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OPTIMIZATION OF TURNING CHATTER THROUGH SIGNAL PROCESSING METHOD

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Abstract

This paper investigates some fundamentals of vibration in cutting tools. It has been reported that chatter phenomenon may be the result of both self-induced and forced vibration where self-induced vibration is considered to be a function of the cutting properties of the metal and the sharpness of the tool, while the forced vibration depends on the interference of the tool with the surface cut during previous revolutions. There are some speed, frequency, and sharpness restrictions in place, with vibration being infrequently seen at low cutting speeds, high tool frequencies, or with recently lapped tools. The vibration's amplitude appears to be unaffected by the depth of cut and appears to be restricted to a value that is just a little bit higher than that at which the maximum vibrational velocity at the tool point is equal to the rate of work. Various methods has been adopted to find the solution by scholars in this direction, such as by predicting chatter occurances earlier or detecting it as soon as it occurs, active and passive control strategies has been tried by researchers to control the chatter. For the identification of chatter tool condition monitioring (TCM) techniques performed through force, vibration and acoustic signals which paly very important role in monitoring process. Signal processing method has been usded to detect the chatter in turning process for stable cutting. The signal processing methods used by earlier researchers have certain benefits and drawbacks. Empirical mode Decomposition (EMD) provides a suitable solution for nonlinear and non-stationary signals, but it has now been discovered that this approach occasionally suffers from the major mode mixing issue while Local mean Decomposition (LMD) has been adopted in order to get over EMD's restriction. This method has mostly, but not entirely, solved the mode mixing problem. Thus, the wavelet denoising and local mean decomposition (WDLMD) technique has been applied, and it has been found that this technique can extract the information from the chatter signal rather precisely while also being able to remove the undesired noise contents. Mode mixing has also been managed more recently. In this paper WDLMD processed signals of all the combinations of experiments have been obtained to develop predition models of chatter severiety and material removal rate.

Keywords: ***Chatter, vibration, signal processing, turning, CNC lathe, EMD, LMD, WDLMD, Wavelet analysis.***

Introduction

Machining process are subject to dynamic effects due to transient or forced vibrations, and dynamic mechanisms inherent to the process like regeneration, which results in high amplitude oscillations, instability and poor quality. Depending on the sources of energy, tool vibrations are engerally

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chategorized as forced vibrations and self-excited vibrations. Force vibrations are associated with disturbing periodics forces resulting from the unbalanced of rotating parts, from the intermittent engagement of workpiece with multi-flute cutters or from errors of accuracy on some driving components. [1] Dynamically unstable system corresponds to unstable vibration between the workpiece and tool and, usually known as self- excited vibrations or chatter, which occur under certain conditions generally associated with the increase of the material removal rate, and these are enerziged by the cutting process itself. By ascertain the exact nature of chatter the effect of chatter vibration can be suppressed, where sensors can be uselful as several scholars have reported in their research. Although, acquired chatter signals gained from these sensors are contaminated with ambient noises which overlap the actual tool chatter signals. Hence, processing of these contaminated signals links to an inappropriate feature extraction. Various signal-processing techniques have been developed depending on the types of chatter signals and features to be extracted, to overcome the problem. To overcome the problem of chatter, true nature of chatter be identified as –

1. Selection of an appropriate signal processing technique to filter out the ambient noises
2. Selection of suitable sensor for recording the machining signals,
3. Identify the exact nature of recorded signals,
4. Suitable methods to extract tool chatter features.

As the title of our project says “Optimal Process of New Material Parameters for Higher Productivity and Stable Turning on CNC lathe”, the research focused on the acquisition, processing and extraction of tool chatter features relating to higher productivity and stable turning on CNC lathe.

In the turning process there are three types of mechanical virbrations are detected due to lack of dymnamic stiffness or rigidity of the machine tool system consisteing of workpiece, cutting tools, toll holder and machine tools. The process was first examined and explained by Tobia [2]. Three types of vibration are, Free virbration, forced vibration and self-excited vibration. Free vibration normally induced by shock, forced vibration generated due to unbalanced effects in machine tool assembalies such as gears, bearings, spindles, etc., these two vibrations can easiliy be detected and appropriate measures can be taken to rectify or suppress the generated vibration. Third vibration is self-excited vibrations which has been still not fully understood till now because of complexity involved in it and are considered to be hazardous for quality production and accuracy in any machining process including turning operations. Self-excited vibrations are generally suggested to be of two type, first primary chatter and second, secondary chatter [3]. Primary chatter is generated due to friction between thermo-mechanical effects, tool-workpiece or by mode coupling effect, while secondary chatter is generated by the regeneration of wavy surface or roughness on the workpice. Regenrative chatter is considered to be more destructive in nature, because it decrease the quality and accuracy of the product. Various methods has been adopted to find the solution by scholars in this direction, such as by predicting chatter occurances earlier or detecting it as soon as it occurs, active and passive control strategies has been tried by researchers to control the chatter.

Machining involves many cmponents works together, hence many sounds results dur to functioning of components. Typically, ambient noise or contaminations corrupt the recorded machining signals and it becomes hard to recognize the actual and accurate signals in contaminated signals recorded. Hence, it becomes necessary to process and filter out the noise components from the recorded raw signals using the appropriate signal processing technology in order to determine the precise nature of chatter or vibration and predict the dependence of replies on the input cutting parameters. Signal processing refers to the manipulation and analysis of recorded or acquired signals. Signals may be electronic or electromagnetic representation of pysicla phenomena and in our experimentation chatter or vibration is exactly what is expected as physical pehenomena. Signal processing involves the extraction of useful information from signals and modifying or improving them for various purpouses. The purpose of signal processing is to extract vital information from complex signals, transform it into useful data, and use it to make decisions and predictions. Filtering, Fourier analysis and Wavelet analysis are fundamental techniques used in signal processing. In our experiment three signal processing techniques, namely Empirical Mode Decomposition (EMD), Local Mean Decomposition (LMD), and Merged Wavelet Denoising and Local Mean Decomposition (WDLMD), have been used to process the recorded signals.

Previous works investigated

Taylor[4], who conducted in-depth research on metalcutting processes as early as the 1800s, was the first to identify chatter as a productivity barrier in machining. Chatter is the "most obscure and delicate of all problems facing the machinist," according to a 3/4 power law cutting force model that was developed. For lathes and other machines, Arnold[5] looked at a variety of influences that a tool is subjected to while cutting both analytically and empirically. He also discussed the mechanisms creating chatter and recommended cutting forces as a function of speed.

It was demonstrated that the most crucial attribute of chatter vibration is that the forces that create and sustain it are generated within the vibratory process (dynamic cutting process), rather than being driven by external periodic forces. Chatter is brought on by instability in the cutting operations, which Tobias and Fishwick[6] and Tlusty and Polacek[7] were the first to recognize. It was found that vibration-induced modulated chip thickness impacts cutting forces dynamically, which in turn causes vibration amplitudes to grow and result in regenerative chatter. Additionally, it was found that the cutting process stability's primary process parameter was the depth of cut.

For orthogonal cutting, Tlusty and Polacek[8] presented a stability condition in which stability limits can be calculated based on the system dynamics. Analytically, they demonstrated that for cuts deeper than the stability limit, the magnitude of the dynamic forces and oscillations increases, leading to instability and resulting chatter vibrations. The solution can only be used to a one-dimensional process because cutting forces and structural dynamics were only resolved in one direction, i.e., the chip thickness direction. Tobias[9] and Meritt[10] researched the modeling of regeneration chatter's dynamic response, structural characteristics, and stability limit issues. These investigations are only applicable to orthogonal cutting, when the system dynamics, chip thickness, and cutting force direction are constant across time.

Quintana and Ciurana[11] recently presented a state-of-the-art review of chatter in machining processes and classified current methods which ensure chatter-free (stable) cutting conditions. The process of chatter analysis, chatter stability prediction and chatter detection is highly complex which needs to be investigated independently for different cutting processes like turning, milling and drilling. The literature available till date on each of these processes is tremendous and it provides motivation to the authors of this paper to produce a state-of-the-art review focusing on the turning process alone. In this paper, some of the chatter stability prediction chatter detection and chatter control techniques are reviewed exclusively for the turning process and scopes for further research in this field have been indicated. Armarego et. al. [12], [13] investigated orthogonal cutting test for a range of cutting speed, rake range and uncut chip thickness to generate and othogaonal cutting database for a certain tool and work material pairs. Experimental stability charts for turing with a simplified machine-tool structure model for various cutting conditions which indicates considerable variations in the level of stability with speed, rake angle and feed rate by Knight[14]. Tlusty and Andrews[15] reviewed several sensors and their capabilities for chatter detection, tool breakage detection in maching processes in order to develop an unmanned machining center. Scholar tested force, vibration and aciystic sensors for turning and milling and found that the force signals are the best signal for chatter detection in comparision to vibration signals. Chatter is a relative vibration between the tool and the workpiece and cutting force is a direct indicator of the relative virbration between ttool and workpiece. The characteristic patters of force vibration make it possible to distinguish chatter in a clear manner hence it is desirable for prediction model. A review was presented by Heyns[16] for signal processing techniques and suggested that the time domain and frequency domain methods is suitable for tool wear and chatter estimation. It was also suggested that frequency domain methids such as wavelet transform have higher capabilities which has not been fully exploited. As per the opinion of Zhu et. al.[17], time domain methods are most commonly used in tool condition monitoring (TCM), but these methods fails in some signal information in the time domain. Wavelet transform (WT) and fast fourier Transfer (FFT) were compared and it was found that WT is far more effective than FFT, due to its localization and scarcity properties. WT produces frequency information in a time-locatilzed fashion and has a great potential in detecting abrupt changes in tool conditions in TCM.

Mechanism and experiment

In unmanned turning operation, automatic detection of regenerative chatter play very crucial role in most of the manufacuting industries in order to avoid detrimental effects on surface integrity and damage on the workpiece or machine tools caused by satastrophic tool failure resulting from large amplitude vibrations. Experimental techniques provide way to predict the stability condition in offline mode and detecting chatter onset in online mode. Analytical SLD could be half way mark in detecting the chatter completely which can be done with actual cutting tests. Theoretical and practical both method should be applied to reach the goal and this identification of chatter onset is

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possible using tool condition monitioring (TCM) techniques. The condition monitoring depends upon the type of machine tool as suggested by Siddhpura et. al.[18]. Tool monitoring can be performed through force, vibration and acoustic signals which paly very important role in monitoring process. Various sensors can play crucial role in verification and detection of predicted chatter stability which can measure force, displacement, velocity, acceleration, acoustic signals generated from a machining process, that can be obtained through different appropriate sensors application. Traditional signal processing techniques such as time-domain, frequency domain and teme-frequency domain analysis are generally explored.

Eexperimental model analysis has used MTAB XLTURN CNC lathe. The selected CNC is a 2-axis benchtop slant bed lathe with 8 station programmable turret. Machine has Fanuc or Siemens emulated control system or MTAB Industrial Control and can be integrated with modular automation components to create Smart Factory Automation Systems(FMS, CIM), sutaible for prototyping. It gives 150-3000 rpm spindle speed, max. turning diameter 32 mm, max. turning length 120 mm and have 8 stations. carbide insert TTSO4 tool has been used in turning process. A1-6061-T6 has been selected for the work. Aluminum 6061-T6 is commonly-used aluminum alloy in manufacturing sectors like aerospace, defense and automobile industries due to its good mechanical properties, good weldability and high corrosion resistance. Machining is important part in these manufacturing chains; hence material has been selected keeping in view its wide applicability.

Machining parameters considered for the experiment has been summurised in Table 1.

Table 1: Experimental cutting condition Input parameters and their levels

S. No.	Experimental Parameters	Experimental levels		
		P1	P2	P3
1.	h_0	0.2	0.3	0.4
2.	Ω	1000	1500	2000
3.	f	30	35	40
4.	D	36.50	35.00	33.50

In the Table 2 given parameters are –

P1 – First Level
P2 – Second Level
P3 – Third Level
h_0 - depth of cut (mm)
Ω – rotary (spindle) speed (rpm)
f – Feed rate (mm/min)
D – Duameter (mm)

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Input parameters considered are –

h_0 = 0.2 mm, 0.3 mm, 0.4 mm
Ω – 1000 rpm, 1500 rpm, 2000 rpm
f – 30 mm/min, 35 mm/min, 40 mm/min
D – 36.50mm, 35.00mm, 33.50mm

Experiment has used three combinations in each level for input parameters, which has been tabulated below :

Table 2: Experimental schedule and parameters set for first phase of experiment

Phase 1				
Experiment No.		**h_0 (mm)**	**Ω (rpm)**	**f (mm/min)**
Experiment combination 1	C1	0.2	1000	30
	C2	0.2	1000	35
	C3	0.2	1000	40
Experiment Combination 2	C4	0.2	1500	30
	C5	0.2	1500	35
	C6	0.2	1500	40
Experiment Combination 3	C7	0.2	2000	30
	C8	0.2	2000	35
	C9	0.2	2000	40

Table 3: Experimental schedule and parameters set for second phase of experiment

Phase 2				
Experiment No.		**h_0 (mm)**	**Ω (rpm)**	**f (mm/min)**
Experiment combination 1	C10	0.3	1000	30
	C11	0.3	1000	35
	C12	0.3	1000	40
Experiment Combination 2	C13	0.3	1500	30
	C14	0.3	1500	35
	C15	0.3	1500	40
Experiment Combination 3	C16	0.3	2000	30
	C17	0.3	2000	35
	C18	0.3	2000	40

Table 4: Experimental schedule and parameters set for third phase of experiment

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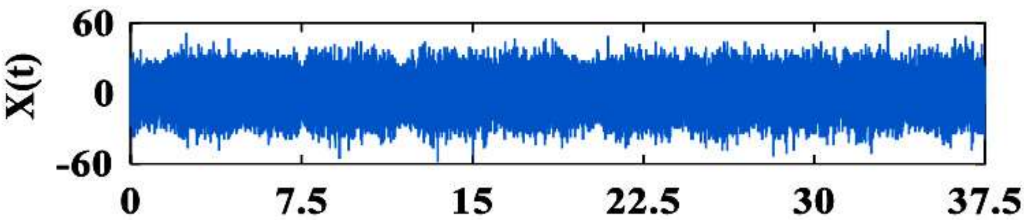
Phase 3					
Experiment No.		h_0 (mm)	Ω (rpm)	f (mm/min)
Experiment combination 1	C19	0.4	1000	30
	C20	0.4	1000	35
	C21	0.4	1000	40
Experiment Combination 2	C22	0.4	1500	30
	C23	0.4	1500	35
	C24	0.4	1500	40
Experiment Combination 3	C25	0.4	2000	30
	C26	0.4	2000	35
	C27	0.4	2000	40

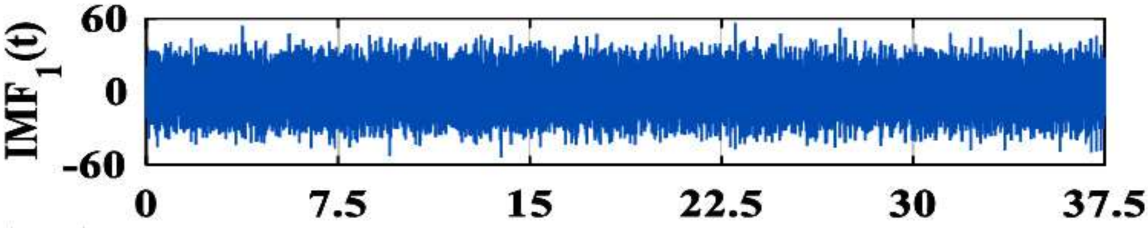
Since experiment has been scheduled to record vibration or noise generated during turning process or to record chatter of the turning experiment high quality microphone has been fitted at appropriate distance of cutting tool and workpice interference. Special attention has been paid during placing the microphone that no subsidery noise or object should come in contact with the microphone. For sound recording sensitive software has been used. The microphone has been connected to the laptop where inut sound of chatter has been filtered and recorded.

Signal processing with Empirial Mode Decomposition

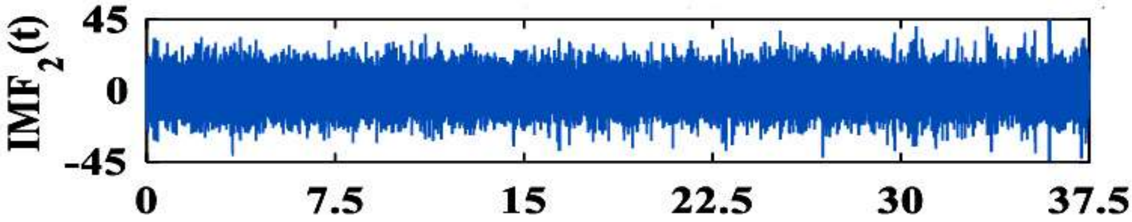
Huang invented the Empirical Mode Decomposition (EMD) approach, which is frequently used to examine vibration signals[19]. Empirical mode decomposition is basically data-daptive multiresoution technique to decompose acquired signal into physically meaningful components which is used to analyse non-linear and non-stationalry signals by separating them into components at different resoultuons. Empirical mode decomposition can be used to prform time-frequency analysis while remaining in the time domain as in these condition components remains in same time scale as the original signal that makes nanlysis easier. For the signal analysis work Wavelet Toolbox, for use with Signals are broken down into a variety of intrinsic mode functions (IMFs) via EMD. Acquired raw chatter signals have been processed using the EMD method, and matching IMFs have been determined.



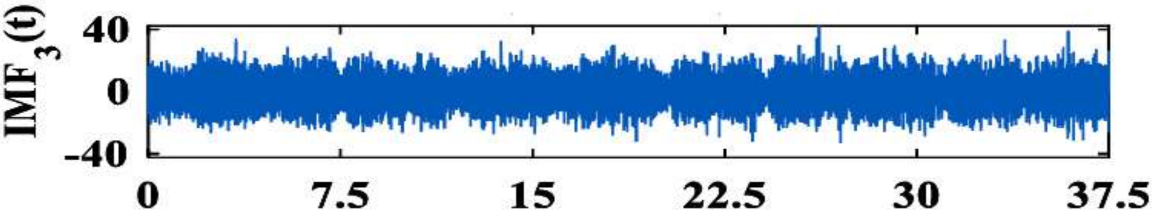
(a)


IMF1(t)
60
0
-60
0
7.5
15
22.5
30
37.5

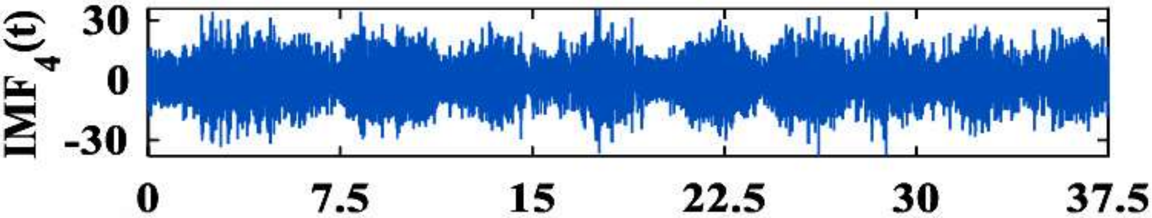
(b)


IMF2(t)
45
0
-45
0
7.5
15
22.5
30
37.5

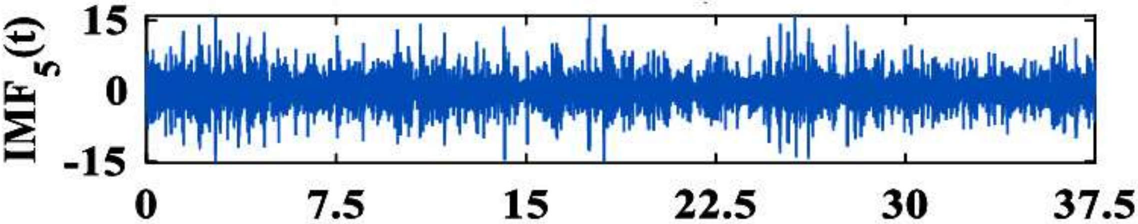
(c)


IMF3(t)
40
0
-40
0
7.5
15
22.5
30
37.5

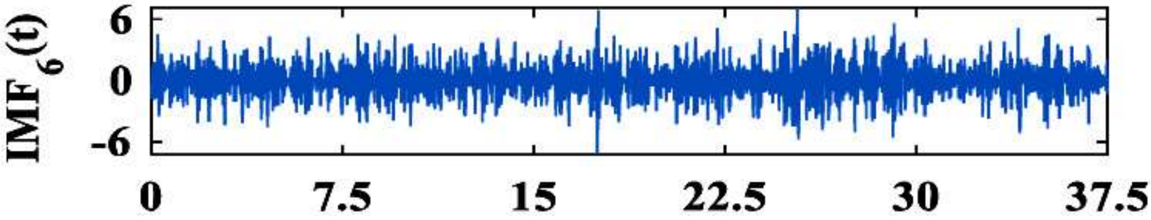
(d)


IMF4(t)
30
0
-30
0
7.5
15
22.5
30
37.5

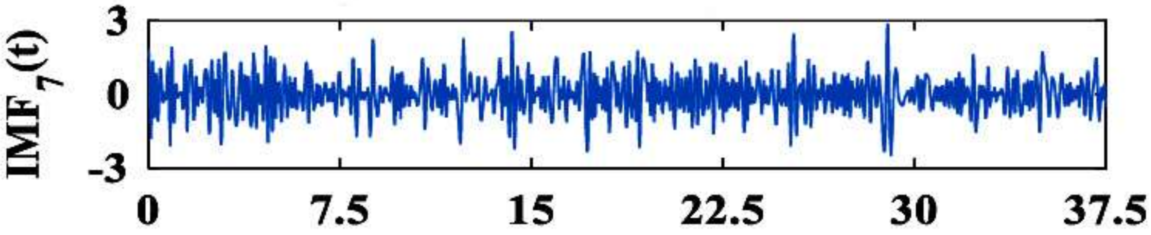
(e)


IMF5(t)
15
0
-15
0
7.5
15
22.5
30
37.5

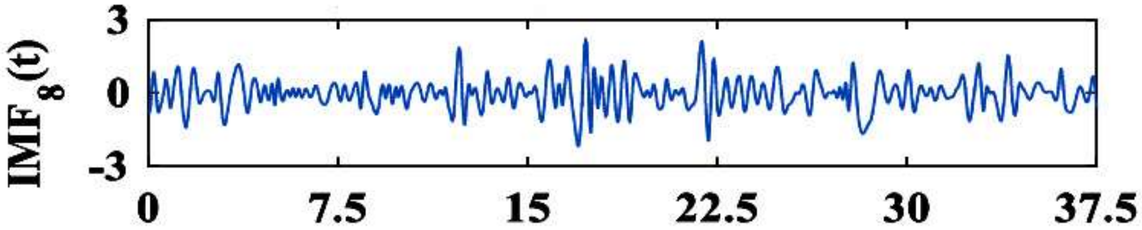
(f)


IMF6(t)
6
0
-6
0
7.5
15
22.5
30
37.5

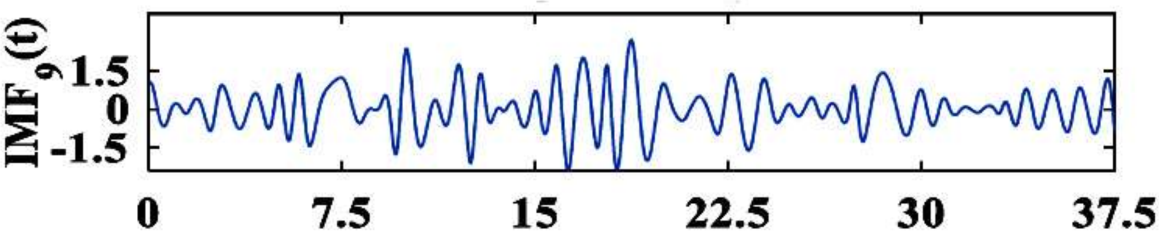
(g)


IMF7(t)
3
0
-3
0
7.5
15
22.5
30
37.5

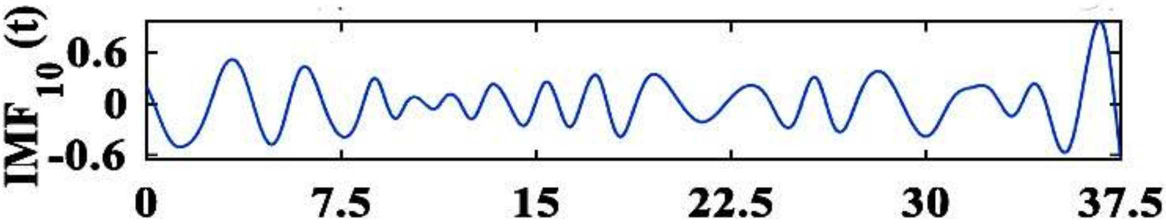
(h)


IMF8(t)
3
0
-3
0
7.5
15
22.5
30
37.5

(i)


IMF9(t)
1.5
0
-1.5
0
7.5
15
22.5
30
37.5

(j)


IMF10(t)
0.6
0
-0.6
0
7.5
15
22.5
30
37.5

(k)

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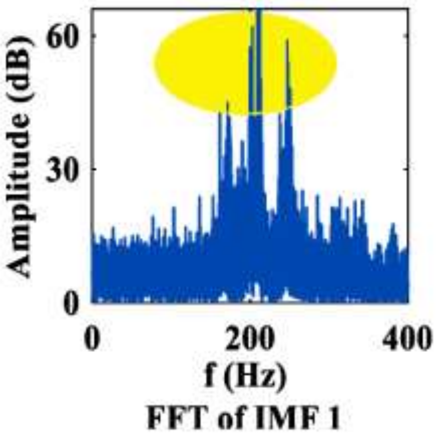
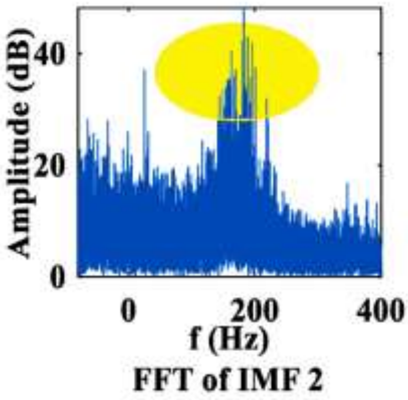


(aa)



(ab)

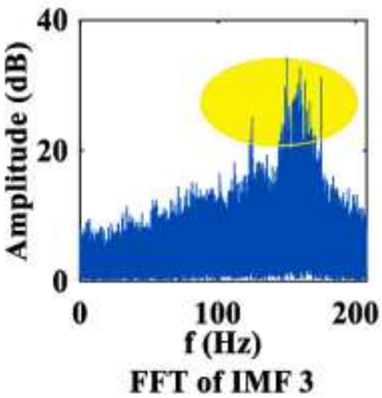


Figure (s) 35 (a…k, aa, ab, ac): IMF (Intrinsic Mode Finctions) and FFTs (Fast Fourier Transforms) of signal acquired at h_0=0.3, Ω = 2000rpm and f=40mm/min. Yellow shadow areas – indicate mode aliasing, no clear peaks.

(ac)

Figure 35 displays the IMFs of one of the recorded machining vibration or chatter signals. The Fast Fourier Transform (FFT) of the associated IMFs has also been shown in Figure 35. In experimental analysis FFT forms the basis for frequency domain analysis or spectral analysis in signal processing and is used for signal filtering, spectral estimation, data compression and other applications. Variations of the FFT has allowed for simultaneous analysis in time and frequency domains. In this experiment the corresponding IMF clearly in charge of chatter may be identified using the FFTs. Despite the fact that EMD has a wide range of applications, problems with modal aliasing, which can be described as the incorrect detection of signal frequency or an undesired effect that is seen in sampled system — persists. Model alisasing can be detected when the input frequency is greater than half the sample frequency, in this case the sampled points do not adequately represent the input signal. The cluster of high frequencies or closed frequency signal components that are visible in the FFT of IMFs as illustrated in Figure 35 cannot be separated using this method i.e. EMD. Mode mixing occurs when the decomposed IMFs have identical frequencies in their overlapping components. In general, aliasing is more likely to occur with high-frequency signals. In comparison to EMD, LMD is a more moderate time-frequency analysis and decreases these effects [20]. This inspired the current research to use LMD to explore the tool chatter characteristics. The signal is broken down by LMD into a number of

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chatter-containing product functions. The LMD signal processing approach can be used to determine the chatter frequency peaks.

Local Mean Decomposition signal Processing

It is very difficult to collect signals from rotating machines because it contains not only the frequency components from the interested rotating machine component but also interference frequencies from other neighbouring components and environment noise. Hence amplitude modulation, frequency modulation and phase modulation becomes common in these signals. And also machines functional characteristics like varying speed and load conditions makes collection of signal more difficult. A self-adaptive time-frequency based Local Mean Decomposition (LMD) approach was put out by Smith[21]. With this technique, the signals are broken down into a group of product functions (PFs) and residue. By multiplying the amplitude envelope signals (IAs – stand fro the instantaneous amplitude(s)) and frequency modulated signals (IFs – stand for the instantaneous frequency(ies)), the product function is created. In the current work, the non-stationary, nonlinear chatter signals' hidden characteristics have been extracted using the LMD approach.

LMD separates the amplitude modulated envelop signals from the frequency-modulated signal. This is accomplished by demodulating the amplitude using envelope functions after subtracting the smoothed signal from the original signal. By measuring the time difference between the successive extrema of the original signal, the smoothed signal and envelope functions are derived. Up till the frequency modulated signal has a flat envelope, this process is repeated. It is possible to determine the instantaneous phase and frequency of this frequency-modulated signal. To obtain the final envelope signal, the corresponding envelope functions are multiplied. The frequency-modulated signal is multiplied by the final envelope signal to produce the first product function PF1(t). Additionally, a new signal is produced by deducting PF1 (t) from the original signal, and PF2 (t) is produced by repeating all of the aforementioned procedures. Up until the final signal becomes monotone or constant, this process is repeated. A residual signal is the name given to this monotone signal.

Following steps presents the LMD algorithm[4] used for decomposing the signal *x (t)* into *PP'.*

1. First Step - Find out all local extrema points *`ki (t) ' of the* original signal *5c (t)* '. Calculate the local mean and amplitude envelope of two successive extrema using equation 1 and equation 2;

$$m_i(t) = \frac{k_i(t) + k_{i+1}(t)}{2} \qquad \text{………..eq41}$$

$$a_i(t) = \frac{|k_i(t) + k_{i+1}(t)|}{2} \qquad \text{………..eq42}$$

In above equation

$m_i(t)$ - the local mean,
$a_i(t)$ - the amplitude envelope

and *i*= *1, 2,........, M-1 (M*= number of extrema). All the mean $m_i(t)$ of successive extrema must form a line.

2. Second Step – Calculate smooth continuous local mean function $m_{ij}(t)$ and amplitude envelope function $a_{ij}(t)$ (*take* moving averaging of $m_i(t)$ and $a_i(t)$).
3. Third Step - Consider $u_{11}(t) = x(t) - m_{11}(t)$ and $s_{11}(t) = u_{11}(t)/a_{11}(t)$, where $s_{11}(t)$ is a pure frequency modulated signal (fluctuates between -1 to 1).
4. Fourth Step - The envelope function $a_{12}(t)$ of $s_{11}(t)$ should satisfy $a_{12}(t) = 1$. In case it fails then $s_{11}(t)$ *should be considered* as a new signal. In this situation step 1to 3 should be iterated until envelope function $a_{1(p+t)}(t)$ of the $s_{1p}(t)$ satisfies $a_{1(p+t)}(t)=1$.
5. Fifth Step – to get the envelop signal use following equation-

$$a_1(t) = a_{11}(t)a_{12}(t)........a_{1p}(t) = \prod_{q=1}^{p} a_{1q}(t) \quad .....eq43$$

Where $\lim_{p\to\infty} a_{1p}(t) = 1$ and q is the number of iterations. The instantaneous phase θ_1 (t)=arccos($s_{1p}(t)$) and the instantaneous frequency can be defined as;

$$f_1(t) = \frac{1}{2\pi}\frac{d\theta_1}{dt} \quad (5.4)$$

6. Sixth Step - multiply envelope signal $a_1(t)$ and the pure frequency modulated signal $s_{1n}(t)$ to get the first PF.

$$PF_1(t) = a_1(t)s_{1n}(t) \quad ....eq45$$

Theoretically $PF_1(t)$ contains the most oscillation information of the signal x(t), and the IA of $PF_1(t)$ is $a_1(t)$ and the IF is calculated through following equation –

$$f_1(t) = \frac{1}{2\pi}\frac{\mathrm{d}[\arccos(s_{1n}(t))]}{\mathrm{d}t}. \quad .....eq46$$

7. Seventh Step - By subtracting $PF_1(t)$ from the original signal *x(t) a new signal is obtained. $PF_2(t)$ derived* by repeating steps 1-6 and steps should be repeated until the last signal becomes monotonic or constant, a residual signal. The original signal *x(t)* can be represented in the form of PFs and residue $u_n(t)$ as given below –

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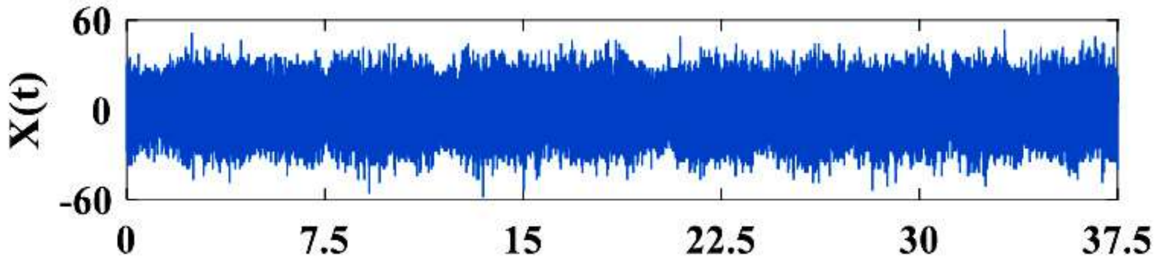
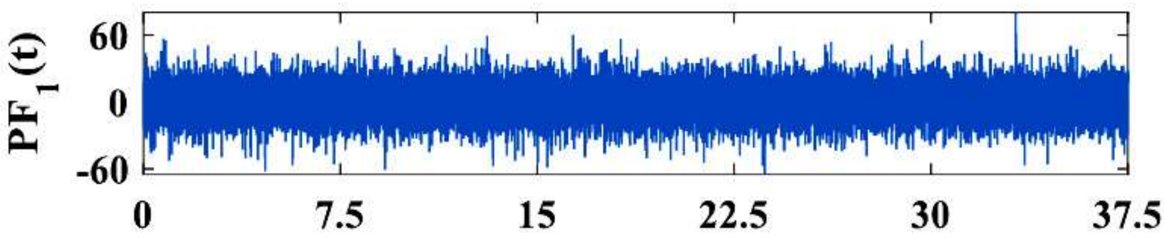
$$x(t)=\sum_{l=1}^{n-1} PF_l(t)+u_n(t)$$

……..eq47

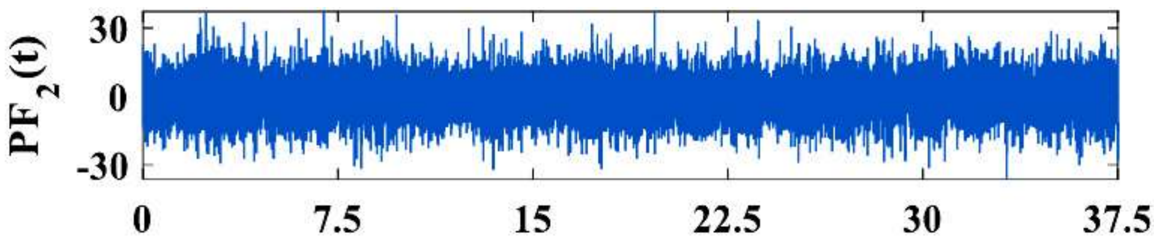
PFs of the recorded chatter or vibration have been obtained through LMD algorithm, and the decomposed signals has been illustrated in Figure 36 which in addition presents the Fast Fourier transform (FFT) of the PFs. Figure 37 illistrate the FFT of all PF_s. In order to identify the corresponding PF the FFTs have been obtained which are prominently responsible for vibration (chatter).



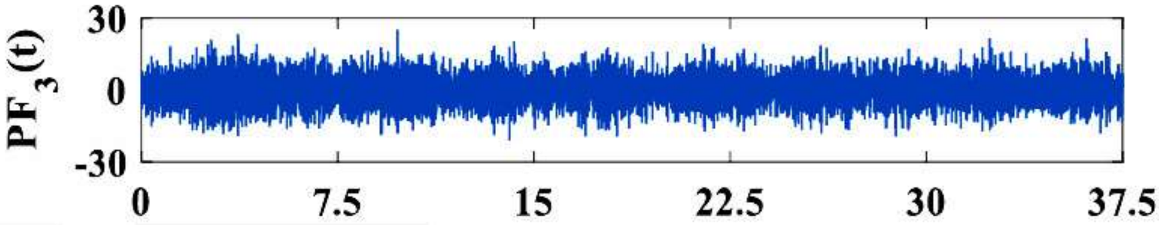
(a)



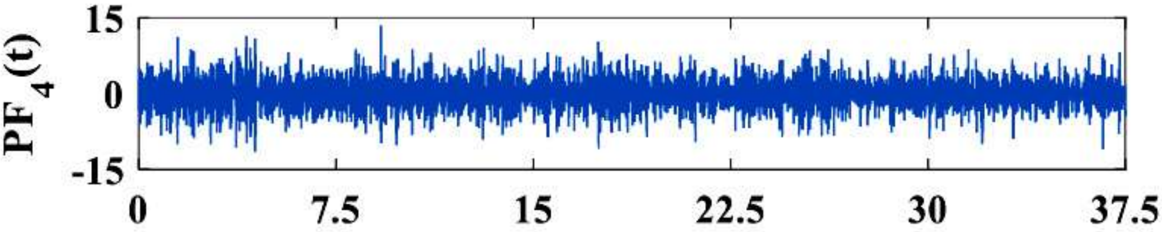
(b)



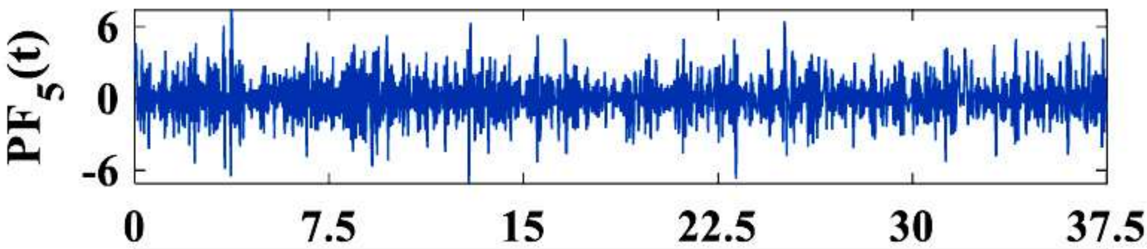
(c)



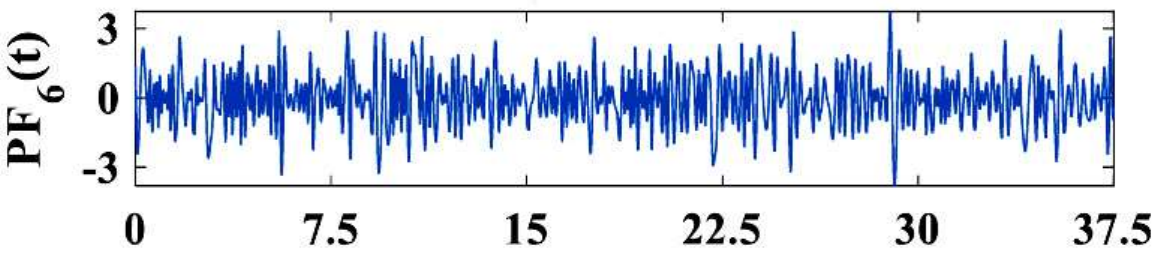
(d)


$PF_4(t)$
15
0
-15
0
7.5
15
22.5
30
37.5

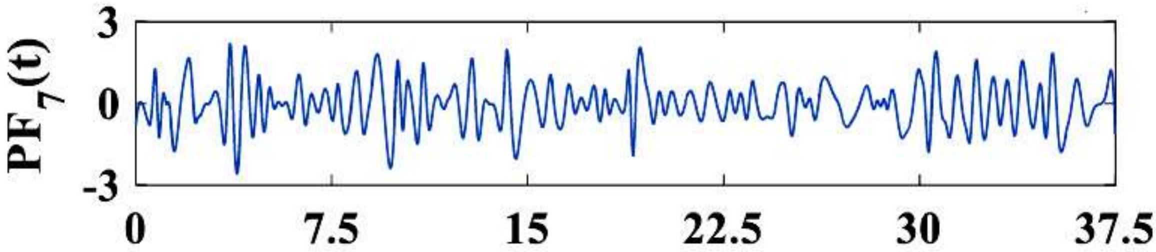
(e)


$PF_5(t)$
6
0
-6
0
7.5
15
22.5
30
37.5

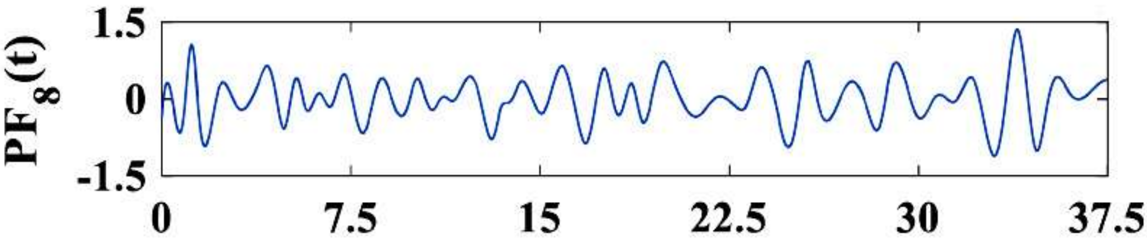
(f)


$PF_6(t)$
3
0
-3
0
7.5
15
22.5
30
37.5

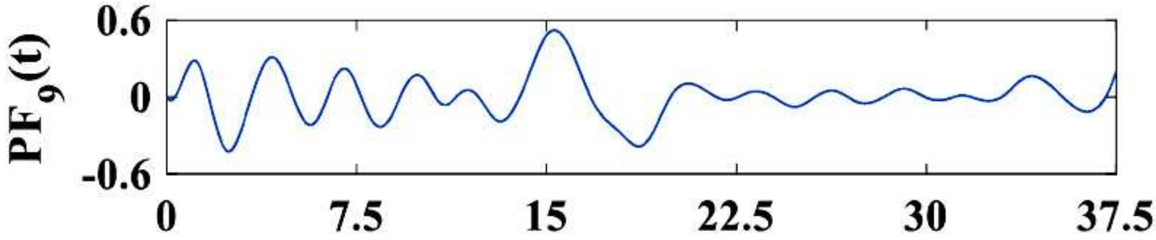
(g)


$PF_7(t)$
3
0
-3
0
7.5
15
22.5
30
37.5

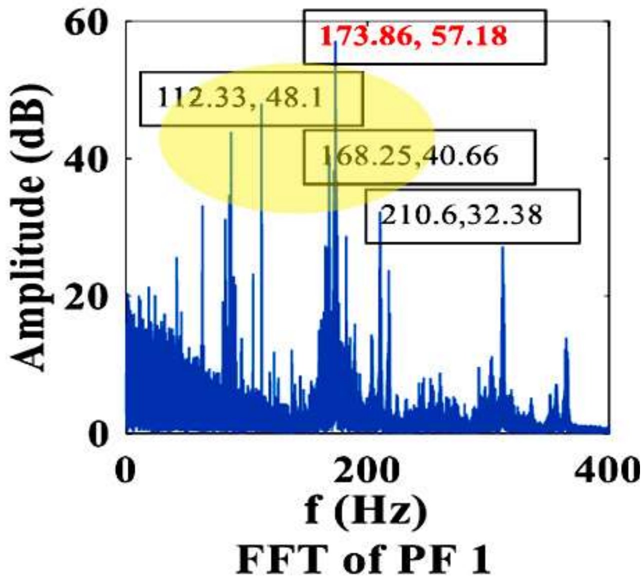
(h)



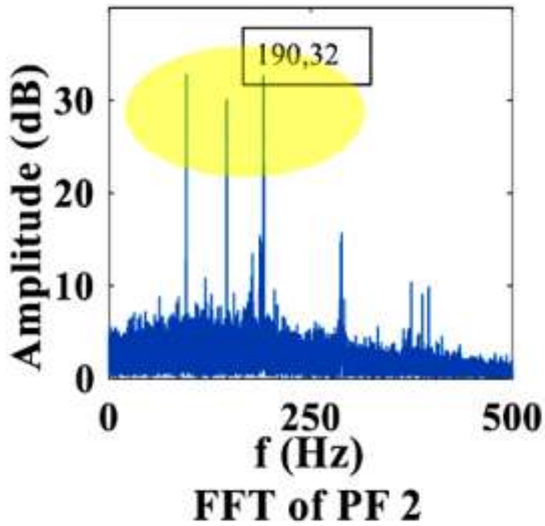
(i)



(j)



(aa)



(ab)

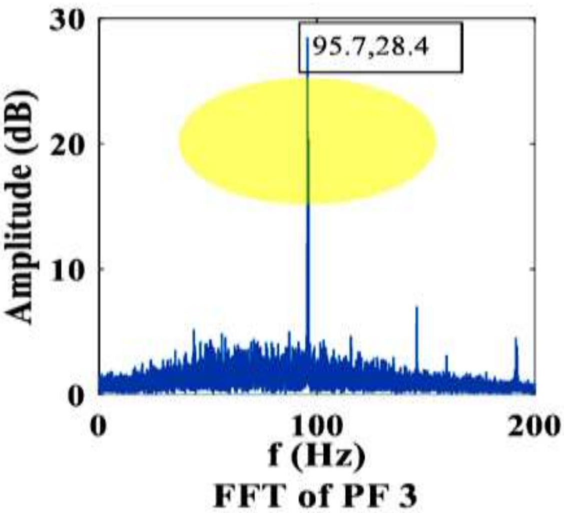
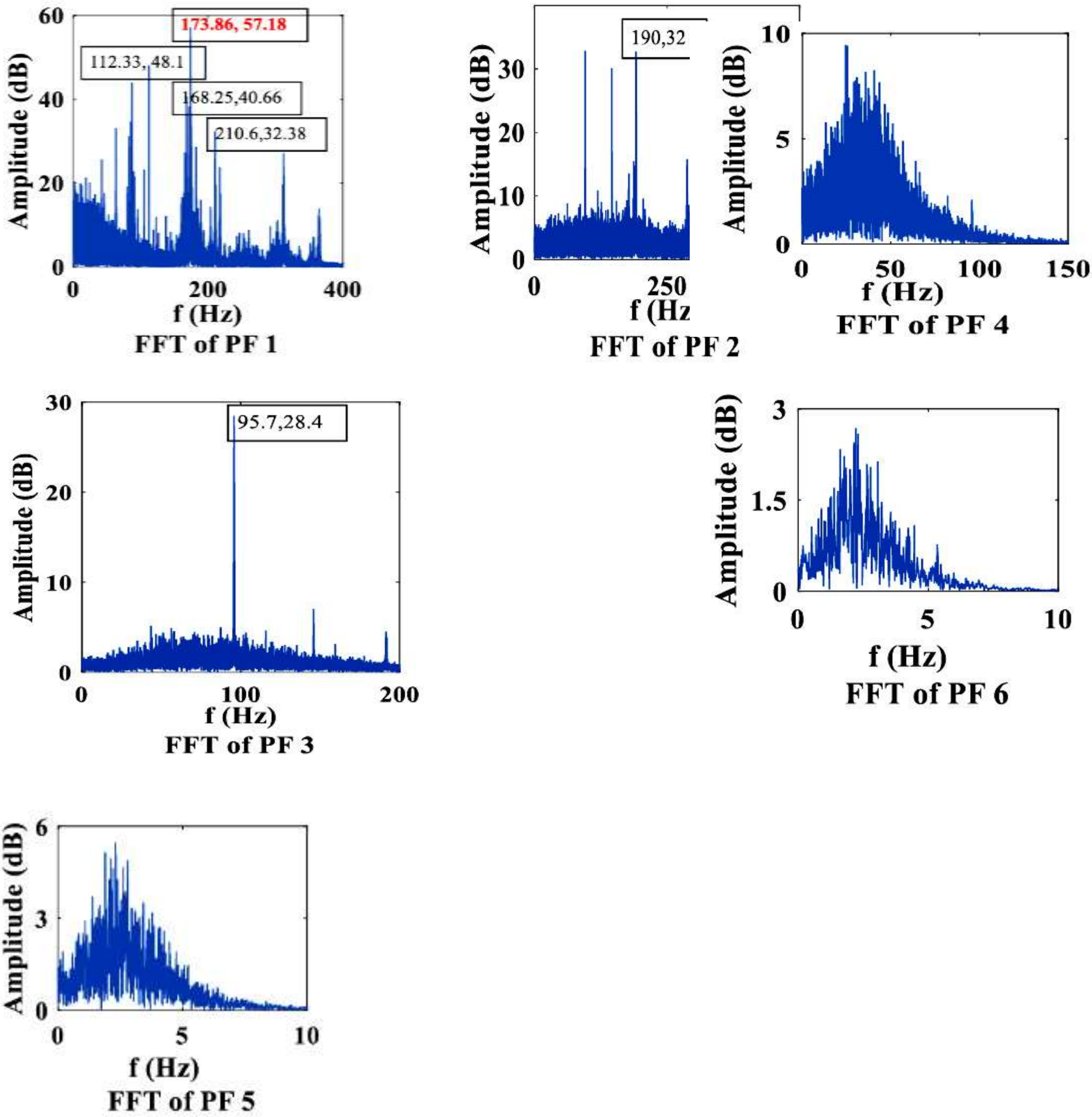


Figure (s) 36 (a…j, aa, ab, ac): Product function and FFTs signals obtained at h_0=0.3, Ω = 2000rpm and f=40mm/min. yesllow shadow area – indicate chatter frequencies cluster with clear peaks.



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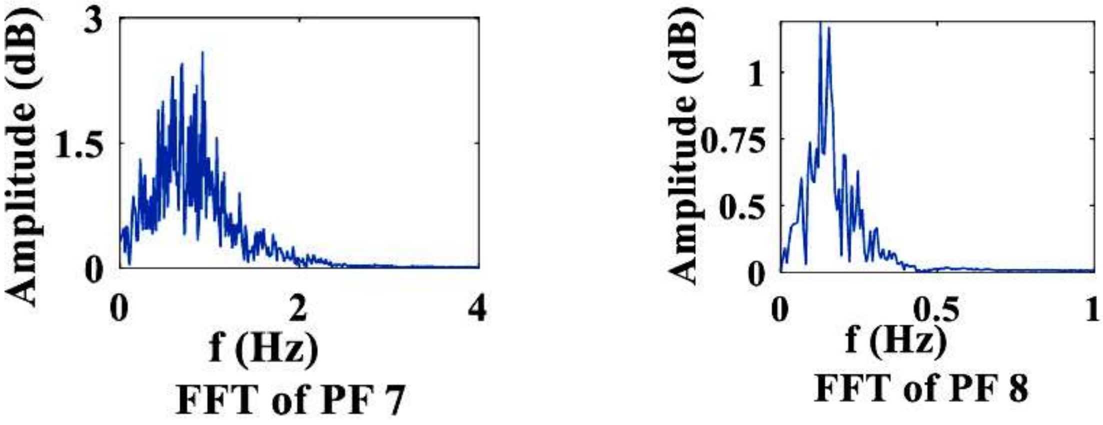


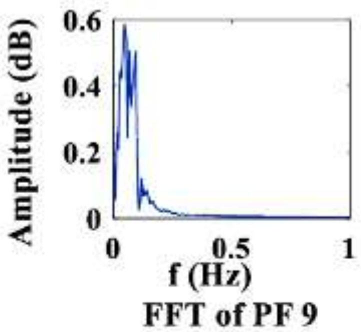


Figure (s) 37 (PF1…PF9): Graphs indicaing FFT of demodulated PFs

By examining the maximum amplitude and cluster of frequencies surrounding the natural frequency, the PF that causes chatter has been chosen. Mode mixing issues may be the cause of the PF1 frequency representation's wide frequency range. Therefore, thorough analysis of both the cluster of frequencies and amplitude is required in order to choose the PFs that resemble the chatter signal. Figure 37 shows that PF1 has the highest amplitudes as well as a group of frequencies close to the natural frequency. The chatter frequency of a given signal's conspicuous PF1 is 173.86 Hz with an amplitude of 57.18 dB, which is higher than the system's natural frequency. Similar to this, the product functions (PF), which are notably accountable for chatter, have been estimated for various recorded signals. Then, in order to extract the tool chatter features, these chosen PF were examined using three statistical chatter indicators.

WDLMD signal processing

EMD is capable of extracting chatter bands but inherited modal aliasing's drawback. Additionally, when Hilbert transformation is applied to the findings of the decomposition of EMD, negative instantaneous frequency and the end effects are more pronounced. By using local mean decomposition, this issue has been mostly handled, and the method produces good outcomes for determining chatter severity. Compared to EMD, LMD produces better decomposition results. The LMD approach does, however, have some drawbacks. End effect and modal aliasing issues are not entirely resolved. As a result, researchers have suggested a novel technique called WDLMD, or wavelet denoising and local mean decomposition combined. Local mean decomposition (LMD) is used to demodulate the chatter signals into a number of product functions, which separates the chatter frequencies. Wavelet denoising is used to eliminate undesirable ambient noise and contaminations from chatter signals. The built simulated chatter signal from Equation 17 has been handled with merged wavelet denoising and local mean decomposition (WDLMD) in order to test the practicality of the proposed method. This updated signal processing technique can restore all frequencies at almost the same simulated signal amplitude.

Simulated signal processing with the help of WDLMD

The signal's noise makes it difficult to identify the chatter frequency precisely. WD is used to clean up undesirable contaminations and denoise the signal. It can eliminate contaminants while preserving crucial information. The two following processes in this strategy are wavelet decomposition and thresholding. The noisy signal is initially decomposed [22,23, 24], with the degree of decomposition determined by the length of the signal (the signal size must be divisible by 2^level). After passing the noisy signal through low- and high-pass filters, coefficients are then calculated. In the subsequent stage, WD concentrates signal characteristics into a small number of wavelet coefficients of large magnitude and denoises the small value coefficients by reducing or eliminating their values without damaging the true informative signal. Undesired noise has resulted into the smaller coefficients. Figure 38. illustrate the outlay of wavelet decomposition.

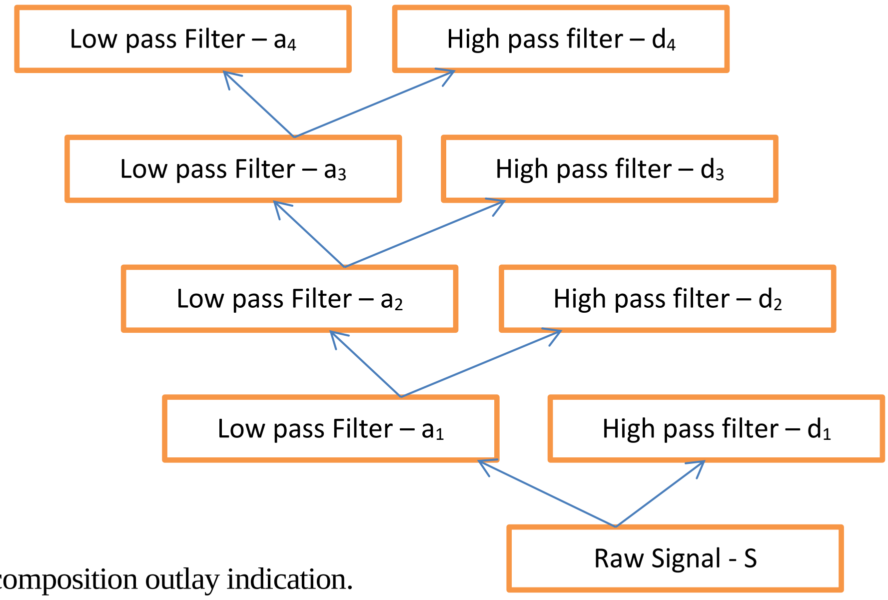


Figure 38: Wavelet decomposition outlay indication.

In wavelet decomposition the selection of thresholding is considered to be important step, where two types of thresholding techniques are used generally, hard thresholding and soft thresholding.

Soft thresholding;

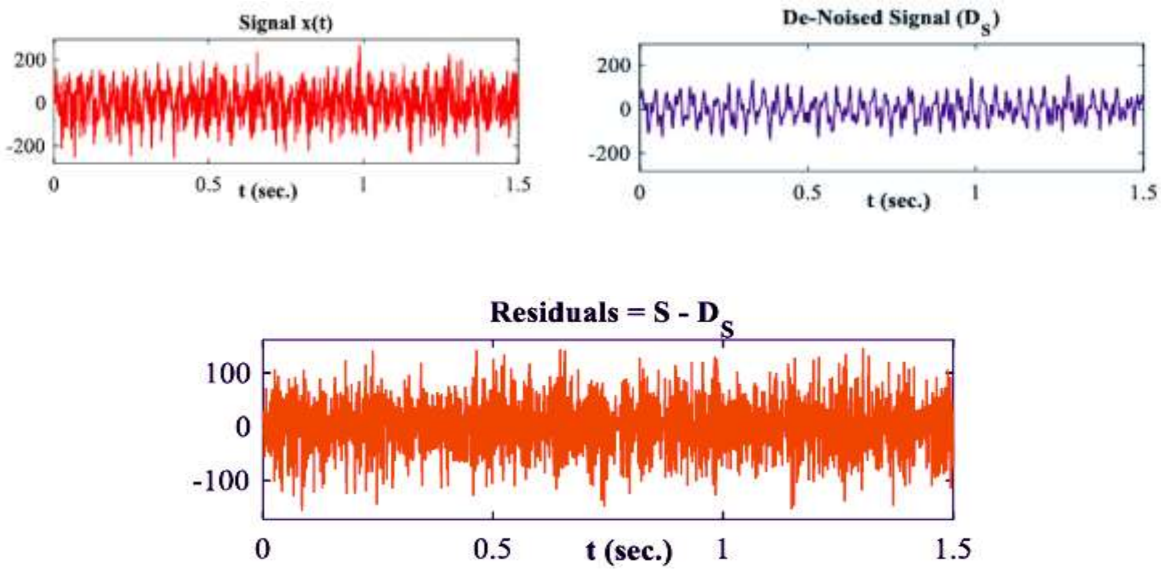
$$W_{\lambda\_s} = \begin{cases} W_\lambda - \lambda & |W_\lambda| \geq \lambda \\ 0 & |W_\lambda| < \lambda \\ W_\lambda + \lambda & |W_\lambda| \leq -\lambda \end{cases}$$

Where, W_λ = noisy wavelet coefficient, λ = threshold.

Hard thresholding;

$$W_{\lambda\_H} = \begin{cases} W_\lambda & |W_\lambda| \geq \lambda \\ 0 & |W_\lambda| < \lambda \end{cases}$$

Inverse wavelet transform produces the original signals that have been denoised after thresholding the coefficients. The non-linear technique of thresholding evaluates each wavelet coefficient [25]. Then, a threshold level is used to compare each coefficient to. When comparing, if the coefficient's value is discovered to be lower than the level, the coefficient is changed until it exceeds the level, at which point it is left alone. Noisy coefficients are eliminated as a result of this method. MATLAB software has been used to put the wavelet denoising approach into practice. First, as shown in Figure 39, Daubechies (db5) wavelet and two level decomposition have been used to filter away the noise from the simulated signal. The stationary detailed coeficients 'd_1' and 'd_2' are produced when the signal goes through the high-pass filter. The achieved 'a_2' denotes the estimated coefficient and denotes the lower frequency.



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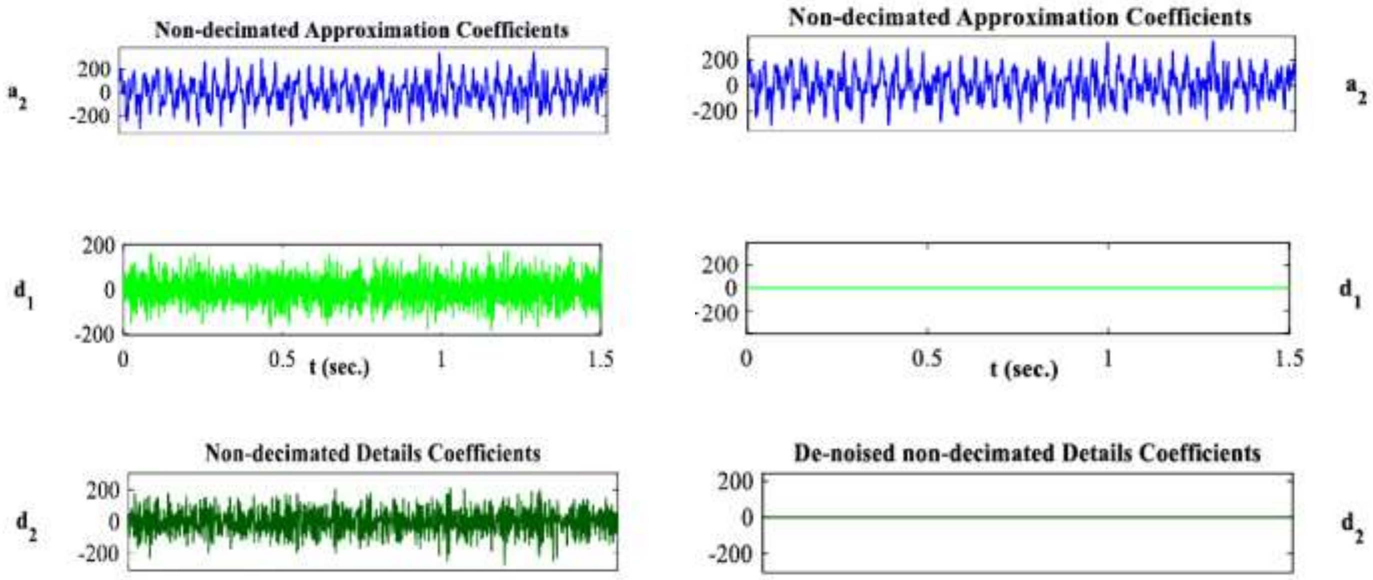
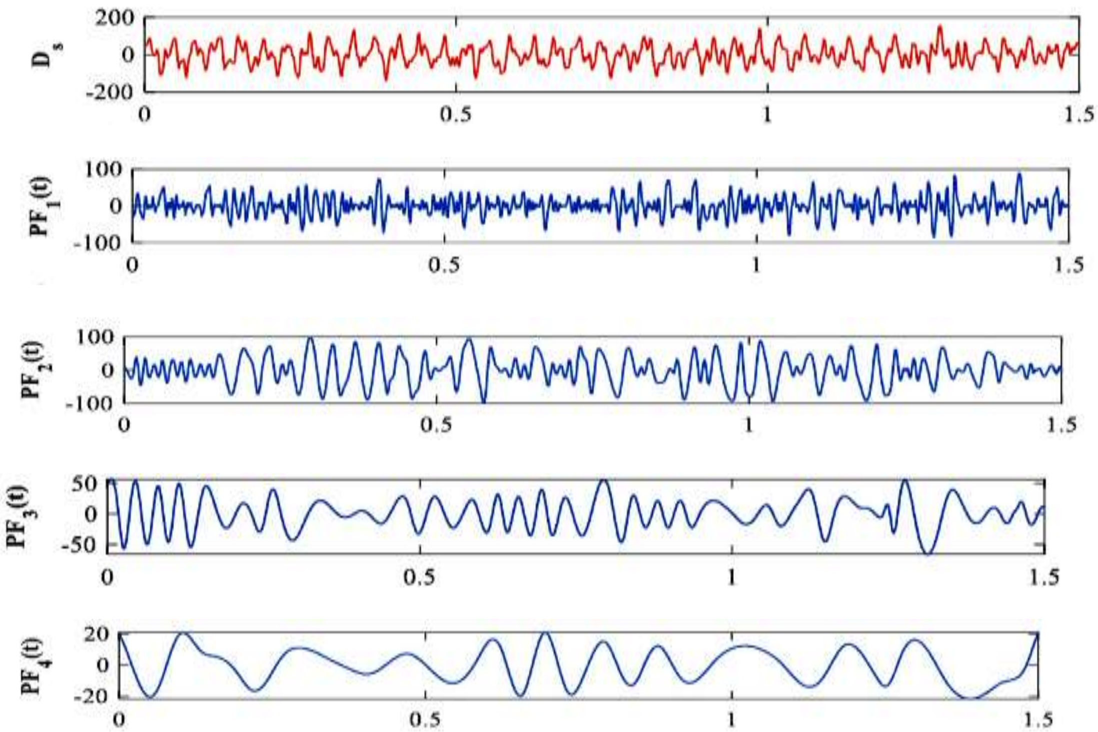
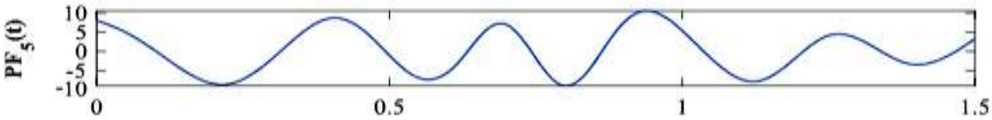


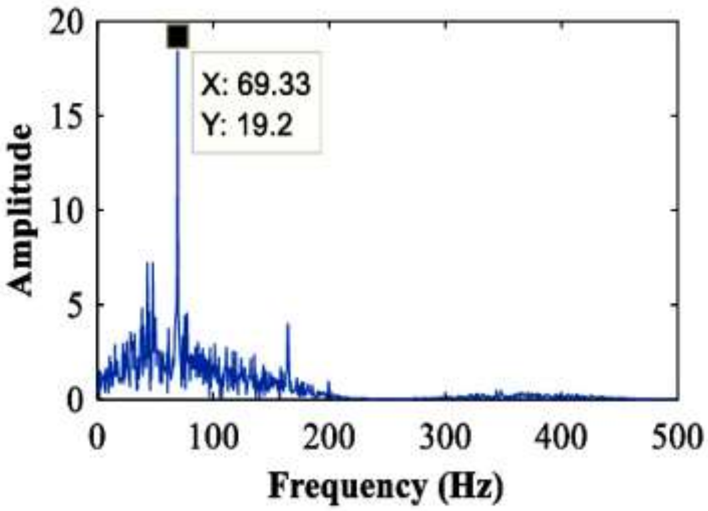
Figure 39: depiction of wavelet denoising



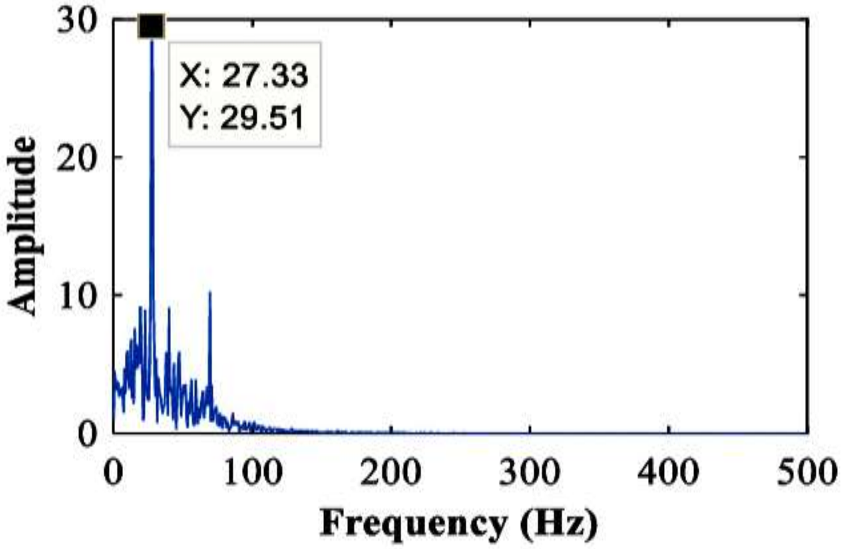


← Time →

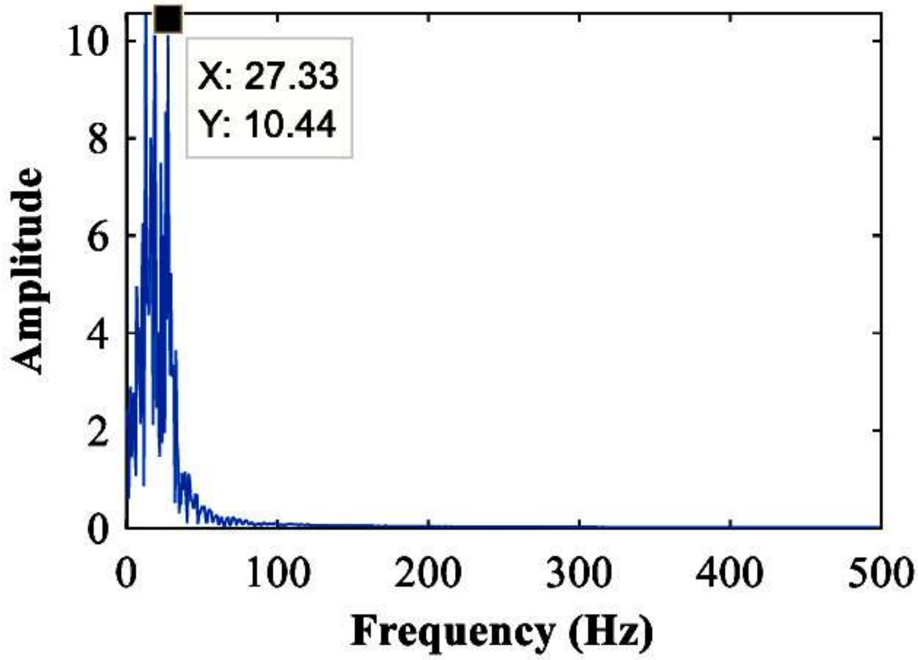
Figure 40: Depiction of Product functions



(a)



(b)



(c)

Fugure 41: Graphs signal indicating denoised FFTs, (a)-PF_1, (b)-PF_2,(c)-PF_3

The original signal components have also been restored using the LMD approach, as seen in figure 40. It is evident from the FFT of PFs in Figure 41 that the mode aliasing issue is all but gone. The deconstructed signal component is known as the PFs, and the frequency bands range from high to low. The correlation coefficient for PF1, PF2, and PF3 is 0.48, 0.69, 0.35, and insignificant for the other product functions. The denoised signal's first three PF components have the highest correlation coefficient. As a result, signal reconstruction is carried out utilizing the first three PFs with a high correlation coefficient. The reconstructed signal's correlation coefficient is 0.92. The significant frequency components of the reconstructed signal are then presented in Figure 42 without mode mixing using FFT. Peak chatter frequencies can be plainly seen in Figure 42.

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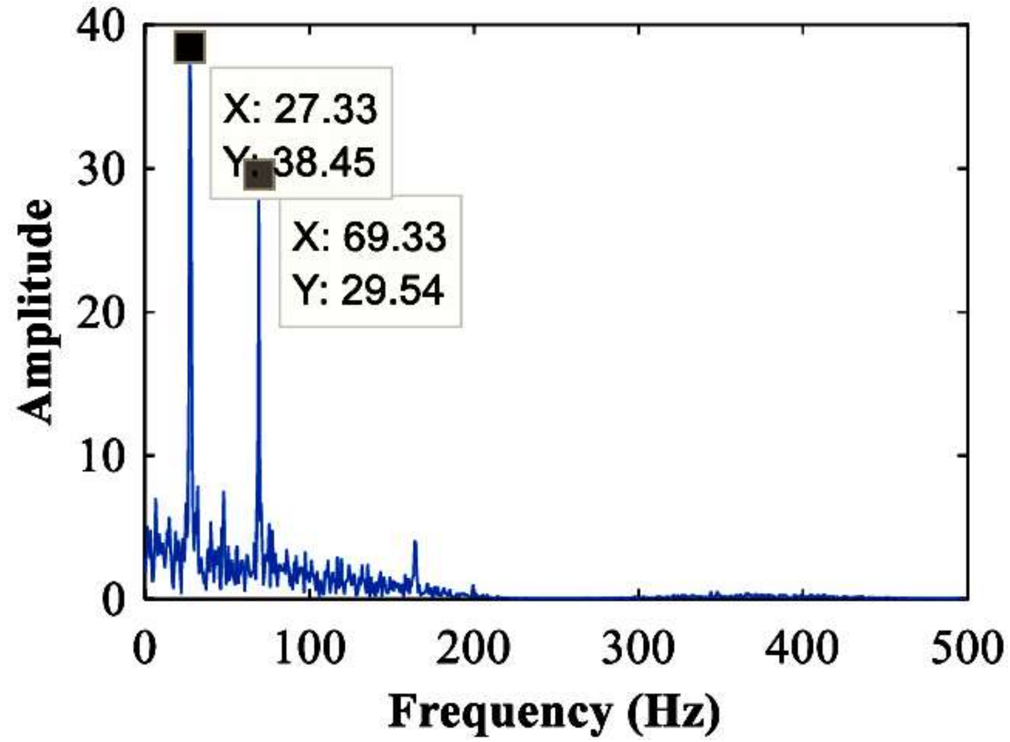


Figure 42: Reconstructed FFT signal

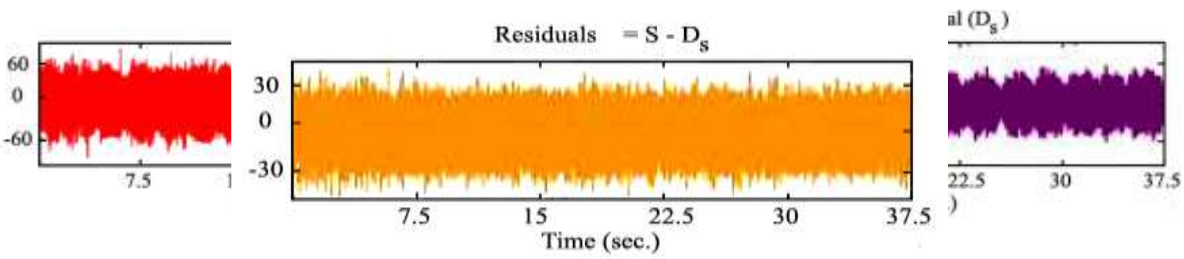
The frequency components were determined using equation 17 from the theoretical analysis in previous third chapter. Thus, it can be concluded that the WDLMD technique is appropriate for processing the unprocessed chatter signals that contain embedded ambient noise contents. The suggested WDLMD technique was verified, and then it was used to analyze the real chatter signal experimentally obtained during the turning operations for all three combination of experiments.

Experimental chatter signals processing through WDLMD

First, as shown in figure 43, Daubechies (db5) wavelet and four level decompositions have been used in MATLAB software to filter away the nose from the machining signals. Trial and error, as well as matching the decomposition to the raw signal, are used to choose the mother wavelet db5. The responsiveness of the chatter is improved by decomposition level 4. Each deconstructed level in this work has been subjected to soft thresholding. Standard deviation has been used to test the threshold (σ);

$$t = \sigma\sqrt{2\log(n)}$$

$where\ n - represnts\ length\ of\ the\ signal$ ……..eq48



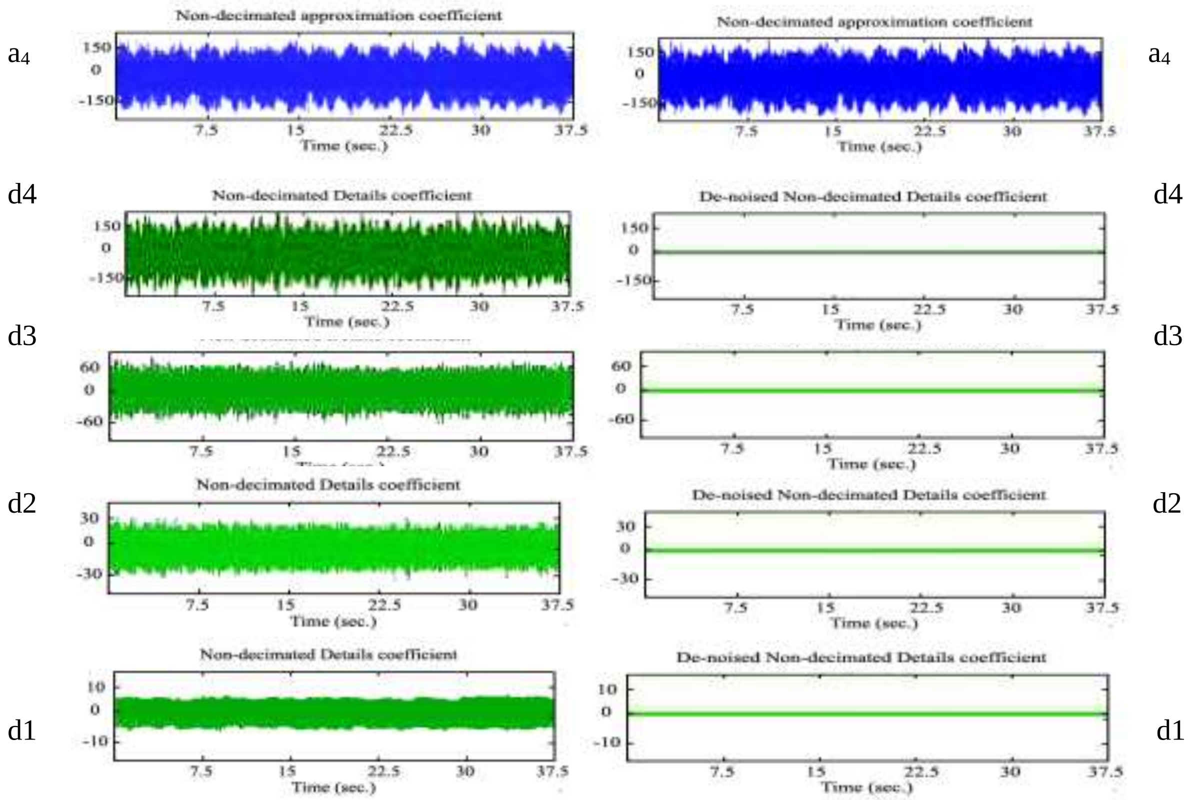
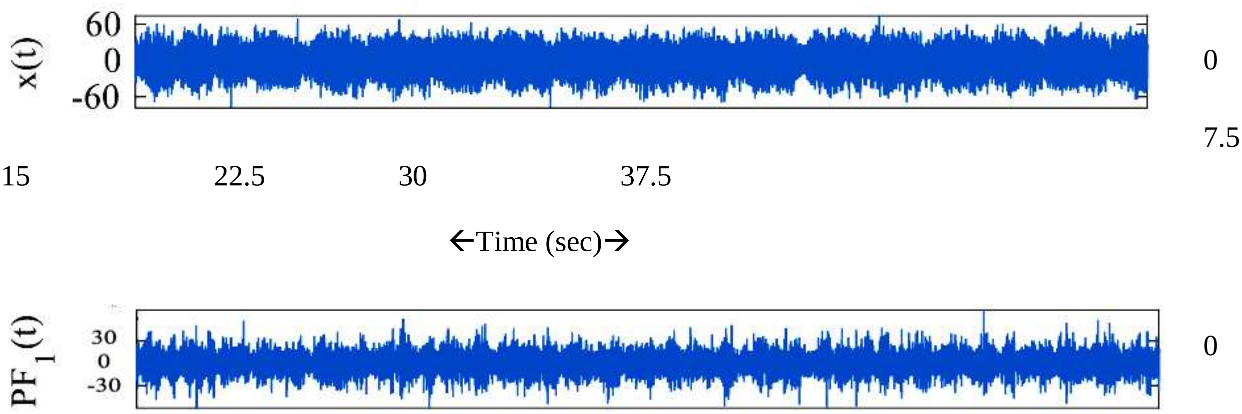


Figure 43: Depiction of denoising wevlaet

LMD was additionally used to process the signal and obtain the demodulated signal. The signal is divided into several PFs by LMD, as seen in Figure 44 [26]. LMD technique extracts signals' hidden properties. The correlation coefficient has been determined from the obtained PFs, and important PFs with built-in chatter information have been chosen.



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7.5 15 22.5 30 37.5

←Time (sec)→

0

7.5

15 22.5 30 37.5

←Time (sec)→

0

7.5

15 22.5 30 37.5

←Time (sec)→

0

7.5

15 22.5 30 37.5

←Time (sec)→

0

7.5 15 22.5 30 37.5

←Time (sec)→

0

7.5

15 22.5 30 37.5

←Time (sec)→

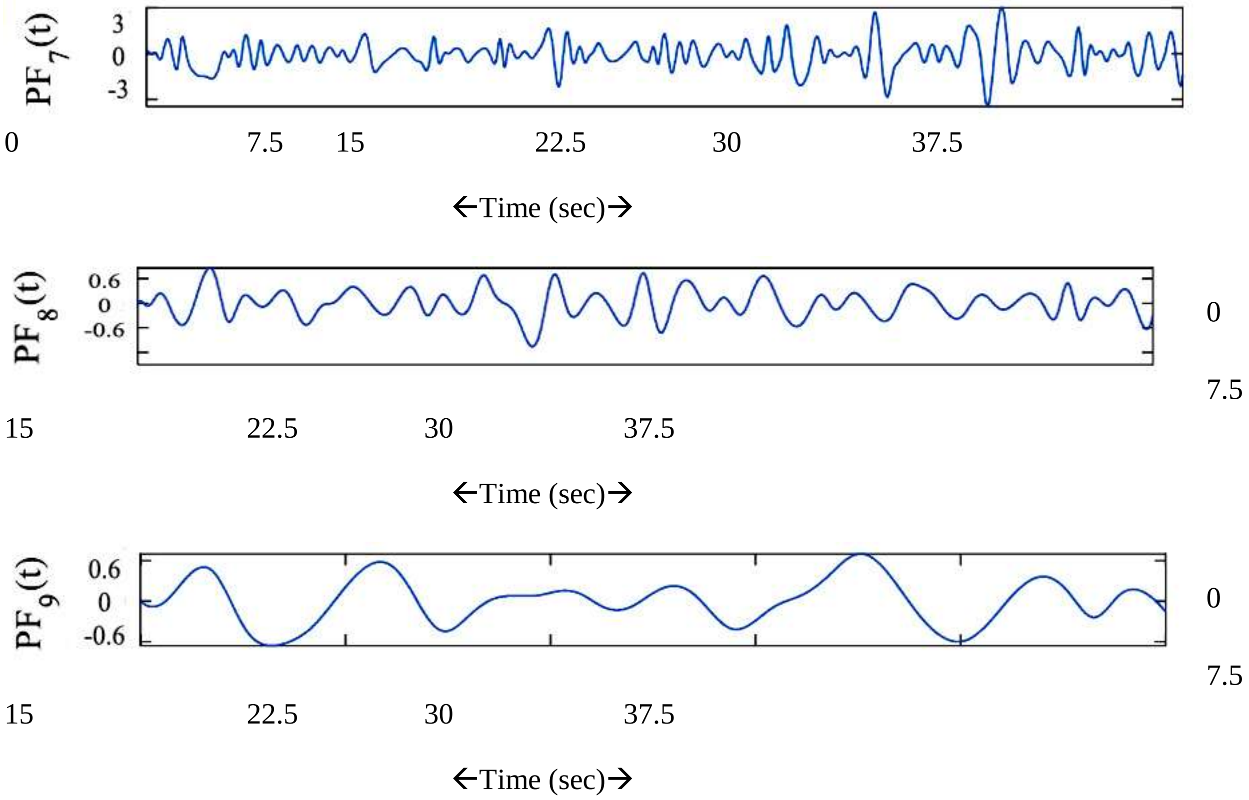


Figure 44: Denoised signal (Signal decomposinon)

Correlation coefficient

The linear link between two random data sets is measured using correlation coefficients [27]. Correlation coefficient values range from -1 to 1. Using equation 49, the Pearson correlation coefficient has been computed;

$$\rho(P,Q) = \frac{1}{L-1}\sum_{i=1}^{L}\left(\frac{P_i - m_P}{\sigma_P}\right)\left(\frac{Q_i - m_Q}{\sigma_Q}\right) \qquad \text{……………………eq49}$$

In the equation 5.10

L – the number of observation
M_p - mean of P
σ_p – standard deviation of P
m_q - mean of Q
σ_q – standard deviation of Q

To combine and reconstruct a new signal, the correlation coefficients of responsible PFs with a similar match to the original signal have been utilised. Figure 45 displays the correlation coefficient of the PFs with respect to the denoised signal (h0 = 0.3, Ω = 2000 rpm, f=35 mm/min).

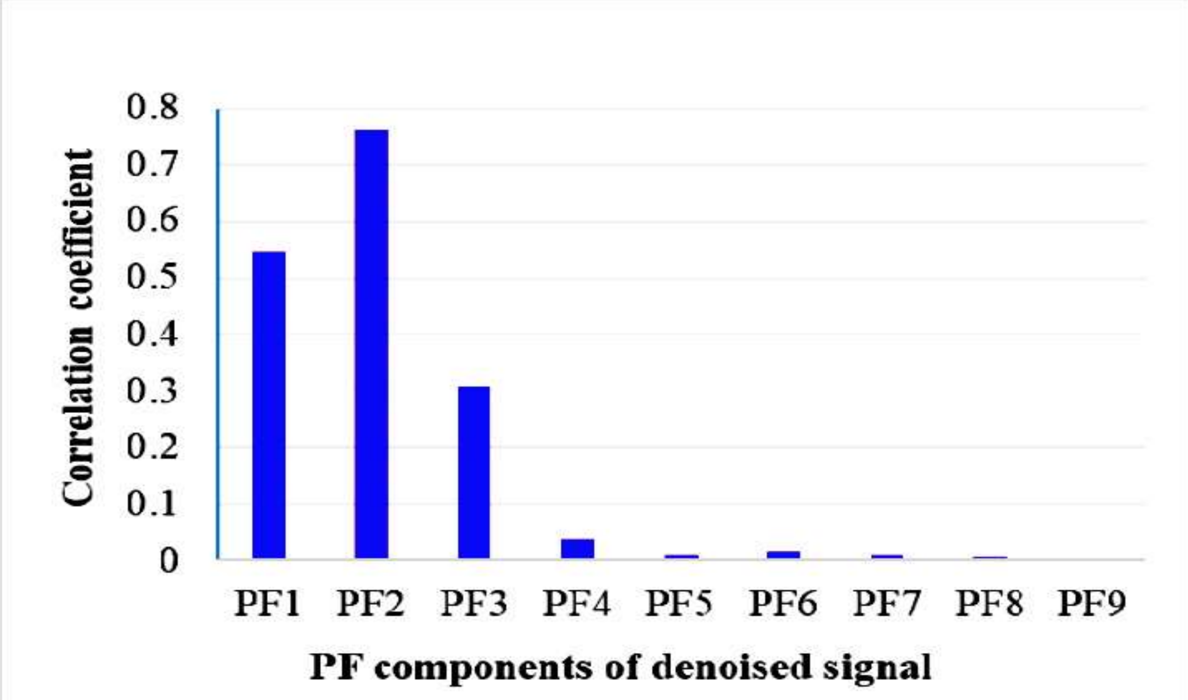


Figure 45 : correlation coefficient of denoised signal (PF)

The PF components in Figure 45 make it clear that for a given denoised signal, the first three PF components have the strongest correlation coefficient. As a result, Figure 46 shows the signal reconstruction using the top three PF components of high correlation coefficient. Since the reconstructed signal's correlation coefficient is 0.978, more than 90% of the original signal's energy is concentrated in it.

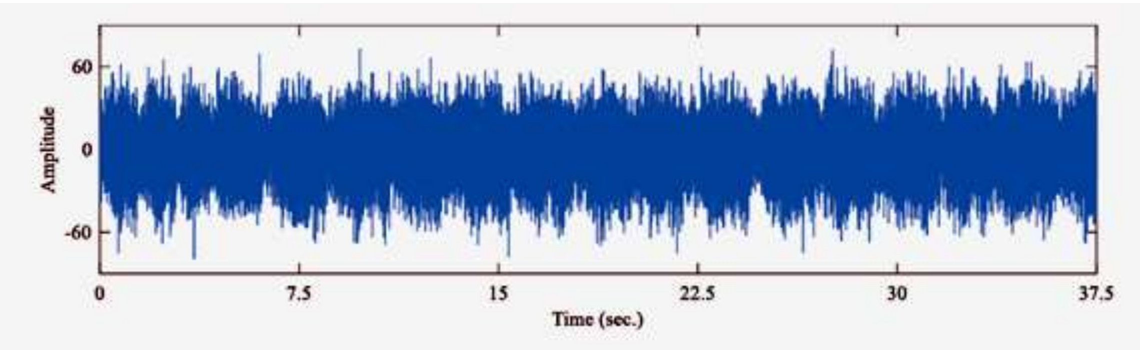
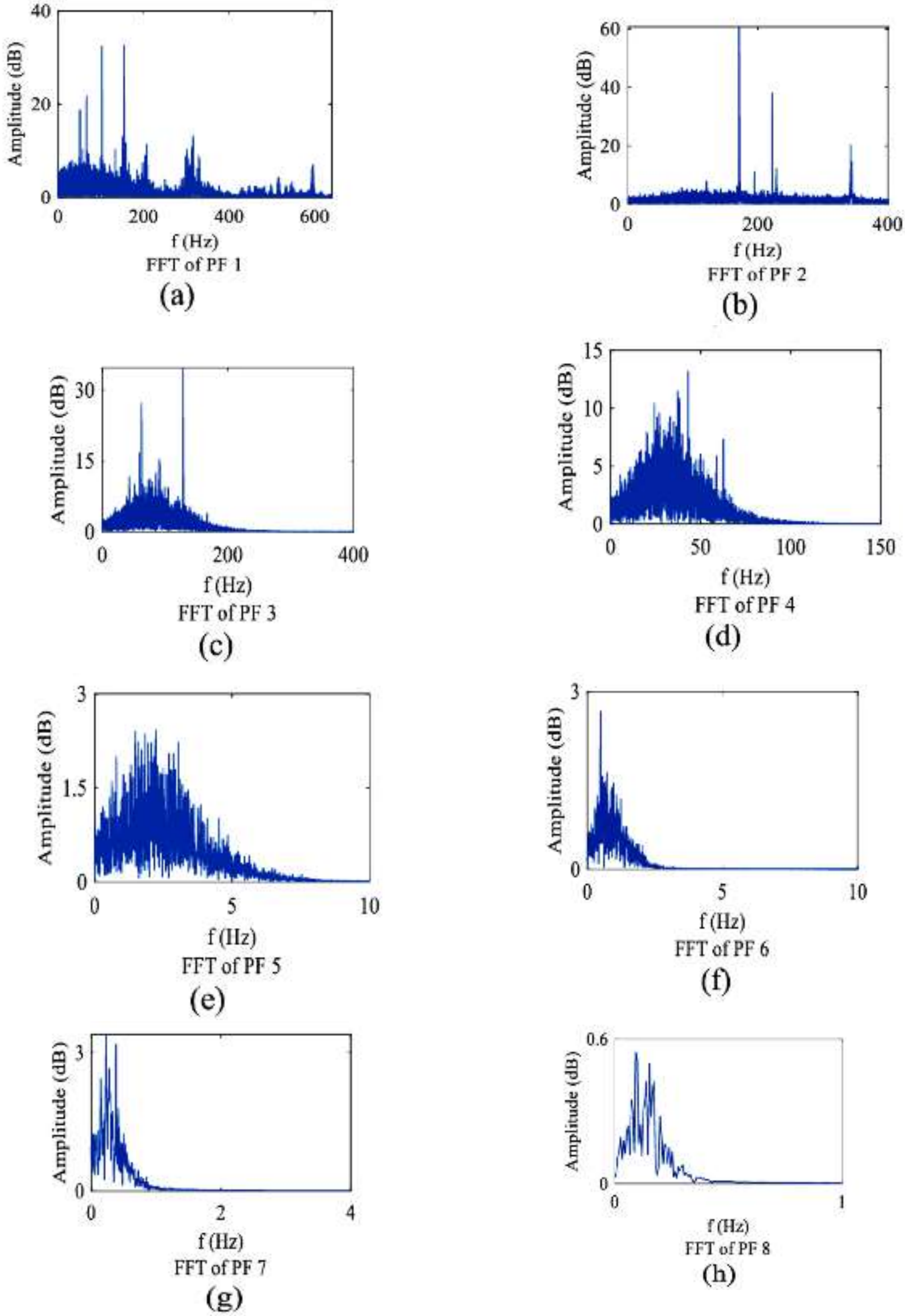


Figure 46: Chatter signal reconstructed at final stage

The FFTs of all PFs and the reconstructed signal are created for amplitude-frequency analysis as depicted in Figures 47 and 48. High correlation coefficient conspicuous PFs are used to build the reconstructed signal. As a result, it contains the most chatter frequency information. The peaks in the reconstructed signal's FFT are seen in Figure 48. There is no mode mixing and no significant noise effect. The chatter frequencies are clearly shown by the FFT peak.


Amplitude (dB)
f (Hz)
FFT of PF 1
(a)
Amplitude (dB)
f (Hz)
FFT of PF 2
(b)
Amplitude (dB)
f (Hz)
FFT of PF 3
(c)
Amplitude (dB)
f (Hz)
FFT of PF 4
(d)
Amplitude (dB)
f (Hz)
FFT of PF 5
(e)
Amplitude (dB)
f (Hz)
FFT of PF 6
(f)
Amplitude (dB)
f (Hz)
FFT of PF 7
(g)
Amplitude (dB)
f (Hz)
FFT of PF 8
(h)

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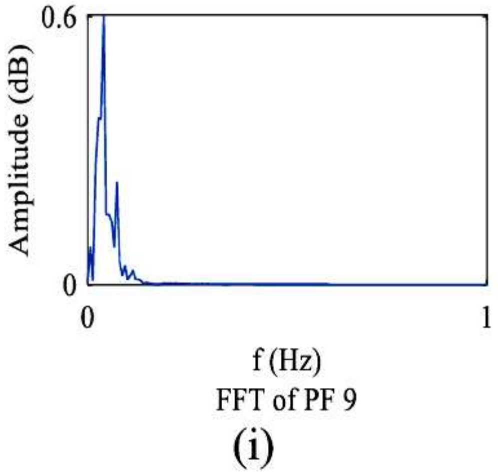

Figure 47 (a…i) : Graph depicting PFs of FFT

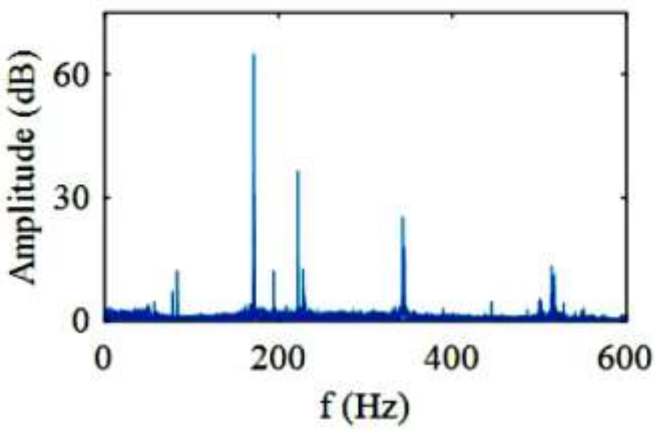

Figure 48: Reconstructed signal FFT

Conclusion

The signal processing methods used by earlier researchers have certain benefits and drawbacks. EMD provides a suitable solution for nonlinear and non-stationary signals, but it has now been discovered that this approach occasionally suffers from the major mode mixing issue. LMD has been adopted in order to get over EMD's restriction. This method has mostly, but not entirely, solved the mode mixing problem. Thus, the WDLMD technique has been suggested, and it has been shown that this technique can extract the information from the chatter signal rather precisely while also being able to remove the undesired noise contents. Mode mixing has also been managed more recently. In the next chapeter, WDLMD processed signals of all the combinations of experiments have een utilized to develop predition models of chatter severiety and MMR in terms of input turning parameters cosndidring response surface methodology (RSM) and artificial neural network (ANN) technique.

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