A New Approach for Detection of Gear Defects using a Discrete Wavelet Transform and Fast Empirical Mode Decomposition

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Summary

During the past decades, detection of gear defects remains as a major problem, especially when the gears are subject to non-stationary phenomena. The idea of this paper is to mixture a multilevel wavelet transform with a fast EMD decomposition in order to early detect gear defects. The sensitivity of a kurtosis is used as an indicator of gears defect burn. When the gear is damaged, the appearance of a crack on the gear tooth disrupts the signal. This is due to the presence of periodic pulses. Nevertheless, the existence of background noise induced by the random excitation can have an impact on the values of these temporal indicators. The denoising of these signals by multilevel wavelet transform improves the sensitivity of these indicators and increases the reliability of the investigation.
Finally, a defect diagnosis result can be obtained after the fast transformation of the EMD. The proposed approach consists in applying a multi-resolution wavelet analysis with variable decomposition levels related to the severity of gear faults, then a fast EMD is used to early detect faults. The proposed mixed methods are evaluated on vibratory signals from the test bench, CETIM. The obtained results have shown the occurrence of a teeth defect on gear on the 5th and 8th day. This result agrees with the report of the appraisal made on this gear system.
Keywords:
Signal vibration, Discrete Wavelet, Fast-EMD, Kurtosis

1. Introduction

A complex electromechanical system containing in rotating machine degrades slowly and can cause emergency shutdown and even equipment breakdown or casualties. Therefore, we need a robust, efficient, and accurate fault diagnosis technique that not only detects a fault after its occurrence, but also predicts an upcoming fault. In recent years, the analysis of vibration signals based on time-frequency analysis of mechanical vibration signals has become a more efficient and successful technique. Many methods have been developed, but Empirical mode decomposition (EMD) has been proven to be an interesting alternative to deal with non-stationary and nonlinear signals such as vibration signals. The EMD approach has been widely studied and applied in several fields, such as process control [5] [6], modeling [7] [8] [9], surface engineering [3], medicine [4], voice recognition [12] and system identification [13] [14].

The concept of the process is to break down the signal into its Intrinsic Mode Functions (IMF) and find the time-frequency distribution which is known as Hilbert–Huang Transform (HHT) [2]. IMF indicates the natural oscillatory mode integrated into the processed signals, which are determined by the signal itself.
Therefore, it is a self-adaptive signal processing technique, able to separate stationary from non-stationary stations. On the other hand, giving the length, complexity of the signals proved by [17], by the application of the EMD / EEMD method, [18] proposed an AMD-EEMD-based method for the diagnosis of rotating machinery failures. [19] proposed Adaptive Fast EEMD (AFEEMD) method associated with the CEEMD for the treatment of EMD problems [1]. [2] A method based on succinct and fast empirical mode to check its efficiency in the diagnosis of failure for rotating machines [2].

Emerging fault detection is considered as a hard task because its characteristics are often very low and hidden by the noise introduced in the signals by various disturbances. This noise produces an effect of a mask that makes the process of fault detection more difficult.
In this paper, the main contribution of our approach is to mixture a multilevel wavelet transforms with a fast EMD decomposition in order to early detect gear defects and extract components related to defects that exist throughout the frequency range of vibration signals. In the proposed method, it is necessary to minimize the noise from the recording tape. However, vibration signals are usually composed of several components, e.g., components related to failures, background noise and interference from other normal parts of the machine. Therefore, it is important to remove the noise and interference components from the raw vibration signals to improve the quality of the extracted impulse shocks. It is known that the EMD method can break a signal down into some self-adapted mono-components, and these mono-components are almost orthogonal according to [22, 23]. Therefore, components related to failures,

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background noise, interference, etc., can be decomposed and treated

Finally, the principal effectiveness of our approach is experimentally confirmed by applying it to the simulation experiment. And then, the practical effectiveness of the proposed method is experimentally confirmed by applying it to the test bench CETIM.

2. Theory Part

2.1. Discrete Wavelet

The first step is to implement noise reduction algorithms to reduce the noise vibratory signals coming from the CETIM bandwidth. The choice of the wavelet denoising method has been extensively researched. This approach is simple and effective in studies related to vibration signals. In this approach, the discrete wavelet transform (DWT) of a signal is calculated, and the resulted wavelet coefficients pass through a test threshold [20].

The discrete wavelet transform (DWT) is derived from the discretization of the continuous wavelet transform CWT given by:

$$\mathrm{DWT}(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} s(t)\ \psi\left(\frac{t-2^j k}{2j}\right) \tag{1}$$

where Ψ denotes the mother wavelet, 2^j and $2^j k$ replaces the scale index and the time shifting of CWT. DWT consisted of decomposing the original signal s(t) into several under-signals of various scales with a pair of filters, namely, low pass filter (LPF) and high pass filter (HPF), and its cutoff frequency is the middle of input signal frequency [12]. From these two vectors, we obtain:

1. The detail coefficients (D1) corresponding to the high frequencies.
2. The approximation coefficients (A1) correspond to the low frequencies.

After the first level, only the approximation coefficients is consequently divided into new approximation and detailed coefficients. During decomposition, the signal S(t) and vectors (Aj) underwent down sampling. The decomposition process is called the wavelet decomposition tree that is shown in Fig. 1.

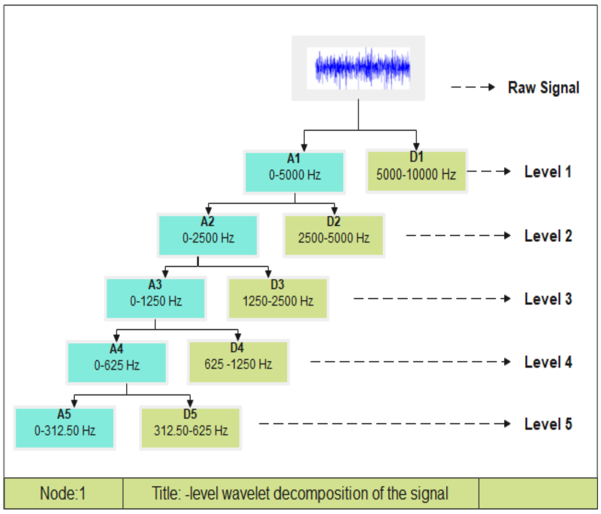


Fig. 1: Five-level wavelet decomposition of the signal related to a meshing frequency

The process after decomposition or analysis is called synthesis where we reconstruct the signal s from the wavelet coefficients. It can be described by Equations (2) and (3) given as follows:

$$cA_{j-1} = cA_j + cD_j \tag{2}$$

$$s = cA_j + \sum_{i \le j} cD_i \tag{3}$$

Where (cA_j) are approximations, (cD_j) are details. i and j are positive integers. In reconstruction, components can be assembled back into the original signal without loss of information.

2.2. Fast Intrinsic Mode Functions Fast-EMD

The Fast-EMD method which is based on EMD differs from the classic EMD basically in the steps of estimating the envelopes and limiting the number of iterations of each IMF to be one, for thus we called it Fast-EMD. In the proposed method, the extreme is considered as the local maximum (or minimum) only when it is located at the middle of a local window, which is named “median extreme” [1]. Interpolation methods have been proposed to create the upper and lower envelopes in the EMD; however, in Fast EMD spatial domain sliding order-statistics filters (OSF) are applied. The upper and lower envelopes, obtained by using OSF, make the method used in this work independently of a stander deviation (SD) value used in classical EMD. Because in the shifting process, each mode is extracted based on the window width of OSF, components that are smaller than the filter window will be extracted from the original signal, and components that are larger than the filter widow will remain for the next.

Algorithm of Fast-EMD:

Step 1 Identify all the local extrema in the signal. Connect all the local maxima by a cubic spline line as the upper envelope

Step 2 For each local maximum (minimum) point in Pi (Qi), the Euclidean distance to the nearest other local maximum (minimum) point is stored in an array dmax(dmin);

$$d1 = \min \{\min (dmax), \min (dmin)\} \quad (4)$$

$$d2 = \max \{\max (dmax), \max (dmin)\} \quad (5)$$

Step 3 Select window size of OSF and then obtain the upper envelope UE and lower envelope LE using OSF;

$$UE = MAX\{Pi(s)\} \quad (6)$$

$$LE = MIN\{Qi(s)\} \quad (7)$$

Step 4 Calculate mean of the upper and lower envelopes

$$Eav(x) = \frac{UE(s)+LE(s)}{2} \quad (8)$$

Step 5 Subtract the mean envelope from the signal Sd(t) and obtain FIMF.

$$Fy = yd - EAV \quad (9)$$

Step 6 Extract ,Fast IMF
if Fy1(t) satisfies the requirements of an IMF, set the first IMF as c1 (t) = Fyy1 (t). Otherwise, let y1 (t) be the raw signal, and repeat step 1 to step 2. It is noted that an IMF is defined as a function that satisfies the following requirements:

(i) In the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one;

(ii) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

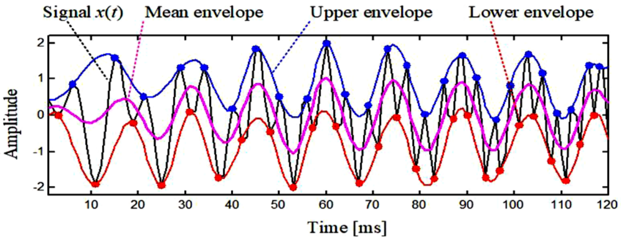


Fig. 2: Schematic plot upper and lower envelopes.

2.3. Proposed method

The objective of this work is to early detect gear faults from a vibratory signal. For this purpose, we applied a discrete wavelet threshold algorithm with a variable decomposition level N. Indeed, noise in the vibratory signal varies with the presence or not of the fault, and to early detect it, we propose to denoise signal before. The signal noise ratio SNR is calculated in each windowed vibratory signal and a wavelet decomposition level is determined. Then we used Fast-EMD method based on Fast Empirical Mode Decomposition to detect a gear fault. The detailed fault diagnosis procedure based on the proposed method is shown in Fig. 3.

The raw vibration signal is first acquired from the machinery. Then, the DWT and the fast EMD method is applied to decompose the raw vibration signal into n IMFs, denoted as c1, c2,..,cn. Selecting the most dominant IMFs with an energy rank. This is based on the hypothesis that vibrations produced by impacts have higher energy.

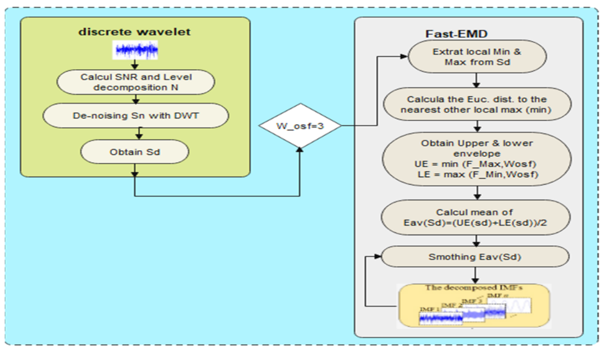


Fig. 3: Algorithm of the proposed method

3. Experimental validation

The vibration signals used in this work were carried out at CETIM, France. The CETIM test bench is a gearbox composed of 20 tooth gear and a wheel of 21 teeth. The rotational speed of the shaft is 1000 rpm or about 16.67 Hz. The rotation frequency of the wheel is equal to 15.87 Hz. The meshing frequency is about 330 Hz. The sampling frequency is 20 kHz. Each recording has 60,000 samples. The experiment lasted 12 days from a good working state of the gearbox to a deteriorating state. The operating conditions (speed, torque) have been set to obtain a flaking along the length of a tooth [15] [18]. This test band has been studied by other researchers [24, 25, 26, 27]. They have used new signal processing techniques.

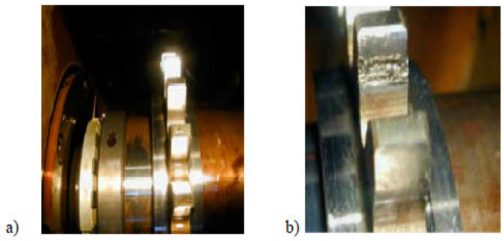


Fig. 4: Photos of a CETIM bench wheel a) without defect, b) with defect [17].

Table 1: Expert report

Days	Observation	Days	Observation
1	No anomaly	**7**	No evolution on tooth 1/2
2	No anomaly	**8**	Spalling on tooth 15/16
3	No anomaly	**9**	Evolution on tooth 15/16
4	No anomaly	**10**	Evolution on tooth 15/16
5	No anomaly	**11**	Evolution on tooth 15/16
6	Spalling on tooth 1/2	**12**	Spalling on entire tooth 15/16

A multi-resolution wavelet analysis explores the signal at different resolution levels and analyses it scale by scale like a digital zoom. The wavelet level decomposition N varies with noise in the gear signal. Regarding the expert report (table 1), and Fig.4 a spelling on tooth ½ and 15/16 appears on day 6 and 8. We choose N=5 for recording in the days (1, 2, 3, 4, and 5) to get noise generated by a possible occurrence of a fault in gear and N=3 for the rest recording signals.

3.1. Condition indicators

To display the difference between the raw signals and the de-noised signals, the DWT and the Fast-IMF methods are used. The Kurtosis index (Ku) is an indicator used for the detection of the impulses; it's widely used for detection and diagnosis of faults in rotating machines.

Kurtosis This is the first order normalized moment of a given signal and provides a measure of the apogee of the signal, i.e. the number and amplitude of the peaks present in the signal [14]. It is given by:

$$K = \frac{N\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left(\sum_{i=1}^{N}(x_i - \bar{x})^2\right)^2} \quad (8)$$

3.2. Simulation and result

Fig.5 and Fig.6 represents the temporal and frequency representation of a vibratory signal, the early defect detection is not possible. That the defect in gears cannot be detected before the 11th day because the features are often extremely weak and masked by the noise. For this, wavelet threshold algorithm was applied. Fig.5 is a temporal representation of a vibratory signal in day 1, 6, 8, 10 and 12; we can see a fault only from a day 10 and become more in day 12.

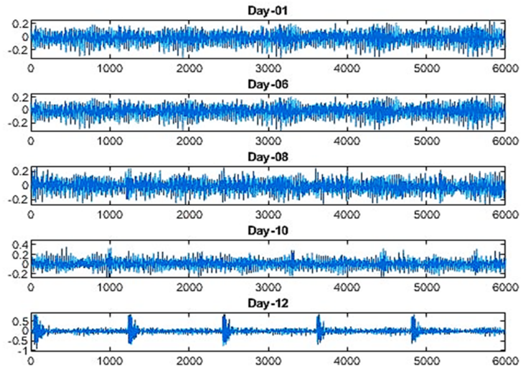


Fig. 5-a: temporal representation of vibratory signals of the 1nd day, 6th day, 8th day, 10th day and 12th day.

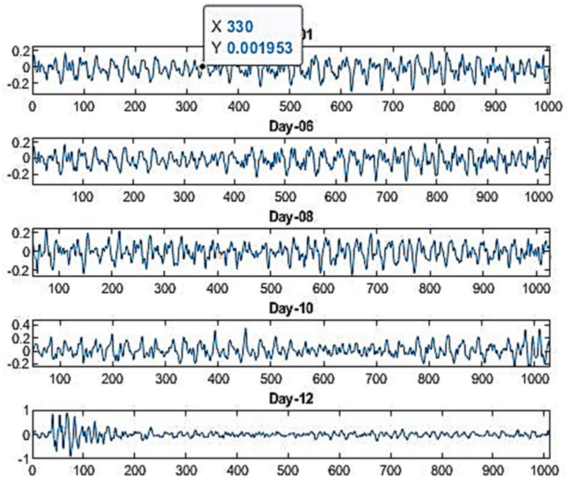
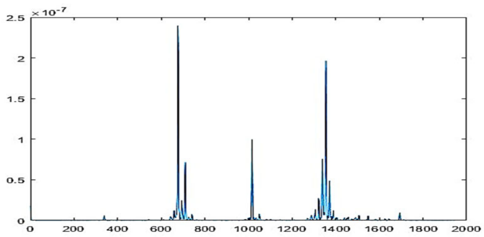
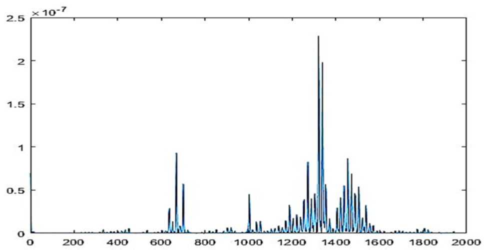


Fig. 5-b zoom meshing frequency of a vibratory signal



(a)



(b)

Fig.6: Spectral representation of vibratory signals
(a): Raw signal (b) : Defect signal

From the curves (Fast-EMD) and (K-mix mode) of (Fig.7), we can see three analyses phases. The first starts from the 1st day and ends on the 5th day, which is the faultless stage. From the 6th day to the 11th day is the second stage. At this stage, the kurtosis coefficient increases begin from the 6th day at a rate of 1.2 with Fast-EMD and 1.8 with a mixed-mode, which means that a defect is burning. Ku coefficients increase with the two methods, and this means that the defect is increasing. However, from the 8th day, a second fault emerges, and it's more observable with Ku evolution using wavelet de-noising

To display the difference between the raw signals and the de-noised signals using Fast EMD and DWT method and as the Kurtosis (Ku) is an indicator used for the detection of the impulses, the kurtosis Values were calculated from day 1 to day 12 (table 2), for the raw signals and our method.

Table.2: kurtosis result proposed method

Days	Raw signal	DWT	Mixing mode
01	2.6557	9.7893	4.69
02	2.6380	4.7713	4.85
03	2.8504	5.6106	4.67
04	2.8597	5.7813	3.9
05	2.9547	6.0235	5.25
06	2.9029	13.3594	6.42
07	2.9966	4.0506	4.39
08	2.9228	7.0501	5.10
09	2.9962	8.0495	6.90
10	3.0175	13.1602	7.48
11	13.5869	28.5208	9.58
12	13.9180	29.6379	10.02

4. Results And Discussion

Fig.7 presents the evolution of kurtosis value as a function of the acquisition day for vibratory signal: without treatment (k-Raw signal), by applying Fast-EMD without denoising and after wavelet denoising (K-mix mode). By analyzing the evolution of kurtosis as a function of the days, we note that for the signals without treatment, the curve presents two phases.

A constant phase extends from the 1st day to the 10th day and a fast-increasing phase which indicates the presence of one or more faults. Looking at the experts' report, we can say that on the 10th day the two faults are already well installed [16]. From the curves (Fast-EMD) and (K-mix mode), we can see three analyses phases. The first starts from the 1st day and ends on the 5th day, which is the faultless stage. From the 6th day to the 11th day is the second stage. At this stage, the kurtosis coefficient increases begin from the 6th day at a rate of 1.2 with Fast-EMD and 1.8 with a mixed-mode, which means that a defect is burning .Ku coefficients increase with the two methods, and this means that the defect is increasing. However, from the 8th day, a second fault emerges, and it's more observable with Ku evolution using wavelet de-noising. By using a denoising signal with a wavelet threshold as an input signal to a Fast-EMD system, we can detect very easily the emergence of the two defects. Indeed, when several faults occur, they can interact with each other, cause vibration, and complicate the feature extraction. By applying the orthogonal wavelet transform, the energy of a useful signal is compressed to a relatively small number of big coefficients, while the energy of the noise is dispersed throughout the transform with small coefficients. Threshold keeps the approximation coefficients unchanged because they represent the useful signal. However, the small coefficients of the details are considered as noise and will be eliminated. We can say that the second stage is related to the occurrence of faults. The last stage is related to the critical state of chipping of the teeth.

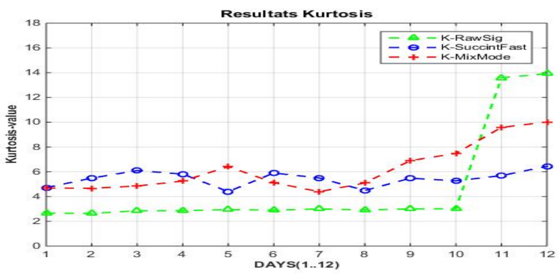


Fig. 7: Kurtosis values variation proposed method
(Green_line: raw signal, Blue_line: fast EMD, Red_line: DWT+FAST EMD)

The figures (8,9,10) give a graphical representation of the IMFs of the Fast EMD decomposition of the signals recorded on day 5, day 8, day 11, . For each signal 12 IMFs were obtained. But only the first 8 IMFs were taken into consideration, the other IMFs were added to the residue.

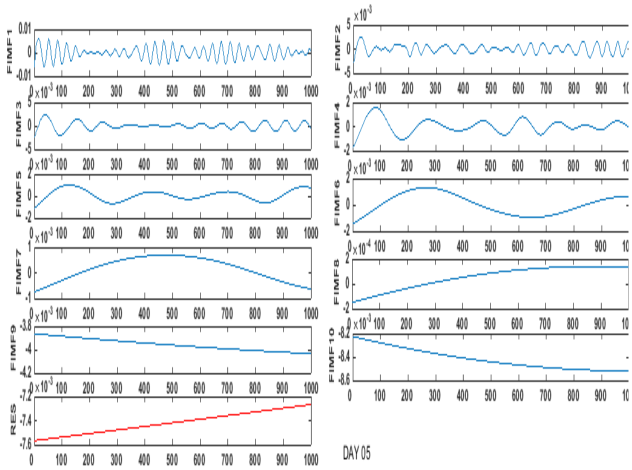


Fig. 8: Proposed method of the signals of the 5th day

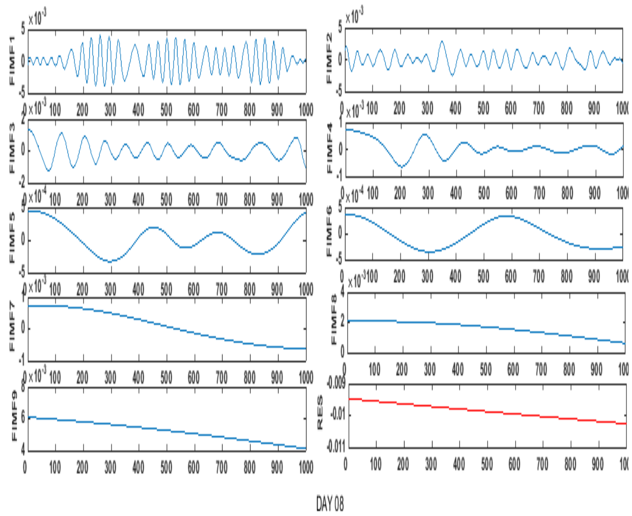


Fig. 9: Proposed method of the signals of the 8th day

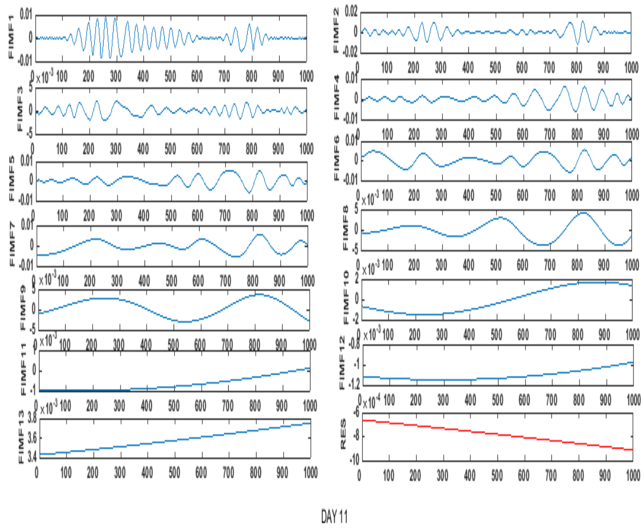


Fig. 10: Proposed method of the signals of the 11th day

5. Conclusion

The main contribution of this paper is to mixture a multilevel wavelet transforms with a fast EMD decomposition in aim to early detect gear defects,
The results presented in this study demonstrated that the combination of Fast-EMD and DWT methods based on denoising can be used to identify early damage in gearboxes. It’s notable, that the appropriate choice of the conservation parameters in the post-treatment phase is significantly important. The numerical results prove that the mixed method can increase the precision of results given by the Fast-EMD.

Finally, a defect diagnosis result can be obtained after the rapid transformation of the EMD. The method and two commonly used methods are applied to the failure diagnostic of a CETIM test strip with a gear scaling defect. The results show that the proposed method effectively detects gear defects and achieves better results than other methods. Our results showed the occurrence of a teeth defect on gear on the 5th and 8th day. This result agrees with the report of the appraisal made on this gear system

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