerable attention in research and plays a key role in industries [3,7].

CM data (e.g., vibration, temperature and oil analysis data) that are measured during machine operation, which can characterize the severity of underlying degradation and failure processes, are typically regarded as degradation data. A typical assumption is that the machine failure will occur when the degradation data cross a threshold that is usually prescribed by practitioners [14,19]. Therefore, the degree of degradation and the residual life of a machine can be determined by comparing the degradation data with the predetermined failure threshold. With the residual life evaluated, condition-based maintenance

techniques essentially promote severe operation avoidance and proactive maintenance strategy, which can lead to less unexpected failure and higher user satisfaction [4, 9].

For a mechanical transmission, wear of friction couplings is not directly observable and can only be indirectly assessed via measured CM data. As a widely used CM technique, oil spectral analysis, which has been demonstrated to be effective and widely applicable to mechanical transmissions with oil lubrication, is always performed at discrete epochs to obtain spectral oil data that can be used to assess the wear debris in lubrication oil [28,29]. Metal debris produced from different friction couplings are uniformly mixed in lubrication oil, and the level of the metal debris is one of the most common types of degradation data that can be used to evaluate the degree of wear in mechanical transmissions [5,6]. When the mechanical transmission is in operation, wear debris accumulates in the lubrication oil, and the concentration increases, which leads to transmission degradation [22, 26]. Therefore, the objective of this paper is to utilize the spectral oil data to build the degradation model and evaluate the residual life of mechanical transmissions.

For many years, numerous methods and techniques have been used in practice to model the evolution of mechanical transmission degradation and failure process and the association with the oil spectral analysis [2, 3, 12, 22, 26]. A comprehensive review of the application of different approaches in oil analysis-based CM and prognostics can be found in [6,18] and the references therein. However, the primary limitation of these studies is that the proposed methods consider only a single spectral oil data for degradation modelling, for example, Fe [3] and Cu [12], and studies have not considered multiple spectral oil data. Although it is possible to use multiple degradation data individually to build the degradation model, this process may lead to significant under- or over-prognosis of the degree of degradation [8,10]. In other words, the wear mechanism of a mechanical transmission has numerous paths and is complex, and it is difficult to characterize the degradation process considering only a single degradation data point. As a result, considering only one degradation data point will lead to the inaccuracy of CM and residual life evaluation.

To solve this problem, the multiple oil spectra must be fused for extracting a composite health index (HI), which can characterize the degree of degradation of the transmission and be used for degradation modeling and residual life evaluation. The two challenges of extracting the HI are the following: 1. the wear debris in a sample has been categorized into 15 groups of concentrations using oil spectral analysis, and different spectral oil data often have different physical meanings [11, 12]. Thus, we must decide which data to use for extracting a composite HI. 2. Not all CM data have the same importance in decision making. Often the CM data that exhibit a clear degradation trend are highly related to machine degradation process, while others may not be so high related [10, 21]. Thus, we need to measure the credibility of different degradation data from heterogeneous sources when fusing the multiple degradation data.

The remainder of this paper is structured as follows: Section 2 describes the mechanical transmission used to illustrate the development of the HI extraction method and describes the degradation dataset used in the experiment. Section 3 develops the HI extraction method based on weighted average and describes some key elements related to the method, including degradation data selection and weight coefficients allocation procedures. Section 4 applies the method that has been developed to extract the HI and demonstrates the improved performance for degradation modelling and residual life prediction based on the dataset provided in Section 2. Section 5 provides the conclusions of this study and discusses future research.

## 2. Overview of the system and dataset

### 2.1. System model description

This paper considers a power-shift steering transmission (PSST) [12, 27] monitored using regular oil spectral analysis to illustrate the HI extraction methodology and the application of the HI to degradation modeling. The PSST (shown in Fig. 1) combines a multispeed shift system with an infinite steering system, which is widely used in tracked armoured vehicles, large engineering machinery and other industries. Fig. 2 shows the test bed that was used in this paper. The test bed contains a diesel engine as a power unit and bilateral symmetrical loads, including inertia discs and loading piston pumps.

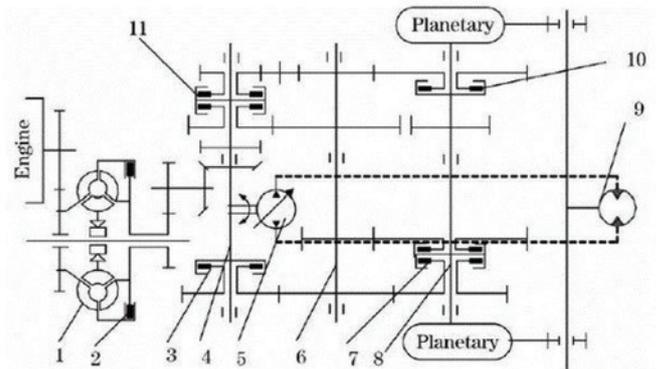


Fig. 1. Sketch diagram of the PSST

1: Hydraulic torque converter; 2: CV clutch; 3: CH clutch; 4: First shaft; 5: Steering pump; 6: Second shaft; 7: C1C2 clutch; 8: Third shaft; 9: Steering motor; 10: C3 clutch; 11: CLCR clutch

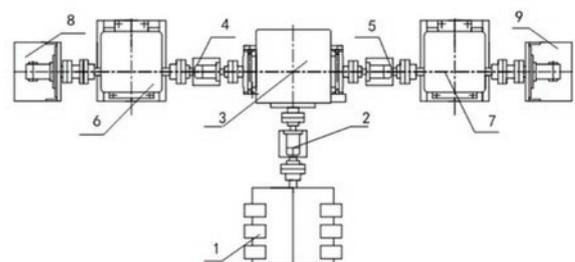


Fig. 2. Life-cycled test bed of the PSST

1: Diesel engine; 2, 4, 5: Torque and speed sensors; 3: PSST; 6, 7: Inertia discs; 8, 9: Loading piston pump

To simulate actual operating conditions, all of the tested PSST units were tested under the cyclic operation of multi-gear, load variance and multi-speed that was prescribed by the manufacturer and defined by the owner. Moreover, the sampling location was selected at the entry of the fine-filter to collect more details regarding wear debris.

## 2.2. Oil sampling and analysing principles

Oil samples have been collected during the life-cycle test. The sampling method is based on the methodology agreed between the entrepreneur and the oil analysis laboratory. Specified, oil samples should be collected/stored/transported and analysed using clean and identical equipment and instrumentation, and a corresponding volume of unpolluted oil should be added to ensure normal lubrication. Despite well-trained and -instructed site operators, inherent human error is still inevitable. To ensure an identical collection error in all instances, the procedural principle for sampling and analysing processes are as given below [22]:

- Oil samples are collected at homogeneous time intervals every 5 hours during the operational life of each PSST unit (motor hour, Mh);
- A sample is always taken immediately in case of failures, such as functional fault, abnormal vibration or noise;
- For the case where the test bed is normally started, the oil sample is taken after the test bed is running stably for at least 15min;
- For the case where the test bed is normally shut down, the oil sampling must be performed within a maximum of 10 min;
- All of the oil samples taken should be analysed by the same instrument at the same day (or at least the following day).

All of the oil samples are obtained at the same location only through systematic sampling, always analysed using the same instrument under standardized operation. Therefore, any measurement error of the oil field datum can be regarded as the same distribution.

## 2.3. Dataset description

We possess oil field data consisting of more than one thousand samples collected over a period of more than 10 years. The dataset used in this paper consists of 20 training units and 5 testing units. Each unit was run to failure under the same cyclic operating condition, and more than 30 oil samples in total are collected from 0 Mh to up to 284 Mh according to the sample period of nearly 5 Mh. The concentrations in parts per million of 15 elements were obtained after oil spectral analysis using AE spectroscopy. Due to space restrictions, the spectral oil datum of one PSST is shown in Tab. 1.

Using these element concentration data, the degradation model can be established and then the degree of degradation of the PSST can be determined. However, not all the CM data can show the same degradation pattern. Thus, to establish the degradation model and to evaluate the residual life, the degradation dataset must be fused, and a composite HI that can be used to characterize the degree of degradation must be extracted.

## 3. Development of HI extraction methodology

In this section, we develop an HI extraction methodology for combining multiple degradation data from oil spectral analysis to characterize the underlying degradation process accurately and carry out the prognostic analysis precisely.

Table 1. Data of oil spectral analysis for one PSST test (unit: ppm)

| Sample | Time/Mh | Zn   | Ca   | Cr  | Ni  | Sn | Na   | Cu   | Al  | Mn  | Pb  | Mg   | Fe   | P    | Mo  | Si  |
|--------|---------|------|------|-----|-----|----|------|------|-----|-----|-----|------|------|------|-----|-----|
| 1      | 5       | 1030 | 2357 | 0.5 | 0.2 | 0  | 15.7 | 10.2 | 3.1 | 0.2 | 6.2 | 19.2 | 10.8 | 1033 | 0.1 | 3.8 |
| 2      | 10      | 1019 | 2545 | 0.6 | 0.4 | 0  | 16.2 | 10.4 | 3.1 | 0.6 | 6.3 | 18.5 | 17.1 | 1027 | 0.1 | 5.1 |
| ⋮      | ⋮       | ⋮    | ⋮    | ⋮   | ⋮   | ⋮  | ⋮    | ⋮    | ⋮   | ⋮   | ⋮   | ⋮    | ⋮    | ⋮    | ⋮   | ⋮   |
| 35     | 175     | 1025 | 2374 | 5.2 | 9.7 | 0  | 14.3 | 17.1 | 3.2 | 4.2 | 6.4 | 17.6 | 614  | 986  | 0.8 | 4.8 |
| 36     | 180     | 1034 | 2412 | 5.4 | 9.9 | 0  | 15.6 | 17.8 | 3.4 | 4.4 | 7.0 | 18.2 | 636  | 1022 | 0.9 | 4.9 |

## 3.1. HI extraction method formulation

The weighted average functions are commonly used to fuse multidimensional data for extracting an index that characterizes the implicit information [1,10]. Among these functions, the linear function has been widely used due to its quick calculation properties. Therefore, we formulate our HI extraction methodology using the linear weighted average function to fuse the multiple degradation data. The HI is given by:

$$d_j = \mathbf{X}_{i,j} \boldsymbol{\omega}', \quad (1)$$

where  $\boldsymbol{\omega} \in R^{N \times 1}$  is a vector of weight coefficients that fuses multiple degradation data at each sampling epoch and  $N$  is the number of selected degradation data;  $d_j$  and  $\mathbf{X}_{i,j}$  represents the value of the HI and the vector for degradation data  $i$  in sampling epoch  $j$ , respectively;  $\boldsymbol{\omega}' \mathbf{M}' \mathbf{1} = 1$ , where  $\mathbf{M} \in R^{N \times N}$  is a diagonal matrix denoting the degradation trend information and the diagonal element is 1 (-1) when the corresponding degradation data have an increasing (decreasing) trend.

The HI is a weighted average of all degradation data using vector  $\boldsymbol{\omega}$  to measure the relative importance of each degradation datum. The linearity assumption is not suitable for all applications, and nonlinear functions may have to be used to extract the HI in some cases.

## 3.2. Data selection and weight allocation

### 3.2.1. Degradation data selection

As noted above, determining which CM data will be selected as the input for extracting a composite HI is a challenge of HI extraction methodology. To solve this problem, we developed a data selection method based on source entropy for selecting degradation data from multiple oil spectra. Assume that the multiple oil spectra are represented by  $\mathbf{Y}_{i,j} = \{y_{i,j} | i = 1, 2, \dots, N; j = 1, 2, \dots, M\}$ , where  $y_{i,j}$  is the spectral oil datum of the  $i$ th element at  $t_j$  monitoring time that indicate the measurement of the target degradation data  $x_{i,j}$  with noise. Thus, the degradation dataset  $\mathbf{X}_i$  can be described by the probability distribution  $p_i(\mathbf{X}_i)$  estimated from the spectral oil dataset  $\mathbf{Y}_i$ . In information theory, the Shannon entropy defined in Eq. (2) is used to measure the information volume in the data series [17]:

$$H = -\sum_{i=1}^N p_i(x) \log p_i(x), \quad (2)$$

where  $p_i(x)$  is the probability of the  $i$ th condition, and  $N$  is the number of conditions that the process  $\mathbf{X}_i$  has.

To select the degradation data for modelling, the CM data that contain more information are more suitable. Based on this criterion, degradation data are selected based on the value of the Shannon entropy, which can measure the information volume in the spectral oil dataset [13, 25]. The objective is to quantitatively select degradation data that leads to a reasonable HI for degradation modelling and re-

sidual life evaluation. Without loss of generality, all degradation data are standardized.

**3.2.2. Fusion weight allocation**

As noted above, another challenge of the HI extraction methodology is to determine the credibility of different degradation data from heterogeneous sources before fusing the multiple degradation data. To solve this challenge, some researchers proposed an average function to combine the degradation data by assuming equal weight [15], but this proposal seems unreasonable since different degradation data have different credibility, and the contribution of different degradation data on the whole is different.

In machine degradation modeling and prognostics, often CM data that exhibit a clear degradation trend are highly related to the machine degradation and failure, while others may not be as related [11, 21]. On this basis, permutation entropy, which is an effective way of measuring the monotonous trend degree of data series [8, 11], is used to allocate the weight in data fusion. According to information theory, the data series  $X_j$  has  $M!$  possible permutation order types. Then, the relative frequency of each possible permutation type  $\pi$  is defined by:

$$p(\pi) = \frac{\#\{t \mid 0 \leq j \leq M - n, (x_{j+1}, \dots, x_{j+n}) \text{ has type } \pi\}}{M - n + 1} \quad (3)$$

where  $n$  means the different numbers for the possible order types. The permutation entropy of order  $n \geq 2$  can be determined by:

$$H(n) = -\sum p(\pi) \log p(\pi) \quad (4)$$

Among these entropies,  $2!$  permutation entropy calculated in Eq. (5) has been widely used in engineering practice:

$$H(2) = -p \log p - (1 - p) \log(1 - p) \quad (5)$$

where  $p$  is the monotony probability of order  $n = 2$ . If  $p$  represents the increasing trend probability, then  $1 - p$  represents the decreasing trend probability.

Therefore, the increasing or decreasing trend of degradation data will be measured by the  $2!$  permutation entropy. Clearly,  $0 \leq H(2) \leq 1$ , where the lower bound can be obtained for an increasing or decreasing data series. In other words, the smaller permutation entropy value  $H(2)$  of degradation data has the better characteristic of monotony. Furthermore, there may be less conflict between the degradation data and the whole dataset. Thus, the weight of each degradation datum in the frame of data fusion is defined in Eq. (6) based on the proportion of permutation entropy.

$$w_i = \frac{1 - H_i}{N - \sum_{i=1}^N H_i} \quad (6)$$

The weight of each degradation datum is determined by the permutation entropy based on the degradation trend. The main idea of the weight allocation method is that if a degradation datum exhibits more degradation trend, this degradation datum has more impact on the final fusion result. In other words, we think smaller permutation entropy, greater weight.

**3.3. Flow chart of the method**

The flow chart of the proposed HI extraction methodology is shown in Fig. 3. The methodology

includes degradation data selection, weight coefficients allocation and data fusion steps that lead to a better degradation model and accurate prognostic results. Based on five steps that are included in Fig. 3, the degradation modeling and residual life prediction of a mechanical transmission can be achieved based on the multiple oil spectra from CM.

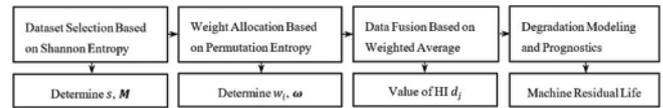


Fig. 3. Flowchart of the HI extraction methodology for degradation modeling and prognostics

The proposed data fusion method has two main advantages compared with the existing data fusion method for extracting an HI for degradation modeling and prognostics: 1) The degradation data used in the data fusion method are quantitatively selected based on Shannon entropy of each CM dataset. Compared to selecting degradation data relying on experience [10, 22], the proposed selection method can address more important information by measuring the information volume contained in the CM data, which means less information loss and contributes to a more accurate characterization of machine condition. 2) The multiple degradation data are properly combined with the proposed weight coefficient, which is useful for combining degradation data from heterogeneous sources and indicates that the proposed method is a practical and efficient tool for fusion of multiple CM data.

**4. Case study**

In this section, a case study is presented using the multiple oil spectra obtained for samples from each PSST in Section 2 to illustrate the entire HI extraction, modelling fitting and residual life prediction procedures and investigating the rationality and effectiveness of the proposed HI extraction methodology.

To numerically evaluate the improved performance of the extracted HI when used for degradation modelling and residual life prediction, the Wiener-based stochastic degradation modelling methodology [20] is used to estimate the residual life distribution of each PSST. In other words, we compare the accuracy of the residual life prediction using the extracted HI and the result using each individual degradation datum based on the same degradation modeling methodology.

**4.1. HI extraction**

**4.1.1. Degradation data selection**

The source entropies were calculated to describe the information contained in the degradation data sets. Set the logarithm in Eq. (2) to base 2, the source entropies of 15 spectral oil data in Tab. 1 are shown in Tab. 2. The base of the logarithm in the entropy may be changed in other applications.

The greater source entropy value of CM data contains more information, as illustrated in Section 3.2.1. Considering the results of source entropy in Tab. 2, Zn, Ca, Sn, Na, Al, Pb, Mg, P, and Si are discarded because the probability of this spectral oil data with a con-

Table 2. Source entropies of preliminary selected degradation data (unit: bits)

| Element | Zn   | Ca   | Cr   | Ni   | Sn   | Na   | Cu   | Al   |
|---------|------|------|------|------|------|------|------|------|
| Value   | 0.47 | 0.62 | 6.38 | 6.53 | 0    | 0.27 | 5.46 | 0.08 |
| Element | Mn   | Pb   | Mg   | Fe   | P    | Mo   | Si   | -    |
| Value   | 2.39 | 0.21 | 0.15 | 7.26 | 0.35 | 4.86 | 0.18 | -    |

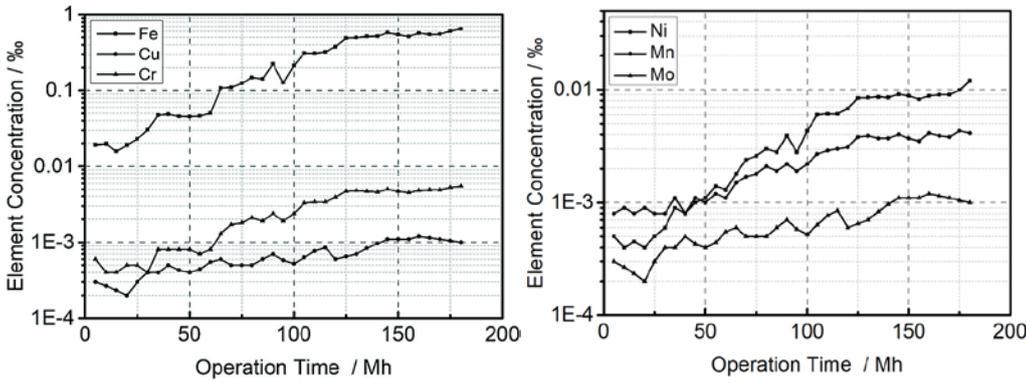


Fig. 4. Curves for degradation data

stant value is close to 1 and the result of the entropy of such spectral oil data is near 0, which means that the information it contained makes no sense. Based on this criterion, the other 6 (i.e.,  $N = 6$ ) spectral oil data are selected, namely, Cr, Ni, Cu, Mn, Fe and Mo. In addition, the corresponding diagonal elements of  $M$  are identified as  $[1, 1, 1, 1, 1, 1]$  based on the degradation trend. Note the value of the diagonal elements may be -1 in other cases, which refers to a decreasing trend. The selected 6 degradation data are shown in Fig. 4.

4.1.2. Weight coefficient allocation

Using the selected degradation data in Section 4.1.1, the  $2!$  permutation entropy values are calculated with Eq. (5), and the weight of each degradation dataset for data fusion is further calculated by Eq. (6), as shown in Tab. 3.

Table 3.  $2!$  Permutation entropies of degradation data (unit: bits)

| Element | Cr     | Ni     | Cu     | Mn     | Fe     | Mo     |
|---------|--------|--------|--------|--------|--------|--------|
| $H(2)$  | 0.7362 | 0.7869 | 0.9681 | 0.9975 | 0.5538 | 0.9826 |
| $w_i$   | 0.2776 | 0.2186 | 0.0327 | 0.0026 | 0.4577 | 0.0178 |

4.1.3. Data Fusion and HI Extraction

In the proposed HI extraction methodology, the weight coefficients of each degradation dataset reports are measured based on the  $2!$  permutation entropy, and at present, the selected multiple oil spectra can be fused with Eq. (1) for extracting a composite HI. The HIs at

Table 4. Health index of PSST

| $t_j / \text{Mh}$ | $x_j$ | $t_j / \text{Mh}$ | $x_j$ |
|-------------------|-------|-------------------|-------|
| 5                 | 0.092 | 160               | 0.838 |
| 10                | 0.229 | 165               | 0.852 |
| 15                | 0.221 | 170               | 0.868 |
| 20                | 0.226 | 175               | 0.882 |
| ...               | ...   | 180               | 0.906 |

each sampling times are shown in Tab. 4.

When the mechanical transmission is monitored based on the proposed method, we can assume that the machine failure will occur when the HI crosses a predetermined threshold  $\Delta$ . Therefore, in engineering practice, potential failure will be determined by comparing HI with the threshold  $\Delta$ . How to decide the value of  $\Delta$  is still an open issue.

4.2. Degradation modeling

4.2.1. Degradation model development

The Wiener process model has been widely used to model the degradation process due to its useful mathematical properties and clear concept [11,15]. Therefore, we assume that the degradation process is represented by the Wiener process, and the degradation model is given by:

$$X(t) = X(0) + \sigma B(t) + \theta t \quad (7)$$

where the degradation process  $\{X(t), t \geq 0\}$  is driven by standard Brown movement  $\{B(t), t \geq 0\}$ ;  $\sigma$  represents the diffusion coefficient;  $\theta$  represents the drift coefficient; and  $\sigma B(t) \sim N(0, \sigma^2 t)$  denotes the randomness and time-varying uncertainty of the degradation process.

4.2.2. Parameter estimation

Using the degradation data of training units, the value of parameter  $\sigma^2, \theta$  in the degradation model can be estimated using the MLE method to initialize the model defined in Eq. (7). The degradation data of the  $i$ th training unit at time  $t_j$  are denoted as  $x_{i,j}$ , and the entire dataset is  $\{X_i(t_j) = x_{i,j}, i = 1, \dots, N, j = 1, \dots, M\}$ . We further

denote the degradation model parameter vector as  $\Theta = (\sigma^2, \theta)'$ .

Then, the likelihood function  $\xi(\Theta|X)$  of all degradation data histories is expressed as:

$$\xi(\Theta|X) = -\frac{NM}{2} \ln(2\pi) - \frac{N}{2} \ln|\Omega| - \frac{1}{2} \sum_{i=1}^N (x_i - \theta t)' \Omega^{-1} (x_i - \theta t) \quad (8)$$

where  $x_i \sim N(u, \Omega) \sim N(\theta t, \sigma^2 Q)$ ,  $Q = \min\{t_i, t_j\}, 1 \leq i, j \leq M$ .

The maximum likelihood estimation of  $\sigma^2, \theta$  can easily be obtained by maximizing  $\xi(\Theta|X)$ . See article [23] for more details on the estimation steps of the MLE method. Tab. 5 illustrates the estimated  $\hat{\sigma}^2$  for all selected degradation data and the extracted HI. The extracted HI clearly fits the degradation process better than the original degradation data.

Recall that we recorded the actual residual life of 25 units. We denote the dataset of the last sampling times before failure in all training units for degradation data  $k$  as  $X_{m, k, n} = [X_{1, k, n_1}, \dots, X_{M, k, n_M}]$ . We denote the average and variance of the failure threshold for degradation data  $k$  as  $u_f^k$  and  $v_f^k$  respectively. Tab. 6 shows the  $v_f^k$  values for all selected degradation data and HI.  $v_f^k$  in the HI is less than

Table 5. Estimated  $\hat{\sigma}^2$  for each selected degradation data and HI

| Element          | Cr    | Ni    | Cu    | Mn    | Fe    | Mo    | HI     |
|------------------|-------|-------|-------|-------|-------|-------|--------|
| Value/ $10^{-3}$ | 2.737 | 3.723 | 2.477 | 3.245 | 2.262 | 4.238 | 0.6825 |

Table 6. Calculated  $v_f^k$  for Each Selected Degradation Data and HI

| Element          | Cr    | Ni    | Cu    | Mn    | Fe    | Mo    | HI     |
|------------------|-------|-------|-------|-------|-------|-------|--------|
| Value/ $10^{-3}$ | 1.255 | 2.148 | 1.042 | 1.883 | 0.858 | 1.977 | 0.3218 |

in any other selected type of degradation data. The extracted HI have little variation in the failure threshold between different unit, which can provide a reliable foundation for condition-base maintenance.

4.3. Prediction results

Since the degradation model parameters are obtained, the model is preferable for predicting the residual life of the testing units. Numerically, after initializing the degradation model with the estimated parameters, the degree of degradation of each unit is estimated using the original degradation data and the extracted HI.

The degree of degradation of a random testing unit is shown in Fig. 5. The first hit time of the HI is 180 Mh, which represents the PSST degradation failure period and provides a foundation for formulating the maintenance interval [16]. Next, the PDF of the predicted residual life is calculated at several monitoring times, which characterizes the uncertainty of the predicted residual life. The PDF curves are provided in Fig. 6.

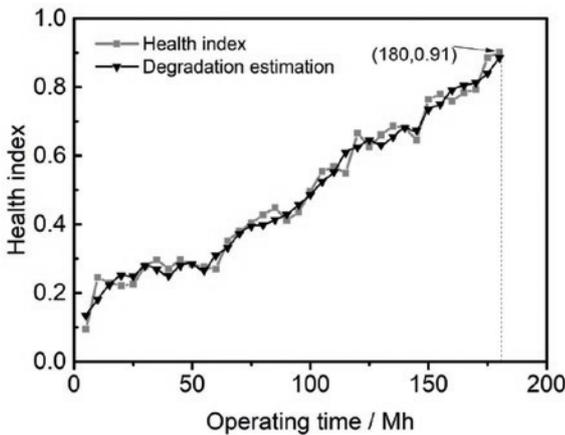


Fig. 5. Degradation estimation for unit #21

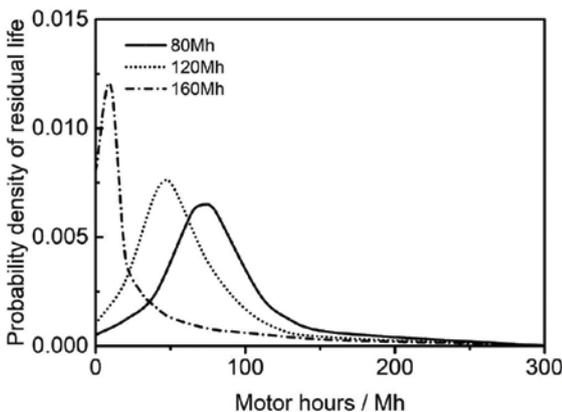


Fig. 6. Predicted PDF for unit #21

To evaluate the performance of the HI extraction methodology for degradation modeling and residual life prediction, the relative error between the predicted residual life and actual residual life is calculated. Two cases are considered for this comparison: 1. The predicted residual life based on the extracted HI and 2. The predicted residual life based on each selected type of degradation data. Specifically, the relative error,  $err_{i,k}$ , is defined as the relative difference between the predicted and actual residual life for unit  $i$  and degradation data  $k$  and is given by:

$$err_{i,k} = \frac{\hat{T}_{i,k} - T_i}{n_i t_s + T_i} \tag{9}$$

where  $T_i$  is the actual residual life for testing unit  $i$ ,  $\hat{T}_{i,k}$  is the predicted residual life for unit  $i$  and degradation data  $k$ ;  $n_i$  is the number of sampling epochs of unit  $i$  at the end of sampling and  $t_s$  is the sampling interval (i.e.,  $t_s = 5\text{Mh}$ ).

The absolute value of the relative error using each selected type of degradation data and the extracted HI at different quantiles of the actual useful life are compared in Fig. 7. The points corresponding to the “0” label are the percentage errors of all five testing units in the initial state, while points corresponding to the “20” label are the percentage errors equal to 20% actual sampling epochs.

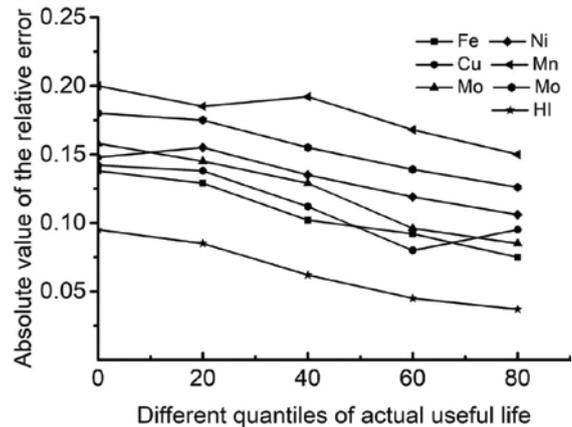


Fig. 7. Relative error between predicted and actual residual life

From Fig. 7, we observe the following: 1. Compared with each selected type of degradation data, the extracted HI provides the best prognostic result when used for degradation modeling and residual life prediction. 2. As the unit operates from the initial state to failure, the prediction using the extracted HI becomes increasingly accurate. 3. The relative error is less than 10% when the unit operates to half the actual lifetime, indicating that our HI extraction methodology is reliable. This useful characteristic of the HI has practical application, especially related to the reliability and safety of equipment.

In addition to the relative errors shown in Fig. 7, the engineers are often interested in comparing the root mean square error (RMSE) [24] of the predicted and actual residual life. A small RMSE value represents a better prediction of the residual life with less absolute error and results in a better condition-based maintenance strategy with lower stock costs. Tab. 7 summarizes the RMSE value for all selected degradation data and the HI. Based on Tab. 7, the HI extracted using our proposed methodology provides the smallest RMSE compared with using each type of degradation data. Thus, the extracted HI re-

Table 7. Comparison between the predicted and actual residual life using selected degradation data and HI

| Element | Cr  | Ni  | Cu  | Mn  | Fe   | Mo  | DI  |
|---------|-----|-----|-----|-----|------|-----|-----|
| RMSE/Mh | 8.4 | 9.5 | 9.7 | 8.4 | 12.7 | 8.6 | 3.0 |

Root mean square error (RMSE); Health index (HI).

sults in a more accurate prediction of the residual life, which provides a useful reference for the rational formulation of a condition-based maintenance strategy for integrated transmissions.

## 5. Discussion and conclusion

This paper developed a systematic methodology that includes data selection, weight coefficients allocation and data fusion procedures combining the multiple spectrometric diagnostic oil data obtained for samples from several mechanical transmissions to extract an HI that accurately characterizes the condition of transmissions. The novelty of this methodology is integrating multidimensional degradation data into a unified HI. Our developed methodology is advanced in that it selects the degradation data and allocating the weight coefficient based on information theory. Our developed method has two advantages compared with the existing individual spectrometric data-based degradation modelling approach: 1. The residual life prediction is more accurate, especially when the unit approaches failure. This

property can help determine when to stop operation and maintain the transmission. 2. The RMSE of the predicted and actual residual life can be reduced using the extracted HI for degradation modeling, indicating that the methodology is a more practical and efficient tool for the prognostic application of degradation systems.

The developed methodology was tested and validated using spectral oil data from several PSST. The Wiener-based stochastic degradation modeling methodology was adopted to evaluate the validity of the extracted HI by estimating the residual life of each PSST in time. The results show that the extracted HI outperforms each type of original spectral oil data.

The main contribution of this paper is to establish a new direction in the degradation modeling and residual life prediction of mechanical transmission by developing an HI via the fusion of multiple types of spectral oil data to enhance the accuracy of prognostic applications. There are several important directions for future research. First, more degradation data (e.g., ferrography) tailored to degradation modeling of mechanical transmission are necessary. Second, kernel methods that can fuse nonlinear degradation data should be investigated.

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