CHEMICAL ENGINEERING TRANSACTIONS
VOL. 33, 2013
Guest Editors: Enrico Zio, Piero Baraldi

ISBN 978-88-95608-24-2; **ISSN** 1974-9791
A publication of
AIDIC
The Italian Association
of Chemical Engineering
Online at: www.aidic.it/cet
DOI: 10.3303/CET1333172

Features for Fault Diagnosis and Prognosis of Gearbox

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Good features are critical for both fault diagnosis and prognosis of gearbox. Most traditional features are effective only when the gearbox is under stationary operating condition. Some features which are modified based on the traditional features are no longer sensitive to load changes and remain sensitive to fault propagation. However, it is only permit the load changing in a very small range. In engineering applications, some machines usually work in a non-stationary operating condition; both speed and load are varying over a wide range (e.g. wind turbine). So, in order to solve this dilemma, we propose using the energy ratio between residual signal and deterministic periodic signal which is separated by autoregressive model as the condition indicator for fault diagnosis and prognosis. The effectiveness of this feature is demonstrated and compared to other traditional features using two run-to-failure data sets of gearbox collected in laboratory.

1. Introduction

Condition-based maintenance (CBM) has attracted considerable attention world-wide in the past three decades. Fault diagnosis and prognosis which are important aspects in CBM have not been sufficiently studied. Gearboxes are one of the most common parts of machinery equipment as the necessity connection and power transmission. Due to its complex structure and severe working environment, faults are easy to appear and may take a heavy toll. So, detecting the incipient fault earlier and predicting the remaining useful life are crucial preventing the mechanical system from failure and to make sure that the production operation can reach maximum capacity.

The features of gearbox used in fault diagnosis and prognosis are different. Fault diagnosis of gearbox needs the features which can be used to classify the different fault modes (such as bearing fault, gear fault, or shaft fault). But the fault prognosis needs the features which can reflect the degradation process of gearbox. The good features are very critical to the effect of fault diagnosis and prognosis. Many condition indicators, which are based on statistical moments of time synchronous average (TSA) and its derivatives (difference and residual signals) were previously proposed. They are ER, FM0, FM4, NA4, NB4, M6A, and M8A etc. which definitions and detailed information can be found in (Samuel and Pines, 2005). For the bearings in gearbox, the major source which masks the relatively weak signals of bearing is discrete frequency noise from gears. Compared to the bearing signal, these signals produced by gears are quite strong even no faults. Therefore, it will be benefit to separate the bearing signals from discrete frequency noise before proceeding with bearing diagnostic analysis. Wang and Wong (2002) presented a more flexible way of removing the discrete frequency noise (deterministic signals) using linear prediction. Chaturvedi and Thomas (1982) proposed to separate the gear and bearing signals using adaptive noise cancellation (ANC). Then, Antoni and Randall (2004) developed the self-adaptive noise cancellation (SANC) which is more efficient than ANC demonstrated using both simulation and real signals. Even removal of discrete frequency noise using above mentioned methods, the bearing signal still be masked by other noise. Because of the influence of transmission path, the bearing signal will be less impulsive than at the source. So, Sawalhi et al. (2007) proposed using minimum entropy deconvolution (MED) to remove the effect of the transmission path. This will enhance the impulse signal produced by fault that enabled the fault found easily. Then, we can use the spectral kurtosis (Antoni, 2006) which can select the optimum band for filtering and demodulation and envelope analysis to determine fault characteristic frequencies.

Please cite this article as: Zhang X., Kang J., Zhao J.S., Cao D.C., 2013, Features for fault diagnosis and prognosis of gearbox, Chemical Engineering Transactions, 33, 1027-1032 DOI: 10.3303/CET1333172

Recently, Klein et al. (2011a) proposed a new method separating bearing signals from other components in gearbox through a few stages of resampling and removal of the TSA of the raw signal. Then, Klein et al. (2011b) combined this method with Mahalanobis distance to diagnose the bearing fault automatically.

However, all the methods mentioned above rely on being able to analyze signals recorded under stationary operating conditions. When speed varies relative slowly, it can be compensated by order tracking. When speed varies rapidly, it is likely to be over a smaller range and associated with rapid load variations. Under vary speed and load condition, how to extract the features which can identify the different fault modes and fault severities of a same fault mode is the problem that needs to investigate. For fault prognosis, some traditional features can reflect the degradation process of gearbox under stationary operating condition. But under non-stationary operating condition, all the traditional features can not reflect the degradation process of gearbox. A good degradation feature must possess a trend that reflects the deteriorating condition of the gearbox. In engineering application, many machines (such as wind turbine) work under vary speed and load. So, we must investigate the features which can possess a trend that reflect the degradation under this condition. Dempsey and Zakrajsek (2001) proposed that the calculation of NA4 can be modified to minimize the load effects. Results indicated the modified NA4 was no longer sensitive to load changes and also can reflect the pitting damage of gear. However, in the experiment, only 10 percent load change was considered. Li et al. (2009) proposed a new method using energy ratio to reflect bearing's degradation under abnormal operating conditions which the bearing spins on the shaft. The energy ratio is the ratio between residual signal and deterministic periodic signal which is separated using auto-regressive model. Inspired by this thought, we can verify if this method can be used to reflect the degradation of gear under non-stationary operating condition and compared to other features described in (Samuel and Pines, 2005).

2. Autoregressive model based feature extraction

The deterministic part of a signal can be perfectly predictable based on the infinite past. This means that a discrete time series can be represented by a linear combination of a certain number of samples in the immediate past. And then, this model can be used to predict the next value of this series. It can be described by a linear regression on itself plus a noise term:

$$x[n] = -\sum_{k=1}^{p} a[k] \cdot x[n-k] + e[n] \tag{1}$$

Where the $e[n]$ is a Gaussian white noise with zeros mean and variance σ^2 and the model order is *p*. The parameters estimation of AR model only involves linear equations and the estimating methods have been established yet, such as Levinson-Durbin recursion and Burg algorithm.

Vibration signal collected from gearbox with gear fault or bearing fault consists of the deterministic periodic signal and the random signal. The random components consist of the impulse generated by the localized fault in gear or bearing, and the random noise. In this paper, we only consider the gear fault. If the gear is normal, the residual signal separated by AR model only represents the prediction error of the AR model. However, when a local fault appears in the gear, the impulse signal produced by fault will not be well predicted by the AR model generated by deterministic signal. So, the AR residual signal of a fault gear mainly contains the impulsive signal produced by fault. When the gear fault severe gradually with time, the energy of the residual signal will increase but the deterministic periodic signal generated by the inherent structure of gearbox will remain same. Therefore, the energy ratio between the residual signal and deterministic periodic signal will increase. So, the energy ratio can indicate the damage level of the tested gear. Furthermore, when the speed and load varies, both the energies of these two signal component will change in the same direction. This property will make this feature more robust to the varying operating conditions. This feature was first proposed by Li et al. (2009) and applied to bearing fault prognosis. Wang and Wong (2002) used AR model for gear fault diagnosis comparing the residual signal of fault condition with normal. If energy ratio can be used to indicate the severe of gear fault need further investigating.

3. Experimental setup

In order to verify the feature mentioned in section 2, two run-to-failure (RTF) data sets of gearbox are collected. Figure 1 (a) shows the experimental system used in this paper. The system includes a gearbox, a 4kw three phase asynchronous motor for driving the gearbox, and a magnetic power brake for loading. The motor rotating speed is controlled by an electromagnetic speed-adjustable motor, which allows the tested gear to operate under various speeds. The load is provided by the magnetic powder brake connected to the output shaft and the torque can be adjusted by a brake controller. The gearbox structure and sensor location are depicted in Figure 1 (b).

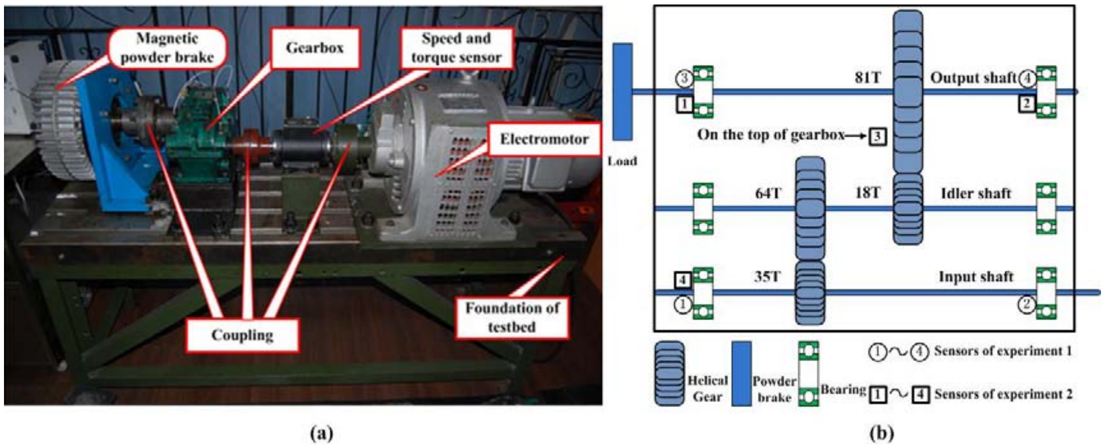

Figure 1: (a) Test-rig of gearbox, (b) Gearbox structure and sensor location

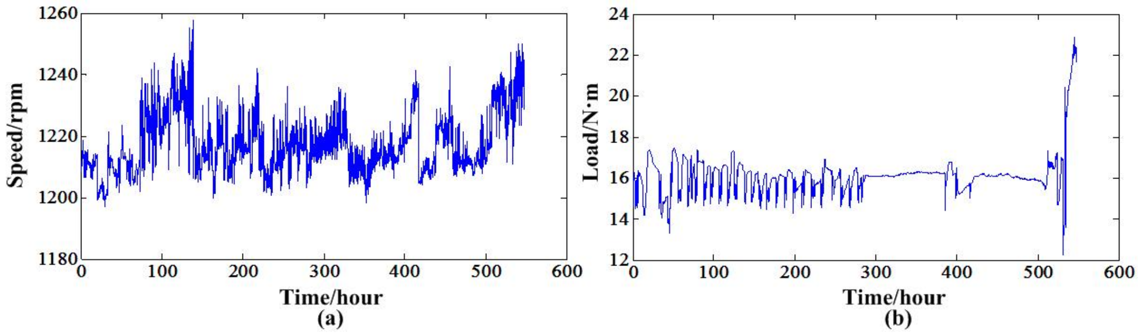

Figure 2: (a) Rotation speed of data set 1, (b) Load of data set 1

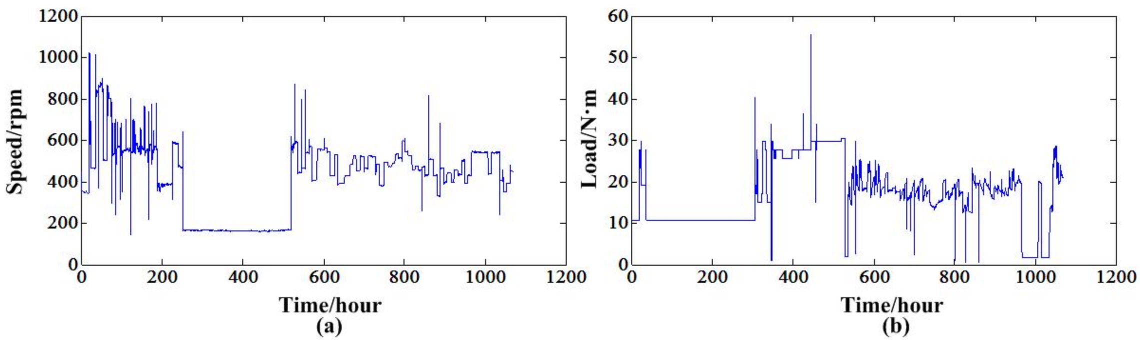

Figure 3: (a) Rotation speed of data set 2, (b) Load of data set 2

For the experiment 1, the rotation speed of input shaft is about 1200rpm and the torque is about 15N·m. For this experiment, the operating condition is relative stationary. The sampling frequency is 20 kHz lasting 6 second. The rotation speed and load of experiment 1 are depicted in Figure 2. For the experiment 2, the rotation speed of input shaft is changed in a wide range by the speed controller. The load is also changed by adjust the current which control the magnetic powder brake. The sampling frequency is 20 kHz lasting 2 second. The rotation speed and load of experiment 2 are depicted in Figure 3. The gearbox's failure time of experiment 1 and 2 are 548 hours and 1068.75 hours respective. The main fault mode of these two experiments is wear of tooth face. For experiment 1, the gear which has 81 teeth is the fault gear. For experiment 2, the gear which has 18 teeth is the fault gear.

4. Feature extraction for diagnosis and prognosis

The statistical condition indicators (ER, FM0, FM4, NA4, NB4, M6A, and M8A etc.) mentioned in section 1 can reflect the gear fault only when the operating condition is relatively stationary. If the operating condition like speed and load change with time in a very wide range, these condition indicators will be ineffective. For fault diagnosis, we can use signal sections selected in a short time. These signal sections are relatively stationary. So, we can find the fault characteristic frequencies through existing signal processing method. However, we do not know if the faults are propagating with time. For fault prognosis, we must extract the features which have consistent degradation trend. The AR model described in section 2 can be used to extract the impulsive signal produced by gear fault from the original signal. In this section, the energy ratio between residual signal and deterministic periodic signal will be used as the robust prognosis indictor under non-stationary operating condition. The AR based energy ratio can be defined as follow:

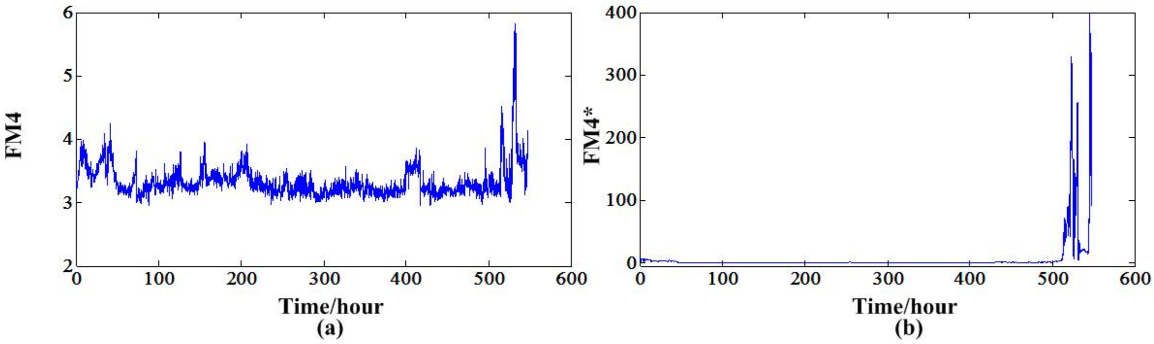

Figure 4: (a) FM4 values of experiment 1, (b) FM4 values of experimental 1*

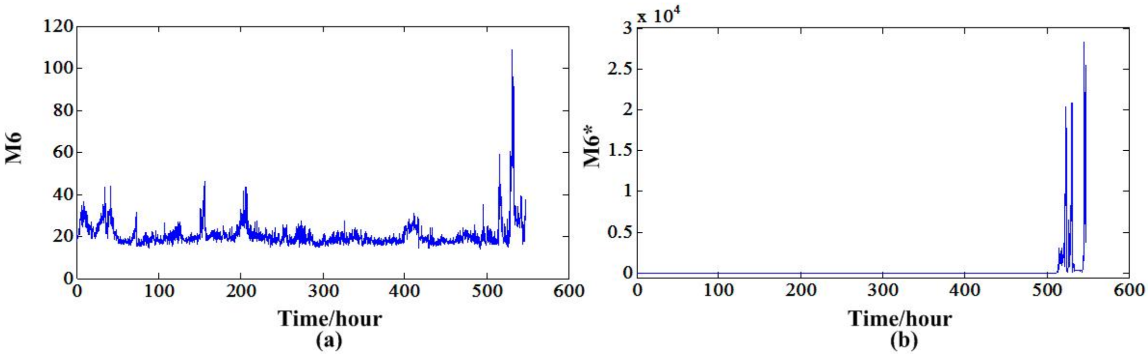

Figure 5: M6 values of experiment 1, (b) M6 values of experiment 1*

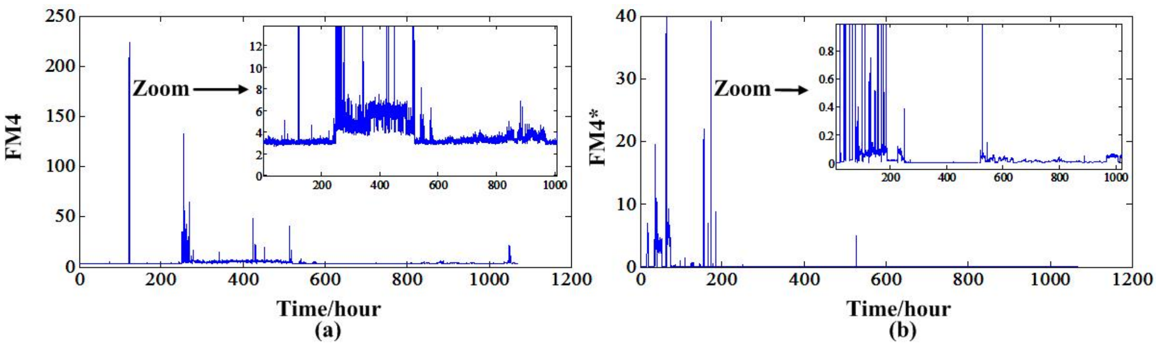

Figure 6: FM4 values of experiment 2, (b) FM4 values of experiment 2*

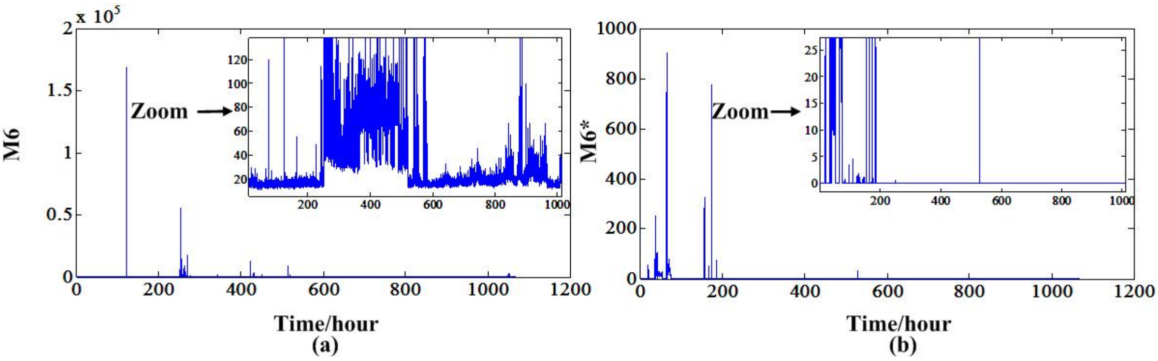

Figure 7: M6 values of experiment 2, (b) M6 values of experiment 2*

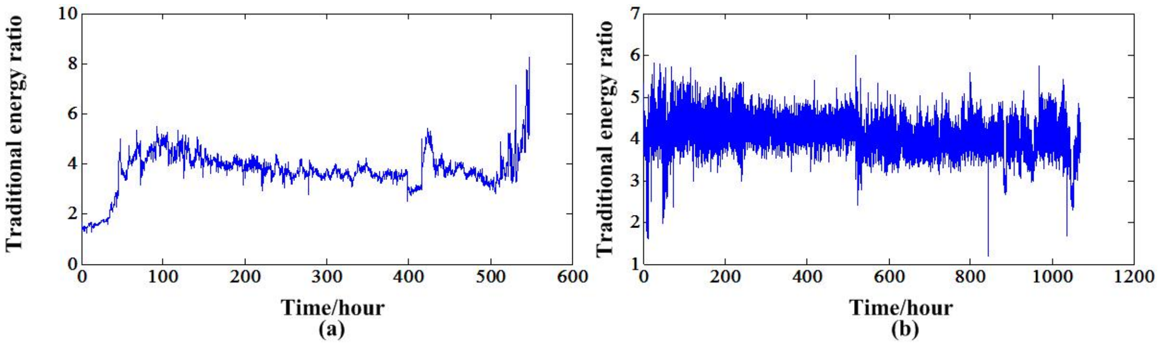

Figure 8: Traditional energy ratio of experiment 1, (b) Traditional energy ratio of experiment 2

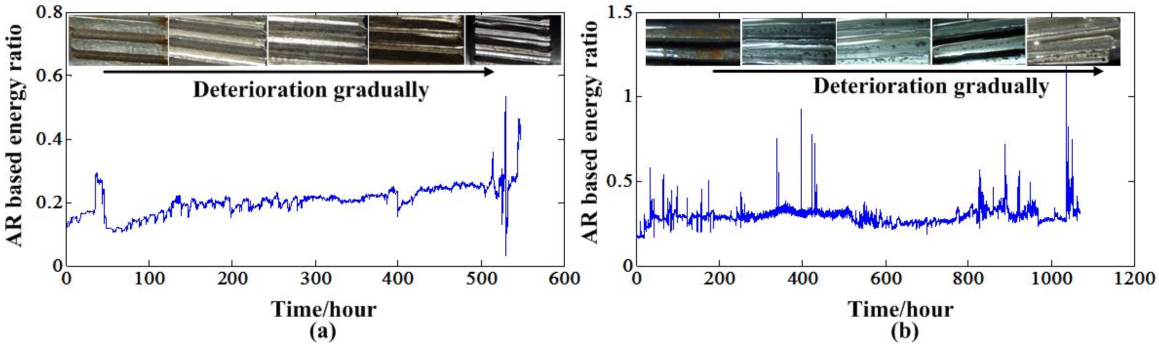

Figure 9: AR based energy ratio of experiment 1, (b) AR based energy ratio of experiment 2

$$\text{Energy ratio}=\frac{\sum_{i=1}^{N} R_i^2}{\sum_{i=1}^{N} D_i^2} \tag{2}$$

Where, R is the residual signal consisting of *N* elements and D is the deterministic periodic signal also consisting of *N* elements.

In order to demonstrate the effectiveness of AR based energy ratio, we compared it to five traditional features named FM4, FM4*, M6, M6*, and ER (traditional energy ratio) through analyzing the two run-to-failure data sets. The results are illustrated in Figure 4, 5, 6, 7, 8 and 9.

From above figures, we can find that the effectiveness of traditional energy ratio is better than the features FM4, FM4*, M6 and M6* under relative stationary operating condition. However, when the speed and load change over a wide range, the traditional energy is also less effective. On the contrary, AR based energy ratio is effective both in stationary and non-stationary condition. For experiment 1, these features are extracted from signals collected by sensor 2 because its outperform others. For experiment 2, these features are extracted from signals collected by sensor 1 for the same reason as experiment 1.

5. Discussion

(1) In this paper, the AR based energy ratio is directly extracted from original vibration signals and it is different from other papers which the energy ratio is extracted from TSA signals. Because the AR based energy ratio extracted from TSA can not reflect the degradation process.

(2) The order of AR model is 30 which is determined by Akaike Information Criterion (AIC) based on the first acquired vibration signal. Under non-stationary operating condition, all the AR models are constructed using a common model order that is optimal for a given operating condition but may not be optimal for other operating conditions. In the application, we find that the optimal orders of the AR models under different operating conditions do not vary a great deal, and a fixed order can be used effectively. For every time point, we use different AR(30) to extract the residual signal and calculate the energy ratio rather than the only one model constructed using first acquired vibration signal. This is different from AR based gear fault diagnosis in (Wang and Wong, 2002).

(3) In (Li et al., 2009), only bearing fault propagation is considered and the residual signal only denotes the impulsive signal produced by bearing fault. In (Wang and Wong, 2002), only gear fault is considered which the residual signal only denotes the impulsive signal produced by gear fault. If both the bearing and gear are damaged, the residual signal will contains the impulsive signal produced by these two parts. So, in this case, we can't distinguish the bearing and gear fault only using AR based energy ratio.

(4) For intelligent fault diagnosis of gearbox under non-stationary condition, we need more features which are insensitive to operating condition. The method of AR based energy ratio gives us a good idea. We can extract a series features based on the deterministic periodic signal and residual signal. Also, we can find other better methods which can separate deterministic periodic signal and residual signal. Through post-processing these signals, we can obtain some other features which can be used for fault diagnosis and prognosis.

6. Conclusion

A new feature named energy ratio based on AR model is proposed for fault diagnosis and prognosis of gearbox under non-stationary operating condition. The effectiveness of this feature is verified using two run-to-failure data sets of gearbox. One is proceeding under relative stationary operating condition. The other is proceeding under non-stationary operating condition. This feature is effective under both stationary and non-stationary operating condition and compared to some traditional features.

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