# Feature Selection Method for Gear Health Indicator Using MIC Ranking

Hongliang Song[1], Hongli Gao[2], Ruiyang Zhou[3], Jianing He[4],and Mengfan Chen[5]

[1,2,3,4,5]*Southwest Jiaotong University, Chengdu, Sichuan, 610000, China*

*cdsonghl@my.swjtu.edu.cn*
*hongli_gao@home.swjtu.edu.cn*
*bk2019111342@my.swjtu.edu.cn*
*hjn1102140379@163.com*
*chenmengfan1997@outlook.com*

## ABSTRACT

In the construction of health indicator for electromechanical equipment, selecting features that exhibit monotonicity, trend characteristics, and a strong correlation with equipment health is paramount to accurately reflect these indices. With the advent of numerous libraries and models for time-series data feature extraction, the range of potential features has expanded significantly. Despite this proliferation, there is a lack of extensive research on effective feature selection. This paper investigates the efficacy of the Maximum Information Coefficient (MIC) method in extracting features that align with the monotonicity and trend-related requirements of electromechanical equipment health indicator. Our experiments indicate that the MIC method adeptly identifies pertinent features for the construction of these indices, underlining its utility in the field of health monitoring for electromechanical systems.

## 1. INTRODUCTION

The construction of health indicator is essential for evaluating the current health status of engineering systems and their critical components, playing a pivotal role in inferring their Remaining Useful Life (RUL). The accuracy of RUL predictions hinges on the ability to develop health indicator that precisely reflect the condition of these components. Gears, for instance, are key elements in transmission systems. Damage to gears can lead to severe economic losses and potential personnel injuries. Therefore, accurately assessing their health status is crucial to prevent accidents caused by gear failures. This underlines the importance of reliable health indicator construction as a preventative measure against unforeseen mechanical breakdowns.

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E-mail addresses: hongli_gao@home.swjtu.edu.cn (H. Gao).

Currently, in the fault diagnosis and predictive analysis of gears, the application of vibration signals collected by accelerometers is the most widespread. Compared to other types of signals, such as temperature and pressure, vibration signals exhibit a higher sensitivity in detecting changes in gear health status [1]. The typical process for constructing health indicator, as illustrated in Figure 1, comprises four distinct stages: data acquisition, feature extraction, feature selection, and feature fusion, culminating in the construction of the health indicator. This structured approach ensures a comprehensive analysis, leveraging the sensitivity of vibration signals to accurately reflect the health status of the gears.

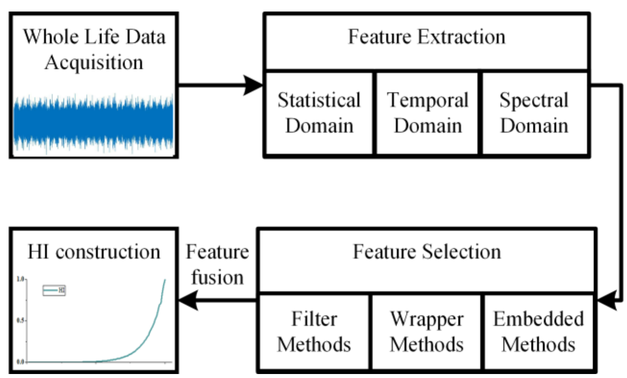


Figure 1. Typical Process for Health Indicator Construction.

In the construction of health indicator, feature extraction methods predominantly yield three types of features [2]-[3]. The first type, statistical domain features, are derived through statistical analysis to capture key characteristics of the data. They describe central tendencies, distribution ranges, and deviations in data shape. The second type, temporal domain features, focus on analyzing changes and dynamic properties in time series data. Finally, spectral domain features are identified through frequency analysis, uncovering periodic components and spectral distributions within the data. Techniques like Fourier transform and other spectral analysis methods are employed to extract frequency components, which are crucial for understanding oscillatory patterns and frequency-related characteristics in the data. These three feature types compress information carried by the original signal from different perspectives. In health indicator construction, they play pivotal roles, complementing and interrelating with each other to provide a robust feature foundation for a comprehensive assessment of health conditions.

In the context of constructing health indicator, three principal methods are employed for feature selection: filter methods, wrapper methods, and embedded methods [4]. Filter methods involve selecting features based on specific metrics, with the selection process operating independently of the health indicator construction algorithm. This approach prioritizes features based on their statistical properties. In contrast, wrapper methods iteratively utilize the algorithm to assess the impact of different feature sets on the performance of the health indicator. This process iteratively evaluates and selects features based on their contribution to the model's effectiveness. Finally, embedded methods integrate feature selection directly into the algorithm's internal structure. This approach leverages the intrinsic properties of the algorithm to optimize feature selection concurrently with model training, leading to a more cohesive and efficient feature selection process.

Filter methods operate independently of any health indicator construction algorithms. In the context of health indicator construction, filter methods generally rely on a single metric for feature evaluation or employ an average of 2-3 metrics to determine the ranking. Medjaher et al. [5] introduced a novel hybrid feature significance ranking metric in their feature evaluation, incorporating monotonicity, correlation, and robustness for Health Indicator selection. Sun et al. [6] proposed the TWM-U2PL, consisting of a teacher model and a student model. The teacher model includes two independent classifiers that assist in extracting and categorizing wear features. Hu et al. [7] presented a method using minimum Redundancy Maximum Relevance (mRMR) to measure the similarity between features and the correlation between features and categories, facilitating the selection of dimensionless indices. Anil Kumar et al. [8] extracted statistical features from time-domain, frequency-domain, and time-frequency domain signals. They identified important features by calculating feature scores based on the differences in feature values between nearest neighbor pairs of instances.

In the process of constructing health indicator, information theory has been applied to enhance the effectiveness of fault feature extraction and health indicator formulation. Akhand Rai et al. [9] utilized multiscale fuzzy entropy extracted from vibration signals as fault features. These multiscale fuzzy entropy feature vectors form probability distributions. The Jensen-Rényi divergence technique is then applied to differentiate the probability distributions of degraded and healthy multiscale entropy feature vectors, thereby establishing the desired health indicator. Sui et al. [10] proposed a bearing RUL prediction method using Mutual Information (MI) and Support Vector Regression (SVR) models to accurately assess the degradation state of mechanical equipment and comprehend bearing RUL information. Ekhi Zugasti et al. [11] introduced feature selection methodologies using Principal Component Analysis (PCA), Uniform Minimum Redundancy Maximum Relevance (UmRMR), and a combination of both, aimed at resolving the damage detection problem. These approaches demonstrate the value of information-theoretic techniques in creating more accurate and reliable health indicator for mechanical systems.

Selecting features based on criteria such as monotonicity and correlation poses a challenge in effectively gauging the relative importance of each metric. This paper introduces a feature selection method for health indicator utilizing the MIC ranking, which is adept at identifying features that encapsulate a comparatively higher quantity of degradation information. The structure of the remainder of this paper is as follows: Section 2 details the proposed MIC-based health indicator feature selection method. Section 3 describes the experimental setup and data acquisition process. Experimental results are presented in Section 4. Conclusions are drawn in Section 5.

## 2. METHODOLOGY

In the construction of health indicator, feature selection constitutes a crucial aspect. Given the plethora of feature extraction methods available, it is imperative to selectively identify features that accurately represent the state of degradation. Such features typically necessitate possessing two key attributes: monotonicity and correlation. These attributes are quantifiable and can be effectively measured using specific formulas, designated as Eq. (1) for monotonicity and Eq. (2) for trendiness, as detailed in the referenced literature [12].

Monotonicity primarily measures the trend of a feature, whether it is consistently increasing or decreasing. A feature with the higher monotonicity indicates the better degradation with an increasing/decreasing trend. The calculation of monotonicity is conducted as follows:

$$Mon(f_i) = \left| \frac{\#(\Delta f_i \geq 0)}{L-1} - \frac{\#(\Delta f_i < 0)}{L-1} \right| \tag{1}$$

where $Mon(f_i)$ is the monotonicity value for the $i^{th}$ feature $f_i$ with length of $L$. $\Delta f_i = f_{i+1} - f_i$ is the difference between consecutive elements. $\#(\Delta f_i \geq 0)$ represents the number of non-negative differences in the $f_i$ sequence. $\#(\Delta f_i < 0)$ represents the number of negative differences in the $f_i$ sequence.

Correlation as a metric primarily reflects the degree of correlation between a feature and the time of degradation. The formula for calculating correlation is as follows:

$$Corr(f_i, T_i) = \left| \frac{cov(f_i, T_i)}{\sigma_{fi} \cdot \sigma_{Ti}} \right| \tag{2}$$

where $cov$ is the covariance of $i^{th}$ feature $f_i$ with the time vector $T$,and $\sigma$ is the standard deviation.

An effective understanding of the concepts of monotonicity and correlation in feature analysis can be easily achieved by referring to Figure 2. This figure is divided into two parts: the left side depicts the behaviors of four distinct features, labeled F1 through F4, across their entire lifecycle. The right side, in contrast, illustrates the corresponding Monotonicity Score and Correlation Score for each of these features. By examining these graphical representations, one can clearly discern how different features exhibit varying levels of monotonicity and correlation over time.

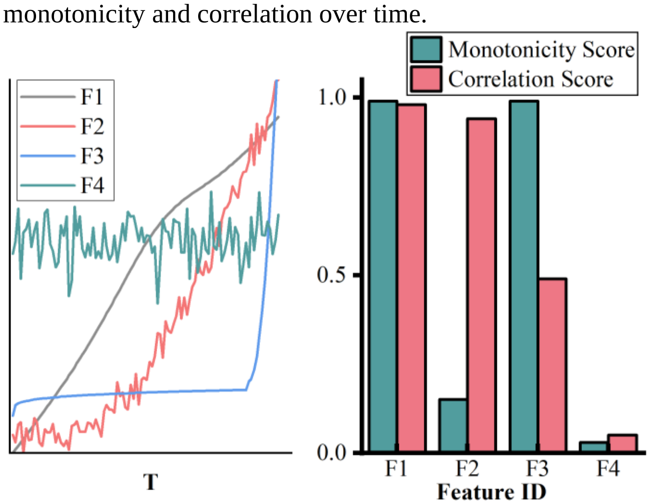


Figure 2. Four representative features. F1 represents high Monotonicity and high Correlation, F2 represents low Monotonicity and high Correlation, F3 represents high Monotonicity and low Correlation, and F4 represents Low Monotonicity and Low Correlation.

The feature selection method for gear health indicators with MIC proposed in this paper is able to complete the feature selection quickly and, at the same time, ensure the monotonicity and trend of the features to a certain extent.

### 2.1. Basic theory of The MIC

The calculation of the MIC [13] necessitates the computation of mutual information values between variables. Mutual information is a concept in information theory that quantifies the degree of mutual dependence between two random variables. It serves as a measure of the amount of information one variable contains about another. The greater the mutual information value, the stronger the interdependence between the two variables. When considering two random variables, $X$ and $Y$, their mutual information, denoted as $I(X,Y)$, is defined as follows:

$$I(X,Y) = \sum_{x\in X, y\in Y} p(x,y) \log \left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{3}$$

Where $p(x,y)$ represents the joint probability distribution of $X$ and $Y$, $p(x)$ and $p(y)$ denote the marginal probability distributions of $X$ and $Y$.

Unlike mutual information, the MIC demonstrates heightened sensitivity to a broader range of relationship types between variables. It is adept not only at identifying linear and non-linear functional relationships, such as exponential and periodic, but also at detecting non-functional relationships, including combinations or overlays of functional relationships. The aim of MIC is to provide a unified measure of similarity for various types of relationships. MIC builds upon the concept of mutual information. It operates by exploring all possible grid partitions of the data, seeking the partitioning that maximizes the mutual information. The value of MIC ranges between 0, indicating no relationship, and 1, signifying a perfect correlation. This range provides a clear and quantifiable indication of the strength and nature of the relationship between the variables. The MIC functions by calculating mutual information across a range of different grid partitions, with the objective of identifying the partition that maximizes this mutual information. Specifically, for a given dataset, the MIC algorithm evaluates various grid sizes and configurations. It systematically computes the mutual information for each of these configurations. The configuration that yields the highest mutual information is then selected, and its corresponding mutual information value is designated as the MIC value.

In a dataset comprising data points with two attributes, X and Y, these points are distributed within a two-dimensional space. To analyze these data, an $m \times n$ grid is utilized to partition this space. The frequency of data points falling within a specific row $x$ of the grid is used to estimate the marginal probability $p(x)$. Similarly, the frequency of data points in a particular column $y$ is used as an estimate for the marginal probability $p(y)$. Furthermore, the frequency of data points located within a specific cell $(x,y)$ of the grid provides an estimate for the joint probability $p(x,y)$.

$$p(x,y) = \frac{N(x,y)}{\sum_{i=1}^{m}\sum_{j=1}^{n} N(i,j)} \tag{4}$$

By altering the method and arrangement of the grid partitioning, a range of mutual information values can be generated. This variation is crucial in the process of calculating the MIC.

$$MIC(X,Y) = \max_{m*n\leq n^a} \frac{I(X,Y)}{\log_2 \min(m,n)} \tag{5}$$

Where $n$ represents the scale of the data. The value of the constant $a$ can be set based on experience or scale. The condition $m * n \leq n^a$ is to limit the size of the grid for the purpose of dividing regions. Dividing by $\log_2 \min(m,n)$

completes the normalization of data in different dimensions, ensuring that their values fall within the interval [0,1].

### 2.2. Features Selection in Health indicator Utilizing MIC Ranking

This paper primarily investigates feature extraction and selection from vibration signals. The features extracted in this study are listed in the accompanying table. For detailed explanations of each feature's significance and technical definitions, readers are referred to literature [2], as this paper focuses on the application rather than the detailed descriptions of these features. It is important to note that some features yield multiple output values. In such cases, each distinct output is assigned a unique Feature ID to facilitate clear identification and analysis.

Table 1. Feature List.

| ID | Statistical Domain Features | ID | Temporal Domain Features | ID | Spectral Domain Features |
|---|---|---|---|---|---|
| 1 | Absolute energy | 2 | Area under the curve | 9 | Fundamental frequency |
| 4 | Average power | 3 | Autocorrelation | 23 | Max power spectrum |
| 6-7 | ECDF Percentile | 5 | Centroid | 33 | Median frequency |
| 8 | Entropy | 24 | Maximum frequency | 39 | Power bandwidth |
| 10-19 | Histogram | 27 | Mean absolute diff | 43 | Spectral centroid |
| 20 | Interquartile range | 28 | Mean diff | 44 | Spectral decrease |
| 21 | Kurtosis | 31 | Median absolute diff | 45 | Spectral distance |
| 22 | Max | 32 | Median diff | 46 | Spectral entropy |
| 25 | Mean | 35 | Negative turning points | 47 | Spectral kurtosis |
| 26 | Mean absolute deviation | 36 | Neighbourhood peaks | 48 | Spectral positive turning points |
| 29 | Median | 38 | Positive turning points | 49 | Spectral skewness |
| 30 | Median absolute deviation | 41 | Signal distance | 50 | Spectral slope |
| 34 | Min | 54 | Sum absolute diff | 51 | Spectral spread |
| 37 | Peak to peak distance | 56 | Zero crossing rate | 52 | Spectral variation |
| 40 | Root mean square | | | | |
| 42 | Skewness | | | | |
| 53 | Standard deviation | | | | |
| 55 | Variance | | | | |

In the context of feature selection for health indicators, it is necessary to first construct a progressively growing sample sequence $\boldsymbol{T} = [1, 2, \ldots, N]$ based on the sampling interval. The feature set composed of features in TABLE I is denoted as $\boldsymbol{F} = \{\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots, \boldsymbol{F_L}\}$ . The pseudocode for feature selection is as follows:

Table 2. Based on MIC Health Indicator Feature Selection.

*Input:* $\boldsymbol{T}, \boldsymbol{F}$
*output:* $\boldsymbol{F}$ *are sorted by MIC*

for each feature $\boldsymbol{F_i} \in \boldsymbol{F}$ do
  MIC of $\boldsymbol{F_i}$ = **0**
  for $(m, n)$ such that $m * n \leq n^a$ do
    Divide $\boldsymbol{T}, \boldsymbol{F_i}$ according to $m, n$ to form a grid $G$
    Calculate the mutual information $I(\boldsymbol{F_i}, \boldsymbol{T})$ of $\boldsymbol{F_i}$ and $\boldsymbol{T}$ on grid $G$
    Normalized mutual information
    if Normalized mutual information> MIC of $\boldsymbol{F_i}$
      MIC of $\boldsymbol{F_i}$ = Normalized mutual information
  Add MIC of $\boldsymbol{F_i}$ in MIC list
Sort $\boldsymbol{F_i}$ in $\boldsymbol{F}$ by MIC list

The two principal characteristics of the MIC offer significant advantages in the context of feature selection for health indicator.

**Generality**: The MIC demonstrates a high degree of applicability across a wide array of relationship types, encompassing linear, non-linear, monotonic, and non-monotonic associations. This Generality enables the selection of features that are representative of diverse functional relationships, thereby facilitating more effective feature fusion in reflecting health indicator.

**Equitability**: MIC exhibits a relatively consistent sensitivity across different types of relationships. This means that whether the relationship between variables is linear, curvilinear, or follows other complex patterns, MIC can identify it with similar efficacy, provided the relationship is sufficiently strong. Consequently, MIC is capable of selecting features that are most relevant and informative, enhancing the accuracy and reliability of the resulting health indicator.

## 3. EXPERIMENTAL PROCEDURE

In this study, the experimental data set was collected through accelerated degradation tests conducted on gears. The experimental platform consisted of a two-stage parallel-axis gearbox. The torque applied to the gearbox was generated by a load motor attached to the output end. An accelerometer was mounted at the output cover to capture vibration signals along the Z-axis of the gearbox. The data collection was conducted with a high sampling frequency of 12,800 Hz, ensuring detailed capture of the vibration characteristics. The input frequency to the gearbox was set at 40 Hz. The platform for accelerated degradation tests conducted on gears is shown in Figure 3. The position relationship of each transmission gear in the gearbox is shown in Figure 4.

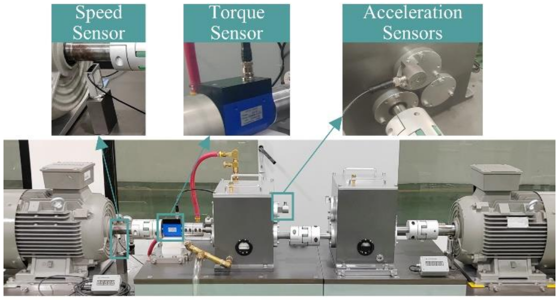


Figure 3. Experimental Platform.

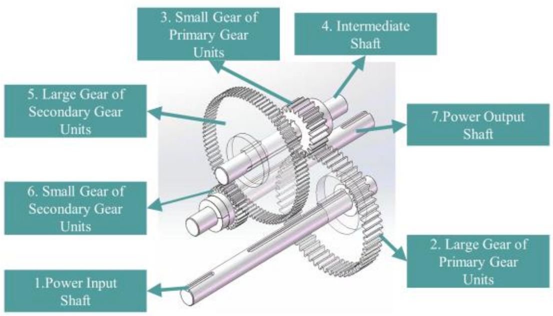


Figure 4. Position Relationship of Each Transmission Gear in the Gearbox

For detailed specifications of the basic gear parameters, readers are directed to Table 3. Additionally, the data set encompasses real-life operational data of gearboxes throughout their entire lifecycle, recorded under three different load conditions. For a more comprehensive understanding of these data sets, including the specific conditions and parameters, please refer to Table 4.

Table 3. Gearbox Parameters.

| Parameters | Primary Gear Units | Secondary Gear Units |
|---|---|---|
| Number of small gear teeth | 29 | 36 |
| Number of large gear teeth | 95 | 90 |
| Pinion tooth width/mm | 15 | 15 |
| Large gear tooth width/mm | 15 | 15 |
| Modulus/mm | 1.5 | 1.5 |
| Pressure angle/° | 20 | 20 |

Table 4. Experimental Data Set.

| Gear ID | torque load | Total Working Hours (H) | Sample Size |
|---|---|---|---|
| $G\_1$ | 50% | 110 | 3303 |
| $G\_2$ | 60% | 102 | 3079 |
| $G\_3$ | 70% | 34 | 1022 |

Figure 5 provides a graphical representation of the vibration signals from the tested gearbox, labeled G_1, over its entire lifecycle. The temporal progression of these signals is distinctly illustrated, with noticeable variations becoming evident as time progresses. This variation in the vibration signals is indicative of changes in the gearbox's condition, suggesting a correlation with the performance degradation of the gear.

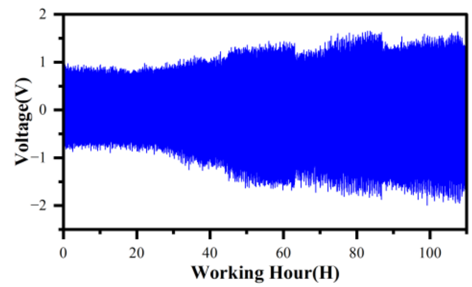


Figure 5. The Z-axis Vibration Signals Over Entire Lifecycle of G_1.

## 4. RESULT AND DISCUSSION

The study involved extracting a comprehensive set of 56 features from the full lifecycle experimental data of three distinct gear sets. Following the extraction, the feature selection process, as detailed in Section 2.2 of this document, utilized the MIC algorithm. This algorithm was applied to each feature to calculate its MIC value, assessing the strength of the relationship between the feature and the gear's health status. Subsequently, the features were sorted based on the average MIC values computed across the three gear sets, providing a comparative view of their significance. The results of this feature selection and sorting process are illustrated in the Figure 6, offering insights into the relative importance of the various features in the context of gear health monitoring.

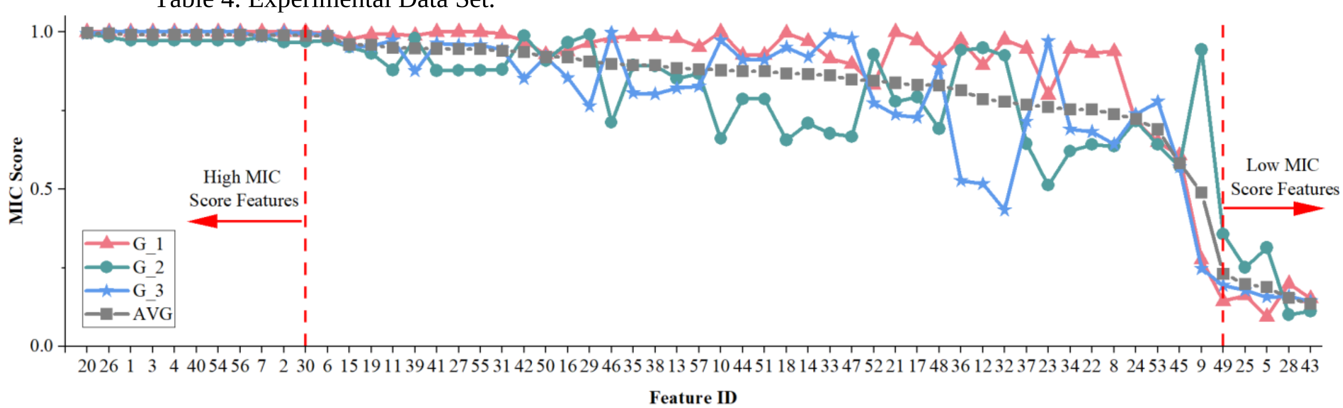


Figure 6. MIC Values for 56 Features of Three Gears.

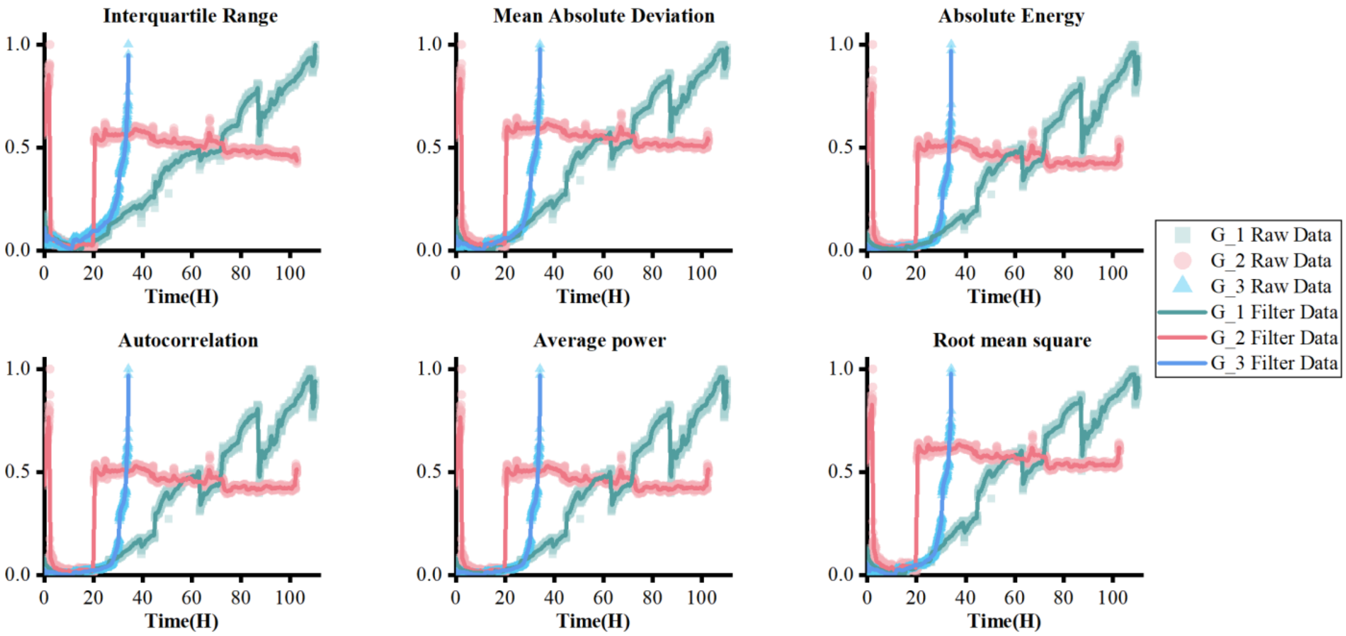


Figure 7. Lifecycle Curves of the Top Six Features Ranked by MIC Score.

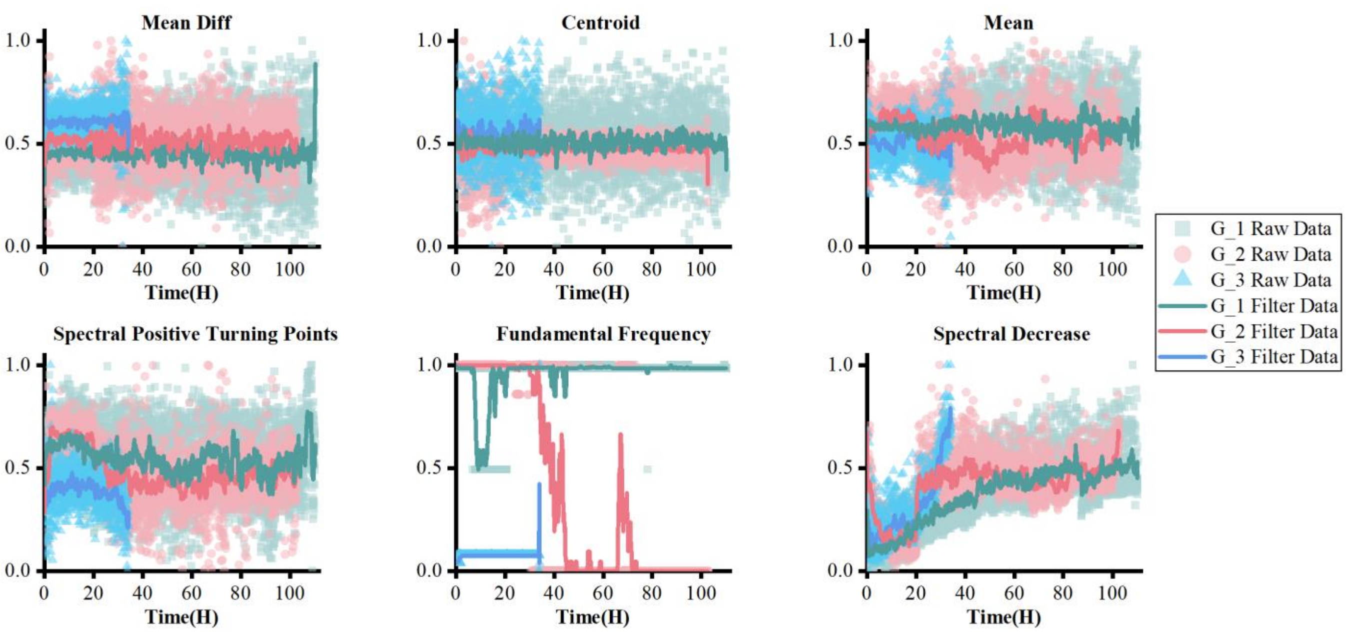


Figure 8. Lifecycle Curves of Features Ranked in the Bottom Six by MIC Score

It is observed that some features exhibit MIC Scores nearing 1 in Figure 6, indicating a significant non-linear relationship between these features and the equipment's degree of degradation. To analyze this further, the features with the top six and bottom six MIC Scores were normalized and their lifecycle variation curves were plotted in Figure 7 and Figure 8. The analysis reveals that the features ranked in the top six display pronounced trendiness and a certain degree of monotonicity, suggesting a strong correlation with the equipment's degradation process. Conversely, the features ranked in the bottom six show little to no discernible trend or pattern. This contrast underscores the efficacy of MIC Scores in distinguishing features that are strongly indicative of equipment health from those that are less informative.

Utilizing Eq. (1) and (2), the monotonicity and trendiness indices of the features were calculated. The analysis revealed a discernible positive correlation between the MIC values and these indices in Figure 9. Specifically, it was observed that features with higher MIC values tend to exhibit more pronounced monotonicity and trendiness. Conversely, features with lower MIC values generally show weaker performance in these aspects. This correlation indicates that the MIC can be a reliable indicator of a feature's relevance, particularly in terms of its monotonic and trend-based behavior, which are critical attributes in assessing the health and degradation of equipment.

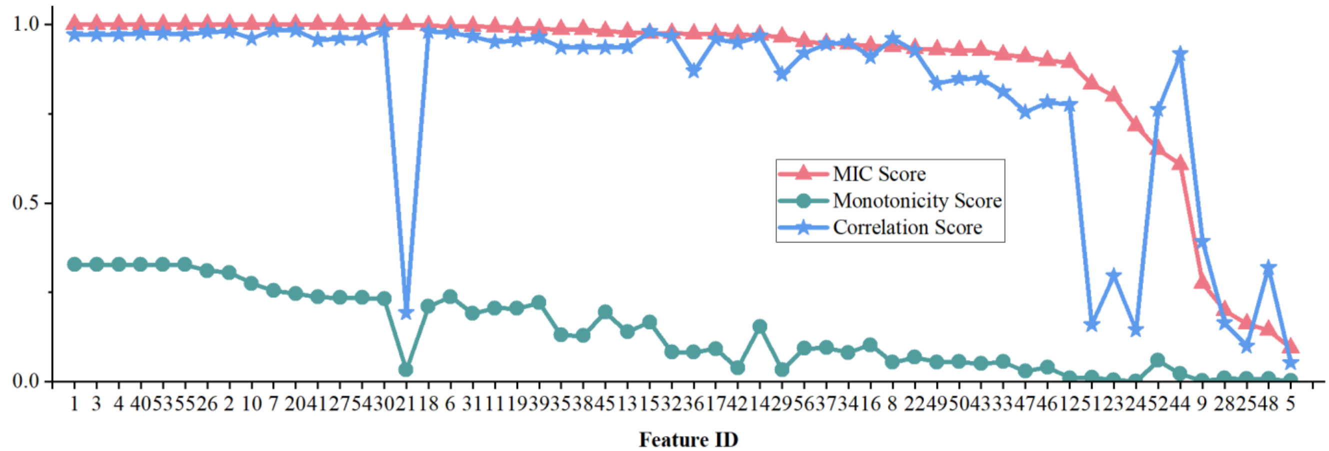


Figure 9. MIC Score, Monotonicity Score and Correlation Score.

## 5. CONCLUSION

The application of the MIC algorithm in this study has proven to be highly effective in selecting features that correlate closely with gear health. This approach ensures that the resultant health indicator exhibit enhanced monotonicity and trendiness, thereby providing a more accurate reflection of the gear's condition. Notably, MIC also effectively compensates for the shortcomings of mutual information by offering a more comprehensive quantification of the correlation between features and equipment health.

However, it is important to acknowledge a key limitation of the MIC algorithm: its reliance on large datasets for meaningful computation. The efficacy of MIC is significantly reduced when applied to smaller datasets. Recognizing this constraint, future research efforts will focus on modifying and improving the algorithm to better suit applications involving smaller data samples. Such advancements will broaden the applicability of this method, allowing for more versatile and reliable gear health assessments across a wider range of data scenarios.

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## BIOGRAPHIES

**Hongliang Song** obtained M.S. degree in Mechanical and Electronic Engineering from Southwest Jiaotong University, located in Chengdu, Sichuan, China, in 2020. He is currently pursuing Ph.D. in the same department at Southwest Jiaotong University. Throughout his academic journey, he has been deeply involved in research related to the fault diagnosis and intelligent maintenance technology of electromechanical equipment.

**Hongli Gao** received the Ph. D degree in mechanical engineering from Southwest Jiaotong University, Sichuan, P. R. China in 2005.

He is currently a Professor at Southwest Jiaotong University. His research interests focus on designing and the reliability analysis of complex electromechanical equipment.

**Zhou Ruiyang** obtained B.S. degree in Mechanical Design, Manufacturing and Automation from Southwest Jiaotong University, located in Chengdu, Sichuan, China, in 2023. He is currently pursuing M.S. degree in the Department of Mechanical and Electronic Engineering at Southwest Jiaotong University. He is actively involved in research related to the fault diagnosis and intelligent maintenance technology of electromechanical equipment.

**Jianing He** earned his B.S. degree in Mechanical Design, Manufacturing and Automation from Southwest Jiaotong University, situated in Chengdu, Sichuan, China in 2023. He is now advancing his studies by pursuing an M.S. degree in the Department of Mechanical and Electronic Engineering at the same university. His main area of research is centered around the fault diagnosis and intelligent maintenance technology of electromechanical equipment.

**Mengfan Chen** obtained a Bachelor's degree in Industrial Engineering from the School of Mechanical Engineering at Southwest Jiaotong University in Chengdu, Sichuan, China, in 2019. Throughout his academic journey, he has been deeply involved in research related to the intelligent monitoring and diagnosis of equipment states, as well as the development of industrial software testing.