The Use of Signal Intensity Estimator for Monitoring Real World Non-stationary Data

Mohamed Elforjani[1,2(✉)] and David Mba[2]

[1] SupervisoryEye, Cranfield MK43 0JA, UK
m.elforjani@supervisoryeye.com
[2] De Montfort University, Leicester LE1 9BH, UK
david.mba@dmu.ac.uk

Abstract. Robustness and operational reliability are some advantages that present rotating machine components as inevitable parts of most mechanical engineering systems. To keep rotating machines function at optimal conditions, control and maintenance of machine components must well be applied. Improper analysis of high modulated non-stationary data, acquired from machine components (e.g. gears and bearings) may lead to complete machine break. Despite the body of research work, available through the literature, most of existing condition monitoring (CM) methods proved to be inefficient for real world applications. Hence, this would still suggest an obvious need for fundamental modifications and/or development of new CM techniques. Here we aim to tackle this issue by proposing Signal Intensity Estimator (SIE) as an alternative technique, tailored to the task for monitoring of high modulated data. Our main interest lies with the introduction of the idea behind the SIE method and its previous successful applications for monitoring Suzlon and Repower (Wind Energy Companies) wind machines.

Keywords: Condition monitoring · Non-stationary data · Wind turbines · SIE method

1 Introduction

Machine components such as bearings and gears have been utilised for various machining and industrial processes since the ancient era. Feasibility for condition monitoring (CM) of bearings and gears using signal processing techniques was off the shelf determined (Elforjani 2020). Observational studies have demonstrated that most of the well-established CM tools are only highly relevant/sensitive in the detection of early presence of machine faults. Also, the potential of the use of these methods for monitoring the well advanced damages remains low (Elforjani and Bechhoefer 2018). Another important constraint on all the work discussed in this area is that the reliability of these techniques to handle and characterize the measured data from machines under non-stationary operating conditions is not yet sufficiently proved (Elforjani 2020). Most of the commonly used time and frequency analysis methods assume that the operating conditions (e.g. speed and load) can be held reasonably constant.

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However, in real world applications, machine data very often is acquired from an environment under non-stationary operating conditions. This type of data consists of very extremely high modulation rates that need capable, efficient and workable CM tools for a thorough analysis. Practical failings of the existing CM methods in tackling the high modulated data were highlighted in the reports provided by some wind energy companies (e.g. Suzlon & Repower) (Elforjani 2020; Elforjani and Bechhoefer 2018). Due to non-stationarity, information of bearings' faults, for instance, from Repower wind machines was superimposed by the gears' meshing signals. As a consequence, what is called high order cyclostationary process (signals with varying properties e.g. statistical variance) was generated. This led the applied CM tools to unworkably observe and locate the carrier frequencies of the bearings under diagnosis.

To tackle the non-stationarity issue, the authors have recently proposed Signal Intensity Estimator (SIE), which was inspirational to numerous subsequent works. SIE exhibited excellent performance in almost all cases and it was shown to be more reliable than the existing methods.

Until recently, the SIE method has passed through major changes, updates and modifications not only to alleviate and ease its computational complexity but also to improve its overall accuracy. It should be telling that early versions of SIE algorithms were only limited to the analysis of the experimental data and there was no definitive method or a single approach universally suitable for how values of the required parameters such as the maximum frequency of analysis and the windows size should be obtained. As a consequence of this, tedious trial and error method remained the only attempt to solve this problem (Elforjani 2016, 2018). Although similar SIE idea is still applied, the most updated SIE version significantly differs in the way it handles the selection of such parameters. It was reported that the updated version does not suffer from any issues raised earlier and its algorithm provides flexibility to tackle very complex challenges in simple, robust and reliable computational process and leaves no requirement for any further calculation steps. However, to our knowledge, there may not be any published documents surrounding the concepts of SIE method in very sufficient and comprehensive details. For the sake of completeness, the main objective of the present chapter is to bring together and thoroughly explain both the basic and advanced concepts of the most updated SIE method in a single standard document that comes in handy when machine diagnostic is performed. The chapter starts with a thorough overview of SIE method and then progresses to highlight its applications for the analysis of data from real world wind machines (Repower & Suzlon wind machines).

2 Signal Intensity Estimator (SIE)

Statistical parameters such as Root Mean Square (RMS), kurtosis (KU), and Crest Factor (CF) are broadly used to extract the carrying information from vibration signals. In general, these fault indicators are attractive to the field analysts, who are mainly practical than theory oriented, because they are very fast to compute and do not need laborious knowledge. Also, they can be incorporated into the monitoring systems at very low cost. However, due to the nature of today's CM data, these fault indicators suffer from issues such as high dimensionality, high modulation rates, and rapid transient changes. When trying to apply KU or CF in practice to vibration data from well-advanced damaged machine, they become insignificant/unresponsive and their levels will drop to that similar to undamaged machines. Yet, KU, CF, and RMS are essentially measured over a predefined signal chunk (one value indicator) and, hence, their values were reported to be unaffected by transient changes that typically occur over micro seconds. Further, these parameters can only provide time domain information, which is not always sufficient to obtain an exact match between the failure mode and the faulty component.

Recently, Spectral Kurtosis (SK) algorithm was proposed to handle this issue (Antoni 2006). Often faulty machine show significant high KU levels, which will give a rise to the impulsive responses. This will lead the acquired data to have varying statistical contents, in particular, if the machine is working under varying operating conditions. Thus, the idea behind the SK method is to locate the varying and/or non-stationary events in the frequency domain. The SK algorithm basically attempts to first calculate the KU values at different frequency bands and then identify the location of the maximum KU. The frequency band of the maximum SK level will eventually be used to design a signal filter to extract the high level impulsive signals. Though several attempts were made to improve the overall calculation procedures and ease the difficulty in the investigation of the entire plane, it should be telling that the method is still highly dependent on an iterative and complicated computational process. Yet, improper selection of the optimal size for the frequency bands has substantial impacts on the overall results. Also, the applicability of this method in the case of high modulated data is not always possible since the calculated KU values by nature are very noisy and the SK, as a result, will not be able to resolve the high modulation rates in the analyzed signals; vibration spectrum very often is overwhelmed by broad and noisy frequency spikes (Elforjani and Bechhoefer 2018).

This motivates the need for an alternative approach that provides the flexibility of being applicable even in the cases of high modulated data. Signal Intensity Estimator (SIE) method has a distinction from the other tools as it employs the cumulative sum (CUSUM) for monitoring any sequential samples (Elforjani 2020). The use of CUSUM will firstly allow the total to be identified at any time interval without having to sum the entire sequence. Secondly, if any particular activities are not individually important, CUSUM can easily save having to record the sequence itself. Thirdly, processing several samples from failure histories using CUSUM's will result in greater sensitivity for detecting transient shifts or variation in trends over time. In practice, SIE is essentially a piecewise windowing method that attempts to analyze any CM data, regardless its physical units, using a twostep process. It is important at this point to note that SIE method is fundamentally different from the classical envelope approaches as the process primarily incorporates the segmentation of the entire signal into equal width segments and CUSUM is then used to statistically chart the signal intensity of current and preceding values.

To apply the SIE, the sum of cumulative sum ($SCS_{segment}$) of a predefined segment (window) in a given time domain signal is normalized to the overall root mean square ($RMS_{overall}$) of the same signal. As well-known, the rotational speed (RPM) is considered to be one of causal factors of the non-stationarity and it is therefore the RPM is employed by the SIE algorithm to calculate the Maximum Frequency of Analysis (F_{max}). Using this approach for the calculation of segment sizes could significantly alleviate the issue of what is called the losses in time localization and frequency localization. With the known of RPM at any time and the Machine Component Constant (β), F_{max} can simply be calculated using Eq. 1.

$$F_{\max} = \beta \cdot \frac{RPM}{60} \tag{1}$$

It is worth to mention that each β value in Eq. 2 is assigned to a specific machine component (e.g. shafts, bearings, gears, etc.). After careful iterative selection process, the validation results confirmed that the process produced β values within appropriate tolerance levels.

$$\beta = \begin{cases} 20, & \textit{for shafts} \\ 40, & \textit{for bearings} \\ 60, & \textit{for pumps} \\ 80, & \textit{for gears} \\ 100, & \textit{for slow rotational speeds} \end{cases} \tag{2}$$

The calculated F_{max} values are compared with published SIE Standard Frequencies (SSF's), which have been quantitatively and qualitatively validated experimentally to eventually ensure the reproducible results. The SSF is very important factor in the SIE algorithm as it allows for a robust calculation of the most appropriate windows (segments) size and significantly helps to avoid any indefinite settings. Table 1 illustrates an example of these SIE Standard Frequencies used for bearings and gears.

Upon the completion of selecting SSF value, SIE algorithm calculates the required number of segments (n) in the analysed signal using the Sampling Rate Frequency (F_S). This can be described through an equation such as the following:

$$n_{segments} = \frac{F_s}{SSF} \tag{3}$$

Mathematically, SIE can be computed using one of two approaches. The first approach is a time domain method where SIE values are directly calculated from the original data (Eq. 4). The SIE values in the second approach are extracted from the resulting Fast Fourier transform (FFT) applied to every individual segment (Eq. 5).

$$SIE_T|_{segment} = \frac{SCS_{segment}}{RMS_{overall}} \tag{4}$$

$$SIE_F|_{segment} = \sum \left| FFT\left(\frac{CS_{segment}}{RMS_{overall}}\right) \right| \tag{5}$$

When non-transient type signals are analyzed, identical statistically SIE charts will be noted and the ratio of SIE between any two adjacent segments will approximately approach a value of one. For the signals associated with transient characteristics, this ratio will be greater than one. It is of interest to mention that SIE algorithm is also integrated with another algorithm for performing the statistical test for normality to identify the

Table 1. Example of SIE standard frequencies for the analysis frequency (Hz).

Machine component (Type of application)	β	Analysis frequency	
		F_{max}[a]	SSF[b]
Bearings	40	$F_{max} < 800$	Equal to F_{max}[c]
Bearings	40	$800 \leq F_{max} \leq 1500$	1000–2000
Bearings	40	$F_{max} > 1500$	2000–4000
Bearings	40	$F_{max} > F_S$[d]	<NF[e]
Gears	80	$F_{max} < 800$	Equal to F_{max}[c]
Gears	80	$800 \leq F_{max} \leq 1500$	2000–4000
Gears	80	$F_{max} > 1500$	4000–6000
Gears	80	Fmax > FS[d]	<NF[e]

[a]This F_{max} is calculated using Eq. (1).
[b]This SSF is selected based according to the calculated F_{max} to obtain the optimal frequency localisation.
[c]The F_{max} value is selected if it is less than 800 Hz.
[d]The F_S is the sampling rate frequency.
[e]The selected SFF value is set to be close to the Nyquist Frequency if F_{max} value is greater than the sampling rate frequency.

variation of statistical contents (e.g. variance and mean) in the data. This algorithm can also perform the test for periodicity using the time domain autocorrelation method. Further, representation of frequency features for the entire SIE signal is the counterpart of SIE analysis. Several spectral frequency tools such as FFT, Wavelet Transform (WT), to name few, are employed to generate the final SIE signal spectrum that eventually depicts the results in both visual and numerical fashions. It was reported that SIE method could produce visibly good results and its feasibility for the analysis of experimental and/or real world data has been proven in a number of published research work (Elforjani 2020; Elforjani and Bechhoefer 2018). In the next section, analysis of datasets from two real world wind machines using SIE algorithm is highlighted.

3 Applications of SIE Method (Case-Studies)

This section aims to provide an overview of previous use of SIE method for handling the non-stationary and high modulated data in some details. For the purpose of this objective, SIE method was applied to two datasets provided by Repower and Suzlon (Wind Energy Companies). Due to the proprietary rights to the wind machines, it is worth remarking here that machine specifications and the measurements setup are briefly discussed. To provide credibility to the SIE method, results were directly compared with the existing standard references commonly used for machine diagnostic.

3.1 Repower Wind Machine (Bearing Case-Study)

For this case-study, vibration data were prospectively collected from one of commercial Repower wind machines (M92). These turbines are fitted with Winergy gearboxes (PEAB 4481.0) to produce a nominal output power of 2.05 MW. Three bearings are used to support the high speed shaft rotating at an average rotational speed of 1374 RPM. Characteristic frequencies for bearing components are summarised in Table 2. The provided vibration data was continuously acquired from one of the machines with an abnormal performance for 6 days (4^{th}, 5^{th}, 6^{th}, 8^{th}, 9^{th} and 11^{th} of March 2014). The acquisition system was connected to one radial accelerometer channel to gather vibration waveforms in (g) once a day, at a sampling rate of 48.828 kHz, and over a recording time of 6 s. Rotational speed was also measured by one tachometer channel at a constant angular sampling rate of 2/rev.

Repower reported that this data was unworkably analysed and only Bore-Scoping method (visual inspection) could detect a faulty bearing outer-race (“High Speed Shaft GS FWD” id = “K”). The forcing frequency of the faulty outer-race is approximately 177.8 Hz. Several analyses have been consecutively undertaken here using SIE method and SK algorithm.

Table 2. Characteristic frequencies of bearing components.

Race name	Bearing convention		
	“High speed shaft RS” id = “J”	“High speed shaft GS FWD” id = “K”	“High speed shaft GS AFT” id = “L”
Retainer	$0.42 f_r$*	$0.43 f_r$	$0.41 f_r$
Roller	$3.26 f_r$	$3.68 f_r$	$2.17 f_r$
Inner	$9.70 f_r$	$10.16 f_r$	$7.07 f_r$
Outer	$7.18 f_r$	$7.77 f_r$	$4.88 f_r$

*f_r is the shaft rate in Hz.

The first set of analysis involved the use of autocorrelation test to examine the periodicity in the resulting SIE and SK values. Illustrated results in Fig. 1 have proven that SIE is adequate for the identification of the periodicity corresponded to the faulty out-race.

Data from day 4 and day 11 was also subjected to additional processing using spectral frequency tools. It is observed that SK algorithm could not efficiently demodulate the analysed vibration signals and the noisy frequency peaks overwhelmed the resulting spectrum, though some signs of faulty outer-race could be spotted in the data from day 11. In contrast to the SK behavior, seen in Figs. 2 and 3, the SIE considerably produced very broad demodulated bands for the two days. The diagrams of SIE spectrum are dominated by clear evidence of cyclic frequencies corresponded to the faulty bearing outer-race. The remarkable feature of the SIE method is that it could clearly show

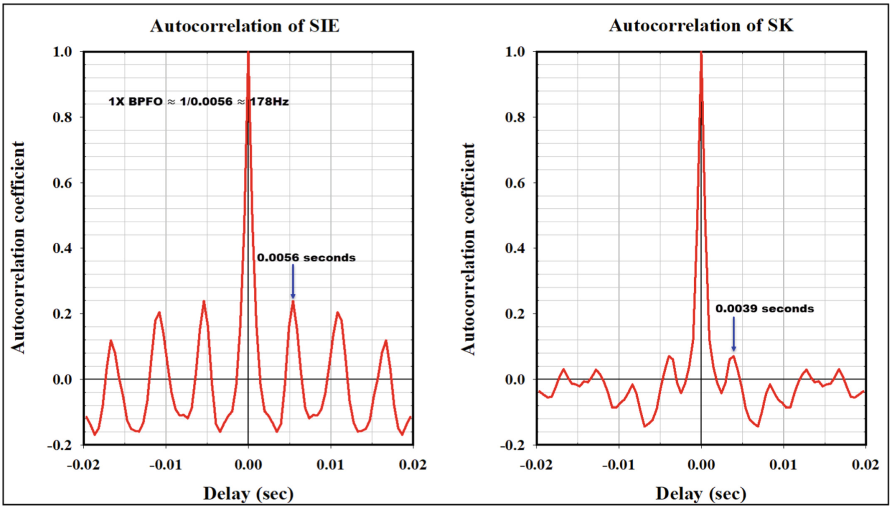

Fig. 1. Results of autocorrelation analysis for SIE and SK

symptoms of faulty bearing installed on a high speed shaft such as high amplitudes at 1BPFO and 2BPFO, which are completely well-matched with those fault signs reported in standard machine diagnostic references (Mobius Institute 2019; Nakhaeinejad and Bukowitz 2011).

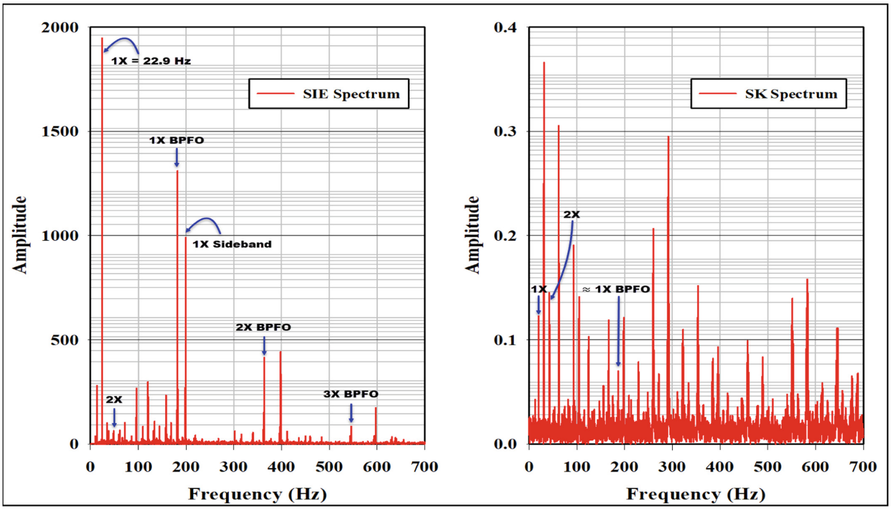

Fig. 2. Results of frequency analysis (day 4)

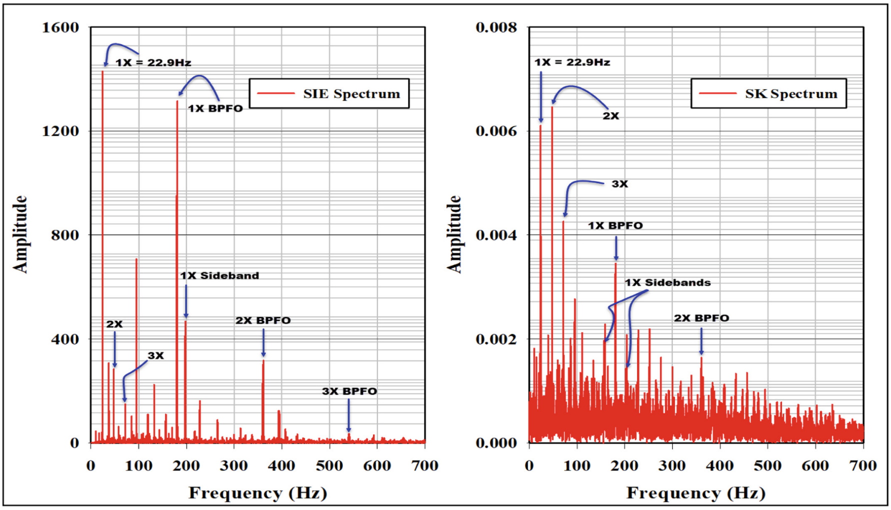

Fig. 3. Results of frequency analysis (day 11)

3.2 Suzlon Wind Machine (Gearbox Case-Study)

In this case, 265 h of measured vibration data was obtained from a Suzlon M88 wind turbine gearbox. The nominal output power and the nominal output speed of all Suzlon M88 wind machines are 3 MW and 1800 RPM respectively. One accelerometer channel was attached to the gearbox casing to measure radial vibration levels from intermediate-high-speed-stage side. The connected acquisition system has continuously recorded vibration measurements in (g) for 6 s, every 10 min, with a sampling rate of 97.656 kHz. Rotational speed was simultaneously recorded over 40 s at a constant angular sampling rate of 8/rev using two tachometer channels. As the measured vibration levels have significantly deviated from the conventional performance, the machine has been taken out of the service. The analysis report indicated that a faulty helical pinion gear with 32 teeth could only visually be detected. It should however be noted that prior to the visual field inspection, some online CM tools were unworkably used to identify the causal factors behind this abnormality.

Figures 4 and 5 provide an overview of the spectral analysis using SIE and SK methods. Based on the results, the SK technique after 200 h into measurements produced very modulated spectrum with very scattered and broad frequency spikes corresponded to the rotational speed (1×). Yet, the first and second Gear Mesh Frequencies (GMF) of the faulty pinion can hardly be located. However, this is not the case for the SIE spectrum, where in the addition to the appearance of 1× and 2× RPM of the damaged pinion, clear damage signs such as high amplitude of the first GMF and multiple sidebands around it, spaced at 1× RPM, can also be noted. One of the key findings from Figs. 4 and 5 is the high excited Gear Natural Frequency (GNF) surrounded by some sidebands at 480 Hz. This spike along with its second and third harmonics and the presence of 1× and 2× RPM also represent clear symptoms for an eccentric gear (Mobius Institute 2019; Nakhaeinejad and Bukowitz 2011).

Also was noted, that the second GNF was eventually convoluted with the first modulated GMF of the pinion. The significant high amplitude in the GMF and the GNF of the pinion gear in SIE spectrum can also be attributed to the high friction and the high load on the pinion teeth. Another cause of these significant peaks may be referred to the gear wear. Important multiple sidebands around these frequencies are not only common signs for the broken tooth but also they are the signs of the presence of pitch diameter wear (Mobius Institute 2019; Nakhaeinejad and Bukowitz 2011).

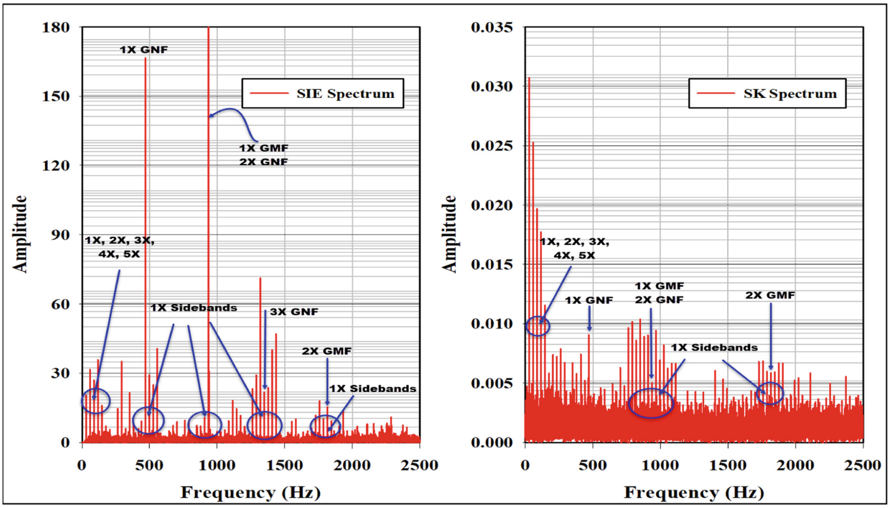

Fig. 4. Results of frequency analysis (200 h)

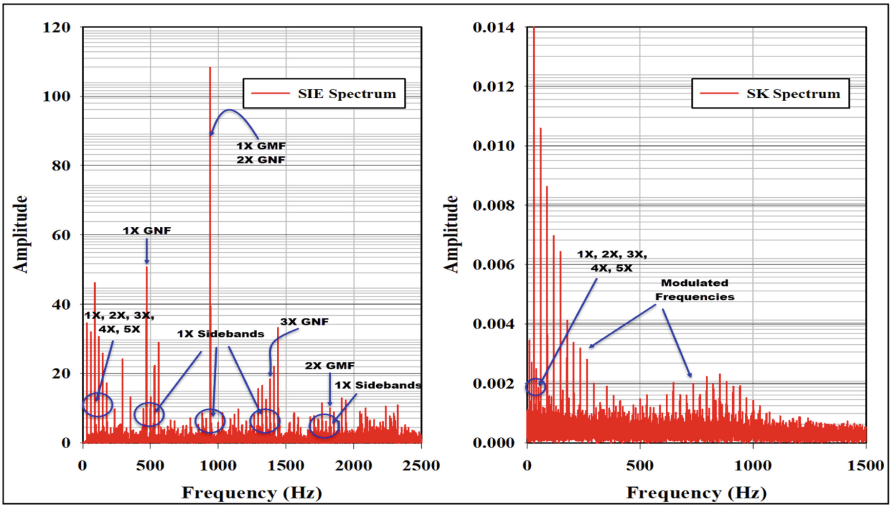

Fig. 5. Results of frequency analysis (260 h)

As the damage has well developed, results from the SK spectrum have become insignificant. This reinforces the above view that the KU values drop to undamaged machine levels when the fault is well advanced. Unlike SK, SIE spectrum, presented in Fig. 5, continued to offer good frequency localization, where the presence of intense peaks corresponded to faulty gear can clearly be noted. These findings are in line with previous results reported in Fig. 4, though relatively lower amplitude in GMF and GNF is noted.

4 Conclusion

As per the earlier published work in the literature, this chapter was edited to serve as notes and standard reference for those who want to learn the detailed computational process of SIE method in the field of machinery condition monitoring. It also summarised the feasibility of analysing the non-stationary vibration data acquired from real world applications using SIE method.

Outcomes of various analysis led to the conclusion that SIE approach can outperform other state-of-the-art CM algorithms such as SK. The SIE results agree well with the existing standard references for machine fault monitoring. Also, the analysis has also shown that it is difficult to draw any firm conclusions based on the observations from the SK spectrum and the obtained results should be interpreted with caution when excessive and high modulation rates are present in the analyzed data.

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