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Tool Wear Monitoring Based On Vibration Signal Analysis Using FFT and EMD

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Abstract – This work investigates the effectiveness of using vibration data to jointly monitor tool wear during machining processes using the Fast Fourier Transform (FFT) and Empirical Mode Decomposition (EMD). A range of instruments and operational settings are examined in order to thoroughly evaluate these methods. Relevant intrinsic modes are found by statistical analysis involving Kurtosis, Skewness, and RMS; IMF 4 is found to be the best mode for tracking tool wear. The efficacy of EMD in tool wear monitoring is further supported by FFT analysis, which validates the veracity of EMD results. It is imperative to exercise caution when interpreting the results, as additional study and validation may be required. However, our work highlights the potential of FFT and EMD techniques for real-world use in precise and trustworthy tool wear evaluation during milling processes.

Keywords: Tool vibration, Wear monitoring, Vibration signals, Machining.

1. Introduction

Machining is a material removal and surface finish operation utilized across various sectors such as aerospace and mechanical industries. It involves the use of a cutting tool to remove material and generate new surfaces. This process is intricately affected by several factors including material properties, tool geometry, machining parameters, cooling conditions during the machining operation [1], [2]. On the other hand, incorrect cutting conditions can lead to undesired tool vibrations during machining, posing significant challenges to achieving optimal productivity and part quality. The vibration during the machining enhances the tool wear which resulted in the poor surface finish quality of the manufactured components [3]. Effectively managing and reducing vibrations is vital for improving productivity, ensuring high-quality part production, and preventing damage to machine components.

There are a lot of research articles that dive into various signals collected from the machining process as possible indications of tool wear, but it's still a tough endeavor [4]. Tool wear monitoring requires a comprehensive approach to accurately evaluate and monitor tool condition during the machining operation because it involves several parameters and signals. Although these methods need improvement, tool vibrations have been useful in managing tool wear [5]. These approaches have exhibited promising outcomes in the surveillance and regulation of tool wear, fostering improved productivity and heightened oversight of the machining process[6].

This paper presents a framework for using vibration measurements to identify and track cutting tool wear in conventional turning. The methodology incorporates the FFT and EMD into time domain analysis and frequency domain procedures. Using an adaptive decomposition approach called EMD, a vibration signal is broken down into its inherent components. This adaptive decomposition makes it feasible to capture the various temporal and frequency scales contained in the data, which is crucial for cutting tool wear analysis. Furthermore, researching intrinsic mode functions, or IMFs, which extract properties like kurtosis, skewness, crest factor, and rms directly from IMFs data changes, can lead to a more comprehensive knowledge and accurate assessment of cutting tool wear.

2. Materials and methodology

2.1. Material and testing

The workpiece material utilized was Inconel 718, a nickel-based superalloy with a low thermal diffusive characteristic, high hardness, and high strength at increased temperatures that makes it difficult to machine. The majority of superalloys used in the aerospace sector are based on nickel, with the remaining alloys being based on iron and cobalt. About 45–50% of the materials used in the production of gas turbines are nickel alloys [7]. The workpiece specimen measured 100 mm in length and 43.62 mm in diameter. The cutting tool used was a carbide insert with a TiC+TiCN+Al2O3 coating, grade YBG205, that was produced using the physical vapour deposition (PVD) method. The insert that was used was DNMA432, and it was securely attached to a tool holder that had the ISO code DCMT11T304-EM. Table 1 provides specifics about the experimental circumstances.

Table 1 Machining parameters and workpiece specifications

Machine Tool	Lathe Machine 3.2 HP
Work Specimen	INCONEL 718
Material	(Ni 50.81 %, Cr 18.9 %, Mn 0.05 %, P 0.004 %, Si 0.27 %, Cu 0.06 %, S 0.001 %, C 0.04 %, Mo 2.90 %, Al 0.45 %, Nb 4.77 %, Ti 1.03 %,
Hardness	35 HRC
Size	φ 43.62 × 100 mm
Density(g/cm3)	8.4
Young's Modulus(GPA)	206
Carbide Insert	PVD-coated carbide, ISO YBG205 (using a physical vapour deposition (PVD) method with TiC+TiCN+Al2O3-coating)
Tool Holder	DCMT11T304-EM
Nose Radius	0.80 mm

2.2. Methodology

This article reported the utilizing vibration measurements to monitor tool wear, with subsequent analysis of the vibration signals primarily employing time domain and frequency domain followed by empirical mode decomposition (EMD). The following subsections offer a comprehensive discussion of these techniques.

2.2.1 Empirical mode decomposition (EMD)

Segregation of the signal into its component parts, called empirical modes or intrinsic mode functions (IMFs), is an integral part of EMD. The decomposition is said to be data-driven, local, sequential, and iterative [8]. Separating a non-stationary signal from systems that may exhibit nonlinear patterns is the fundamental principle of EMD. This allows for efficient time-frequency analysis in situations where wavelets and Fourier analysis would not be successful.

In actuality, measuring IMFs requires a few preliminary actions: finding local maximum points in the signal and joining them to create a lower envelope using cubic splines. The initial signal component is obtained by subtracting the central value of the upper and lower envelopes from the initial signal. [9], [10].

$$\boldsymbol{h_1(1) = x(t) - m_1(t)} \tag{1}$$

Here, $\boldsymbol{x(t)}$ represents the original signal and $\boldsymbol{m_1}$ denotes the calculated mean value, the first IMF (Intrinsic Mode Function) is determined as follows: If $\boldsymbol{h_1}$ meets the IMF criteria upon calculation, it is designated as the first IMF; otherwise, the iteration continues by substituting the original signal $\boldsymbol{x(t)}$ with $\boldsymbol{h_1}$. Once the criteria are fulfilled, the first IMF is retained and subtracted from the original signal as follows:

$$\boldsymbol{x}_{\text{new}}\boldsymbol{(t) = x(t) - c_1(t)} \tag{2}$$

c_1 represents the first IMF. The original signal is then replaced by the updated signal $n_{new}(t)$ initiating the process anew for subsequent IMFs. The final IMF is referred to as the residual, denoted as r(t). The original signal reconstruction can be achieved by combining the residual with the various IMFs calculated, expressed as:

$$x_{\text{new}}(t) = \sum_{i=1}^{k} c_i(t) + r(t) \tag{3}$$

where number of IMFs calculate represents by k.

3. Results and discussion

Three stages of tool usage were incorporated in the measuring campaigns: "no wear," "medium wear," and "high wear." The experiment's goal was to compile a large dataset that represented a typical turning procedure. Tool life is defined by ISO 8688 [18], as the entire amount of cutting done up until a given life requirement is reached.

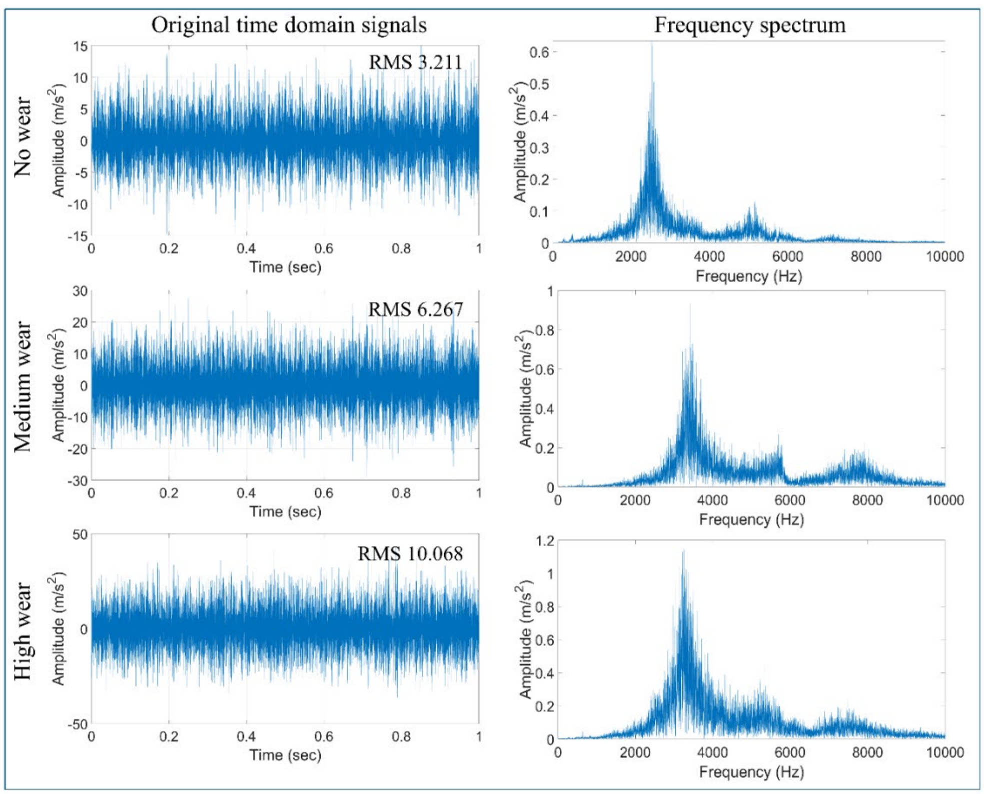

Fig. 1 Tool vibration signals and its corresponding frequency spectrum under no wear, medium wear, and high wear

The most common kind of wear in normal machining circumstances is flank wear. The allowed limit for non-uniform wear is 0.6 mm, whereas for uniform wear it is 0.3 mm. This study adopts the 0.6 mm limit. The amplitude of tool vibrations along with the rms value and corresponding frequency spectrum under no wear, medium wear, and high wear is depicted in the Fig. 1. It is observable from the figure that rms amplitude of the vibration signals has been increased with the increased in the tool wear. As in no tool wear condition rms value of 3.211 was recorded and rms value of 6.267 was recorded in the medium tool wear condition. Also, the high tool wear recorded the maximum rms value of 10.068 which indicated the higher amplitude of tool vibration can be correlated with the tool wear.

On the other hand, by analysing the corresponding frequency spectrum of the vibration signals it can be noted that the natural frequency of the tool holder in the range of 2-4kHz was dominated. The magnitude of the dominating frequency was also increased with the increase in the tool wear. Additionally, it was observed from the frequency spectrum that as the tool wear increased from no wear to high wear, the dominating frequency was shifted a little and the magnitude of side bands was increased. Thus, FFT analysis of the tool vibration confirms the progression of tool wear during the machining operation.

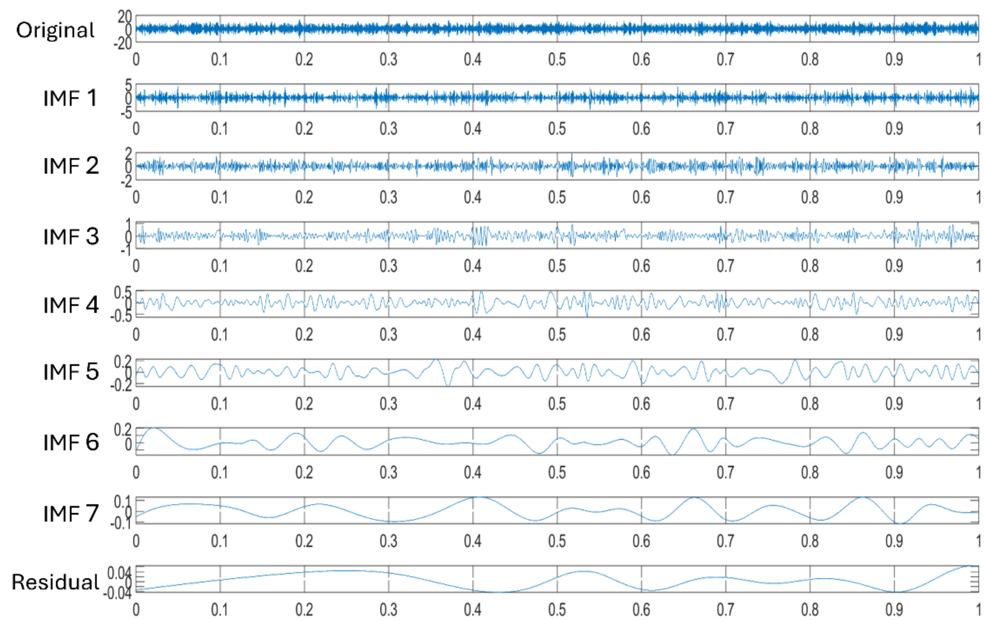

Fig. 2 Different IMFs generated with the vibration signals under “No wear”

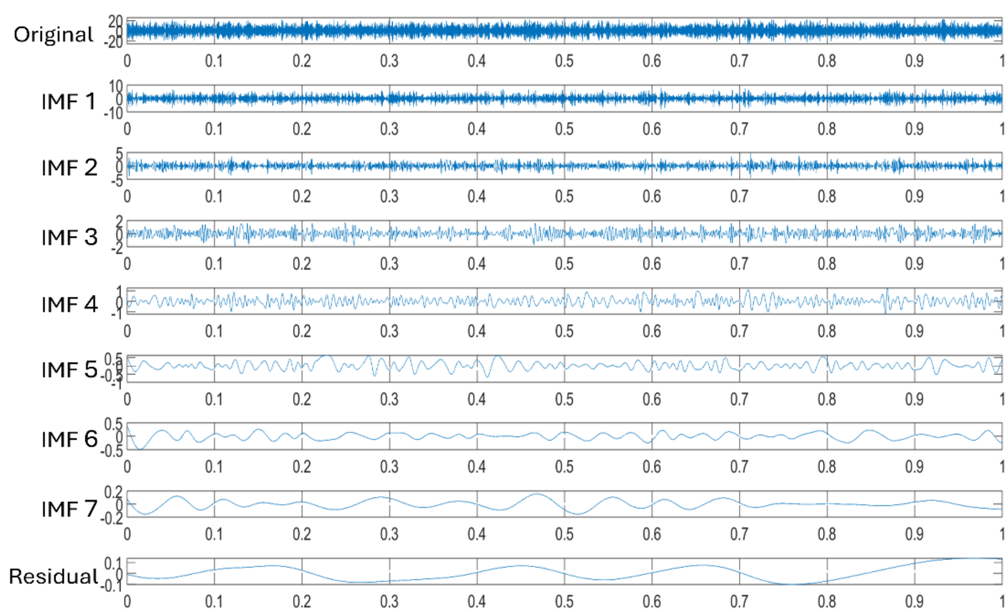

Fig. 3 Different IMFs generated with the vibration signals under “Medium wear”

Fig. 2-4 represents the application of EMD analysis under the no wear, medium wear, and high wear conditions. The EMD techniques applied to the vibration signals under various states of tool wear is illustrated in the Fig. 2-4. The three states of tool wear i.e. no wear, medium wear and high wear of the cutting tool inserts were analysed. As indicated in Table 2, the examination of several IMFs and pertinent time domain indicators were chosen for this study in order to assess the information carried by each IMF. Kurtosis, Skewness, and crest factor were among the statistical measures used to assess how well the IMF represented the evolution of tool wear.

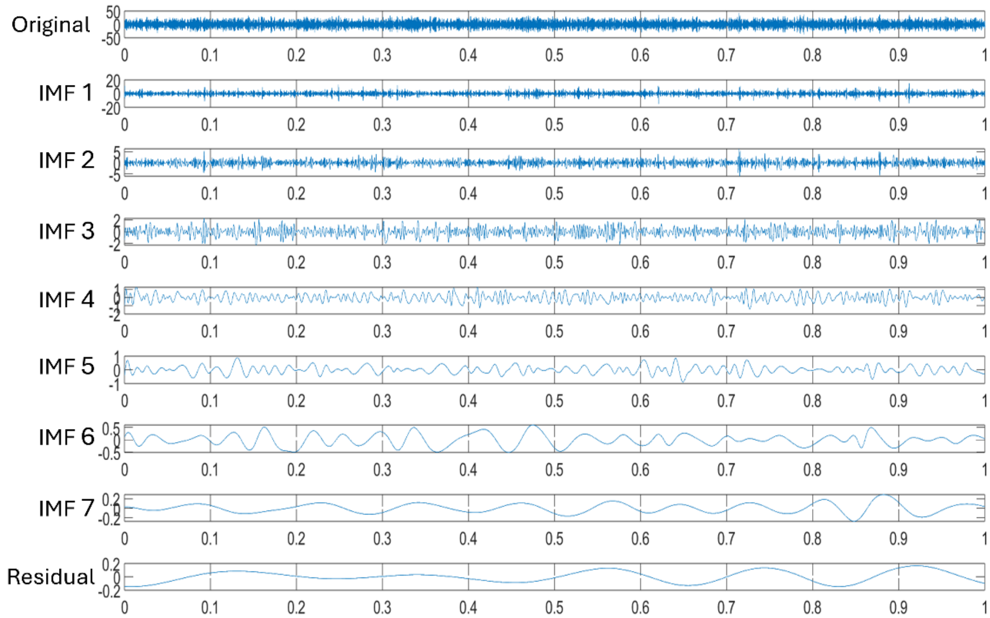

Fig. 4 Different IMFs generated with the vibration signals under "High wear"

Table 2 Scalar representing original signal, different IMFs, and their residual.

	No wear			Medium wear			High wear		
	Kurtosis	Skewness	Crest factor	Kurtosis	Skewness	Crest factor	Kurtosis	Skewness	Crest factor
Original	4.985911	-0.00397	3.89211	6.554758	0.027925	4.171219	6.671544	0.040657	3.96475
IMF-1	3.274066	-0.0059	4.695565	8.0129	0.004842	4.058561	7.549729	0.00218	4.697623
IMF-2	5.543025	-0.00108	3.833538	4.428864	-0.00431	4.025821	3.338102	-0.02405	4.575458
IMF-3	4.933656	-0.00011	4.271407	7.816806	0.003591	4.204195	3.681434	-0.00432	4.454895
IMF-4	4.845988	0.00366	3.885224	8.030911	0.021761	4.168838	11.116524	0.031371	4.611095
IMF-5	7.003905	0.03339	3.313584	4.744757	-0.00111	3.553904	3.843674	0.000329	3.437051
IMF-6	7.99201	0.01853	4.006664	7.386124	0.04345	2.956325	3.205786	-0.07078	2.374953
IMF-7	8.060724	-0.08385	2.82936	5.571005	-0.02472	2.926709	3.246126	0.009569	3.281571
Residual	7.765217	-0.0382	2.474241	6.598563	0.03399	2.861022	5.041694	-0.08801	3.31872

IMF4 was chosen out of all the IMFs because of its strong relationship to the advancement of tool wear. IMF4 displayed a CF of 3.885, a Skewness of 0.00366, and a Kurtosis value of 4.845 for the "no wear" condition. IMF4 showed a CF of

4.168838, a Skewness of 0.021761, and a Kurtosis value of 8.030 in the medium wear scenario. Finally, IMF4 had a CF of 4.611095, a skewness of 0.031371, and a Kurtosis value of 11.116524 under extreme wear. Kurtosis was considered the most important indicator due to its remarkable ability to track the development of tool wear. Wear on cutting tools produces a vibration signal, and kurtosis does a great job of capturing its impulsiveness. Due to its ability to capture the impulsive vibration signal, kurtosis is a great choice for monitoring and evaluating the development of tool wear.

4. Conclusion

In order to monitor tool wear in machining processes, this research compares the efficacy of empirical mode decomposition (EMD) with that of fast Fourier transform (FFT) for vibration measurements. The machining of the Inconel-718 superalloy is an integral part of the comprehensive evaluation of these solutions' efficacy. The research validated the EMD methodology's usefulness in tracking tool wear and showed promise for future integration with other approaches to improve the accuracy of tool condition decision-making. The utility of EMD in determining the underlying dynamics of tool wear has been proven by its capacity to breakdown signals into intrinsic modes. Kurtosis, Skewness, and Crest Factor were used in a statistical analysis to determine the intrinsic modes; IMF 4 was found to be the most favoured mode because it was in line with the features of tool wear. The Fast Fourier Transform (FFT) was used to validate the EMD results, proving its use for tracking tool wear and bolstering the hypothesis.

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