APPLICATION OF PREDICTIVE MAINTENANCE TO INDUSTRY INCLUDING CEPSTRUM ANALYSIS OF A GEARBOX

BY

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SUMMARY

The economic implications of equipment failure are called for effective maintenance techniques. The research investigates current maintenance practice in several New Zealand industries and the improvements that could be obtained by the use of predictive maintenance techniques.

Initial research was undertaken in a series of case studies within New Zealand industries situated in Auckland. The first two cases studies were of preventative maintenance techniques of two conveyor lines in a biscuit manufacturing company. The results showed a well defined preventive maintenance schedules that was Systems Applications Products (SAP) programme was used to managed for daily, weekly, monthly and yearly maintenance activities.

A third case study investigated current predictive maintenance technique involving Fast Fourier Transform analysis of shaft vibration to identify a bearing defect. The results diagnosed a machine with a ball bearing defect and recommendation was given to change the bearing immediately and install new one. The machine was opened up, a big dent was on one of the balls as predicted by the analysis and the bearing was changed.

Research then looked at a novel technique called Cepstrum analysis that allows the deconvolution of vibration spectra from separate sources. This allows identification of several defects from the monitoring of a single vibration signal. Experiments were carried out to generate transfer functions for different gear faults at two different loadings. Blind deconvolution of the signal using a homomorphic filter was used to separate the source forcing frequencies from the structure resonance effects of the two gear faults, indicating that the technique could be used successfully to monitor equipment for a range of gear faults occurring simultaneously.

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DECLARATION OF ORIGINALITY

I, Matthew Aladesaye, declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given in this thesis.

I also acknowledge that I have pursued the PhD course in accordance with the requirements of the university's regulations:

- Research practice and ethical policies have been complied with appropriately
- This thesis does not exceed 100,000 words, excluding appendices.

Signed...

Chapter 1

Introduction

1.1 The Topic of this Thesis

The funding for this project was obtained from Technology New Zealand by the consulting firm SchemNZ, which was investigated and presented for my PhD research work. The aim of the project was to investigate the maintenance practices of different manufacturing companies in NZ and present the best maintenance practice that would improve equipment reliability, predict failures, reduce maintenance costs and augment profitability. The following are the common maintenance practices in manufacturing companies:

- Breakdown
- Preventive
- Predictive.

This thesis was carried out to meet the following objectives:

1. Explore maintenance and diagnostic strategies
2. Identify possible techniques to diagnose machine faults.

1.2 Why Predictive Maintenance?

The economic implications due to equipment failure are severe. The losses suffered by manufacturing companies due to machinery failure and downtime for repairs are pronounced.

Table 1.1 shows the causes of the aircraft accidents between the 1950s and 1990s. Human errors can be reduced by observing the safety regulations, but the mechanical failures can be avoided by installing condition monitoring and fault diagnostic systems which would give warning as soon as a fault develops.

Table 1.1: Fatal Accident Causes By Category (by percentage) [2]

CAUSE	1950s	1960s	1970s	1980s	1990s
Pilot Error	43	34	26	29	30
Pilot Error (Weather Related)	9	19	16	17	20
Pilot Error (Mechanical Related)	7	5	4	4	6
Total Pilot Error	58	58	46	49	56
Other Human Error	2	8	9	7	7
Weather	15	9	12	14	8
Mechanical Failure	19	19	21	19	20
Sabotage	5	4	9	11	8
Other Cause	0	2	3	1	1

For an ocean-going merchant vessel carrying 100,000 metric tonnes of liquid natural gas as cargo, losses amount to between US$80,000.00 and US$1,000.000.00 per day in the event of any machine failure or repair. In addition, it is estimated that more than 2000 lives have been lost as a result of marine accidents caused by machinery failure [1].

A Boeing 737 veered off the runway due to the collapse of the right landing gear. A private plane experienced engine trouble and crashed. Another one experienced mechanical failure, disintegrated and crashed soon after taking off [1].

Another example is the gearbox of an emergency coal conveyor of a steel manufacturing company where the author carried out investigations on predictive maintenance. The conveyor was out of service for two weeks due to overheating. The cost of replacement, production and maintenance was about $2.5 million dollars.

1.3 Aims

The aims of this thesis are:

- The first and primary objective is to investigate the maintenance practices in different major manufacturing companies in New Zealand outlined in chapter 2 and review predictive maintenance – the use of vibration a sensor and FFT data collector - to predict machine failures.

- The second objective pertains to the use of existing Fast Fourier Transform (FFT) algorithms for predictive maintenance and its limitations (presented in chapter 4).
- The third objective is the use of a mathematical relationship between the FFT data and a faulty machine component to determine the root cause of the failure (presented in chapter 4). This technique identifies the root cause of a failure instead of treating failure symptoms that FFT data analysis presents in most cases.
- The fourth objective is to formulate and develop an extension of the cepstrum technique using homomorphic blind deconvolution filtering to separate the forcing and transmission path effects in the signals measured from a gearbox (outlined in chapters 5 and 6).

1.4 Thesis Overview

This thesis is organized as follows:

Chapter 1: Introduction

This chapter presents the topic of this thesis, why predictive maintenance, existing work on the predictive maintenance and scope of the present work.

Chapter 2: Literature Review

In this chapter, different work that had been done on predictive maintenance are reviewed and machine diagnosis and reliability, vibration monitoring and blind deconvolution are discussed.

Chapter 3: History of Maintenance and its Strategies

This chapter presents the history of maintenance and its strategies, evolution of maintenance, its costs and strategies.

Chapter 4: Fast Fourier Transform Technique and Pitfalls

The theory of the Fast Fourier Transform (FFT) is discussed with the use of complex numbers and the operation of a piezoelectric accelerometer. Case studies are presented using the FFT technique, and the pitfall of this technique is discussed.

Chapter 5: The Theory of the Cepstrum Technique

This chapter presents the theory of the cepstrum technique to diagnose the vibration of a gearbox. The theory of homomorphic deconvolution is also presented, coupled with the cepstrum analysis and poles and zeros.

Chapter 6: Experimental Analysis

This chapter presents the experimental analysis. The gear test rig is explained and the instrumentation for the data collection is described. The application of the cepstrum technique, homomorphic deconvolution, the poles and zeros analysis are presented.

Chapter 7: Conclusion and Recommendations

A summary of the work is given, followed by a list of contributions of this thesis. Then we bring in some discussion about the proposed methodology and conclude the thesis with some recommendations for the future work.

Chapter 2

Literature Review

2.1 Machine Diagnosis and Reliability

Maintenance is an activity to ensure that equipment is in a satisfactory condition and reliable. The goal of maintenance is to ensure that the performance of the equipment is satisfactory.

A good maintenance system contributes to efficiency, customer service, high quality, safety, on-time delivery, and customers' satisfaction.

McFadden [3, 4, 5, 12, 18] presented various papers on the application of Wavelets to gearbox vibration signal and analysis of gear vibration in the Time-Frequency domain. Techniques like Adaptive Noise Cancellation, Computer Order Tracking, Non Stationary Modelling of Vibration Signals and Synchronous Averaging were used to diagnose machine faults[6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 19, 20, 21, 22, 23, 24, 25] these papers could not provide solutions to resonance effect in the transmission path.

Toliyat et al [26], described how maintenance has long been a powerful source of know-how and when to best schedule production, which needs to comply with customers' schedules. Siyambalapitiya et al [27] also described the maintenance support activities of manufacturing companies and Vas [28] presented a paper on the use of a maintenance programme to manage maintenance strategies. Abrecht et al [29] described the basic elements necessary to implement maintenance programs.

Despite what Toliyat, Siyambalapitiya, Vas and Abrecht said on maintenance strategy and programs, there is still a misrepresentation of the maintenance strategies in industry. The misrepresentation relates to the inability of the authors to clearly present the maintenance strategy associated with each company, which would have given a true reflection of the strategy most companies practice and why. This is one of the objectives of this research, investigating three key maintenance practices; reactive, preventive and predictive and the companies associated with each type and why.

Diagnosis is the process of determining the fault responsible for a set of symptoms. Blunt et al [30], defined it as the formulation and investigation of a hypothesis about the malfunctioning equipment.

If the real cause of the problem is not corrected, then further breakdown is likely to occur.

Diagnosis is the process of determining the fault responsible for a set of symptoms. It is also the formulation and investigation of hypotheses about the malfunctioning equipment [30]. Zakrajsek et al [31], defined diagnosis as "knowing the difference" between normal and abnormal behaviours of a machine, then one needs to have more functional knowledge about the internal structure of the machine and the interaction of its constituent parts. Minns and Stewart[32], presented a five step strategy for diagnostic problem solving which they summarised as "formulation and investigation of a hypothesis about the malfunctioning equipment": (i) formulation of the problem by analyzing the situation, making observations, and developing a plausible hypothesis; (ii) developing expectations for each of the hypothesis; (iii) selecting the hypothesis with the highest expectations for leading to the cause; (iv) collecting and analysis of data (v) evaluating the hypothesis (vi) in the case of indecisiveness of the hypothesis, the first five steps are repeated as many times as required until the cause is identified. Eshleman [33], described in his work that component life expectancy and wear rates can only be assessed on the basis of recorded information that represents a true reflection of operating conditions.

Heinz P. Block [34], writes on machine reliability improvement and maintenance cost reduction. He divided machinery reliability management in process industries into three phases: equipment selection and pre-erection reliability assurance; preparation for effective start-up; and post-start-up reliability assurance and maintenance cost reduction. The techniques and procedures that covered each phase have led to improved equipment reliability and maintenance efficiencies.

Eisenmann [35] with over 33 years of experience in solving machinery problems coupled with numerous technical notes on how to use the application of engineering principles to diagnose and correct machinery malfunctions. The machinery under discussion in the book operates within the heavy process industries such as oil refineries, chemical plants, power plants, and paper mills. He asserted that the majority of machinery problems that do occur fall into what he calls the ABC category, which are generally related to Alignment, Balancing, and incorrect Clearances (typically on bearings). Although machines also exhibit other types of failures, he devoted more time to each of this ABC problem categories due to the continual appearance of these malfunctions. 52 detailed case histories are combined with numerous sample calculations and examples to solve real world problems.

Doebelin [36] developed an understanding of the operating principles of measurement hardware and the problems involved in the analysis, design, and application of such equipment. He wrote on the treatment of dynamic responses for all types of inputs: periodic, transient, and random, on a uniform basis, utilising the frequency domain. He further gave detailed consideration of problems involved in interconnecting components. He also presented a detailed study of measuring instruments and their characteristics, which are used in the monitoring of processes and operations, control of processes and operations, and experimental engineering analysis.

Kuhnell [37] states that managers are breaking out of the vicious cycle by improving the maintenance processes and increasing the effectiveness or productivity of asset and human resources. Improving maintenance processes involves re-engineering the process and increasing resource effectiveness by moving to a mostly condition-based maintenance philosophy and adding maintenance tasks to manage economically preventable failure modes that historically have caused failures.

Hill [38], described design methodology for fault diagnosis in linear systems, which can also apply to non-linear cases [38].

Iserman [39] surveyed the detection of process faults based on modelling and estimation methods, coupled with the estimation of unmeasurable process parameters and variables. Frank and Koppen-Seliger [40], presented fuzzy logic and neural networks as another new approach to system modelling, a paper outlining the most up-to-date developments in artificial intelligence for fault diagnosis.

Block and Geithner [41], presented how the profitability of modern industry and process plants is significantly influenced by the reliability and maintainability of the machines. They described the probabilistic and statistical way of thinking when dealing with matters of process machinery reliability, availability and safety.

Jeffrey [42] described the techniques designed to monitor machine operation and generate information that can be used to anticipate breakdown. He maintained that advances in sensors, algorithms, and architectures should provide the necessary technologies for effective incipient failure detection.

Despite the breadth and clarity of the literature on this subject of fault diagnosis, there is also a problematic narrowness, a concern with the fact that diagnostic strategy is experience-based and relies on an experienced diagnostician to have been "conditioned" over time for the task. If the diagnosis is defined as responding to symptoms and trying to determine the cause(s) of the symptoms, then the diagnostic decision making relies more on rule-of-thumb and less on fundamental (functional and behavioural) knowledge about the equipment. The literature on this subject of fault diagnosis only identified the symptoms of machine problems and not the root cause.

Examples of machine failures include bearing, gear failures; shaft misalignment, looseness and imbalance etc.

Whether the component was operating within operating parameters is the question requiring an explanation. Knowledge of previous incidents could be even misleading in this situation. Relying on the patient,s history primarily as the basis for diagnosis could have severe consequences if the true cause is not the usual one. To explain how a fault took place, one needs to trace the situation back until a satisfactory cause is identified. The fact that a component broke down in a machine is not necessarily the satisfactory cause of the fault, rather, what led to the breakdown of the component is part of the objectives of this research.

2.2 Predictive Maintenance – Vibration Monitoring

The few companies that have vibration monitoring gears use data collectors that operate on Fast Fourier Transform Technique. This has been the most widely adopted form of condition monitoring, recording and analysis of machine vibration signatures. The literature presented here on this subject – Predictive Maintenance-Vibration Monitoring, lacks the improvement needed to make a machine reliable, reduce the number of breakdowns and augment profitability. None of this literature is interested in the root cause of a failure. Even though a lot of work has been done on fault detection, none of the faults detected by these writers have been traced down to the root cause.

The application of statistical analysis to measured diagnostic signals is as old as the science of measuring the signal. A review of time domain analysis using statistical methods forms part of virtually every PhD thesis and masters dissertation conducted in the field of vibration monitoring.

In general, time domain analysis entails calculating the root mean square, peak value, crest factor and kurtosis values of a signal. The root mean square value gives an indication of the continuous or steady state amplitude in a time varying signal. The peak level or value is defined as half of the difference between the maximum and minimum values in the signal. This is not a statistical value and it is known not to be a reliable indicator of damage. The crest factor is defined as the ratio of the peak value divided by the root mean square value of the signal.

The kurtosis is the normalised fourth statistical moment of a signal. The parameters defined above are also referred to as overall vibration parameters. In general, they are calculated for each measurement and trended over time to give an indication of machine condition, rather than the condition of specific components in the machine. The parameter does not provide any diagnostic information. However, the parameters are easy to implement in low cost online monitoring equipment.

Komura et al. [43] developed a hand held vibration monitoring sensor which utilises the root mean square, kurtosis and mutations thereof to classify a machine's condition according to three categories namely; normal, warning and alert. This is no longer widely used because it only provides overall vibration level on a spot which will tell you where a fault is coming from and what sort of fault it is, but there is no diagnostics advantage in this measuring equipment.

Martin et al. [44] Ismall et al. [45] and Oguamanam et al. [46] applied statistical distributions to experimental data measured on gears and gear pump test rigs. A synchronous, or time domain average, of the vibration signal was calculated before applying the statistical distribution to segments of the time domain-averaged signal. The segmentation of the signal enables local fault detection on the gear teeth of the gears. A beta distribution was fitted since the kurtosis of a normal distribution was too sensitive to noise in the vibration data. It was indicated that the reciprocal of the beta kurtosis value could indicate the presence of a local defect on a gear.

Howard [47] developed a composite signal averaging technique to overcome the monitoring problems encountered when monitoring gears in an epicyclic gearbox. Typical problems were the varying transmission path to the transducer and the fact that multiple components mesh at the same frequency. Experimental tests were done with a progression in induced gear damage and vibration measurements were taken for the various fault conditions in order to validate the technique. The composite signal averaging technique was applied to the experimental data and the modulation of the averaged signals was calculated. Kurtosis values for the modulation were estimated and it was shown that the kurtosis increased as the extent of gear damage increased. The kurtosis value of the modulation therefore proved to be an effective indication of gear condition once composite signal averaging had been done.

Forrester[48] did tests to detect early fatigue cracks in gears. The test was of a time domain signal processing technique that compares two signals to indicate the likelihood that the two signals have the same probability density function. In essence, the tests determined whether two signals were similar or not. Forrester [49] stated that a fault condition could be indicated by comparing a signal with a number of signal templates of known fault conditions. The technique was applied to experimental data and its results indicated that the technique could successfully detect the presence of a fatigue crack.

McFadden[50] utilised multivariate statistics in combination with principal component analysis to detect localised faults in a two stage helical gearbox. (Principal component analysis is utilised to reduce the dimension of a data set to fewer samples. In essence, it is utilised for data compression). Vibration signals under different fault conditions where measured. Principal components were calculated for the *normal or no-fault-present* condition. These components, where statistically represented were calculated for the new measurements to observe any deviations from the normal condition. The square predictor error is the sum of the squared difference between the data indicating the normal condition and the measured data. A deviation in the value will indicate a deviation in the condition of the machine.

According to Randall [51] the amplitude modulation of the time domain average signal can be calculated by taking the absolute value of the signal's analytical signal. The analytical signal is a complex time signal of which the imaginary part is the Hilbert transform of the real part. Note that the phase modulation can be calculated by calculating the phase of the analytical signal.

McFadden and Smith[52] band-pass filtered the time domain averaged signal around the prominent gear-meshing harmonic and removed the gear mesh harmonic itself in order to obtain what they referred to as a residual signal. The amplitude modulation of the residual signal were analysed and the statistical parameters of the residual signal was analysed and statistical parameters of the residual signal modulations were calculated. The methodology proved to be an effective way to detect local defects on gears.

McFadden [52, 53 & 54] utilised the amplitude and phase modulation of the time domain average they band-pass filtered around the prominent gear mesh harmonic to detect fatigue cracks in the gears of a helicopter's main rotor gearbox.

McFadden & Howard [55] extended the technique to incorporate all of the gear meshing harmonics and applied the technique to torsional vibration measurements measured on an experimental test rig with artificial seeded defects. They concluded that the technique is more sensitive in detecting gear defects when compared to a narrow band-filtered approach.

Brie *et al.* [56] developed an adaptive amplitude and phase demodulation approach, which has lower numerical complexity when compared to the conventional route of calculating the modulation using the Hilbert transform. The algorithm is sequential which allows it to be implemented in real time.

Wang [57] applied a resonance demodulation technique common to rolling element bearing defect detection and monitoring to detect incipient gear tooth cracks. The methodology is based on the fact that a root crack will lower gear tooth stiffness in the gear mesh resulting in impacts as the gear tooth after the damaged gear tooth enters the gear mesh. This impacting will excite the structural resonance. A residual signal is calculated from the time domain average and band-pass filtered around the structural resonance. The band-pass filtered residual signal is then demodulated to detect sudden changes in the modulation, which are related to the presence of fatigue cracks in the gears.

Spectrum analysis entails the conversion of a time signal to a frequency domain representation through a discrete Fourier transform. The term spectrum is used for the amplitude representation versus the positive frequency range of the time signal's Fourier transform.

Frequency domain analysis is widely used due to the simplicity in analysing machine faults. At the beginning of this research work, the analysis carried out on various machines was made with the FFT technique.

The advantage in using spectrum analysis lies in the fact that the amplitude at each discrete frequency can be monitored in contrast to the overall amplitude monitoring approach of time domain analysis. A log scale for the amplitude axes can be chosen to improve the dynamic range of the representation. Defects that will cause a small change in amplitude at a certain frequency with low amplitude will therefore be detected much easier in comparison with time domain analysis.

Lots of work has been done with this technique and the literature on it is vast.

The frequencies at which a certain defect on a particular component will cause an increase in the amplitude of the spectrum are referred to as defect frequencies. Hence, diagnostic capability can be obtained by relating amplitude growth at a certain frequency to a particular component in the machine based on its physical parameters. This type of analysis is conventionally used in practice to monitor plant equipment.

Forrester [58], Matthew [59] and Mechefske [60] have described spectral analysis in detail.

The book of Goldman [61] on Vibration Spectrum Analysis is based on his experience when he worked at Nash Engineering in the early 1970s. The book is about problem solving in general based on his many years experience.

Forrester [62] states that the gear mesh vibration measured on the casing of a gearbox descends from the fluctuation in gear meshing stiffness as the gears rotate in and out of the gear mesh. If a time domain average or synchronous average of the vibration on the gearbox casing is calculated and band-pass filtered around the fundamental gear mesh harmonic, the resulting signal will approximate a sinusoid where each peak in the sinusoid represents the structural response due to a gear tooth entering the gear mesh.

The author will improve the current diagnosis techniques that rely only on monitoring some physical characteristics that reflect the condition of the machine or identify the machine faults but not the root cause. The author will use mathematical relationships between the condition monitoring data and the faulty components to determine the root cause of a failure; this is presented in chapter 4.

2.3 Artificial Neural Network

Predictive maintenance, or condition monitoring, is based on continuous monitoring of equipment through sensor-based data collection equipment and specialised technologies to measure specific system variables. All machinery generates vibration; the analysis of the system variables will render valuable information about the condition of the machines.

Artificial neural nets (ANN) are increasingly being used in fault diagnosis systems. The popular approach to developing ANN-based diagnostic systems is to induce several artificial faults into specific machinery sub-components, acquire data representative of each fault and train the nets to classify them, cross-validating and testing the trained system with data not used for training [3].
There has been research work carried out on neural network to detect gear fault because of its time series prediction capabilities [3], [15], [21], [46], [50],[60].

Data from simulation models have been used occasionally with varying degrees of success. The major gap in the existing work is that there is no proper quantification of the fault induced. Without the knowledge of how severe or subtle the fault induced is, there is no way of evaluating the predictive method used. On a similar note, many of the faults detected are either too trivial or too severe; and do not justify the use of sophisticated detection methods. Another major drawback in the field is that there are no benchmarks. What may appear as a serious fault to the uninitiated may be nothing more than a blemish to the experienced mechanical engineer.

2.4 Blind Deconvolution and Cepstrum Analysis

The term cepstrum analysis is the inverse Fourier Transform of a spectrum. It is utilised to detect a series of harmonics or sidebands and to estimate their strength. The various harmonics in a conventional spectrum are reduced to predominantly one peak in what is referred to as the quefrequency domain. Periodicity in the conventional spectrum is therefore detected. Only a single peak needs to be detected to diagnose a fault condition. Logarithmic values of the spectrum are utilised in the calculation of the cepstrum in order to improve the dynamic range of the analysis [63].
The vibration spawning from the meshing of a gear pair in a gearbox has to be transmitted through the shaft, roller element bearings and casing before being measured. It is common knowledge that this transmission path has structural impedance characteristics in terms of amplitude and phase. If the gears rotate at a certain frequency, the force being transmitted from the meshing gears will be subject to amplitude and phase changes induced by the structural impedance at the particular frequencies. However, if the rotational speed changes the forces being transmitted

from the meshing gears are subject to different amplitude and phase changes induced by the transmission path impedance at the alternative frequencies. As a result, the amplitude and relative phase of the measured structural response will be different depending on the structural dynamic characteristics [64].

Schaum [64] covers both continuous-time and discrete-time signals and systems, develops the fundamental input-output relationship for linear time-variant systems and explains the unit impulse response of the system and convolution operation. He explored the transform techniques for the analysis of linear time-invariant systems and dealt with the z-transform and its application to discrete-time linear time-invariant.

Schaum [65] described the fundamental of digital signal processing, description and characterisation of discrete-type signals and systems, convolution, and linear coefficient difference equations.

Randall [66] suggests that the ceptsrum exists in various forms, but all can be considered as a spectrum of algorithmic (amplitude) spectra. He used these techniques for detection of a periodic structure in the spectrum, e.g from harmonics, sidebands or the effects of echoes. He demonstrated that the effects which are convolved in the time signal (multiplied in the spectrum) become additive in the cepstrum, and subtraction there resulted in a deconvolution. He described the applications of cepstrum, including the study of signals containing echoes (land-based and marine seismology, aero-engine noise, loudspeaker measurements) speech analysis (format and pitch tracking, vocoding) and machine diagnostics (detection of harmonics and sidebands).

Haykin [67] stated that the book he edited in 1994 on blind deconvolution contained various algorithms for solving the blind channel-equalisation problem. Haykin [68] presents a theory that blind deconvolution and blind source separation originated independently, yet they are related to each other and constitute the two pillars of unsupervised adaptive filtering.

Randall [69] described how Fourier analysis led to different types of signal encountered in practice and how they appear in spectra and other representations. He also treated the convolution subject in some detail and that the output of a linear physical system is obtained by convolving the input signal with the impulse response of the system.

Dalpiaz [70] compared the results obtained from the time-frequency and cylco-stationarity analysis, and those from cepstrum analysis and time-synchronous average analysis on a gear pair affected by a fatigue crack, considering two different depths of the crack. He concluded that the time-synchronous average and demodulation techniques are able to localise the damaged tooth, but the demodulation technique is affected by the transducer location. However, the wavelet transform seems to be a good tool for crack detection, if the residual part of the time-synchronous averaged signal is processed.

Lee [71] used higher-order statistics based on third-, fourth-, fifth- and sixth-order statistical blind deconvolution on impacting signals. He recovered the impulse impact signals and improved the estimation time between the impacts by comparing the efficiency and robustness of the schemes.

Randall [72] and Angelo [73] stated that cepstrum analysis is insensitive to the phase variations in the transmission path. The power spectrum of a signal measured at an external point on the casing of a rotating machine such as a gearbox can be expressed as the product of the power spectrum of the source function with the squared amplitude of the frequency response of the transmission path. By taking the log of the transform, the multiplication turns into an addition of the logarithmic source function power spectrum and the logarithmic frequency response function, to obtain the logarithmic spectrum of the response. This implies that the source and transmission path effects are additive in the cepstrum. The transmission path transfer function has low quefrequency components, which will be well separated from the high quefrequency components representing the source function. Randall [73] applied the cepstrum analysis to the vibration measured on a gearbox at two different positions on the casing. He concluded that the spectra of the two signals were different but the cepstra were almost identical.

Forrester [74] however stated that cepstral analysis is not very useful in the analysis of synchronously averaged signals, since the signals is not periodic in the so-called angle domain and periodicity is lost when translated to the quefrequency domain.

A variety of expressions and forms of the cepstrum have been developed. Childers et al. [75] described the relationships between the various forms. Wu and Crocker [76] developed a modified cepstrum technique to determine the magnitude of a structure's frequency response function. The novelty of the technique is based on the fact that no prior knowledge of the input force is required to calculate the magnitude of the structural transfer function. Debao et al. [77] applied cepstrum analysis to detect misalignment, unbalance and bearing damage in generators. Van Dyke and Watts [78] utilised the cepstrum analysis as a data pre-processor for an expert system, which can detect rolling element bearing deterioration and predict fault severity.

Badaoui et al. [79] proposed a moving cepstrum integral to detect and localise tooth spalls in gears. The technique applies a moving window in order to isolate the gear tooth faults. This enables the detection and localisation of local tooth spall on gear teeth. The technique was applied to numerical and experimental data and the authors where able to detect light spalling on gear teeth.

Jeung [80] said that a direct measurement of an excitation pulse is not simple because locating sensors at the exact source location is not practical in many engineering applications. He presented an indirect method for detecting a transient source waveform by using a sensor at a remote position and using cepstral analysis as a robust inverse filter to smooth out the transmission path.

Zhinong [81] reviewed the application of blind source separation in machine fault diagnosis, considering noise elimination and extraction of weak signals, the separation of multi-fault sources, redundancy reduction, feature extraction and pattern classification based on independent component analysis. The application of blind source separation in machine fault diagnosis has been developed rapidly for the last several years [82]. Blind source separation provides a new technique for the separation of mechanical source signals under high-level background noise and diagnosis of the compound fault [82].

Mirko [83] carried out an assessement for blind source separation [BSS] algorithms with respect to machine diagnosis and verified the applicability of a new BSS algorithm.

The sound of a rotating machine is periodically (or at least first order cyclostationary) and therefore stationary. The typical interfering sources are normally not stationary, like human speech, hammer blows or clicking of switches [84]. Machine faults modify the machine sound characteristically, therefore observing the machine sound can be a useful means for fault diagnosis and classification [85]. Blind source separation deals with the problem of recovering several sources from linear mixtures without knowledge about the mixture [85].

A gearbox is an example of an extremely difficult case to measure the force at the gear mesh which is roughly fixed in space, but moving with respect to the meshing gears [86]

A methodology was outlined to determine poles and zeros corresponding to the frequency response function (FRF) of a signal transmission path from response measurements alone, without the need to measure the forcing function.

Gao [87] presented a paper on the determination of frequency response functions from response measurements – extraction of poles and zeros from response cepstra by adopting the Levenberg-Marquardt and Ibrahim time domain methodologies for the curve-fitting purpose. He used the blind source separation techniques to separate the vibration sources in internal combustion engines. He used the blind source separation techniques to separate the vibration sources in internal combustion engines.

Cepstrum analysis and Hilbert transform techniques may be useful in situations where frequency analysis alone or time signal analysis alone does not enhance those features of the signal that characterise the fault to be diagnosed [88].

Traditional frequency analysis techniques are not very useful due to the overlap of the different sources over a wide frequency range [89].

Peled [90] used a blind deconvolution to separate signals from different sources which are convoluted and mixed by the mechanical systems before being measured. He based his methodology on blind deconvolution separation, considering the kurtosis of the separated signals coming from bearings as the measure to be maximised. He tested his methodology on simulated and experimental cases. The results showed the elimination of the effect of structural resonances, which often causes severe problems in classical diagnostic methods.

Jerome [91] used industrial cases to demonstrate how the spectral kurtosis can be efficiently used in the vibration-based condition monitoring of rotating machines. He introduced the concept of kurtogram, from which optimal band-pass filters can be deduced as a prelude to envelope analysis.

Jerome [92] established the extent to which spectral kurtosis is capable of detecting transients in the presence of a high noise-to-signal ratio and thereby proposed a short-time Fourier-applications.

Jerome [93] proposed two robust separation techniques based on the short-time Fourier transform to separate the convolutive mixtures of sources. He ascertained that blind source separation is the issue of recovering the various independent sources exciting a system given only the measurements of the outputs of the system, and it has become the focus of intensive research work due to its high potential in many applications.

Having reviewed the above extensive literature, gear faults still remain a difficult problem to analyse because of the overlapping of the frequencies, sidebands and harmonics, which is the reason for this research work; developing a novel technique to solve this problem by using cepstrum technique that uses homomorphic blind deconvolution to remove the effect of transmission path transfer functions from externally measured gearbox signals.

Homomorphic filtering is unique because it will extract a smooth envelope, which enables the detection of events that are suspected. It will decompose (deconvolve) the additive components into cepstra components for better diagnosis. This is the missing piece in the work just outlined.

The reason for the homomorphic filtering over other work on the cepstrum technique is of two parts:

- The first part is the detection of those parts in the cepstrum which ought to be suppressed in processing.
- The second part includes the actual filtering process and the problem of minimising the random noise which is enhanced during the homomorphic procedure.

Chapter 3

Maintenance Strategies

3.1 Introduction

The function of maintenance is to ensure that plant and equipment are available in a satisfactory condition for operation when required. The determination of what constitutes a satisfactory condition for rotating machinery will depend largely on the operating situation, type of industry, process requirements and business objectives.

In all cases, however, the performance of the maintenance function can be judged by the condition of machinery, which the following factors will indicate [42]:

- *Performance*, this is the ability of the machine to perform its functions.
- *Downtime*, operation of the machine must be within an acceptable level of downtime.
- *Service life*, before replacement of the machine is necessary; it must provide a good return on investment.
- *Efficiency*, the level of efficiency of the machine must be acceptable.
- *Safety*, the machine must be safe to the personnel.
- *Environmental impact*, the operation of the machine must be friendly to the environment and other equipment.
- *Cost*, it is expected to have a maintenance cost within an acceptable level.

The goal of maintenance is to ensure that machinery performance is satisfactory, considering the above factors. This chapter covers the brief history of traditional machine maintenance and maintenance strategies.

Most management now see maintenance efficiency as a factor that can affect business effectiveness and risk-safety, environmental integrity, energy efficiency, product quality and customer service and that it is not constrained only to plant availability and cost. Thus, as the climate of doing business changes, so does the need for better maintenance programs.

3.2 Evolution of Maintenance

In general, the evolution of maintenance is categorized into 3 different generations:

- the period of 1930's-1940's which is referred to as the First Generation,
- between 1950's to 1970's as the second generation, and
- the 1980's untill date as the third generation [139].

The growth in maintenance efficiency has become more complex due to equipment automation.

3.2.1 *First Generation*

The first generation describes the earlier days of industrialization where mechanization was low. Most equipment in the factory was basic and the repairing and restoration process was done in a very short time. Thus, the term downtime did not matter much and there was no need for managers to put maintenance as a high priority issue.

3.2.2 *Second Generation*

The second generation emerged as the results of growing complexity in equipment and plant design. This had led to an increase in mechanization and industry was beginning to depend on these complex machines. Repair and restoration had become more difficult with special skills and more time needed to mend the machinery. As this dependence grew, downtime became a more apparent problem and received more attention from management. People were beginning to think that these failures should be prevented which led to the concept of preventive maintenance. As maintenance cost started to rise sharply relative to other operating costs, there was a rising interest in the field of maintenance planning and control systems.

3.2.3 *Third Generation*

Reliability had become vital in the maintenance circle from the 80s; failure of machines would be detrimental to productivity and profitability. At this time a machine breakdown could have an adverse effect on a plant and its operation. The complexity of machinery and automation system had been on the increase.

The evolution of the maintenance strategy is demonstrated in the table 3.1 and the development between the first and third generations are summarised as follows:

- More focus on equipment reliability and root cause analysis to enhance better performance.
- The technology that can predict and reduce a machine breakdown is available. The trend of this development is pointing at ways to attain zero breakdowns.
- Maintenance tools have improved.

Many organizations have stated zero breakdowns/zero in-service failures as their maintenance goals. However, since no amount of maintenance can guarantee the total elimination of failures (there is always a probability of failing but it may be very close to zero) it is not a realistic objective. A more realistic approach is to avoid, reduce or eliminate the consequences of failures.

Table 3.1 and figure 3.2 present a summary of the survey that the author carried out. The survey was conducted through phone calls to twenty manufacturing companies that have local branches spread across New Zealand. The survey was also conducted among the attendees of Vibration Association of New Zealand Conference in the two years I attended the conference. Attendance at each was 200 and the attendees represented the managers and maintenance planners of various companies across New Zealand. The author spoke to either the maintenance manger or the maintenance planner and asked the following questions in Table 3.1

Table 3.1: Questionnaires

Questions	Answers
Company's Name	
Type of Processes	
Is your maintenance reactive or preventive or predictive	
What is your maintenance software?	
What is your predictive maintenance gear?	

The answers to the above questions were collected by the author and are demonstrated in Table 3.2 and figure 3.1 respectively.

The difficulties the author encountered during the survey were that the maintenance manager or planner were not interested in the survey. This was the reason the author decided to use telephone instead of sending out questionnaire forms.

Patience and perseverance helped the author to overcome these difficulties. The Patience helped to call as many times as possible to speak to the right person; and the perseverance helped keep ringing back to get the information the author needed for this survey.

Table 3.2: The Summary of Maintenance Evolution

First Generation	**Second Generation**	**Third Generation**
*Break and fix maintenance strategy. *65% of companies in New Zealand use this strategy.	*Preventive maintenance strategy *Job scheduling and planning *Low-tech maintenance programme *30% of companies in New Zealand use this strategy. *About 45% have the preventive maintenance programmes, only about 30% follow the routine and procedures, the rest 15% still fix the machines when it break down.	* Predictive maintenance strategy * Equipment reliability * Hazard studies and safety * Root cause analysis * Various maintenance programmes. *About 5% claim to have the predictive maintenance programmes, only about 3% practice this strategy with diagnosis and reliability, the rest 2% still fix the machines when it breaks down and also use preventive maintenance programmes.

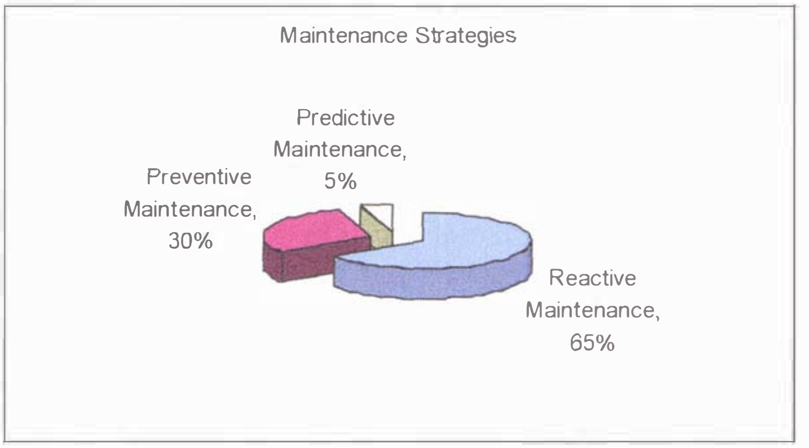


Figure 3.1: Maintenance Strategies Based on the Practices in New Zealand Companies

The increased usage of computer modelling in maintenance strategies, rapid development of computer technology (especially in the area of artificial intelligence and expert systems) and computer simulations have increased the predictive maintenance tools. Today computers help in data collection, data storage, signal processing and analysis of equipment failure.

The reactive maintenance is mostly practised by many companies because of lack of information on predictive maintenance or the cost of it or lack of interest.

For the purpose of clarity, reactive maintenance is broader than many people used to see it. Many see it as a type of maintenance other than preventive and predictive; there is more to it. The following are the broader definitions of reactive maintenance, considering the results of the survey, therefore reactive maintenance is where [42]:

- There is no preventive and predictive maintenance, but run the machine until a fault develops, is sopped and is fixed.
- There is no predictive maintenance, preventive maintenance is in place, but the routine work is never done or ignored by the maintenance personnel; the machine runs until a fault develops, is stopped and is fixed.
- Predictive maintenance is in place (either online or off line) but the recommendations based on this strategy are ignored by the plant owners or technicians, the machine is run until failure occurs and then fixed.

3.3 Maintenance Cost

Maintenance costs have been a great concern in past years, which also affected productivity and profitability. Maintenance is the largest single manageable expenditure in the plant, which surpasses the annual net profit of some companies. It is widely accepted that maintenance strategies like preventative and predictive maintenance programs produce savings of up to 25%, yet 1/3 of these maintenance costs can be saved [42]. Maintenance costs are classified into two types:

- Labour, materials, services and overhead are costs that are easily measured.
- The second one is not easy to measure, these are the unexpected stops of machine, unplanned plant shutdown and breakdown.

Therefore, it is very important for companies to maximize the effectiveness of their maintenance and equipment uptime. According to a survey carried out by the author on manufacturing companies across New Zealand, most of their maintenance departments are about 30% productive, due to lack of proper maintenance of their machines.

However, maintenance productivity can be drastically improved by the planning and scheduling of maintenance activities. For the past 20 years, most manufacturers have only focused on reducing costs in the manufacturing processes to stay competitive as a low cost producer [94]. This effort would yield some measurable productivity gain but still excludes the opportunity for the maximum gain in overall productivity since maintenance was often excluded from these improvement plans [95]. Clearly, it is also important to integrate a maintenance program into the improvement agenda of the manufacturing companies [96].

3.4 Maintenance strategies

All machines have some physical characteristics that reflect their conditions. A normal running level for that characteristic is established when the machine is in good condition, any significant deviation from that level gives a warning that a fault may be developing and maintenance will be required.

Although the specific requirements of an individual machine are rarely quantified, it is important that the criteria by which performance can be assessed are understood and monitored. Despite the fact that definite levels of acceptability are hard to establish, trends in machine conditions can be observed and should be used as indicators of maintenance requirements. Three types of maintenance strategies are discussed in this chapter.

3.4.1 Breakdown Maintenance (Reactive)

This type of maintenance strategy is referred to by some people as reactive or corrective or 'break and fix' maintenance. In Auckland and Wellington about 65% of the companies surveyed use this strategy to maintain their machines. The approach is reactive when the machine breaks down or the machine is in the process of breaking down. This process shortens the life of the equipment, which often results in the replacement of the machine or components. The costs of labour, production, repair and parts make the overall maintenance cost under this strategy the highest among the maintenance practices. This maintenance strategy is basically "run the machine till it breaks". Advantages to reactive maintenance can be viewed as a double-edged sword. If we are dealing with new equipment, we expect minimal incidences of failure. If our maintenance strategy is only reactive, we will not expand manpower, dollars or incur cost until something breaks.

Since there is no associated maintenance cost, this could be viewed as saving money. On the other hand, by waiting for the equipment to fail, its life is being shortened which would result in more frequent replacement. The labour cost associated with repair will be higher than normal because the failure will most likely require more extensive repairs than would have been required if the piece of equipment had not been run to failure.

3.4.2 Preventive Maintenance (PM) Strategy

This is a 'time-scheduled' task to prevent breakdown, which is performed on machines periodically or by schedules. During this maintenance period, machines are opened up and inspected, and then repairs are made. Items are replaced or overhauled at a specified time, no matter their condition. This research work investigated maintenance strategies in different companies in New Zealand (see Table 3.2 and Figure 3.1); about 30% of them operate PM effectively. Some of these companies incorporated their maintenance routine into SAP software and collected the list of machines due for inspection each week. Examples of this routine work are in Appendix B. This was the PM strategy that was set up for a company that claimed to have a preventive program but still practised a reactive maintenance strategy. The following were investigated before the PM was set up: machine history, hypothetical failure history, manufacturers manual as well as interviews with the operator of the machine and the maintenance team. PM has two features, which are, activity to be performed and frequency at which it is performed. Failure to assess the two features will result in either under-maintaining or over maintaining the machines. Under-maintaining machines occurs when PM is not performed often enough, while over maintaining is when PM is performed at more frequent intervals than necessary or performing activities that add no value to the machine output. The companies visited during the investigation showed their preferences for the following intervals when specifying the PM frequencies: weekly, monthly, quarterly, six-monthly and annually.

3.4.2.1 Preventive Maintenance Costs By Frequency

Breakdown is when a machine is operating less than satisfactorily. Despite all attempts at prevention, machine breakdowns of various kinds do occur and often need to be fixed on an urgent or emergency basis. It is important to make sure that the real cause of the breakdown is found and remedied and not just the effect patched up. Root cause analysis should be rigorous in finding the inherent cause of the problem. If the real cause of the problem is not corrected then further breakdown is likely to occur.

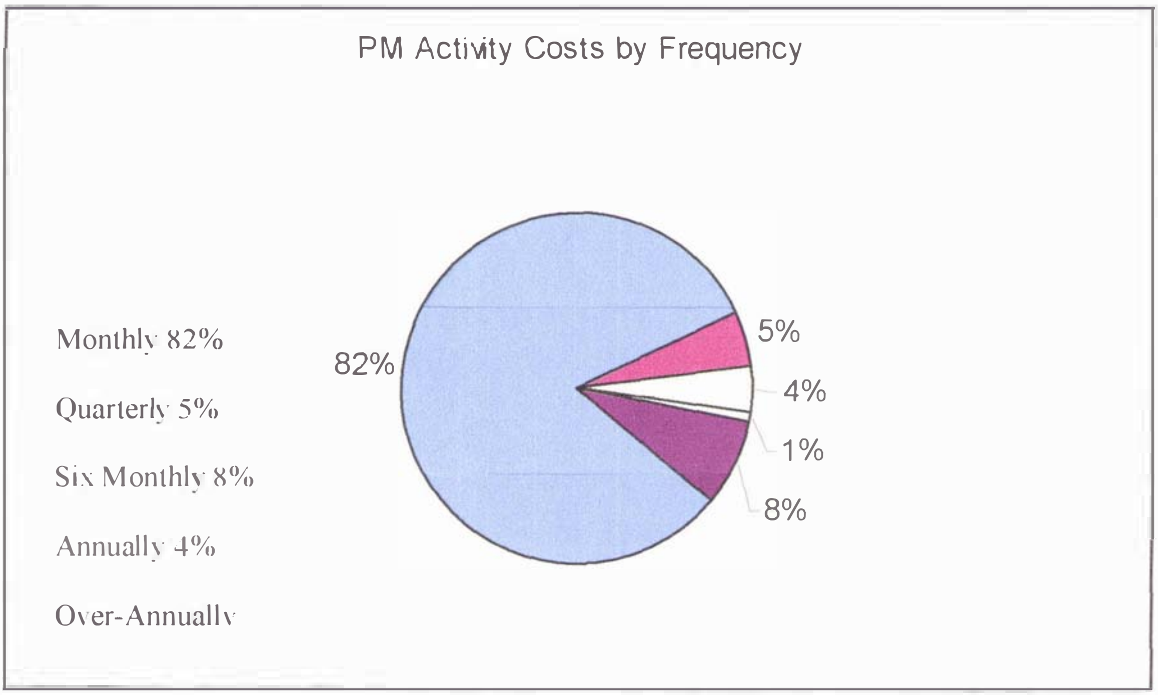


Figure 3.2: Preventive Maintenance Costs by Frequency

Figure 3.2 shows over 80% of the PM expenditure on activities with a frequency of one month or less, whereas the six-monthly and annual activities are only 8% and 4% of maintenance costs respectively. The figure outlines the costs involved during preventive maintenance.

3.4.2.2 *Case Study 1: Fan Drive End Bearing Under Preventive Maintenance*

A steel manufacturing company shown in Figure 3.3 performs different operations in six plants, which are; Iron, Steel, Meta Coating Line, Colour Coating Line, Rolling Mills and Mine Site. The maintenance strategies in these plants were preventive and predictive. The plant owners designed preventive maintenance (PM) for some machines and predictive for others.

Figure 3.3: Steel Manufacturing Company in Auckland New Zealand

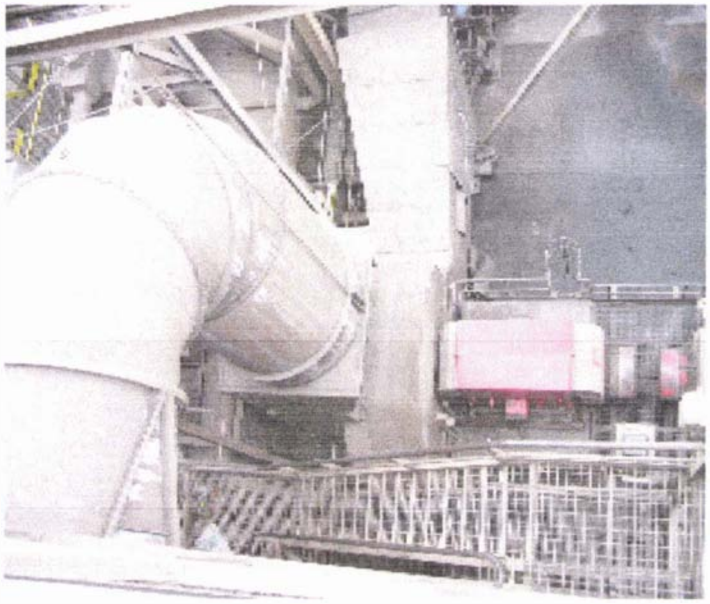


Figure 3.4: Multi-Hearth Furnace Fan

Figure 3.5: Fan DE Bearing

This case study will discuss a machine under preventive maintenance. The machine is shown in figure 3.4, a multi-hearth furnace fan that had a history of premature bearing failure at the fan drive end (DE) shown in figure 3.5. The preventive maintenance on this machine scheduled its lubrication frequency and when to change bearings as shown in Table 3.3, more PM schedules can be found in Appendix B.

Table 3.3: PM Schedule

Component	Frequency
Motor Bearings	Check Lubrication level weekly
Fan Bearings	Change bearings yearly

The PM schedules for the bearings shown in Table 3.3 were based on the following:

- Plant experience
- Manufacturer's recommendation

3.4.2.3 Plant Experience

Local knowledge of machine performance in the longer term, proved to be a more appropriate method of establishing the frequency of major overhaul and other maintenance requirements. Before this experience could be used to set up the preventive maintenance, accurate maintenance records were kept so that performance patterns and characteristics could be clearly established. Component life expectancy and wear rates can be assessed on the basis of recorded information that represents a true reflection of operating conditions. This information will not be detailed enough; the use of a predictive maintenance technique provides the kind of detailed information on which maintenance records can be based.

3.4.2.4 *Manufactures' Recommendation*

Most equipment manufacturers provide details of recommended maintenance requirements, from basic lubrication schedules to major overhaul information. This information was used as an initial basis on which to determine preventive work, such as overhaul and routine replacement of components, to be carried out during annual or other planned shutdowns. Until plant experience indicates otherwise, it is good to follow these recommendations in the early stages of operation.

In this case study, the problem was that the DE fan bearing always failed within 3-4 months and never lasted the one year predicted by PM and not in any way near the bearing life. The plant maintenance team resorted to this routine without knowing the root cause of the premature failure.

Some investigators [97] state that, by performing PM as the equipment designer envisioned, the life of the equipment would be extended close to the design, but would not prevent catastrophic failure. The problem with the idea of using PM to extend the equipment life has the following missing components which this thesis will address:

- The root cause of the failure
- No valid data that quantifies and validate when a component be changed or replaced.

One of the aims of this research was to use a vibration sensor and a data collector (Predictive Maintenance-PDM) to collect valid measured data to diagnose faults and find the root cause of the failure, using a mathematical approach and compare the calculated values with the component's standard to substantiate the deviations from the designed values. This will be discussed in chapter 4.

3.4.3 Predictive Maintenance (PDM)

The condition of all machinery should be under continual surveillance by both operating and maintenance personnel. The casual and routine monitoring of equipment all yield information regarding the operating condition on which maintenance requirements can be planned. It is vital that maintenance personnel realise the importance of being critically aware of the operating condition of machinery and ensure that their observations are accurately reported. Inspection requires the use of the senses and maintenance personnel should develop an eye, ear and a nose, for machine condition. Recognition of normal running characteristics are the basis from which deviations can be observed and trends in machine condition can be predicted.

In recent years a variety of techniques have been developed by which the operating condition of machinery can be either intermittently or continuously monitored. These techniques will use mechatronics sensors for inspection and detect when machinery deviates from normal operating conditions. The most important aspect of these techniques is the ability to provide information on which maintenance requirements can be based.

Machines are regularly monitored to determine the condition of the machine components while the machine is running. It is a more condition-based approach to maintenance, which uses a vibration technique to determine if the machine will fail during some future period, and then takes a corrective action to avoid the consequences of that failure. By contrast preventive maintenance is based on a time interval. Condition monitoring involves the acquisition, processing and analysis of sensor data related to machine parameters, such as vibration. Developing problems can be detected and identified at early stages by comparing the data being collected continuously, and appropriate decisions can be made to fix the problem before the failure becomes a catastrophic one.

Improvement in operation costs and safety has made predictive maintenance a viable and cost effective choice for the optimum operation of modern plants. The development of new sensor and computer technology has provided research opportunities for scientists and engineers to investigate problems in the area of condition monitoring and fault diagnosis. Condition monitoring can be off-line or on-line. Off-line is when the data collector is being used at scheduled intervals to monitor the machines, while on-line is when the sensors are permanently fixed on the machine for continuous monitoring. Data from both methods are processed until useful quantities that best describe the current health of the machine are extracted. The processed information is then compared against some known or predetermined normal quantities, and finally, fault or failure indicating signals are generated. The system behaviour can be predicted under various fault conditions for a given set of signals and parameters.

3.4.3.1 *Case Study 2: Identification of Deep Grove Bearing Defects by Spectra Analysis.*

Data collection is the most important step in the evaluation of machinery condition. Data should be collected by placing the transducer in the load zone, the drive end. If this is not done, the best signal definition may not be obtained. In order to know where to place the transducer, it is good to know the internal machine geometry and which problems generate radial or thrust loads. For example, with a radial load, the best signal can be obtained in the radial position. With an angular contact bearing or a radial bearing in a thrust load, the best signal definition can be obtained in the axial direction. Data can also be taken where the transfer function is best, for example, put the transducer on a bolt head, not the cover. A machine with a defective bearing can generate at least five frequencies that have been associated with defective bearings, which can be computed by using the following formulae. Equations 3.1- 3.5 are valid for a bearing mounted with outer race stationary and inner race rotating [98].

$$RPS = \frac{RPM}{60} \qquad 3.1$$

$$FTF = \frac{RPS}{2}\left(1 - \frac{B_d}{P_d}\cos\phi\right) \qquad 3.2$$

$$BPFI = \frac{N_b}{2}.RPS.\left(1 + \frac{B_d}{P_d}\cos\phi\right) \qquad 3.3$$

$$BPFO = \frac{N_b}{2}.RPS.\left(1 - \frac{B_d}{P_d}\cos\phi\right) \qquad 3.4$$

$$BSF = \frac{P_d}{2B_d}.RPS.\left(1 - \frac{B_d^{\,2}}{P_d^{\,2}}\cos^2\phi\right) \qquad 3.5$$

RPM = Revolution per minute

RPS = Revolution per second

FTF = Fundamental train frequency

$BPFI$ = Ball pass frequency of inner race

$BPFO$ = Ball pass frequency of the outer race

BSF = Ball spin frequency

B_d = Ball or roller diameter

N_b = Number of balls or rollers

P_d = Pitch diameter

ϕ = Contact angle

The above data and definitions are needed to compute values for the frequencies.

Rolling element bearing fault frequencies are guaranteed as a result of fatigue, wear, improper installation, improper lubrication, and manufacturing faults in the bearing components. It is possible to use the manufacturer's data to find the ball diameter, pitch diameter, number of rolling elements and the angle between the surface of each rolling element and the races (called the contact angle). Knowing these three values, the four fundamental defect frequencies can be calculated accurately.

The following equations are needed to compute the frequencies of bearings mounted with the inner race stationary and outer race rotating. Equations 3.6- 3.9 are valid for the bearing mounted with inner race stationary and outer race rotating [98].

$$FTF = \frac{RPS}{2}\left(1 + \frac{B_d}{P_d}\cos\phi\right) \tag{3.6}$$

$$BPFI = \frac{N_b}{2}.RPS.\left(1 - \frac{B_d}{P_d}\cos\phi\right) \tag{3.7}$$

$$BPFO = \frac{N_b}{2}.RPS.\left(1 + \frac{B_d}{P_d}\cos\phi\right) \tag{3.8}$$

The formula for BSF is identical for both cases:

$$BSF = \frac{P_d}{2B_d}.RPS.\left(1 - \frac{B_d^{\,2}}{P_d^{\,2}}\cos^2\phi\right) \tag{3.9}$$

When the bearing fault frequencies that appear in the vibration spectra do not match the calculated frequencies, an unanticipated load in the bearing changes one of the parameters used in the calculation. The typical parameter that changes is the contact angle ϕ [98].

3.4.3.2 *Equipment Specifications*

RION VA - 10

The following are the details on the data collector used for this case study.

Name of data collector: Rion VA-10

Analogue

Channels: 1

Transducer:

Rion PV-55

Pizo crystal with built in charge amplifier.

Signal conditioning:

Butterworth filters Slope -18dB/oct

High pass: 3,10,1k Hz. (at -10% point)

Low pass: 1k, 5k, 15k, 50k Hz. (at -10% point)

6 input ranges: (half decade steps)

Integration and double integration.

Rms and 0 to Peak detectors.

Amplitude demodulation,

Antialiasing, low pass filter, 5^{th} order Chebyshev, (tied to sample rate).

Analogue to Digital:

8 bit

Dynamic range 48 dB

Digital:

Sampling:

Window size; 256, (512 and 1024 with zoom)

Internal triggering; setable level and slope, post and pretrigger.

Averager modes; instantaneous, linear, exponential and peak.

Window time weighting; Rectangle (none), Hanning, Flat top.

FFT: Standard; 256 points to 100 lines,

Zoom; 512 points to 200 lines and 1024 points to 400 lines.

Other functions:

Crest Factor, Probability density, overall level, enveloped acceleration.

Memory:

100 line spectra; 180

Overall level and crest factor; 500

Display:

128 x 128 pixel lcd.

Cursor units:

X axis: Hz, Kcpm, Order, ms

Y axis: G, m/s^2, mm/s, in/s, mm, mils, %, dB

Interface:

RS-232, 1200 - 9600 baud.

Ambient operating conditions:

0 to 40° C, 20 to 90% RH

Dimensions:

215 (H) x 124 (W) x 43 (D) mm

700g

3.4.3.3 *Measured Frequency*

The theory on the four fundamental defect frequencies was used to detect bearing failure in an Arrol crane, (60tons), which carries steel from a furnace to the casting machine in a steel manufacturing company. The crane was noisy before we were told to do a vibration check. There was previous vibration data. The accelerometer was placed on the bearing housing of the input shaft of the primary gearbox in the radial direction and the readings were taken and analysed to identify the defect bearing. The spectra in figures 3.3 and 3.4 were generated by the data collector.

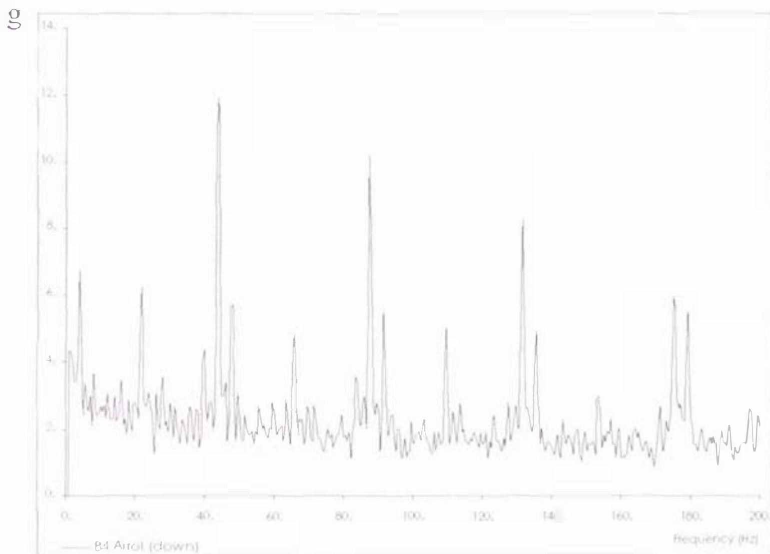


Figure 3.6: Spectrum Showing the Bearing Defect

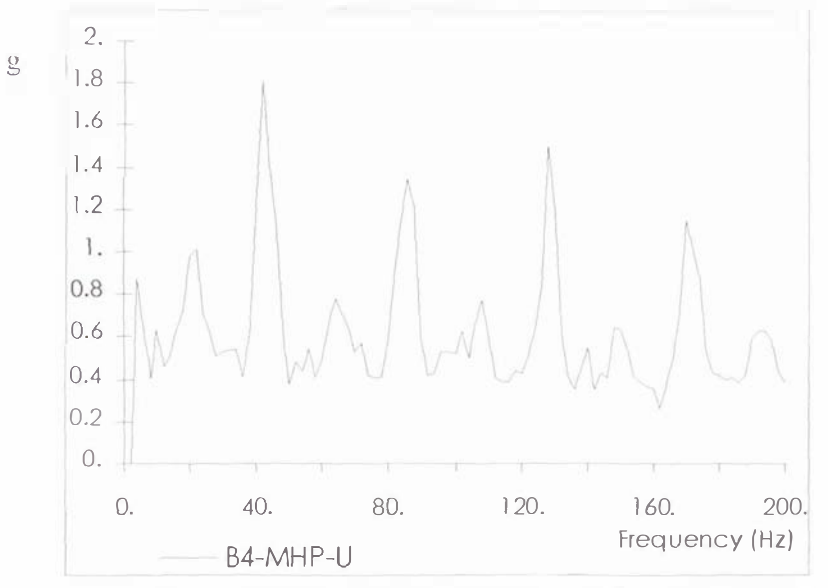


Figure 3.7: Acceleration Amplitude versus Frequency

The spectra shown in figures 3.6 and 3.7 indicate a serious bearing problem. figure 3.6 has its highest frequency peak with velocity amplitude of 12mm/s and the measured frequency was 43.4Hz. Figure 3.6 is the envelope, it is a good technique to detect bearing faults, and the fact that it is peaky is an indication of bearing fault. The envelope technique enables precise diagnosis of ball bearing faults.

In order to validate the type of bearing defect, the predicted frequency was calculated by using the bearing's parameters.

3.4.3.4 *Predicted Frequencies*

- Frequencies associated with the various bearing defects can be obtained by using equations 3.1 – 3.5.
- Shaft running speed = 10Hz
- B_d = 34.93mm
- P_d = 159.12mm
- N_b = 8 balls
- Angle = 6^o

- Fundamental Train Frequency (FTF) = 3.91Hz, using equation 3.2
- Ball pass frequency inner race (BPFI) = 48.73Hz using equation 3.3
- Ball pass Frequency of the outer race (BPFO) = 31.27Hz using equation 3.4
- Ball spin frequency (BSF) = 21.7Hz using equation 3.5

The measured frequency was 43.4Hz and the predicted frequency of the ball spin frequency was 21.7Hz. The effect of the ball hitting both outer and inner race will result in a total frequency of (21.7 x 2) 43.4Hz. This confirms that the problem was coming from the balls. When the bearing was dismantled, the defect ball bearing causing the high peak was found as shown in figure 3.8.

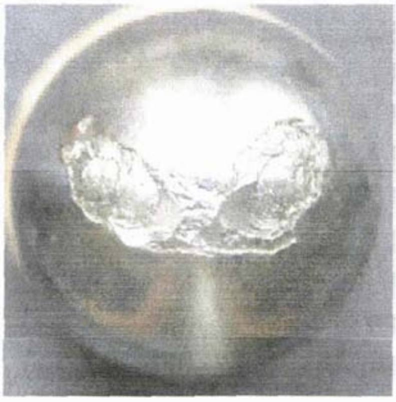


Figure 3.8: The Defect Bearing

The corrective action the author recommended was that the bearing be changed. This was done and another set of readings were taken to see if the acceleration amplitude had dropped. Figure 3.9 shows the new spectrum after the bearing was replaced. It has a low acceleration amplitude, the noise was eliminated and the crane worked smoothly.

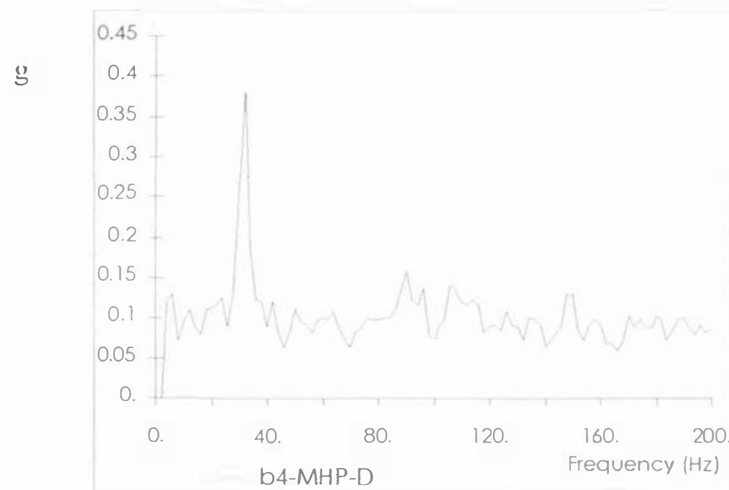


Figure 3.9: New Spectrum with Low Acceleration Amplitude

PDM is a good technique with valid data to predict system behaviour - its application and pitfalls of its Fast Fourier Transform (FFT) algorithm are discussed in chapter 4.

CHAPTER 4

Fast Fourier Transform Technique and Its Pitfalls

4.1 Introduction

The Fourier transform converts time-domain signals to the frequency domain. Fourier analysis can be used to describe systems and their properties in the frequency domain, by breaking down the complex signal into its components at various frequencies. This makes the input and output of systems easier to analyse by expressing them as a function of frequency domain instead of time.

In this chapter, a system response to inputs of different frequencies is presented. The signals are complex and comprise of real and imaginary components. In the frequency domain, the Fourier transform is mathematically represented as complex numbers. Different case studies are presented here; using the FFT technique to identify various machine faults. A number of case studies are presented to investigate where the FFT technique could not be used to identify the root cause of failures: A mathematical modelling approach was used, together with the FFT data, to find the root cause.

It will be seen that the forcing frequencies and the resonance effect can overlap in an FFT making diagnosis difficult. Conversely, the cepstrum technique using a homomorphic filter will be shown (in the next chapter) to separate these two effects making diagnosis much easier.

4.2 Complex Numbers

A complex number consists of both real and imaginary components. The Fourier analysis algorithm converts the time domain to frequency domain, which is the representation of frequency components. In order to have in-depth understanding of the functions available in FFT spectrum analysers, complex numbers are presented. The possibility to find the square root of minus one is the reason why complex number is adopted. Mathematicians solve this problem by giving a value of i to be the square root of minus one, the electrical engineers use this as a symbol of current, hence the use of j as a symbol for the square root of minus one. In this thesis, the notation j of the electrical engineers will be used. Figure 4.1 shows a complex number plotted on the real and imaginary plane, assuming a complex number b + cj.

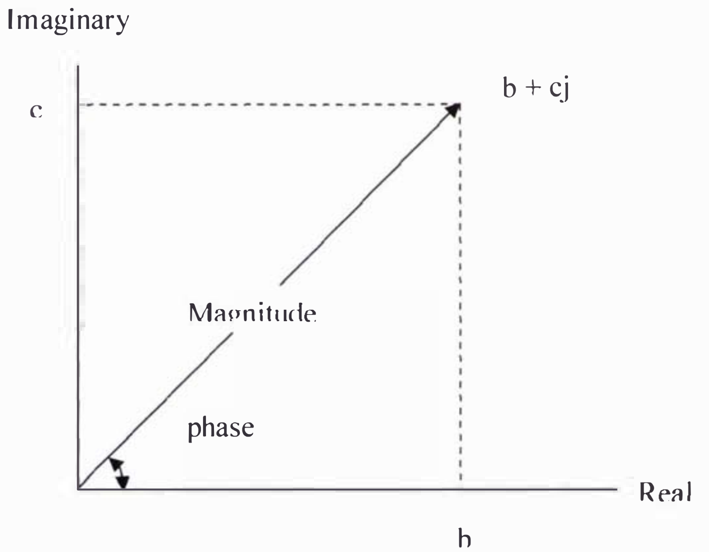


Figure 4.1: Real and Imaginary Plane of a Complex Number

$$(Magnitude)^2 = (real\ component)^2 + (imaginary\ component)^2$$
$$Phase = \tan^{-1} imaginary\ component/real\ component$$
$$Complex\ number\ (n) = b + cj \qquad 4.1$$

Where

n = complex number

b = real number

cj = imaginary number

The multiplication of c and j will result to a rotation of it by $\Pi/2$ radian. The number j describes the square root of negative real numbers, hence

$j^2 = -1$

The other way to represent a complex number is in form of its magnitude and phase. Fourier analysis can be explained by using the Fourier series of a periodic function after the application of the complex number.

If $x\ (t)$ is a periodic function, therefore,

$$x\ (t) = x\ (t + nT) \qquad 4.2$$

Where

T = periodic time

n = any integer

The continuous-time Fourier transform is shown in equation 4.3.

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-2\pi ft} \tag{4.3}$$

The periodic T → ∞, while the spacing 1/T between harmonics approaches zero and X (f) becomes a continuous function of f and equation 4.4 becomes the continuous-time Fourier transform.

$$X(f_k) = \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)e^{-j2\pi f k t}\,dt \tag{4.4}$$

Where

$f_k = kf_1$

kth = harmonic of f_1

1/T to be kf_1, *k* is zero and negative integers, however, the *kth* component is obtained from the integral.

Multiplying the signal by $e^{-j2\pi fxt}$ will cause all the components at other frequencies to rotate and eventually integrate to zero over the periodic time.

Since complex numbers can be plotted on the real-imaginary plane, it is evident that the spectrum analyzer will handle the complex numbers the same way as vector mechanics, calculating both magnitude and phase.

4.3 Theory of FFT Analyser

The FFT analyser is the most commonly used piece signal analysis equipment in the vibration field. Spectrum Analysis defined as the transformation of a signal from a time-domain representation to frequency has its roots in the early 19th century [99]. It took a practical man, an engineer with a good mathematical background to develop the rationale upon which almost all our modern spectrum analysis techniques are based. That engineer was Jean Baptiste Fourier, working for Napoleon during his invasion of Egypt on a problem of overheating cannons when he derived the famous Fourier series for the solution of heat conduction. It may seem a far cry from overheating cannons to frequency analysis, but it turns out that the same equations apply to both cases [100].

Fourier later generalized the Fourier series into the Fourier Integral Transform.

The advent of digital signal analysis naturally led to the so-called Discrete Fourier Transform and the Fast Fourier Transform (FFT). The FFT is simply an algorithm for calculating the DFT in a fast and efficient manner.

Cooley and Tukey discovered FFT in 1967, but it existed much earlier. The FFT algorithm places certain limitations on the signal and the resulting spectrum. For instance, the sampled signal to be transformed must consist of a number of samples equal to a power of two [101].

Most FFT analyzers allow 512, 1024, 2048 or 4096 samples to be transformed. The frequency range covered by FFT analysis depends on the number of samples collected and on the sampling rate.

Spectrum analyser is a powerful device that is able to do a proper vibration diagnosis on machinery. The condition of the machine and its mechanical problems are determined by measuring its vibration characteristics, which are frequency, displacement, velocity, acceleration and phase.

The vibration amplitude is the measure of the severity of the trouble in the machine and the frequency components indicate the type of faults.

Case studies are presented on few of the common vibration problems in machinery, which are:

- Bearing defects
- Imbalance of rotating parts
- Worn or damaged gears

The characteristics of the Entek FFT spectrum analyser the author used in this research, are shown in table 4.1

Table 4.1: Entek Spectrum Analyzer Characteristics

Resolution	400 lines
Frequency range	10kHz
Dynamic range	96dB
Number of channels	2

4.4 Case Study 3: Bearing Failure Due to Shaft Deflection

The data presented in the figures 4.2 and 4.3 was acquired by the author on the drive end of the fan bearing housing of the multi hearth furnace (MHF) Flakt fan, which supplies draught to Flakt venturi scrubbers in the iron plant of a steel manufacturing company in New Zealand.

There are four multi-hearth furnace (MHF) Flakt fans and each one is powered by an inline, direct drive 1.3mW electric drive. They were installed on site in late 1989 and modifications to the bearing pedestals were undertaken in late 1996/early 1997, which included trialling of different bearing types in an attempt to achieve an acceptable bearing life. The shaft has a simply supported boundary condition with a diameter of 150mm. The fan impeller has not been fitted with anti-thrust vanes, however, circular stiffening rings have been fitted to prevent flutter of the back plate and front sheet and these preclude the fitting of anti-thrust vanes. Both the shaft and fan impeller are made from Sandvik SAF 2205 stainless steel. The fan bearing at the drive end suffers premature failures. The following investigations had become necessary to evaluate the root cause of such failures and a corrective action was recommended. Investigations were carried out to validate whether the premature bearing failure was due to excessive shaft flexing or whirling producing large angular misalignment at the bearing journal.

In this investigation, historical and new data were used to evaluate the shaft and impeller deflections, critical speed, loading on the bearing and lubrication system. The predicted values and the manufacturer's standard values (SKF & NSK) for the bearing [103, 104, 105] were compared, and recommendations were given, considering the system operating conditions, natural frequency, critical speed and deflection.

4.4.1 Natural Frequency & Critical Speed

Rotating shafts become dynamically unstable at certain speeds, and large vibrations are likely to develop. The speed at which this phenomenon occurs is the critical speed. Vibration difficulties frequently arise at the lowest or fundamental critical speed. Equations 4.13 and 4.14 for a simply supported shaft boundary condition were used to calculate the speed [106].

$$f = \sqrt{\frac{g}{\delta}} \qquad 4.13$$

$$N_c = \frac{30}{\pi}\sqrt{\frac{g}{\delta}} \qquad 4.14$$

Where:

f = Natural frequency (Hz)

g = Acceleration due to gravity (m/s^2)

δ = Deflection (m)

N_c = Critical speed (rpm)

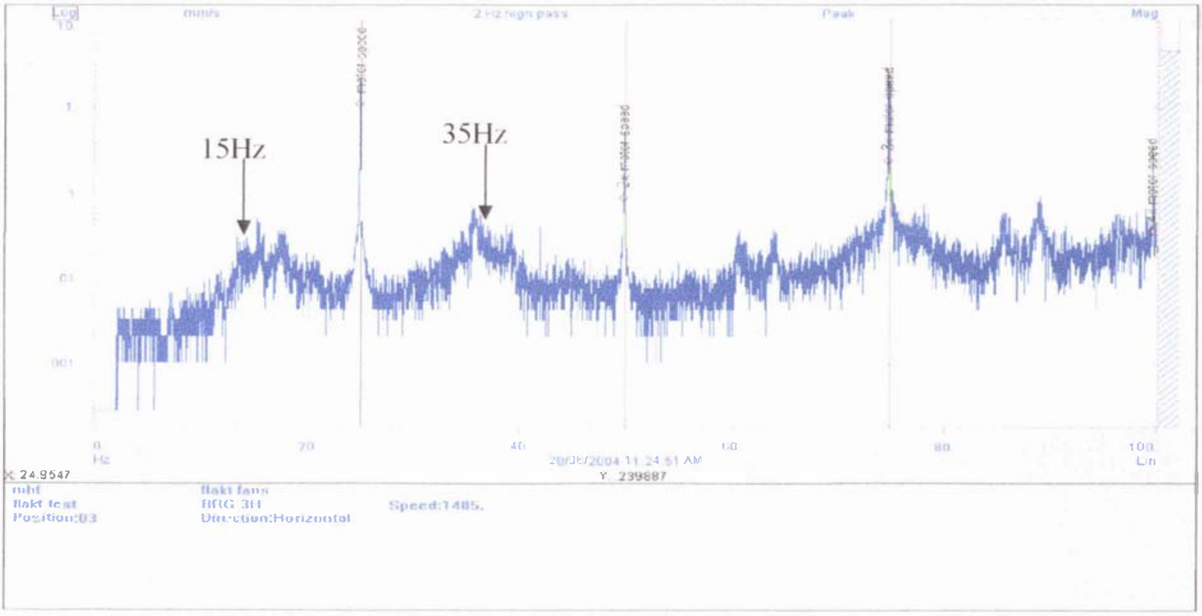


Figure 4.2: Fan Bearing Housing at Drive End, Horizontal Direction.

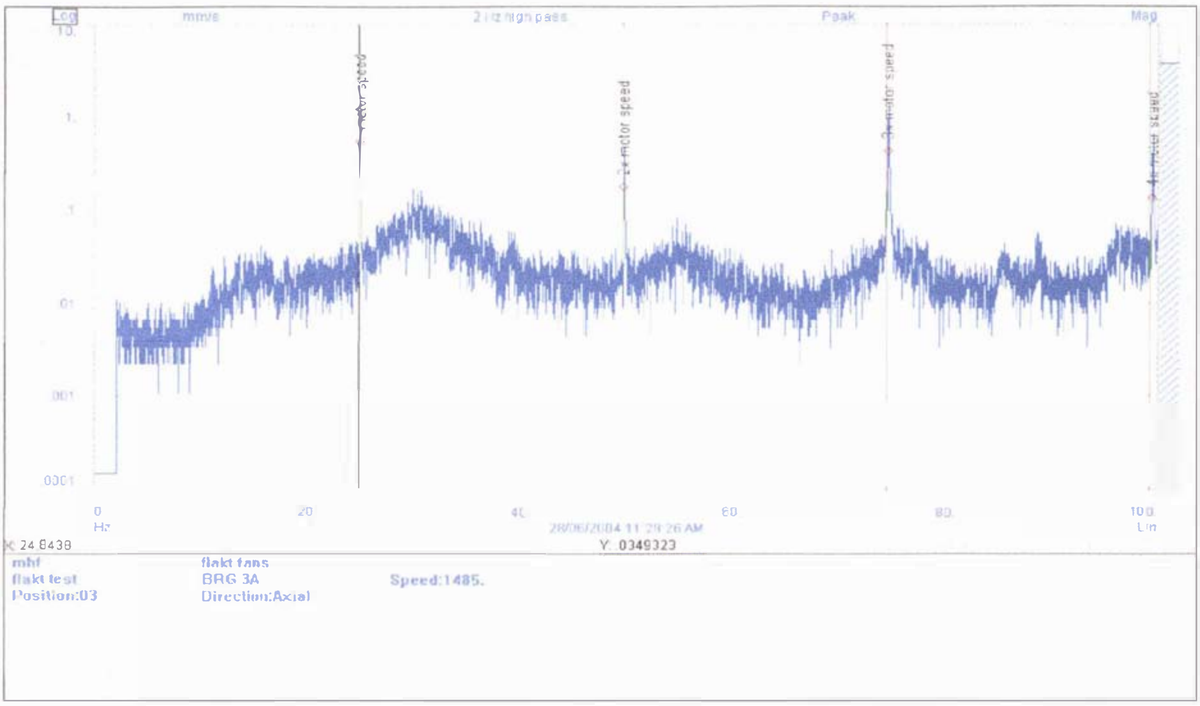


Figure 4.3: Fan Bearing Housing at Drive End, Axial Direction.

The shape of the spectrum in Figure 4.2 is a system response at 15Hz, 35Hz and 75Hz respectively; however, the 75Hz coincides with 3x running speed harmonic. Figure 4.3 is in the axial direction, while Figure 4.2 is in the horizontal direction. The indication is that the fan is running between the first and second critical speeds.

4.4.2 Whirling of Shaft & Critical Speed

Critical speed of shafts may be found by any of the means for calculating the natural frequencies with equations 4.13 & 4.14 [106]. Whirling, i.e. violent vibration at critical speeds occurs in vertical as well as horizontal shafts. In non-vertical shaft like the one in this case study, gravity effects may introduce additional critical speeds of second order.

4.4.3 Deflection & Stiffness

A shaft may be designed and still be unsatisfactory because it lacks rigidity. Insufficient rigidity, or stiffness, can result in poor performance of various shaft-mounted elements such as bearing. When a shaft is turning, eccentricity causes a centrifugal force deflection which is resisted by the shaft's flexural rigidity (*EI*). As long as deflections are small, no harm is done.

In this case study, the deflection due to both impeller and shaft was used to evaluate the criticality between the bearing's axial and radial loads ratio, using equations 4.15 & 4.16 for a shaft with a simply supported boundary condition [106, 107, 108]

$$\delta_{\max .shaft} = \frac{5Wl^4}{384EI} \qquad 4.15$$

$$\delta_{\max\, impeller} = \frac{Wab}{27EIl}(a+2b)\sqrt{3a(a+2b)} \qquad when\, a \angle b. \qquad 4.16$$

Where:

δ = Deflection

W = Load (kN)

l = Length (m)

E = Young's modulus of elasticity (Gpa)

I = Moment of inertia (m^{-4})

a = Distance from impeller to reaction 'A'

b = Distance from impeller to reaction 'B'

4.4.4 Permissible Angular Misalignment

The deflection of the impeller was used to evaluate the bearing angular misalignment. The predicted values were compared with the manufacturers' catalogues to obtain a valid F_a/F_r ratio.

4.4.5 Results

The shaft has a bearing simply supported boundary condition and a concentrated load (impeller) of 900kg.

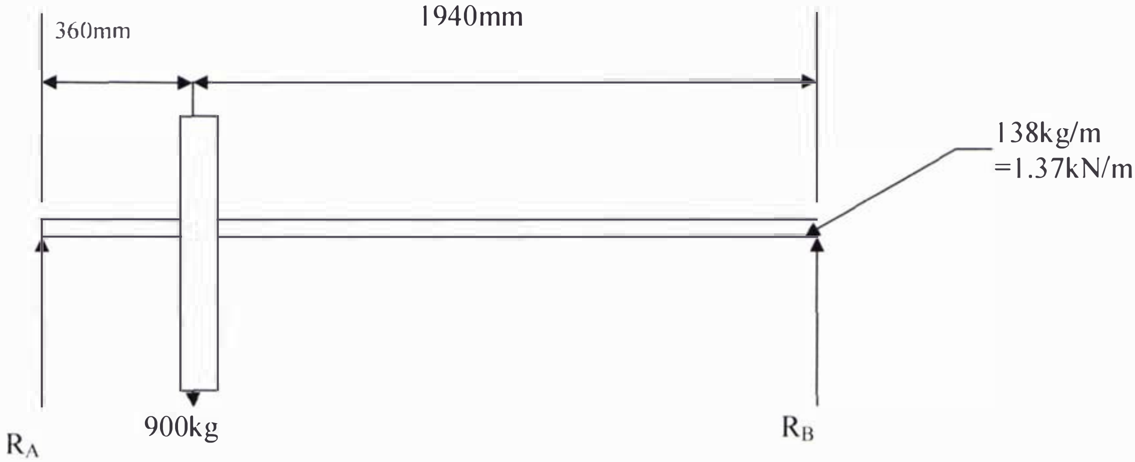


Figure 4.4: Concentrated Load (Impeller) on a Simply Supported Shaft

Applying clockwise moment = anticlockwise moment; R_B = 2.93kN

Applying upward force = downward force;
R_A = 9kN

Impeller Venturi Eye Diameter = 1.358m

Area of Impeller = πr^2 = 1.4484m2

Assume 100 millibar is the gauge pressure on one side:
Axial Thrust Force (F) = P x A = 14.47kN

Deflection

Shaft diameter = 150mm

Moment of inertia (I)

$$I = \frac{\pi r^4}{4}$$

I = 24.85 x 10^{-6}mm

Maximum deflection due to weight of shaft (δ_{max}), using equation 4.15.

$$\delta_{max} = \frac{5wl^4}{384EI}$$

$= 0.099$mm

Maximum deflection due to impeller (δ_{max})

$(\delta_{max}) = \frac{wab}{27EI}(a+2b)\sqrt{3a(a+2b)}\ when\ a \angle b.$

$= 0.181mm$

Total deflection = 0.28mm

Permissible Angular misalignment (PAM)

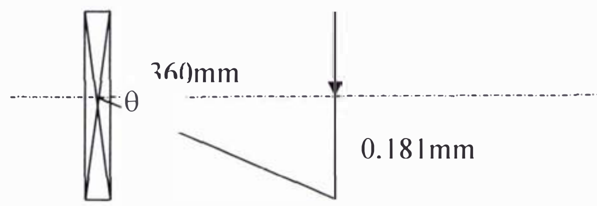


Figure 4.5: Effect of Shaft Deflection on Bearing

From Figure 4, $\theta = 0.029^{\circ}$

PAM from manufacturer's catalogue = 2° (The bearing is SKF 22228 CCK W33 C3, tapered bore spherical roller bearing) [104]

Effect of Axial Load on Bearing

Radial load from impeller = 14.7kN @ 0.029°

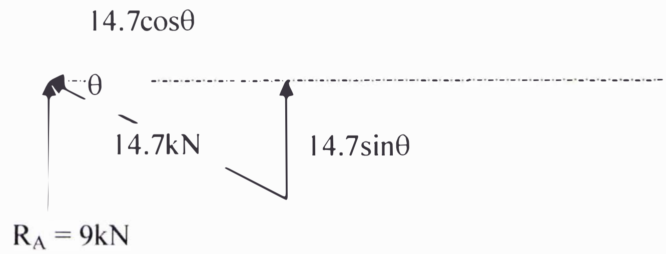


Figure 4.6: Effect of Misalignment Angle on Bearing

Axial load (F_a) from figure 4.4 = 14.7kN

Radial load (F_r) = 9.01kN

$F_a/F_r = e = 1.63$

Critical Speed

From equations 1 & 2, critical speed (N_c) = 1785rpm.

Assuming 60% increase on shaft rotational speed:

Rotational speed = 1480rpm

Considering 60% increase, N_c = 2368rpm

Deflection due to the 60% increase, using equations 4.13 & 4.14.

δ = 0.16mm

Deflection

Shaft diameter = 150mm

Moment of inertia (I) =
$$\frac{\pi r^4}{4}$$

I = 24.85 x 10^{-6}mm

Maximum deflection due to weight of shaft (δ_{max}), using equation 4.15 [109].

$$\delta_{max} = \frac{5wl^4}{384EI}$$

= 0.099mm

Maximum deflection due to impeller (δ_{max}), using equation 4.16 [110].

$$(\delta_{max}) = \frac{wab}{27EI}(a+2b)\sqrt{3a(a+2b)}\ when\ a \angle b.$$

= 0.181mm

Total deflection = 0.28mm

4.4.5.1 Minimum Shaft Diameter

Assumption

60% increase over the shaft rotational speed, using equation 4 to find deflection due to impeller

$$(\delta_{max})\ \text{Impeller} = \frac{wab(a+2b)\sqrt{3a(a+2b)}}{27EIl}$$

$$\frac{4wab(a+2b)\sqrt{3a(a+2b)}}{27E\pi r^4 l} \qquad 4.17$$

$$\frac{wab(a+2b)\sqrt{3a(a+2b)}}{21.2\,E\,r^4\,l} \tag{4.18}$$

$$\frac{wab(a+2b)\sqrt{3a(a+2b)}}{48.8\,E\,r^4} \tag{4.19}$$

Total deflection = Maximum deflection due to shaft + Impeller

δ_{Total} =

$$\frac{wl^4}{60.3\,E\,r^4} + \frac{wab(a+2b)\sqrt{3a(a+2b)}}{48.8\,E\,r^4} \tag{4.20}$$

$$w = \rho v \tag{4.21}$$

0.00016 =

$$\frac{7850\,\pi\,r^2\,l^4\,9.81}{60.3\,E\,r^4} + \frac{wab(a+2b)\sqrt{3a(a+2b)}}{48.8\,E\,r^4} \tag{4.22}$$

$0.00016r^4 = 5.614 \times 10^{-7}r^2 + 5.73 \times 10^{-9}$
(13)

r = 0.0894m, hence shaft minimum diameter = 178.8mm.

Therefore the shaft minimum diameter is 180mm

Table 4.2: Shaft Conditions

Shaft Parameter	**Present Condition**	**Recommended Condition**
Critical speed	120% of running speed	160% of running speed
Shaft diameter	150mm	180mm
Maximum shaft deflection	0.099mm	0.07mm
Maximum impeller deflection	0.181mm	0.09mm

In order to validate the value of the maximum deflection obtained, it was used to calculate the bearing permissible angular misalignment and then compared with the angle specified by the manufacturers. The predicted angle was 0.029^0. the permissible angular misalignment indicated by the manufacturer was 2^0 (SKF catalogue), hence the deflection was not the issue at this stage.

Axial & radial load ratio for the bearing in question is governed by the manufacturer's standard (SKF & NSK), $F_a/F_r = 0.25$ [103, 104].

The axial load on the bearing was inclined at a small angle, which was insignificant to its horizontal and vertical components as shown under results.

The F_a/F_r = e. The ratio obtained was 1.63 which was higher than the 0.25 value recommended by the manufacturers.

The critical speed was 1785rpm, which was only higher by 20% of shaft running speed. 50% or more is a recommended value for a critical speed to avoid resonance effect.

The predicted F_a/F_r ratio is 1.63, while the required value should be 0.25, this would require the bearing to be greased more often, otherwise the cage wear is likely to become a great concern as a result of the high ratio of 1.63.

The critical speed should be at least 50% more than the shaft running speed. The deflection has a significant influence on the critical speed. The critical speed was increased to 60% of the shaft running speed, the total deflection of the shaft and impeller was calculated as 0.07mm + 0.09mm = 0.16mm. Therefore the minimum shaft diameter of 180mm is recommended to reduce the total deflection from 0.28mm to 0.16mm and increase the life span of the bearing.

4.5 Case Study 4: Fan Imbalance

Machinery Imbalance is one of the most common causes of vibration. Mass Imbalance in a rotating machine often produces excessive synchronous forces that reduce the life span of various mechanical elements. Unbalance is caused by an asymmetry in the rotating element that results in an offset between the shaft centreline and centre of mass. It represents the most common type of synchronous excitation on rotating machinery. Unbalance results from the fact that the centre of gravity of a rotating member does not coincide with the centre of rotation, which causes a centrifugal force pointing radially out from the centre of rotation and rotating at a speed equal to the speed of the rotating member itself. The equation that governs the amplitude of the unbalance force is as follows:

$$F = Mw^2r \tag{4.23}$$

Where

F = Force (N)

M = Mass (kg)

ω = Angular velocity (rad/sec)

r = radius (m)

The case study is about a dedust fan in an iron plant. It runs at a speed of 1450rpm and the impeller has eight blades. The analysis of the vibration data showed a high velocity amplitude of 11.8mm/s at 1x fan speed, which was an indication of imbalance.

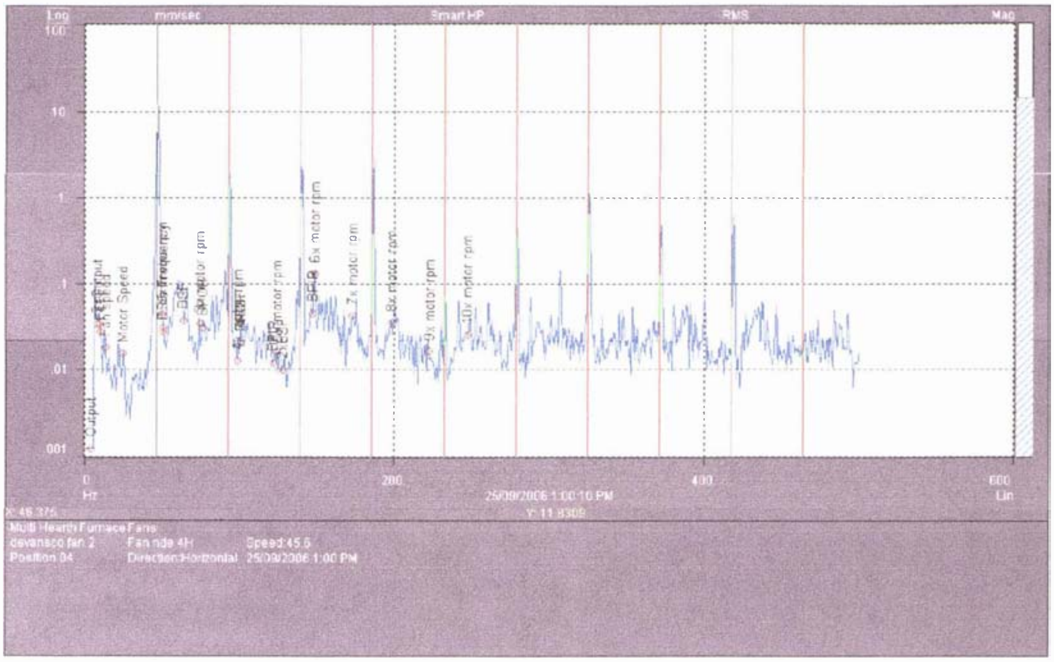


Figure 4.7: Imbalance Spectrum with High Amplitude at 1xFan Speed

The amplitude is proportional to the amount of imbalance, which was larger in the radial directions of measurement of 11.8mm/s velocity amplitude as shown in figure 4.7. The figure was obtained by using an Entak Enpac 2500 data collector.

A serious unbalance like the one in this case study could destroy the fan or any of its components like the bearings. Severe unbalance could tear the machine from its foundation; therefore corrective action was taken by balancing the fan. The fan was balanced by using the two-channel Enpac 2500 spectrum analyser with a balancing program. A reference and trigger point was located on the shaft by sticking on a small piece of tape. The laser light centred on the shaft triggered the analyser each time the reference point on the shaft crossed the laser light. The machine was run for about one minute and was stopped when the phase angle was seen to be stable. The phase angle is relative to the arbitrarily selected trigger position on the shaft used to trigger the analyser.

A trial mass of 22g was placed on the impeller at zero degree with reference to the trigger point on the shaft and the fan was run second time for one minute. The data collector displaced the actual mass that would reduce the imbalance amplitude and the phase angle. When a machine was out of balance, a sinusoidal time waveform with a frequency of the running speed and a large peak would be seen in the spectrum at the 1 x running speed. After the balancing, more vibration data was collected; the spectrum showed the imbalance amplitude reduced to 1.2mm/s from 11.8mm/s as shown in figure 4.8.

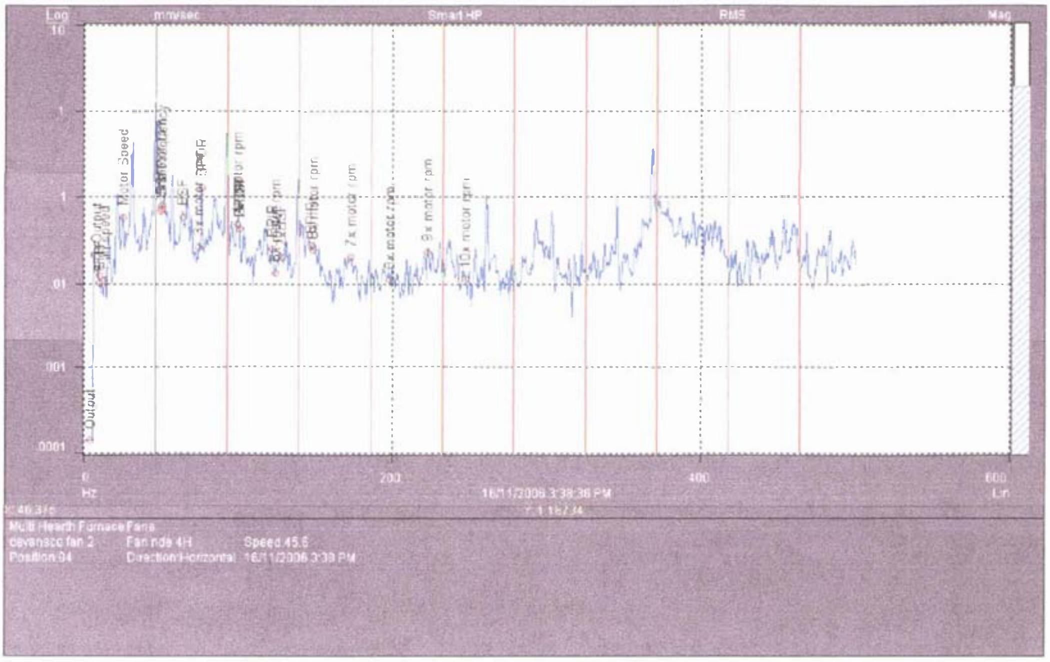


Figure 4.8: Spectrum after Balancing of Fan

4.6 Case Study 5: Root Cause Analysis Technique to identify gearbox Failure

During the March shutdown in the iron-sand mine site, the raw sand gearbox was removed, sent to the central workshop, overhauled and returned to service on the 9th March. On the 18th of March, a noise was reported from the gearbox and there was oil leaking from the output shaft. The vibration data collector was used to collect data on the gearbox and later analyzed; the diagnosis indicated a strong possibility of broken teeth. On the 29th March, during a down day, the lid was lifted for an inspection and broken bevel wheel teeth were discovered as shown in figure 4.9. Investigations were conducted to ascertain the root cause of the bevel gear broken teeth.

Firstly, the gearbox vibration level was investigated, using a Fast Fourier Transform (FFT) data collector. Secondly, the predicted values obtained for contact and bending stresses were compared with the American Gear Manufacturers Association Standards (AGMA) and the manufacturer's data to validate the root cause failure of the gearbox tooth mesh [111].

The design, manufacturing and tooth mesh parameters were investigated to ascertain the root cause of the gearbox broken teeth.

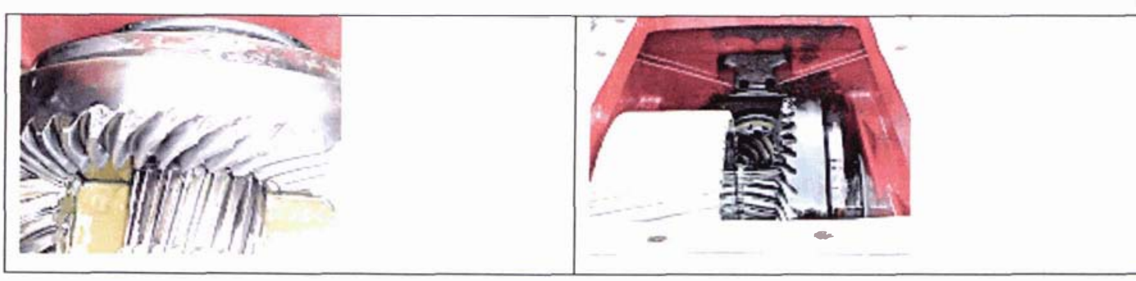


Figure 4.9: Gear with the broken teeth

After the vibration data was collected and analysed the spectrum in figure 4.9 was obtained. Gears generate a mesh frequency equal to the number of teeth on the gear multiplied by the rotational speed of the shaft driving it. A high vibration level at the mesh frequency is typically caused by tooth error due to wear of the meshing surfaces, improper backlash or any other problem that would cause the profiles of meshing teeth to deviate from their ideal geometry.

Gears generate a large number of possible sidebands about the mesh frequency as shown in figure 4.10, which is a pitfall of fast Fourier transform.

Figure 4.11 is the envelope: this indicates that there is no bearing problem, due to the low acceleration amplitude level in the figure.

Figure 4.10: Gearbox Spectrum

Figure 4.11: The Envelope

Table 4.3 shows the information on the gearbox.

Table 4.3: Design and Manufacturing Considerations

Parameters	**Pinion**	**Both**	**Gear**
Gear ratio		3.5454:1	
Material		Steel grade 2	
Mounting		Straddled	
Number of teeth	11		39
Facewidth		80	
Surface hardness		58+4 HRC	
Heat treatment		Gas carburised	

Motor speed = 1480 rpm

Motor Power = 250kw

Pinion Torque

$$T_1 = \frac{9550p}{n_1} \tag{4.24}$$

where:

p = power (kw)

n_1 = pinion speed (rpm)

T_1 = 1613Nm

Contact Stress (σ_H)

$$\sigma_H = Z_E \sqrt{\frac{2000T_1}{bd^2{}_{e1}Z_1} K_A K_v K_{H\beta} Z_x Z_{xc}} \tag{4.25}$$

where:

Z_E = elastic coefficient (N/mm2)

T_1 = operating pinion torque (Nm) = 1613N/m

K_A = overload factor = 1.0

K_v = dynamic factor = 1.0

$K_{H\beta}$ = load distribution factor = 1.0

Z_x = size factor = 1.0

Z_{xc} = crowning factor = 1.5

b = facewidth (mm) = 80mm

d_{e1} = pinion outer pitch diameter (mm) = 95mm

Z_I = pitting resistance geometry factor = 0.12

$$Z_E = \sqrt{\frac{1}{\pi\left(\frac{1-v_1^2}{E_1}+\frac{1-v_2^2}{E_2}\right)}} \qquad 4.26$$

where:

v = Poisson's ratio = 0.3

E = Young's modulus of elasticity = 200,000N/mm^2

Z_E = 187N/mm^2

Therefore:

σ_H = 1383N/mm^2

= 4 x 10^8 cycles = 31years

Permissible Contact Stress (σ_{Hp})

$$\sigma_{Hp} = \frac{\sigma_{H\lim} Z_{NT} Z_w}{S_H K_\theta Z_z} \qquad 4.27$$

where:

σ_{Hlim} = allowable contact stress number (N/mm^2) = 1550N/mm2

Z_{NT} = stress cycle factor

Z_w = hardness ratio = 1.0

S_H = contact safety factor = 1.0

K_θ = temperature factor = 1.0

Z_z = reliability factor = 1.0

$Z_{NT} = 3.4822n_L^{-0.0602}$

$= 3.4822 \times (4\times10^8)^{-0.0602}$

$= 1.1$

Therefore:

$\sigma_{Hp} = 1706N/mm^2$

$\boldsymbol{\sigma_{Hp} > \sigma_H}$, ***OK***

Bending Stress (σ_f)

$$\sigma_f = \frac{2000T_1 K_A K_v Y_x K_{H\beta}}{b d_{e1} m_{et} Y_\beta Y_J} \qquad 4.28$$

where:

$T_1 = 1613Nm$

$K_A = 1.0$

$K_v = 1.0$

M_{et} = outer module = 10

Y_x =size factor

$K_{H\beta} = 1.0$

$b = 80mm$

$d_{e1} = 95mm$

$Y_x = 0.4867 + 0.08399m_{et}$

$= 0.57$

$$Y_\beta = 0.211\left(\frac{r_{co}}{R_m}\right)^q + 0.789 \qquad 4.29$$

where:

r_{co} = cutter radius

R_m = mean cone diameter

$$q = \frac{0.279}{\log_{10}(\sin \beta_m)} \tag{4.30}$$

where:

β_m = mean spiral angle

Hence:

$Y_\beta = 1.0$

$Y_J = 0.21$

Therefore:

$\sigma_f = 115.2 \text{N/mm}^2$

Permissible Bending Stress (σ_{FP})

$$\sigma_{FP} = \frac{\sigma_{F\lim} Y_{NT}}{S_F K_o Y_Z} \tag{4.31}$$

$\sigma_{Flim} = 240 \text{N/mm}^2$

$Y_{NT} = 1.6831 n_L^{-0.0323}$

$= 0.89$

$S_F = 1.0$

$K_o = 1.0$

$Y_z = 1.0$

Therefore:

$\sigma_{FP} = 213.6 \text{N/mm}^2$

$\boldsymbol{\sigma_{FP} > \sigma_f}$, **OK**

Since the main objective was to investigate the transmission error due to broken teeth of the bevel gear, the following could be of great influence; design, manufacturing and meshing problems. The design and manufacturing problems were investigated by analytically comparing the manufacturer's data with the American Gear Manufacturers Association (AGMA) standard, and then the gearbox life was estimated to be 31years from the pitting resistance of the pinion shown under equation 4.26. Since the permissible contact and bending stresses were more than the actual contact and bending stresses, the design and manufacturing problems could be ruled out. The only option left was the transmission problem due to tooth mesh. Good tooth mesh would reduce the dynamic factor K_v, while a bad mesh would increase it and could lead to tooth breakage. The dynamic factor makes allowance for the effects of gear tooth quality as related to speed and load, hence high tooth mesh accuracy requires a lower K_v. Having used the above methodologies to validate the design, manufacturing and tooth mesh parameters, however, the most likely cause of the broken gear tooth was a mesh problem.

Trained and experienced fitters should carry out the assembly of gear and pinion to avoid mishandling problems, and all documentation be properly kept for future record. On installation and run up, condition monitoring checks should be carried out to establish a vibration signature and quality control maintenance work.

The spectrum could be analysed to detect gear broken teeth, but would not tell you the root cause of the problem. The mathematical approach was used with the vibration data to find the root cause of the problem. The theory of the cepstrum technique to diagnose gearbox problems is presented in the next chapter.

Chapter 5

The Theory of Cepstrum Technique to Separate Gear mesh and Transmission Path Effects

5.1 Introduction

The vibration produced by mating gears contains physical information pertaining to the operating condition of the gear teeth. The major sources of vibration in a gearbox are the rotating components related to the input and output shafts, which are gears, shafts and bearings.

There are three major forcing frequencies involved in a gearbox, which are the input speed, gearmesh and output speed. Tooth error is developed when the meshing teeth deviates from their ideal geometry. The following could cause tooth error; poor machining, wear and improper backlash. Resonance effect from the gear casings can increase the gearmesh frequency and the sidebands energy would become large due to gear tooth error. The FFT technique will not tell you if changes are coming from the source (meshing frequency) or the transmission path (structure resonance), instead this technique will overlap both frequencies on a particular order. Cepstrum technique and homomorphic deconvolution are discussed in this chapter as a solution to this short coming. Techniques in the literature review for machine diagnosis like artificial neural network, adaptive noise cancellation, order tracking, synchronous averaging and cepstrum analysis [63 – 93] did not address this problem.

This chapter presents a new technique for separating forcing frequency and transmission path effect which employs two signal processing tools; homomorphic deconvolution and cepstrum to diagnose gearbox fault and overcome the overlapping and sidebands problems in the current FFT technique.

5.2 Gearbox Vibration

The mesh frequency generated by gears is equal to the number of teeth on the gear multiplied by the rotational speed of the shaft. Sidebands of the mesh frequency are due to a modulating rotational motion from a failure of mating teeth to impact one another at the proper time.

Vibration analysts are concerned to differentiate between high vibration amplitudes at mesh frequencies, high energy content in the sideband and the resonance effect from the structure.

Goldman [61] presents in his book on Vibration Spectrum Analysis that a high amplitude level at the mesh frequency can indicate an interference fit between mating gears, but a large number of high level sidebands can indicate non parallel shaft due to excessive shaft deflection, gear tooth crack or spall. He claims that it is rare for gear tooth vibration to be high without a resonance effect, which causes the vibration intensity to become large.

No work has been done to separate the overlapping resonance effect from the meshing frequency; Goldman only presents the effect of resonance on mesh frequency, but not how to separate it from the source.

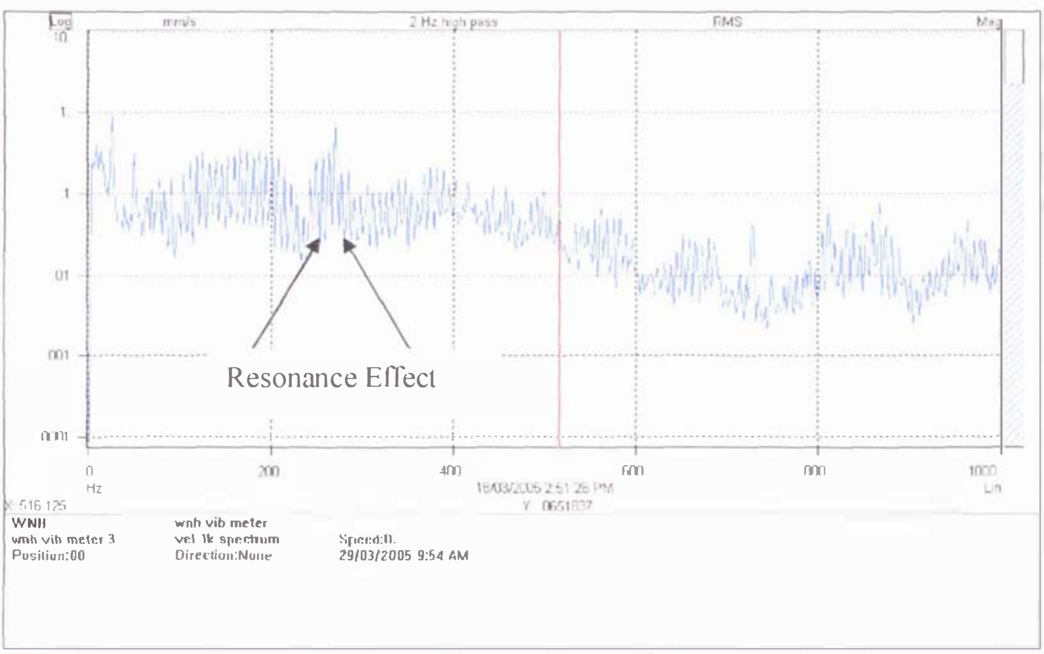


Figure 5.1: Gearbox Spectrum from the Case Study

Some machines, such as gearboxes, produce very complicated spectrum signatures like the spectrum shown in figure 5.1, which was collected on a gearbox handling raw iron sand in the mine site of a steel manufacturing company. The spacing of the sidebands around gearmesh frequencies is usually equal to one times the running speed of the shaft. The diagnosis of the gearbox is presented in chapter 4 by using the FFT technique, but the limitations are the overlapping of sidebands, meshing frequency and resonance effect, which is where the cepstrum and homomorphic deconvolution filtering techniques offer a way to simplify the analysis of these signals.

5.3 Transmission Path

The vibration signal of a gearbox is normally measured at a convenient position on the outside of the gearbox casing by using an accelerometer, which converts a mechanical vibration signals into an electrical signal. There is corruption of the vibration signal from the source to the measurement point; this is the transmission path effect. The transmission path consists of the structure providing a mechanical path from the vibration source to the measurement point. This includes the shafts, bearings, gears and the gearbox static structure, which are between the source and the transducer and modifies the amplitude and phase of the vibration signal.

The periodic variations due to changes in the number of the meshing teeth, the motion of rolling elements in a bearing, as well as non periodic variations like flexure of the gearbox casing and operating temperature are factors which can cause changes in the transmission path [117]. In addition, structural damage like cracks in the gearbox casing will also change the transmission path effects.

5.4 Transmission Error (TE)

Transmission error is defined as the non conjugacy of a gear pair, that is, the motion error defined by the difference between the output gear's actual position and its position if the gear teeth were perfect in shape and infinitely stiff. TE is defined by equation 5.1 [118].

$$TE = R_{bp}\left[\theta_p - \left(\tfrac{N_g}{N_p}\right)\theta_g\right] \tag{5.1}$$

Where

Θ_p = *Rotation of the pinion*

Θ_g = *Rotation of the gear shaft*

N_p = *Number of teeth on the pinion*

N_g = *Number of teeth on the gear*

R_{bp} = *Radius base of the pinion*

5.4.1 *Static Transmission Error (STE)*

The static transmission error is the composite effect of any deviation of the gear teeth from perfectly formed involute surfaces. The assumption is that the gears are uniformly spaced, perfectly formed and completely rigid. In practice, gears deviate slightly from perfect involute surfaces and elastically deform under load, which results in an unsteady force component of the torque. The unsteady forces are transmitted as vibration from the gear, through the shaft and bearings to the gearbox casing where it is measured.

The static transmission error is widely accepted as the principle source of vibration in gearboxes. Mathematically, this unsteady forcing function due to the pinion is best described by a complex Fourier series with fundamental frequency equal to the pinion rotational rate, f_r [119]

$$s(t) = \sum_{n=0}^{\infty} c_n . e^{jn(2\pi f_r)t} \qquad 5.2$$

The Fourier transform of the complex Fourier series is a one-sided pure line spectrum at multiples of the gear rotational rate [120].

$$s(t) = \sum_{n=0}^{\infty} c_n . e^{\delta(f - nf_r)} \qquad 5.3$$

We can now present a mathematical expression for the composite vibration due to both the position and the gear. This is accomplished by summing two infinite complex Fourier series. Therefore, if the pinion has N teeth and the gear has M teeth, then equation 5.2 describes the composite vibration due to both gears [121].

$$s(t)=\sum_{n=0}^{\infty} c_n.e^{jn(2\pi f_r)t}+\sum_{m=0}^{\infty} c_m.e^{jm(2\pi f_r)\left(\frac{N}{M}\right)t} \qquad 5.4$$

Referring to equation 5.2, f_r is the pinion frequency and $(N/M)f_r$ is the gear rotational frequency. The Fourier transform of the composite vibration is also a one-sided pure line spectrum [122].

$$s(t)=\sum_{n=0}^{\infty} c_n.\delta^{(f-nf_r)}+\sum_{m=0}^{\infty} c_m.\delta\left[f-mf_r\left(\tfrac{N}{M}\right)\right] \qquad 5.5$$

The two summations share a common set of frequencies. In the second summation, wherever m equals any integer multiple of M, the summations share the same frequency component. Therefore, equation 5.3 can be further decomposed as equation 5.4 [123].

$$s(f)=\sum_{\ell=0}^{\infty} c_\ell.\delta^{(f-\ell nf_r)}+\sum_{n=0,n\neq\ell N}^{\infty} c_n.\delta(f-nf_r)+\sum_{m=0,m\neq\ell M}^{\infty} c_m.\delta^{(f-nf_r)} \qquad 5.6$$

If we transform back to the time domain, we arrive at the following equation [124].

$$s(t)=\sum_{\ell=0}^{\infty} c_\ell.e^{j(2\pi\ell(Nf_r)t}+\sum_{n=0,n\neq\ell N}^{\infty} c_n.e^{j(2\pi nf_r t+\alpha_n)}+\sum_{m=0,m\neq\ell M}^{\infty} c_m.e^{j(2\pi mf_r t+\beta_m)} \qquad 5.7$$

The first summation in equation 5.4 is composed of vibration components from both the pinion and the gear. The first summation's fundamental frequency (Nf_r) is the gear mesh frequency. We have just shown that the components of vibration due to the gear mesh frequency and its harmonics are due to both the pinion and the gear. This is a fact that is neglected in the literature on gear diagnostics.

5.4.2 *Residual Error Signals*

Mark [126] showed the component of the static transmission error that occurs at multiples of the gear meshing frequency is caused by elastic tooth deformations and the mesh deviations of the tooth faces from perfect involute surfaces. The remaining components of the static transmission error that occur at multiples of the gear rotational frequency are caused by the dynamic components of the tooth face deviations. Thus, we have a concrete, physical justification for using the static transmission error for gear diagnostics. The dynamic component of the static transmission error is a physical measure of any gear tooth surface deviation. This includes, but is not limited to, worn teeth, missing teeth and cracked or chipped teeth.

Wang and McFadden [127] described the gear motion error as the real part of the static transmission error. The gear motion error is a real signal, described by an infinite cosine series with fundamental period f_r. The static transmission error was developed for predicting the amount of vibration produced by meshing gears; the gear motion error was developed for gearbox diagnostics.

The decomposition of the composite gear motion error has three components; the harmonic error component Sey(t), the residual error component due to the pinion Ser.p(t), and the residual error component due to the gear Ser.g(t) [127].

$$s(t) = s_{eh}(t) + s_{er.p}(t) + s_{er.g}(t) \qquad 5.8$$

Equations 5.1-5.8 are expressed graphically in figure 5.7. The figure shows the spectra produced by a pinion and gear.

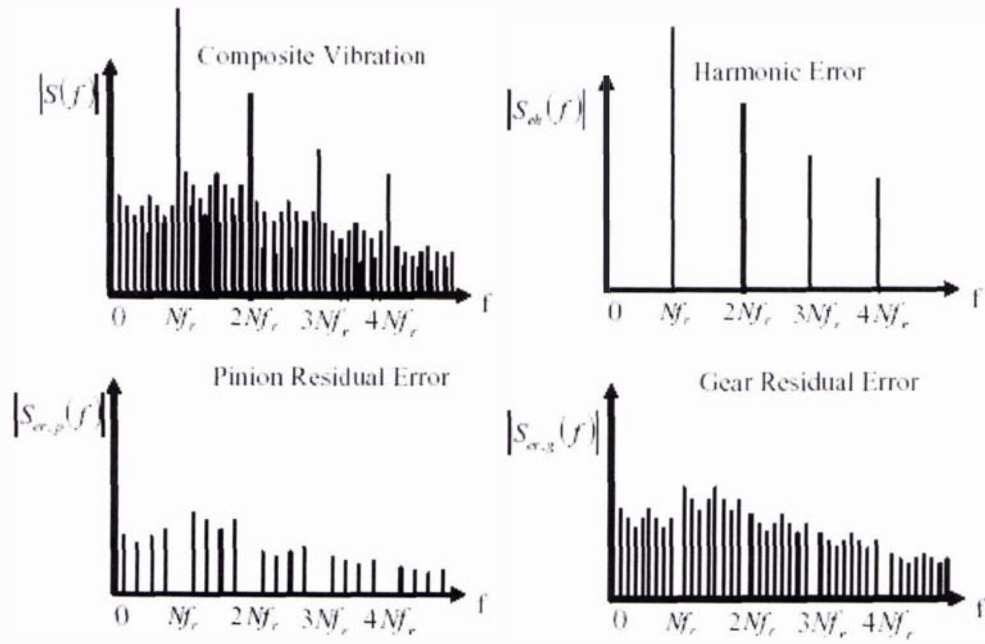


Figure 5.2: Frequency Domain of Graphical Representation of Equation 5.8 [127]

5.5 Signal Processing

The concept of a signal processing technique to achieve the diagnosis of the gearbox is presented in this section. The main objective of the signal processing technique is to extract the echoing fault pulses from the mixture, which comprises the measured vibration signal.

The vibration 'y' of a gearbox can be described as a convolution between the Impulse Response Function (IRF) of the transmission path 'h' and the combined effect of an anomaly caused by a localized gear fault (fault impulses) 'w', the deterministic signals 'e' inherent in operating gears and the noise 'n' as shown in figures 5.3 and equation 5.5.

$$y = (e + w + n) * h \qquad 5.9$$

Where

y = *Vibration of the gearbox*

h = *transmission path*

w = *gear fault*

e = *deterministic gear excitation (inherent in gear vibration)*

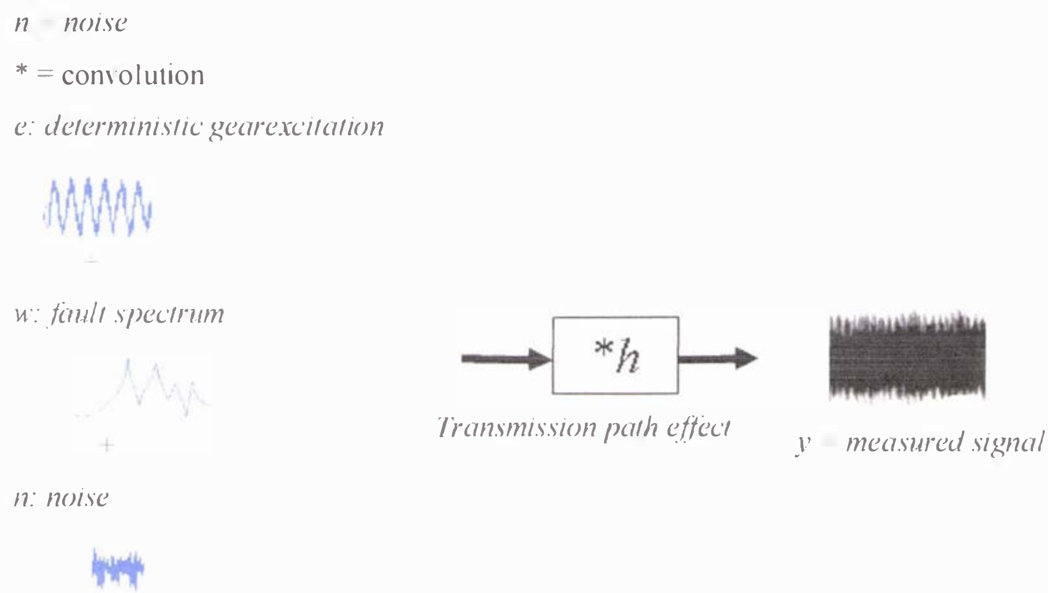


Figure 5.3: Vibration of a Gearbox

Gears with a crack or a spall can be diagnosed by comparing the vibration characteristics of the faults. Figure 5.4 presents a proposed signal processing method for the gearbox diagnosis.

The first step of the signal processing is the extraction of the impulse from the mixture of vibration signals shown in figure 5.3. The negatively inverted echo shown in figure 5.4 characterizes the effect of both the spalled and cracked teeth, however, the type of the fault can be determined by examining the properties of the fault signals in the cepstrum.

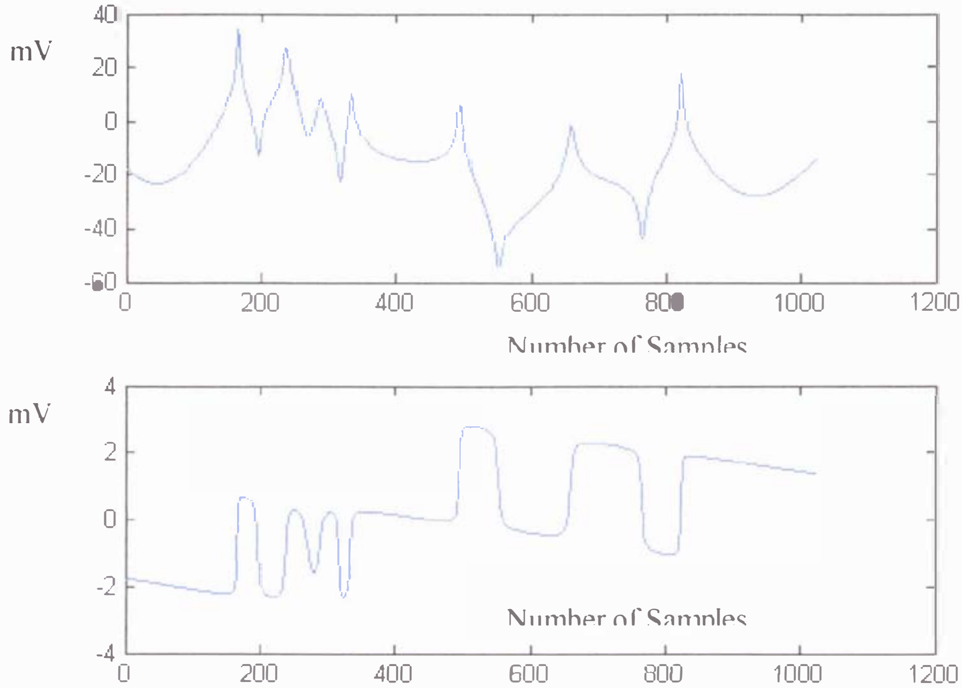


Figure 5.4a: The Negatively Inverted Echo Due to the Cracked Tooth

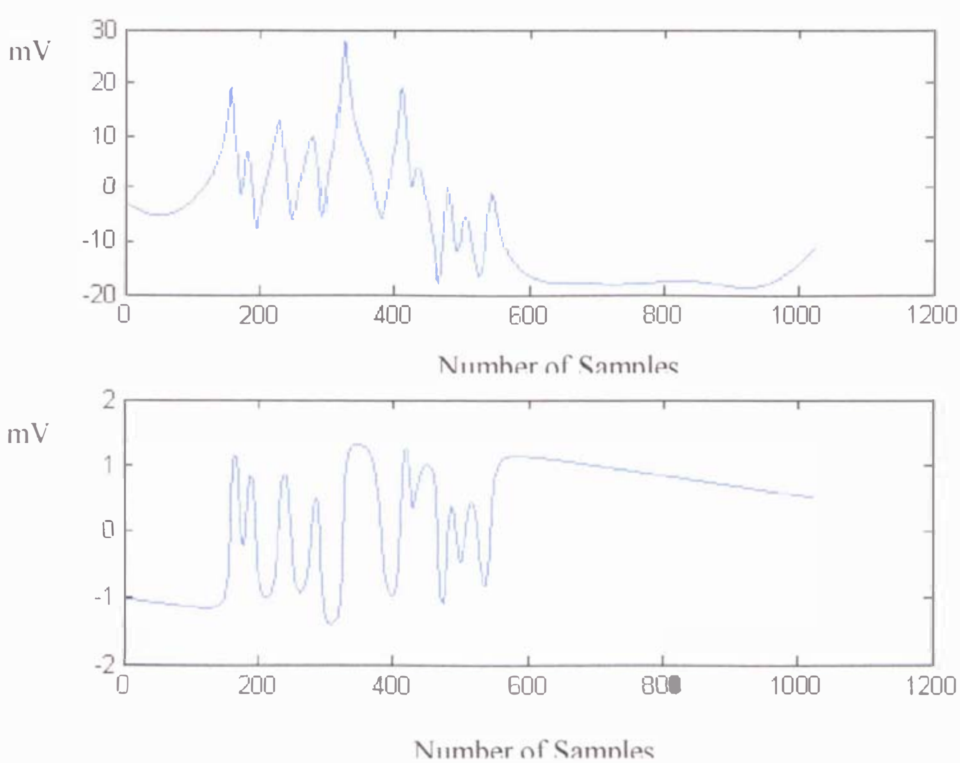


Figure 5.4b: The Negatively Inverted Echo Due to the Spall in a Tooth

The complex cepstrum transformation is central to the theory and application of homomorphic systems, that is, systems that obey certain general rules of superposition [128].

Randall demonstrates in [129] the powerful application of the cepstrum technique in monitoring and diagnosing gears and rolling element bearings.

The harmonics and the sidebands in the spectrum represent the concentration of excitation energy caused by the rotating machine components and they are typically monitored to detect any abnormality in the operating machinery.

The advantage of using the cepstrum in machine condition monitoring is that the combined effect of the harmonics and sidebands in the spectrum appear in the cepstrum as a smaller number of clearly defined rahmonic peaks: i.e. in compressed form, and it is therefore easier to monitor the changes occurring in the system. It is able to detect the presence and growth of sidebands, and to extract the spectrum periodicity.

5.6 Homomorphic Theory

Systems which the output is a superposition of the input and impulse signals by an operation that has the algebraic characteristics of convolution of the impulsive and forcing responses, (by exploiting the properties of the Fourier transform and the complex cepstrum) are called homomorphic systems.

The method of homomorphic filtering described by Oppenheim et al [133], Schafer [131], and Buhl [130] is primarily developed for the problems of echo detection and echo removal.

The algorithm transforms the convolution process into an additive superposition of its components with the result that single parts can be separated more easily. Ulrych [132] has demonstrated the application of this method in seismology for the separation of overlapping signals. The practical application of the homomorphic filter process in seismic reflection work is discussed for the first time by Scafer [131], Buhl [130] and Bryan [134].

A homomorphic system accepts a signal composed of two components and returns the signal with one of the components removed. Its processing offers a great advantage because no prior assumptions or knowledge of the impulse response of the transmission path is necessary; it has a property of blind deconvolution.

A convolved signal is shown in equation 5.10

$$y(t) = x(t) * h(t) \tag{5.10}$$

The components $x(t)$ and $h(t)$ could be isolated in order to study each individually. This research will present a gearbox with convolved signals from good, spalled and cracked teeth and use the cepstrum technique for homomorphic blind deconvolution to separate the forcing function from the transmission path effect, i.e. a homomorphic filter (complex cepstrum) is applied to do the deconvolution of the signals. The procedure of homomorphic filtering is shown in figure 5.5. (The act of applying a homomorphic filter is called liftering).

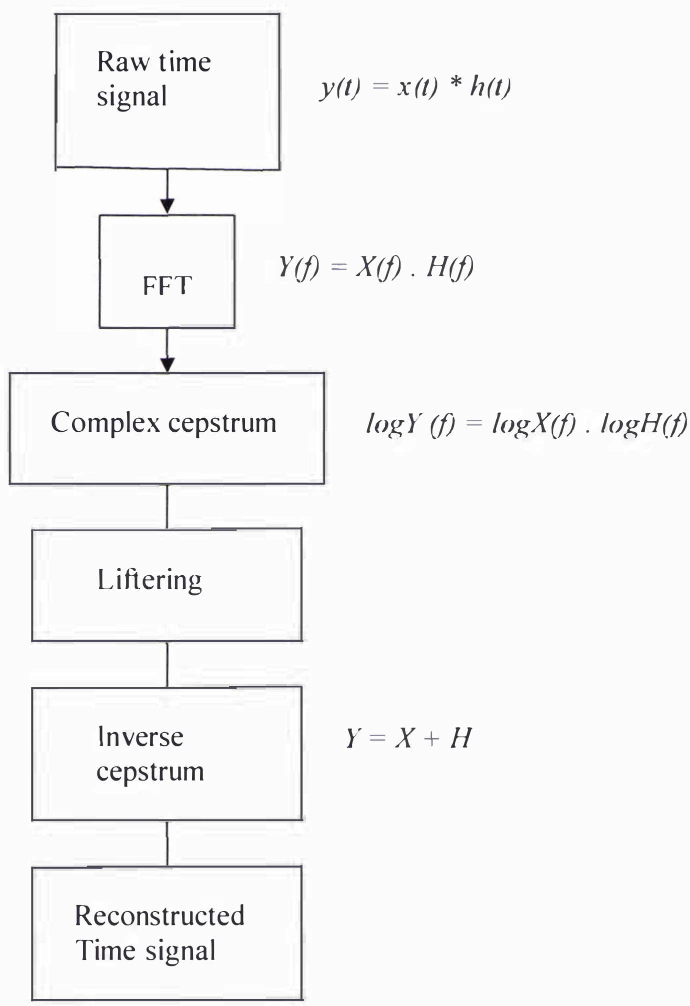


Figure 5.5: Signal Processing for a Homomorphic Blind Deconvolution

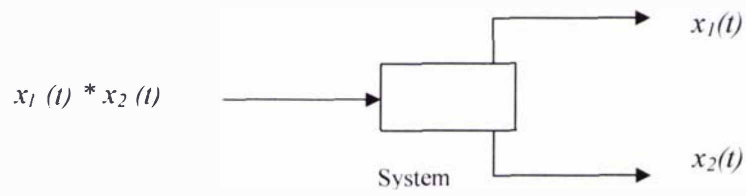


Figure 5.6: Two Signals Deconvolved to Two Separate Signals

Deconvolution is undoing the convolution of two signals and isolates them as shown in figure 5.6. This is useful for analysing the characteristics of the input signal and the impulse response when only given the output of the system.

Homomorphic filtering is a deterministic process because fixed and pre-given parts of the complex cepstrum, which are related to the undesired components, are eliminated. The success of the method depends primarily on the rate of the separation of the individual components in the complex cepstrum. Therefore the successful application of the method in a gearbox diagnosis is critically determined by the simplicity and predictability of the individual components of the gearbox cepstrum. In order to demonstrate the possibilities and difficulties of homomorphic filtering, figure 5.7 shows the cepstra of the gearbox with different fault cases under 100Nm loading.

5.7 Cepstrum Technique

The Fourier transform and the inverse Fourier transform are complex domain processes, the cepstrum is complex if the phase information of the original time waveform is preserved. Complex cepstrum can be used for noise reduction and signal separation, such as echo cancellation. Figure 5.5 demonstrates the procedures of the complex cepstrum and homomorphic filtering, equations 5.12 – 5.15 are its algorithm. This research presents an application of cepstrum technique that uses homomorphic blind deconvolution to remove the effect of transmission path transfer functions from externally measured gearbox signals. For a better diagnosis of gear faults, the cepstrum technique is used to separate source and transmission path effects into different quefrency regions. The poles and zeros of the transfer functions

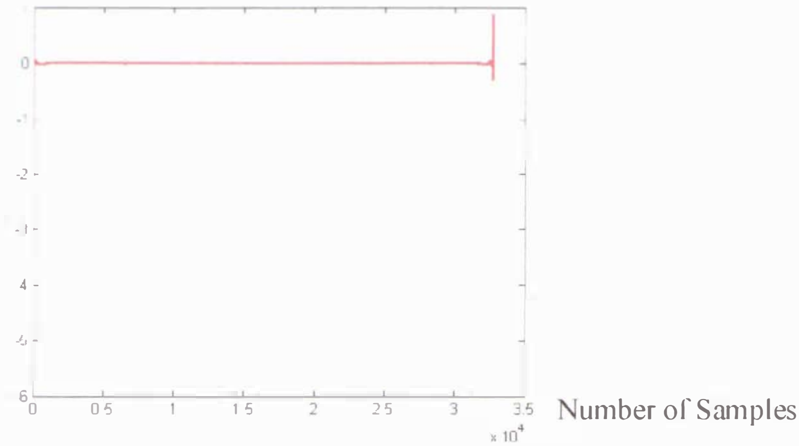


Figure 5.7a: Cepstrum of the gearbox with cracked tooth

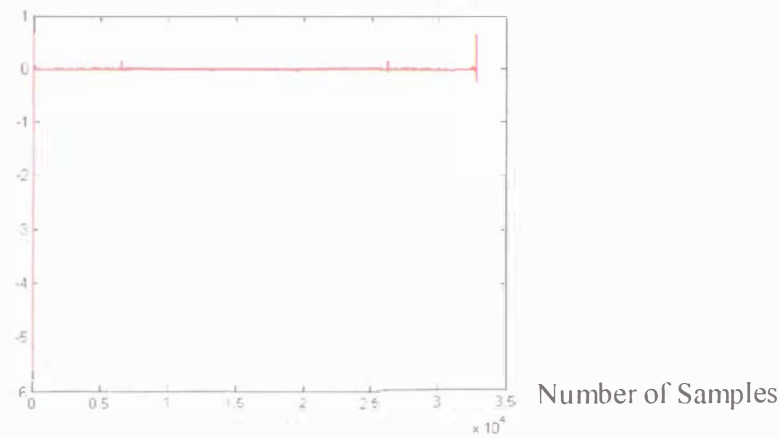


Figure 5.7b: Cepstrum of the gearbox with a spalled tooth

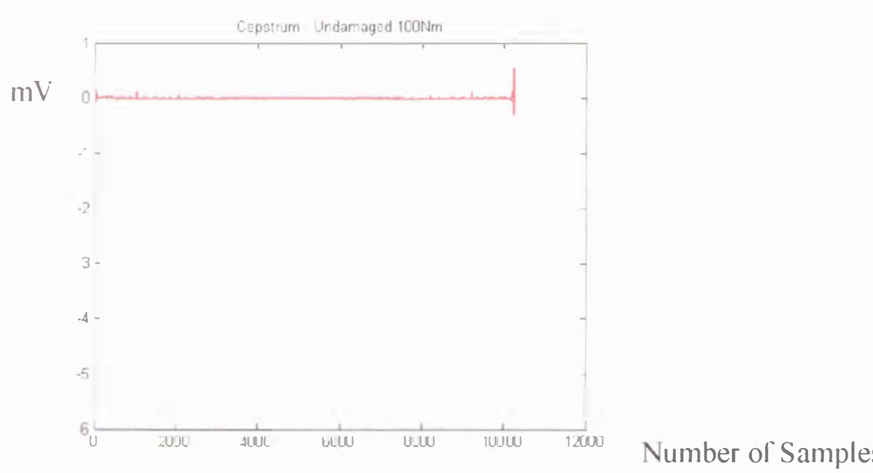


Figure 5.7c: Cepstrum of the gearbox with undamaged teeth

from the response vibrations are extracted from the region in the cepstrum shown in figures 5.7a, 5.7b and 5.7c, by curve-fitting expressions using a homomorphic filter.

The separation of the gear mesh excitation force from the transmission path transfer functions was obtained by using the cepstrum technique of homomorphic blind deconvolution without measuring the forcing function at the gear mesh. The poles and the zeros of the forcing function were used to validate the changes in the frequency response function (FRF).

The transformation of a signal into its cepstrum is called a homomorphic transformation, and the concept of the cepstrum is a fundamental part of the theory of homomorphic systems for processing signals that have been combined by convolution.

The Cepstrum is the inverse Fourier Transform of the natural logarithm of the Fourier transform of a signal series. The definition of the complex cepstrum is given in Equation 5.11. The spectrum of a gearbox signal consists of a number of harmonic families. These harmonic families originate from the different ball bearings in the gearbox and, from the tooth mesh frequencies of the gears. These are difficult to separate in the spectrum. Cepstrum is a practical tool that makes it easy to find these different harmonic families, and the individual families can be monitored for changes that might indicate that something is wrong. The cepstrum can be mathematically defined as follows [135].

$$C_{(\tau)} = \Im^{-1}\{\log F_{xx}(f)\} \tag{5.11}$$

$F_{xx}(f)$ is the autospectrum (power spectrum)

Where:

$\tau = quefrency$

$\Im = fourier\ transform$

$C = cepstrum$

Cepstrum can be edited or liftered as it is called (paraphrasing of 'filtered') [135]. The equivalent spectrum, called the liftered spectrum, can be found by applying an FFT to the liftered cepstrum. τ has units of time, but is known as 'quefrency'. Harmonically related components in the cepstrum are known as 'rahmonics'. Table 5.1 compares the terms used in the spectra and cepstral analyses.

Table 5.1: Comparison of Terms used in Spectral and Cepstral Analysis

Spectra Analysis	**Cepstral Analysis**
Spectrum	Cepstrum
Frequency (Hz)	Quefrency (milliseconds)
Harmonic	Rahmonics
Filter	Lifter
Phase	Saphe
Magnitude	Gamnitude
Frequency analysis	Quefrency alanysis

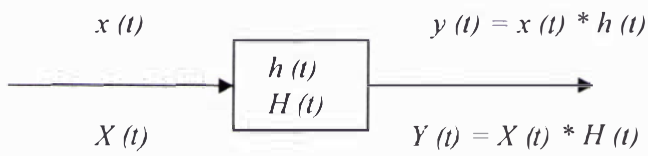


Figure 5.8: Frequency Response of a System

Figure 5.7 describes a simple system with an input and output relationship. The output $y(t)$ is equal to the convolution between the input $x(t)$ and the impulse response $h(t)$, which is mathematically shown as follows [121,129,130]. This is homomorphic deconvolution.

$$y(t) = x(t) * h(t) \tag{5.12}$$

Using the convolution algorithm, equation 5.12 will transform to equation 5.13 by applying the Fourier transform.

$$Y(f) = X(f) \,.\, H(f) \tag{5.13}$$

Taking the logarithm of equation 5.13 will result in equation 5.14.

$$Log\ Y(f) = log\,X(f) + H(f) \tag{5.14}$$

After the homomorphic deconvolution shown in equations 5.12 – 5.14, an inverse transformation of equation 5.14 to the cepstral domain will produce the cepstrum in equation 5.15.

$$\Im^{-1}\{\log Y(t)\} = \Im^{-1}\{\log X(f)\} + \Im^{-1}\{\log H(f)\} \tag{5.15}$$

Equation 5.15 defines the cepstrum of the signal measured, which is the sum of the cepstra of the source and transmission path functions. The signal from the externally measured gearbox is the convolution of the path and source effects. After transformation to the cepstrum domain, the source and the path effects are deconvolved and become additive. Equation 5.16 shows how the structural response functions are treated in the Laplace domain as a ratio of polynomials in the Laplace variable s.

$$H(s) = \frac{a_0 + a_1 s + a_2 s^2 + \ldots + a_m s^m}{b_0 + b_1 s + b_2 s^2 + \ldots + b_n s^n} \tag{5.16}$$

Applying partial fraction expansion to equation 5.16 results in poles and residues for the individual modes in equation 5.17 [1,7,8].

$$H(s) = \sum_{k=1}^{n/2} \left[\frac{r_k}{s - p_k} + \frac{r_k}{s - p_k} \right] \tag{5.17}$$

Equation 5.18 can be obtained in terms of poles and zeros by finding the roots of the numerator and denominator using rational fraction expansion [121, 127, 128].

$$H(s) = \frac{\prod_{k=1}^{m} (s - z_k)}{\prod_{k=1}^{n} (s - p_k)} \tag{5.18}$$

The z-transform of the equation 5.18 will result in equation 5.19 [121].

$$H(z) = \frac{A \prod_{k=1}^{mi} (1 - a_k z^{-1}) \prod_{k=1}^{mo} (1 - b_k z)}{\prod_{k=1}^{p_i} (1 - c_k z^{-1}) \prod_{k=1}^{mo} (1 - d_k z)} \tag{5.19}$$

Where a_k, b_k, c_k, $d_k < 1$

Equation 5.20 is the cepstrum that presents the transfer function in terms of poles and zeros [127,128].

$$C(n)=\sum_{k=1}^{m_i}\frac{a_k^n}{n}+\sum_{k=1}^{p_i}\frac{c_k^n}{n} \qquad 5.20$$

$$=\sum_{k=1}^{m_0}\frac{b_k^{-n}}{n}-\sum_{k=1}^{p_0}\frac{d_k^{-n}}{n}$$

a_k and c_k are minimum phase and are the poles and zeros in the unit circle, while b_k and d_k are the poles and zeros outside the unit circle [136,137]. Minimum phase occurs at positive quefrencies. The maximum phase at negative quefrencies can be neglected because the poles are unstable and it will not affect the detection of the changes in the resonances.

5.8 Poles and Zeros Analysis

The transfer function provides a basis for determining important system characteristics without solving the complex differential equation. The poles and zeros are the properties of the transfer function and therefore of the differential equation describing the input-output system dynamics as shown in figure 5.9.

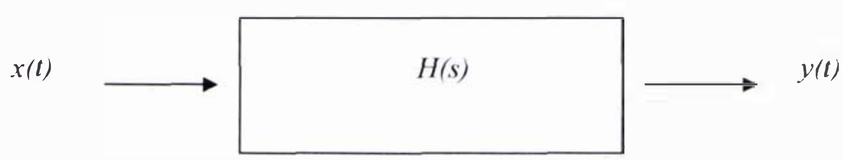


Figure 5.9: System with Input-Output Relationship

$$Y(s) = H(s).X(s) \qquad 5.21$$

$$H(s) = Y(s)/X(s) \qquad 5.22$$

The system function is $H(s)$, which represents the characteristics of the system.
The poles and zeros govern the system's behaviour, they specify the set of complex frequencies for which the eigenfunction response is infinite or zero respectively. The

number of poles in a system corresponds to the number of independent state variables in the system.

The plots are necessary because they help to easily design a filter and also obtain its transfer function. The numerator roots are the zeros of the filter and the denominator roots are the poles of the filter. The location of the poles and zeros will allow us to quickly understand the magnitude response of the filter.

The aim of using a poles and zeros analysis in this chapter is to present the theory of how the complex or differential cepstra of the path effects are curve fitted to extract poles and zeros.

The polynomial form is another way that the process transfer function can be represented as shown in equation 5.16; the ratio of polynomials is called the transfer function. The values of s that cause the numerator of the equation to equal zero are known as the zeros of the transfer function, which are also the roots of the numerator polynomial. The values of s that cause the denominator of the equation to equal zero are known as the poles of the process transfer function, which are the roots of the denominator polynomial.

The pole-zero form is another way that the transfer function can be represented as shown in equation 5.23.

$$H(s)=\frac{k_{pz}(s-z_1)(s-z_2)......(s-z_m)}{(s-p_1)(s-p_2).....(s-p_n)} \qquad 5.23$$

The complex poles or zeros must occur in complex conjugate pairs.

The gain-time constant form is the one that we use most often for control system design.

$$H(z)=\frac{z}{(z-\frac{1}{2})(z+\frac{3}{4})} \qquad 5.24$$

The zeros are: {0}

The poles are: {1/2, -3/4}

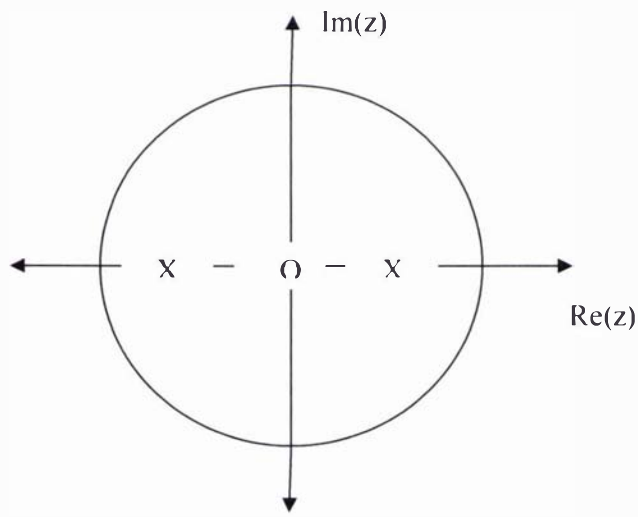


Figure 5.10: Poles and Zeros Plot From Transfer Function

Once poles and zeros have been found for a given Z-transform, they can be plotted onto the z-plane, which is complex with an imaginary and real axis referring to the complex-valued variable z. The plots help to easily design a filter and obtain the transfer function. Depending on the location of the poles and zeros, the magnitude response of the filter can be quickly understood. The example in figure 5.10 shows the locations of poles and zeros in the z-plane, the poles represent the mechanical natural frequencies and the zeros reflect the locations where the vibration cancels to zero.
The next chapter is the deals with experiments using the cepstrum technique and homomorphic filtering to demonstrate their practical application to diagnose gearbox faults.

Chapter 6

Experimental Analysis

6.1 Introduction

In this chapter, an experimental apparatus is described which generated the data used to test the cepstrum technique for homomorphic blind deconvolution and the results. Vibration signals measured on the casing of a gearbox are always a compound of source effects and transmission path effects. The gearbox is a special case; where the tooth-mesh is the principal source and hence signals measured would differ primarily because of the differences in the transmission path. The aim of this research is to develop a technique to separate the forcing function at the source, which is the gear mesh from the transmission path function of a measured gearbox vibration signal. This was achieved by collecting vibration data from the gearbox having good, spall and cracked teeth profiles under different loadings. The data was recorded in a MATLAB™ data file to demonstrate where the entire change was. The procedure was implemented by using the signal processing package of MATLAB. The forcing function is concentrated in the discrete regions in the cepstrum; the transfer function is located below the first rahmonics of the forcing function and was separated by a shortpass lifter. Since the poles and zeros occur in the complex conjugate pairs, the poles and zeros of the transfer function were extracted from the response signal by curve fitting analytical expressions to the appropriate regions of the cepstrum. The homomorphic deconvolution filtering was employed as a novel application to a gearbox fault diagnosis, separating the resonance effect from meshing frequency.

6.2 Gear Test Rig

The test rig was powered hydraulically as shown in figure 6.1. It had an electric induction motor, which ran the rig to its specified speed, while the hydraulic pumps generated the load for the rig. The pumps operated on a closed loop by returning the fluid at the high-pressure outlet to the hydraulic motor and later powered the rig.
When the rig was running at a constant speed, the purpose of the electric motor was to compensate for any losses in the system.

Some of the components of the test rig in figure 6.1 are described below:

Induction motor (AC) *(1)*

This was a 5.5kW, 8 poles, AC induction motor, which powered the rig to have a specified rotational speed. The stable speed that the gear operated was between 2Hz and 14Hz of shaft speeds under a torque of 120Nm.

Figure 6.1: Gear Test Rig

(Courtesy of NSW University)

Hydraulic Motor (2)

This was a fixed volume type, which was connected in series with the electric motor and ran by using re-circulated power from the pressure compensating pumps (loading devices).

Variable Volume Pump (3)

This was a pressure-compensating pump that generated the loading on the gears. Setting a slosh plate angle controlled the loading on the gears and the output pressure.

Variable Volume Pump (4)

This was trunnion controlled and also generated the loading on the gears. Adjustment of the trunnion on the console controlled the loading and adjusted the output pressure.

Gears

The gears are undamaged; cracked and spall, shown in figure 6.2. Each one has 32 teeth.

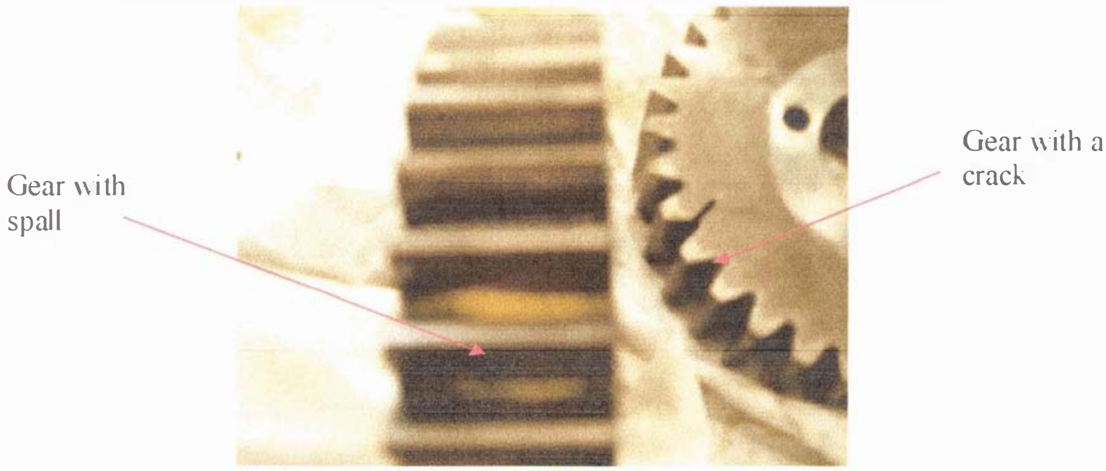


Figure 6.2: Cracked and Spall gears

Flywheel (5)

It attenuated the torsional vibration induced by loading.

Torque Transducer (6)

This was connected in series with the input shaft with shear pins (to prevent torsional overloading). The transducer was capable of measuring over 200Nm of torque.

Control Console (7)

This consisted of a speed controller for the electric motor (frequency converter) and sequence valves to remotely control the loading applied to the gears.

Coupling

This type of coupling was an elastic type that allowed only the torque to be transmitted between the shafts.

6.3 Instrumentation

The following instruments were used in measuring the gearbox signals:

Six acceleration signals, two encoder outputs and one tachometer output were measured in the experiment. Figure 6.3 shows the positions of the accelerometers and encoders set up for the experiment. The tachometer is enclosed in the encoders.

The signals measured from the accelerometers and encoders were processed and recorded by a Bruel & Kjaer PULSE system. The two encoders are connected to the input and output shaft with special precision diaphragm couplings. The power supply for the encoders is 5V.

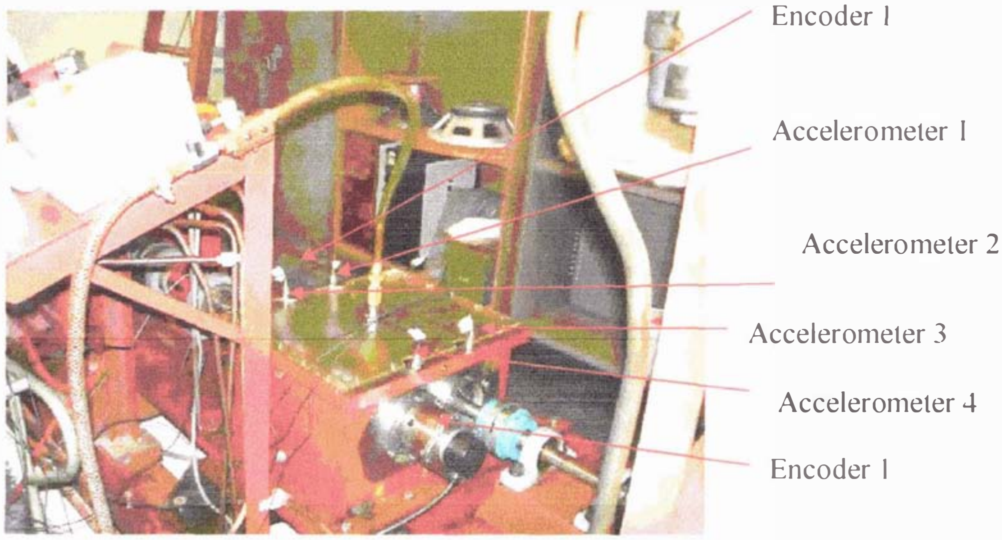


Figure 6.3: Gear Test Rig

6.4 Instrumentation for Data Collection [138]

- Bruel Kjaer, PULSE System: Front-end 3560C, Control Module: 7536, Input/Output Module: 3109
- Bruel & Kjaer, PULSE Software
- Bruel Kjaer, Accelerometers, Type 4384
- Bruel Kjaer, Charge Amplifier, Type 2365
- Heidenhain ROD 426 Encoders

6.5 The Structure of the Data Files:

Four acceleration signals, two encoder signals and one tachometer pulse were measured on the test rig. These data were recorded in a MATLAB™ data file. The tachometer is enclosed in the encoders. The acceleration was recorded from the accelerometer's signals, then the signals measured from the accelerometers and encoders were processed and recorded by a Bruel & Kjaer PULSE system.

Each signal was measured for five seconds with a sampling frequency of 65,536Hz and passed through a low pass filter.

6.6 Blind Deconvolution

Some machine components such as gearboxes produce very complicated spectrum signatures, because the signal coming from the gearbox consists of a number of harmonic families and sidebands, which can be difficult to separate in the spectrum. The cepstrum analysis offers a way to simplify the analysis of these signals and is a practical tool and a non-linear signal processing technique used to find different harmonic families. The input signal to the physical system represents $x(t)$ and the impulse response of the system represents $h(t)$, while $y(t)$ is the output of the system.

The deconvolution methods that are suitable for gearbox diagnosis are:

- Cepstra Analysis
- Homomorphic filtering

In gearbox vibrations any deviations from the exact uniformity of each tooth-mesh tends to show up partly as harmonics of the shaft speed and also as sidebands around the toothmeshing harmonics caused by modulation of the tooth-mesh signal by the lower rotational frequencies. The sideband spacing thus contains valuable information as to the source of the modulation and can be extracted using the cepstrum. The cepstrum has two advantages of being able to measure it very accurately because it gives the average sideband spacing over the whole spectrum.

When trying to diagnose a vibration signal in order to identify possible faults in the machine, the following are investigated in chapters 4 and 5:

- Harmonic relations
- Presence of sidebands
- The relation of energy in different sideband and harmonic families.

Cepstrum analysis, as described in chapter 5:

- Simplifies the analysis of a complicated spectrum and
- is independent of the signal path

Cepstrum is an anagram of spectrum, is a non linear signal processing technique used to identify and separate harmonic families in the spectra of gearbox signals. The calculation of cepstrum involves the inverse Fourier transform of the natural logarithm of a kind of spectrum. The following equations 6.7 to 6.9 define the cepstrum forms

Complex Cepstrum

$$C_{ccx} = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log\left[X\left(e^{jw}\right)\right] e^{jwn}\, d\omega \qquad 6.7$$

Real Cepstrum

$$C_r = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log\left|X\left(e^{jw}\right)\right| e^{jwn}\, d\omega \qquad 6.8$$

Power Cepstrum

$$C_p = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log\left[XX^*\right] e^{jwn}\, d\omega \qquad 6.9$$

Since both the Fourier transform and the inverse Fourier are complex domain processes, the cepstrum is complex if the phase information of the original time waveform is preserved. The complex cepstrum can be used for noise reduction and signal separation, such as echo cancellation. If the input of the Fourier transform is real (no phase information), for example, the power spectrum or the magnitude of the Fourier transform of the signal, the cepstrum cannot be reconstructed back to the time domain, we still can "lifter" a harmonic family in the quefrency domain and obtain a liftered spectra.

When the gearbox wears, the gear profile will gradually change due to slidding between two teeth in mesh at any point except at the pitch point. This indicates that changes due to wear in a gearbox will turn up at the second harmonic of the toothmesh frequency, and since the change is not sinusoidal, higher harmonics will be revealed as well as indicated in a simplified form.

In the vibration signals from gears, the force at the mesh and the transfer function from the mesh to the measurement point, largely separate in the cepstrum, in that the forcing function is periodic and most of it concentrates at rahmonics corresponding to the tooth-mesh frequency and individual shaft speeds. Removing these with a suitable comb lifter allows the remaining part of the log spectrum, dominated by the transfer function to be reproduced by a forward transform. This can reveal whether resonance peaks have changed, and thus whether measured changes are due to changes at the source or in the signal transmission path.

The output of a linear physical system can be expressed in terms of the excitation signal and transmission path properties as a convolution in the time domain (both in the complex and power spectra) and a summation in the logarithmic spectrum (both in the complex and power spectra). Because the Fourier transform is a linear operation, this additive relationship is maintained in the cepstrum (both in the complex and power cepstra).

Not only are the source and transmission path effects additive in the cepstrum, they are often largely separated into different regions because of their characteristics with respect to frequency.

6.7 Results

Figures 6.4 to 6.6 illustrate a typical gearbox signals with undamaged, cracked and spall teeth under 50Nm loading. The two gears have 32 teeth respectively. The input shaft was rotating at a speed of 10Hz (600rpm). When the gearbox was operated under several loads the vibration signals were acquired through the acceleration signals.

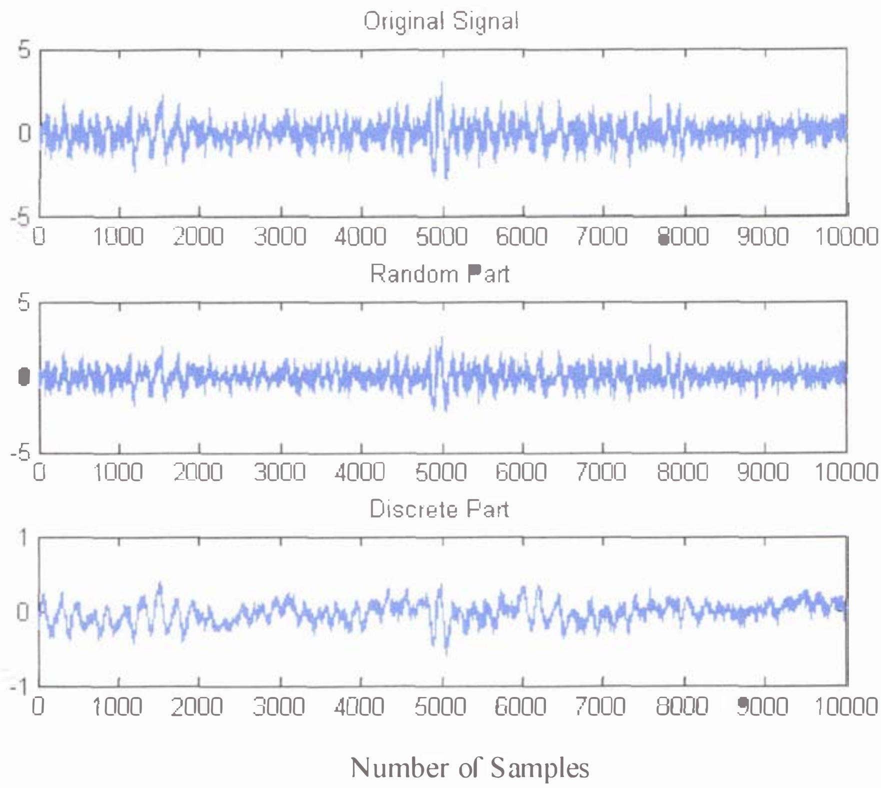


Figure 6.4: Undamaged Gear Vibration Signal

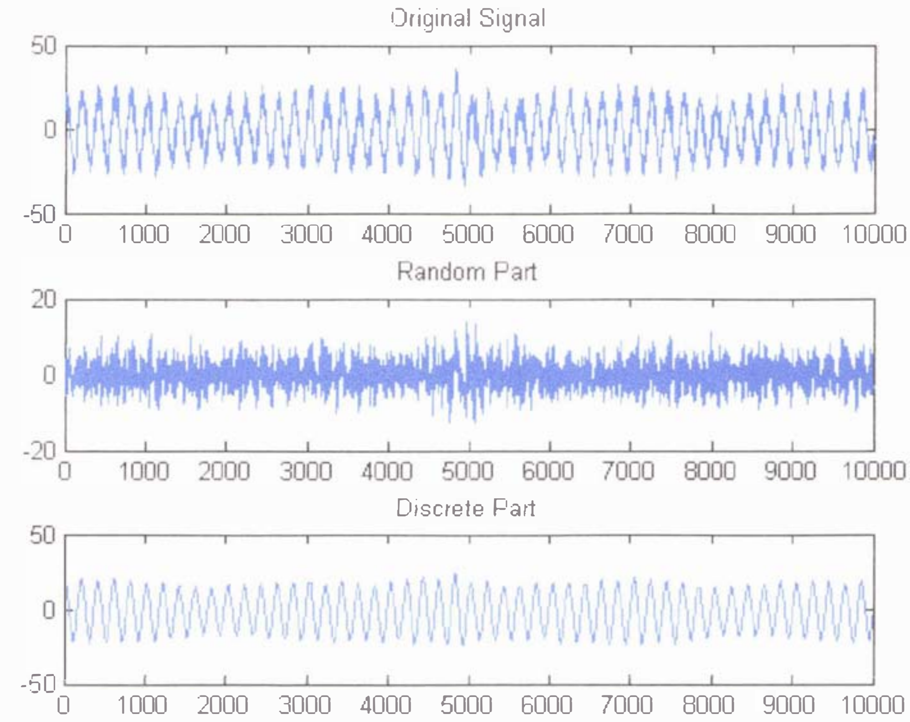
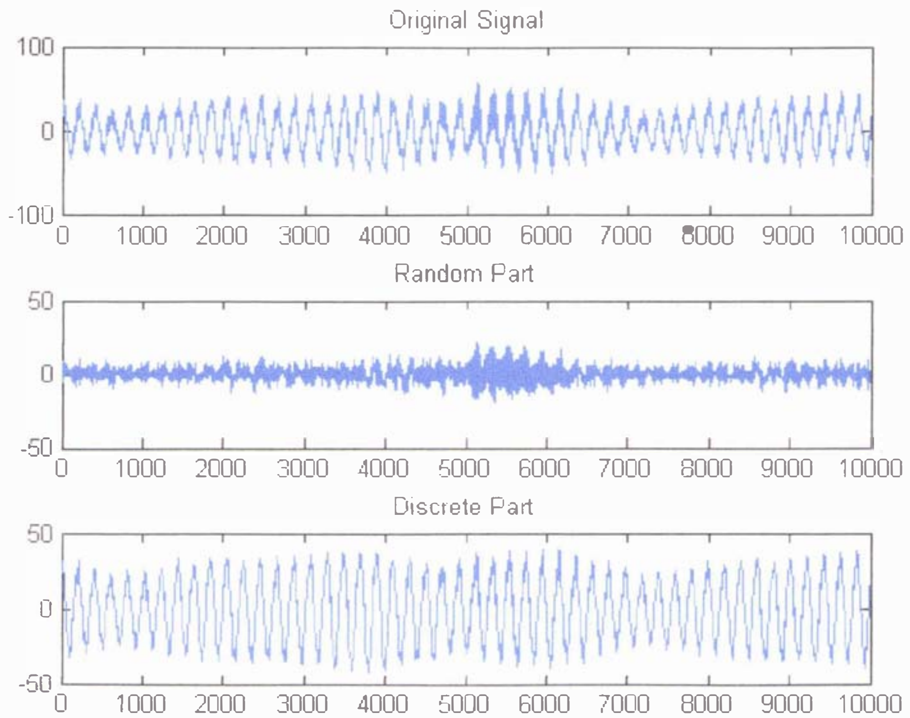


Figure 6.5: Cracked Tooth Vibration Signal



Number of Samples

Figure 6.6: Spall Tooth Vibration Signal

Figures 6.7 – 6.12 show the cepstra for good, cracked and spall teeth. When the first run was carried out, the good gears were engaged, figures 6.7 and 6.8 show the spectra. The second run involved the good and the cracked gear, with the cepstra in figures 6.9 and 6.10. The last run was when the good gear engaged with the spall one, figure 6.11 and 6.12 demonstrates the cepstra. Each run was done under two different loadings 50Nm and 100Nm respectively.

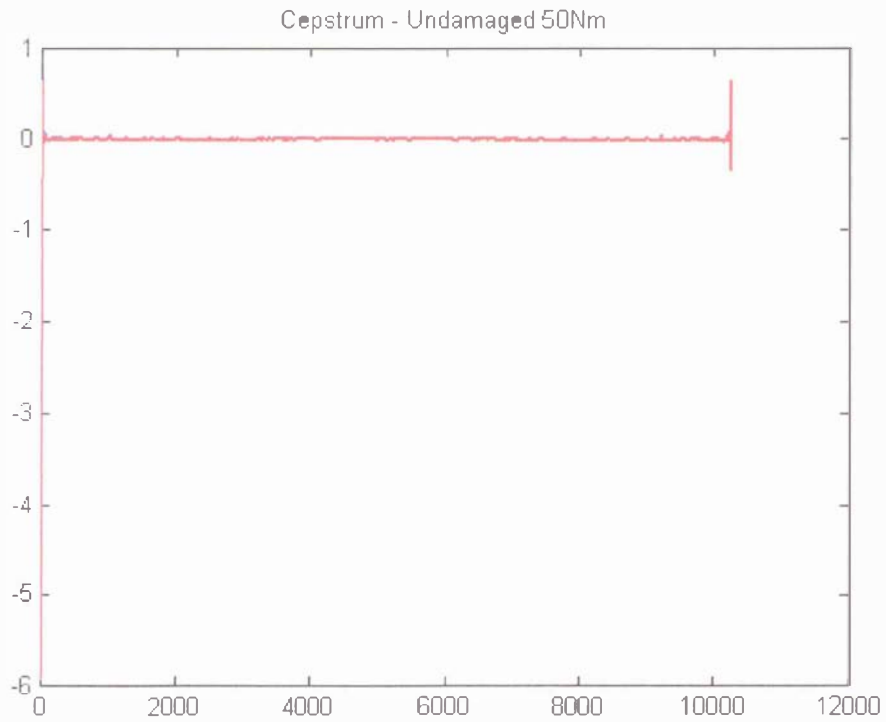


Figure 6.7: Cepstrum of Undamaged Teeth under 50Nm Load

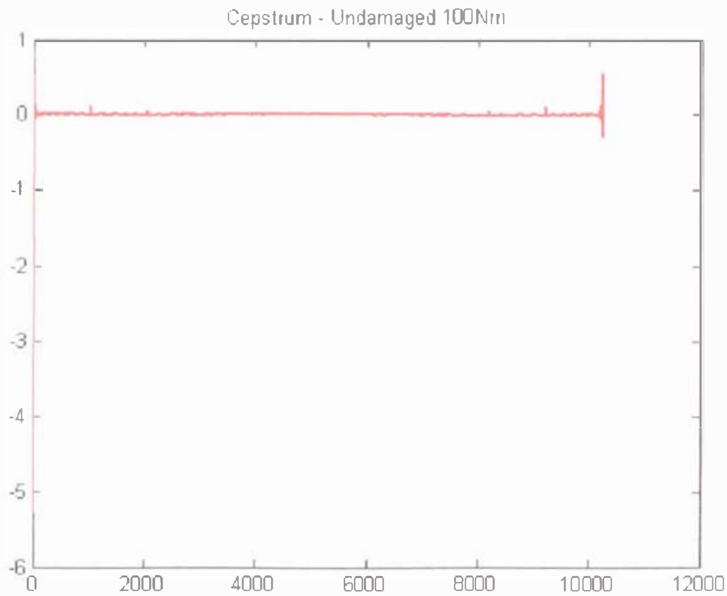
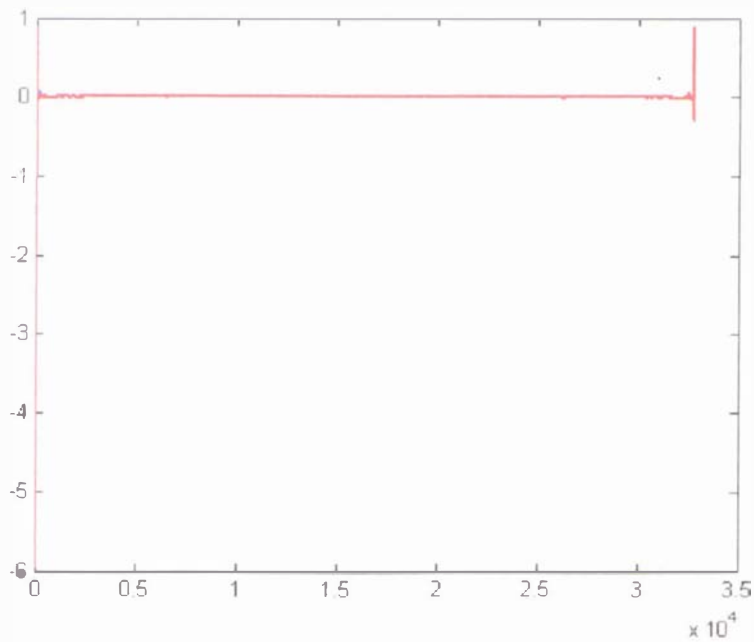
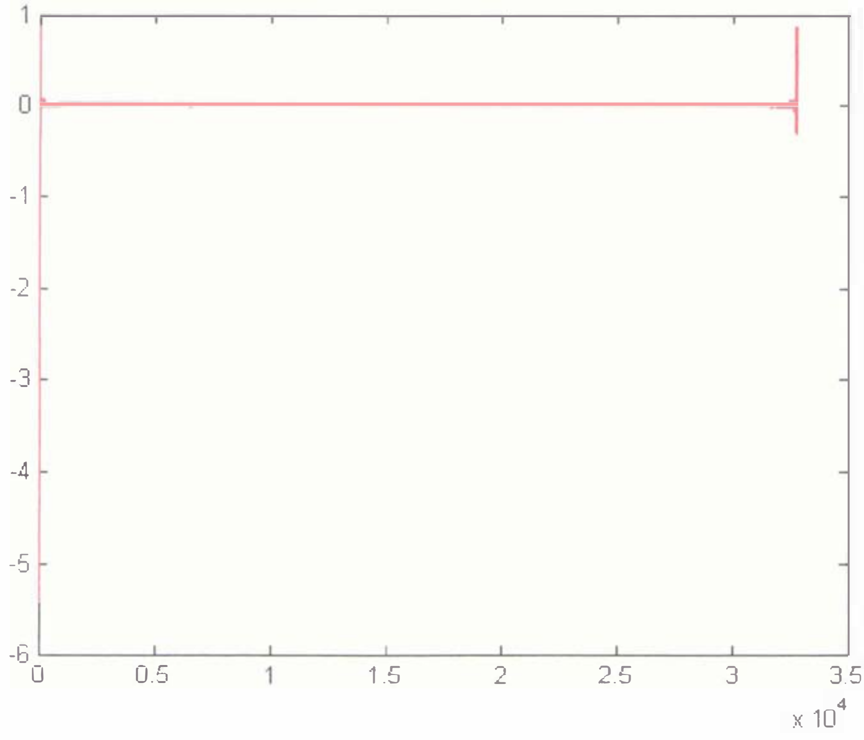


Figure 6.8: Cepstrum of Undamaged Teeth under 100Nm Load



Number of Samples

Figure 6.9: Cepstrum of Cracked Tooth under 50Nm Load



Number of Samples

Figure 6.10: Cepstrum of Cracked Tooth under 100Nm Load

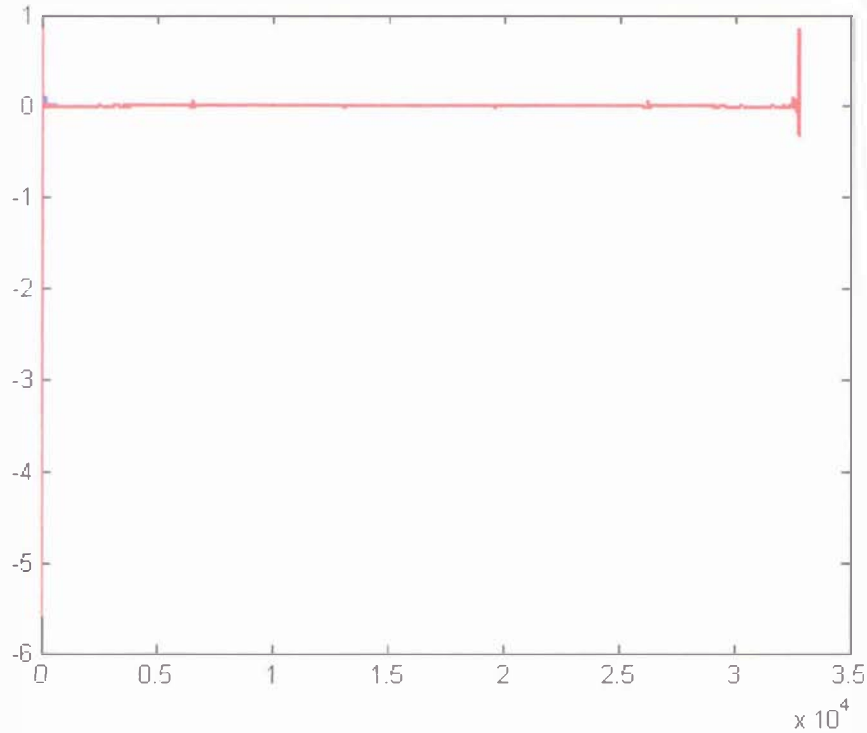


Figure 6.11: Cepstrum of Spall Tooth under 50Nm Load

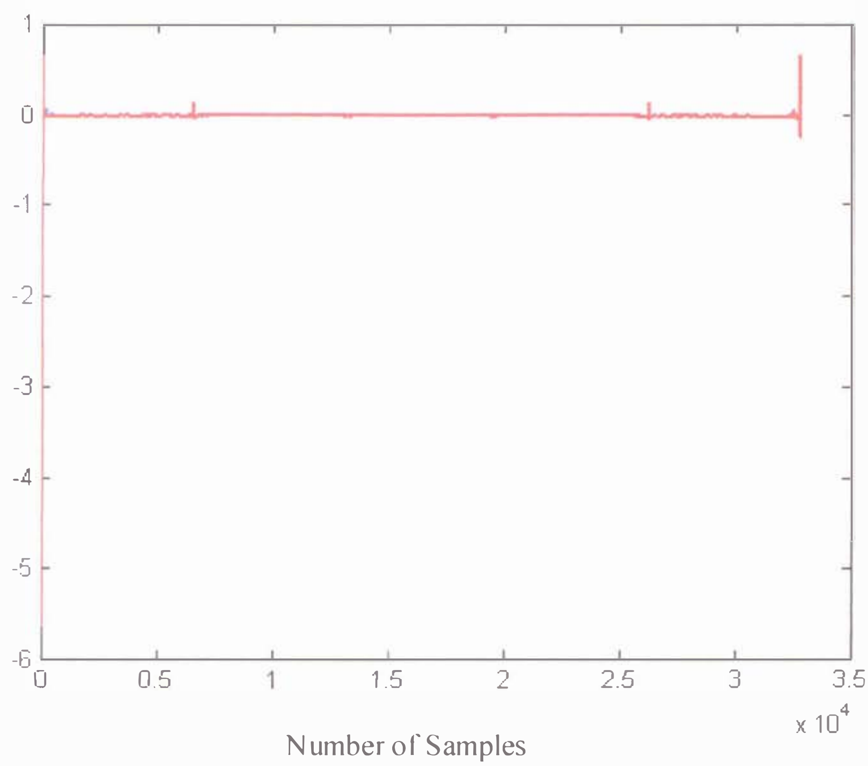


Figure 6.12: Cepstrum of Spall Tooth under 100Nm Load

6.7.1 Homomorphic Deconvolution

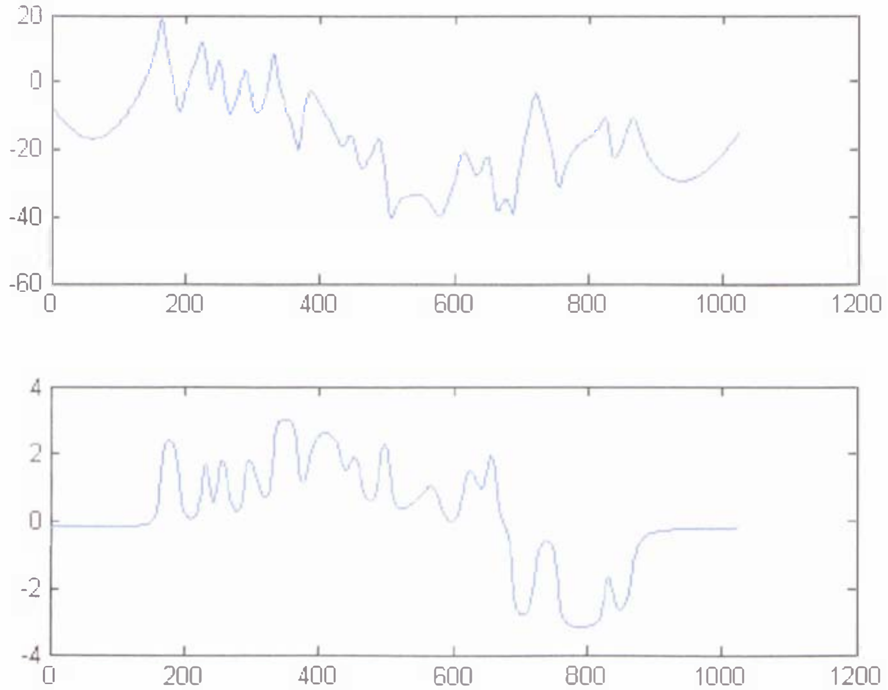
The application of homomorphic filtering in the diagnosis of a gearbox is achieved by using cepstrum technique to detect those signals that need to be suppressed and the actual filtering process which includes random noise reduction.

In order to demonstrate the various possibilities of homomorphic filtering, the application of the method is shown with three different cases, undamaged, cracked and spall gears.

Homomorphic blind deconvolution offers a considerable advantage in that no prior knowledge of the impulse response of the transmission path is necessary. The transmission path is recovered by homomorphic deconvolution filtering, using the steps in the equations 6.4 to 6.6.

Homomorphic filtering is a deterministic process in the sense that fixed and pre-given parts of the complex cepstrum which are related to the undesired components are eliminated. The success of the method depends primarily on the rate of the separation of the individual components in the complex cepstrum.

The homomorphic filtering was applied to the cepstra shown in figures 6.7 – 6.12 to elucidate its possibilities and difficulties, the results of the filtering is shown in figures 6.13 – 6.15, considering only 100Nm loading.



Number of Samples

Figure 6.13: Undamaged Gear under 100Nm after Filtering

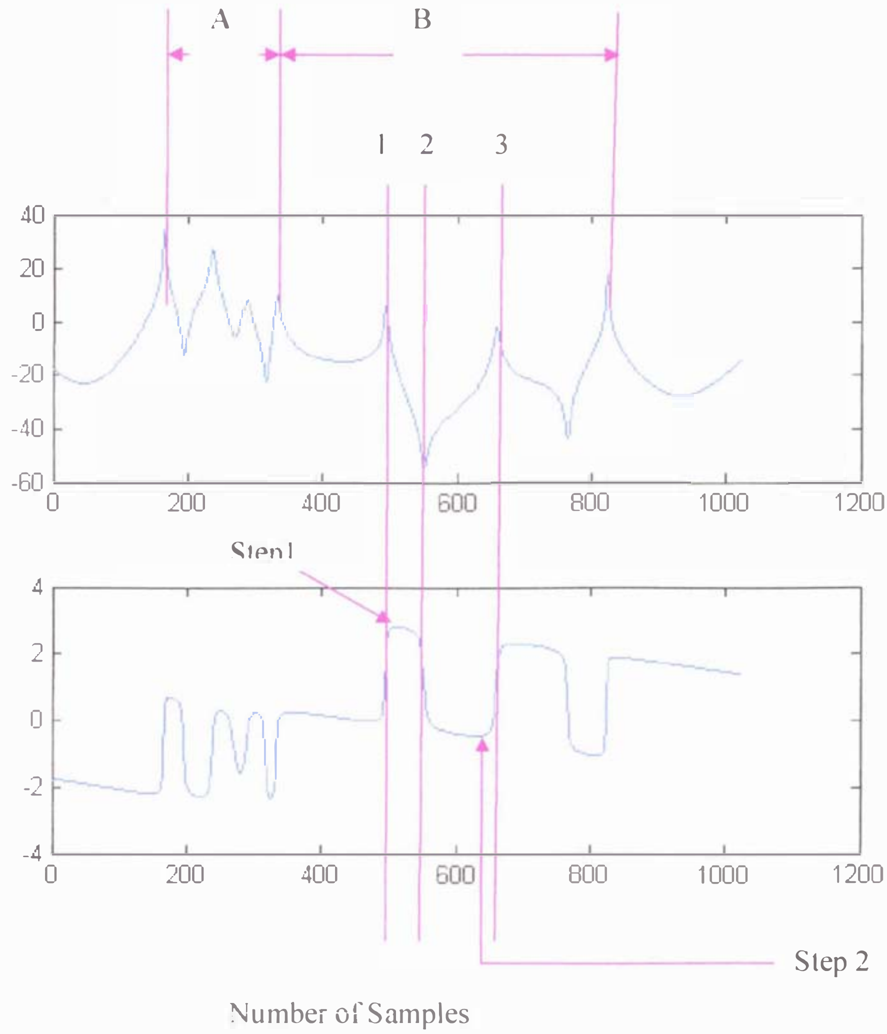


Figure 6.14: Cracked Gear under 100Nm after Filtering

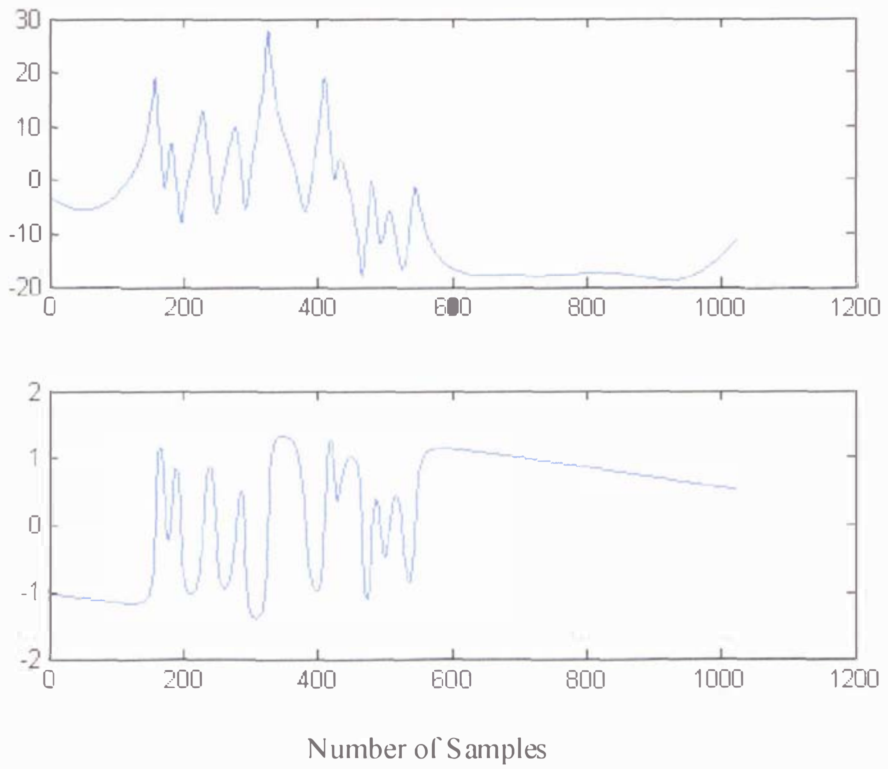


Figure 6.15: Spall Gear under 100Nm after Filtering

The results from the homomorphic filtering are shown in figures 6.13 – 6.15 for different fault cases under 100Nm loading.

The Residual Motion Errors (RME) generated by the faulty gears (cracked and spall) are shown in figures 6.14 and 6.15.

The first and second derivatives of the RMEs estimate the corresponding velocity and acceleration as shown 6.14 (A) and 6.14 (B) respectively. The sudden change in the magnitude of the RMEs appears as inverted pairs of pulses in their second derivatives. In a constant load environment the magnitude of the TE resulting from the gear tooth cracks changes linearly with the stiffness of the gear mesh. Presence of the crack in a gear tooth reduces the effective stiffness of the gear mesh as expected because of the crack induced increase in compliance.

The TE caused by a tooth crack results in a double stepped rectangular shape. The smaller step 1, Figure 6.14 is a result of the deflection when the load is carried by an undamaged and a damaged tooth pair and the larger step 2, Figure 6.14 occurs when the load is carried only by the tooth pair with a crack.

The peaks in the second derivative of the RME occur deterministically at the three positions where the number of contacting tooth pairs switches from two to one and back to two.

The second derivative of the TE from a gear mesh having teeth that contain spalls is a pair of "inverted echo pulses". The shapes of the RMEs are determined by the size and shape of the spalls and are independent of the load carried by the gears.

Unlike the tooth cracks, the positions of the pulses appearing in the acceleration signal of the spalls are not synchronized with the meshing cycle of the gear teeth.

Figures 6.14 and 6.15 illustrate the differences of the inverted echo pulses caused by a cracked tooth gear and a spall. A diagnostic method to differentiate these faults is possible by recognizing the two properties that affect only one of the two faults:

1. The effect of tooth crack is load dependent while the effect of spall is load independent; thus, reducing the load should reduce the symptoms of the fault if it is caused by tooth crack.

2. The amount of delay between the inverted echo pairs is different for the tooth crack and the spall. The delay caused by the tooth crack is more predictable and correlates to the meshing pattern of the gears. Thus, if a correlation exists the fault may be identified a tooth crack and if the correlation is absent the fault may be identified as a spall.

The advantage of use of the cepstrum in machine condition monitoring is that the combined effect of the harmonics and sidebands in the spectrum appear in the cepstrum as a smaller number of clearly defined rahmonic peaks: i.e. in compressed form, and it is therefore easier to monitor the changes occurring in the system.

6.7.2 Poles and Zeros Analysis

The poles and zeros provide useful information about the response of the filter. The plot is a graphical representation of the transfer function which is a function in the complex variables, this helps to check the system stability.

Poles and zeros plots is necessary because it helps to easily design a filter and also obtain its transfer function. The location of the poles and zeros will allow us to quickly understand the magnitude response of the filter.

Equation 6.6 defines the cepstrum of the measured response signal, which is the sum of the cepstra of the source and transmission path functions. The externally-measured signal from a gearbox is the convolution of the path and source effects. After transformation to the cepstrum domain, the source and the path effects are deconvolved and become additive. Equation 6.10 shows the transfer function in the polynomial form. The values of 's' that cause the numerator to equal to zero are 'zeros' and the ones that cause the denominator to equal to zero or infinity are 'poles'.

$$H(s)=\frac{a_0+a_1 s+a_2 s^2+\ldots+a_m s^m}{b_0+b_1 s+b_2 s^2+\ldots+b_n s^n} \qquad 6.10$$

Applying partial fraction expansion to equation 6.10 results in poles and residues for the individual modes [1,7,8].

$$H(s)=\sum_{k=1}^{n/2}\left[\frac{r_k}{s-p_k}+\frac{r_4}{s-p_k}\right] \qquad 6.11$$

Equation 6.12 can be obtained in terms of poles and zeros by finding the roots of the numerator and denominator using rational fraction expansion [1,7,8].

$$H(s)=\frac{\prod_{k=1}^{m}(s-z_k)}{\prod_{k=1}^{n}(s-p_k)} \qquad 6.12$$

The z-transform of the equation 6.12 will result in equation 6.13 [1].

$$H(z)=\frac{A\prod_{k=1}^{mi}\left(1-a_k z^{-1}\right)\prod_{k=1}^{m0}(1-b_k z)}{\prod_{k=1}^{p_i}\left(1-c_k z^{-1}\right)\prod_{k=1}^{m0}(1-d_k z)} \qquad 6.13$$

Where $a_k, b_k, c_k, d_k < 1$

Equation 6.14 is the cepstrum that presents transfer function in terms of poles and zeros [7, 8].

$$C(n)=\sum_{k=1}^{m_i}\frac{a_k^n}{n}+\sum_{k=1}^{p_i}\frac{c_k^n}{n} \qquad 6.14$$

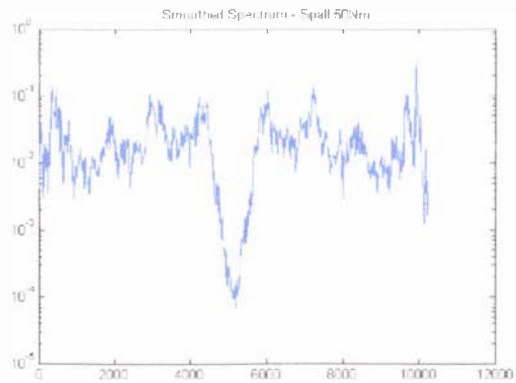
$$=\sum_{k=1}^{m0}\frac{b_k^{-n}}{n}-\sum_{k=1}^{p0}\frac{d_k^{-n}}{n}$$

a_k and c_k are minimum phase and are the poles and zeros inside the unit circle, while b_k and d_k are the poles and zeros outside the unit circle [1,2]. Minimum phase occurs at positive quefrencies. The maximum phase at negative quefrencies can be neglected because the poles are unstable, and it will not affect the detection of the changes in the resonances.

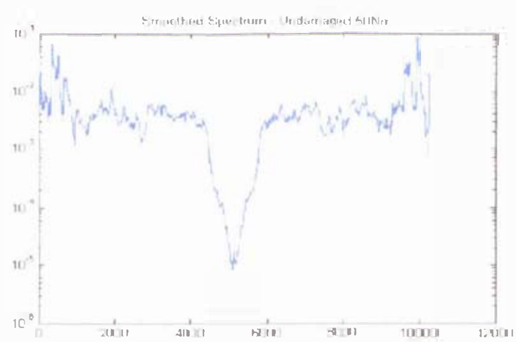
The poles and zeros of the transmission paths to each measurement point over different fault cases at 50Nm loading represent the transfer function between the gear mesh and response measurement location for each case. Figure 6.18 shows the transfer functions' smoothed spectra of the good gear, gears with spall and crack, that were separated from the source using the homomorphic deconvolution.

The signals due to a resonance effects are extracted for different gear faults; cracked and spall gear teeth, and undamaged gear. Figure 6.16 shows that the spectra are the same, resonance peaks have not changed, however, under each gear case, the change was not in the transmission path. The poles and zeros of the FRF were extracted by curve fitting from the region of the cepstrum (or differential) as shown in figure 6.17, the changes between the poles and the zeros were used to evaluate the stability of the system. Cepstra analysis was used to separate the source and the transmission path, however, the reverse transformation was carried out to provide a smoothed spectrum.

This process is known as homomorphic filtering and the result is shown in figure 6.19.

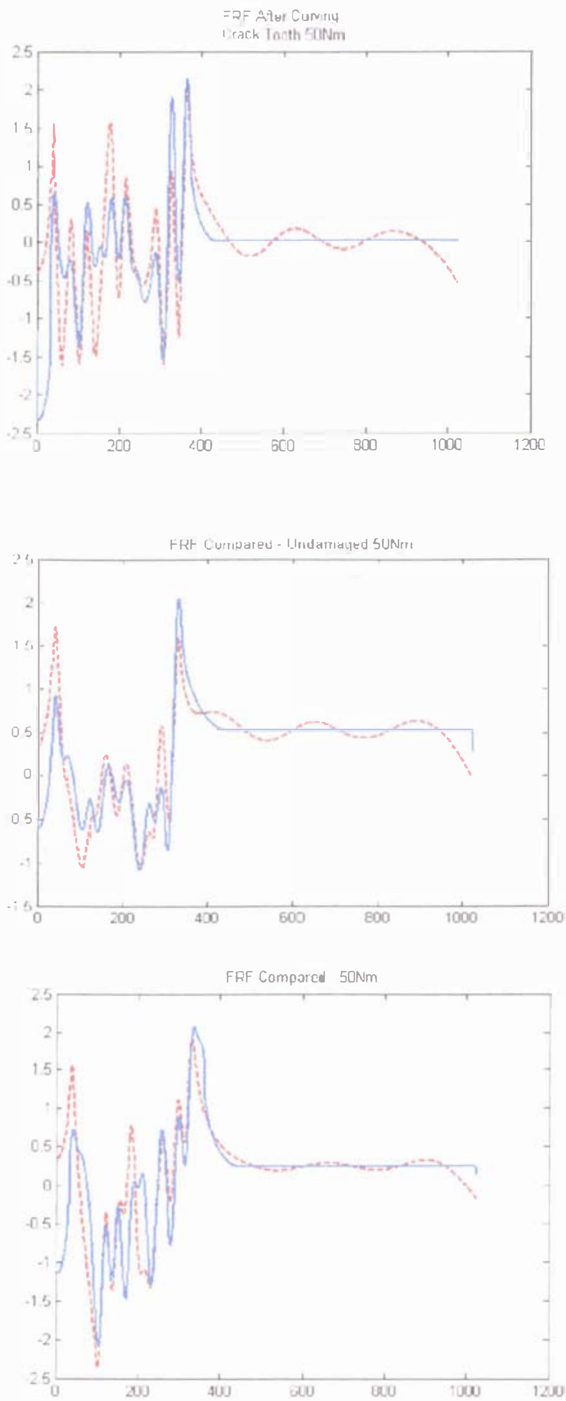


Number of Samples



Number of Samples

Figure 6.16: Smoothed Spectra for Undamaged, Spall and Cracked gears



Number of Samples

Figure 6.17: Frequency Response of System with Cracked, Spall and Undamaged Teeth

Table 6.1: The Poles and Zeros from Curve Fitting Cepstra

Crack Tooth	Spall Tooth	Undamaged
Output Poles	Output Poles	Output Poles
0.9927 40.2523	0.9847 40.0371	0.9893 164.0475
0.9835 84.8058	0.9821 121.7873	0.9865 225.1507
0.9838 122.8589	0.9715 154.6904	0.9869 249.0926
0.9743 172.0098	0.9794 184.4931	0.9858 288.6942
0.9818 180.3605	0.9306 187.0917	0.9907 331.2494
0.9834 216.0168	0.9686 259.1794	0.9741 384.0393
0.9816 290.6066	0.9768 297.8621	0.9754 445.4255
0.9899 327.2236	0.9793 329.4671	0.9843 489.0010
0.9899 363.8738		0.9316 559.7729
		0.9778 614.5842
		0.9815 648.9281
		0.9823 720.2248
		0.9835 825.1824
		0.9783 864.9938
Output Zeros	Output Zeros	Output Zeros
0.9838 61.8044	0.9816 103.2626	0.9862 191.3261
0.9847 104.4020	0.9793 139.0656	0.9850 236.5377
0.9796 141.7871	0.9747 167.7449	0.9794 263.2265
0.9159 162.9074	0.9741 233.3018	0.9670 305.0647
0.9833 197.4097	0.9772 280.2142	0.9880 367.8278
0.9880 309.4931	0.9747 313.1636	0.9728 433.6325
0.9904 344.9680	0.9777 202.7121	0.9764 460.2263
		0.9871 504.7227
		0.9671 578.6067
		0.9651 633.7310
		0.9861 663.6466
		0.9891 687.2795
		0.9874 755.0808
		0.9794 835.9365

Table 6.1 is generated from the FRFs in figure 6.17. The figures in the table are represented in poles and zeros and their relative angles where they would stand in a circle. In the FFT spectrum, figures 6.16 and 6.17 would overlap, but the new technique separated the resonance effect shown in figure 6.16 from the meshing effects in figure 6.17.

Chapter 7

Conclusion and Discussion

7.1 Introduction

As discussed in the earlier chapters, the current FFT technique has its pitfall of overlapping of frequencies, which makes it difficult for vibration analysis. Solving this problem has prompted the last part of this project.

An investigation to explore this subject has been carried out and as a result, the cepstrum technique using homomorphic filtering was presented. It has been shown to be an effective and efficient tool in the experimental part in Chapter 6.

This chapter briefly provides an overview of the previous chapters in this thesis, and presents the conclusion and the recommendations for future work.

Chapter 1 introduced what this thesis is all about and the reason for the cepstrum technique. Chapter 2 presented various previous researches and the methodologies on predictive maintenance and chapter 3 described the maintenance strategies and the history, that is, where the technology was, where it is and where is going as far as maintenance is concerned. Chapter 4 introduced FFT technique and presented case studies using the techniques and the pitfalls were identified, which is the reason why cepstrum was presented. Chapter 5 explained the theory of cepstrum, homomorphic and poles and zeros representations and Chapter 6 was the experimental part that demonstrated the effectiveness of the cepstrum technique and homomorphic filtering to separate resonance effects from the meshing frequency.

7.2 Discussion

The survey on the maintenance strategies presented in this thesis shows that preventive maintenance is not as cost effective as predictive maintenance. The predictive maintenance FFT technology has been extremely useful in accurately diagnosing machinery condition. The major FFT pitfalls are:

- FFT can diagnose any bearing fault or a gear with broken teeth, but will not diagnose the root cause. Examples of how mathematical approach was used in addition with the FFT data to establish the root cause of the failures are presented in chapter 4.

- The overlapping of many harmonics, sidebands, resonance effect and mesh frequencies that make diagnosis of a gearbox cumbersome; this was the reason the author used cepstrum technique to diagnose gearbox faults under different loadings, which was presented in chapters 5 & 6, where resonance effect was separated from meshing frequency.

The test results demonstrated that noise generation is a complex mechanism, and the cepstrum technique has successfully recovered the original sources. An externally measured vibration signal is the convolution of the impulse response and the source signals. After transformation to the cepstrum domain, the source and the transmission path effects are deconvolved and become additive. Gearbox vibration spectra normally contain sidebands due to modulation of toothmeshing frequencies and their harmonics, and the strength of such sidebands usually indicates deteriorating condition.

The spacing of such sidebands gives valuable diagnostic information as to their source, since both amplitude and frequency modulation at the same frequency give sidebands with the same spacing. Most faults give a combination of amplitude and frequency modulation at the same time, the relative proportions and phase relationships being dependent in a complex way on the response properties of the individual machine, and so a division into the two categories is less useful than a measure of the overall sideband "activity" with a given spacing.

The cepstrum is good both for detecting the presence and growth of sidebands in gearbox vibration spectra, and for indicating their mean spacing over the entire spectrum, which has proved suitable for the detection and diagnosis of faults.

Cepstrum has advantages in able to extract spectrum periodicity with respect to fault detection and insensitive to secondary effects like signal transmission path and phase relationship of amplitude and frequency modulation.

The cepstrum, with respect to fault diagnosis, was able to measure the average sideband spacing over a very wide range of the spectrum, thus allowing a very accurate measure of the spacing, being representative of the whole spectrum. The cepstrum has the ability to concentrate the significant sideband information in a very efficient manner.

The cepstrum can be considered as an aid to the interpretation of the spectrum, in particular with respect to sideband families, because it presents the information in a more efficient manner.

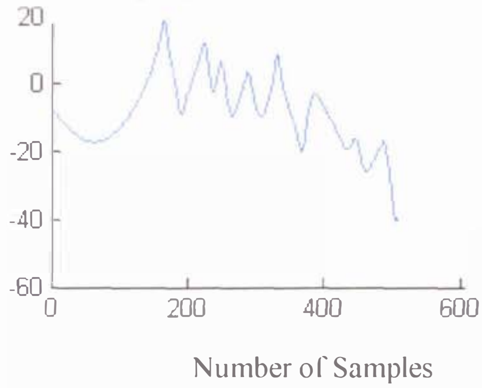
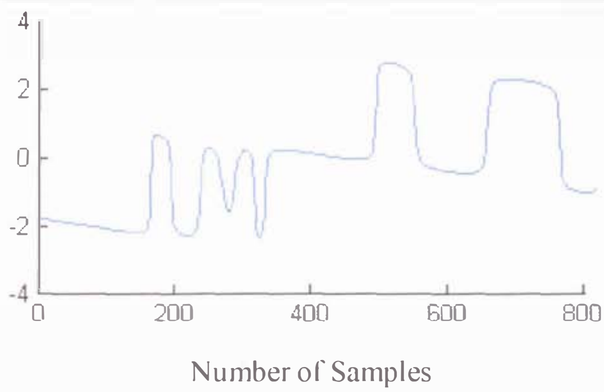
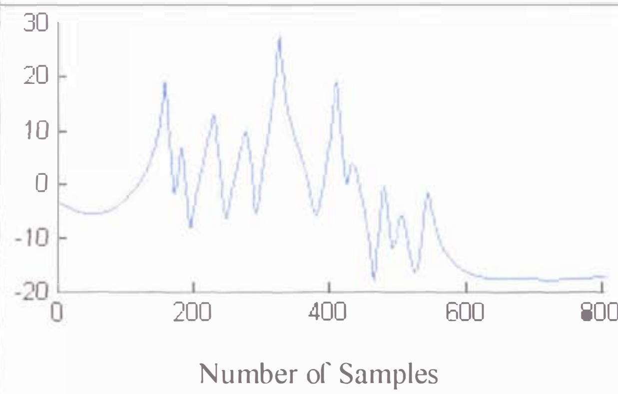
Gear Condition	Cepstra after Homomorphic Filtering Loading: 100Nm
Undamaged	
Cracked Tooth	
Spall Tooth	

Figure 7.1: Cepstra for Different Measurements

The experimental data shows the diagnosis of a gearbox with a number of measurement points on the same gearbox with undamaged, cracked and spall tooth meshing excitations. The results shown in figure 7.1 are the cepstra of the three different cases.

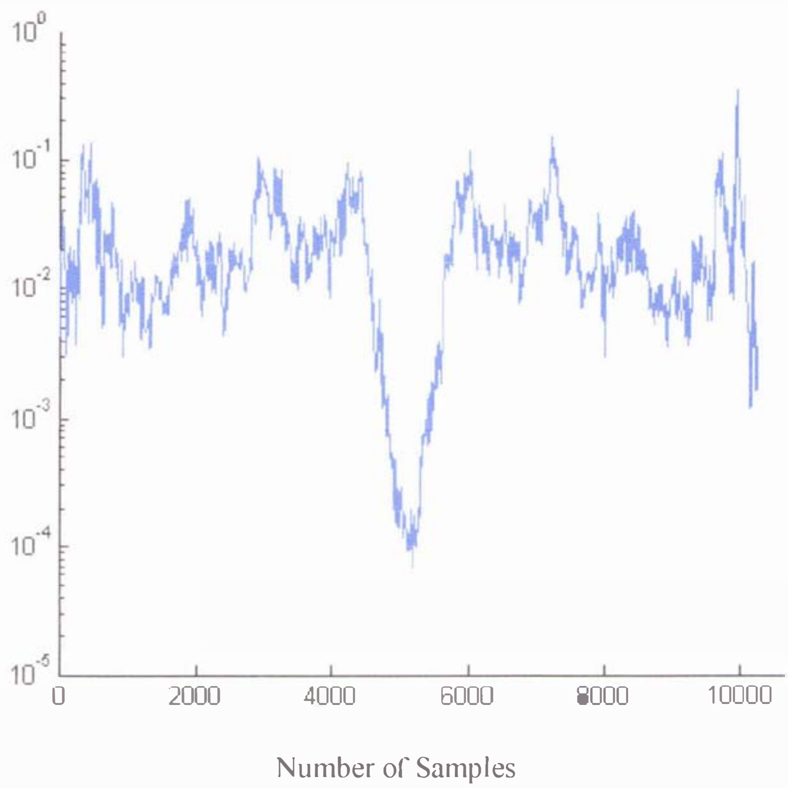
Gear Condition	Smoothed Spectra after Homomorphic Filtering
Undamaged	

Figure 7.2: Cepstra for Different Measurements

All machines have some physical characteristics that reflect their conditions. A normal running level for that characteristic is established when the machine, in this case a gearbox is in good condition, any significant deviation from that level gives warning that a fault may be developing and maintenance will be required. The three different cases in figure 7.1 demonstrate a variation in the cepstra, which is an indication that faults have developed. The faults are the crack and spall, which would overlap under FFT analysis, but cepstrum technique separate them, through homomorphic filtering.

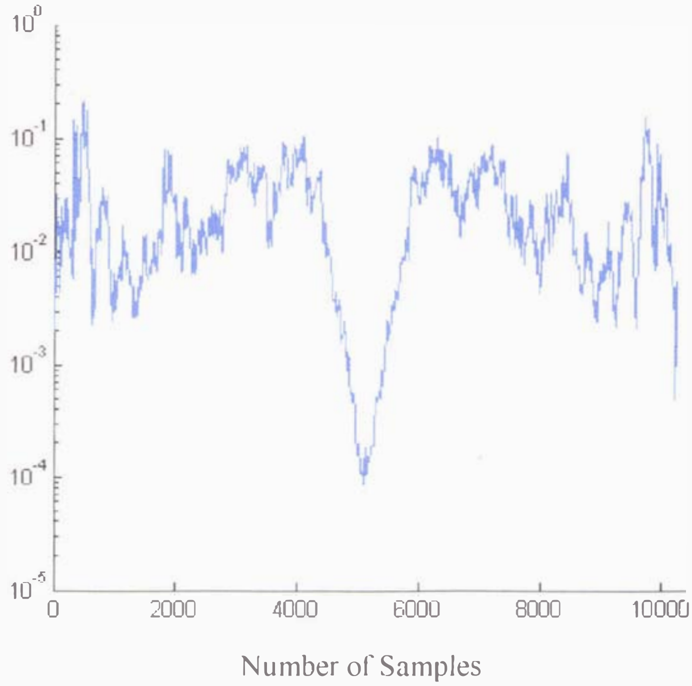
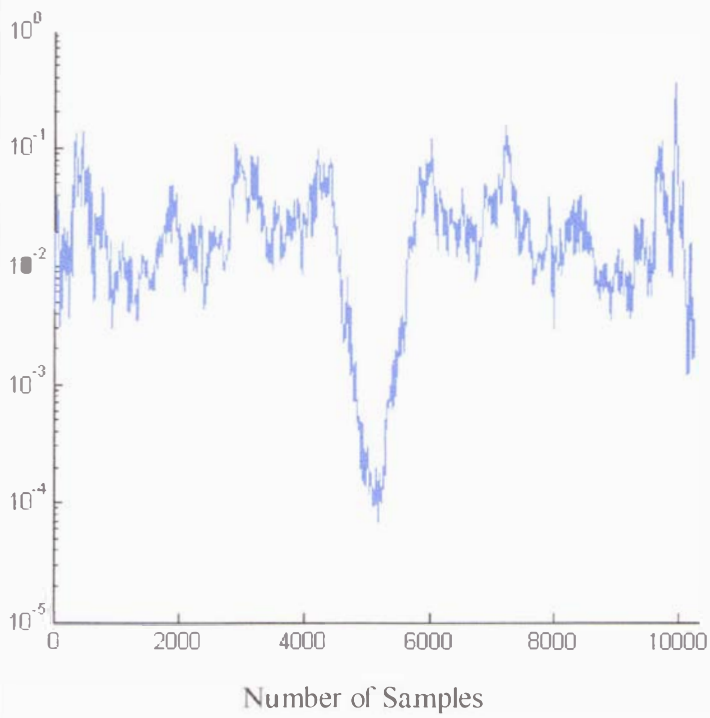
Gear Condition	Smoothed Spectra after Homomorphic Filtering
Cracked Tooth	
Spall Tooth	

Figure 7.3: Cepstra for Different Measurements

Figures 7.2 and 7.3 are the resonance peaks, which are due to the nature of the structure of the machine, including all its components like the gearbox, piping, and support system. They are not self excited but can be viewed as lurking within the structure of the system, ready to cause violent reactions when excited. They result functions of the mass, stiffness and damping of a structure.

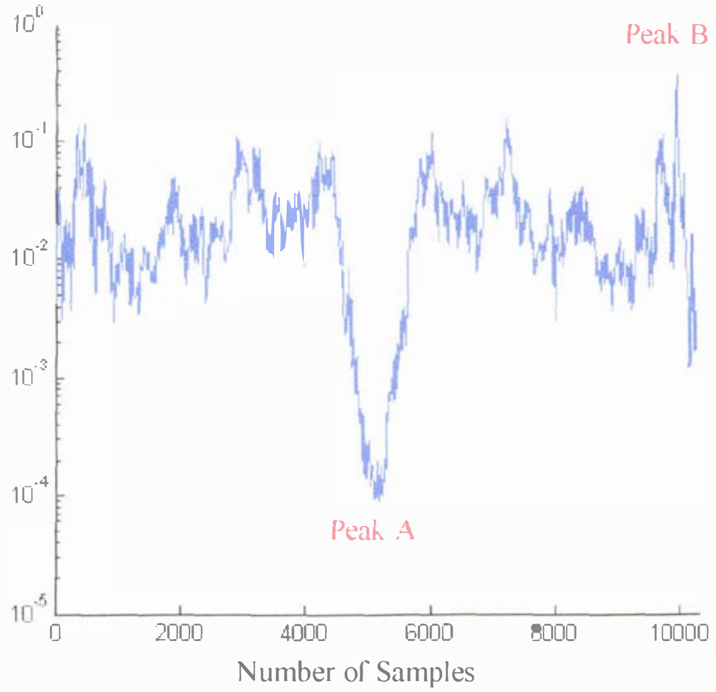


Figure 7.4: Effect of Resonance

When the natural frequency of the gearbox was excited, it blew up peak B (figure 7.1) which resulted in a large increase in the amplitude of vibration of that frequency. Peak A demonstrates the effect of resonance, which is not in peak B. The resonance effect, which is in the transmission path, is lurked together with the forcing effect to produce the output signal. The FFT technique could not identify if the change was in the transmission path or from the forcing frequency, which the cepstrum technique has separated as shown in figure 7.4.

Comparing the resonance peaks for the different cases: undamaged, cracked and spall gears, the peaks are the same, showing that the change was not in the transmission path but from the forcing frequency, due to the spall and the crack.

Figures 7. 5 and 7.6 show how, similar to the mechanical vibration case, poles and zeros of the frequency response functions (FRF) of the gearbox could be created and evaluated. The poles and zeros alone suggests whether the gears are undamaged or damaged, but the changes in the FRF also confirm the claim that the changes are due to the forcing effect from the spall and crack and not the transmission path effect, by using the cepstrum technique of homomorphic blind deconvolution.

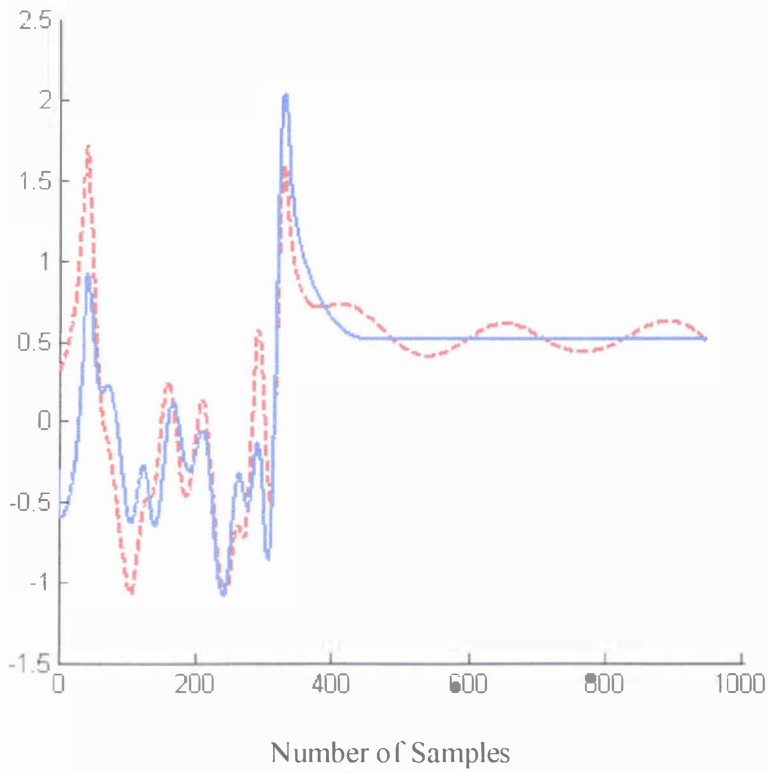
<table>
<tr><td>Gear Condition</td><td>Frequency Response Function</td></tr>
<tr><td>Undamaged</td><td>
</td></tr>
</table>

Figure 7.5: Cepstra for Different Measurements

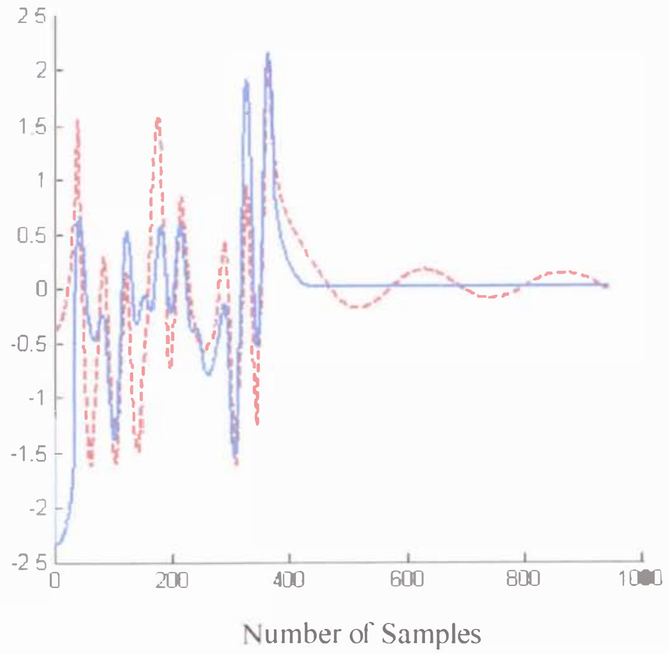
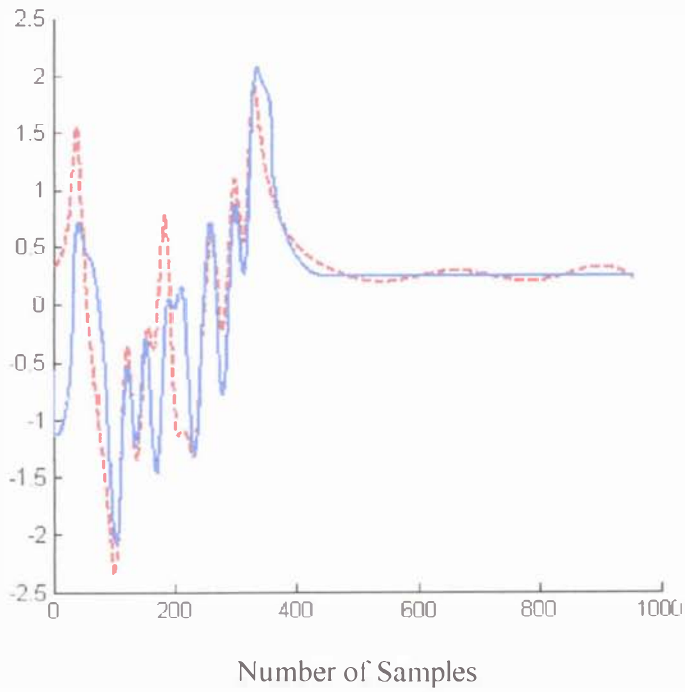
Gear Condition	Frequency Response Function
Cracked Tooth	
Spall Tooth	

Figure 7.6: Poles and Zeros Frequency Response Function (FRF)

7.3 Conclusion

In conclusion, this thesis makes the following contributions:

- The nature of maintenance practices in New Zealand major industry was the first contribution in this thesis. The maintenance practices were reactive, preventive and predictive. The survey showed that most of the companies operate on reactive maintenance and few on predictive. My visits to the power stations showed that only Genesis Power Station has on-line monitoring, the rest only employ the services of vibration analyst to monitor their machines once a year. Only Fonterra out of other food companies operate on predictive maintenance. My visit to Griffins Food and its associated ones revealed that they practice preventive and reactive maintenance. New Zealand Steel out of other steel manufacturing companies practice preventive and predictive maintenance. The medium size companies mainly practice reactive maintenance, although some of them claim to practice preventive, but after investigations into these practices, they did not observe the routine checks that preventive maintenance required.

  Predictive maintenance was demonstrated in some of the companies, using FFT technique that was presented in the case studies to identify machine problems, which was helpful in scheduling the necessary repairs and saved the companies thousands of dollars in terms of lost production and wasted manpower and materials or parts. It put the manager in charge of the machine, instead of the machine being in charge of the manager. When the FFT technique identified the machine problem, it allowed the maintenance manager to direct the correction of that problem at his convenience. When he did not know the problem, he must react when the machine broke regardless of the day and hour. This demonstration made the companies understand the huge benefits in predictive maintenance, using FFT technique. The main pitfall of the FFT technique is the overlapping of many harmonics, sidebands and resonance effects, which make the diagnosis more cumbersome, this is a problem cepstrum technique using homomorphic filtering has resolved.

- The cepstrum technique was originally applied to analyse speech with the aim of detecting the harmonic structure of voiced sounds and measuring voice pitch, but now presented for the purpose of condition monitoring especially in the diagnosis of a gearbox faults.

- The cepstrum technique included homomorphic filtering to separate the gearbox cepstra, which resulted to the identification of the cause of the changes in the expected good performance of the gearbox. The filtering separated the signal due to the undamaged gear from the cracked and spall ones as shown in table 7.1.

- The inclusion of poles and zeros analysis in the cepstrum technique produced the frequency response function of the gearbox as shown in figures 7.5 and 7.6. The changes in the outlook of the poles and zeros frequency response functions also validate that the changes are from the meshing and not the transmission path.

- Finally, the resonance effect in figures 7.2 and 7.3 also validate that the changes are in the transmission path because they are the same to the different cases.

7.4 Recommendations for Future Work

Although a significant amount of work with regard to gearbox condition monitoring based on cepstrum technique was carried out, still there are lots to be done to gain a thorough understanding in this respect.

- This thesis has gone through series of tests. This technique needs to be extended to gearboxes with variable speed.
- More research needs to be carried out to reduce or replace the zooming on the sidebands and mesh frequencies of the gearbox.
- The work could further be extended by averaging the excitation-dominated parts of the original cepstra to obtain the best estimate of the excitation function. This average could be subtracted from all the individual cepstra,

which could be curve-fitted in either the cepstrum or spectrum domain for estimation of the structural response functions.

- More research needs to be carried out for further understanding of the relationship between the signal energy and the fault severity so that tables or charts can be produced to help in the gearbox condition monitoring.

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APPENDIX A

A. 1 Transducers

The selection of the proper transducer can be as important as any of the steps in data acquisition. The selection should be made with some care and thought as to the types of defects to be detected, frequency range involved, required location of the transducer, etc.

Vibration data for machinery can be gathered by selecting the right transducer from displacement, velocity or acceleration transducers. The equations that govern displacement, velocity and acceleration transducers are presented.

A.1.1 Displacement Transducer

Under this application, x_i and x_m are the absolute displacements [120], while x_0 is zero as weight M acts along the x-axis, hence equation 5.

$$\frac{x_o}{x_i}(D)=\frac{D^2/\omega_n^2}{D^2/\omega_n^2+2\xi D/\omega_n+1} \qquad \text{A.1}$$

Where

$$\omega_n=\sqrt{\frac{K_s}{M}}$$

$$\xi=\frac{B}{2\sqrt{K_s M}}$$

Where

M = Mass

D = Integrating Device

Ks = Stiffness

B = Damping

Frequency response for this displacement sensor is shown in equation 4.6

$$\frac{x_o}{x_i}(i\omega)=\frac{(i\omega)^2/\omega_n^2}{(i\omega/\omega_n)^2+2\xi i\omega/\omega_n+1} \qquad \text{A.2}$$

Displacement transducers measure vibratory displacement where a fixed reference for relative displacement measurement is not available. The transducer is drilled into a stationary reference. Displacement transducers are called Eddy Current Probes. It is has low frequency response, measures the actual displacement of the shaft within the bearing [120]. The limitations are inability to measure high frequency, expensive to install and only used for low speed machines below 600 cycles per second [120].

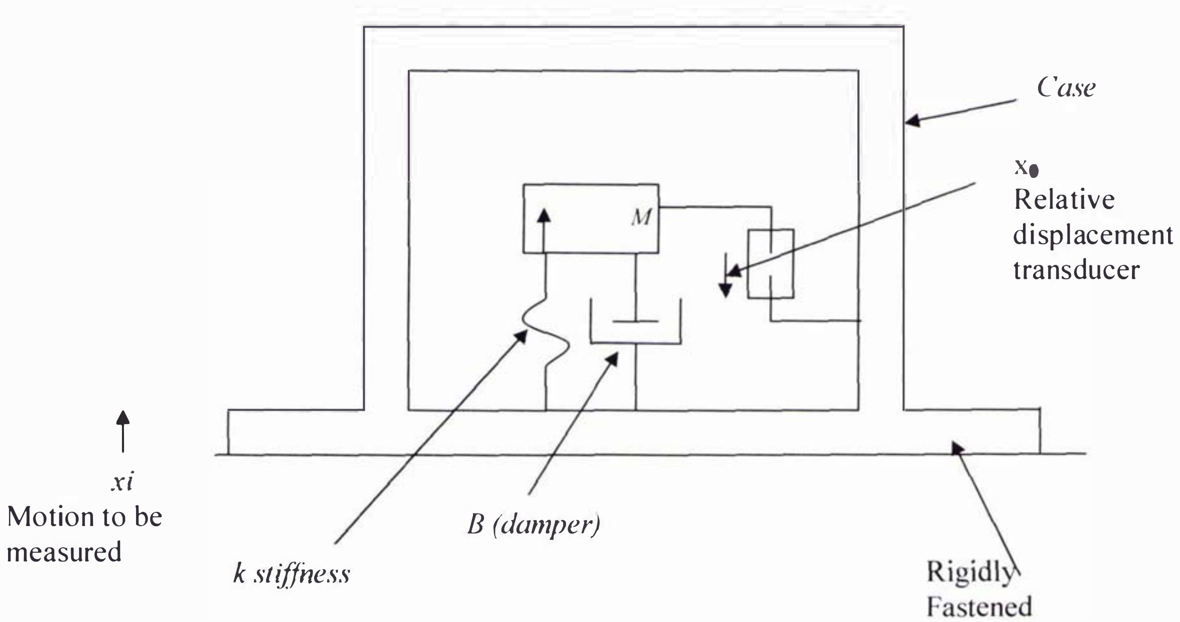


Figure A.1: Displacement Sensor

A.1.2 Velocity Transducer

$e_0 = k_e \dot{x}_0$

$$\frac{e_0}{\dot{x}_i}(D) = \frac{k_e D^2 / \omega_n^2}{D^2 / \omega_n^2 + 2\xi D / \omega_n + 1} \qquad \text{A.3}$$

Equation A.5 can be rewritten as shown in equation A.4

$$\frac{x_0}{Dx_i}(D)=\frac{D}{D^2+2\xi\omega_n D+\omega_n^2} \qquad \text{A.4}$$

Therefore,

$$\frac{x_0}{\dot{x}_i}(i\omega)=\frac{1}{2\omega_n-i\left[\left(\omega_n^2-\omega^2\right)/\omega\right]} \qquad \text{A.5}$$

The configuration of velocity transducer is similar to figure A.1, but measures velocity x_i instead of displacement x_i. It is an electromagnetic sensor, when it vibrates; its magnet remains stationary due to inertia. The magnet moves within a coil that eventually generates electricity that is proportional to the velocity of the mass. It has the ability to operate under high temperatures and easy to use. Its limitations are that is has low signal to noise ratio and not suitable for low or high frequency measurements [120].

A.1.3 Acceleration Transducer

The desired input in this respect is $\ddot{x}_1$ equation 5 can be written as shown in equation A.6.

$$\frac{x_0}{D^2 x_i}=\frac{x_0}{\ddot{x}_i}(D)=\frac{k}{D^2/\omega_n^2+2\xi D/\omega_n+1} \qquad \text{A.6}$$

$$k=\frac{1}{w_n^2}cm/(cm/s^2)$$

A.2 Operation of Piezoelectric Accelerometer

The transducer selected with this spectrum analyzer is a piezoelectric accelerometer, because It has very wide range of frequency, amplitude and temperature.

It is of the same configuration as figure A.2. The mass M accelerates at x_i, the spring deflection x_0 causes the force that will produce the acceleration, therefore, x_0 is a measure of acceleration x_i.

It is the most important pickup for vibration, shock and general-purpose absolute motion measurement [120].

Piezoelectric came mainly in two types of material; quartz and synthetic ceramic, but the most used is the quartz. The piezo-electric element in figure A.2 is squeezed between the mass and the base, when it experiences a force, then generates an electric charge between its surfaces. The force required to move seismic mass up and down is proportional to the acceleration of the mass. The force on the crystal produces the output signal, which is proportional to the acceleration of the transducer. The following should be considered while selecting accelerometers:

1. Frequency Range
2. Dynamic range

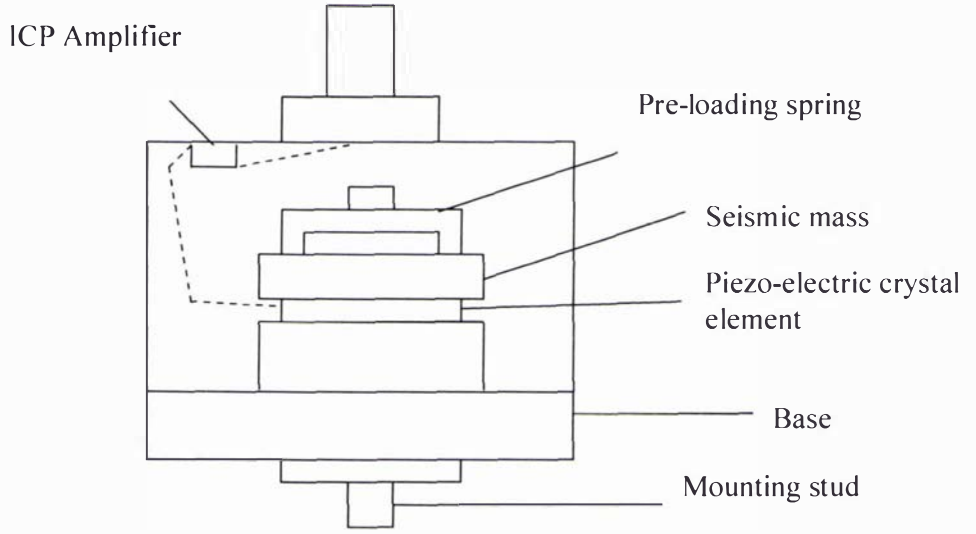


Figure A.2: The Piezoelectric Accelerometer

A.2.1 Frequency Range

The high frequency response is limited by the resonance of the seismic mass coupled (or bolted) to the springiness of the piezo element.

The resonance produces a very high peak in the response at the natural frequency of the transducer, about 30kHz.

A rule of thumb is that an accelerometer is usable up to about 1/3 of its natural frequency. Data above this frequency will be accentuated by the resonant response.

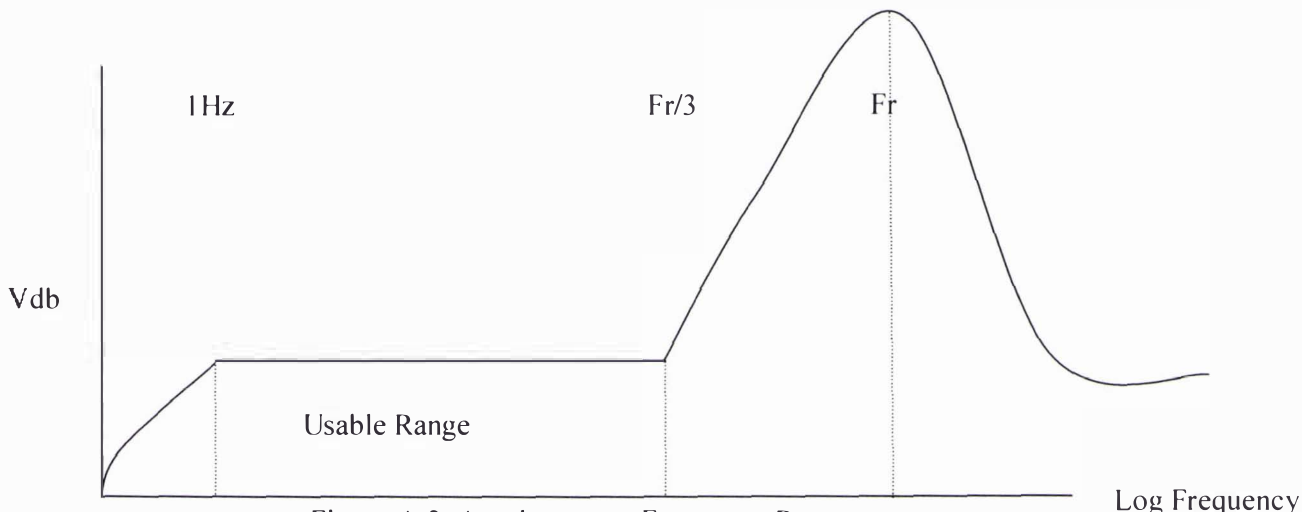


Figure A.3: Accelerometer Frequency Response

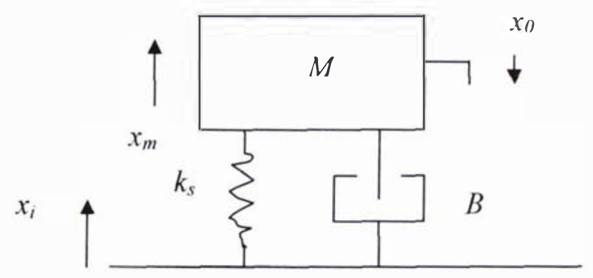


Figure A.4: Construction of a Transducer

Equation 4.11 is obtained by applying Newton's law to the mass M

$$k_s x_0 + B\dot{x}_0 = M\ddot{x}_m = M(\ddot{x}_i - \ddot{x}_0) \qquad \text{A.7}$$

A.2.2 Dynamic Range

It is the range of variable that an instrument is designed to measure, signal to noise ratio (SNR). The variable is the ratio of the amplitude of the largest signal to the smallest detectable dynamic input that the instrument can accurately and faithfully measure. Linear or RMS averaging can be used to reduce the noise floor and improve the dynamic range. Dynamic range is represented in decibels (dB), where the dB of a number N is defined in equation A.8.

The 96dB dynamic range of the data collector indicates that the instrument can handle a range of input of 65,536 to 1. Most spectrum analysers have gone up to 16 bit analog-digital (AD) converters and claim 96 dynamic range.

$$dB = 20 \log N \qquad \text{A.8}$$

A. 3 Cepstrum and Homomorphic Filtering

The major application of the power spectrum in machine vibration is to detect and quantify families of uniformly spaced harmonics, such as bearing faults, missing turbine blades and gearbox faults.

The cepstrum and auto-correlation are closely related. The main difference is that the inverse FFT is performed on the logarithm of the power spectrum itself. The auto-correlation is mainly dominated by the highest values of the spectrum. The logarithm used when computing the cepstrum causes it to take lower level harmonics more into account than auto-correlation. The cepstrum mainly reacts to the harmonics present in the auto-spectrum, but the autocorrelation is strongly influenced by the shape of the time signal. The auto spectrum of the different gear cases the author investigated are shown in the following figures. When we look at the auto-spectrum of the signal, "forest" of harmonics is clearly seen. Figure .. illustrates that the forcing function and transfer function effects are separated in the cepstrum

Looking at the cepstra of different gear fault cases shown in the following figures, the advantages of using homomorphic filter would be appreciated. Homomorphic filtering is a deterministic process in the sense that fixed and pre-given parts of the complex cepstrum which are related to the undesired components are eliminated. The success of the method depends primarily on the rate of the separation of the individual components in the complex cepstrum. The main advantage of homomorphic filters for different deconvolution problems over other deterministic filters is the fact that no prior knowledge is necessary, the necessary parameters can be determined during the process itself.

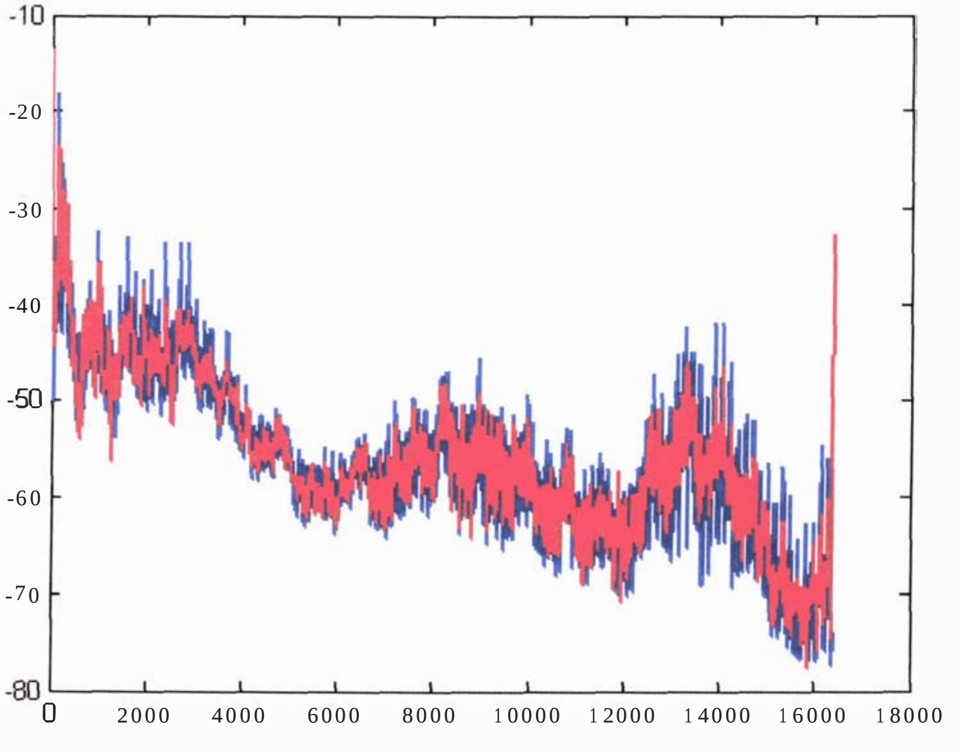
Deconvolution by homomorphic filtering is an attractive method as it reduces a convolution to an additive superposition of the components and the separation of the individual components in the complex cepstrum.

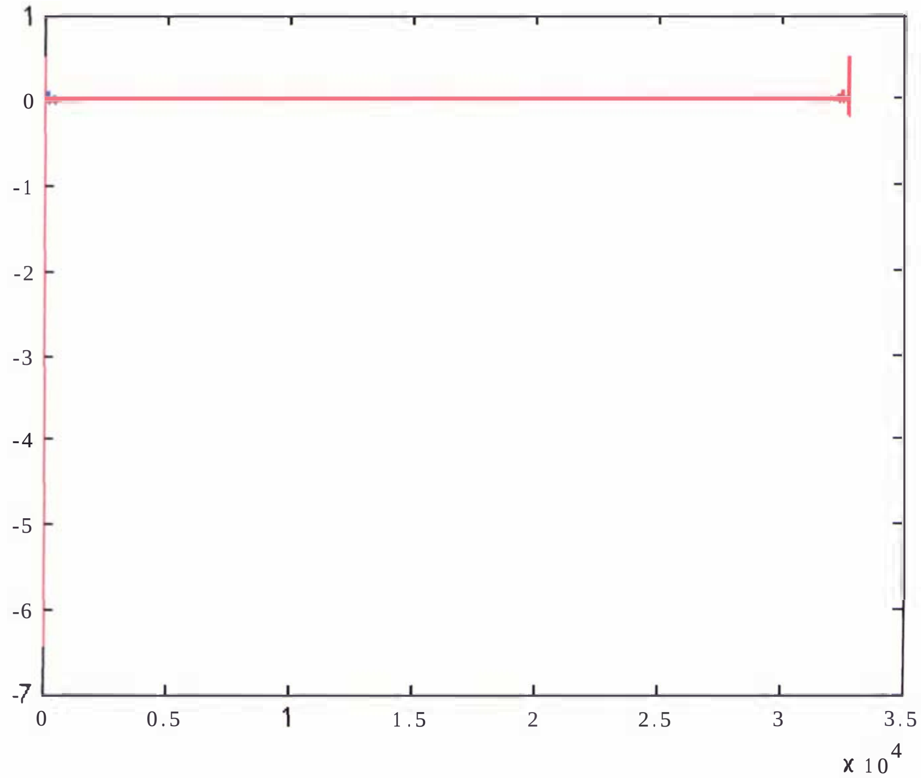
The poles and zeros of the FRF were extracted to evaluate the stability of the system. Poles and zeros give useful insights into a filter's response, and could be used for filter design. Poles outside the unit circle would represent instabilities and could presumably be neglected.

Zeros outside the unit circle could not be dismissed, if they were, it would still be possible to detect changes in the resonances (or poles) which is the primary aim in monitoring. The best bit transfer function could be seen in figures …

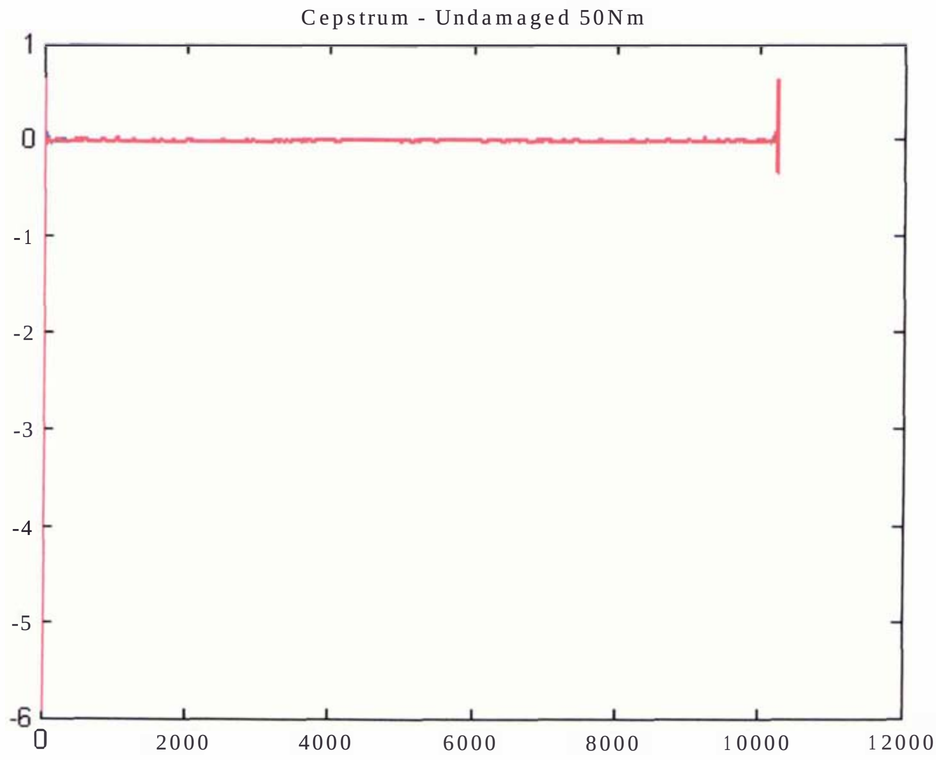
Appendix A: Cepstrum Technique and Homomorphic Filtering

Undamaged Gear - Autospectrum

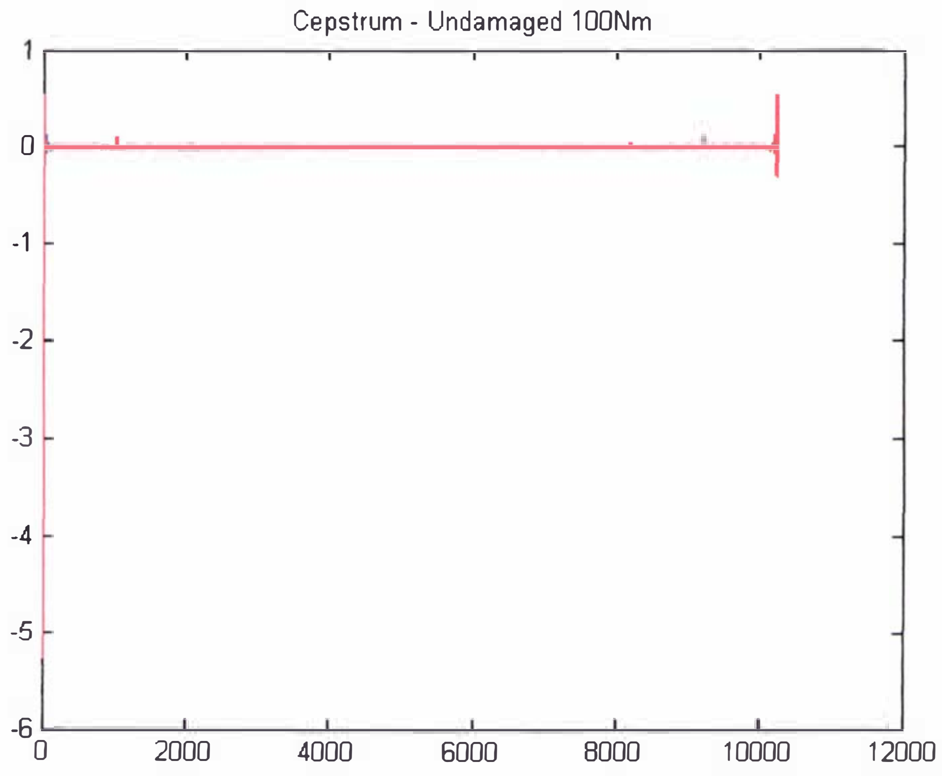




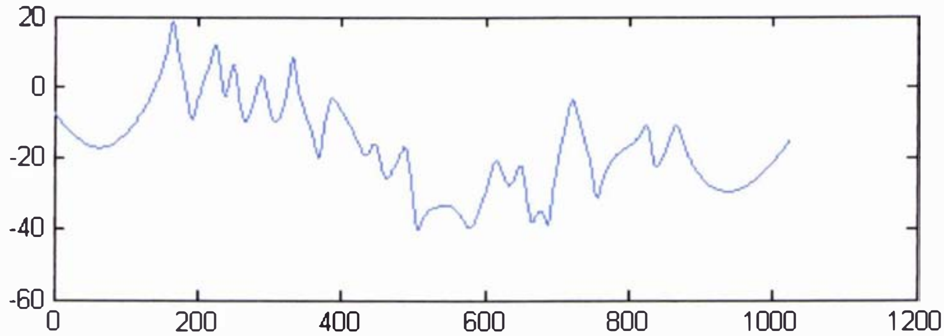
1
0
-1
-2
-3
-4
-5
-6
-7
0
0.5
1
1.5
2
2.5
3
3.5
x 10^4

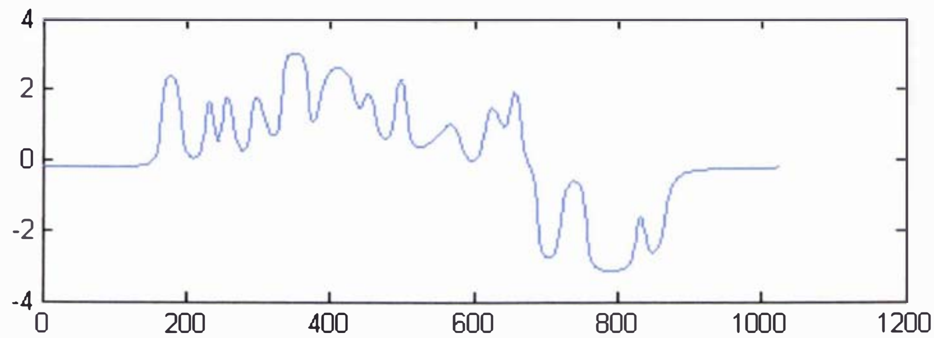


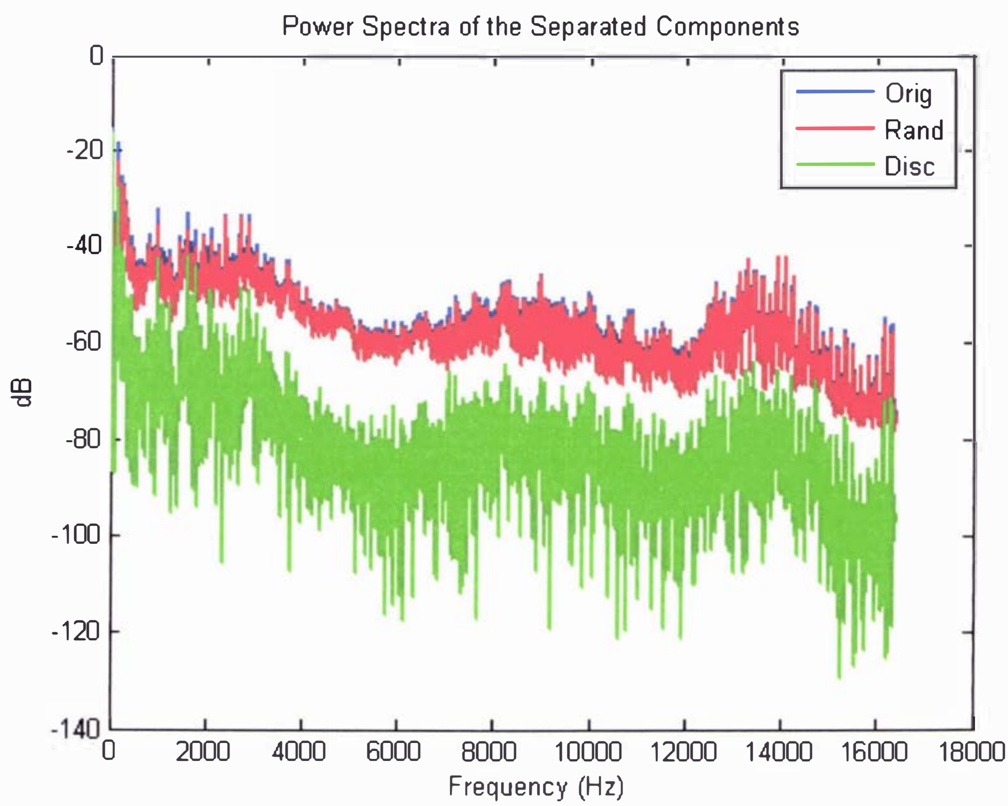
Cepstrum - Undamaged 50Nm
1
0
-1
-2
-3
-4
-5
-6
0
2000
4000
6000
8000
10000
12000

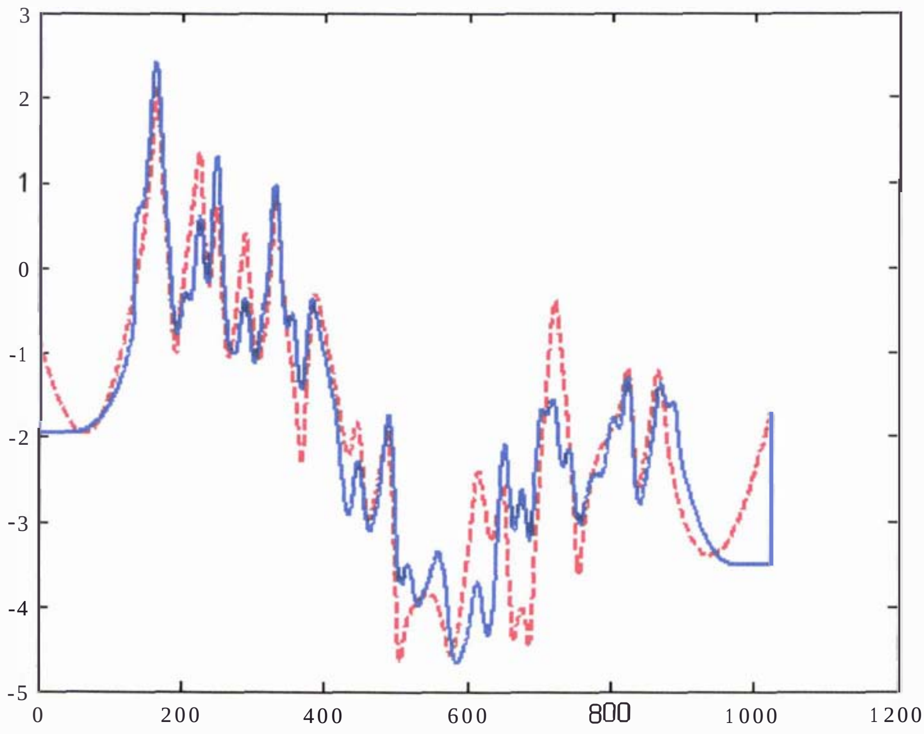

Cepstrum - Undamaged 100Nm
1
0
-1
-2
-3
-4
-5
-6
0
2000
4000
6000
8000
10000
12000

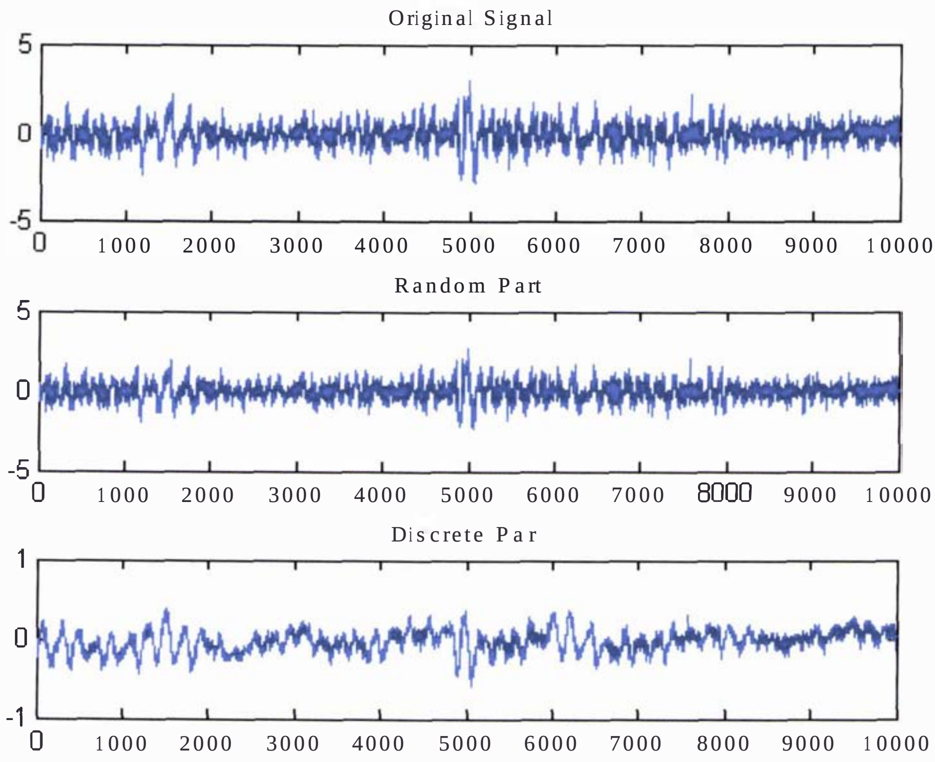
FRF & Phase


20
0
-20
-40
-60
0
200
400
600
800
1000
1200

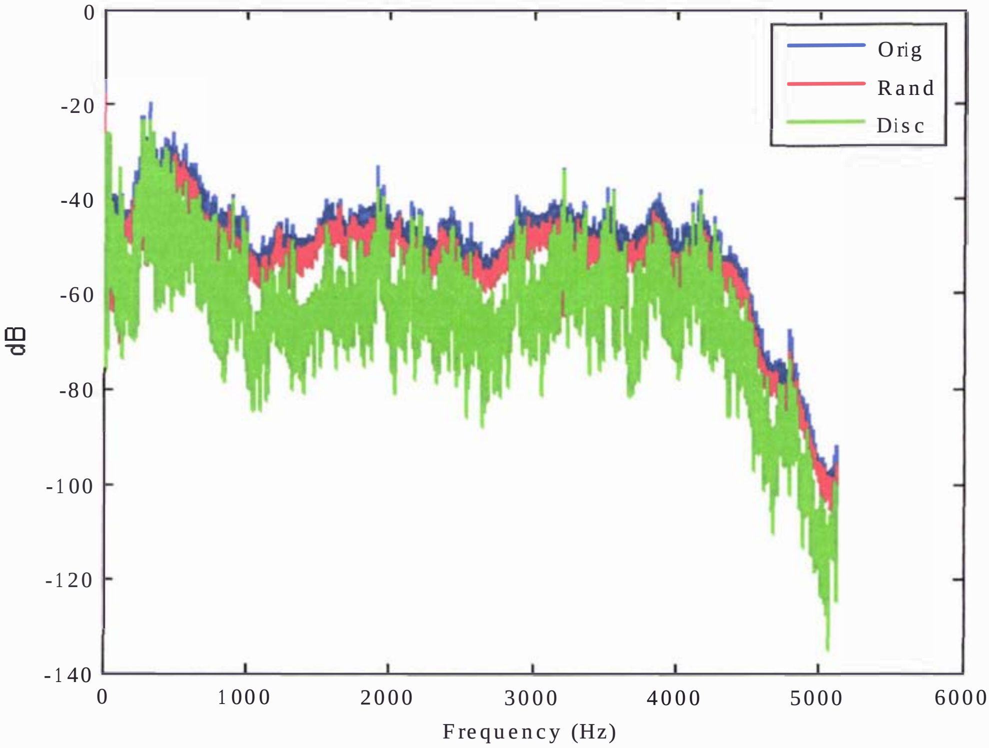

4
2
0
-2
-4
0
200
400
600
800
1000
1200


Power Spectra of the Separated Components
Orig
Rand
Disc
dB
0
-20
-40
-60
-80
-100
-120
-140
0
2000
4000
6000
8000
10000
12000
14000
16000
18000
Frequency (Hz)

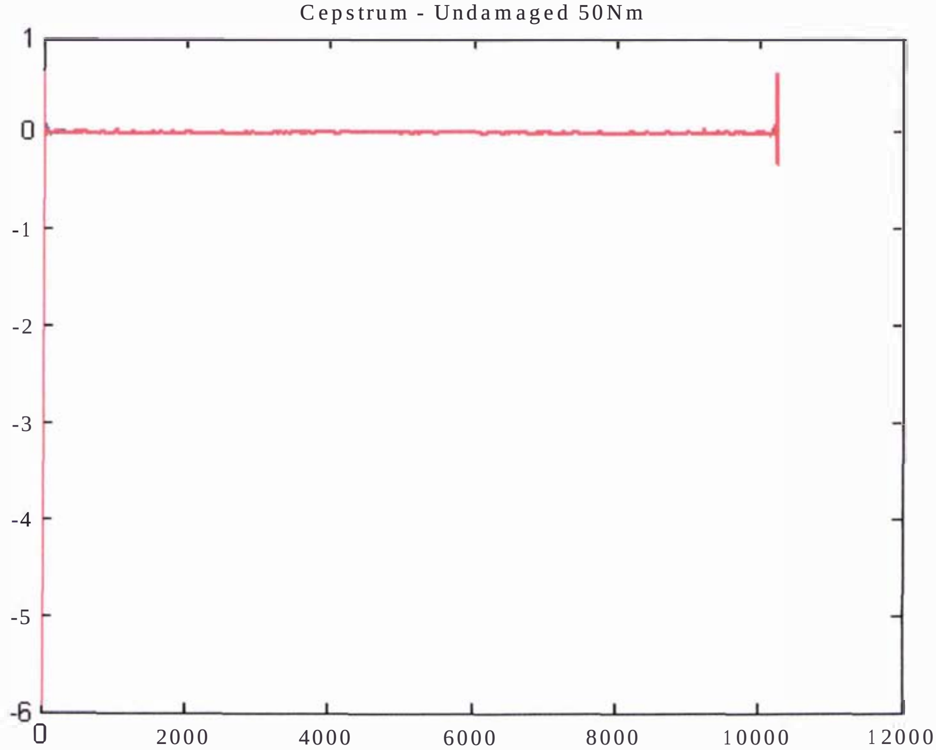

3
2
1
0
-1
-2
-3
-4
-5
0
200
400
600
800
1000
1200

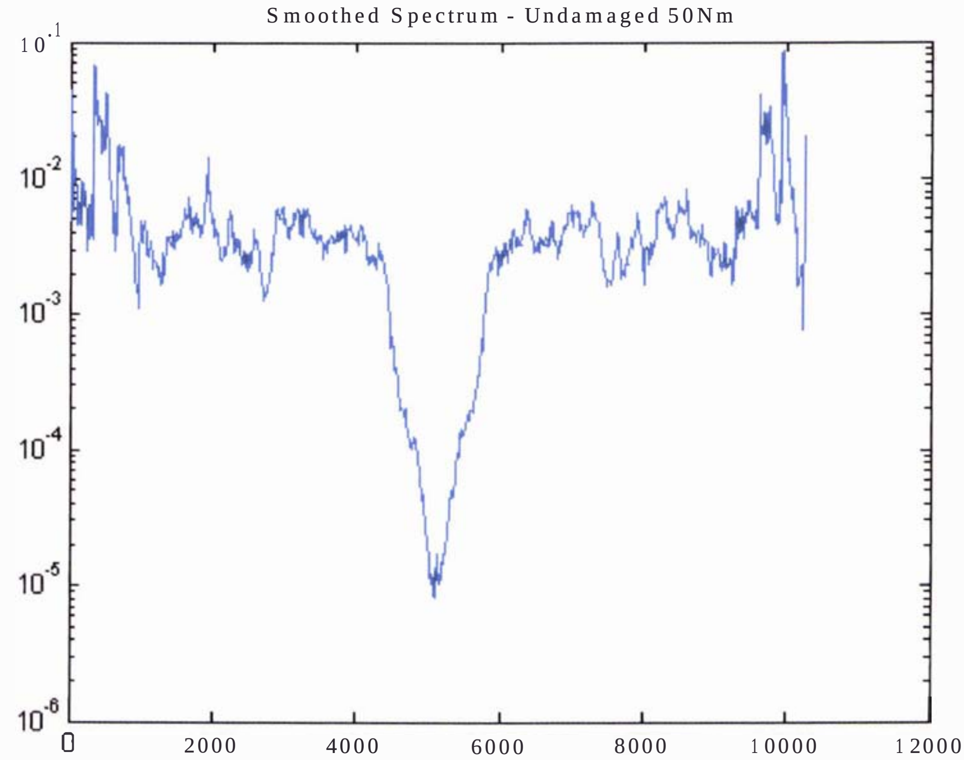

Original Signal
5
0
-5
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Random Part
Discrete Par

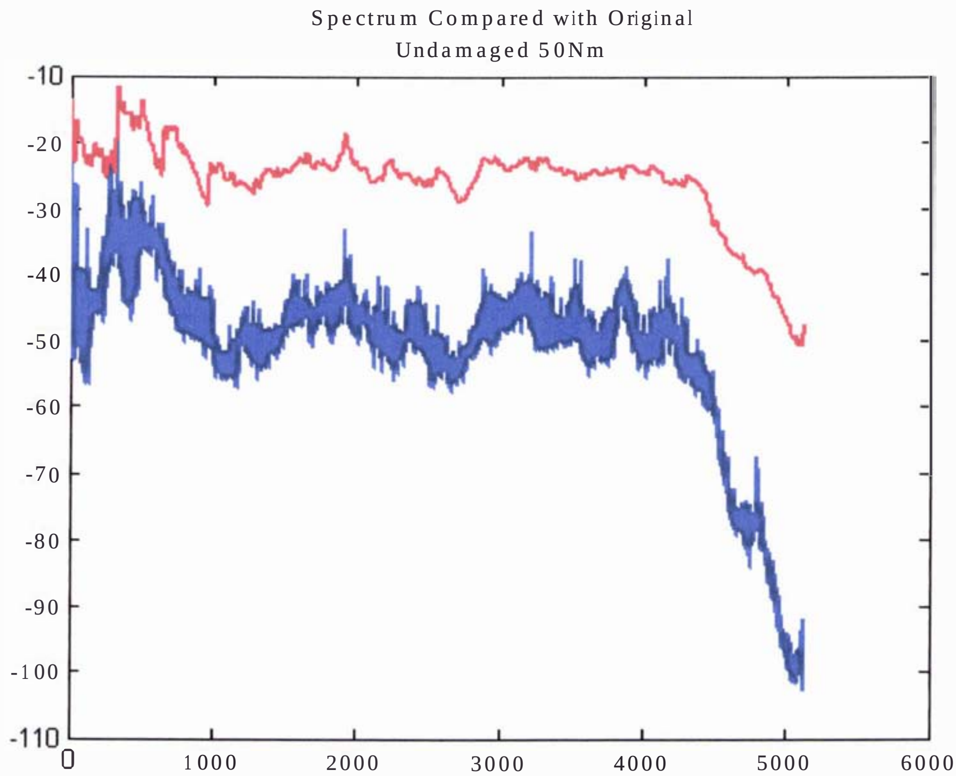
Power Spectra of the Separated Components
Undamaged 50Nm

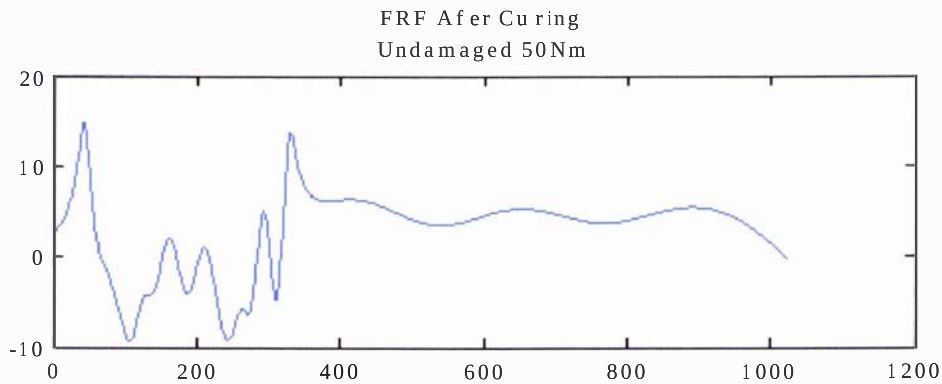


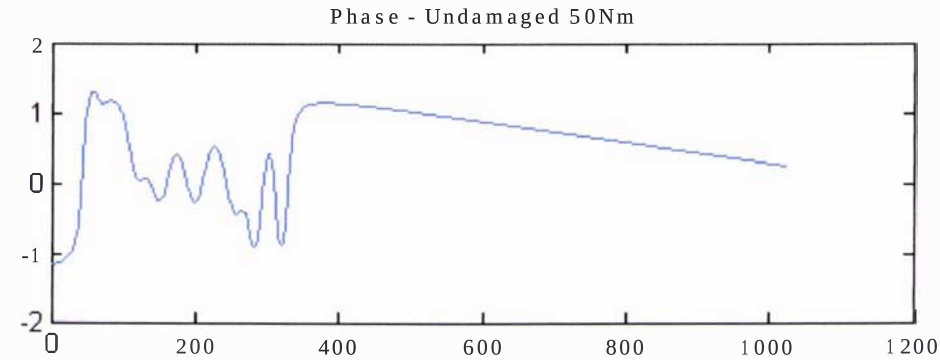
Cepstrum - Undamaged 50Nm

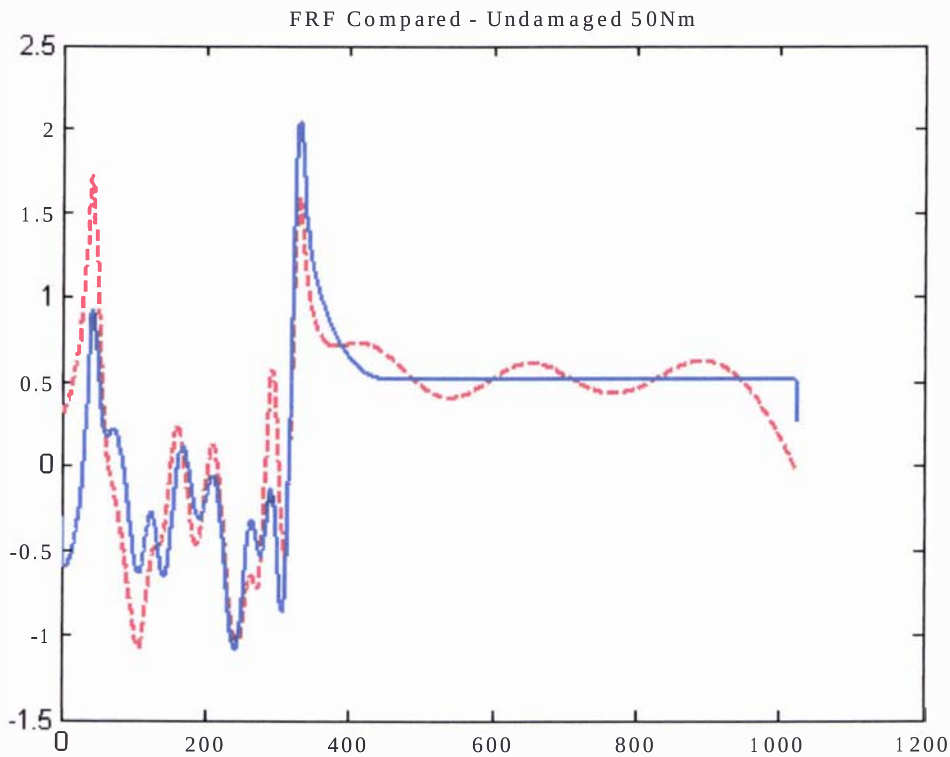


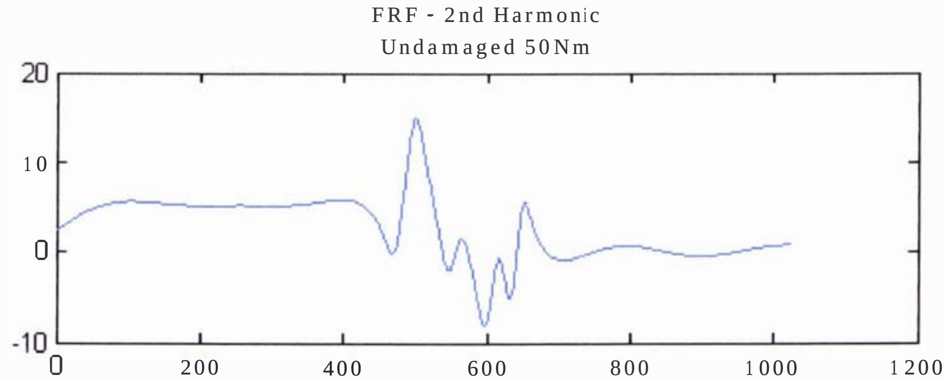

Smoothed Spectrum - Undamaged 50Nm
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
0
2000
4000
6000
8000
10000
12000

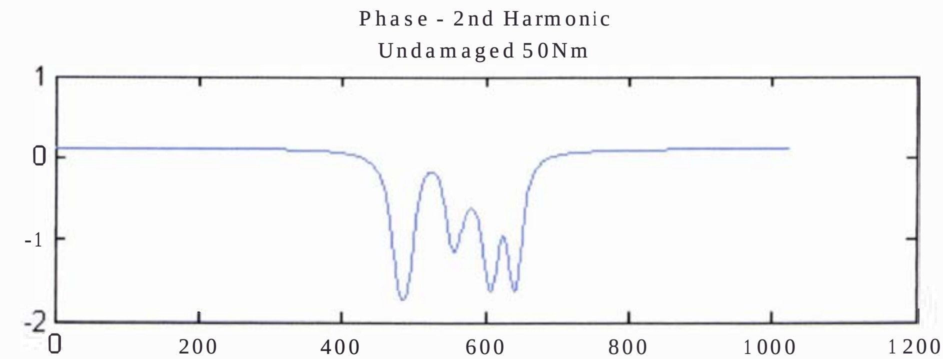

Spectrum Compared with Original
Undamaged 50Nm
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100
-110
0
1000
2000
3000
4000
5000
6000

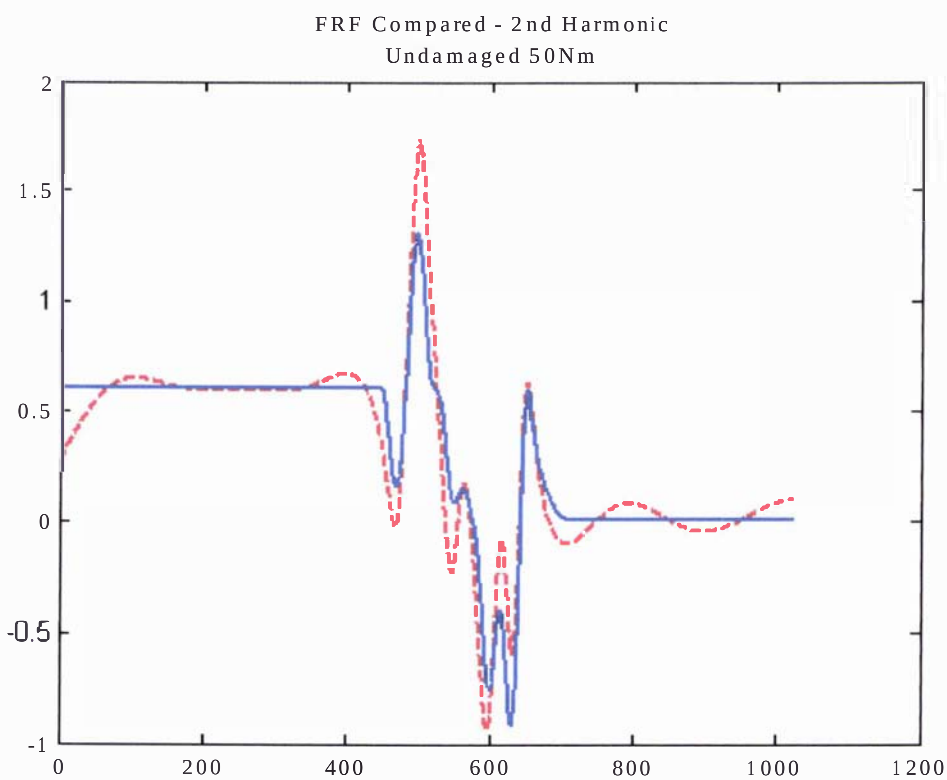

FRF Afer Cu ring
Undamaged 50Nm

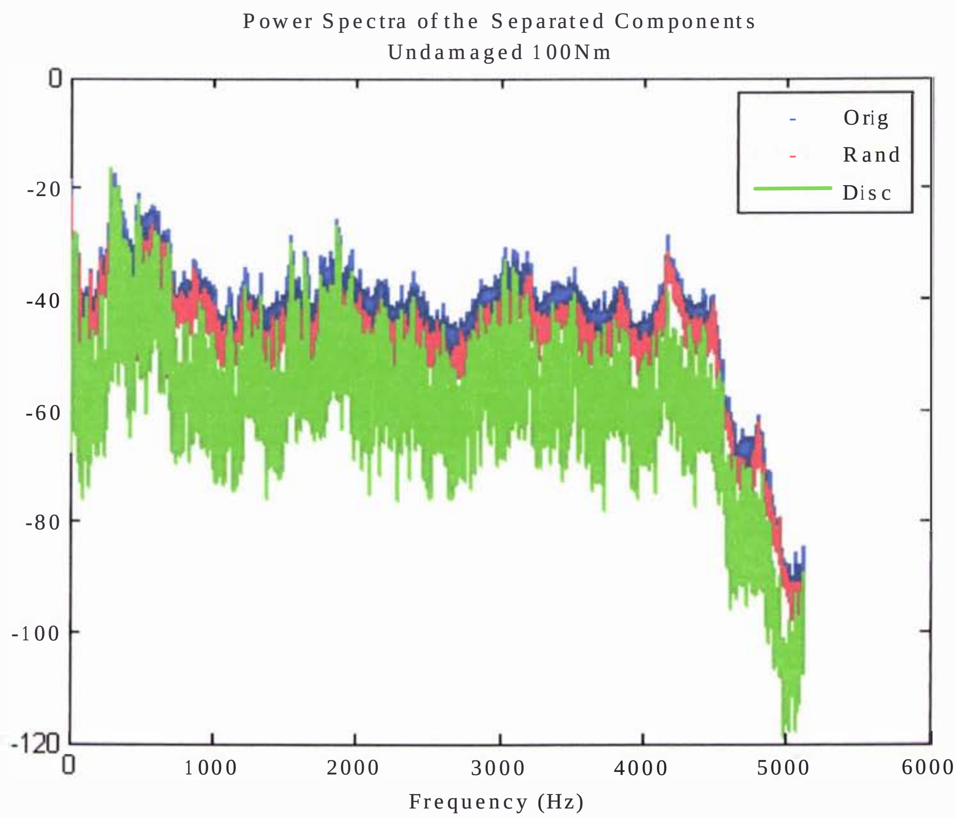

Phase - Undamaged 50Nm

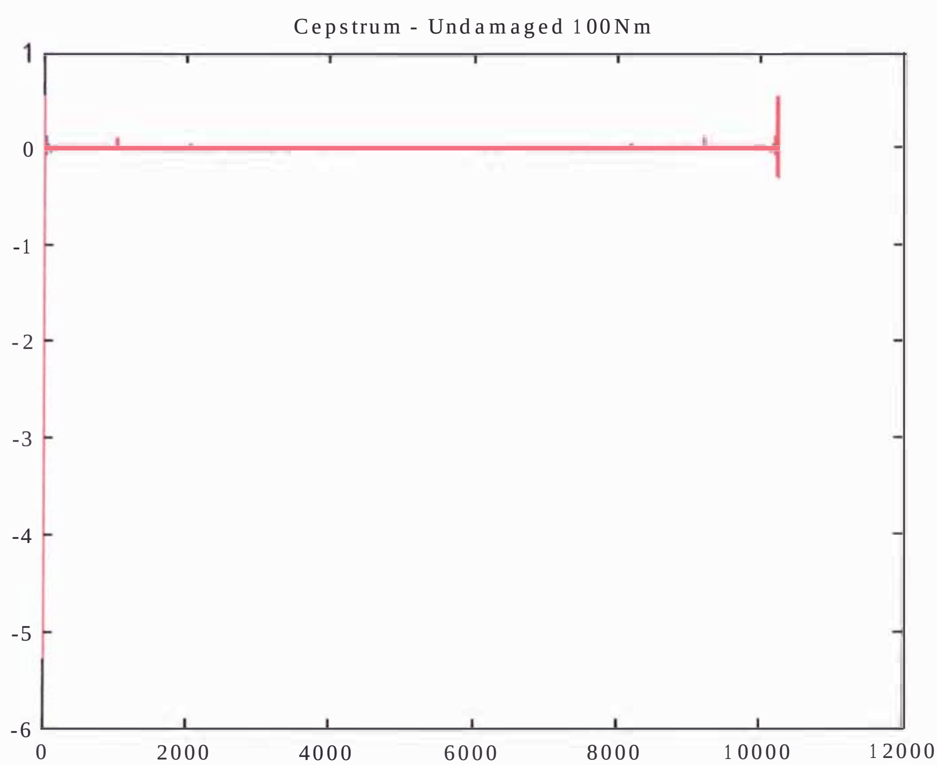

FRF Compared - Undamaged 50Nm

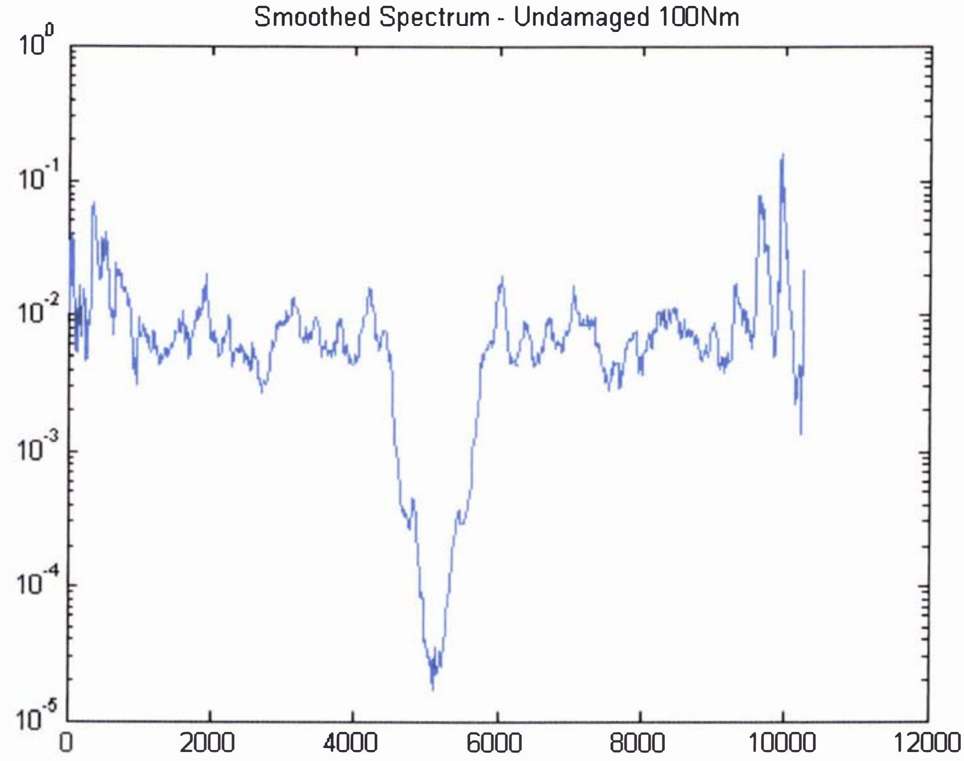

FRF - 2nd Harmonic
Undamaged 50Nm
20
10
0
-10
0
200
400
600
800
1000
1200

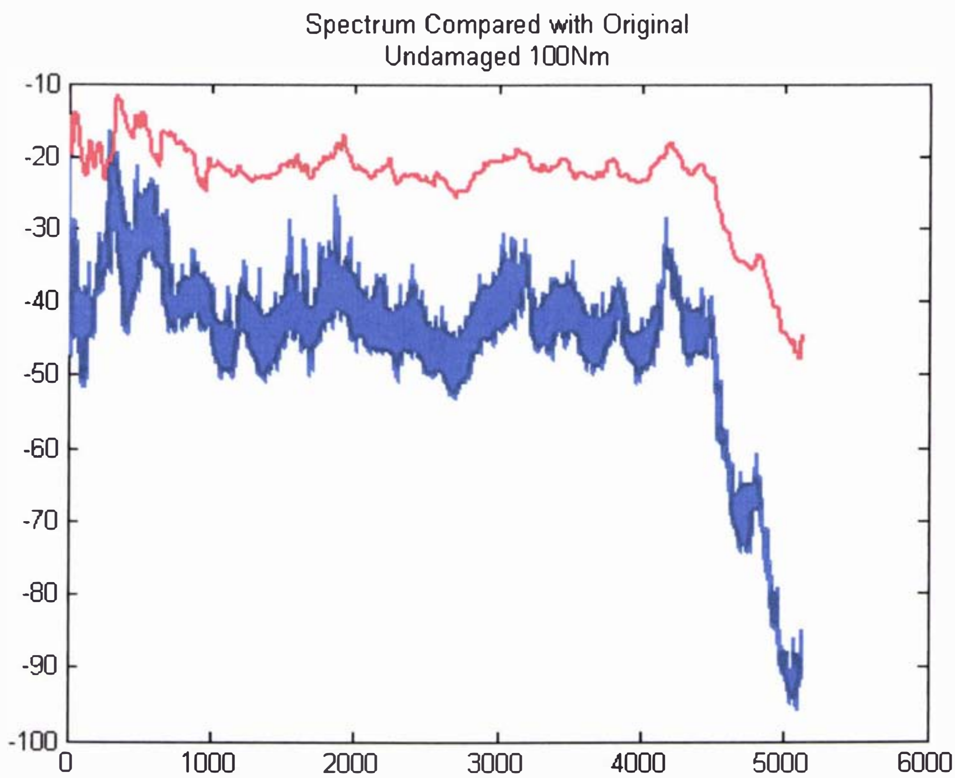

Phase - 2nd Harmonic
Undamaged 50Nm
1
0
-1
-2
0
200
400
600
800
1000
1200

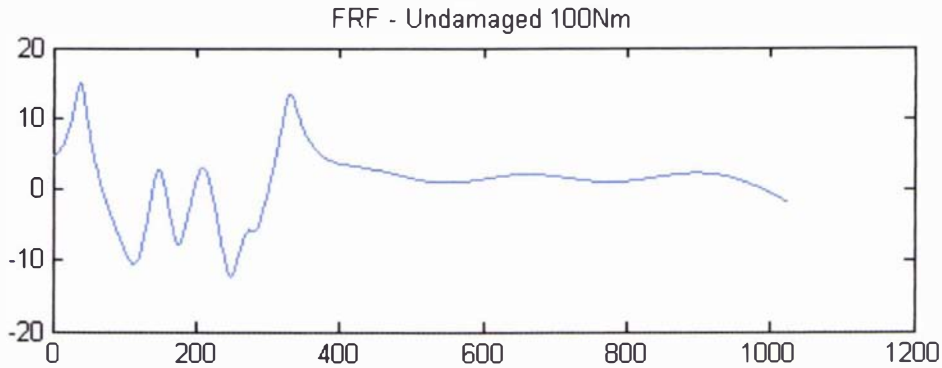

FRF Compared - 2nd Harmonic
Undamaged 50Nm
2
1.5
1
0.5
0
-0.5
-1
0
200
400
600
800
1000
1200

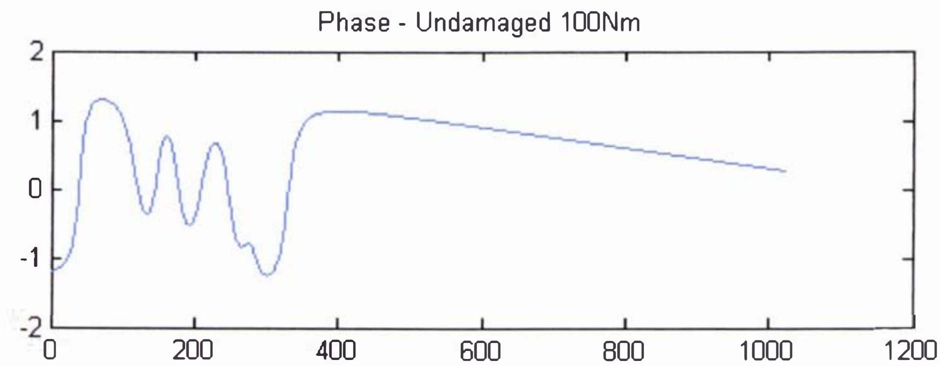

Power Spectra of the Separated Components
Undamaged 100Nm
Orig
Rand
Disc
0
-20
-40
-60
-80
-100
-120
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)

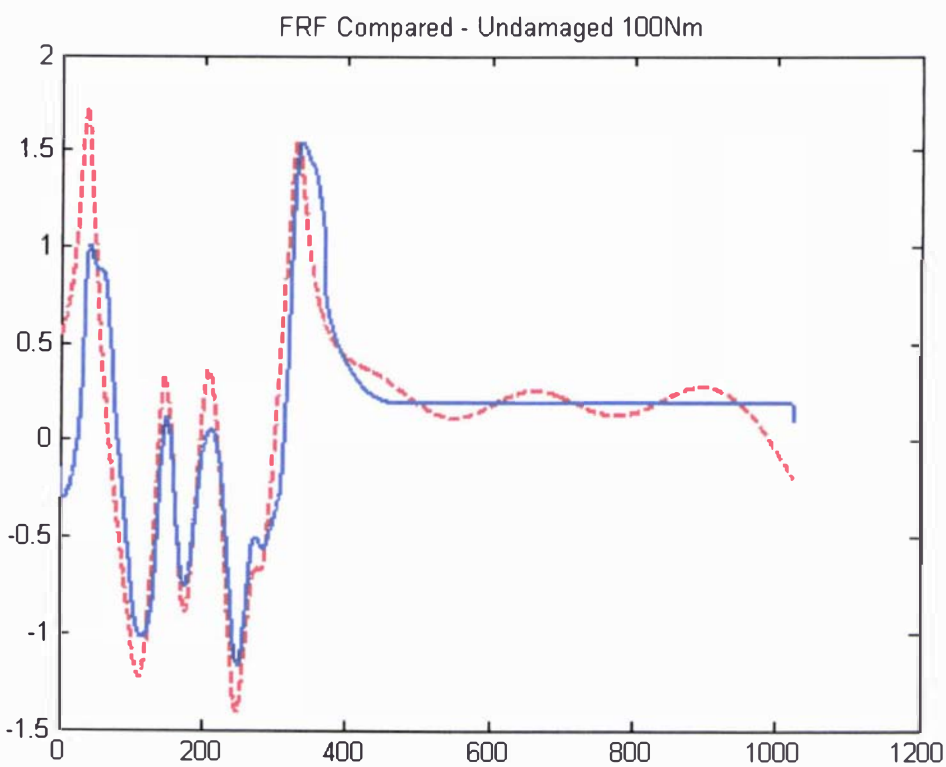

Cepstrum - Undamaged 100Nm
1
0
-1
-2
-3
-4
-5
-6
0
2000
4000
6000
8000
10000
12000


Smoothed Spectrum - Undamaged 100Nm
10^0
10^-1
10^-2
10^-3
10^-4
10^-5
0
2000
4000
6000
8000
10000
12000

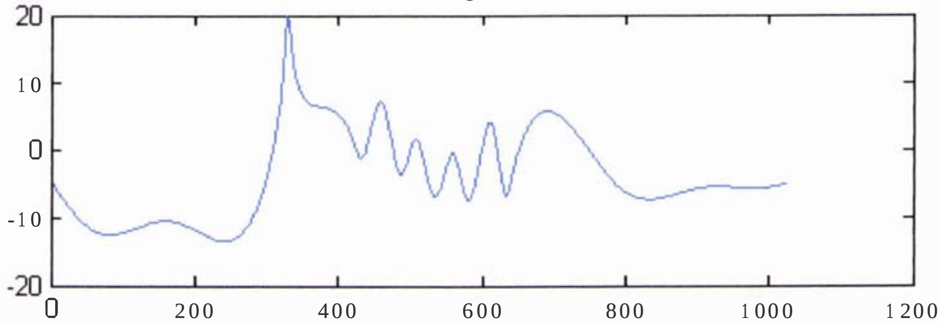

Spectrum Compared with Original
Undamaged 100Nm
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100
0
1000
2000
3000
4000
5000
6000


FRF - Undamaged 100Nm
20
10
0
-10
-20
0
200
400
600
800
1000
1200

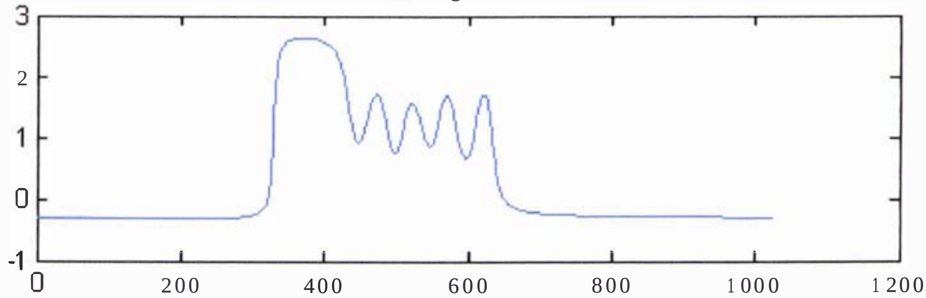

Phase - Undamaged 100Nm
2
1
0
-1
-2
0
200
400
600
800
1000
1200


FRF Compared - Undamaged 100Nm
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
200
400
600
800
1000
1200

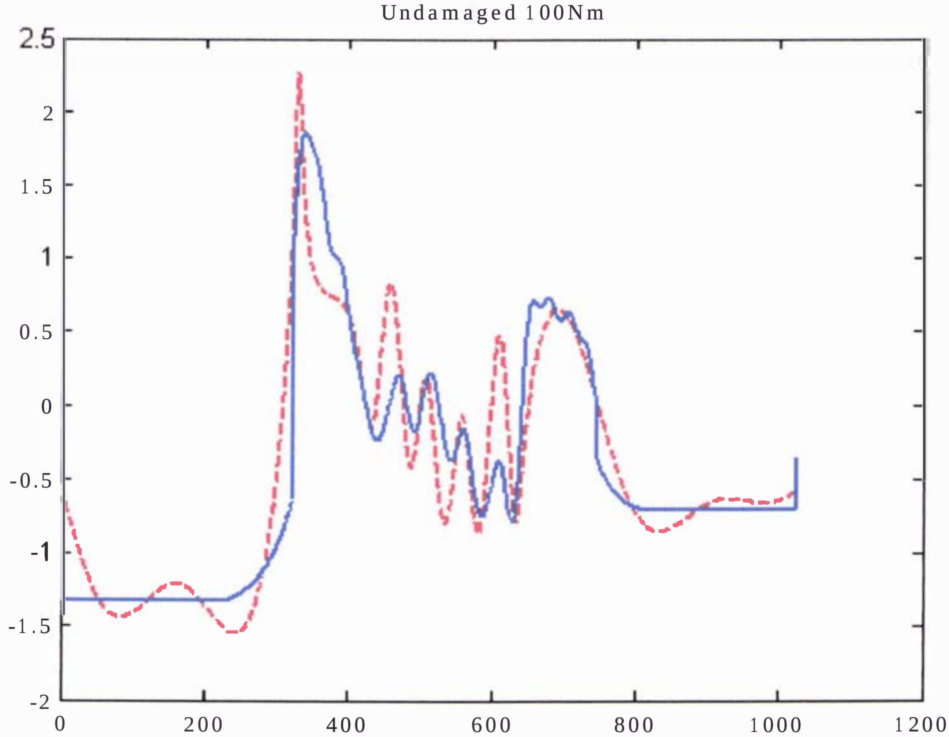
FRF Afer Cu ring - 2nd Harmonic
Undamaged 100Nm



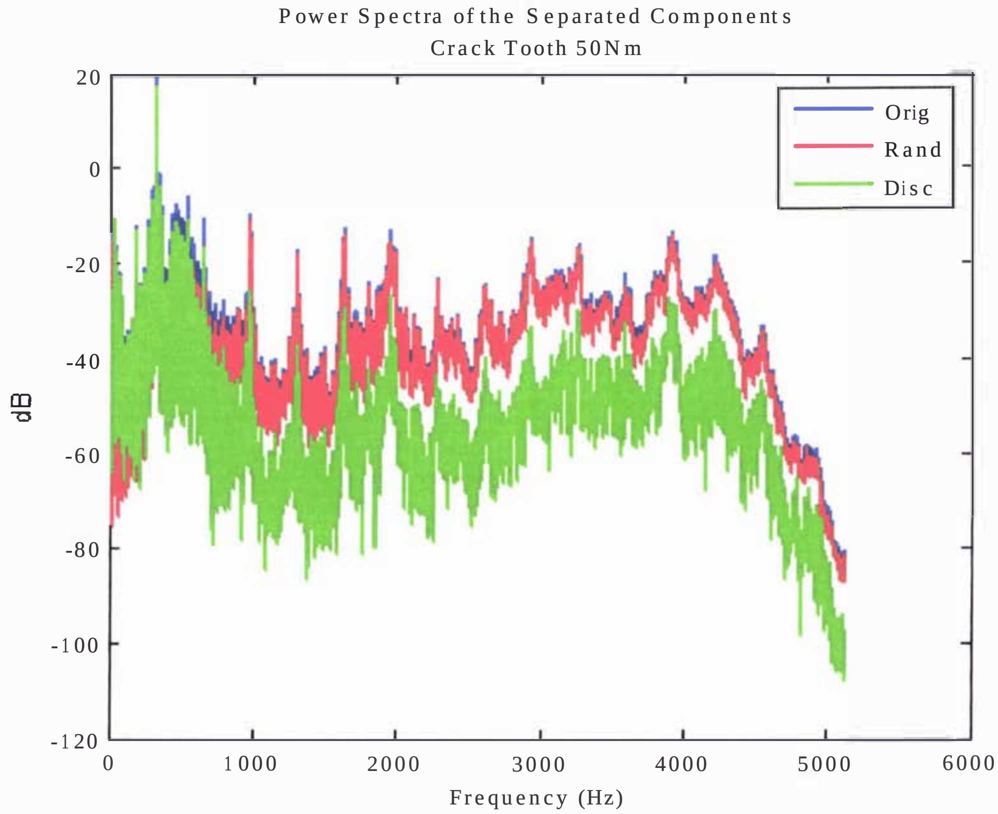
Phase - 2nd Harmonic
Undamaged 100Nm



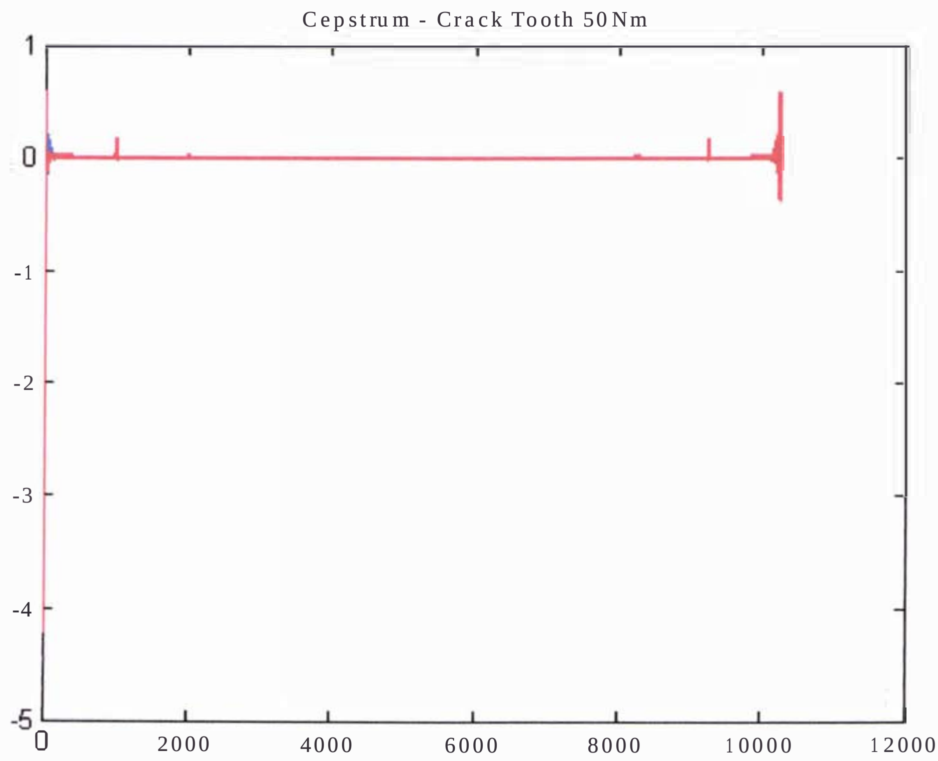
FRF Compared - 2nd Harmonic
Undamaged 100Nm



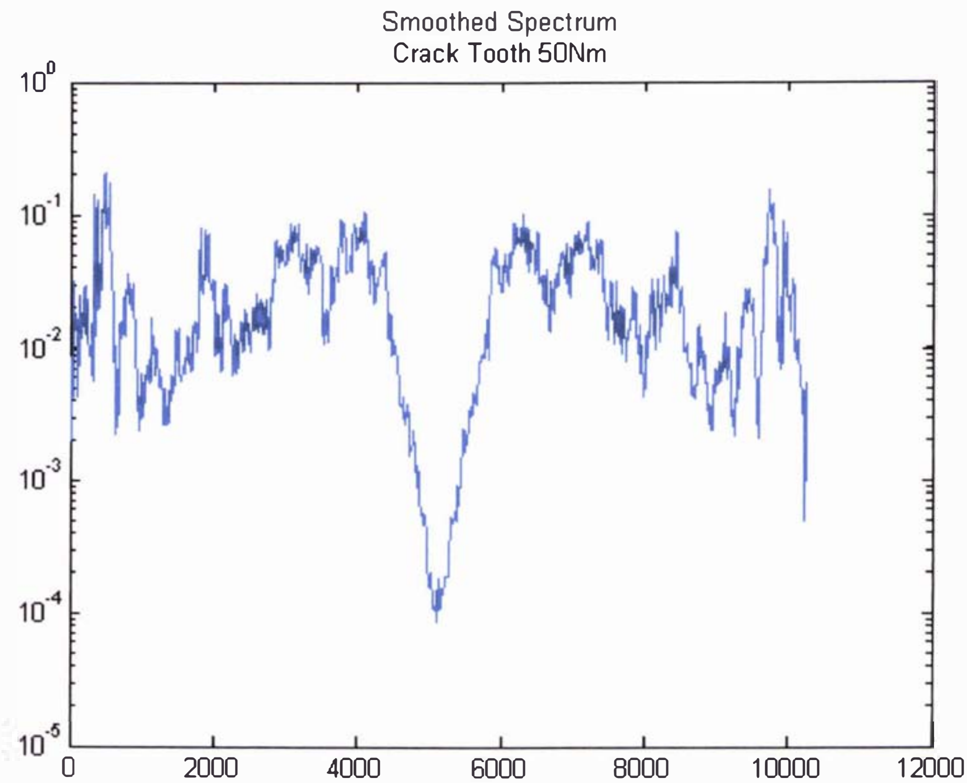
Cracked



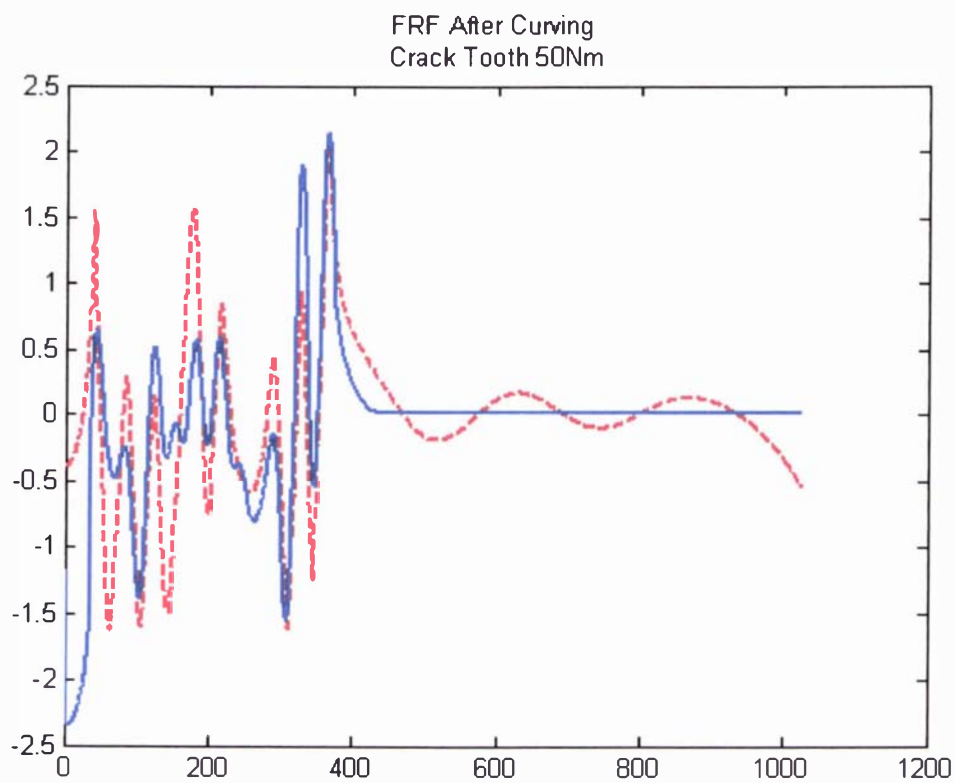
Power Spectra of the Separated Components
Crack Tooth 50Nm
Orig
Rand
Disc
dB
20
0
-20
-40
-60
-80
-100
-120
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)



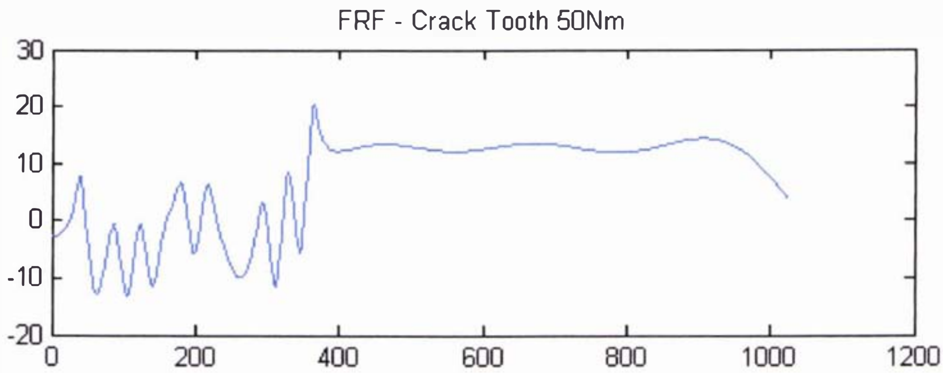
Cepstrum - Crack Tooth 50Nm
1
0
-1
-2
-3
-4
-5
0
2000
4000
6000
8000
10000
12000

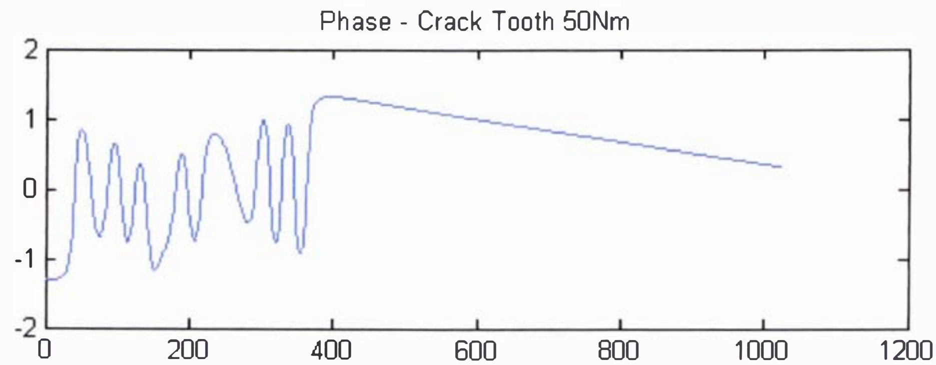


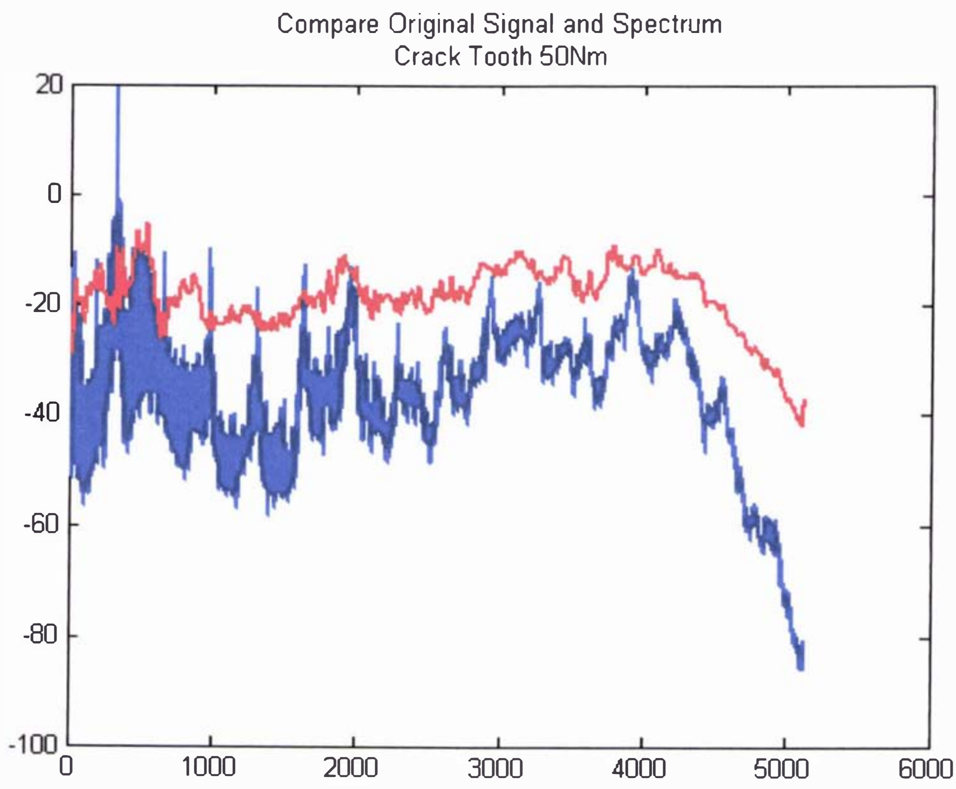
Smoothed Spectrum
Crack Tooth 50Nm
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
0
2000
4000
6000
8000
10000
12000

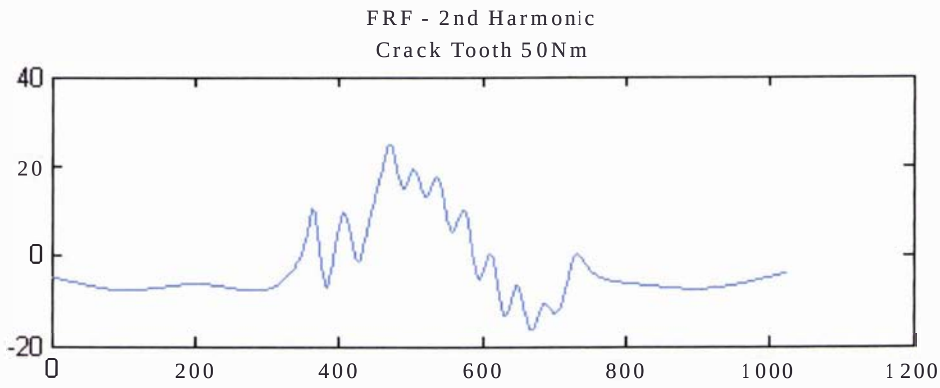


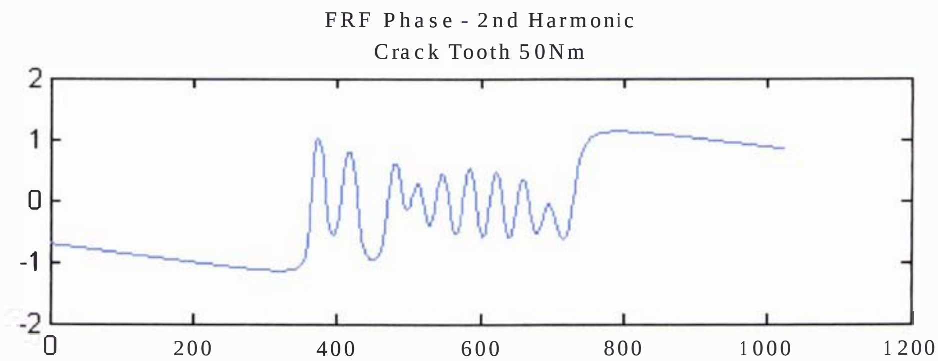
FRF After Curving
Crack Tooth 50Nm
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
200
400
600
800
1000
1200

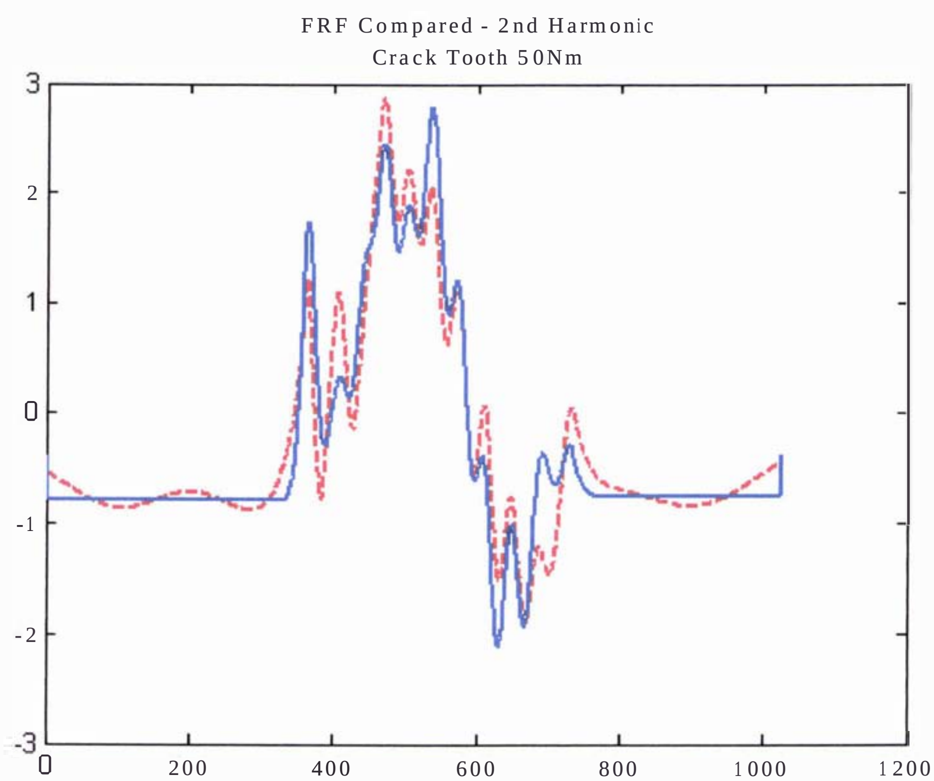

FRF - Crack Tooth 50Nm
30
20
10
0
-10
-20
0
200
400
600
800
1000
1200

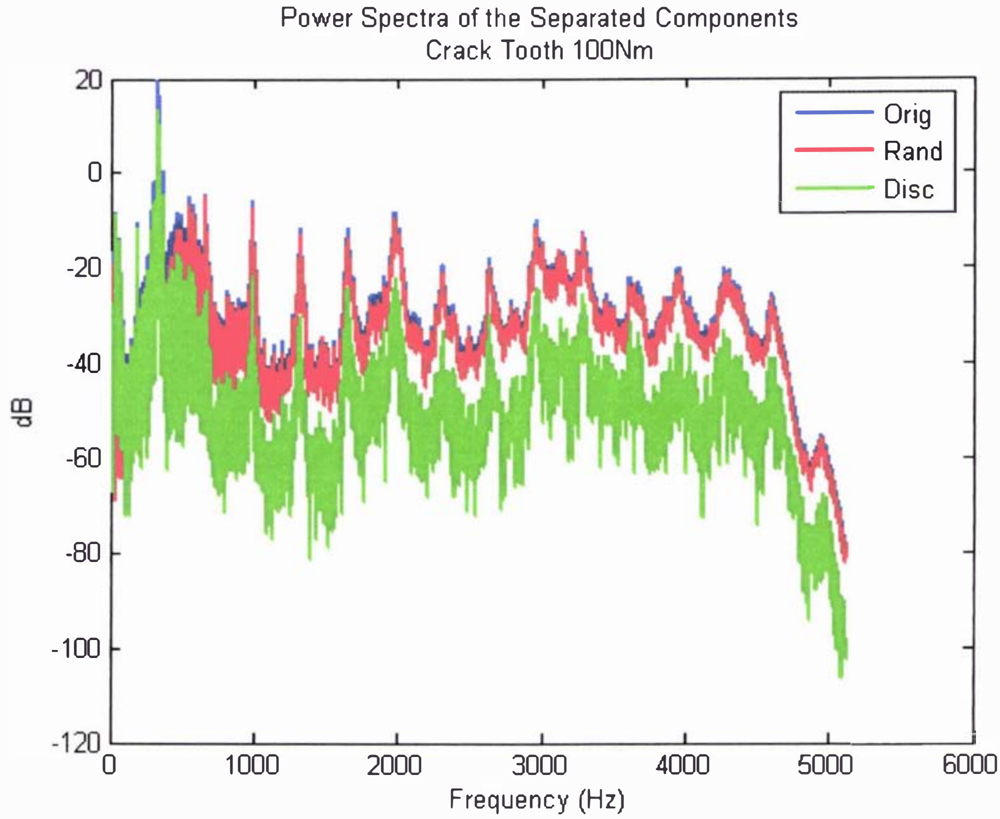

Phase - Crack Tooth 50Nm
2
1
0
-1
-2
0
200
400
600
800
1000
1200

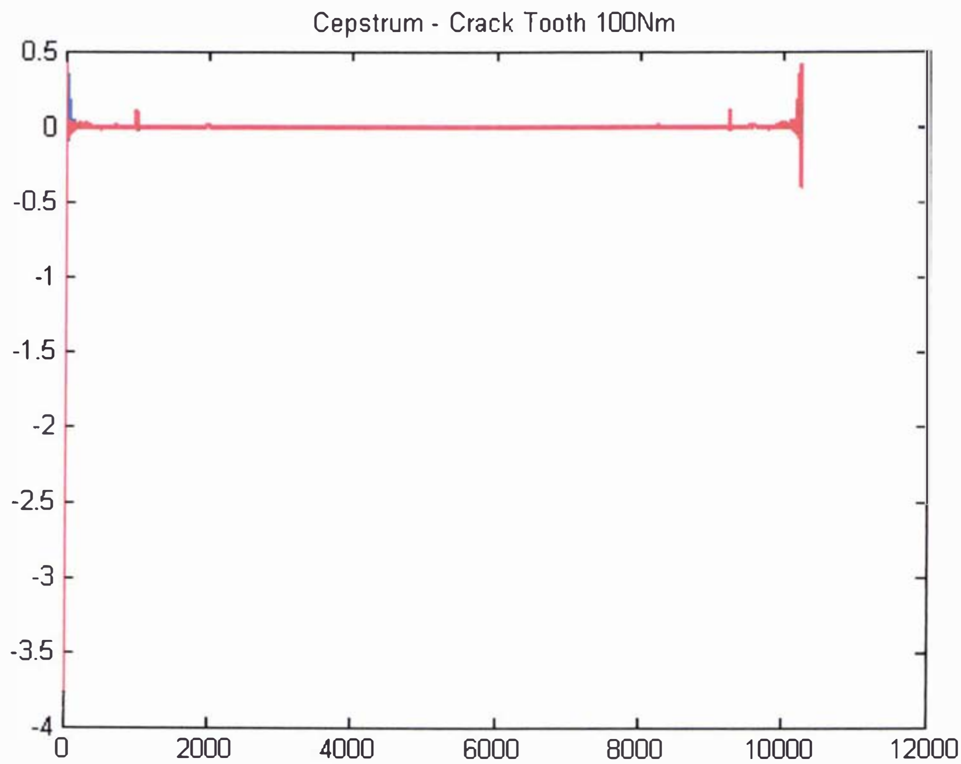

Compare Original Signal and Spectrum
Crack Tooth 50Nm
20
0
-20
-40
-60
-80
-100
0
1000
2000
3000
4000
5000
6000

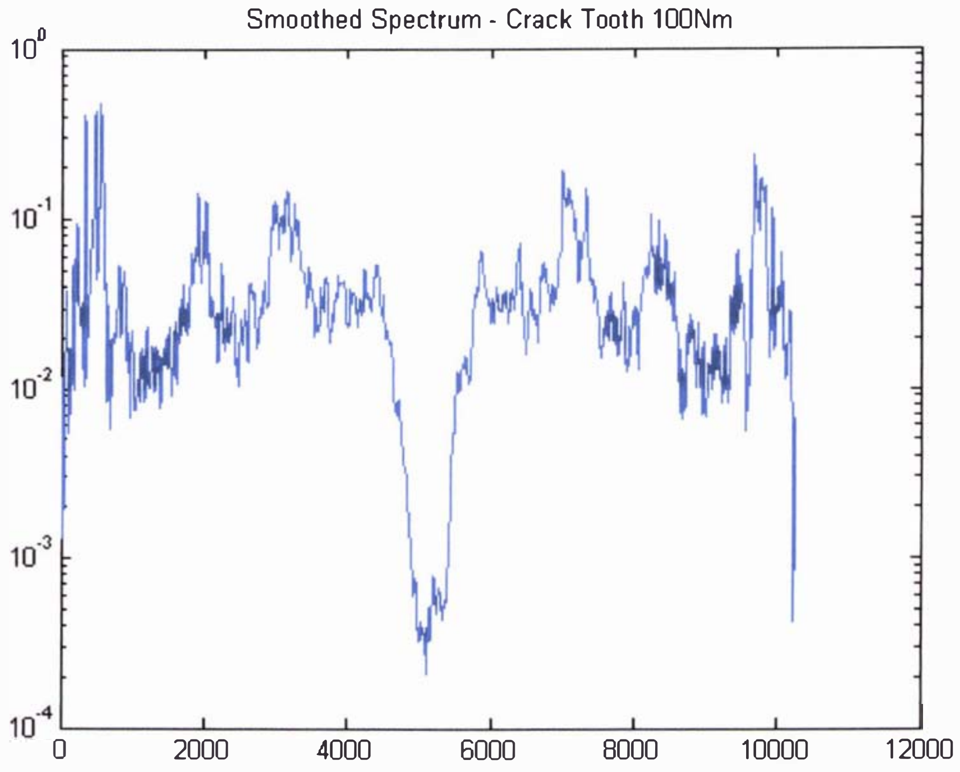

FRF - 2nd Harmonic
Crack Tooth 50Nm
40
20
0
-20
0
200
400
600
800
1000
1200

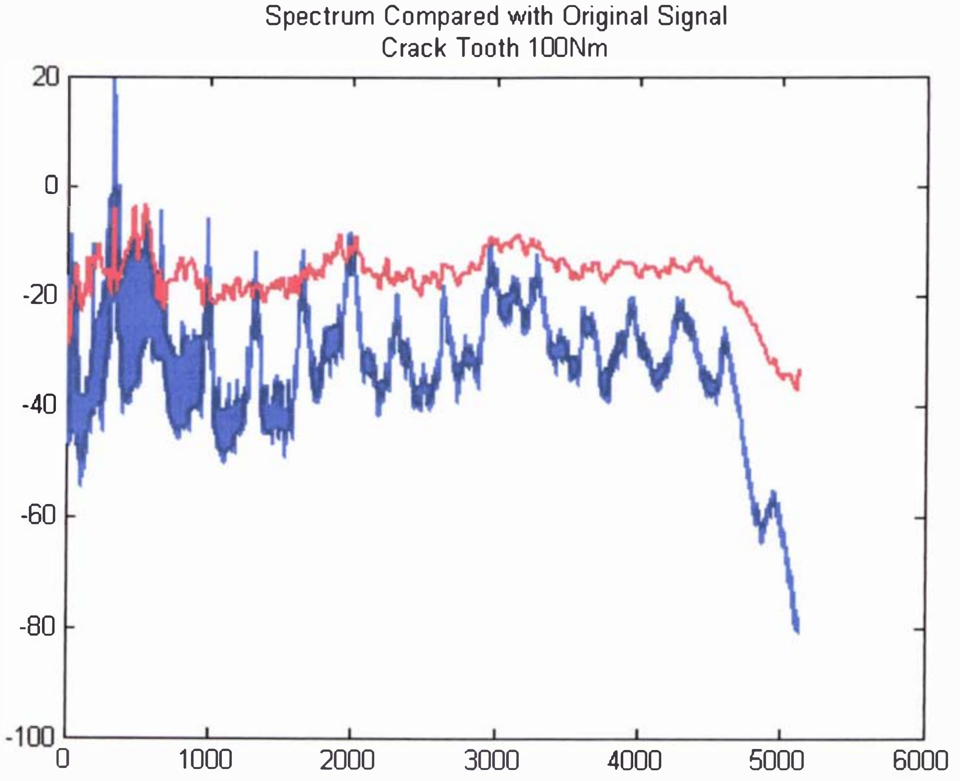

FRF Phase - 2nd Harmonic
Crack Tooth 50Nm
2
1
0
-1
-2
0
200
400
600
800
1000
1200

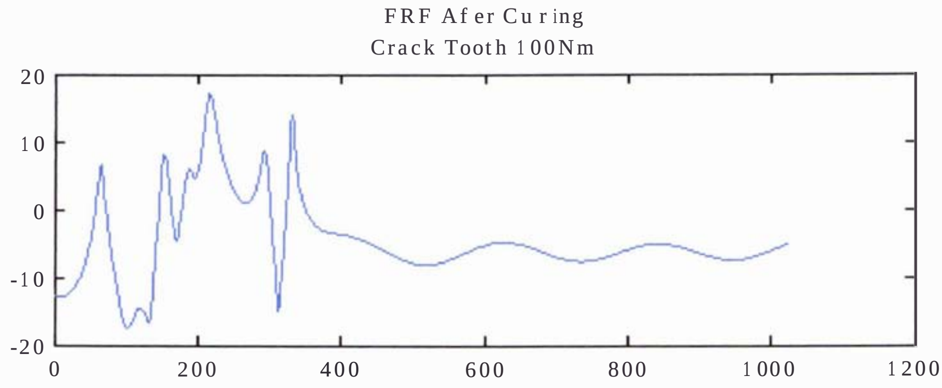

FRF Compared - 2nd Harmonic
Crack Tooth 50Nm
3
2
1
0
-1
-2
-3
0
200
400
600
800
1000
1200

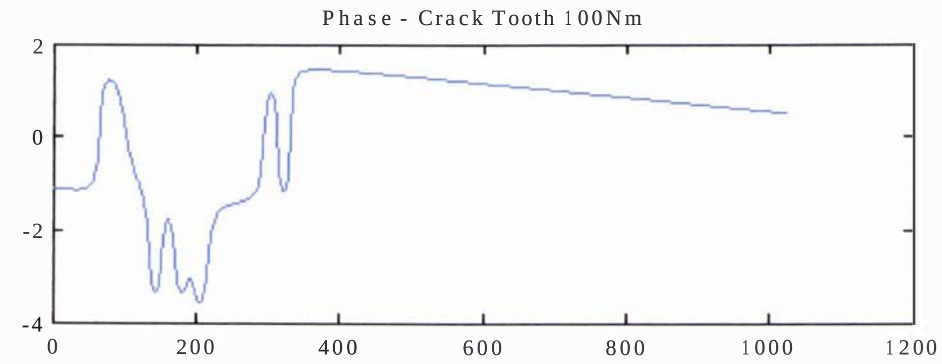

Power Spectra of the Separated Components
Crack Tooth 100Nm
Orig
Rand
Disc
dB
Frequency (Hz)

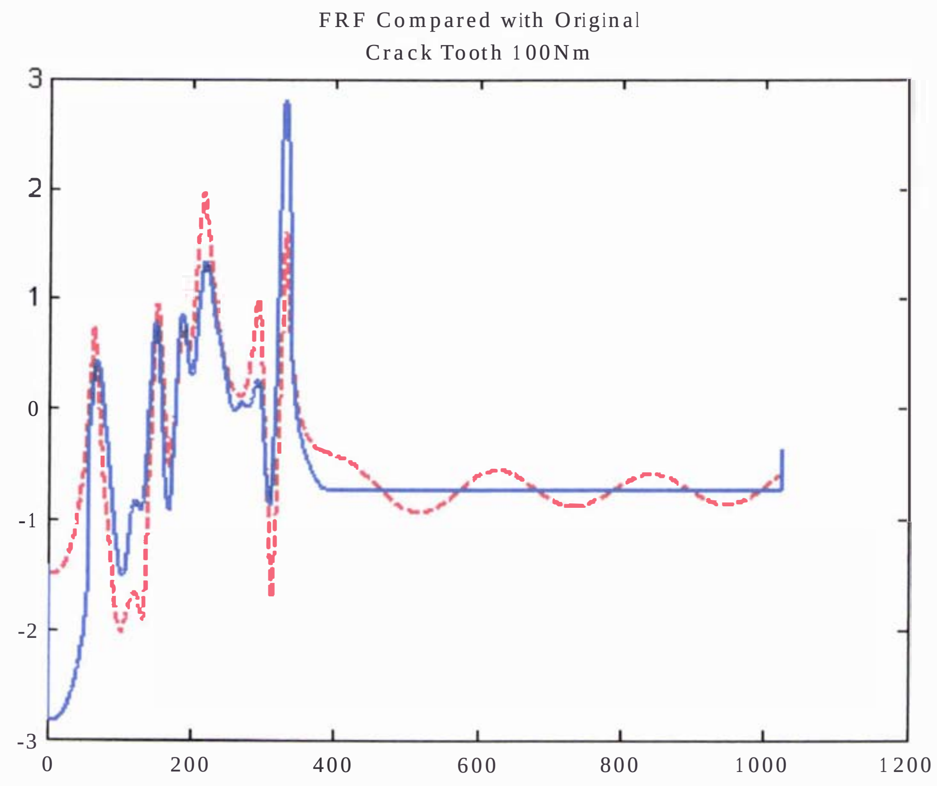

Cepstrum - Crack Tooth 100Nm

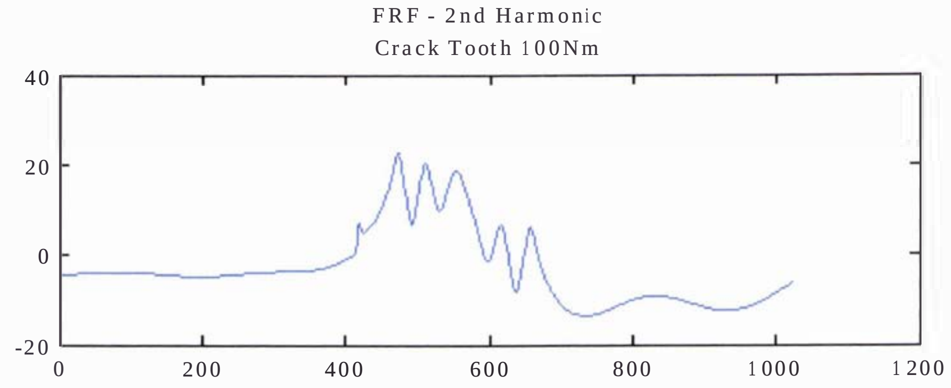

Smoothed Spectrum - Crack Tooth 100Nm
10^0
10^-1
10^-2
10^-3
10^-4
0
2000
4000
6000
8000
10000
12000

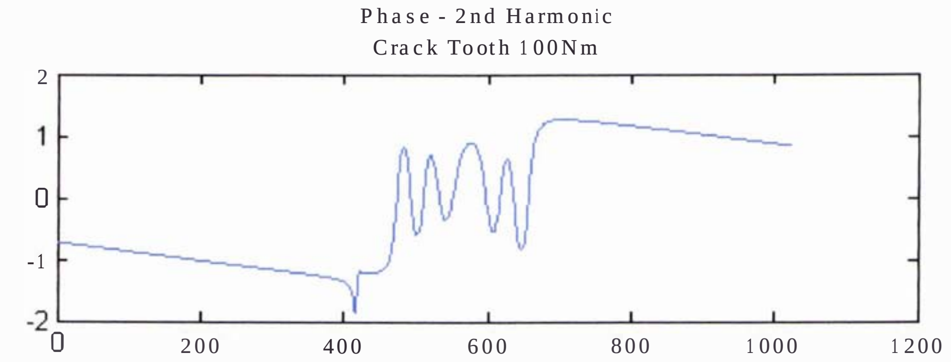

Spectrum Compared with Original Signal
Crack Tooth 100Nm
20
0
-20
-40
-60
-80
-100
0
1000
2000
3000
4000
5000
6000

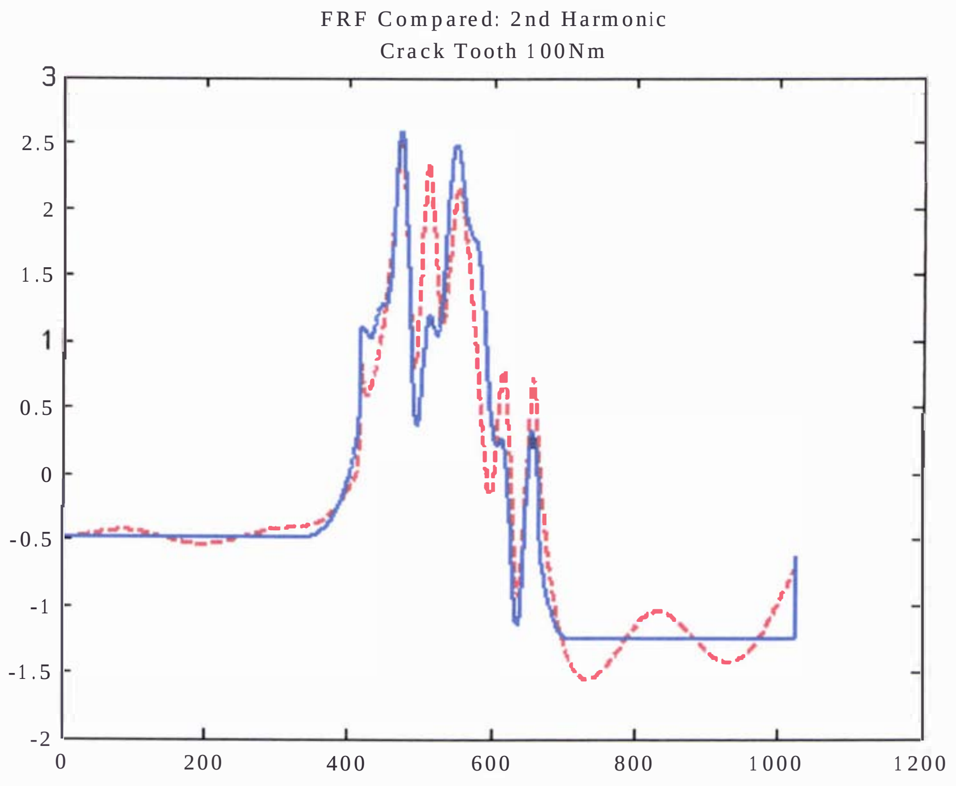

FRF Afer Curing
Crack Tooth 100Nm
20
10
0
-10
-20
0
200
400
600
800
1000
1200

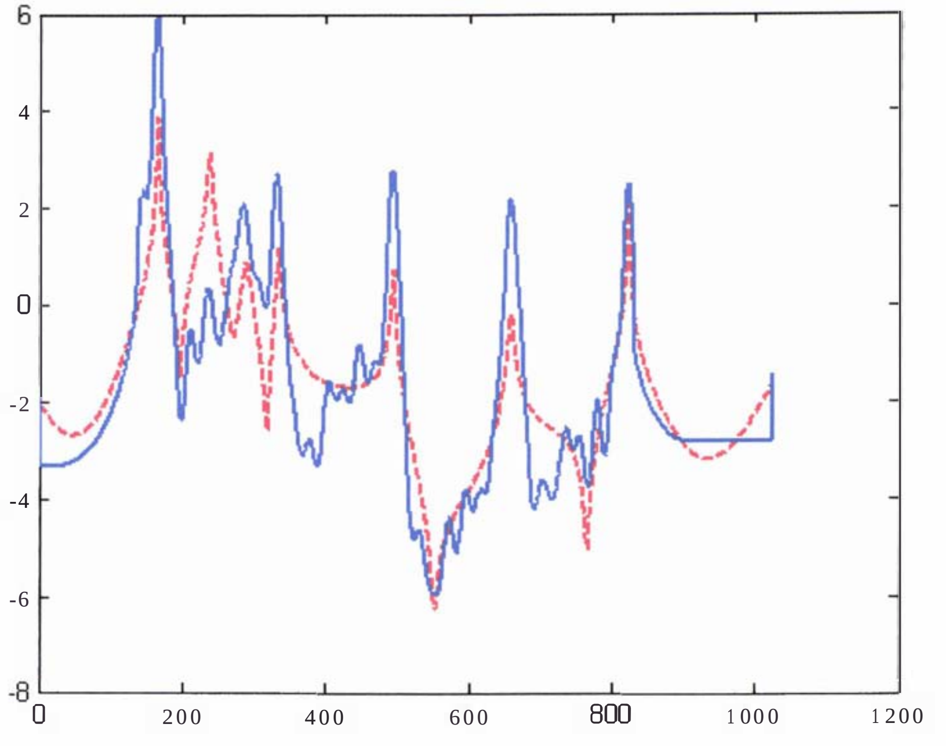

Phase - Crack Tooth 100Nm
2
0
-2
-4
0
200
400
600
800
1000
1200

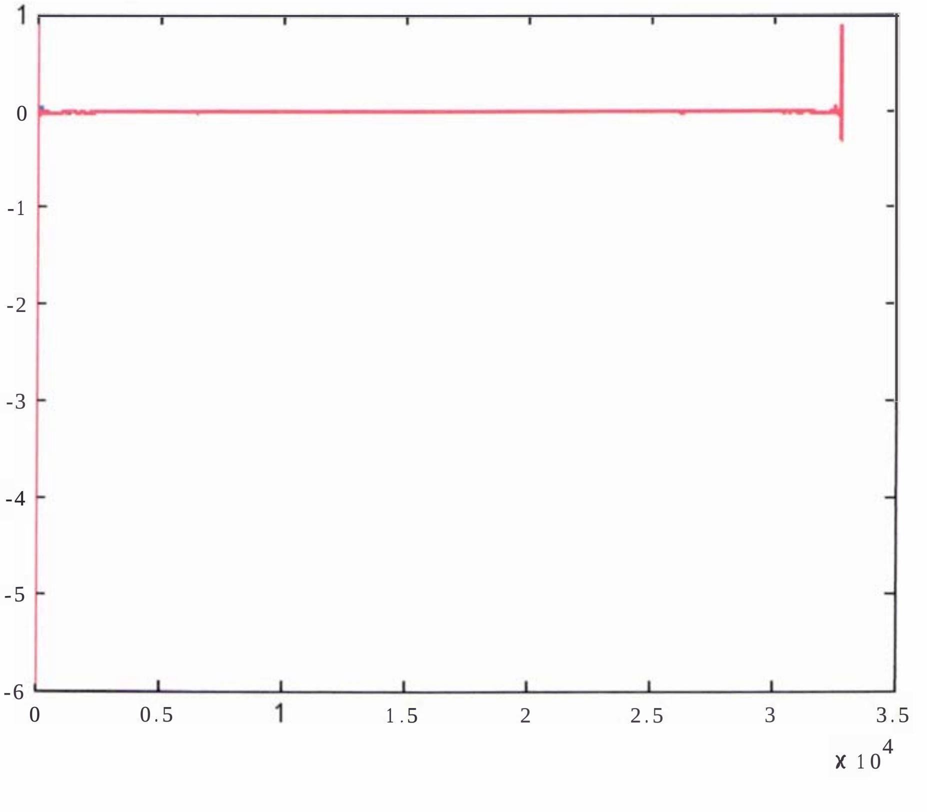

FRF Compared with Original
Crack Tooth 100Nm
3
2
1
0
-1
-2
-3
0
200
400
600
800
1000
1200

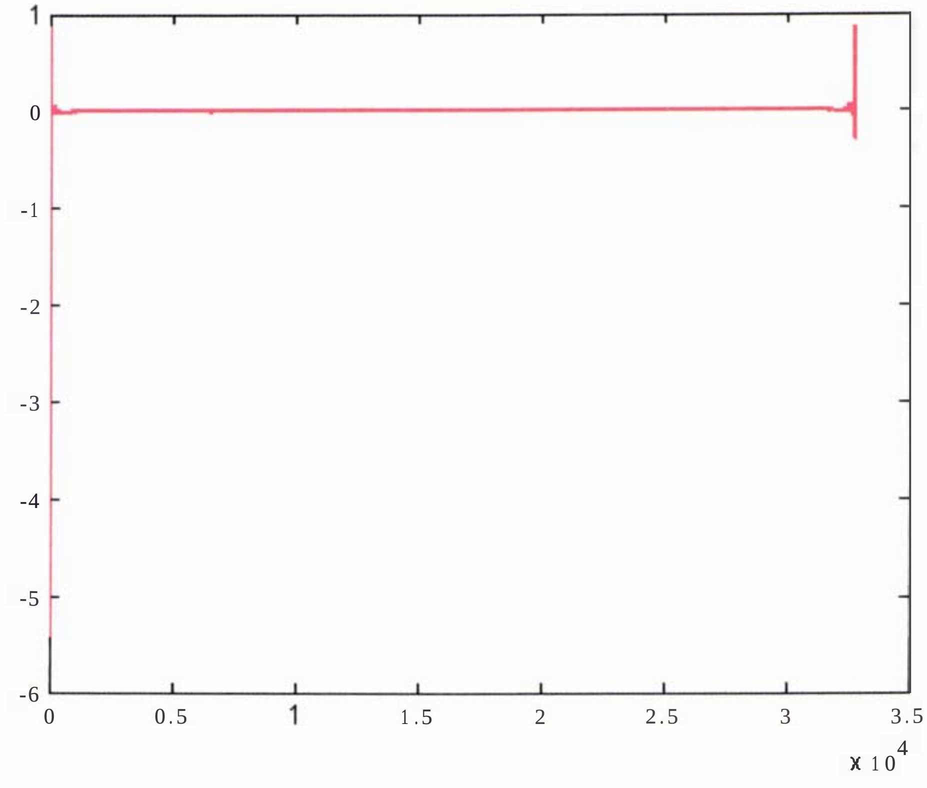

FRF - 2nd Harmonic
Crack Tooth 100Nm
40
20
0
-20
0
200
400
600
800
1000
1200

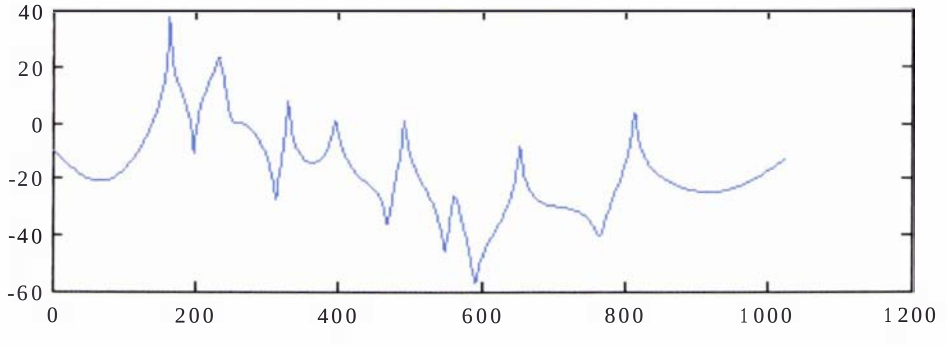

Phase - 2nd Harmonic
Crack Tooth 100Nm
2
1
0
-1
-2
0
200
400
600
800
1000
1200

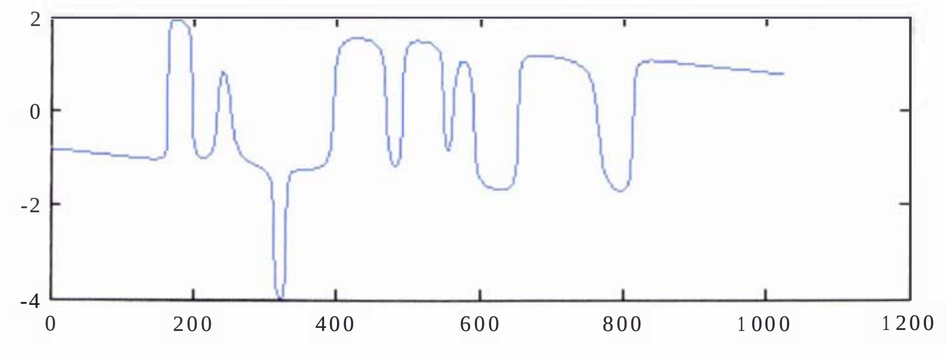

FRF Compared: 2nd Harmonic
Crack Tooth 100Nm
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
200
400
600
800
1000
1200

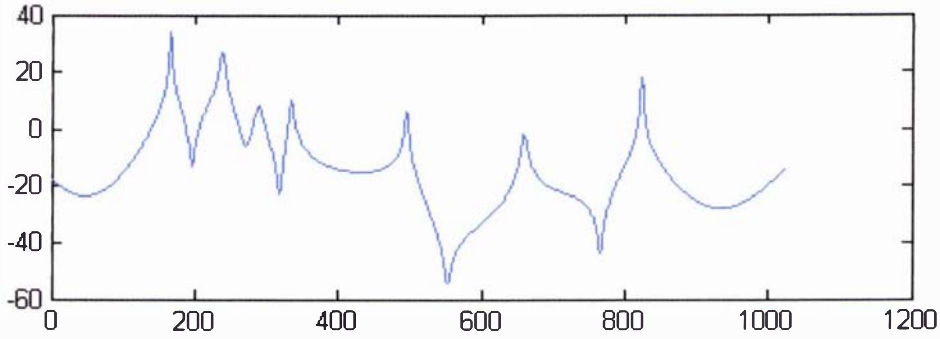

6
4
2
0
-2
-4
-6
-8
0
200
400
600
800
1000
1200

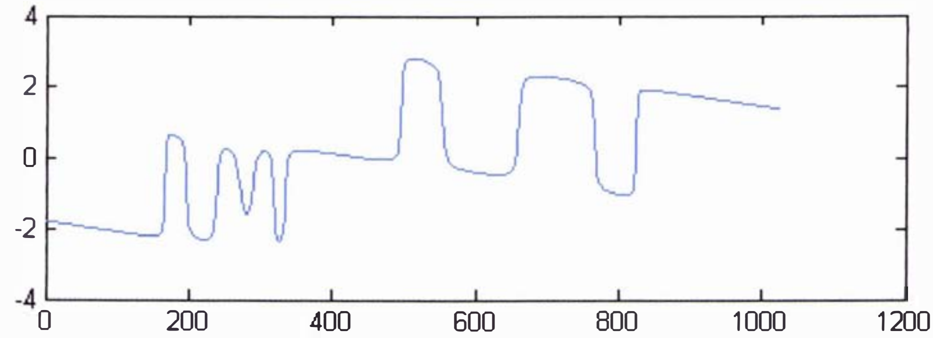

1
0
-1
-2
-3
-4
-5
-6
0
0.5
1
1.5
2
2.5
3
3.5
x 10^4

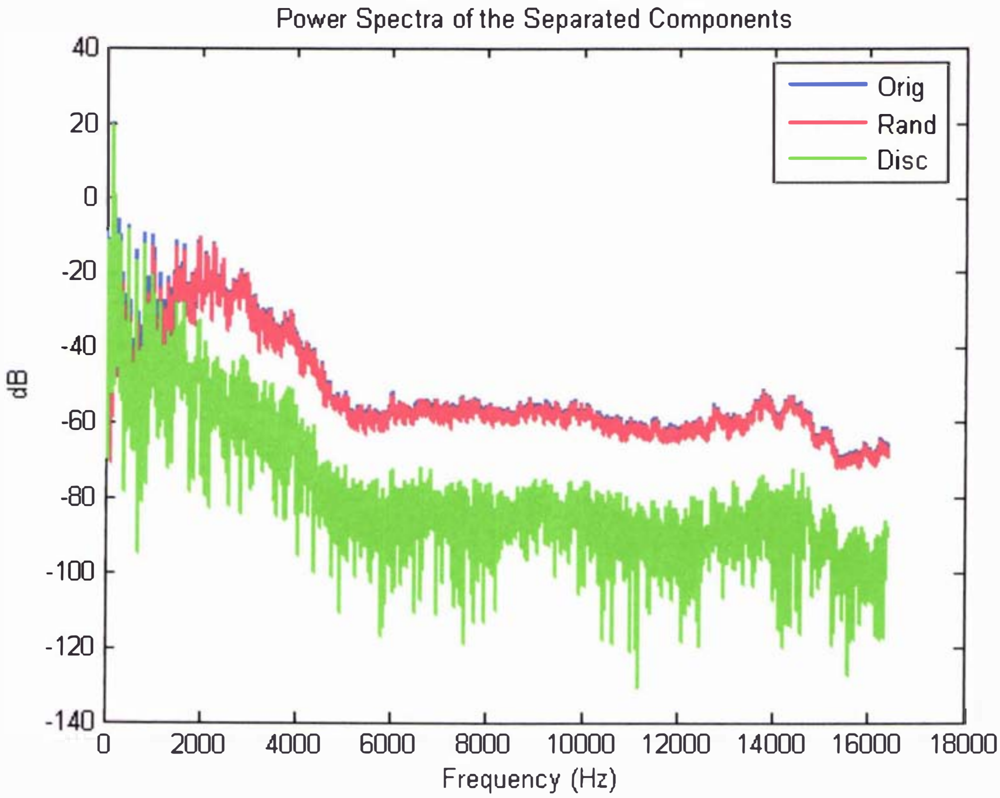

1
0
-1
-2
-3
-4
-5
-6
0
0.5
1
1.5
2
2.5
3
3.5
x 10^4

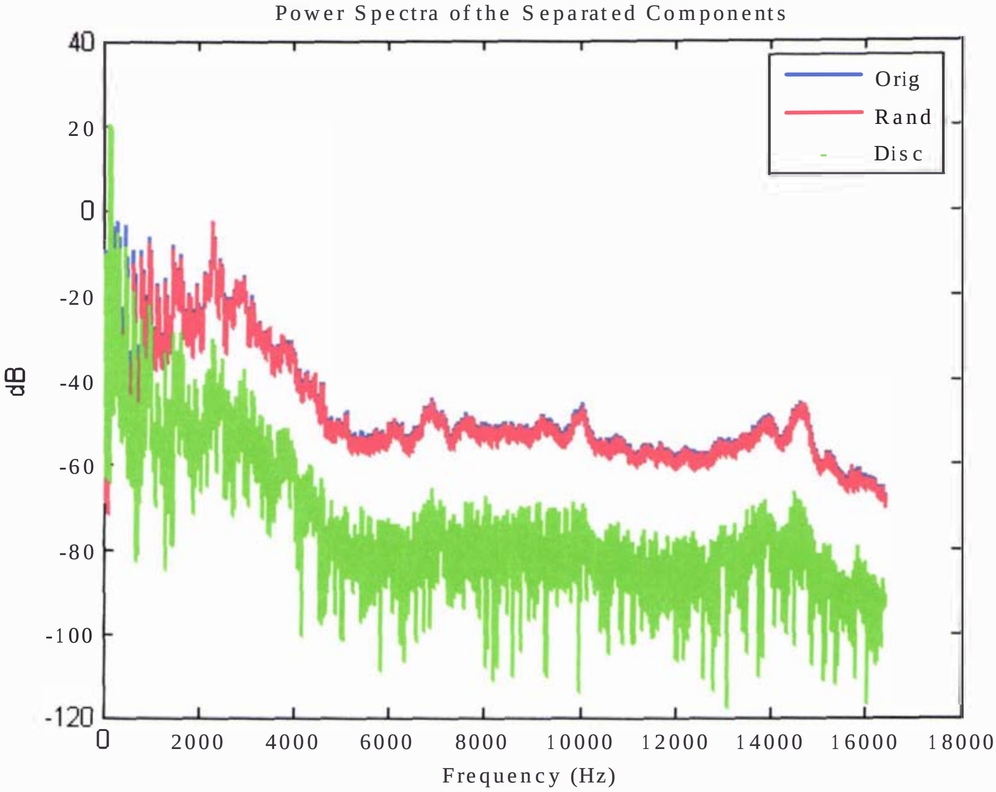

40
20
0
-20
-40
-60
0
200
400
600
800
1000
1200

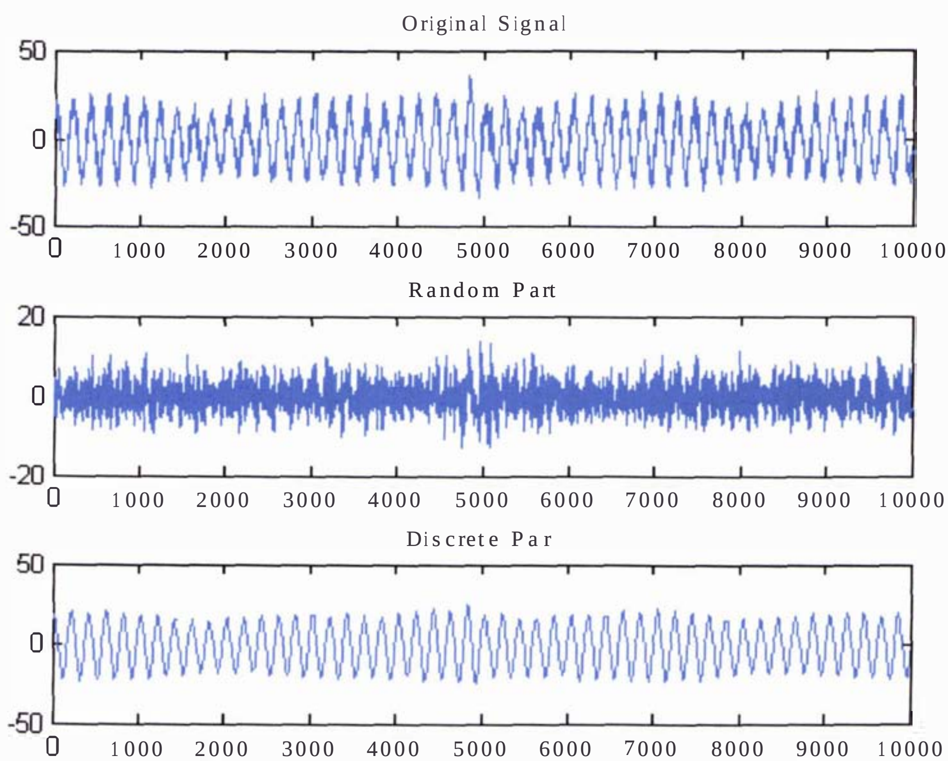

2
0
-2
-4
0
200
400
600
800
1000
1200

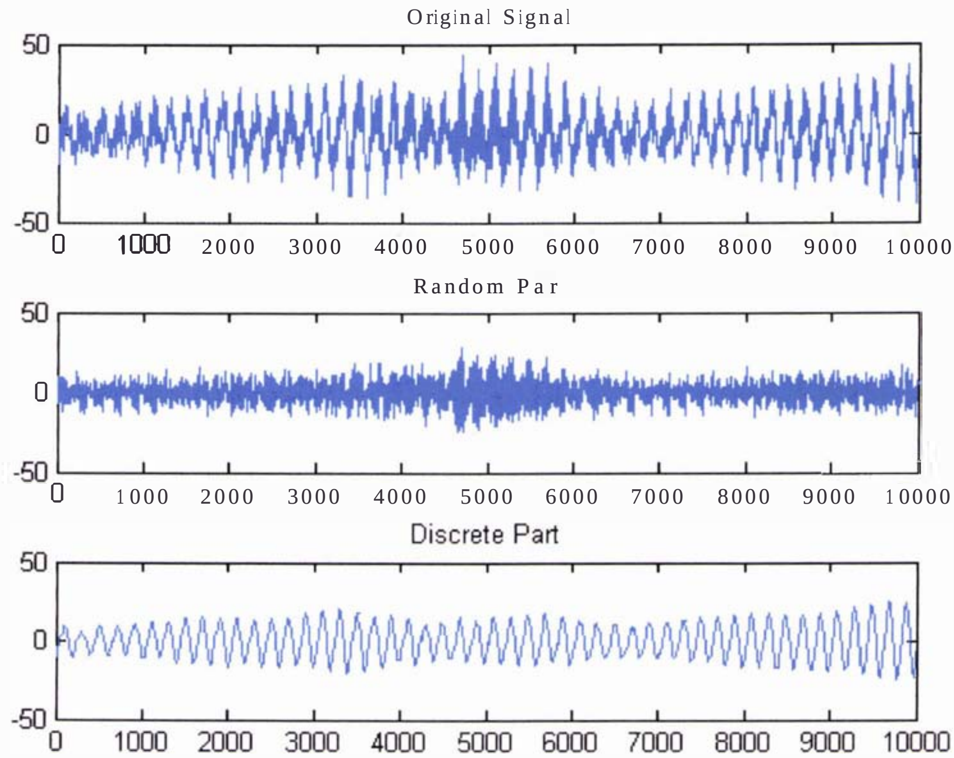

40
20
0
-20
-40
-60
0
200
400
600
800
1000
1200

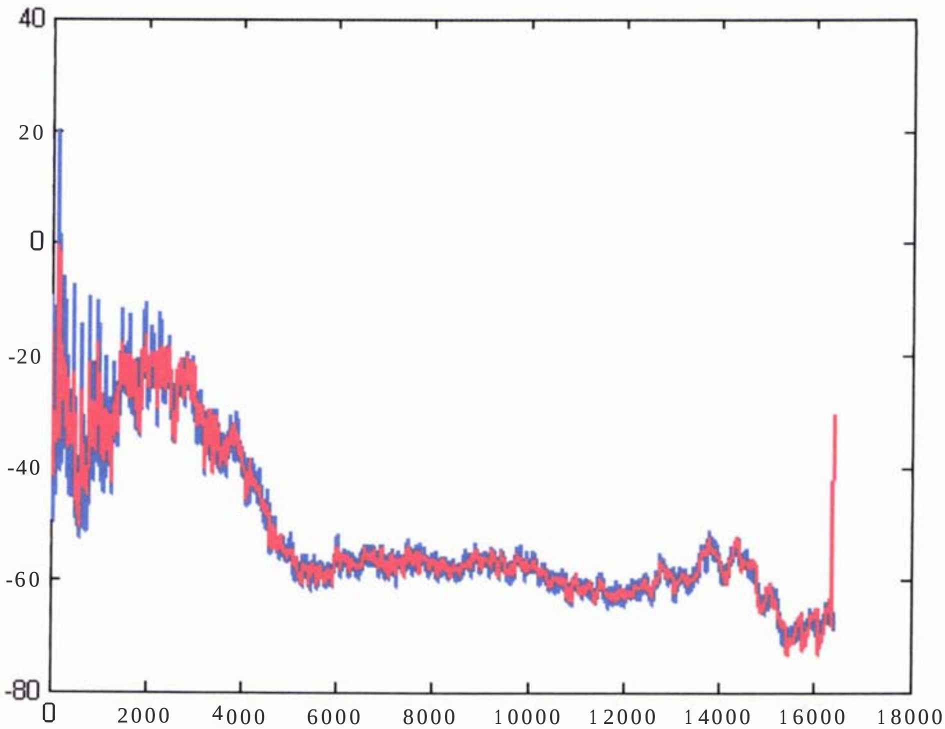

4
2
0
-2
-4
0
200
400
600
800
1000
1200

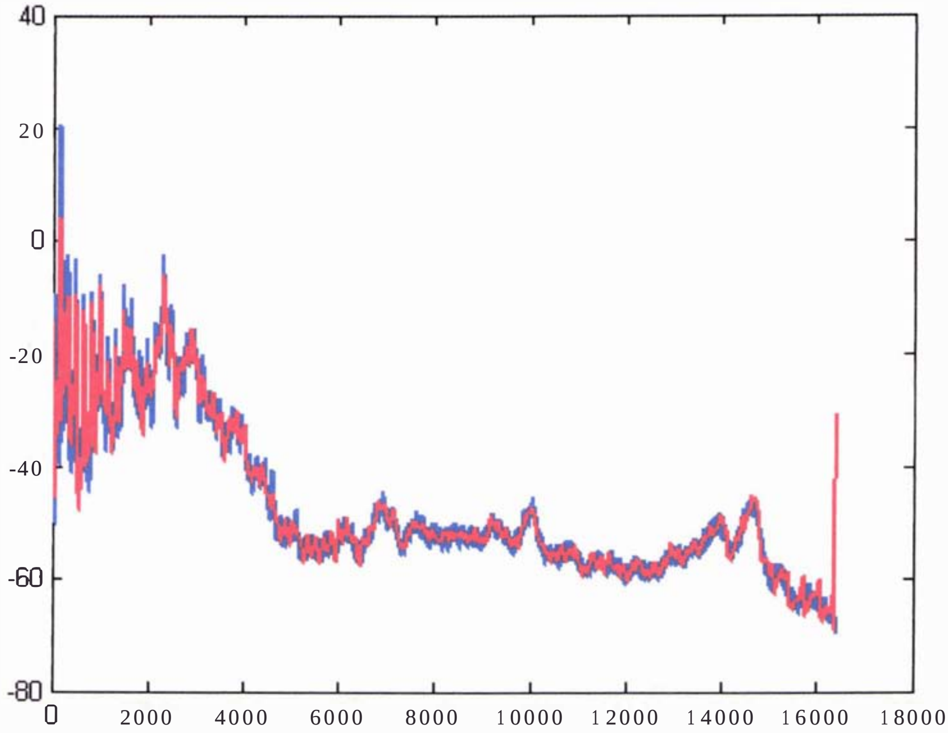

Power Spectra of the Separated Components
Orig
Rand
Disc
dB
40
20
0
-20
-40
-60
-80
-100
-120
-140
0
2000
4000
6000
8000
10000
12000
14000
16000
18000
Frequency (Hz)


Power Spectra of the Separated Components
Orig
Rand
Disc
dB
40
20
0
-20
-40
-60
-80
-100
-120
0
2000
4000
6000
8000
10000
12000
14000
16000
18000
Frequency (Hz)

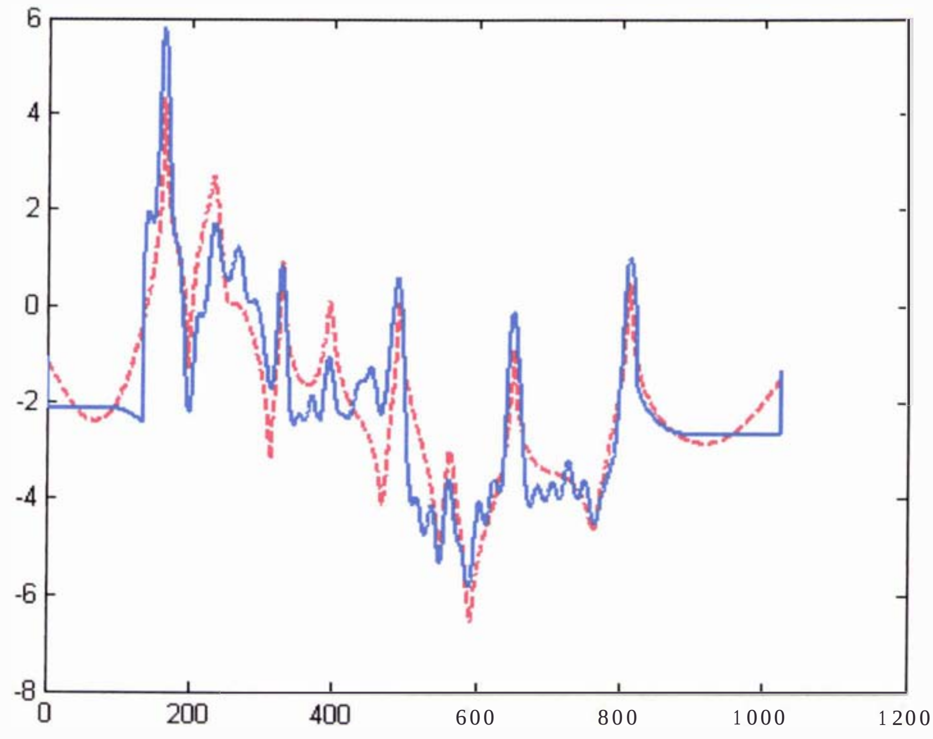

Original Signal
50
0
-50
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Random Part
20
0
-20
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Discrete Par
50
0
-50
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000


Original Signal
50
0
-50
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Random Par
50
0
-50
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Discrete Part
50
0
-50
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000

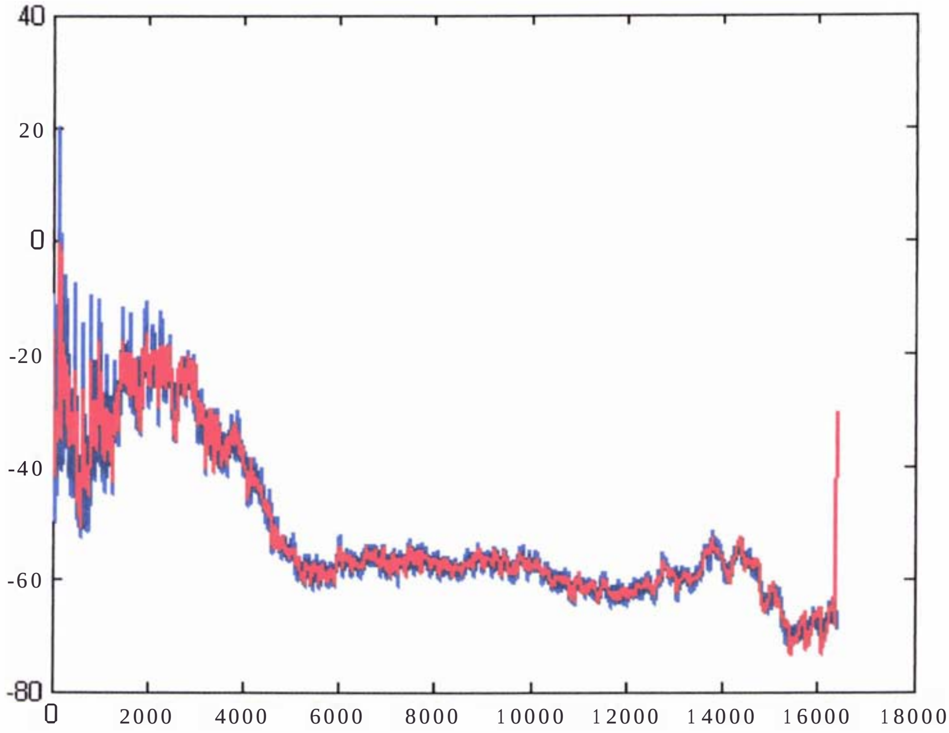

40
20
0
-20
-40
-60
-80
0
2000
4000
6000
8000
10000
12000
14000
16000
18000

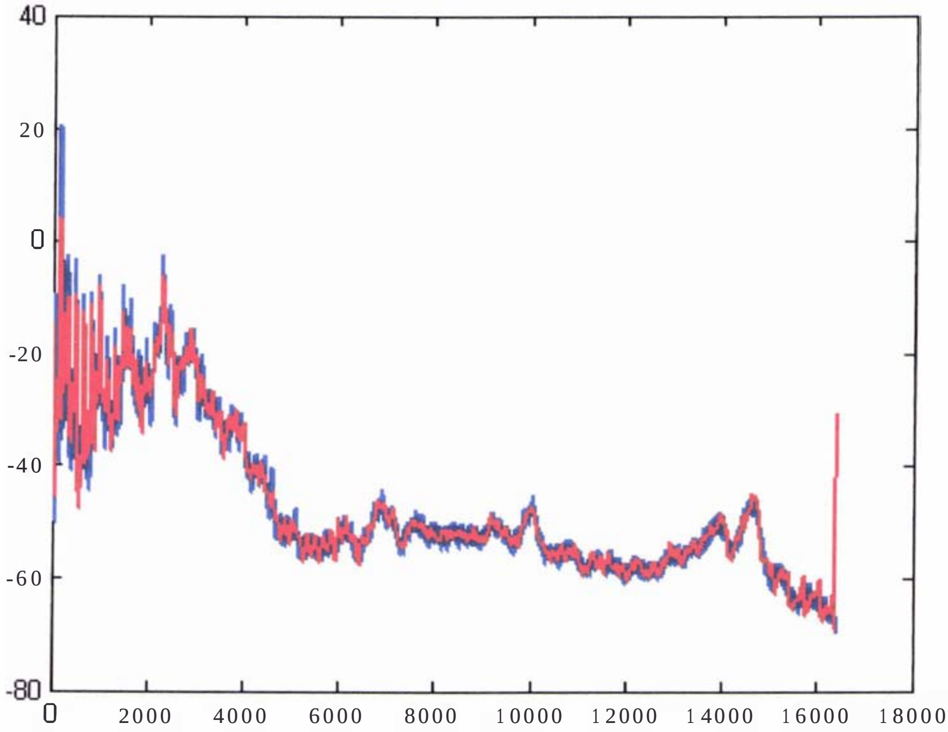


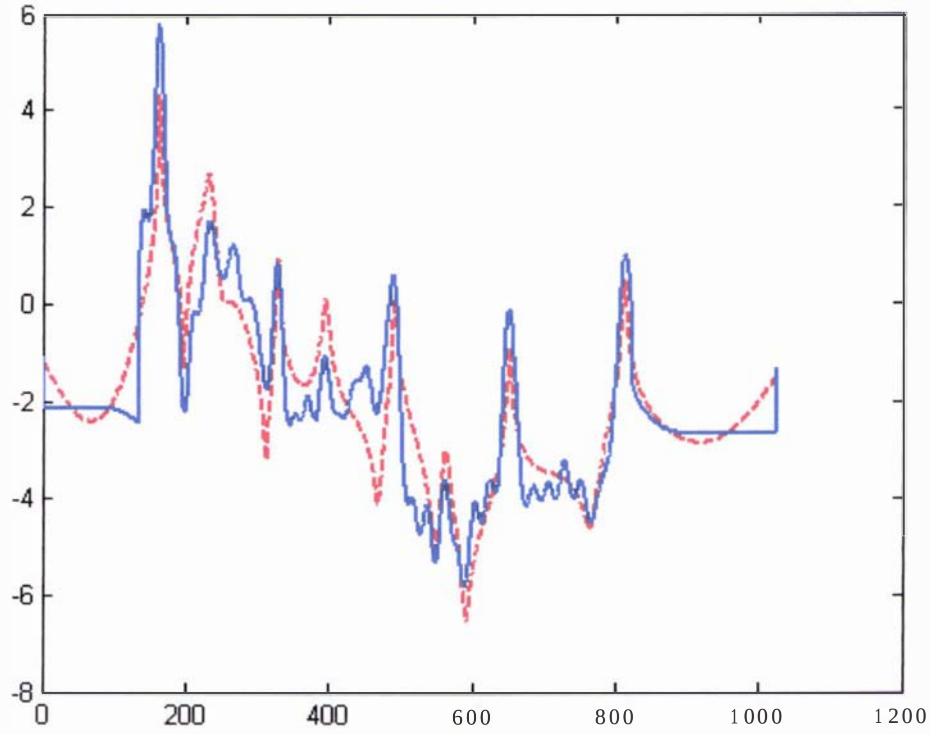
40
20
0
-20
-40
-60
-80
0
2000
4000
6000
8000
10000
12000
14000
16000
18000

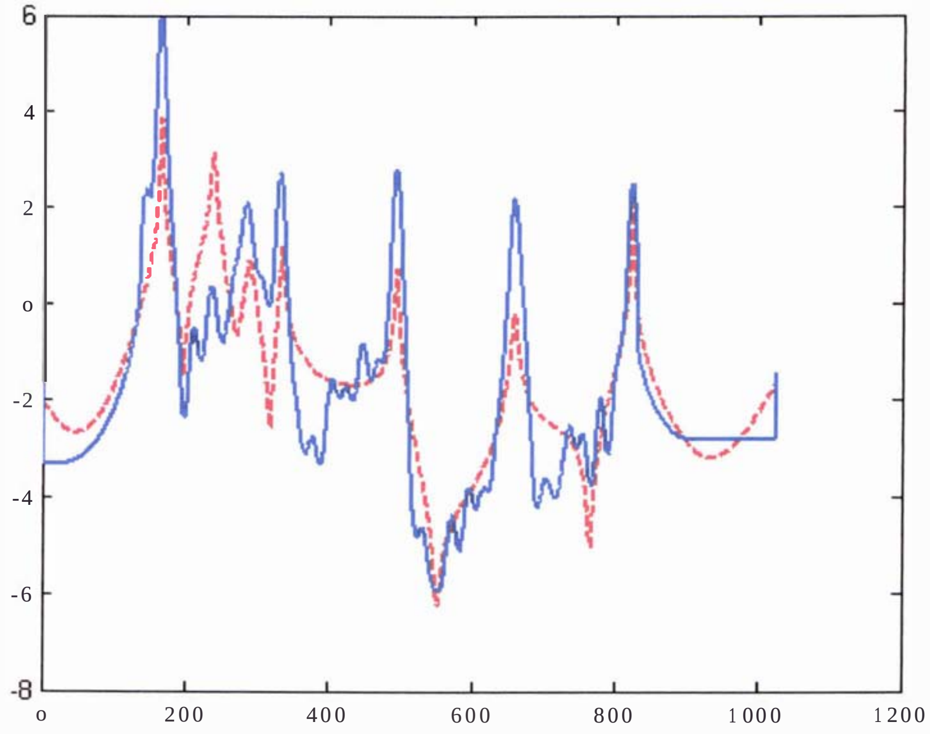


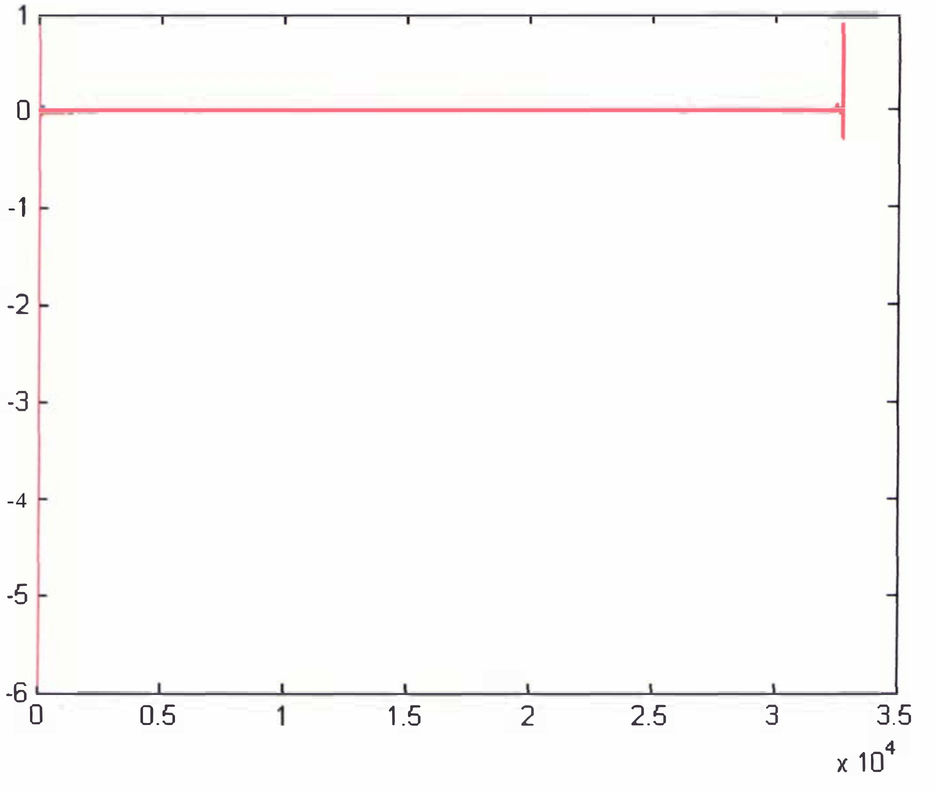
6
4
2
0
-2
-4
-6
-8
0
200
400
600
800
1000
1200


40
20
0
-20
-40
-60
-80
0
2000
4000
6000
8000
10000
12000
14000
16000
18000

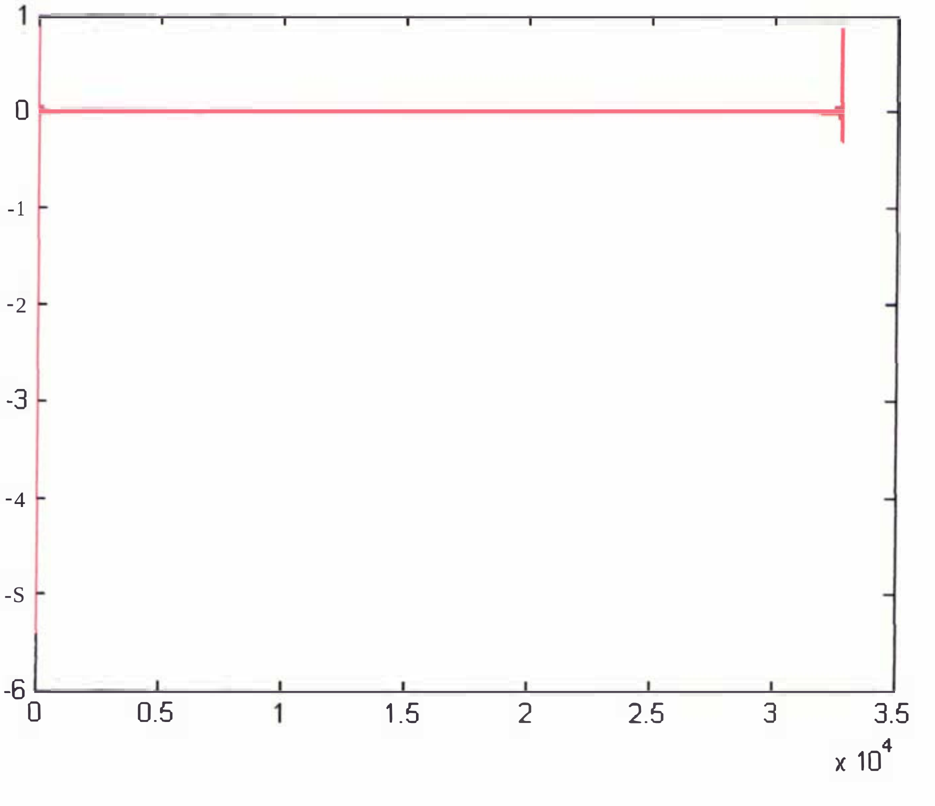

40
20
0
-20
-40
-60
-80
0
2000
4000
6000
8000
10000
12000
14000
16000
18000

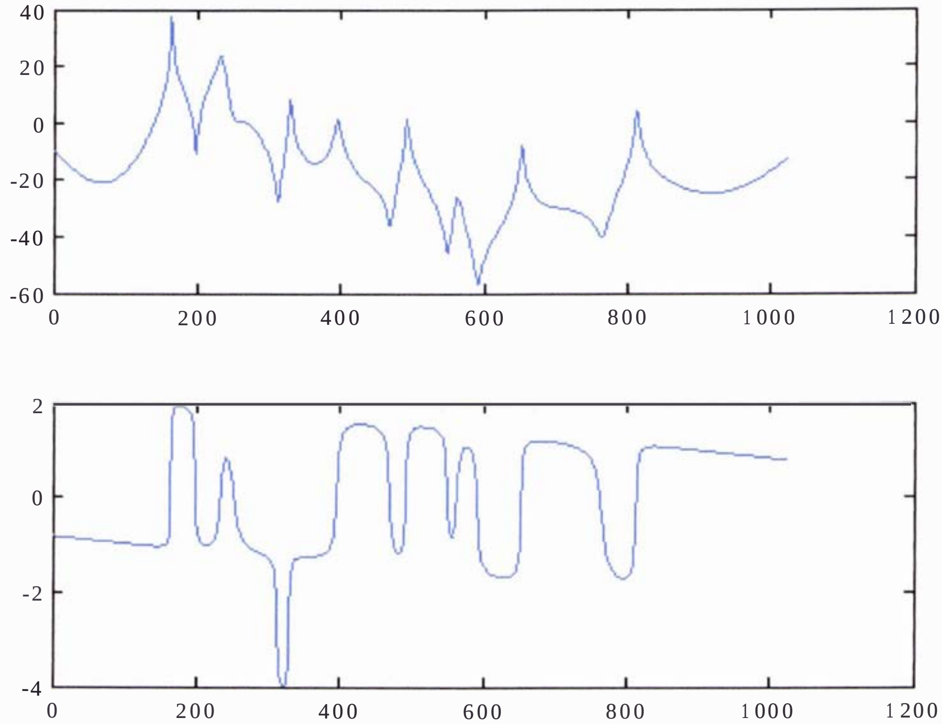

6
4
2
0
-2
-4
-6
-8
0
200
400
600
800
1000
1200


6
4
2
o
-2
-4
-6
-8
o
200
400
600
800
1000
1200

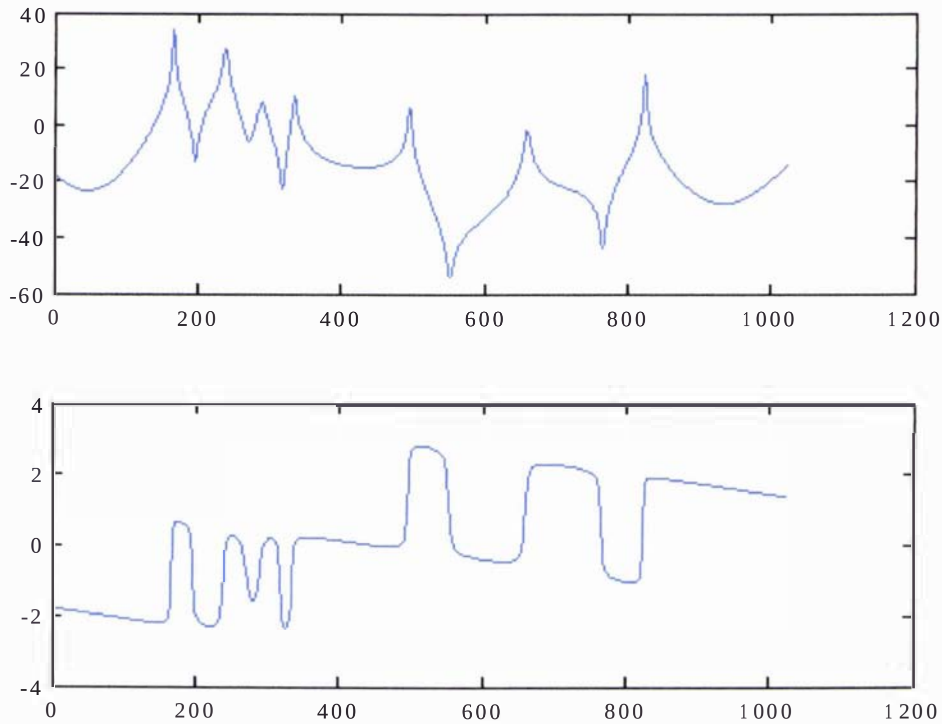


Cepstrum 5&100Nm

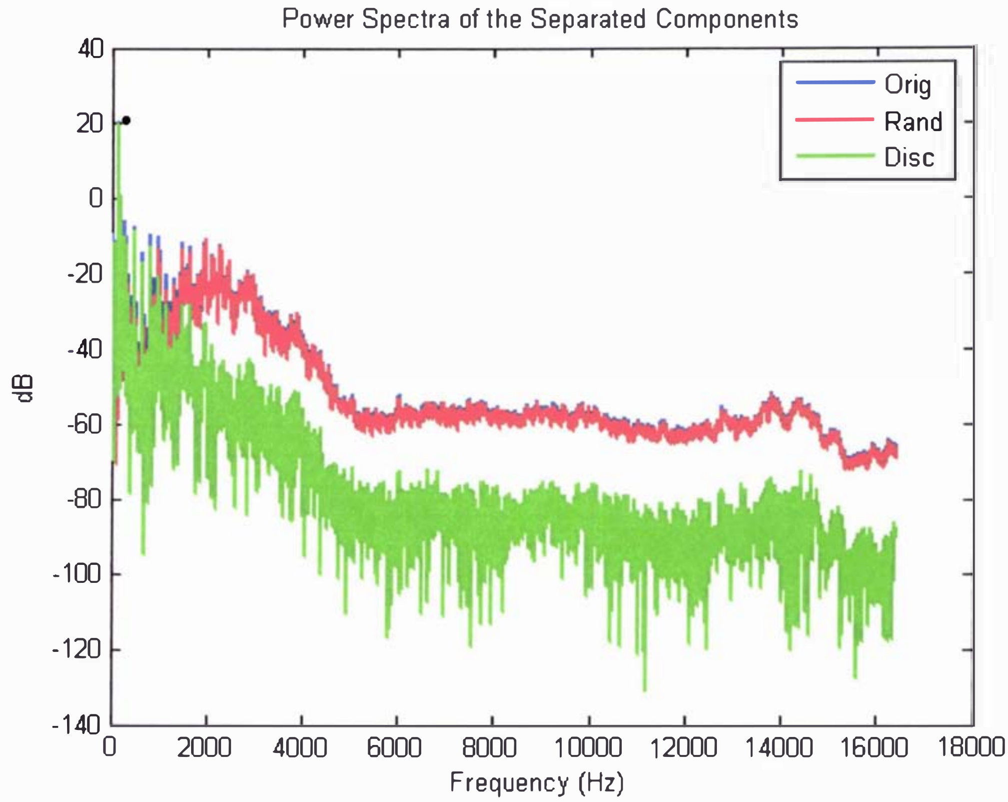




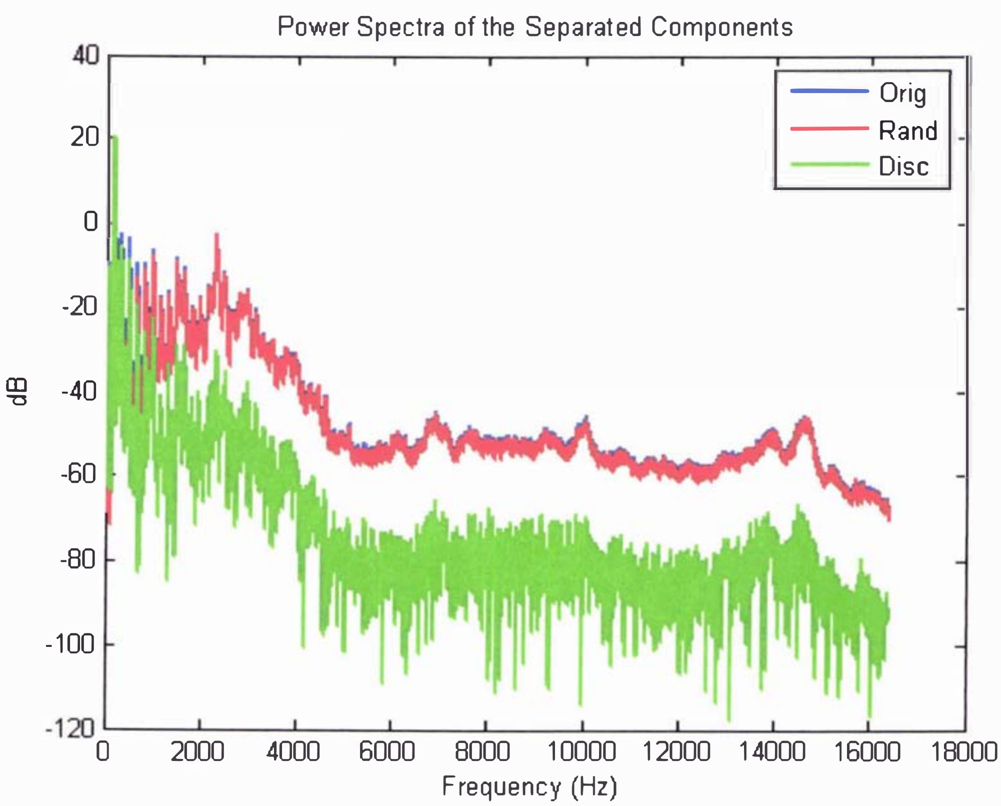
50Nm



FRF 100Nm

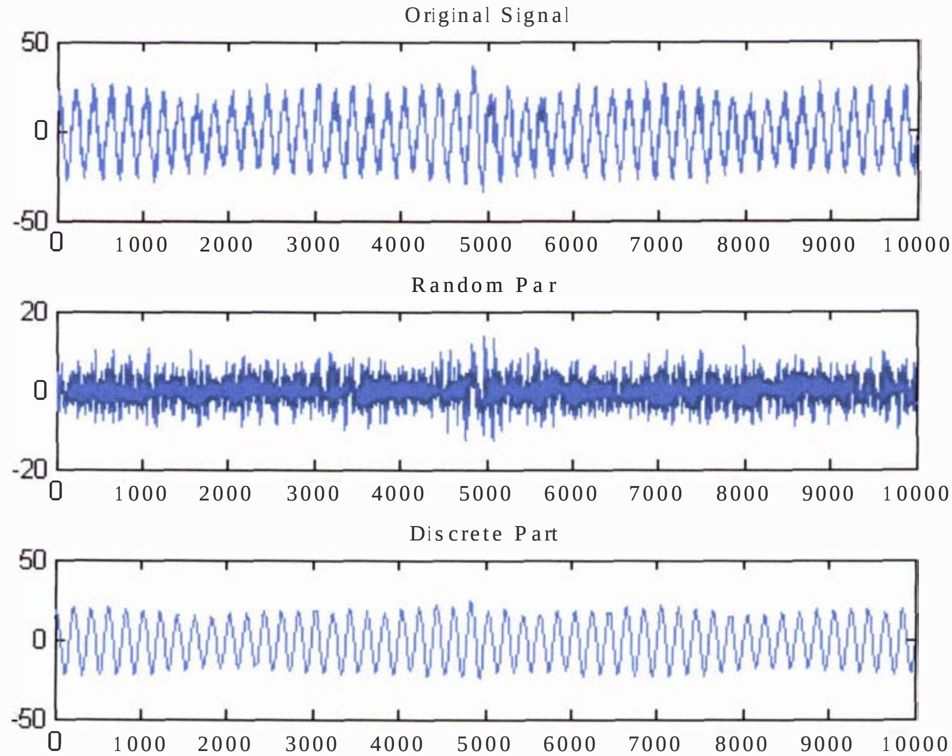


Power spectrum 50Nm

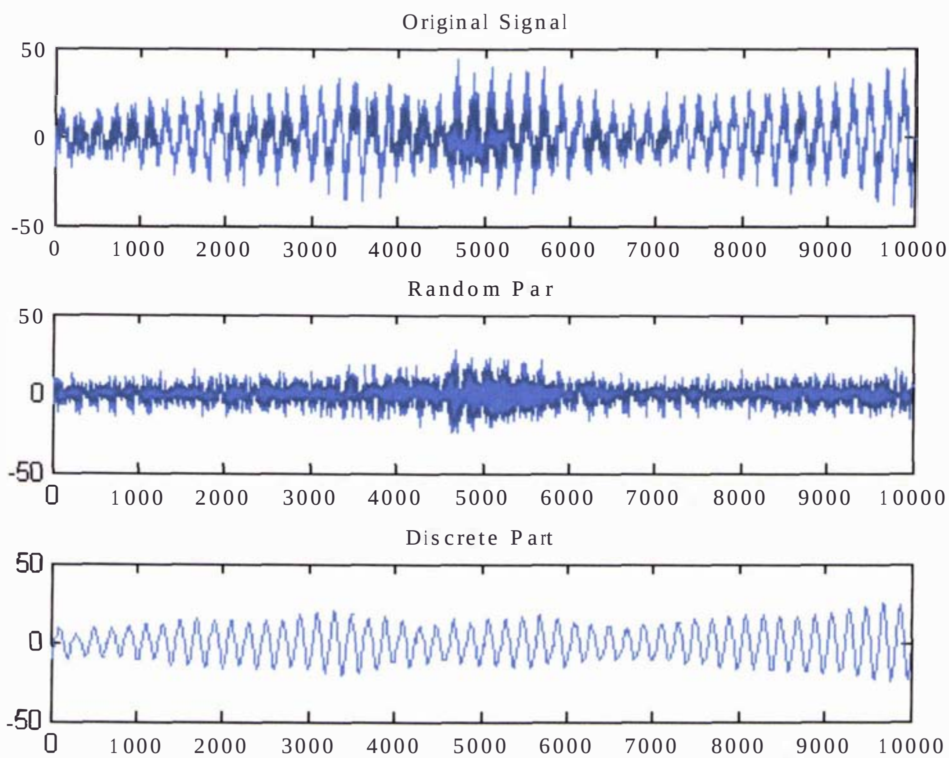


100Nm

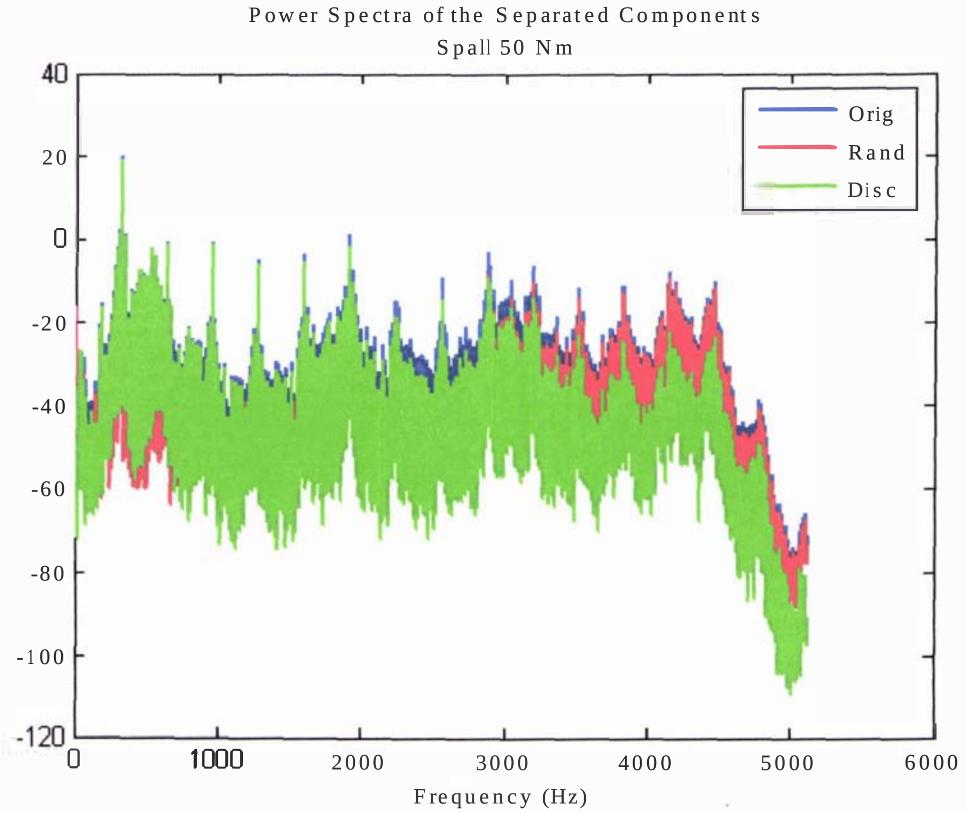
Raw Signal 50Nm

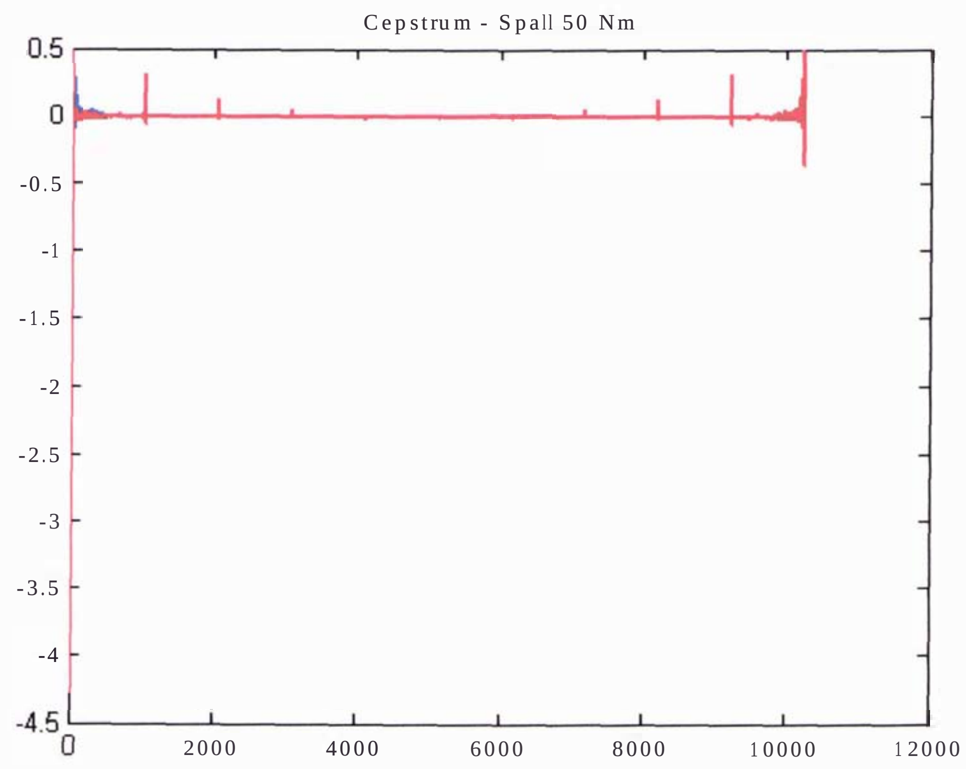


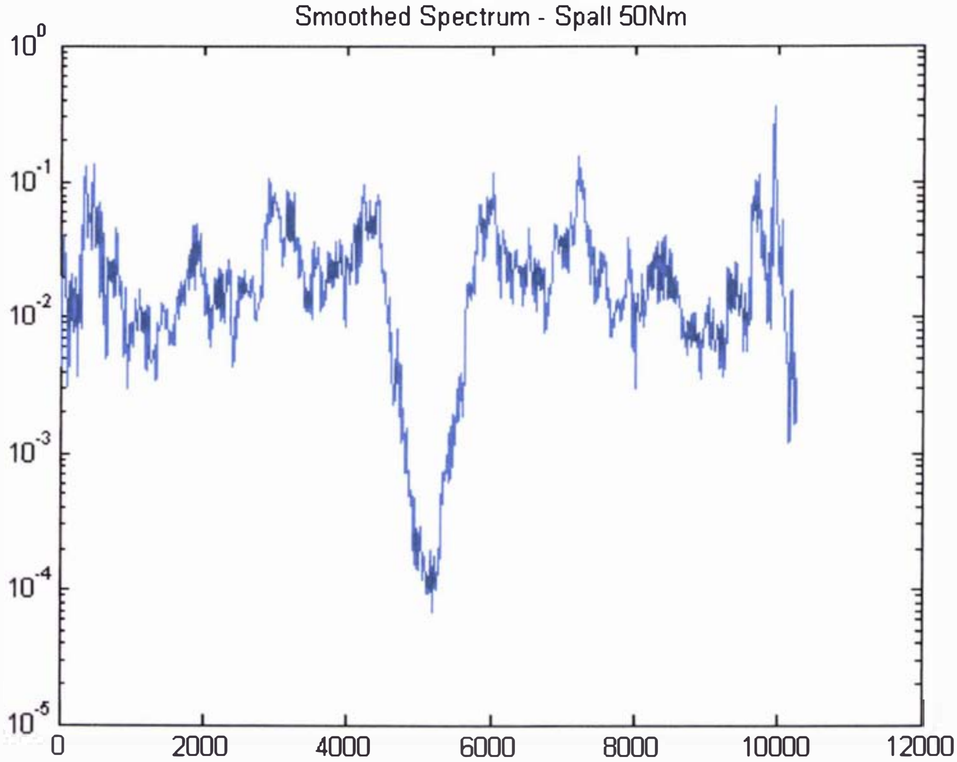
100Nm

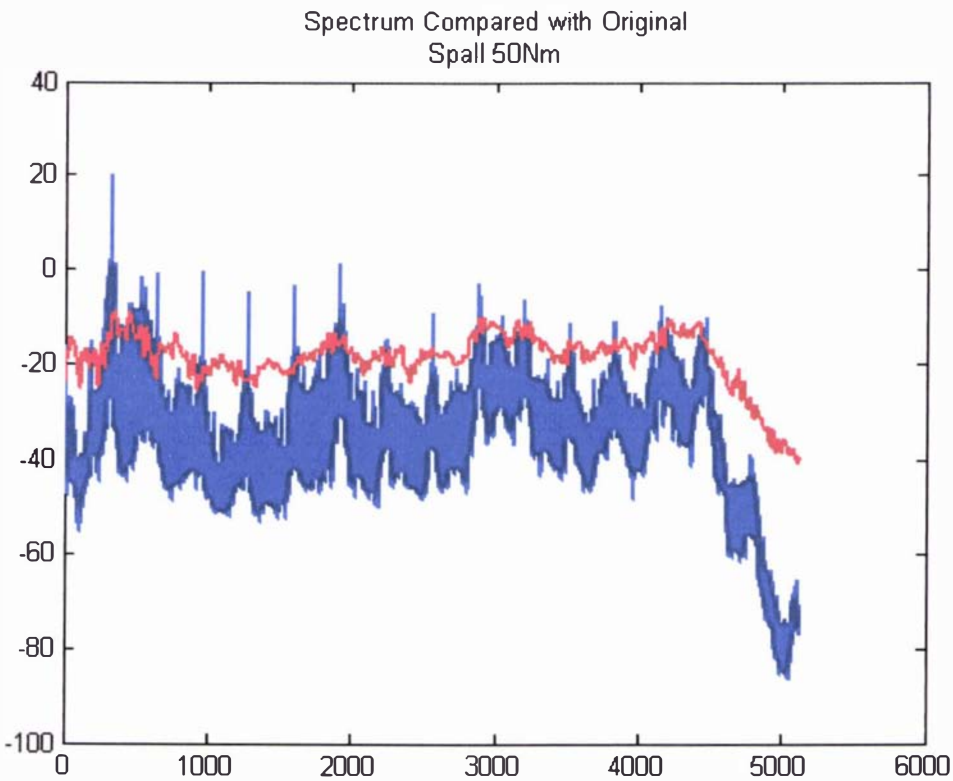


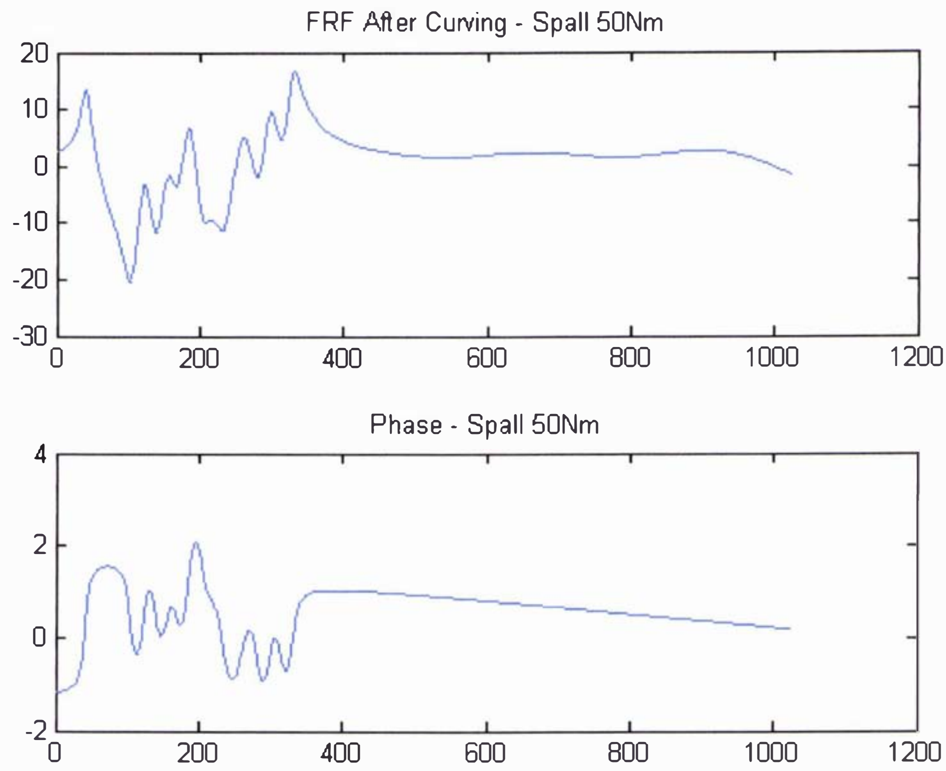
Spall 50Nm

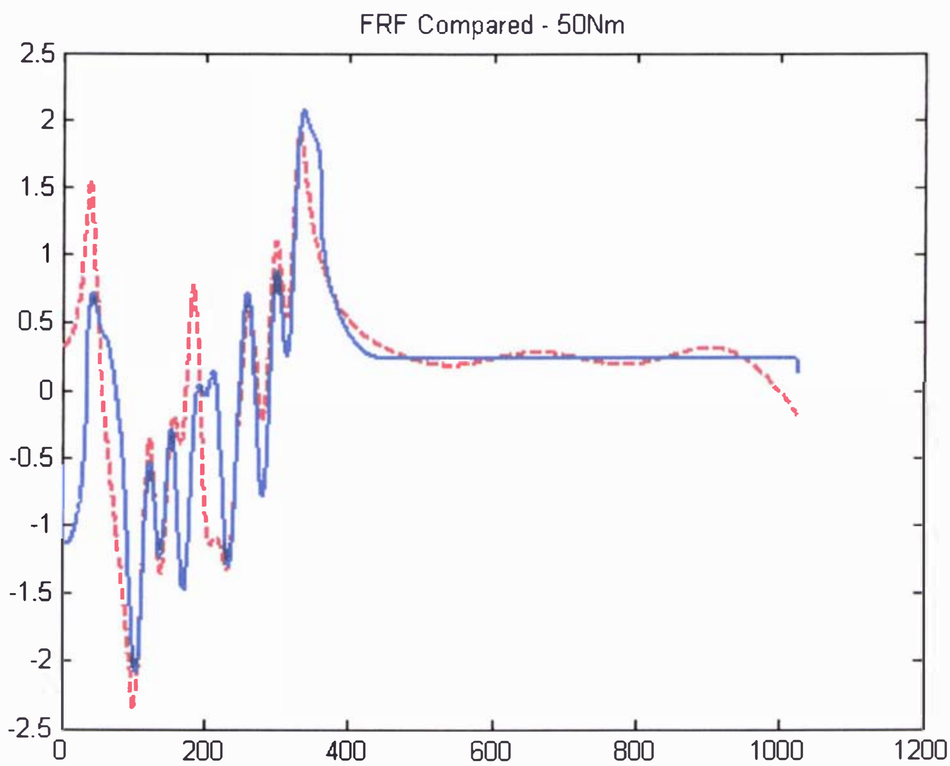

Power Spectra of the Separated Components
Spall 50 Nm
Orig
Rand
Disc
40
20
0
-20
-40
-60
-80
-100
-120
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)

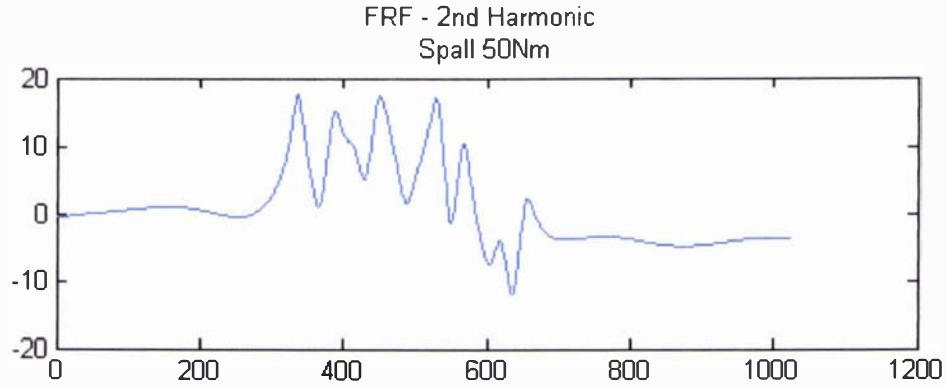

Cepstrum - Spall 50 Nm
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
0
2000
4000
6000
8000
10000
12000

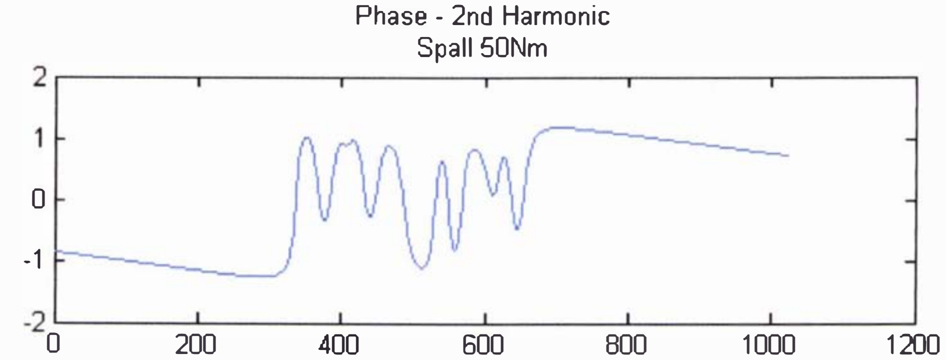

Smoothed Spectrum - Spall 50Nm
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
0
2000
4000
6000
8000
10000
12000

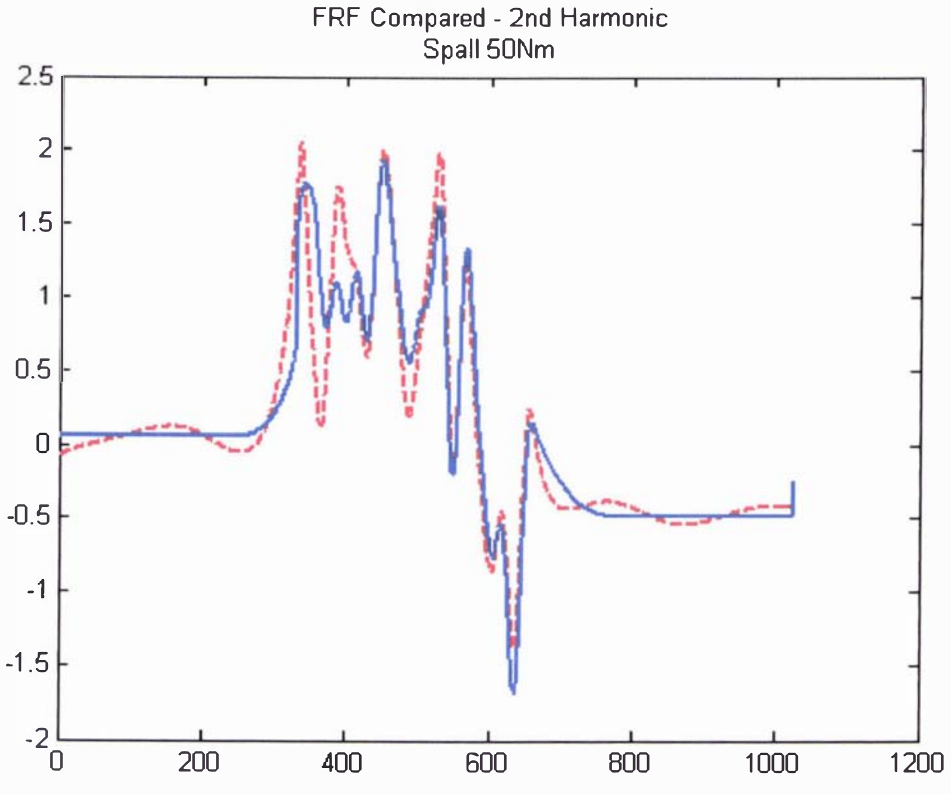

Spectrum Compared with Original
Spall 50Nm
40
20
0
-20
-40
-60
-80
-100
0
1000
2000
3000
4000
5000
6000


FRF After Curving - Spall 50Nm
Phase - Spall 50Nm

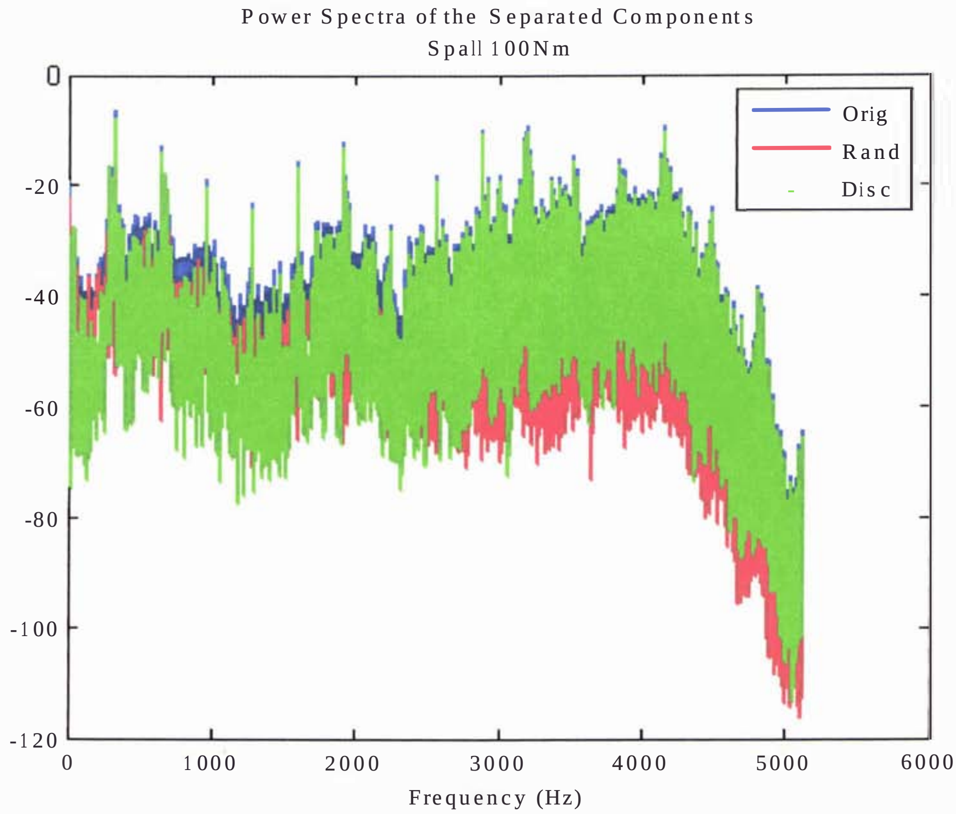

FRF Compared - 50Nm


FRF - 2nd Harmonic
Spall 50Nm
20
10
0
-10
-20
0
200
400
600
800
1000
1200

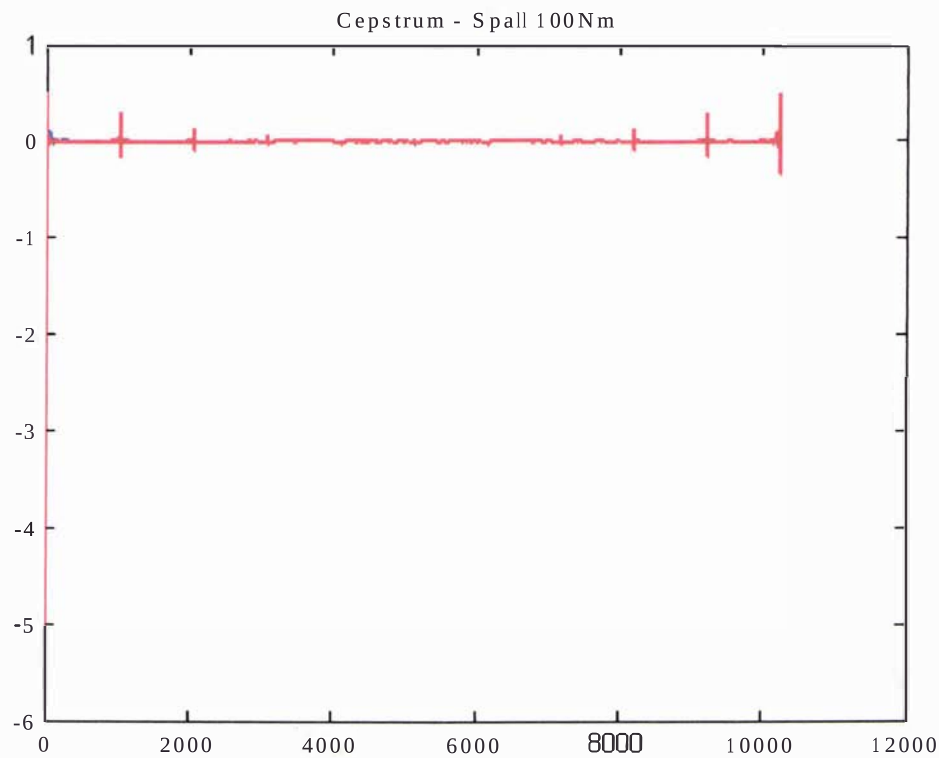

Phase - 2nd Harmonic
Spall 50Nm
2
1
0
-1
-2
0
200
400
600
800
1000
1200


FRF Compared - 2nd Harmonic
Spall 50Nm
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
200
400
600
800
1000
1200

100Nm

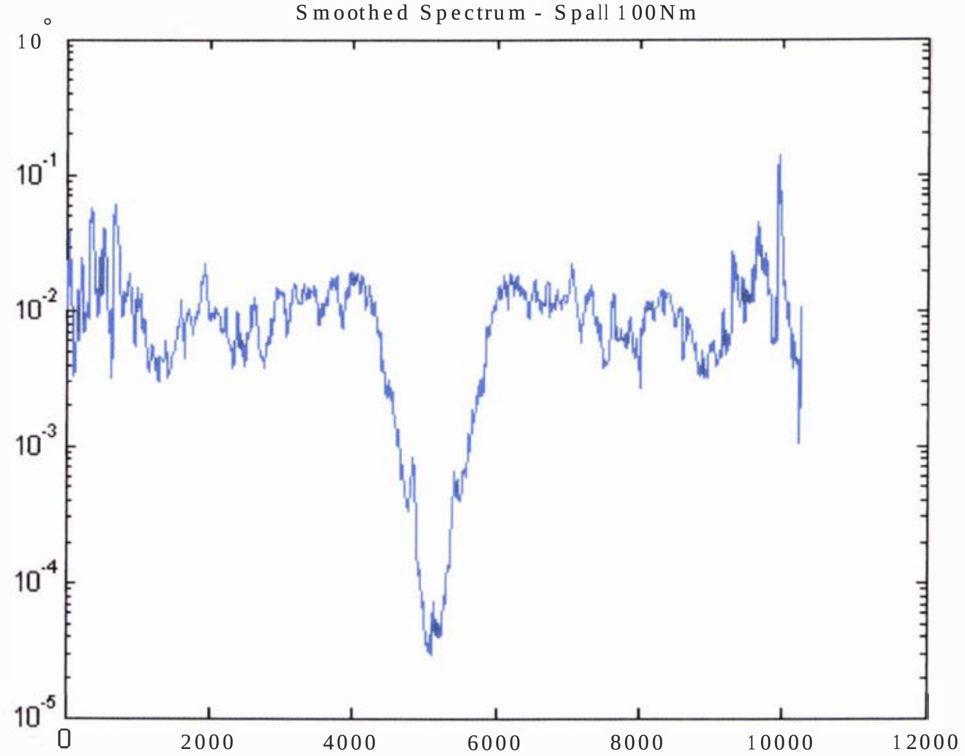


Power Spectra of the Separated Components
Spall 100Nm
Orig
Rand
Disc
0
-20
-40
-60
-80
-100
-120
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)

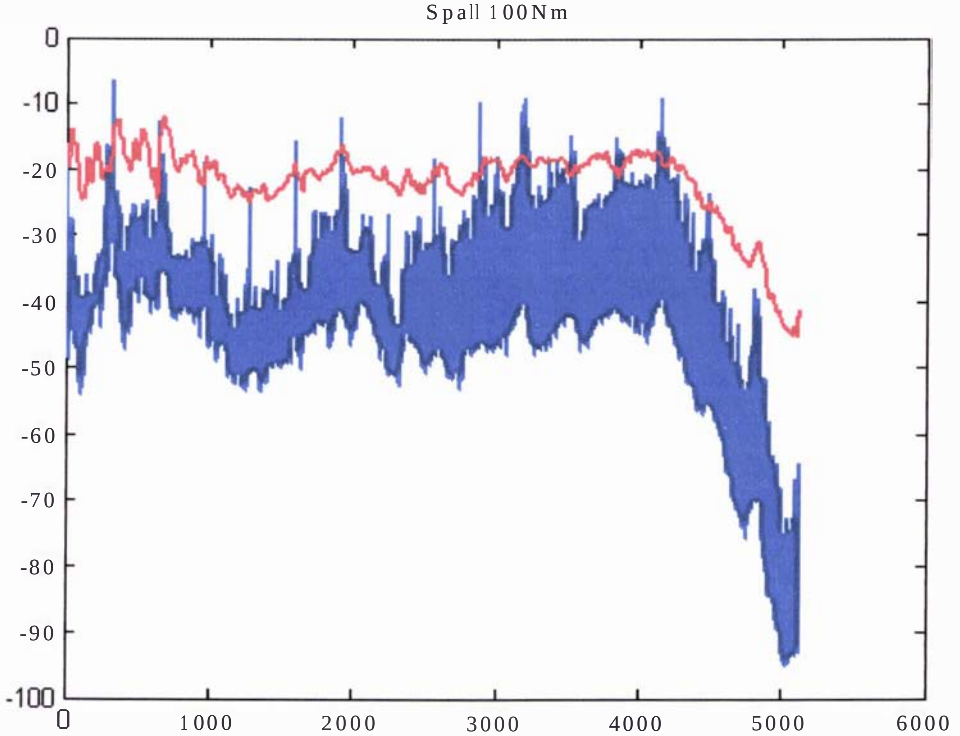


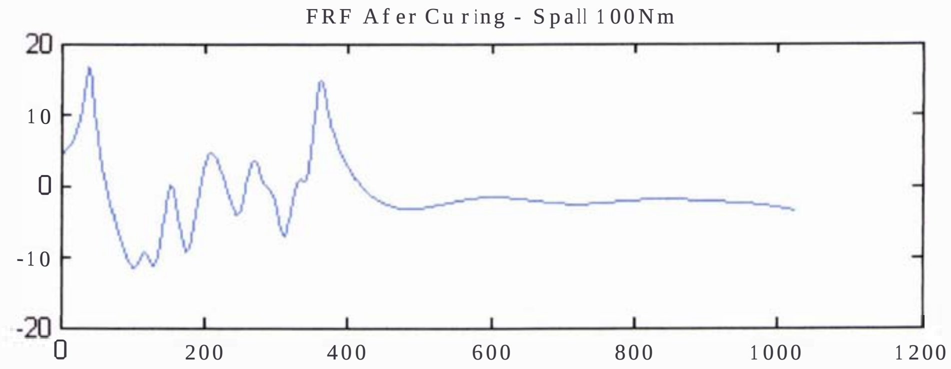
Cepstrum - Spall 100Nm
1
0
-1
-2
-3
-4
-5
-6
0
2000
4000
6000
8000
10000
12000

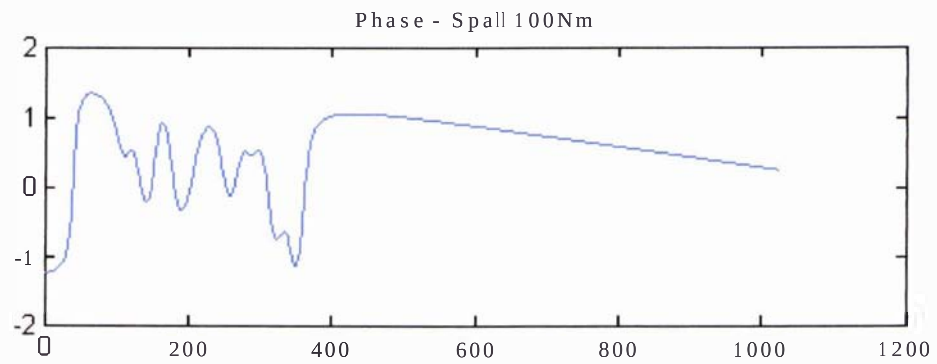
Smoothed Spectrum - Spall 100Nm

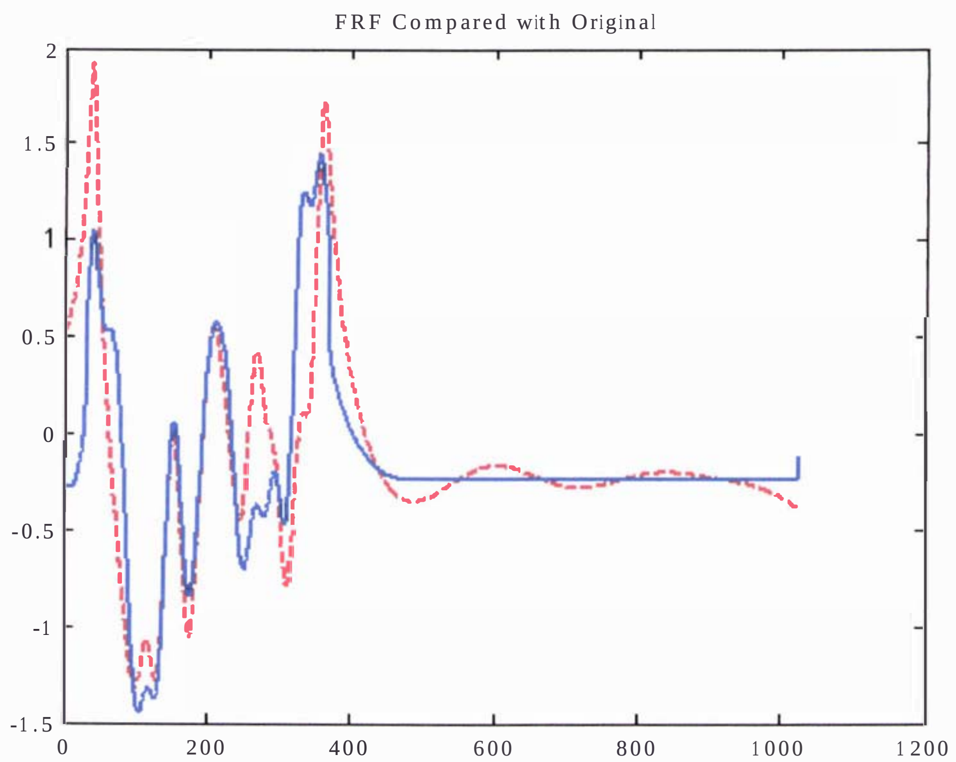


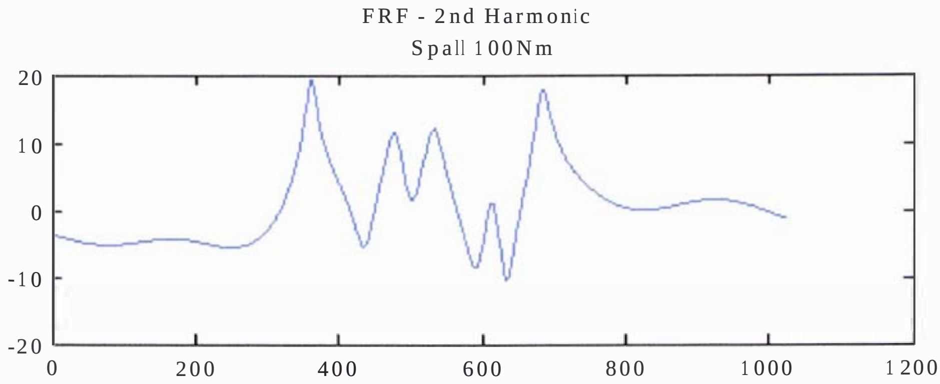
Spectrum Copared with Original
Spall 100Nm

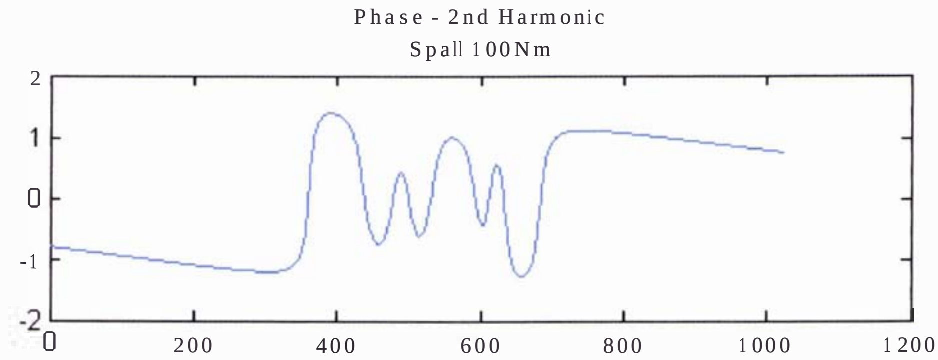


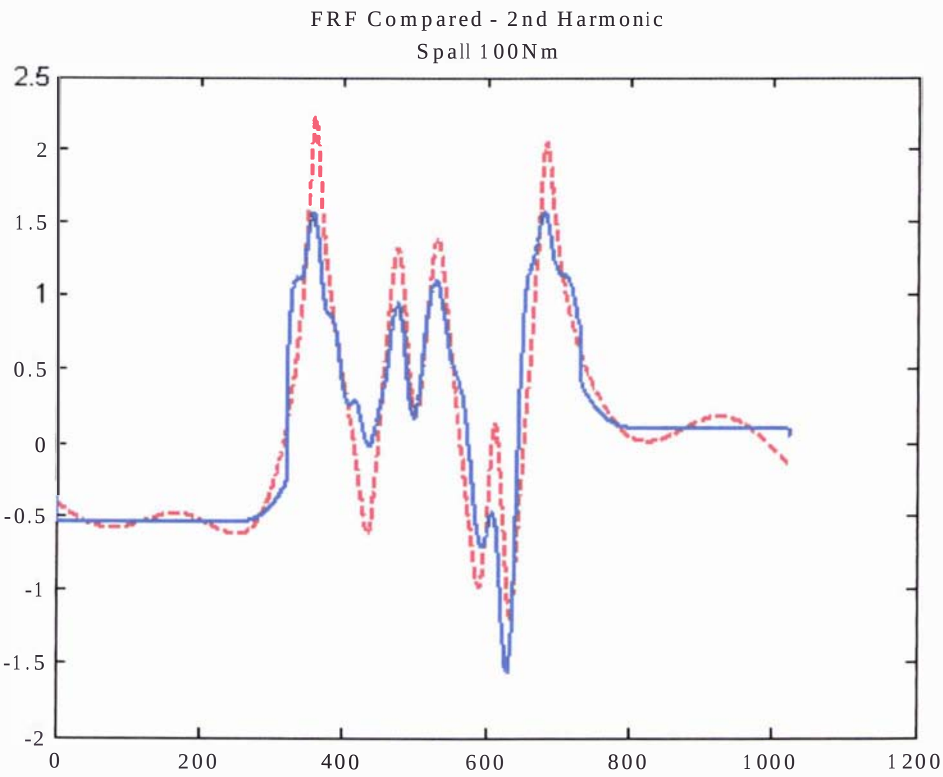

FRF Afer Curing - Spall 100Nm
20
10
0
-10
-20
0
200
400
600
800
1000
1200


Phase - Spall 100Nm
2
1
0
-1
-2
0
200
400
600
800
1000
1200


FRF Compared with Original
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
200
400
600
800
1000
1200







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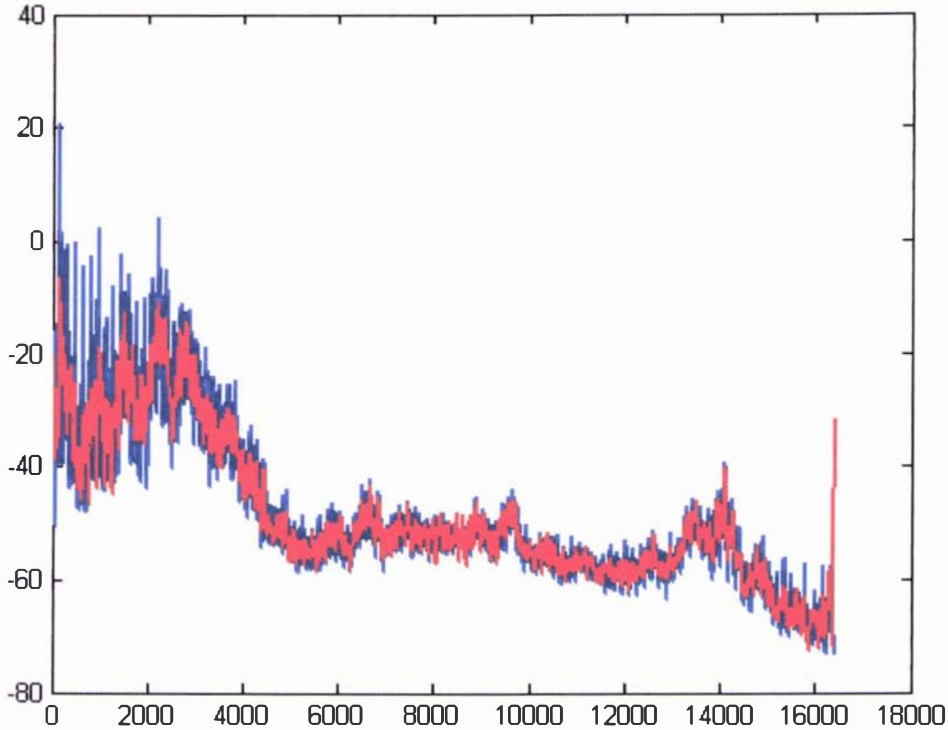

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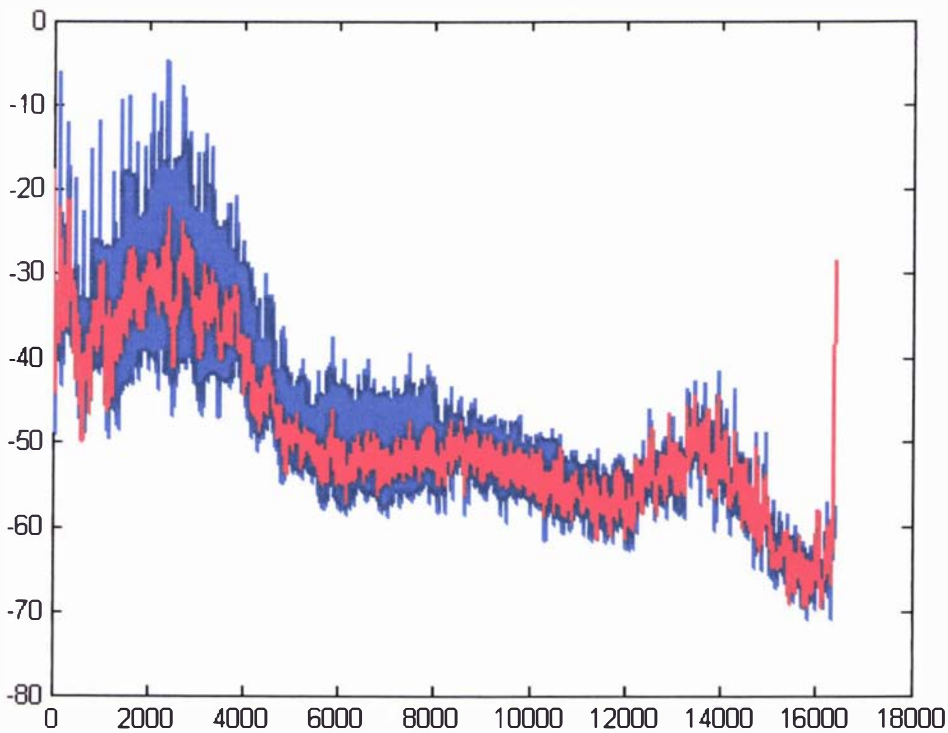

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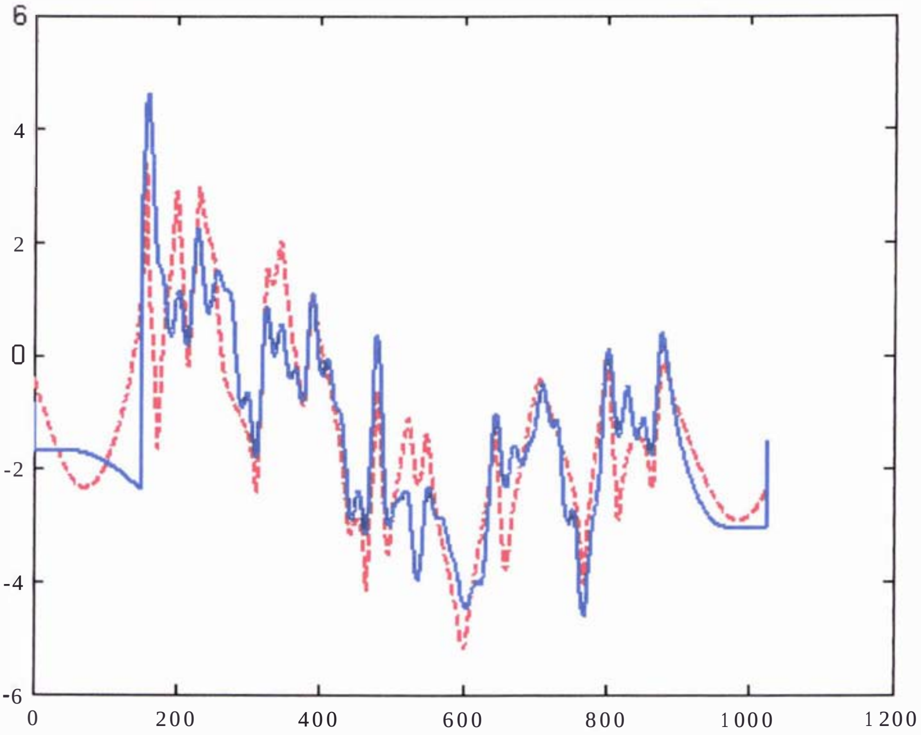

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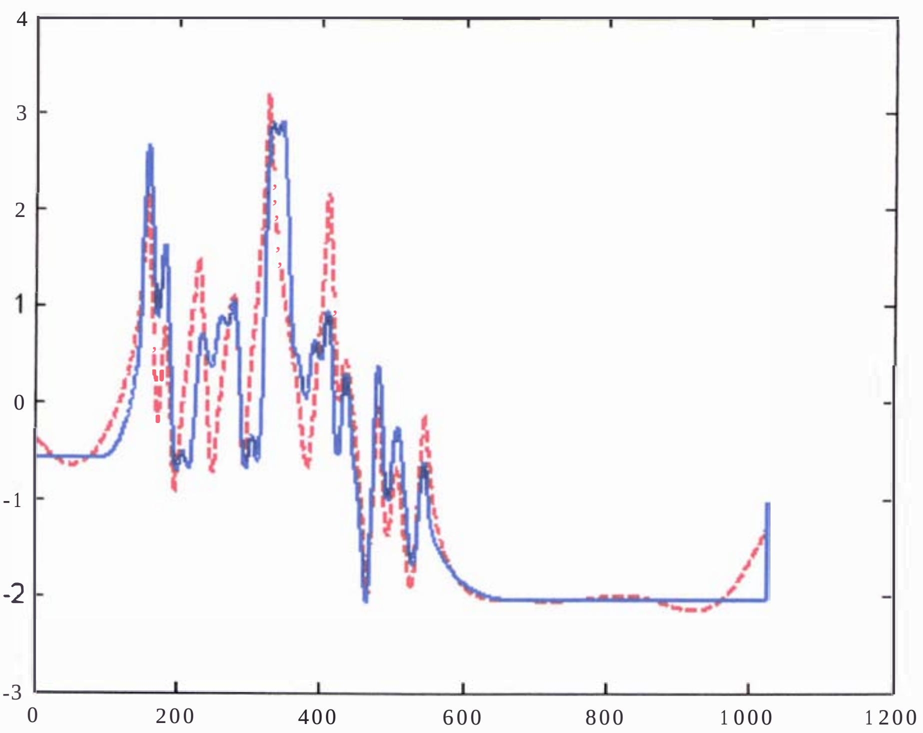
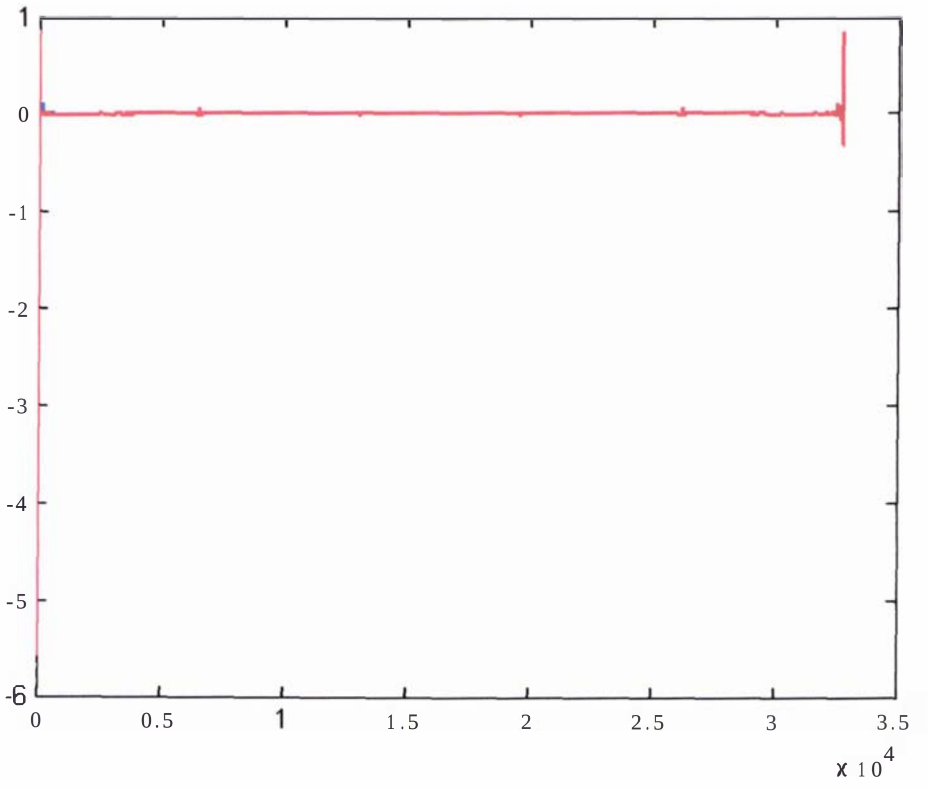


Cepstrum 50 & 100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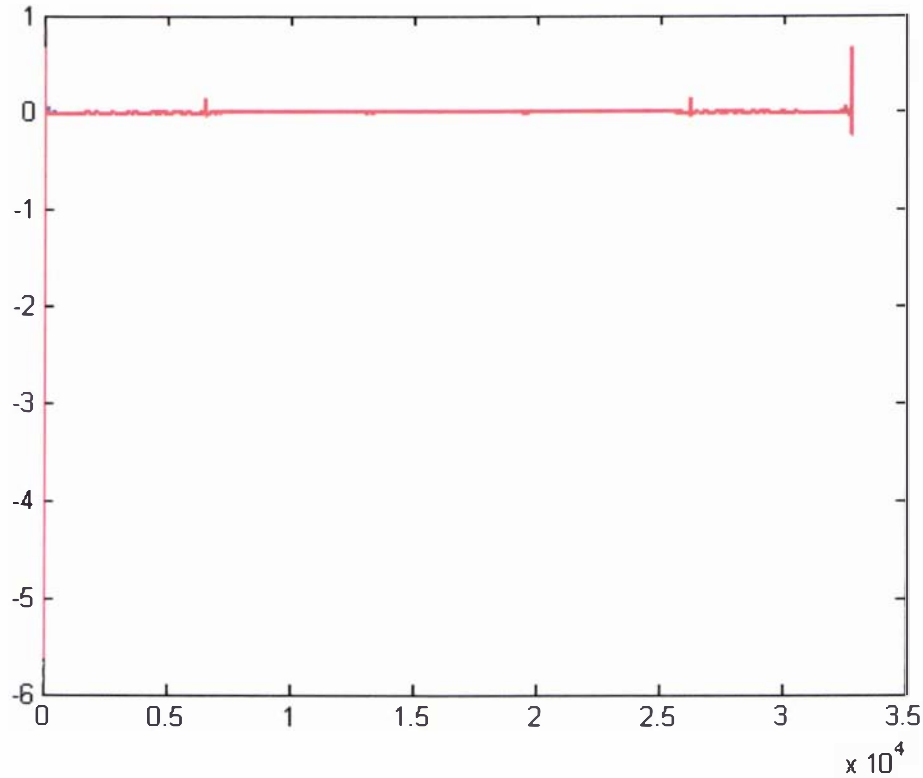

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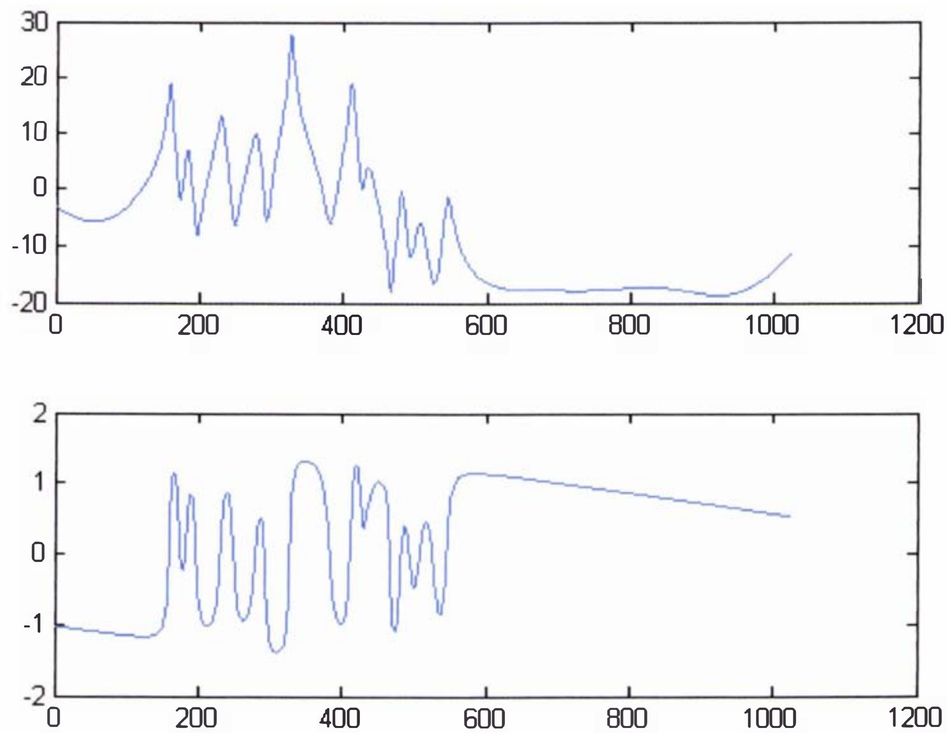

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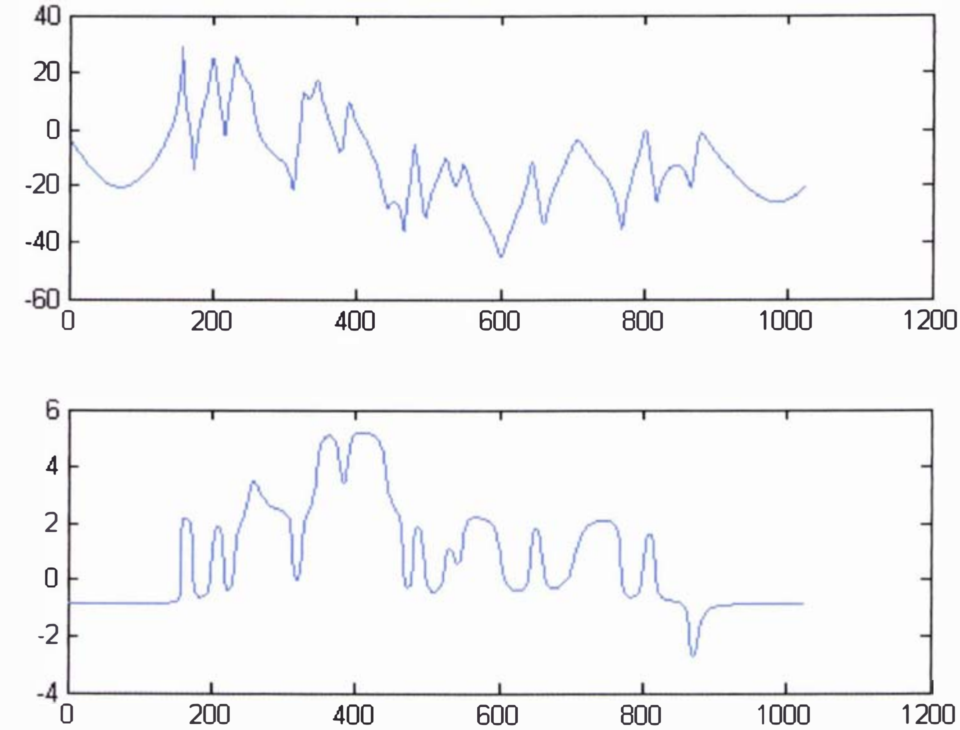

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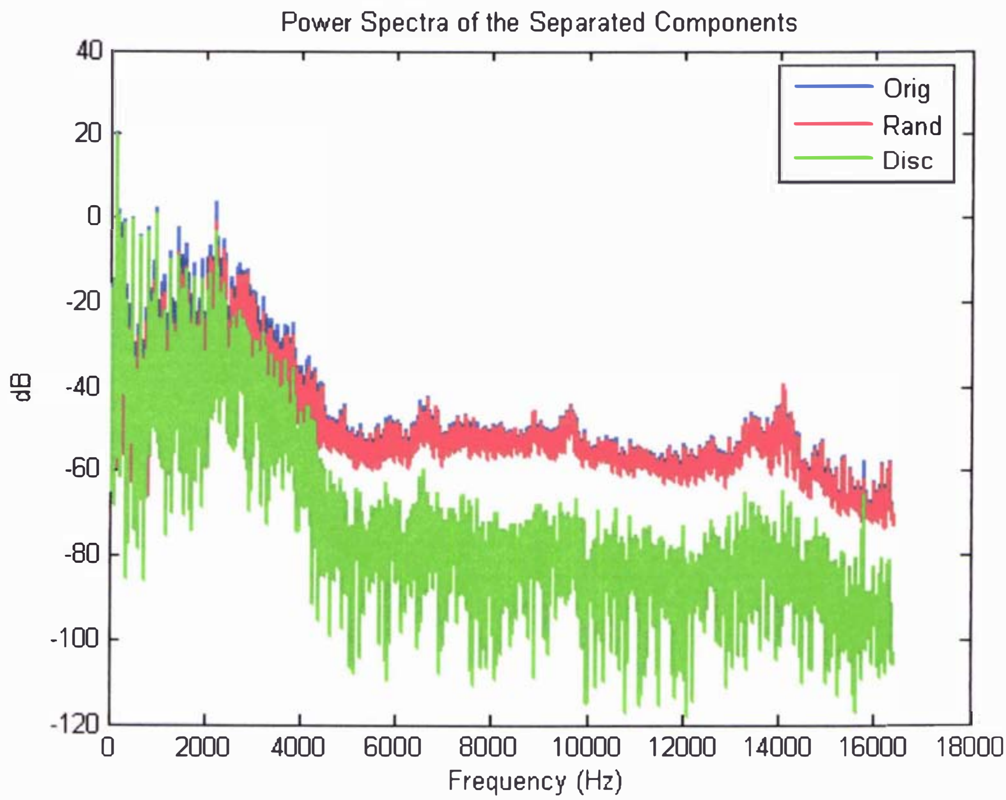

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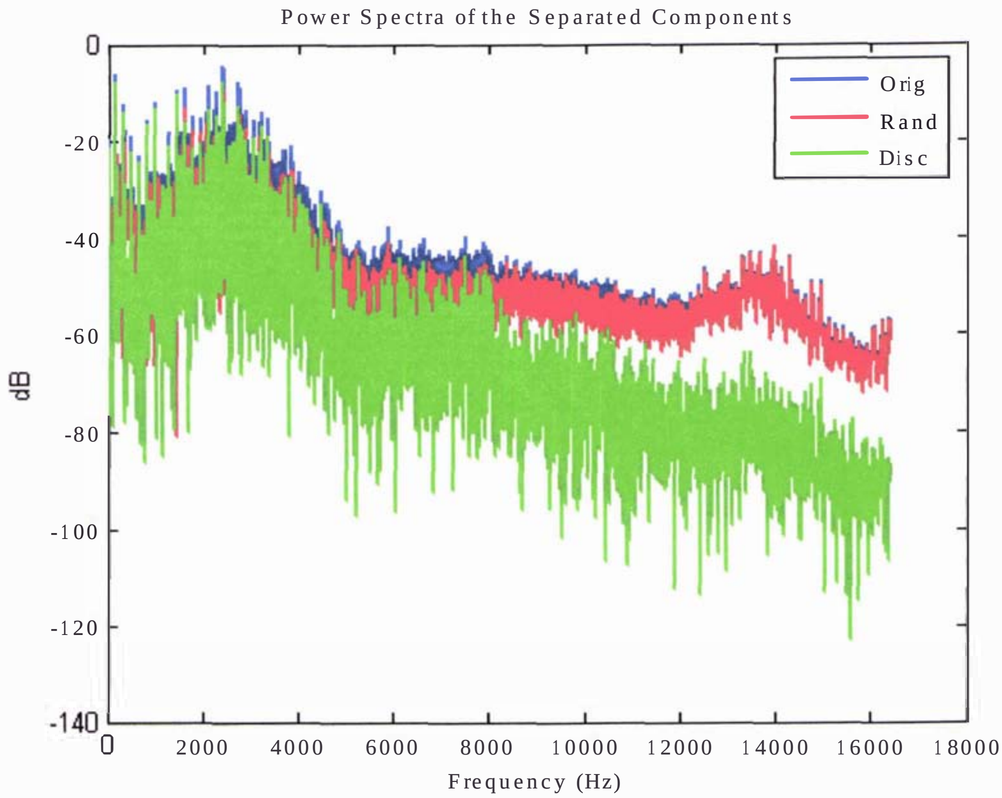

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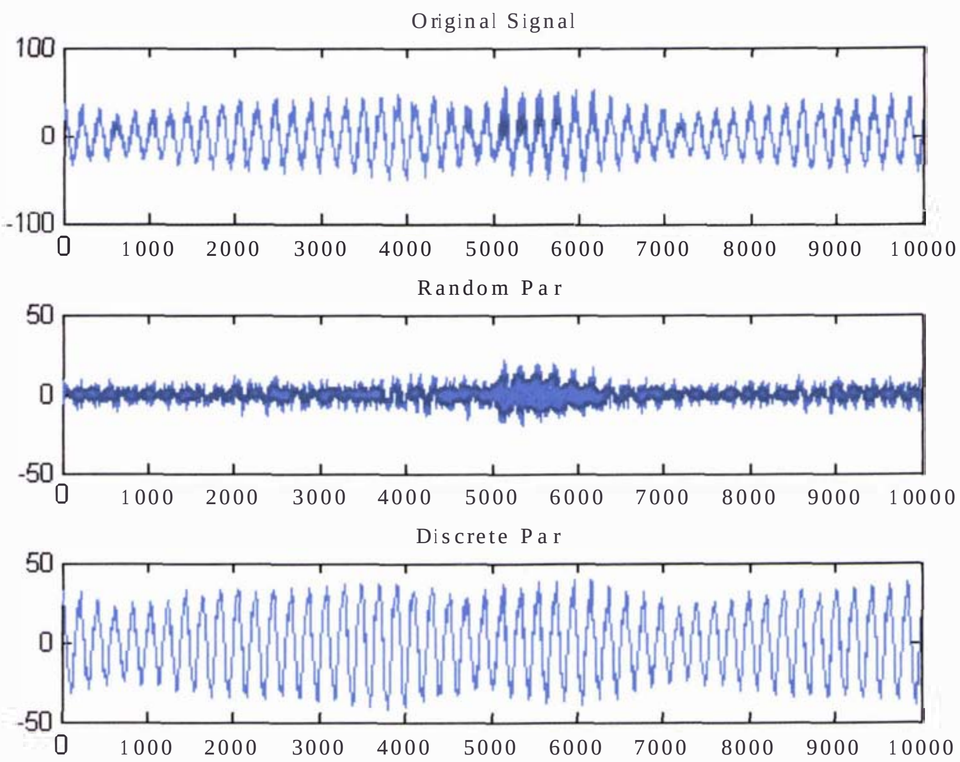

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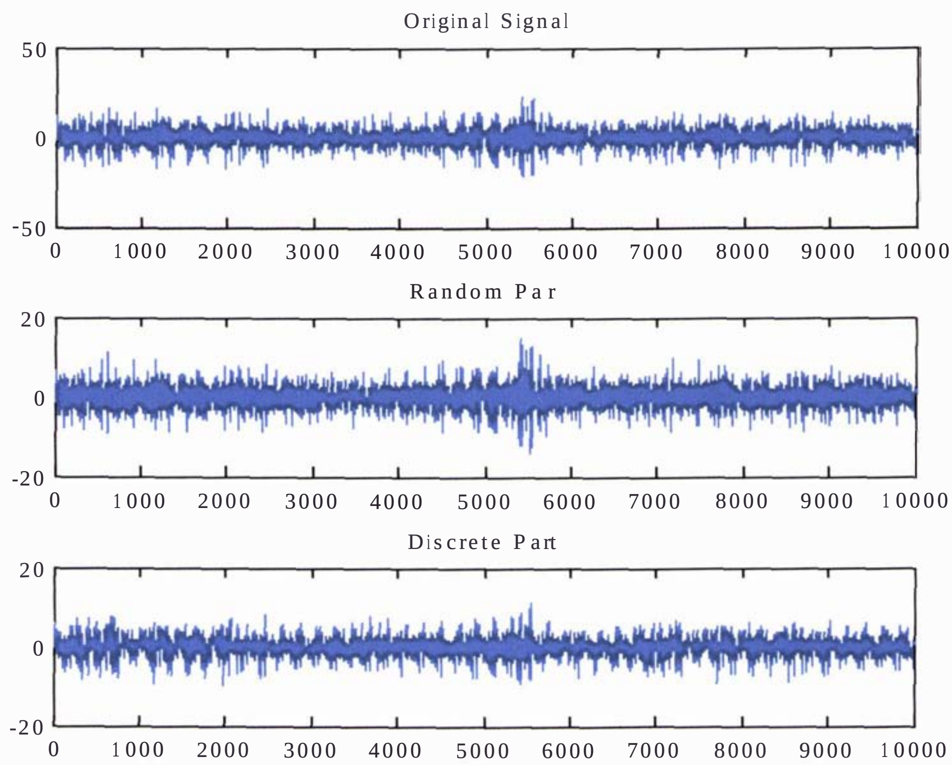
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Discrete Part
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APPENDIX B

Preventive Maintenance Activities

The routine inspection carried out under preventive maintenance by various companies do not allow them to track equipment performance, failure history or any other data that could, and should be used to plan and schedule tasks that would prevent premature failures, extend the useful life of critical plant assets and reduce their lifecycle cost.

Instead, maintenance scheduling has been, and in many instances still is, determine by equipment failures or on the perceptions of maintenance personnel who arbitrarily determine the type and frequency of routine maintenance.

For example, most facilities that employ thermography inspections have it done once a year or every six months. This is a purely arbitrary decision, not supported by any kind of factual data.

The following schedules shown in this appendix were the results of the work done by the author, stripping downs machines in a biscuit manufacturing company to come up with a well define preventive maintenance that was embedded into SAP program. This was based on the history of the machines, manufacturers' details and failure rate. This result was not based on a data just as predictive maintenance is based on a valid data, predictive maintenance differs from preventive maintenance by basing maintenance need on the actual condition of the machine rather than on some preset schedule. Preventive maintenance is time-based; activities such as changing lubricant are based on time, like calendar time or equipment rum time, just as shown in the author's schedules for PM in this appendix.

Most people change the oil in their vehicles every 1,500 to 3,000 km travelled. This is effectively basing the oil change needs on equipment run time, without considering the actual condition and performance capability of the oil; it is changed because of time, this methodology is associated with PM task.

Appendix B: Preventive Maintenance (PM)

The PM was set up for the machines shown in this chapter for a biscuit manufacturing company; the information was transferred to SAP software for their implementations

Introduction

The term Preventive Maintenance (PM) refers to any activity that is designed to:

- Predict the onset of component failure
- Detect a failure before it has an impact on the asset function
- Repair or replace asset before failure occurs

PM has two features:

- Activity to be performed
- Frequency at which it is performed

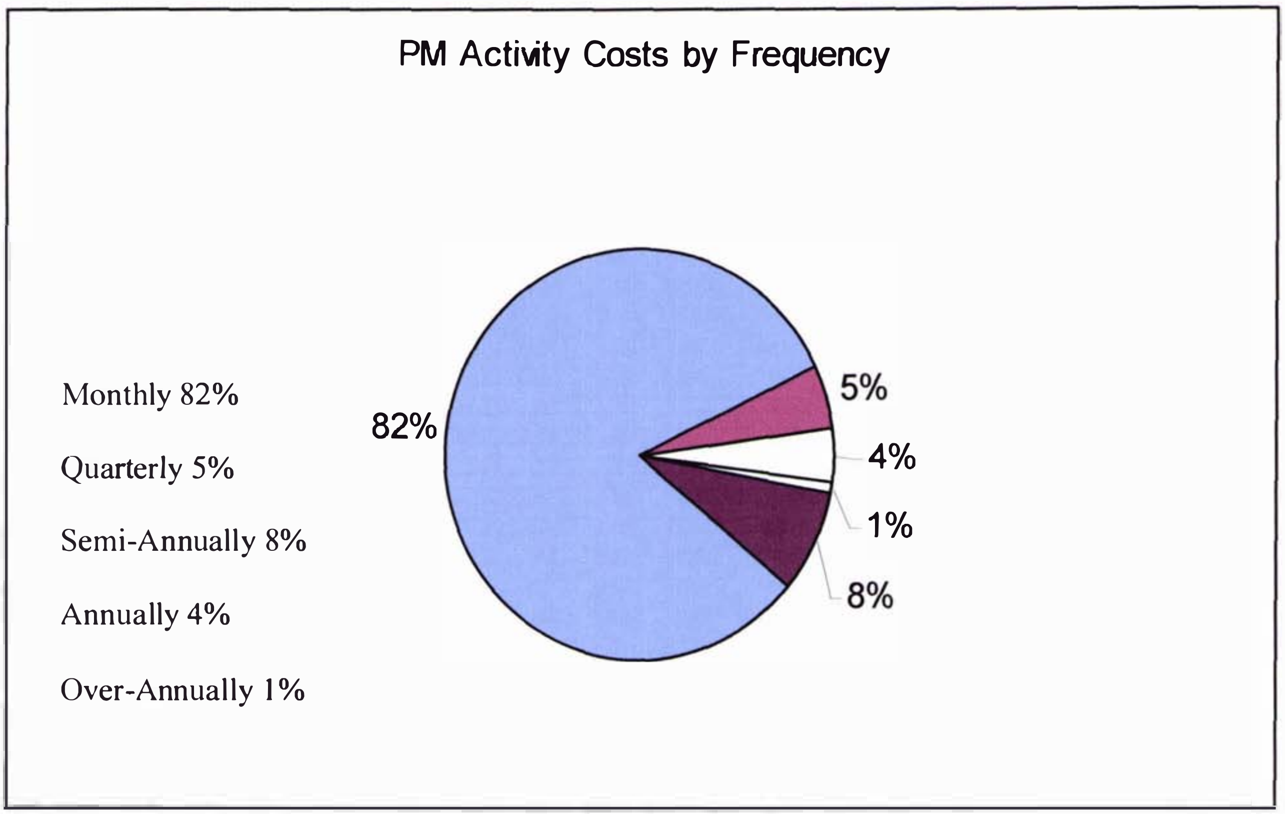
Failure to assess the two features will result to either under-maintaining or over maintaining of assets, although continuous improvement will identify and eliminate these wastes (under-maintaining and over-maintaining of machines).

Under-Maintaining of Machines

- This is when preventive activities are not performed at too long intervals.

Over-Maintaining of Machines

- Performing PM at more frequent intervals than necessary
- Performing PM activities that add no value to the output.



SOLLICH ENROBER

Preventive Maintenance

1. **CLEANING:**
   - Clean and service **CHOCOLATE PUMPS** every **12 – 24 months.**
   - Clean water **FILTERS** in the tamperer every **3 months** to ensure full penetration regularly.
   - Thoroughly clean the machine **weekly**
   - External cleaning of the machine **daily**
   - Clean the blower tip **weekly**
   - Clean blower turbine **annually.**

2. **VISUAL INSPECTION - *<u>DAILY</u>***
   - Visual inspection for possible damage

- External cleaning of the machine
- Lubricate the sliding bearing of the detailing shaft with a lubricant approved for foodstuff.
- Adjust clutch for chocolate pump when starting to work with tempered mass, especially when the clutch slides despite being adjusted previously.

3. **LUBRICATION:**
   - Lubricate the **CHAINS FROM GEAR DRIVE monthly** (Renolds chain tube spray recommended).
   - Lubricate **CHOCOLATE PUMP weekly** (if critical, once every 3 days).
   - Lubricate the **SPREADER DISCS** of the regulatory gears **weekly**. (if critical, once in 3 days).
   - All **shafts** of the **machine** run in **ball bearings**. These are sufficiently greased and need lubrication after a longer period of time, **6-12 months.**

BEARINGS DETAILS

Bearing Location	**Bearing Type**
Sollich Enrober	2205 – 2 off
	6207 D – 3 off
	6205 – 2 off
	6007 – 2 off
Other items	**Size**
Oil Seals	• 35 x 50 x 7 – 10 off • 25 x 40 x 7 – 2 off
ASS 207N (NTN)	10 off
Flush Back. Parallel	Parallel OD. 72 OD. 35 OD

BEARINGS DETAILS

Bearing Location	**Bearing Type**
Sollich Enrober. Flow Pans	6004 D – 2 off
	• INA Brg. Rale 20 NPP FA 106 • 20mm ID • 42mm OD – Parallel OD. Flush Back 2 off
Other items	**Size**
Oil Seals	20 x 47 x 7 – 2 off

BEARINGS DETAILS

Bearing Location	**Bearing Type**
Sollich Main Drive/Pump	6308 2RSR – 1 off
	2205 RSR – 1 off
Other items	**Size**
Oil Seals	• 68 x 90 x 8 – 2 off • 50 x 68 x 8 – 4 off • 30 x 40 x 7 – 3 off
FAG 16212 – Flush Back	60mm ID – 1 off

- Greased packed bearings should be cleaned and re-greased every **6-12 months**
- Fill only **1/3 of free volume** of the bearing with grease.

4. **CHAIN TENSIONING:**
   - Check **CHAIN DRIVES** tensioning every **3 months.**

5. **WIRE BELT TENSIONING:**
   - Check **INFEED BELT** every **3 months**
   - Check **ENROBER CARRIAGE BELT** every **3 months**

- Check **WIRE BELT TENSION** every **3 months.**

6. **AIR FILTER REPLACEMENT:**
   - Replace **AIR FILTER** every **12 months** depending on the quality of air.

7. **DRIVE SECTION:**
   - The fitted belt cleaning brush assists with the removal of build up on the embossed belt. This build up is removed and ejected on to the **bottom stainless steel drip trays** and they should be removed and emptied **daily.**

> **Note:** The **set pressure** is recommended not to be set beyond **5 PSI** as this is all that is required to **tension** the **belt** fully.

- All painted surfaces should be cleaned with a mild detergent and wiped dry **daily.**
- All stainless steel beds or drip trays should be washed **daily** as your normal practice regularly.
- The product transfer belt (type 1-GM-087) should be washed with a mild detergent raised and wiped **daily**.
- Roller No. 1 and the main drive roller should be kept clean **weekly.**
- Rollers #3 & #4 have been fitted with multiple loaded spring steel, individually adjustable roller scrapers, should be checked for tension against the roller **every 3-4 months** and reset if required.

SOLLICH
HEAT EXCHANGER

Preventive Maintenance

8. **CLEANING:**
   - Clean **heat exchanger** every **6 months**.

1. In case of deposit within the tank, clean with current solvents
2. For cleaning within the pipes, use brush for pipe cleaning.
3. Use new gaskets after cleaning

CHECK

- Chocolate infeed temperature = 45°C
- Chocolate output temperature = 28.5°C
- Cooling water infeed temperature = 12°C
- Cooling water output temperature = 18°C

SOLLICH TUNNEL /COMPRESSOR

9. CLEANING:

- **Rotary knife edge** at the inlet section must be cleaned **daily** to ensure trouble free tracking.
- Inspect **evaporator section** every **6 months** to ensure rollers are rotating correctly and have no excessive powdered chocolate build up.
- The **Chocolate crumb collecting trays** have to be cleaned **daily**
- The **supporting armatures of the conveyor belt have** to be cleaned from chocolate **weekly.**
- Clean the **condensed water drain valve** of the **evaporator weekly**.

10. LUBRICATION:

- Check oil level in the **compressor crank casing weekly.**
- Change oil after **2-3 years** to prolong the life of compressor.
- Lubricate all **hood seals** with food grade approved silicone spray every **3 months** to ensure the seals slide together and prolong the life of the seals.

> **Note:** The bottom faces between the bed and the hoods have sentoprene R seals but require no lubrication

11. REFRIGERATION MAINTENANCE:

- Check the efficiencies of **COMPRESSORS** and **CONDENSER** as per the ***Refrigeration Maintenance Check Lists*** every **2 – 3 months.**

(see PTL manual for the check list, check items that apply to this machine)

12. GEARBOX

- Motor gearbox is an S.E.W. type: R73 DT90 N4 0.75KW at 18 rpm.
- All SEW gear units require minimum maintenance, but check oil levels **daily.**
- Check chain tension every **3 months**

SOLLICH TEMPERER

- Examine water circulation systems for leaks **daily**
- Clean filter in the cooling water feed pipe and filter elements in the pressure reducing valve **weekly**
- Check transmission oil **annually**
- Clean the cooling water system **annually**

Note: Clean surface with a dry cloth or wash in light soap water or water soluble detergent.

- Clean the 4 water filters in the temperer **weekly** to ensure full penetration.
- Clean solenoid valves of impurities from the water pipes **weekly**, such as scales of rust.
- Retighten every **6 months** the bolts between top and bottom covers.

13. Temperer's Gear – Worm Gear

- Change oil every **12-18 months**

14. Vibration Analysis

It is recommended to do vibration analysis of the machine every **six months** to check:

- Alignment
- Oil analysis (send about 0.5 litre sample to supplier oil analyst if it is alright for use)
- Bearings outer & inner races, cage and balls

- Looseness
- Parameters from the interoperability of machine components

The vibration report will be used to optimise the settings of the machine parameters and move the maintenance strategy forward to both predictive and proactive

PTL ENROBER 1050 CHOCOLATE
Serial #2739

Preventive Maintenance

15. CLEANING:

- Clean and service **CHOCOLATE PUMPS** every **12 – 24 months.**
- Clean **FILTERS weekly**.
- Clean **ENROBER BELT CARRIAGE weekly,** use long thin nozzle.

NOTE: Never steam clean the in-feed conveyor, this may damage the electrics.

- Clean **DETAILER** and **INFEED** plate by scrapping off as much chocolate as possible **daily.**

NOTE: Never steam clean or water on any of these items, it may damage the trace heating.

16. LUBRICATION:

- Lubricate the **ENROBING CARRIAGE CHAINS monthly**.
- Apply spray lubricant (Renold Chain Lubricant Recommended) on **MAIN DRIVE CHAIN,** which drives the carriage drive coupling and stirrer **weekly.**
- Change oil for **OIL - LUBRICATED GEAR annually.**
    1. Rossi MRV32-63B: Enrober belt shaker gerabox
    2. Rossi MRCI 64 U03A D90: Enrober pump drive gearbox
    3. GPP 12525 gearbox: Enrober decorator DC drive gearbox

Note: Lubricate bearings for every change of oil for lubricated gear.

LUBRICATE BEARINGS. GREASE NIBBLES

- Lubricate/grease **BEARING** nibbles **monthly.**

BEARINGS DETAILS

Bearing Location	**Bearing Type**
Enrober wire belt drive housing roller bearings	SKF – 6005 LLU: 2 off
Enrober stirrer housing bearing	SKF – 61905 LLU: 2 off
Enrober shaker shaft bearing unit	SKF – YAR207 – 2RF: 2 off
Enrober wire belt drive bearing unit	SKF – YAR206 – 2RF: 1 off
Enrober decorator linear bearings	LGW20CC: 2 off

17. CHAIN TENSIONING:

- Check **ENROBING CARRIAGE CHAINS** tensioning every **3 months.**
- Check **MAIN DRIVE CHAIN** every **3 months.**

18. WIRE BELT TENSIONING:

- Check **INFEED BELT** every **3 months**
- Check **ENROBER CARRIAGE BELT** every **3 months**
- Check **WIRE BELT TENSION** every **3 months.** Always replace the exact number of broken wire strips, adjust tension if replacement is less or more than the number of broken strips.

NOTE:

- Do not **over-tighten**; adjust equally either side to avoid damage to the wire belt. Manufacturer recommends an engineer to adjust tension.
- The replaced wire strip must maintain the same shape after replacement. If twisted, it may break again. Engineers are recommended to carry out the replacement.

19. AIR FILTER REPLACEMENT:

- Replace **AIR FILTER** every **12 months** depending on the quality of air.

20. GEAR MOTOR

- Overhaul the **GEAR MOTOR** after **3-5 years.**

Gearbox & Motor Frame Numbers

Description	**Type**	**Qty**
Enrober belt shaker gearbox	Rossi MRV32-**63B** 10:1 ratio 0.18kW 3PH motor	1
Enrober wire belt drive motor	Rossi MRIV50-**71B** 2.54X25 0.25 KW 3PH motor	1
Enrober pump drive gearbox	Rossi MRCI 64 UO3A D90 1.5kW 3PH motor	1

PTL COOLING TUNNEL

Serial #2739

Preventive Maintenance

21. CLEANING:

- Clean **MACHINE daily** from product build-up to ensure correct and trouble free operation.
- Clean **ALL ROLLERS weekly** to prevent product build-up. Dirty rollers will affect belt tracking and lead to belt damage.

22. LUBRICATION:

- Lubricate **DRIVE CHAIN** with chain spray **monthly**
- Inspect **DRIVE CHAIN** for correct tension and wear every **3 months**
- Change **OIL SEPARATOR (OF 303)** every **12 months**
- Change **GEAR** grease (double reduction maintenance free type shown below) after **3/5 years** operation, this will ensure a longer service life.
    1. CNHX4135DC Cyclo: Cooling tunnel belt drive gearbox
    2. Qty of grease = 50% of space volume = 65g of grease.

The grease recommended is ALVANIA GREASE RA, 10 -50^{o}C ambient temperature

Inspect the **NOISE** and **VIBRATION** of gear **daily** to ensure proper and continued optimum operation.

LUBRICATE BEARINGS. GREASE NIBBLES

- Lubricate/grease **BEARING** nibbles **monthly**.

BEARINGS DETAILS

Bearing Location	Bearing Type
Cooling tunnel drive shaft bearings	SKF – FYTB 50 – TF: 2 off
Cooling tunnel take up bearings	SKF – YAR207 - 2RF: 2 off
Cooling tunnel belt roller bearings	SKF – 6307 – 2RS1: 22 off
Cooling tunnel tracking bearings	SKF – 6005 – 2RS1: 4 off

23. AIR LEAKAGE:

- Check the **COOLING SYSTEM** for air leakages **daily**.

24. REFRIGERATION MAINTENANCE:

- Check the efficiencies of **RECIPROCATING COMPRESSORS** and **CONDENSER** as per the ***Refrigeration Maintenance Check Lists*** every **2 – 3 months**.

25. GEARBOX

- It is pre-packed with grease and sealed and requires **NO** regular check

26. FILTER REPLACEMENT

- Replace **SUCTION FILTER (Sporlan RCW 48)** every **12 months**

27. Vibration Analysis

It is recommended to do vibration analysis of the machine every **six months** to check:

- Alignment
- Oil analysis (send about 0.5 litre sample to supplier oil analyst if it is alright for use)
- Bearings outer & inner races, cage and balls
- Looseness

- Parameters from the interoperability of machine components

The vibration report will be used to optimise the settings of the machine parameters and move the maintenance strategy forward to both predictive and proactive types.

A: MULTI CO-EXTRUDER: UX 110

Preventive Maintenance

1. **CLEANING:**
   - Strip machine, clean and grease **weekly** or after a **complete production cycle.**
2. **Lubrication:**
   - Grease up all the gears, grease nipple, chain and sprockets at the extruder section every **month.**
   - Grease up the grease nipple at the flow controller section every **month.**

Note:
Grease Brand & Grade: Mobilux 2 (mobil), Ristan 2 (EXXON) or equivalent

3. **Checks:**
   - Check chain tension every **3 months**
   - Check gear teeth for wears/cracks every **6 months**

B: HIGH SPEED ENCRUSTER: EN 310

4. **Lubrication:**

Drive Section Side View: *OIL LUBRICATION*

Lubrication	Frequency	Oil Grade	Oil Brand
Lubricate speed reducer gearbox with oil	every 3 months	Gear 632	Mobil
Lubricate bevel gearbox with oil	every 3 months	DTE-100	Mobil
Lubricate the parallel index with oil	every 3 months	OMALA 71	Shell

- Clean and change oil every **6 months**

Drive Section Top & Encrusting Section Side Views: ***GREASE LUBRICATION***

Lubrication	Frequency	Grease Grade	Grease Brand
Grease up the gears, rod ends, sprocket and chains	**Monthly**	Mobilux 2 (mobil)	Ristan 2 (Exxon)
Grease up slide shafts, drive gears, cam follower and linear bearing	**Monthly**	Mobilux 2 (mobil)	Ristan 2 (Exxon)

5. CHECKS:

- Check **weekly** if the clearance between encrusting pieces and housing are the same.
- Check chain tension every **3 months**
- Check gear teeth for wears/crack every **6 months**.

C: STAR WHEEL ENCRUSTER: ON 113
&
PRESS ROLLER: MR 210

6. LUBRICATION:

Top View

- Grease up all gears **monthly**

Front View

- Grease up screw jack **monthly**

7. CHECKS:

- Check wears/crack on gear teeth every **6 months**

D: LATTICI ROLLER: OR 295

Side View

- Grease up pillow block and worm wheel **monthly**
- Check roller clearance **regularly**

Note: Make sure that the clearance of rollers in horizontal adjustment is the same on both sides (equidistant).

E: UNDERNEATH CONVEYOR: 2C 316

8. LUBRICATION:

TOP VIEW - (Conveyor under multi co-extruder)

- Grease up the gears, sprocket & chain **monthly**

TOP VIEW – (Row multiply unit)

- Grease up the gears, worm and worm wheel, sprocket, chain, linear bearings, rod-end bearing and cam **monthly.**

9. CHECKS:

- Check belt tension **monthly** and adjust if necessary
- Check gear teeth for wear/crack every **6 months.**

F: GUILLOTINE CUTTER: OK 774

SIDE VIEW

10. LUBRICATION:

- Grease up clevis pins, rod end, joint pins and linear bearings **monthly**

11. CHECKS & CLEANING:

(Air Case Section)

- Clean dirt on air filter & auto-drain function **weekly**

Note: Clean with neutral detergent or replace if necessary

- Check abnormal change in air pressure **daily**. Normal setting is $4kg/cm^2$

(Solenoid Valve)

- Check solenoid valve **monthly,** for unusual noise, change the valve.

(Air Cylinder & Cutter Section)

- Check **monthly** for wear on clevis pin, bushing, knuckle joint pin, bearing, pin, linear bearing, cutter, air cylinder and air joints. Change any worn part as soon as possible.

<u>G:</u> EGG GRAZER

12. LUBRICATION:

(SIDE VIEW)

- Grease up the chain & sprocket **monthly**

13. CHECKS:

- Check chain tension **monthly**
- Check roller clearance **monthly**. Clearance between rollers 1 & 2 and rollers 2 & 3 should be **0.2mm**

<u>H:</u> CONVEYOR WITH BELT CLEANER: 1C 358

14. LUBRICATION:

- Grease up the sprockets, chain & grease nipple **monthly.**

15. Checks:

- Check the chain & belt tension **monthly**

Note:

- Conveyor belt tension should be adjusted with tensioner bolts at both sides
- Adjust the drive tension with the tension sprocket

VIBRATION ANALYSIS

It is recommended to do vibration analysis of the machine every **six months** to check:

- Alignment
- Balancing (rotor/coupling sleeves)
- Oil analysis (send about 0.5 litre sample to supplier/ oil analyst if it is alright for use)
- Bearings outer & inner races, cage and balls
- Looseness
- Parameters from the interoperability of machine components

The vibration report will be used to optimise the settings of the machine parameters and move the maintenance strategy forward to both predictive and proactive types.

OVENS

Preventive Maintenance

6. **Cleaning:**
   - Clean big rollers **annually.**
   - Clean small rollers every **3 months.**
   - Clean big rollers "cleaning blades" **monthly.**

7. **Checks:**
   - Check rollers smoothness, repair as required to remove rust or product build up every **6 months**.

NOTE:

Uneven rollers (for example, due to product build-up or rust or wear) may cause bearing failure.

- Check gear teeth for wears/cracks every **6 months**
- Inspect machine **daily** for loose nuts and bolts resulting from machine vibration and tighten as required.
- Check driving chain and belts tension **weekly** and adjust as necessary.

8. **Lubrication:**
    - Lubricate all bearings **monthly.** Grease up from the bearing nipples.

OVEN FANS

9. **Lubrication:**
    - Lubricate all bearings every **monthly**. Grease up from the bearing nipples.
10. **Checks:**
    - Check driving belt tension **weekly**, adjust or change belt as required.
    - Check pulley grooves for wear and repair as required every **6 months**.
    - Check pulleys alignment **weekly** and adjust as required

VIBRATION ANALYSIS

It is recommended to do vibration analysis of the machine every **six months** to check:

- Alignment
- Balancing (rotor/coupling sleeves)
- Oil analysis (send about 0.5 litre sample to supplier oil analyst if it is alright for use)
- Bearings outer & inner races, cage and balls
- Looseness
- Parameters from the interoperability of machine components

The vibration report will be used to optimise the settings of the machine parameters and move the maintenance strategy forward to both predictive and proactive types.

RAW MATERIAL HANDLING & MIXING EQUIPMENT – *Item 1.00*

Preventive Maintenance

11. **Cleaning:**
    - Clean sifting machine **weekly**: Dismantle and clean
12. **Bearing:**
    - Grease up through nipples **monthly**

- The bearings are sealed-type but further application of grease ejects the old grease and replenishes the bearing whilst still maintaining a seal

13. Couplings – Spider Type Coupling

- Check every **6 months** to ensure the spider is not unduly worn
- Any undue wear will be caused through misalignment of the motor and sifter shafts and should be carefully checked.

Note: Adjustments can be made by loosening off the inlet end bearing and re-tightening correctly.

14. Motor Bearings:

- These are to be cleaned out and supplied with fresh grease every **3 years**

15. Sprocket Chains:

- Clean and lubricate every **3 months**

Note: It is recommended to mount a new chain wheel when replacing the chain, as a new chain running in a partly worn chain wheel will have a considerable shorter life.

HYDRAULIC SYSTEM/EXTRUDER: *ITEM 2.00*

- The filter placed on the delivery of the pump must be checked **weekly**
- Drain hydraulic oil every **6 months** and carry out a complete cleaning to get rid of any impurities accumulated at the bottom of the tank

Note: Drain the lubrication reservoir or thoroughly filter oil reservoir every **3 months**

- Clean the worm-sleeve unit (extruder) at the end of **one production circle** or weekly.
- Check worm –sleeve for wear **weekly**
- Check lubrication level **daily**
- Check all pipes for leakages **daily**
- Check oil level **daily**
- Check oil for contamination **monthly**
- Change oil every **3-6 months**

D.C. MACHINE

- Clean external part of machine **daily**
- Check tightness of connections **daily**

- **Main Gearbox/other Gears**
  1. Check gears teeth every **6 months** for wear or crack
  2. Rotate them at intervals to be sure they are covered in oil **weekly**
  3. Check temperature of main gearbox **daily**
- **Brushes:**
  1. Check brushes of cooling fan motor for wear **weekly.**

Note: Brushes should be set so that they are just clear of the screen. They must NOT be allowed to touch the screen. Use brushes up to 2/3 of their initial length.

- **LUBRICATION:**
  - Life lubricated machine: LSC 80, LSC 90, LSC 112, LSC 132 & LSC 160
  - Bearings have been lubricated by manufacturer; no lubrication should be carried out.

  - Check oil seals **weekly**, replace if necessary
  - The ball bearings of the driving drum are equipped with grease nipple through which the ball bearings should be lubricated at **monthly.**
  - The ball bearings of the tension drum is lubricated through grease nipple in the link brackets **monthly.**
  - Check driving chains every **3 months** for tension and lubrication
  - Lubricate all sprocket chains every **3 months**
  - All movable links should be lubricated **annually**
  - Lubricate the guide way every **6 months**

Note: For the lubrication of the driving chains, a thin non-corrosive, pure mineral oil will be preferable.

CONVEYOR BEFORE COOLING TUNNEL

- Check rollers for wear every **3 months**
- Check chain belt tension every **3 months**
- Check sprocket chains every **3 months** and lubricate, adjust tension or change chain if necessary.

COOLING TUNNEL

- Check the efficiencies of **RECIPROCATING COMPRESSORS** and **CONDENSER** as per the ***Refrigeration Maintenance Check Lists*** every **2 – 3 months** (see PTL manual for the check list, check items that apply to this machine).
- Clean all the ventilation apertures and vent holes **weekly**

VIBRATION ANALYSIS

This machine is designed to be vibration less; any vibration located must be eliminated.

It is recommended to do vibration analysis of the machine every **six months** to check:

- Alignment
- Balancing (rotor/coupling sleeves)
- Oil analysis (send about 0.5 litre sample to supplier oil analyst if it is alright for use)
- Bearings outer & inner races, cage and balls
- Looseness
- Parameters from the interoperability of machine components

The vibration report will be used to optimise the settings of the machine parameters and move the maintenance strategy forward to both predictive and proactive types.

NOTE: The **cleaning instructions** outlined in the **"Litebread Extruder Area Cleaning – Daily"** sheet (Ref: CLN/09/02) must be adhered

OVERHEAD WIRECUT

Preventive Maintenance

16. Cleaning:

- The extruder should be cleaned at the end of **each day's production.**
- The die should be removed for cleaning **daily.**
- Clean the feed rolls **daily**:
  1. Use compressed air stream into the grooves of the feed rolls to remove product
  2. Clean the rolls, dies and filler block with hot water or steam. **DO NOT SPRAY WATER DIRECTLY ONTO THE FEED ROLL BEARINGS.**
  3. After cleaning with water, blow dry with air.

SAFETY:

1. **DANGER:** The use of water, especially when sprayed from hand held hoses, increases the risk of an electrical shock which could cause severe injury or even loss of life. Turn off electrical power source and lock-out before using water around the motors of electrical panels and controls.
2. **WARNING:** Under no circumstances should any cleaning procedure be performed while the machine is running. A momentary distraction could result in a serious injury.
3. **CAUTION:** Always wear safety glasses to protect your eyes when using compressed air.

17. Checks:

- Inspect drive chain tension and adjust as required **daily**.
- Check gear teeth for wears/cracks every **6 months**
- Inspect machine **daily** for loose nuts and bolts resulting from machine vibration and tighten as required.
- Check hydraulic pipes **daily** for any leakage and repair as required
- Check pneumatic pipe lines **daily** for any leakage and repair or replace as required.

18. Lubrication:

- Lubricate wire drop slides with food machinery lubricant **weekly.**
- Lubricate drive chain and sprockets with Chevron SAE 30W oil (asphalt base) or equivalent lubricant **weekly.**
- Lubricate the drive gears with food machinery lubricant every **2 weeks.**
- Lubricate grease fittings in shaft ends and in frame with food machinery lubricant **monthly**
- Lubricate swing arm shaft pivot and eccentric housing with food machinery lubricant **monthly**.
- Lubricate all threaded screw adjustments with Chevron SAE 30W oil or equivalent **monthly.**
- Lubricate all bearings with grease fittings with food machinery lubricant every **3 months.**

VIBRATION ANALYSIS

It is recommended to do vibration analysis of the machine every **six months** to check:

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- Bearings outer & inner races, cage and balls
- Looseness
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The vibration report will be used to optimise the settings of the machine parameters and move the maintenance strategy forward to both predictive and proactive types.