

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE
ENGINEERING AND TECHNOLOGY

**CONDITION MONITORING AND FAULT DETECTION FOR INDUCTION
MOTORS BY SPECTRAL TRENDING AND STATIONARY WAVELET
ANALYSIS**

Ph.D. THESIS

Duygu BAYRAM

Department of Electrical Engineering

Electrical Engineering Programme

FEBRUARY 2015

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**Duygu BAYRAM
(504082005)**

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Thesis Advisor: Prof. Dr. Ş. Serhat ŞEKER

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**SPEKTRAL TREND VE DURAĞAN DALGACIK DÖNÜŞÜMÜ YARDIMIYLA
DURUM İZLEME VE ARIZA TANISI**

DOKTORA TEZİ

**Duygu BAYRAM
(504082005)**

Elektrik Mühendisliği Anabilim Dalı

Elektrik Mühendisliği Programı

Tez Danışmanı: Prof. Dr. Ş. Serhat ŞEKER

ŞUBAT 2015

Duygu Bayram, a Ph.D. student of ITU Graduate School of Science Engineering and Technology, 504082005, successfully defended the thesis entitled “**Condition Monitoring and Fault Detection for Induction Motors by Spectral Trending and Stationary Wavelet Analysis**”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor : **Prof. Dr. Ş. Serhat ŞEKER**
Istanbul Technical University

Jury Members : **Doç. Dr. Özgür ÜSTÜN**
Istanbul Technical University

Doç. Dr. Erkan MEŞE
Yıldız Technical University

Doç. Dr. Emine AYAZ
İstanbul Technical University

Prof. Dr. Osman Nuri UÇAN
İstanbul Aydın University

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To my family,

FOREWORD

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ABBREVIATIONS

ATFD	: Adaptive Time Frequency Distribution
CCDF	: Cohen's Class Distribution Function
CH	: Convex hull
CR	: Convex region
CWT	: Continuous Wavelet Transform
DWT	: Discrete Wavelet Transform
EDM	: Electrical Discharge Machining
EPRI	: Electric Power Research Institute
FL	: Fuzzy Logic
HHT	: Hilbert Huang Transform
IEEE	: Institute of Electrical and Electronics Engineers
MRWA	: Multi Resolution Wavelet Analysis
NN	: Neural Network
PSD	: Power Spectral Density
SNR	: Signal-to-noise ratio
STFT	: Short Time Fourier Transform
UDWT	: Undecimated Wavelet Transform
UTK	: University of Tennessee Knoxville
WT	: Wavelet Transform
WVD	: Wigner-Ville distribution

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CONDITION MONITORING AND FAULT DETECTION FOR INDUCTION MOTORS BY SPECTRAL TRENDING AND STATIONARY WAVELET ANALYSIS

SUMMARY

In this study, a spectral trending method is developed as a simple and feasible condition monitoring technique for electric motors. Considering the situation of the motor, a fault detection approach benefiting from the redundancy property of Stationary Wavelet Transform (SWT) is proposed. Through this, the study presents an integrated condition monitoring and fault detection approach using vibration signals of an induction motor.

Today's world industry constitutes of electric motors and their control applications. Induction motors are the most preferred type in industry due to several advantages. In the industrial application the most important concept is reliability. This is due to the fact that, any interruption or deceleration in the industrial process may result in huge financial losses. Therefore, condition monitoring of induction motors is a very popular research area. There are important surveys related to the failures of induction motors. As the result of these surveys, it can be concluded that the most common failure mode is bearing failures with a rate of approximately 40%. Winding faults are also very frequent with 30%, whereas rotor related faults are at around 9%. In order to detect these faults, several condition monitoring techniques are used, according to the needs of the system. This way, the machine performance can be tracked and required precautions can be considered. These monitoring techniques are listed as: electrical current, flux, power, mechanical vibration, temperature, wearing and electrical discharge. In order to interpret and assess the monitoring information, a diagnostic system is designed and established. Diagnostic systems are classified in three categories: model based, statistical data based and signal based. In this study, vibration signals are employed due to their capability to reflect either electrical or mechanical fault signatures. SWT is employed as the signal based diagnostic method.

Conventional condition monitoring and fault detection systems calculate specific fault frequencies for each motor and track them regularly. However, the faults do not suddenly pop up, they progress in time and raise the critical aging condition in the motor. Considering this gradual and progressive nature, the aging is trended in this study. This way, the motor situation can be classified as healthy or not. If the motor is not healthy, there are plenty of techniques to identify the fault. However, if it is healthy, there might still be some minor indications which may amplify in the future. For that reason, redundancy of SWT is employed to detect the potential faults of the motor.

The study has two parts as classification and analysis. In the classification part, Power Spectral Densities (PSD) of vibration signals for different aging cycles are calculated logarithmically. In order to express each aging cycle individually, linear models are fitted to logarithmic PSDs. Hence, linear models become an alternative

tool for the spectral domain and these linear variations can define a closed region in sense of convexity. The geometric interpretation of trends in the convex region is achieved, thus a new and efficient vibration monitoring strategy is proposed. In addition, a classification approach is introduced to determine the situation of the motor.

In the second part, the situations named as healthy are taken into consideration. An early and sensitive detection method is aimed using SWT. SWT is a redundant transform due to its nature. This redundancy is preserved on purpose to amplify the existing small fault signatures.

The method is developed on an artificial data and then verified on an experimental data.

The experimental data has been taken from The University of Tennessee Knoxville (UTK). The experimental setup had been built in a research and development project supported by *The University of Tennessee Maintenance and Reliability Centre*. The project was an extensive research on fault detection in induction motors. For this purpose, an accelerated aging experiment, which contains two phases as electrical discharge machining and thermal-chemical aging operations, is realized.

This study has six sections; they are listed and described as below;

In the first section, the reason for preferring induction motors is given. Their failure modes, monitoring techniques and fault detection algorithms are introduced with several references. In order to emphasize the need for SWT, signal based detection methods are given in detail.

In the second section, the convex region approach, spectral trending and types of wavelet transforms are presented as the mathematical background of the study. Redundancy concept is explained through reconstruction operations.

In the third section, the aging procedure is presented. Then the accelerated aging experiment is given in detail with standards and aging actions. The aging cycles are introduced through time and frequency domain representations.

In the fourth section, the classification part of the study is performed. Logarithmic PSDs are calculated and linearly trended to determine the situation of the motor. Thus, the progress of aging becomes trackable. These trends define an Euclidian plane and they create a convex region together with the measurement boundary. The cycles within this region can be rated and graded in terms of health.

In the fifth section, a modification is proposed for the reconstruction algorithm of SWT to conserve the redundancy. The modified approach is named as the algebraic summation method. The development phase of the method is improved on artificial data, then it is applied to healthy cycle data. It is seen that it amplifies very small fault indications as a reflection of redundancy. Through this, an early and sensitive detection method is introduced. In addition, the catastrophe limits for a motor is identified originating from algebraic summation.

In the conclusion section, the findings and comments are given, the contributions are highlighted. Spectral trending is a very simple method to estimate the situation of the motor and it is very applicable for industry. The study defines the health of a motor as a rateable variable. The definition of the convex region approach is a new and original concept for motor monitoring. The study increases the effectiveness of vibration monitoring by new monitoring strategy. Algebraic summation in the signal

reconstruction step of SWT brings an early and sensitive detection possibility for the healthy case data. In addition, the degradation limits are determined inspiring algebraic summation and convexity concept.

These contributions are very significant in terms of effective condition monitoring and detection of incipient faults.

This study presents an integrated condition monitoring and fault detection approach which may be used by maintenance engineering widely, because it is practical, simple and applicable. The study can be employed to reschedule and reinterpret the maintenance. Furthermore, rating of aging is a complicated process and it is required for critical applications. This study meets this need successfully, as well.

From a wider perspective, geometric interpretations of trends and redundancy based fault detection are suitable to be employed in different fields of engineering for monitoring and diagnostic aims.

SPEKTRAL TREND VE DURAĞAN DALGACIK DÖNÜŞÜMÜ YARDIMIYLA DURUM İZLEME VE ARIZA TANISI

ÖZET

Bu tez çalışmasında elektrik makinalarının durum izlemesi için spektral tabanlı basit ve kolay uygulanabilir bir trend yöntemi geliştirilmiştir. Durum izleme sonucunu takiben, motorun sağlık durumu göz önüne alınarak da Durağan Dalgacık Dönüşümünün artıklık özelliğini kullanan bir arıza tanısı yöntemi önerilmiştir. Bu anlamda çalışma, asenkron motorun titreşim sinyalleri kullanılarak gerçekleştirilen, bütünsel bir durum izleme ve arıza tanısı algoritması olarak yorumlanabilir.

Günümüz endüstriyel dünyası elektrik makinaları ve onların ileri kontrol stratejileri üzerine kurulmuştur. Asenkron motorlar, basit yapıları ve düşük bakım ihtiyaçları sebebiyle bu elektrik makinalarının en çok tercih edilenleridirler. Endüstriyel süreçlerin, son derece rekabetçi tabiatları gereği herhangi bir kesilme veya yavaşlamaya toleransları yoktur. Bu sebeple durum izleme ve performans değerlendirme hayati öneme sahiptir.

Literatürde IEEE ve EPRI tarafından asenkron makina arızalarını konu alan iki adet büyük anket gerçekleştirilmiştir. Bu anketler sonucunda en büyük arıza kaynağı olarak %40 ile rulmanlar gösterilmiştir. Sargı arızaları %30 ile ikinci, rotorla ilgili arızalar ise %9 ile üçüncü sırada gelmektedir. Kalan yüzde ise stator çekirdek arızaları, sürtünme - vantilasyon arızaları ya da beklenmedik mil gerilimlerinin sebep olduğu arızalar arasında paylaşılmaktadır. Bütün bu arızaları tespit etmenin ilk adımı, sisteme uygun durum izleme yapmaktır. Böylece makine performansı yakından takip edilebilmekte ve gerekli önlemler alınabilmektedir. Durum izleme yöntemleri; elektriksel akım, akı ve güç, mekanik titreşim, sıcaklık, kimyasal aşınım, elektriksel boşalma izleme şeklinde sıralanabilmektedir. Durum izleme sonuçlarının değerlendirilmesi amacıyla bir arıza tespit ve tanı yöntemi kullanılmalıdır. Kullanılan yöntem model tabanlı, istatistiksel veri tabanlı ya da sinyal tabanlı olabilmektedir.

Bu tez çalışmasında mekanik ve elektriksel hatalara ait göstergeleri taşıyabilme yetisinden ötürü titreşim sinyalleri kullanılmıştır. Arıza tanısı için ise sinyal tabanlı bir yöntem geliştirilmiş ve bu amaçla Durağan Dalgacık Analizi kullanılmıştır.

Geleneksel durum izleme ve arıza tespiti yöntemleri, belirli arıza frekanslarını hesaplayıp, düzenli olarak bu frekansların genliklerini takip etmektedir. Ancak arızalar bir anda gelişen durumlar değildirler. Zaman içinde gelişir ve olgunlaşırlar, belirli bir eşik değerin üstüne çıkınca da görünür olurlar. Bu durum makinanın bütün olarak yaşlanmasına sebep olmaktadır. Bu kademeli artan yapısından ötürü yaşlanma trendlenebilir bir olgudur. Bu çalışma yaşlanmanın değerlendirilmesini, motorun durumunun anlık olarak sağlıklı veya değil şeklinde tanımlanmasını sağlamaktadır. Trend uygulamasına göre motorun sağlıklı olmadığı durumlar için arıza tespitinde kullanılabilecek birçok teknik vardır. Ancak motorun sağlıklı olduğu durumlar, motorda çok küçük arıza göstergelerinin olmadığı anlamına gelmez. Söz konusu

küçük göstergeler zaman içinde büyüyüp etkilerini artırabilir ve motorda arızaya sebebiyet verebilirler. Bu ihtimal göz önünde bulundurularak, bu çalışmada durağan dalgacık dönüşümünün artıklı yapısından faydalanılmak suretiyle bir arıza tanısı yöntemi geliştirilmiştir.

Bu bağlamda bu tez çalışması; sınıflandırma ve analiz olarak iki kısımdan oluşmaktadır. Sınıflandırma kısmında, motorun farklı durumlarına ait titreşim sinyallerinin güç spektrum yoğunlukları logaritmik olarak hesaplanmaktadır. Her spektruma birer lineer model uydurulmaktadır. Böylelikle motorun her durumunu temsil eden lineer eğriler, aslında motorun durum değerlendirmesi için tanımlanmış araçlar haline getirilmektedirler. Bu lineer modeller, ölçüm sınırı ile motorun farklı durumlarının değerlendirilebileceği bir konveks bölge oluşturmaktadırlar. Bu şekliyle yöntem geometrik bir yaklaşım halini almaktadır; söz konusu geometrik yaklaşım sayesinde yeni bir titreşim izleme stratejisi önerilmiştir. Bununla beraber motorun durumu hakkında kestirim yapmak amacıyla bir derecelendirme yaklaşımı tanımlanmıştır.

Tez çalışmasının ikinci kısmında ise sağlıklı olarak sınıflanan motorlardaki çok küçük arıza belirtilerini görünür kılma amacıyla erken ve hassas bir arıza tespit ve tanı yöntemi önerilmiştir. Bu arıza tanı yöntemi yapısı itibariyle artıklı bir dönüşüm olan durağan dalgacık dönüşümü kullanılarak tanımlanmıştır. Durağan dalgacık dönüşümü sinyal ayrıştırma esnasında artıklı bileşenler oluşturur. Kusursuz sinyal geri yapılandırma algoritması için ise artıklıkları ortadan kaldıran filtrelerle sahiptir. Bu tez çalışmasında bu filtrelerin çalışması engellenmiş ve ayrıştırma sayesinde kazanılan artıklı bilgi muhafaza edilmiştir. Bu artıklık, güç spektrumunda var olan ancak fark edilmeyecek kadar zayıf olan hataların kuvvetlendirilmesi sağlamaktadır.

Çalışma, yapay olarak üretilmiş bir titreşim sinyali üzerinde geliştirilmiş sonrasında deneysel veriye uygulanmıştır.

Deneysel veri, The University of Tennessee Knoxville (UTK)'den temin edilmiştir. Deney düzeneği, *The University of Tennessee Maintenance and Reliability Centre* tarafından tanımlanmış bir araştırma geliştirme projesi kapsamında oluşturulmuştur. Proje asenkron motorlarda arıza tespitine yönelik olarak tasarlanmış geniş bir çalışmadır. Bu amaçla 5HP, üç fazlı, dört kutuplu asenkron motorlar seçilmiştir. Deneyler kapsamında hızlandırılmış bir yaşlanma testine yer verilmiştir. Hızlandırılmış yaşlanma deneyi yedi aşamada motoru kullanım sınırlarının üstüne dayandırmış ve deney sonlandırılmıştır. Her yaşlandırma aşaması ikişer fazdan oluşur. Bunlardan ilki, motorlarda yaygın olarak karşılaşılan rulman arızasını yaratmayı hedef alan elektriksel boşalma fazıdır. Bu fazda motor miline dışardan bir kaynak bağlanır ve akım akıtılır. Söz konusu akım, rulmanlarda yorulmaya sebep olmaktadır ve rulman arızasını hızlıca gerçekleştirebilecek düzeydedir. İkinci yaşlandırma fazı ise kimyasal ve ısıl fazdır. Bu fazda motorun uzun vadede maruz kalacağı nem ve sıcaklık bol miktarda uygulanarak ısıl ve kimyasal yaşlandırma hedeflenmektedir.

Bu tez çalışması 6 bölümden oluşmaktadır, bölümlerin içerikleri aşağıda kısa özetler halinde verilmiştir;

Birinci bölümde öncelikle bu çalışmada asenkron motor tercih edilmesinin sebebi vurgulanmıştır. Sonrasında makinanın arıza durumları, durum izleme teknikleri ve arıza tanı yöntemleriyle ilgili geniş bir literatür özeti verilmiştir. Durağan dalgacık yöntemi tercih edilmesinin arkasındaki amacı ifade edebilmek için, sinyal tabanlı

arıza tanı yöntemleri ayrıntılı olarak ele alınmıştır. Bölümün sonunda bu tez çalışmasının arkasındaki motivasyon sunulmuş ve olası katkılar sıralanmıştır.

İkinci bölüm, çalışmanın matematiksel arka planıdır. Öncelikle konveks bölge tanımı ve spektral trend yaklaşımı verilmiş, mühendislik alanlarındaki uygulamalarına değinilmiştir. Sonrasında dalgacık dönüşümü bütün tipleriyle birlikte tanıtılmış ve durağan dalgacık dönüşümü verilmiştir. Son olarak da artıklık kavramı sinyal geri yapılandırma algoritmalarına dayandırılarak anlatılmıştır.

Çalışmanın üçüncü bölümünde, motorun yaşlanma mekanizması tasvir edilmiştir. Bu çalışmadaki deneyin odağında olan rulman yaşlanması ve ısı yaşlanmadan bahsedilmiş, konuyla ilgili standartlar sunulmuştur. Sonrasında hızlandırılmış yaşlanma deneyi ayrıntılı olarak anlatılmış ve veri toplama sistemine ait detaylar verilmiştir. Son olarak da deney çıktısı olarak kullanılan yedi adet yaşlanma verisi zaman ve frekans tanım bölgesinde verilmiştir.

Dördüncü bölümde, çalışmanın sınıflandırma kısmı olan spektral trend yaklaşımı anlatılmıştır. Logaritmik güç spektrumlarına birinci dereceden polinomlar uydurulmuştur. Bu eğrilerin oluşturduğu 2 boyutlu Euclid düzlemi tanımlanmış ve ölçüm sınırı ile bu düzlem üçgen bir konveks bölgeye dönüştürülmüştür. Bu geometrik yorumlamada ilk (en sağlıklı) ve son (en sağlıksız) durumlara ait ölçümlerden çıkan trendlerin eğimleri ters işaretlidir ve bir kesişim noktaları vardır. Olası bütün durumların bu üçgen içinde olması beklenmektedir. Bu sayede motorun farklı durumları birbirlerine göre karşılaştırılabilir hale gelmiştir. Bu anlamda motorun sağlık durumu ölçülebilir bir büyüklük olmuştur. Aynı zamanda son derece karmaşık bir kavram olan ve modellenmesi zor olan yaşlanma; izlenebilir bir büyüklük haline dönüştürülmüştür.

Beşinci bölüm ise zaten yaşlanmış olan motorların arıza tanımlarının başka yöntemlerle yapılabileceği kabulü ile sağlıklı durumdaki motorun olası arızalarının tanısı üstünde çalışılmıştır. Bu amaçla durağan dalgacık dönüşümünün kusursuz sinyal geri yapılandırma sistemine müdahale edilmiş ve artıklık korunmuştur. Bu yöntem cebirsel toplama olarak adlandırılmıştır. Yöntem yapay veri üzerinde geliştirilmiş, deneysel veriye uygulanmıştır. Yapay veri üzerinde geliştirilmiş olmasının sebebi yapay verinin içeriğinin bilinir olması ve aranan frekans bileşenlerinin tespitiyle ilgili doğrulama sağlanabilir olmasıdır. Yöntem yapay sağlıklı durum verisinde çok yüksek başarı göstermiş, bu sebeple tezin sınıflandırma kısmında sağlıklı olarak değerlendirilen duruma uygulanmıştır. Uygulamanın sonucunda sinyalin güç spektrumunda görünmeyen bazı frekansların kuvvetlendiği görülmüştür. Bu frekans bileşenlerinin motor için hesaplanmış eksenel kaçıklık frekanslarına çok yakın oldukları saptanmıştır. Bu bağlamda yöntem erken ve hassas bir arıza tanısı yöntemi olarak değerlendirilebilir. İlaveten, cebirsel toplam yönteminin sinyalin spektral içeriğinin değiştirmesi sebebiyle trendini de değiştirdiği fark edilmiştir. Bu durum, trendlerin alabilecekleri en yüksek ve en düşük eğimler hakkında yorum yapmaya olanak sağlamıştır. Bu sayede trendler için katastrofi sınırları belirlenmiştir.

Tez çalışmasının sonuç kısmında, tüm bulgular ve yorumlar liste halinde verilmiş, bilimsel katkıların altı çizilmiştir. Bu bulgular ve katkılar kısaca aşağıda özetlenmiştir:

Spektral trend yönteminde eğrinin eğimi basit bir durum belirteci olarak kullanılabilir. Farklı motor durumları birbirlerine göre değerlendirilip, motorun sağlık durumunu bir metrikle ifade etmek mümkündür. Bu şekilde motorun

yaşlılık durumu ölçülebilir bir büyüklük olmaktadır. İlk ve son duruma ilişkin trendler kullanılarak, yaşlılık izlemesi yapılabilir bunun için tüm frekans bölgesini izlemeye gerek yoktur. İzlenmesi gereken frekans bölgesi, yöntem sayesinde 16.67 katı kadar küçülmektedir.

Cebirsel toplama ile arıza tanısı yönteminde ise ayrıştırma sayısı yükseldikçe düşük frekans bölgesindeki artık bilgi yoğunluğunun arttığı gözlemlenmiştir. Bu durumdan ötürü yöntem bütün bilgisini düşük frekans bandında taşıyan sağlıklı durum verilerinde daha başarılıdır. Yöntem deney verisine uygulandığında eksenel kaçıklıkla ilgili frekansları kuvvetlendirdiği görülmektedir. Bu anlamda yöntem erken arıza tespiti ve tanı konusunda son derece başarılıdır. Cebirsel toplanmış sinyallerin trendleri göstermektedir ki metot yaşlanmayı yapay olarak artırmaktadır. Yöntemin bu özelliğinden yola çıkılarak motorun en yüksek oranda bozulabileceği limitler felsefi olarak belirlenmiştir.

Bu bulgular ışında çalışma basit ve pratik bir yaşlanma belirteci sağlamış ve bu alanda daha önce uygulanmamış olan konveks bölge yaklaşımı ile durum izleme stratejisini değiştirmiştir. Motor sağlığını ölçülebilir bir kavrama dönüştürülmüştür. Durağan dalgacık dönüşümü temelli yeni bir arıza tanısı yöntemi önerilmiştir. Arıza tespiti, tanı ve durum izleme açısından bu katkılar son derece dikkat çekicidir.

Katkıların yanı sıra bu tez çalışmasında önerilen yöntemler endüstriyel uygulamalarda kolaylıkla yer bulacak türdendir. Bakım mühendisliğine yeni bir bakış açısı getirecek kavramlar içermektedir.

Daha geniş ölçekte, bu tez çalışmasında sunulan, hem trendlerin geometrik yorumlanması hem de artıklık temelli arıza tespiti, tanısı durum izleme ve diagnostik ile ilgilenen her mühendislik alanında uygulanmaya son derece elverişlidir.

1. INTRODUCTION

This chapter defines the general structure of this study.

1.1 Overview

Electric motors are the mainstay of industrial processes in today's world, due to their advanced control strategies, high efficiency and reliability. Induction motors are the most preferred electrical machines because of their simple structure, robustness, low maintenance need and high power density [1]. Modern-day's industrial world is very expeditious and competitive, and thus does not tolerate any interruption and deceleration. This is because every threat, which may cause a deterioration in system efficiency or continuity, should be removed. In this context, monitoring the performance and the health of the favorite and most encountered element of the industrial system is vital. The performance ratings and failures of induction motors have been investigated since early 1980s [2].

The main reasons of failures in induction motors are generally misapplications and mislead choices, generally. Every motor has specifications which are expected to be respected by the user. The specifications define the mechanical, electrical and environmental conditions that the machine is designed for. Mechanical specifications determine the characteristics of the load. For example, unexpected fluctuations of load or tiring and arduous duty cycles may cause overheating or bearing damages. Electrical specifications are about the system to which the motor is connected. Voltage fluctuations or unbalanced systems are forbidden considering the possibility of insulation failures, decrease of output power and even interruptions in operation. And finally, the environmental specifications designate the characteristics of the surroundings like temperature, humidity and cleanliness. For instance, high temperatures may cause insulation and bearing defects whereas low temperatures may result in frosting. In addition, high humidity is a factor which can accelerate corrosion, while the dirt is a reason for contamination on insulation surfaces and heat exchangers [3, 4].

If system specifications can not be met, there is no need to use an advanced monitoring technique. Changing the machine is the most reasonable option. However, it is not always possible to choose a machine which satisfies all the specifications for a particular application. For such cases using a monitoring system becomes crucial [4].

Other than specifications, lifetime, low production quality and faulty maintenance are the reasons for motor fails. The lifetime of a regular motor is 25000 hours, the aging is expected afterwards [5]. Unqualified fabrication and wrong applications during a repair process are the reasons for motor failure as well [3]. To summarize, in order to have high system performance, the user should choose the appropriate machine, follow the specifications, and execute regular-accurate maintenance and repairs. Missing one of these factors can amplify a root cause of a fault which may lead to a failure [6].

The most common failure modes in electrical machines can be observed in two groups; mechanical and electrical. Electrical failures can be listed as winding and insulation failures for stator and rotor, slip ring failures, core insulation failures, brush gear failures and commutator failures. Mechanical failures are bearing failures and integrity failures for stator and rotor, resulting in air gap irregularities and eccentricity [7, 8]. All of these faults are expected to produce some failure symptoms (fault) like unbalanced air gap voltages and line currents, increments in torque pulsations, decrement in average torque, high losses and low efficiency, over heating [9].

1.2 Literature Survey

Investigation of faults are discussed extensively for induction motors as they have wide spread use in industry. Their failure may cause downtimes followed by missing targeted production and huge financial losses. That is why there are several surveys [2, 6, 10-12] which are done by the IEEE and EPRI. As a brief result of these studies induction motor bearings have the highest possibility of breakdown with around a rate of 40%. The second possible defect is winding failures with an approximate rate of 30%. Finally, rotor related failures are at a rate of about 9%. The remaining percentage is mentioned as other faults such as stator core faults, ventilation faults and unexpected shaft voltages etc. [3, 4].

Bearing faults may occur due to wrong lubrication, improper mounting or alignment and load related radial-axial stresses. These may result in high amplitudes in vibration and noise, shaft deflection, eccentricity and fast aging. The best way to detect bearing faults is vibration, shock pulse or acoustic emission monitoring.

Stator winding faults can be caused by insulation defects occurred turn-to-turn. These faults may result in time harmonics on flux or current and phase imbalance. The fluctuations in current are expected to be very small so it is difficult to detect the fault with current monitoring. In such cases, flux monitoring may be a good option. Stator faults may originate from external drives as well.

Rotor faults are caused by cracked or broken bar or end rings. As a result of this, the bar current increases and leads to big fractures. These faults cause torque pulsations, speed fluctuations and vibration. They can also cause undesired flux linkages in magnetic circuit and oscillate the supply current by disturbing frequency components. The physical indicators of a rotor fault are noise, vibration, overheating and arcing [6, 13-16].

In order to detect potential faults, in an induction motor an appropriate condition monitoring system should be employed. A condition monitoring system observes the trends of performance parameter of the machine. Thus, the motor performance may be analyzed and some life extending precautions can be arranged. Considering the possibility of occurrence of the aforementioned faults, condition monitoring should be run continuously or periodically. Condition monitoring has a great importance for both fault detection and maintenance planning. It prevents malfunctionings and long downtimes in the system and thus enhances system quality [8].

The condition monitoring technique should be accomplished considering the needs of an application. Typical monitoring techniques can be listed as;

- Electrical current, flux and power monitoring: Electrical performance monitoring directly shows the circuit defects within the motor. Current monitoring especially is one the most informative indicators about the motor's condition. The reason for this is that current signal carries hints about both electrical and mechanical faults. The biggest advantage of this type of monitoring is its easy accessibility [10, 14, 16-18].

- Mechanical vibration monitoring: It is vital for the detection of all mechanical failures. In addition, magnetic or aerodynamic imbalances can be monitored by vibration successfully as well [6, 19]. For example, bearing fault is the most common failure type with a high percentage of occurrence (40%). It can be detected easily by vibration monitoring due to its nature, whereas current is a poor indicator of it. The vibration level is already an indication of the fault existence by itself [8]. Moreover, there are some specific frequencies associated with several faults of bearings [20-22]. In addition, vibration is a result of electromagnetic forces, so any disorder in the electric or magnetic circuit can be monitored using the vibration signal [23]. In the literature a detailed list of electrical and mechanical faults is given for induction motors and their induced vibration components are also included [22]. To summarize, vibration monitoring is the most important and satisfying method of estimating the overall condition of the motor [24, 25].
- Temperature monitoring: Monitoring temperature is very important for insulation health [3]. It shows the ventilation and friction problems as well.
- Chemical and wear monitoring: Oil and wear debris can be detected by monitoring the chemical properties of insulation [8]. It is a late indicator for the aging of the system.
- Electrical discharge monitoring: It is important for high voltage motors because several discharges (corona, partial, spark and arcs) may result in slow degradation [8].

And also, some uncommon monitoring techniques can also be developed considering special requirements of the system [7]. These are acoustic emission monitoring [26, 27], radio-frequency emission monitoring [28] and infrared recognition [29].

In order to define any fault, a diagnostic procedure is determined and fault detection is accomplished following condition monitoring. This process lets the operator detect the parts which begin to degrade. Thus, the continuity and high efficiency of the system can be provided. Moreover, fault detection and diagnostic systems enable the utilization of condition-based maintenance instead of scheduled maintenance.

Diagnostic systems can be observed in three classes: model based, statistical data based and signal based. All of these diagnostic systems usually use signal processing methods in order to define a fault indication.

Model based methods are built considering the mathematical model of the system. They compare the theoretical response and the actual response of the system to detect any anomaly [30]. If the system contains deterministic features, then building a mathematical model is easy, so it is employed commonly. However, if an embedded magnetic circuit or high order differential equations are included, then they can have very heavy computation loads.

Statistical data based methods are independent from the theoretical approaches, so the complexity of the system is not a consideration. The data is classified using clustering and some statistical techniques, then artificial intelligence (AI) methods or pattern recognition applications are used to define the fault. AI applications are used for decision processes (i.e. defining the fault). They definitely expedite this process. Reliability analysis based upon the data is another approach in this field [31]. The most commonly used AI techniques are: Expert systems, fuzzy logic and artificial neural network applications [30].

Expert systems are run by a list of rules and a database which represent the knowledge. These systems decide using instantaneous data, trend analysis, maintenance reports, offline tests and most importantly the operator initiative [8, 32]. Fuzzy logic is also a knowledge based algorithm like expert systems. But the difference is that; it specifies the knowledge by the membership functions and fuzzy inference methodology [30]. A rule-base is created which is the list of all states from better to worse. A membership function is assigned considering the characteristics of the system. Fuzzy Logic applications take their power from the case-special membership function and inference capability [33, 34]. Artificial neural networks (ANN) are capable of learning the complicated and nonlinear relationships using a pattern representation [35]. The systems which are difficult to express analytically can be modelled successfully using ANN [25, 36]. In some applications, with induction motors the hybrid version of these techniques like adaptive neuro-fuzzy inference system is adopted [37]. Pattern recognition is also used as Bayes minimum error classifier to detect eccentricity and phase unbalance [38].

Signal based methods observe the data using several signal processing methods to define the fault indication. It is a well known fact that the signals obtained during the condition monitoring carry very important hints about the motor's situation in terms of time and spectral properties. So, signal processing methods are observed in five classes;

- Time domain techniques
- Spectral estimation techniques
 - Non-parametric,
 - Parametric
 - High resolution methods.
- Time-frequency techniques
- Time-scale techniques
- Other hybrid techniques

Time domain techniques are based on statistical variables of the data such as root mean square value, crest factor, skewness or kurtosis. The situation of the system can be evaluated using these parameters, even a model can be extracted [39]. Useful information can be achieved for non-stationary signals, in some conditions. However, the problem with this technique is that these variables can change rapidly by any noise [40].

Spectral analysis is a very handy tool for the analysis of most signals like current, flux, torque or vibration. However spectral techniques are not capable of analyzing non-stationary signals. Whereas, in a case of a defect, machines usually produce some non-stationary signature [30, 40]. Spectral analysis techniques can be classified as parametric, non-parametric and high resolution techniques.

Non-parametric (classical) methods are based on the estimation of autocorrelation sequence of the data. The spectral estimation can be realized using Fourier transform of the autocorrelation sequence. Then it can be concluded that conventional Fourier transform, periodogram (Welch's method, Barlett's method) are non-parametric approaches. Some autocorrelation related expressions like bispectrum [41] and cepstrum [42] are also used as non-parametric methods [30, 40]. The problem with the non-parametric methods is that they do not provide a fine frequency resolution on limits and they are very sensitive to signal-to-noise ratio (SNR).

Parametric (non-classical) methods are based on time series modelling to estimate the covariance and spectral density of the signal. Autoregressive moving average models are good examples for this category [30]. They are widely used in performance evaluation and remaining useful lifetime calculation studies [43, 44]. In terms of frequency resolution, they are better than non-parametric methods however, they are still very sensitive to SNR.

High resolution methods have examples like eigen-based frequency estimation [18] and multiple signal classification [45]. These methods are successful even with low SNR [30].

As mentioned before, neither time domain nor frequency domain technique are successful with non-stationary signals. Today's technology commonly includes adjustable speed drives. These drives change supply frequency which tends to the non-stationary electrical signals. As a result of changing supply frequency, the mechanical output of the system is expected to be non-stationary or to have transients [30]. Moreover, it is known that the mechanical signals generated by some faults are of a non-stationary nature because of the modulation of other mechanical components' rotation [40]. In order to solve the problems which have non-stationary signals and transients, time-frequency techniques are used.

The commonly used time-frequency technique which is used for fault detection in electric motors is Short-Time Fourier Transform (STFT) [46-48]. Wavelet transform can be considered as a time-scale technique in this grouping [49, 50]. Other hybrid technique can be presented as follows: Wigner-Ville distribution (WVD) [51], Adaptive Time Frequency Distribution (ATFD) [52, 53], Cohen's Class Distribution Function (CCDF) [54, 55] and Hilbert-Huang Transform (HHT) [56-58]. All of these techniques provide time, amplitude and frequency or scale information at the same time. There are studies which benefit from the combinations of these methods such as Fuzzy Auto Regression Moving Average Models [59] or Wavelet based Neural Networks [60] or Power Spectral Density based Discrete Wavelet Transforms [49]. In order to compare the properties of the frequently used time-frequency methods Table 1 is given [61-63].

Table 1.1 : Evaluation properties of time-frequency, time-scale and other hybrid techniques.

	Resolution	Interference	Computational complexity
Continuous Wavelet Transform	Good	Few	Medium
Discrete Wavelet Transform	Good (very good at low frequencies)	No	Low
STFT	Depends on window size	No	Low
WVD	Very good	Too much	High
Cohen's Class Distributions	Good	Less than WVD	Medium
HHT	Very good	No	High

Among these techniques, Wavelet Transform (WT) has a reasonable achievement in motor fault detection and diagnostic studies. WT is first defined to deal with the shortcomings of classical spectrum methods. It is very prosperous to extract the time-frequency information of non-stationary signals. It is even successful with data which has breakdown points, higher derivatives and self-similarities.

The first thing that comes to mind to cope with Fourier Transform's drawbacks, is applying the Fourier Transform on overlapping segments and aggregating the results. This way, Short Time Fourier Transform is introduced. STFT is a windowing operation which observes the signal through sliding the window through the time. However, a fixed window size rises a natural tradeoff between time and frequency resolution. A small window size provides very good time resolution whereas it involves few data samples which result in bad frequency resolution. Vice versa, large windows which give high frequency resolution with lots of data can not precise the time information [63]. In this regard, STFT is successful with quasi-stationary signals, assuming the segment is stationary within the window but the overall signal is not. Another disadvantage of STFT is its slow and non-efficient and non-effective computation process [62].

Because of these facts, WT introduces the concept of window size variation in addition to sliding through time. Moreover, it is defined on orthogonal bases which make it easy and fast to calculate. Basically it compares the signal with shifted and scaled versions of a base wavelet (mother wavelet) and evaluates their resemblances [64].

Various types of wavelet transforms are used for diagnostics and condition monitoring of electrical machinery. Of these different types, Continuous Wavelet Transform (CWT) is a redundant transform because it outputs a uniform resolution with continuous shifting and scaling parameters on a continuous scaling concept [65, 66]. The reconstruction process becomes very time consuming as well because of the produced redundant data. Scalogram, which corresponds to a spectrogram for wavelet transform, is usually encountered as the most common output of CWT. However, because of the convolution operation of CWT, interference terms come into existence. These terms make the interpretation of the scalogram difficult or may lead to wrong interpretations [62].

Discrete Wavelet Transform (DWT) is introduced to eliminate the aforementioned redundancy by discretizing the scaling and shifting parameters [49, 67, 68]. Sampling the scaling and shifting parameters provide high time resolution at higher frequencies and high frequency resolution at low frequencies [49]. Moreover, the transform can be interpreted as a filtering operation, which has a dyadic strategy, by this sampling action. One of the most important accomplishment of the wavelet transform is introduced as the multi-level implementation of DWT which is usually called as Multi Resolution Wavelet Analysis (MRWA) in the literature [17, 69]. For this method, a decomposition tree is created by low-pass and high-pass wavelet filters. The scale is adjusted by a down-sampling operation at each decomposition level. The time and frequency resolution is kept good enough at desired frequency levels by this strategy [66].

However, it is well known that redundancy creates a time invariant structure on the transforms; that is why redundant transforms are preferred in some engineering problems [70]. The drawback of redundant transforms is their slow nature. Nevertheless, their advantage over non-redundant transforms is that redundancy makes it easier to define instantaneous changes and transients [71]. In time variant structures the coefficients of a shifted or delayed signal can be obtained by shifting the coefficients which are calculated for the non-shifted signal [72]. Time invariant structures, are a very beneficial tool for detection and estimation in statistical signal analysis[70] and signal de-noising [73] and in fault classification [74].

Stationary Wavelet Transform (SWT) is first introduced with the aim of providing a time invariant structure which is lost with DWT. The down-sampling operation is

omitted and the filter coefficients are kept up-sampled at each level. That is why another name of the SWT is Undecimated Wavelet Transform (UDWT). This is also known as “Algorithm à Trous” [75-77]. When any time shifting is applied to the signal, the time frequency information is preserved using SWT [77]. Based on this property, it is suitable for the motor aging and fault detection problems, because these kinds of problems have non-stationary and complicated context [30, 40]. For example, bearing faults create non-stationary signals because of the modulation provided by the rotational parts (gears and shafts) mostly [40].

1.3 Problem Definition and Motivation

The vibration signature carries all information caused by mechanical faults, electrical faults and unbalanced magnetic pull problems. Due to this rich information content, vibration signals are commonly used in diagnostic problems. Vibration signals are capable of recognizing the aging situation of the motor. In that manner, there is always a need for a simple and feasible vibration monitoring technique in order to estimate the aging of the motor.

There are some fault frequencies which are calculated using the physical dimensions, pole numbers and the supply frequency of the motor [22, 78]. In order to detect and define the fault, it is very useful to look for these fault frequencies after aging occurs. In addition to these frequencies, their high ordered harmonics are encountered commonly in the spectra as well [60]. This is how a conventional condition monitoring and fault detection system works.

In the mean time, aging is a gradual and progressive mechanism. Evaluation of the spectral properties can provide an answer to when and how this process is evolving. Through this, a spectral based monitoring technique is proposed in this study, to detect and rate the aging of the motor. If the motor is aged, it is easy to detect and define the defects. However, if it is healthy some special techniques are needed. For this aim, a sensitive detection approach is developed, benefiting from the redundancy property of the Stationary Wavelet Transform.

The study consists of two parts; classification (spectral based trending) and analysis (sensitive detection with SWT). In the first part, logarithmic PSD based trending [79] is introduced for different aging cycles. Through these trends and a measurement

boundary, a critic convex region is defined in a two dimensional (2D) Euclidian space for general condition monitoring. This approach aims at a classification regarding the trend of the motor; i.e. whether the motor is healthy or not. The study becomes a spectral trending application on frequency domain. Aging Region concept is introduced to designate a new condition monitoring strategy. Thus, vibration monitoring is refined to a smaller scale. Therefore, a new simple and feasible monitoring approach is proposed. In the next step, a rating parameter is introduced in order to estimate the situation of the motor. As a result, the aging status at any random state can be determined as a percentage by using this method.

In the second part, the regular reconstruction algorithm of SWT is changed, cancelling the down-sampling operation during the reconstruction in order to conduct a more accurate detection. The goal of this modified reconstruction operation is realizing a more sensitive detection by amplifying the anomalies and fault frequencies intentionally, using the redundancy of SWT. In other words, stationary wavelet decomposition is followed by an algebraic summation operation.

This process is then tested on artificial and experimental (real) data. All of these data sets contain healthy and faulty vibration signals of an induction motor. The artificial data is produced by the sum of random noises which is then enriched with specific fault frequencies. The real data is obtained from an experimental setup which belongs to The University of Tennessee Knoxville (UTK). This experimental setup was designed as a part of a research and development project which is sponsored by *The University of Tennessee Maintenance and Reliability Centre*. The goal of the project was improving online fault detection methods for incipient faults. In order to do this, the experiment includes an accelerated aging process [80, 81]. These data have been in previous cooperated research and studies which were run by UTK and Istanbul Technical University [31, 39, 60, 65, 78, 82, 83]. A simplified flow chart of the study is given in Figure 1.

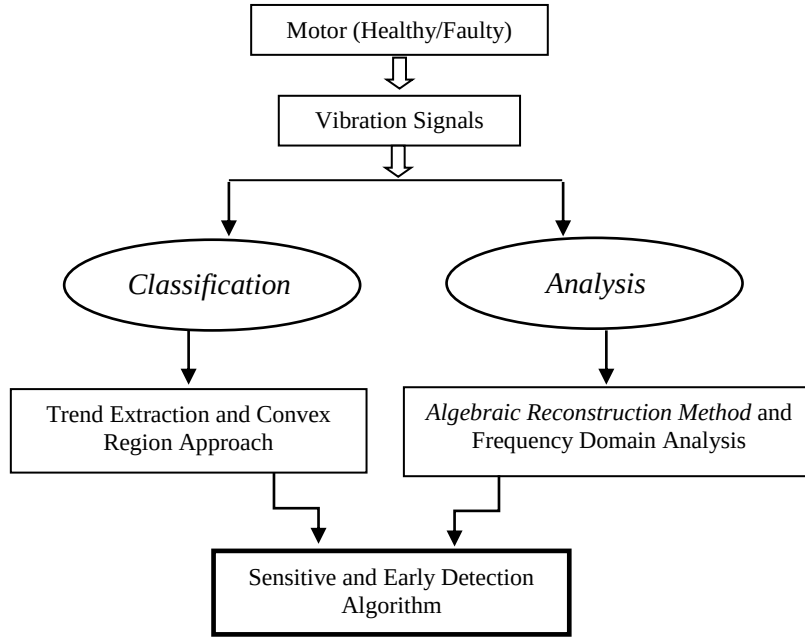


Figure 1.1 : Flowchart of the study.

The organization of the thesis is as follows;

The introduction section presents the utilization of induction motors in industrial systems, their failure modes and monitoring techniques. Then, fault detection methods are given with a literature survey. Signal based techniques are investigated largely with the aim of making clear the need for employing Stationary Wavelet Transform in this study. The problem definition and motivation is given also in this section.

In the second section, mathematical background of the study is given. Wavelet transform and their types are introduced. Redundancy concept is explained within SWT. Convex region approach and spectral trend extraction concept are presented.

In the third section, experimental study is presented. Aging mechanism of an induction motor is explained and standards on motor aging are investigated. Accelerated aging experiment, which is held on University of Tennessee Knoxville, is given in detail. The experimental setup is represented. The aging cycles and the vibration signals of cycles are given on time and frequency domain.

In the fourth section, spectral trending of frequency domain signatures is given. The classification is done using logarithmically interpreted PSD to decide if the motor is healthy or not. In order to improve the technique an artificial vibration data is produced. A simple aging indicator is defined. Progress of aging is observed through

spectral trending. Aging region concept is introduced and the condition monitoring region is refined to this region. And finally health rating concept is defined for any random state of the motor.

In the fifth section, an algebraic summation is proposed for SWT reconstruction. This operation preserves the redundancy of the transformation during the reconstruction process. This type of reconstruction eases to detect the potential defects which are not noticeable at the health case of the motor. By this way, a fault detection operation is executed. The procedure is improved using artificial data and applied to experimental data. And also, regular SWT reconstruction and algebraic summation operation are compared and investigated in terms of redundancy.

In the conclusion section, benefits of the spectral trend based monitoring technique are introduced. The refined condition monitoring region is emphasized. The use of redundancy is highlighted for fault detection in induction motor. Since therefore, the sensitive detection approach is presented with these two components as classification and analysis. And also, the outstanding properties of the study over other methods are reported.

As the contribution, the study presents a sensitive detection method consisting classification and analysis parts. The classification is realized during the monitoring and then analysis is accomplished by algebraic summation. Spectral trending application on frequency domain is introduced as a very simple monitoring approach. It is easy to apply and feasible on industrial processes because of the rating capability about the situation of the motor. And also, this is done creating a 2D Euclidian space and convex regions which are totally new and original in condition monitoring of electric machines. And also, the algebraic summation reconstructs the signal preserving the redundancy on purpose. It is used to amplify fault frequencies deliberately, by this way the sensitivity of fault detection is increased. These novelties may be counted highly significant in terms of defining an easy and feasible condition monitoring and sensitive fault detection.

2. MATHEMATICAL BACKGROUND

In this study, condition monitoring and aging detection are conducted using vibration signals of an induction motor. The study comprises of two sections; classification and analysis. For classification purposes, logarithmic interpretations of PSDs are used. Trends are fit to these PSDs and these trends and their measurement boundaries are used to form a decision plane which is a 2D Euclidian space.

The main idea beyond the trending application is extracting spectral based linear trends for vibration signals. It is well known that spectral properties of the vibration signals vary with aging. Moreover, linear trends are expected to differ from case to case. Interpreting these trends allows the estimation of the situation of the motor. The least square algorithm is used to fit a linear interpretation to the logarithmically calculated PSD.

For the analysis part of the study, the regular reconstruction algorithm for SWT is modified. SWT is a redundant transform due to its nature. The redundancy, which is obtained after a decomposition process, is eliminated during the regular reconstruction operation. In this study, the redundancy is intentionally preserved on the reconstruction phase. Thus a modified reconstruction operation is defined. This preserved redundancy is used to amplify the potential faults which are normally not distinguishable.

The mathematical background of the study consists of three sections. First of all, the convex region approach and spectral trends are presented. Then basics of Wavelet Transform (WT), Continuous (CWT) and Discrete Wavelet Transforms (DWT) and Stationary Wavelet Transform (SWT) are introduced. As the last section, the redundancy concept is explained and its benefits are elaborated.

2.1 Convex Region Approach

In a vector subspace $\mathbb{A}$ of the Euclidian Space, any v and u vectors can be defined. If a line segment assigned between their pointers is included by $\mathbb{A}$, then the subspace $\mathbb{A}$ is convex. In other words, the region is convex, if (2.1) is satisfied [11].

$$\{\alpha u + (1 - \alpha)v \text{ for } 0 \leq \alpha \leq 1\} \subset \mathbb{A} \quad (2.1)$$

Practically, a convex region includes all the straight lines joining any two points within it. For example, triangle, circle and trapezoid are convex regions (Figure 2.1.a) on a two dimensional Euclidian space whereas crescent and star are not (Figure 2.1.b).

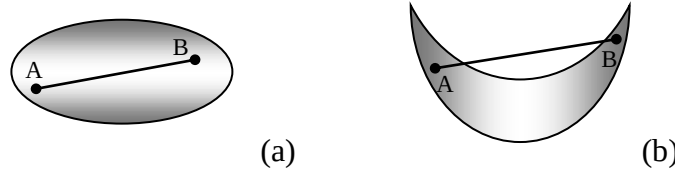


Figure 2.1 : (a) Convex region (b) Non-convex region.

Moreover, if some random pegs are set in a convex region $\mathbb{A}$, the subset which is bounded by a stretched rubber band embracing these pegs can be defined as a convex hull. The convex hull concept is used in pattern recognition and statistics problems [13, 14]. A convex hull, which is defined in a convex region, is shown by Figure 2.2.

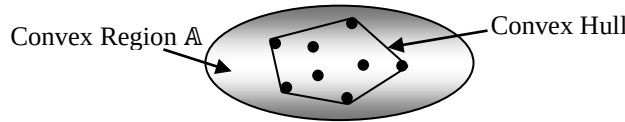


Figure 2.2 : A convex hull in a convex region $\mathbb{A}$.

Convex geometry calculus is widely used in engineering applications and it requires geometric programming [84]. Convexity is a useful geometric definition for many grouping and clustering applications. Many image processing applications use the convexity for grouping. The primary reason for this is the possibility of encountering convex objects in the observed image. The second reason is the ability to create convex sets by combining boundaries of not fully convex regions [85-87]. In this sense, convexity is a necessity in image segmentation [88]. In communication system applications, the geometric approach is used to define convex regions to locate spectral nulls resulting from poor system performance [89, 90].

Moreover, convexity is used in various detection problems encountered in computer vision, object recognition, and image understanding. Some examples include edge and boundary detection, moving target detection, shape defect detection, and retinal vessel detection [1, 2, 5, 6, 91-93]. However, subsets of convex regions (CR), termed Convex Hulls (CH), are used rarely in fault detection problems [7, 12]. In this study, CRs and CHs are used to evaluate the condition of an electric motor. These concepts have not been applied to electric machinery fault detection and diagnostics before, and provide an innovative approach for machinery monitoring.

2.2 Spectral Trends

Trending is a very useful method in monitoring and investigating gradual system degradation. The approach is to define a trendable variable associating the condition of the system [63]. Trending is used for condition-based operations and maintenance planning in industry. There are studies aiming to measure and identify the degradation of mechanical systems [94, 95]. Aging is also a gradual system which can be monitored by trends of some signals.

It is well known that aging manipulates the spectral properties of the vibration signal. By this point of view, their trends based on spectral information will be different. In this study, Power Spectral Density (PSD) of the vibration signals are used to extract spectral trends. These logarithmic PSDs are employed to calculate linear trends using the least square algorithm. The measurement boundary is represented by the highest frequency which may be obtained through the experimental setup. An anti-aliasing filter is employed with 4 kHz cutoff frequency for the experimental setup. So the boundary frequency is set to 4 kHz in order to form a convex region. More detailed information about the experiment is given in Section 3.

2.3 Wavelet Transforms

Signal representation can be successfully achieved by choosing a basis function defined in the time domain. A signal $x(t)$ can be represented on a different form through a basis function $\phi_k(t)$, $k \in \mathbb{Z}$ as seen in (2.2).

$$x(t) = \sum_k c_k \phi_k(t) \quad (2.2)$$

If the signal $x(t)$ is infinite then it is natural to have a basis function $\phi_k(t)$ with infinite duration. However, if the signal $x(t)$ is a finite duration signal, then it is clumsy to use an infinite duration basis function $\phi_k(t)$. For example, in order to do the best representation of a rectangular pulse with sinusoidal bases, infinite number of sinusoid waves are needed. That is why finite duration basis functions are defined.

Signal representation was achieved by power series before Fourier analysis. The basis function of this representation was $\{t^k\}$, $k \in \mathbf{Z}_+$. Then Fourier analysis proposed that infinite-duration signals can be represented as the linear combination of sinusoidal functions. If the signal is periodic and stationary, Fourier analysis is the best way of representation. Then Haar basis was introduced claiming that a signal may be represented closely using an orthonormal basis with local support (finite duration). However, Haar basis wasn't very popular because of its discontinuous nature. Representing signals using orthonormal basis with finite duration became very popular after the Daubechies' orthonormal approximation function [96].

2.3.1 Evolution of Wavelet transform from Fourier transform

It is known that Fourier analysis is very useful tool for periodic and stationary signals. However, it does not provide any time information. In order to obtain time information within the signal Windowed Fourier Transform, which is also known as Short Time Fourier Transform (STFT), is introduced. It investigates the signal in a specific time interval, then it slides the window.

$$STFT_{\phi}X(\omega, b) = \int_{-\infty}^{\infty} x(t) \overline{\phi(t-b)} e^{-j\omega t} dt = \langle x(t), \phi(t-b)e^{j\omega t} \rangle \quad (2.3)$$

As seen in (2.3) the window width is fixed with constant ϕ , only the location (b) and frequency (ω) vary. This fact makes the transformation useless for non-stationary signals and transients. To analyze such signals, a transform kernel with adjustable scale and time is needed as seen in (2.4) [96]. In these equations, $\bar{\phi}$ defines the complex conjugate of ϕ and $\langle x, \phi \rangle$ defines the inner product of x and ϕ .

$$\phi(t-b)e^{j\omega t} \rightarrow \frac{1}{\sqrt{a}} \overline{\psi\left(\frac{t-b}{a}\right)} \quad (2.4)$$

2.3.2 Continuous wavelet transform

Wavelet transform researches began with Continuous Wavelet Transform (CWT) which computes the correlation between the signal and the chosen wavelet. CWT can be expressed with (2.5) where $x(t)$ is a square integrable function and $\psi(t)$ is the mother wavelet, and $\psi_{a,b}$ is wavelet family where $\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$. It is a very redundant transform with continuous scaling (a) and shifting (b) parameters.

If the mother wavelet function satisfies the admissibility condition, then the signal's CWT can be invertible. The admissibility condition on $\psi(t)$ is given in (2.6), where $\Psi(\omega)$ is the Fourier transform of $\psi(t)$.

$$CWT_{\psi}X(a, b) = \int_{-\infty}^{+\infty} x(t) \overline{\psi_{a,b}(t)} dt = \langle x(t), \psi_{a,b}(t) \rangle \quad (2.5)$$

$$C \equiv \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega \quad (2.6)$$

If $0 < C < \infty$, then the inverse transform is given in (2.7).

$$\begin{aligned} x(t) &= ICWT_{\psi}(X(a, b)) \\ &= C_{\psi}^{-1} \int_{a=-\infty}^{+\infty} \int_{b=-\infty}^{+\infty} \frac{1}{|a|^2} CWT_{\psi}X(a, b) \psi_{a,b}(t) db da \end{aligned} \quad (2.7)$$

In (2.5), adjusting the scale parameter a , changes the width of the window. Using different sized windows, details can be split from the signal at specific locations of time [68, 96].

2.3.3 Discrete wavelet transform

In order to step up the calculation and avoid the redundant information which is provided by CWT, Discrete Wavelet Transform (DWT) is introduced. The transform remains applicable on continuous signals by discretizing scaling and shifting parameters only. The scaling and shifting parameters are discretized as $a = a_0^k$ and $b = mb_0 a_0^k$ where a_0 and b_0 are constants while $a_0 > 1$ and $b_0 > 0$. And also, m and k are integers. The discretized wavelet becomes as seen in (2.8).

$$\psi_{k,m} = a_0^{-\frac{k}{2}} \psi\left(\frac{t - mb_0 a_0^k}{a_0^k}\right) \quad (2.8)$$

Thus, the discrete wavelet transform can be given as in (2.9).

$$DWT_\psi X(k, m) = \int_{-\infty}^{+\infty} x(t) \overline{\psi_{k,m}(t)} dt = \langle x(t), \psi_{k,m}(t) \rangle \quad (2.9)$$

If these parameters are defined as dyadic samples as $a = 2^k$ and $b = 2^k m$, where $a_0 = 2$ and $b_0 = 1$, then the expression which is given in (2.10) can be helpful to understand this concept.

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} d(k, m) 2^{-\frac{k}{2}} \psi(2^{-k}t - m) \quad (2.10)$$

Here the terms of $d(k, m)$ are related to values of CWT of $x(t)$ at $a = 2^k$ and $b = 2^k m$. From this point of view, it is easy to see that the wavelet coefficients for an orthonormal DWT are the samples of CWT on dyadic grid. For discrete signals it is required to do the discrete interpretation of $CWT_\psi X(a, b)$ where $a = 2^k$, and $b = 2^k m$ and $x(t)$ is sampled at integer n [97]. And also, DWT algorithm is equivalent of convolution operation followed by decimation.

2.3.4 Multiresolution analysis

$DWT_\psi X(a, b)$ generates a set of spaces nested in each other. Analysing the signal using these spaces is named Multiresolution analysis. At that point the scaling function $\phi(t)$ definition related to the mother wavelet is introduced to simplify the multi scale (multiresolution) representation [68].

$$\psi(t) = \sum d(n) \phi(2t - n) \quad (2.11)$$

In order to express the signal $x(t)$ by the basic sum of scaling and wavelet function are used, where d_j s are the detail coefficients at different scales and c_0 is the approximation coefficient at last scale.

$$x(t) = \sum c_k(n) \phi(t - n) + \sum_n \sum_{k=0}^{K-1} d_k(n) 2^{\frac{k}{2}} \psi(2^k t - n) \quad (2.12)$$

This process can be represented by convolution of the expansion coefficients (c_j and d_j) with the wavelet function and the scaling function followed by decimation (down-sampling by 2). And the wavelet coefficients, which is seen in (2.12), can be represented by high-pass filters whereas scaling coefficients can be represented by low pass filters [98-101]. In digital signal processing system representation, DWT and MRWA are equivalent to filter bank algorithms. The scheme which is equivalent to MRWA can be seen in Figure 2.3.

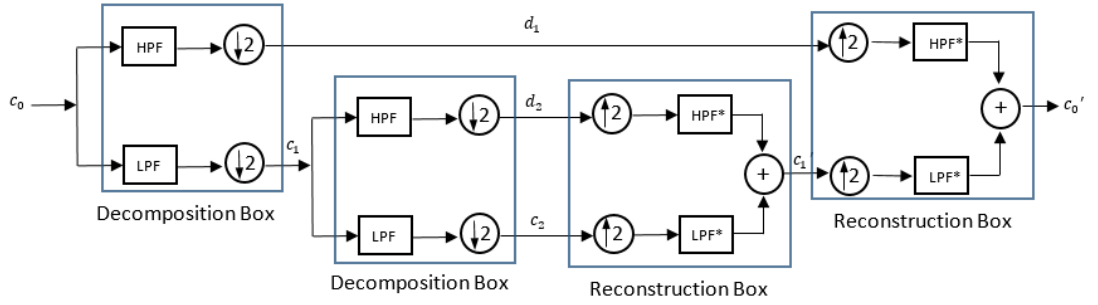


Figure 2.3 : The scheme for a two level multiresolution wavelet decomposition and reconstruction system.

2.3.5 Stationary wavelet transform

Discrete Wavelet Transform is not a time-invariant transform. This means that any translation in time applied to the signal may change the DWT coefficient of the signal, even if the signal is periodic. The time invariant structure which is lost with the definition of DWT is regained with Stationary Wavelet Transform (SWT). In order to understand SWT, à Trous Algorithm should be explained.

For this aim, the DWT expression is calculated for $k = 0$ and $k = 1$, in other words for Scale 1 and Scale 2, respectively.

$$\begin{aligned}
 \text{Scale 1} \quad DWT(1, m) &= \sum_n x(n) \psi(n - m) \\
 \text{Scale 2} \quad DWT(2, 2m) &= \frac{1}{2^{1/2}} \sum_n x(n) \psi\left(\frac{n}{2} - m\right)
 \end{aligned} \tag{2.13}$$

For Scale 1, $\psi(n)$ is used at integer samples and for Scale 2, the samples of $\psi(n)$ are used at values of n that are integer multiples of $\frac{1}{2}$. Storing sampled values of $\psi(n)$ is an option. However, instead of doing this, a sampling rate can be specified and a “filling in” operation can be executed with approximated values for higher sampling

rates. This “filling in” operation can be realized through interpolation or inserting holes to the signal. The formal way of saying “inserting holes” is *à trous filter* of impulse response $h(n)$. Here, the $h(n)$ filters are the lowpass filters which are used to obtain the approximation coefficient of the scale.

This algorithm can be shown schematically on Figure 2.4.

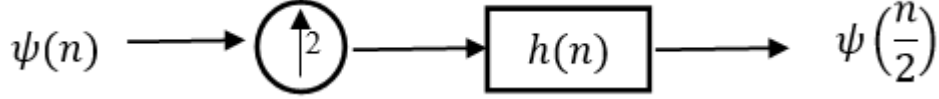


Figure 2.4 : Acquiring sampled wavelet using *à trous* filter.

First of all, the decimated *à trous algorithm* is introduced. It requires to use a down-sampling operator after each convolution (each level). The block diagram of this algorithm can be seen in Figure 2.5.

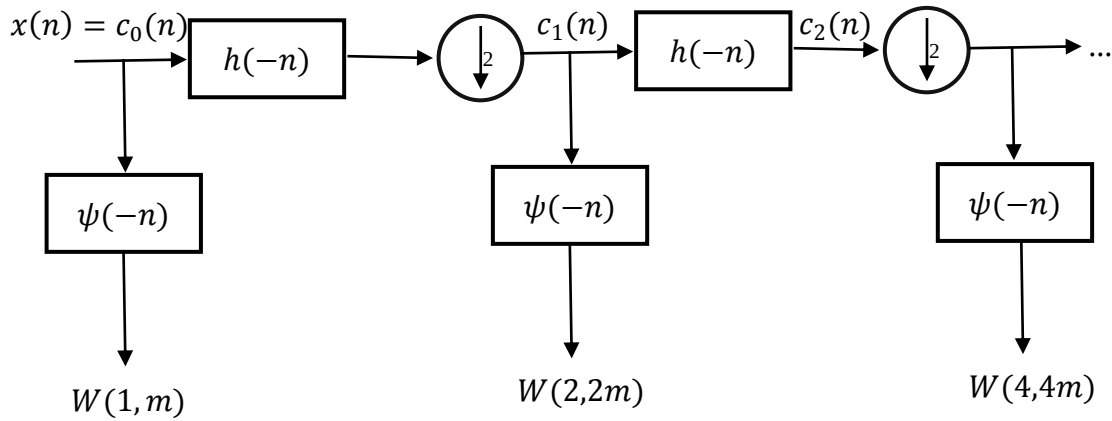


Figure 2.5 : Decimated *à trous* algorithm.

This algorithm is a time varying algorithm. This means that any time shift in $x(n)$ will result in changes on $W(2^k, 2^k m)$. In order to obtain a time invariant structure, wavelet transform has to be calculated at uniformly separated time shifts even though the scale sampling is dyadic. To realize this, noble identities are used to move the down-sampling blocks.

As seen in Figure 2.6 the decimation rate is adjusted up to the scale level. This action helps the user to have a non-redundant dyadic result $(W(1, m), W(2, 2m), W(4, 4m) \dots)$. In addition, approximations are convolved with low-pass filters which have different sampling rates. Then they are convolved with the relevant wavelet functions $(\psi(n), \psi(2n), \psi(4n) \dots)$. At that point, the wavelet

transformation results are located at uniformly separated time shifts. This algorithm makes the transformation time invariant. In order to obtain a dyadic wavelet coefficient series, a down-sampling (decimation) operation is needed [68, 70, 102, 103].

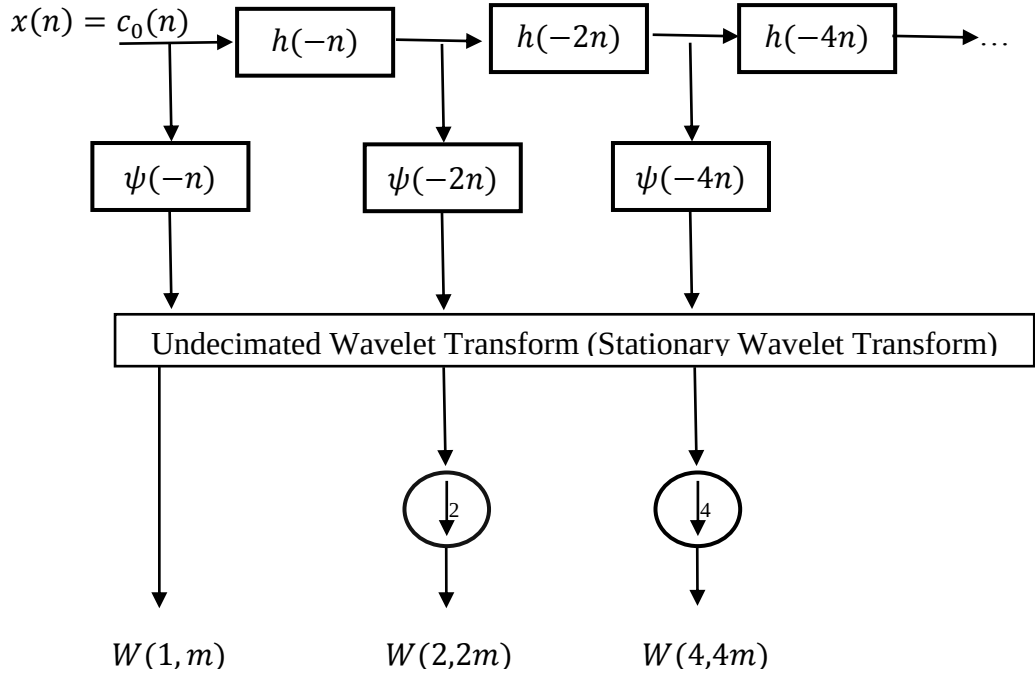


Figure 2.6 : Block Diagram for stationary wavelet transform.

It should be noted that low-pass (scaling functions) and high-pass filters (wavelet functions) all use standard the Mallat Algorithm to decompose the signal [16, 19, 75]. The filter outputs are up-sampled by 2 as seen in Figure 2.7. Because of the up-sampling operation, SWT is a redundant transform.

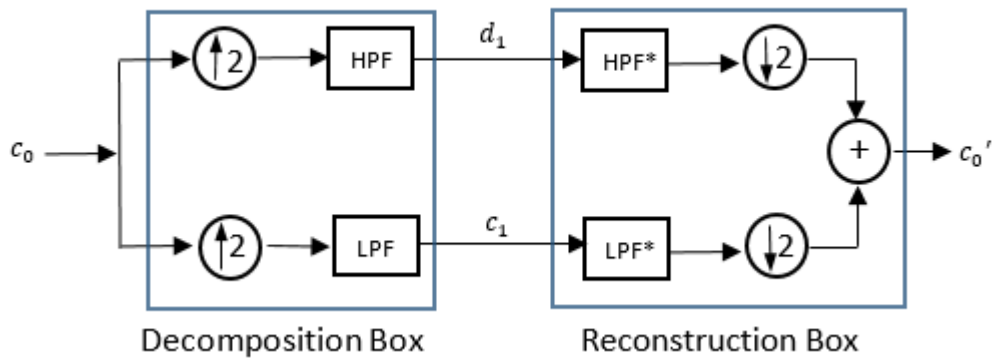


Figure 2.7 : Schematic for stationary wavelet decomposition and reconstruction.

The main advantage of SWT, over the standard DWT, is its time invariant structure [19]. For example, a delayed signal's SWT coefficients are equal to the time shifted

version of the signal's coefficients [20, 22, 24]. Time invariant structures are a very beneficial tool for detection and estimation in statistical signal analysis [70] and signal de-noising [73]. Redundancy creates a time invariant structure on the transforms, that is why redundant transforms are preferred in such problems [70]. The drawback of redundant transforms is their slow nature. However their advantage over non-redundant transforms is that redundancy facilitates the definition of instantaneous changes, transients [71].

2.4 Redundancy

The best way of defining redundancy can be achieved by referring to the reconstruction process. In order to reconstruct a signal, a sufficient number of decomposition results are needed. Decomposed signal fragments may be redundant or not. Here, three questions arise about the perfect reconstruction:

- Is the chosen set of wavelet able to represent and define the signal $x(t)$?
- Are the sampled transformation (DWT) outputs able to reconstruct the signal itself?
- Can the signal $x(t)$ be represented as the superposition of wavelets?

As mentioned earlier, to define DWT the scaling and shifting parameters are discretized as $a = 2^k$ and $b = 2^k m$. This operation samples the $[\omega, t]$ plane. It is obvious that in order to reconstruct the signal perfectly, at least one sample is needed from any window $[\Delta\omega, \Delta t]$. If the sampling grid is not fine enough, then the reconstructed signal will have low quality. If it is fine, the reconstruction may be made perfectly using the redundant data [67].

At this point, sampling density definition should be introduced. The sampling density is ρ , where A and B are the bounds of the window, and $[B - A]$ is width of the window and τ_s is the time interval between samples.

$$\rho = \frac{B - A}{\tau_s} \quad (2.14)$$

For example if $\tau_s = \frac{B-A}{3}$, then the sampling density becomes 3 and so does the redundancy. Or if the samples are very close which means $\tau_s \rightarrow 0$, then the

redundancy goes to infinity. Then adjusting the τ_s with a fixed window width tunes the redundancy. Thus the inequality, seen in (2.15), is necessary for the reconstruction of the signals. To put it simply, in order to do the reconstruction, at least one sample is needed from each window.

$$0 < \frac{\tau_s}{B - A} \leq 1 \quad (2.15)$$

For an efficient sampling operation, τ_s is set as high as possible. However, having a high τ_s may result in a discontinuous window function $\phi(t - b)$ for the Fourier Transform or $\psi_{a,b}(t)$ for the Wavelet Transform. The discontinuous window function may result in discontinuities and noise in the reconstructed signal. If $\tau_s \approx B - A$, then the window function is forced to change rapidly near endpoints so high frequency components will be introduced. So it is obvious that window function should be hold continuous within the constraint $\tau_s < B - A$. If the window width is not fixed then the possibility of overlaps between consecutive windows should be considered. Such an overlap may cause unstable reconstruction. In summary, the choice of sampling density is a very sensitive issue [63].

It can be concluded that redundancy provides a high level of quality during the reconstruction. Even if the precision of the decomposition coefficients is not high enough, the signal can easily be obtained using the redundancy (stored extra data). This is an obvious proof that redundancy provides robustness. Although the orthonormal decompositions provide coefficients with higher precision, it cannot be claimed that the signal may be reconstructed perfectly using the orthonormal decomposition outputs, due to the fact that they are not robust enough by the lack of redundancy. However, a signal may be reconstructed perfectly, following a redundant transform, using the stored data which have low precision [63, 67].

From this point of view, the redundancy of SWT can be perceived considering Fig 2.8. The upsampling operators provide redundancy during the decomposition process. The reconstruction process would not have information loss due to these redundant decompositions. However, as MRWA (Figure2.3) applies the downsampling operation to create its decompositions, it is not possible to reconstruct

the signal without information loss in such a case. The redundancy comparison for SWT and MRWA is given in Fig 2.8.

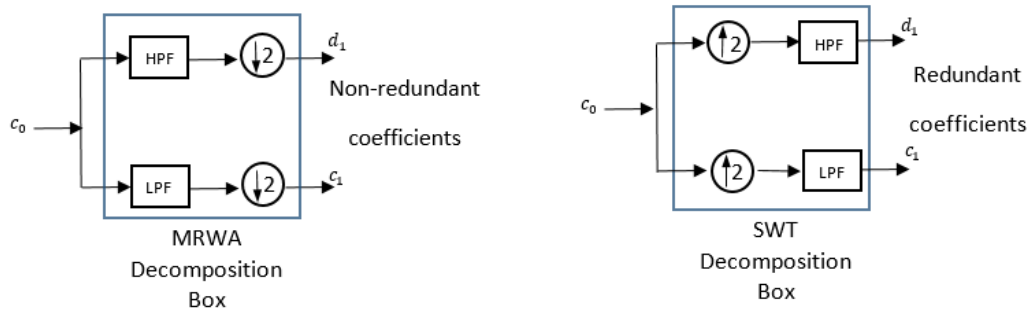


Figure 2.8 : Redundancy comparison for SWT and MRWA.

3. EXPERIMENTAL STUDY

In this section the experimental study and its background is given. First of all, the aging mechanism is introduced. Next, the standards judging if the motor is aged or not are presented. Finally, the artificial aging process and its results are given.

3.1 Aging Process for Induction Motors

It is previously mentioned that there are surveys managed by IEEE and EPRI on induction motor fault potentials. As a brief result of these surveys, induction motor bearing faults are encountered commonly (40%). The second possible defect is winding failures with approximately 30%. And finally, rotor related failures are about 9% [3, 4]. All of these failures may drag the motor to an aged situation. The experiment used in this study focuses on bearing and thermal aging. Thus it is important to express how they occur and lead to aging.

3.1.1 Bearing aging

Unexpected shaft voltages are the main cause of bearing damages. There are 4 different potential root causes of shaft voltages: external voltage applied to the rotor windings, the unbalanced magnetic field on the air-gap, the electromagnetic and electrostatic forces within the motor [95]. If the motor speed is high, then shaft voltages may reach the breakdown voltage of the oil surrounding the bearings and then they cause electrical discharges in the form of sparks. If the motor speed is low, shaft voltages may cause a current between contacting element. These two types of current are called as discharge mode and transmission mode currents, respectively. Transmission mode currents are inductive currents, they continuously exist in bearings and they do not cause an instant damage. However, discharge mode currents are capacitive currents and they cause random discharges relevant to the voltage amplitude. So, they can be very harmful. These discharges may cause damages and degradations on the bearing surfaces. High bearing currents break off micron sized particles (fluting) and distort the oil as well. As a result of this distortion, the

vibration and noise increase in a trend exceeding the standards. The transmission and discharge mode currents can be modeled mathematically. Transmission mode currents occur in low speed levels which cause 10^{-10} m grease oil film and 0.5 ohm resistance. The transmission mode can be modelled by a resistance. Discharge mode currents occur in high speed levels which cause grease oil film to get thicker and can be modeled by a capacitance. Then the following circuit model should be considered for the bearing. R_b is the summation of the inner and outer race resistances and n rolling elements' internal resistances. C_b is the capacitance between the rolling elements and the races. C_{sf} and C_{rf} are the capacitance between the stator-carcass and the rotor-carcass, respectively. C_{sr} is the capacitance between the stator and the rotor along the air-gap [104].

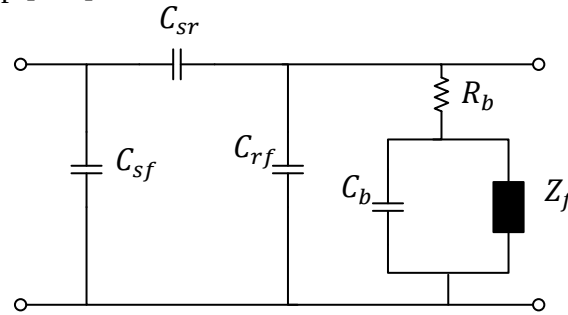


Figure 3.1 : Equivalent circuit for motor and bearings.

3.1.2 Thermal aging

The thermal risks for an induction motor can be classified in two parts: the degradation of stator insulation and deformation of rotor bars. The stator insulation failures can be presented as a chemical process which can be formulated using Arrhenius equation. NEMA Motor Insulation Classification gives the maximum allowable temperature in a specific ambience. High temperature does not cause an immediate failure but it decreases the expected insulation lifetime [105]. Insulation lifetime models for electric motors are based on two main factors as insulation lifetime and magnitude of the stress.

The deformation of rotor bars is another thermal risk for squirrel cage induction motors. The bars do not have any insulation and during high temperature operation, they might melt. It is difficult to define and measure a rotor bar temperature. However, as a rule of thumb, the safe stall time is used to define the rotor thermal limit [105].

3.1.3 Standards on monitoring degradation and aging

The standards followed during this study can be categorized in two subsections. These are standards relevant to thermal aging and standards relevant to bearing aging.

For insulation (thermal) aging: The principle standards which are followed during the experiment are “IEEE Standard Test Procedure for Evaluation of Systems of Insulating Materials for Random-Wound AC Electric Machinery” (IEEE Standard 117-1974) [94] and “Standards for System of Insulation Materials” (ANSI C50.32.1976) [94]. The IEEE Standard 117-1974 [106] is built on some other studies and standards. For example the temperature index is provided by the IEEE General Principles for Temperature Limits in the Rating of Electric Equipment (IEEE Standard 1-1969). The available copy of this document is [107]. Employed documents for the classification and combination of the insulation materials are IEEE Standard 1-1969 and supplementary documents IEEE Standard for the Preparation of Test Procedures for the Thermal Evaluation of Solid Electric Insulating Materials (IEEE Standard 98-1972) [108] and IEEE Recommended Practice for the Preparation of Test Procedures for the Thermal Evaluation of Insulation System for Electric Equipment (IEEE Standard 99-1970) [106].

For bearing aging: According to NEMA Standards Publication Condensed MG 1-2007 [109], the shaft voltages exceeding 300mV may cause high shaft currents which are able to create fluting and pitting. The bearing aging can be best detected by vibration monitoring. Vibration monitoring of electric motors is organized according to several other standards, the most important being ISO 10816 Mechanical Vibration- Evaluation of Machine Vibration by Measurements on Non-rotating Parts [110].

3.2 Accelerated Aging Study

Aging on electric motors occurs by heating, electrical or mechanical stress exposure and bad environmental conditions as such humidity, dust, etc. An accelerated aging process applies some of these to an electric motor for short time periods, in high amplitudes.

In this study, vibration data of an accelerated aging study are used. The data are supplied by University of Tennessee, Nuclear Engineering Department. The experiment is executed based on the “IEEE Standard Test Procedure for Evaluation of Systems of Insulation Materials for Random-wound AC Electric Machinery” and “Standard for Systems of Insulating Materials”.

In order to ensure accuracy, the experiment is repeated on three identical 5HP squirrel cage induction motors. The nameplate information of the induction motors can be found in Appendix A. The test motors are loaded by a 3 kW, 1800 rpm dynamometer, excited by [0-2] Amperes and [0-200] Volts DC and loaded with 21.63 Ohms resistance. The necessary information about the dynamometer can also be found in Appendix A.

The artificial accelerated aging experiment has two approaches as chemical and mechanical. These are Electrical Discharge Machining (EDM) and the thermal - chemical aging actions, respectively. A scheme relevant to the aging experiment can be seen in Figure 3.2.

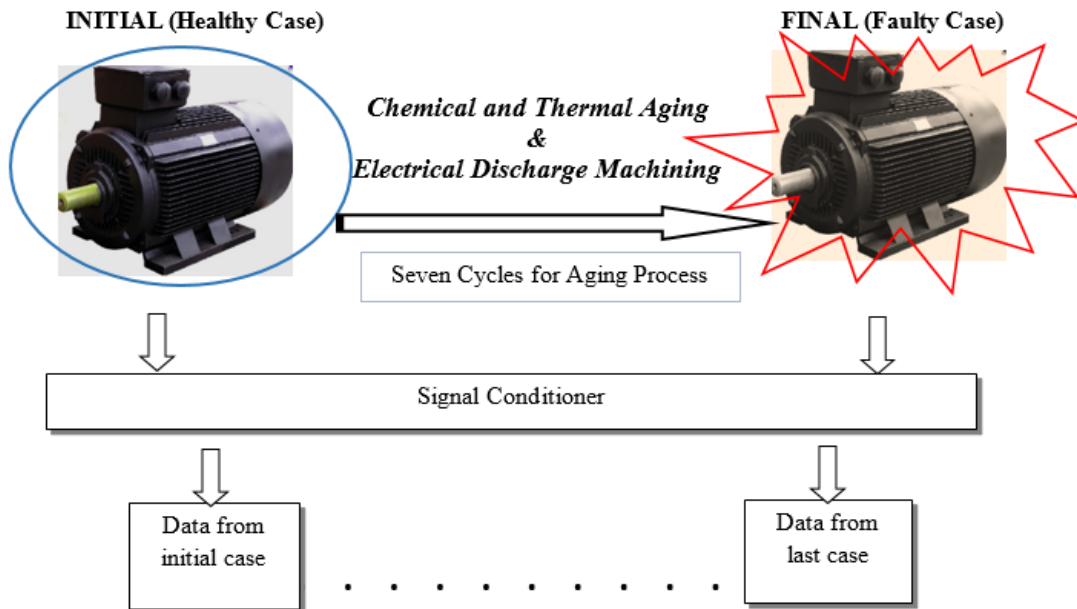


Figure 3.2 : A representative scheme for aging experiment.

EDM is an imitation of shaft voltage discharge. In order to simulate the discharge, 30 V is applied to the shaft from an external source, and 27 A of alternating current is provided through the bearings. A representation about the EDM can be seen in Figure 3.3.

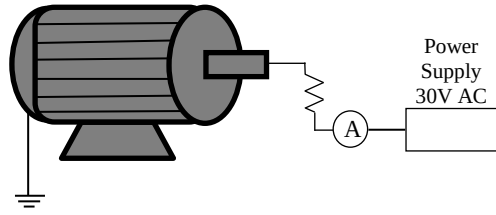


Figure 3.3 : Representation for electrical discharge machining.

Chemical and thermal aging actions are also applied to the motor in order to accelerate the process besides EDM. In order to realize thermal aging, the test motor is placed into an oven heated up to 140 °C. Then it is sunk inside a water tank in order to realize corrosion. One aging cycle can be summarized by Figure 3.4. After seven aging cycles, the experiment is terminated considering the condition of the motor. The details of the experiment can be found in the PhD thesis of Dr. A.S. Erbay [80].

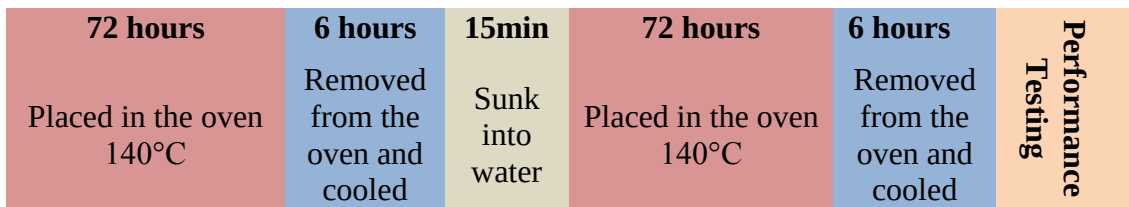


Figure 3.4 : One thermal aging cycle.

3.2.1 Experimental setup and data acquisition system

Following each aging cycle, a performance test is run for a load range from 0% to 115%. These tests provide the information about the motor situation by monitoring electrical, mechanical and thermal parameters. The collected signals from the motor are:

- 12 temperatures
- 3 phase voltages
- 3 phase currents
- Dynamometer load current
- Dynamometer load voltage
- Motor speed
- Load torque
- Acceleration from 6 different spots of the motor

Sensitive measurement was the most important consideration of the experiment. The data acquisition system which collects, amplifies and filters the signals is built by

National Instruments hardware and software. The test setup includes a dynamometer, adjustable motor platform, universal coupling, tachometer and torque sensor. The design and installation of all of these equipment can be found in [80].

The schematic of the motor performance setup can be seen in Figure 3.5.

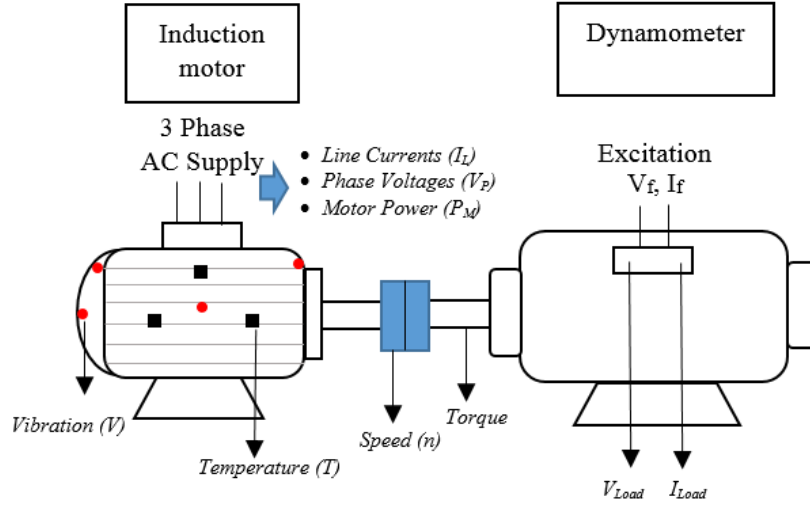


Figure 3.5 : Schematic of the motor performance test setup.

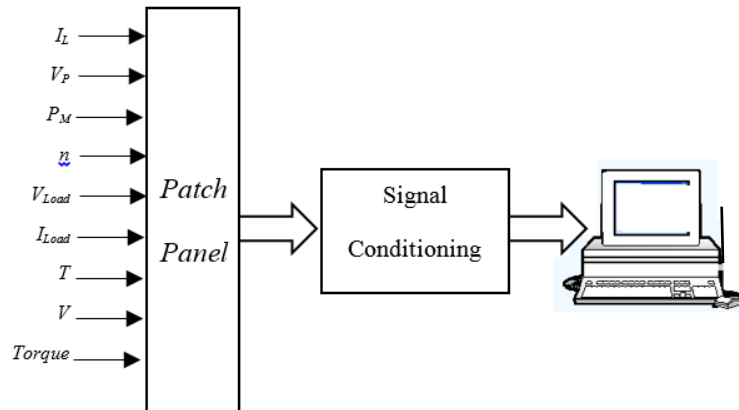


Figure 3.6 : Schematic of data acquisition system.

In this study, only the vibration signals of the experiment are used. The electrical and mechanical signals are not taken into account. The vibration signals are collected from 6 different locations on the motor. These locations are;

- cover vibration,
- short end axial,
- short end horizontal,

- short end vertical vibrations,
- pulley end 45 degrees left of vertical vibrations,
- pulley end 45 degrees right of vertical vibrations.

A representation of the accelerometer orientation can be seen in Figure 3.7. Technical details about accelerometers can be found in Appendix A.

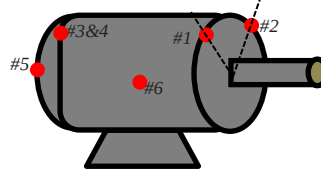


Figure 3.7 : Orientation of accelerometers.

NI SCXI is employed as the signal conditioning interface. The sampling frequency of the recorded data is 12 kHz. For the aim of conditioning the vibration signals, an NI SCXI-1142 8-channel elliptic low-pass filter module is used. In order to avoid the high frequency noise interference, an anti-aliasing filter with a cut off frequency of 4 kHz is used. The anti-aliasing filter is an eighth-order elliptic low-pass filter with a -80 dB stop-band and 135 dB/octave roll-off.

3.2.2 Aging cycles and results

Six identical accelerometers are used in the experiment. In order to record the vibration measurements at the process end (pulley end) two accelerometers are used. In this study, only the data obtained from sensor #2 is used. Seven aging cycles are applied to the motor. The time domain and frequency domain representations can be seen in Figure 3.8. Table 3.1 shows the basic statistical properties of each cycle.

Table 3.1 : Basic statistical properties of aging cycles.

Aging Cycles	Mean	Standard Deviation	Variance
<i>Initial</i>	0.0016	0.1135	0.0129
<i>1. Cycle</i>	0.0014	0.1553	0.0241
<i>2. Cycle</i>	0.0012	0.2082	0.0433
<i>3. Cycle</i>	0.0013	0.2894	0.0837
<i>4. Cycle</i>	0.0009	0.3275	0.1073
<i>5. Cycle</i>	0.0010	0.3548	0.1259
<i>6. Cycle</i>	0.0005	0.4147	0.1720
<i>7. Cycle</i>	0.0030	0.6040	0.3648

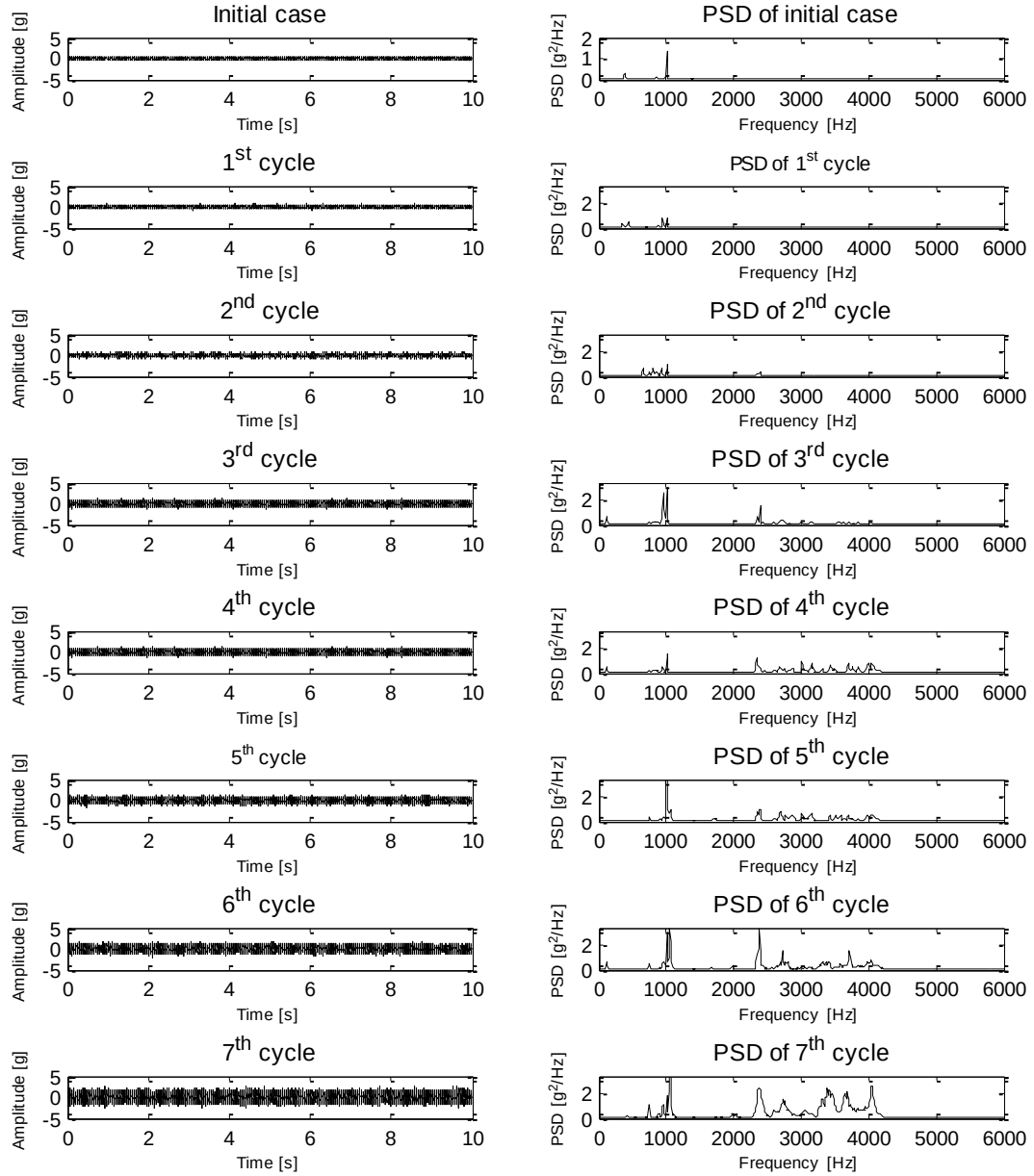


Figure 3.8 : Time and frequency domain representations of aging cycles.

4. SPECTRAL TRENDING OF FREQUENCY SIGNATURES

In this study, in order to evaluate and rate the health situation of the motor, a spectral trending application is used. The motivation is defining and assessing the aging using spectral properties of vibration signals. For this aim, vibration signals from different aging conditions of the same induction motor are investigated. Logarithmic interpretation of PSDs are used as the spectral investigation tool. After obtaining spectral properties, linear models are fitted performing the trends of the data. These linear models form a 2D Euclidian space and they constitute a convex region with a measurement boundary. This convex region helps to refine the monitoring region focusing on the aging indications of the motor. Through this way, the condition monitoring strategy is improved.

It is known that aging is a gradual process. Using the obtained trends, the growth of aging within a motor is observed through the slopes of linear models. Thus, a simple aging indicator is introduced. Then a health rating concept is defined for any random state of the induction motor. An angle based health rate is introduced using the convex region. Convex regions and convex hulls are used to evaluate the condition of an electric motor. This is a new concept for fault detection and diagnostics in electric machinery. Thus, the study constitutes an innovative approach for machinery monitoring. The objective of the study is the interpretation of motor aging as a convex region problem.

For the trending application, the vibration signals of the healthy and aged cases of the same induction motor are employed. There are 2 types of vibration signals; artificial vibration signals and real vibration signals. The trending technique is improved on artificial data and then it is tested on experimental (real) data.

4.1 Obtaining Artificial Vibration Signals

For the study, two types of vibration data are artificially generated. In order to choose a rotating speed close to the real experiment, the rotating frequency of the

shaft is assumed as 29 Hz, because the speed of the motor in the experiment is 1742 rpm which associates 29.03 Hz. The signals are constructed by the sum of specific harmonics of the rotating frequency and weighted noise sources. Noise sources are normal distributed random signals. Noises are used to make the data have a stochastic and nondeterministic character. The random normal distributed noises are filtered by four different 5th order Butterworth filters to obtain specific band noises. The assigned measurement boundary frequency is 4 kHz for the system. The following equations (4.1, 4.2, 4.3, 4.4) can be given to identify these two artificial data where Table 4.1 is admissible.

Table 4.1 : Components of artificial data.

Component	Content
FC	Fundamental Component: Harmonics of rotation frequency
N1	[0-1kHz] normal distributed random signal
N2	[1.5-4kHz] normal distributed random signal
N3	[0-4 kHz] normal distributed random signal
N4	[1.2-4 kHz] normal distributed random signal

Data can be defined by the summation of these components, where $w_n^{low} \leq w_n^{high}$.

$$Data_1 = FC + N_1 \cdot w_1^{low} + N_2 \cdot w_2^{low} \quad (4.1)$$

$$Data_1 = FC + \sum_{n=1}^2 N_n \cdot w_n^{low} \quad (4.2)$$

$$Data_2 = FC + N_3 \cdot w_3^{high} + N_4 \cdot w_4^{high} \quad (4.3)$$

$$Data_2 = FC + \sum_{n=3}^4 N_n \cdot w_n^{high} \quad (4.4)$$

The aim is producing two artificial vibration data which can represent different conditions of the same motor. The first one has dominantly low frequency components which are the harmonics of rotational frequency. It is a simulation of a new induction motor's vibration signal. Amplitude of this signal varies in a small interval. The second one has dominantly high frequency components which are the indication of faulty operation. Data 2 is a simulation of a damaged induction motor's vibration data with higher amplitude values.

Then the artificial signals are enriched with specific fault and anomaly frequencies. These anomalies are listed as follows:

- Ball spin anomaly (137 Hz)
- Ball pass outer race anomaly (105 Hz)
- Ball pass inner race anomaly (157 Hz)

These components are the representation of low frequency anomalies which are identified at 137 Hz, 105 Hz and 157 Hz, respectively. These frequencies are listed based on previous studies [60, 78, 111]. The amplitudes of these anomalies are adjusted up to the type of the data. The anomalies are added to Data 1 and then they are amplified when they are added to Data 2.

The time domain (Figure 4.1) and frequency domain (Figure 4.2) plots of the artificial data can be seen below.

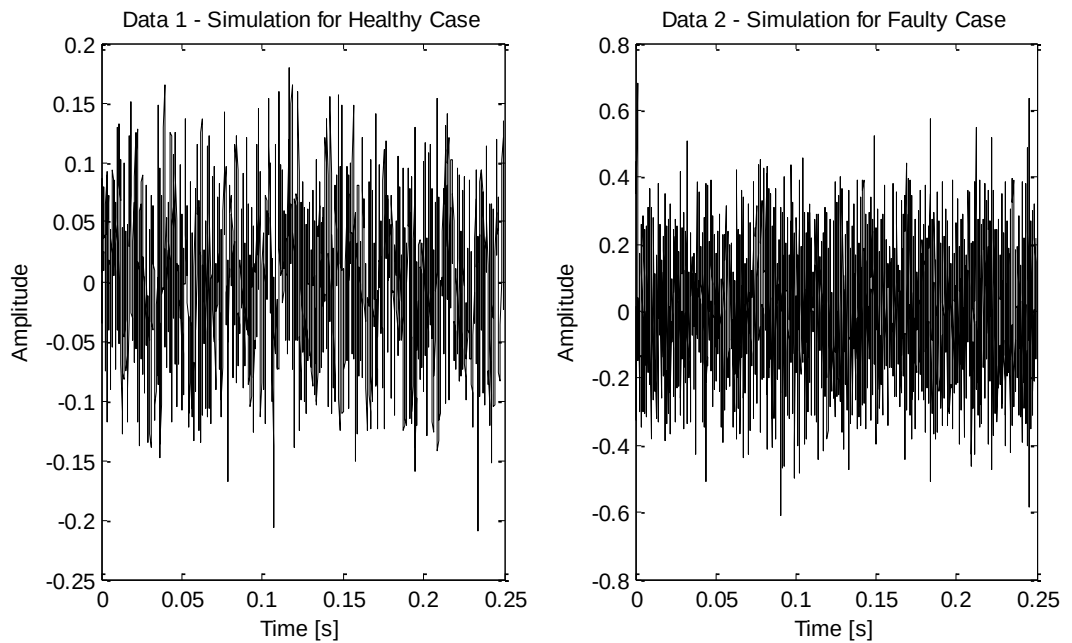


Figure 4.1 : Time domain representations for artificial data.

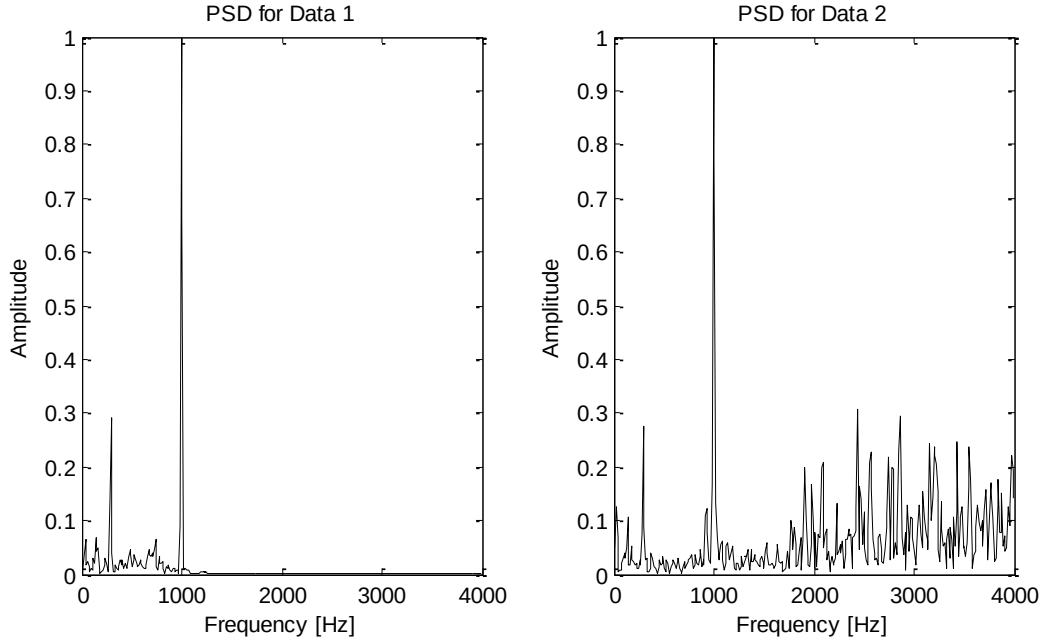


Figure 4.2 : Normalized PSDs of artificial data.

4.2 Power Spectral Density based Trending Approach

The PSD based trending is developed using artificial data then it is applied to experimental data. Vibration signals from different cases of the same motor are acquired, and their PSDs are calculated logarithmically. Linear models are fitted to the PSDs for representing their trends. These trends define a 2D Euclidian space; and this space is assumed as a convex region (CR) with a maximum frequency. This CR is employed to identify the aging. It is noticed that the PSDs diverge after a frequency value. Trends for different cases, divergency, and boundary (maximum) frequencies, enable us to define convex hulls in that CR. This study gives the opportunity to decide the situation of the motor by the help of this region and its convex hulls. Using this region and hulls some unknown cases can be rated and identified during the aging process.

4.2.1 Spectral trending with artificial data and its geometric interpretation

The logarithmically interpreted PSDs are given in Figure 4.3. As seen obviously, they diverge after 1023 Hz, corresponding to 3.01 in the logarithmic axis. The difference between high frequency regions of these two data is easily monitored. The highest frequency component of the artificial data is 4000 Hz. This frequency is assigned as the boundary frequency for this application. Figure 4.3 includes

divergency frequency, boundary frequency, divergency line and measurement boundary, as well.

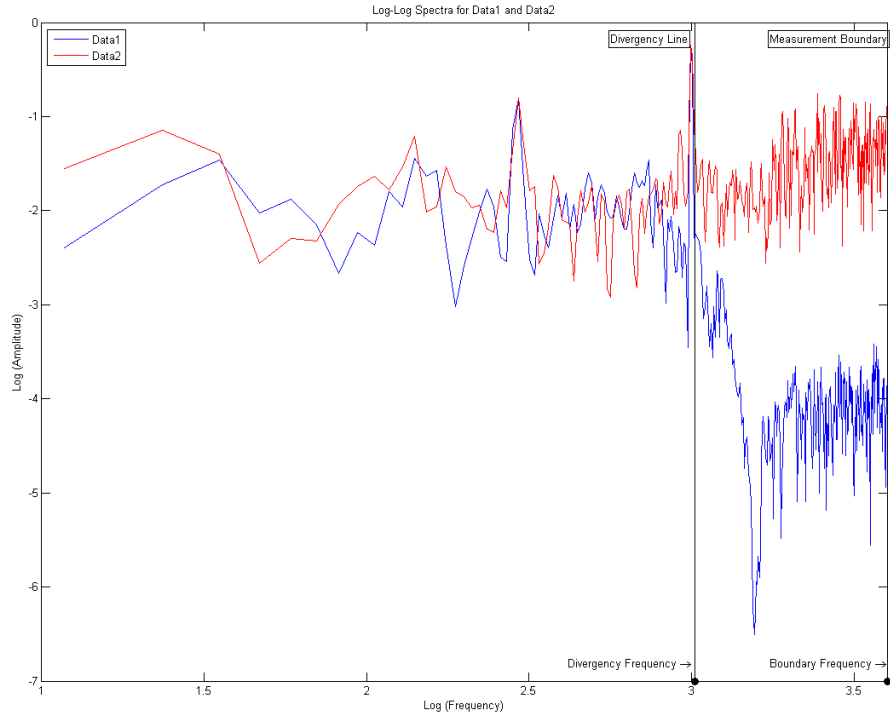


Figure 4.3 : Log-log spectra for artificial data with important lines and boundaries.

Linear models are fitted to logarithmic spectra to emphasize the difference between the different states. Least square algorithm is used for linear model fitting. Fig 4.4 shows the linear models and relevant PSDs. The sign of the slope changes from negative to positive while the aging advances. So the slope of linear fit of any case can be used as a simple indication of aging. Monitoring the slope value is a very simple and easy way of defining the situation of the motor.

As mentioned earlier, these linear models constitute a 2D Euclidian space and they define a convex region with the measurement boundary. The monitoring region is refined using this convex region.

The intersection coordinates of these trends are important in terms of aging monitoring, as they define the vertical and horizontal thresholds to refine the condition monitoring. The vertical and horizontal thresholds provide the amplitude and frequency information, respectively.

The linear models $Y_1(\log f)$ and $Y_2(\log f)$ are the representations of Data1 and Data2, respectively.

$$Y_1(\log f) = a_1 \log f + b_1 \quad (4.5)$$

$$Y_2(\log f) = a_2 \log f + b_2$$

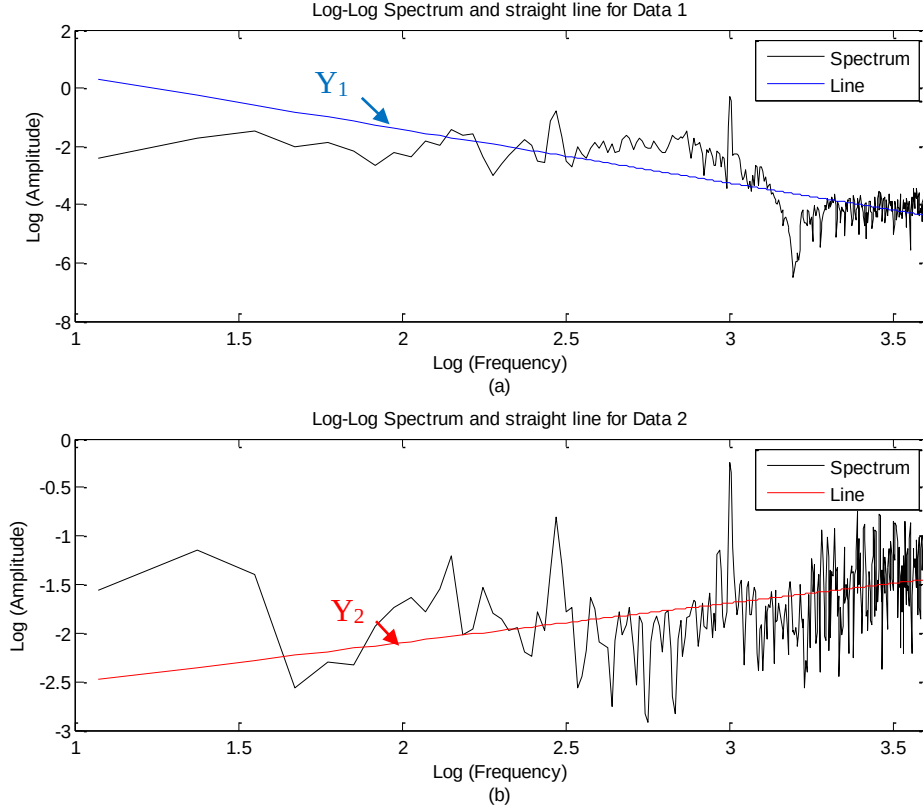


Figure 4.4 : Logarithmically interpreted PSDs and the corresponding linear models for artificial data.

The intersection point in the frequency domain is the critical frequency ($\log f_c$) and is computed as follows;

$$Y_1(\log f_c) = Y_2(\log f_c) \quad (4.6)$$

Solving for $\log(f_c)$ gives;

$$\log f_c = \frac{b_2 - b_1}{a_1 - a_2} \quad (4.7)$$

According to this result the horizontal threshold is defined as;

$$Y_{threshold_hor} = a_1 \log f_c + b_1 \quad (4.8)$$

or

$$Y_{threshold_hor} = a_2 \log f_c + b_2$$

Thus, the required condition for vibration monitoring of the motor can be refined as $\log f > \log f_c$, and *logarithmic amplitude of PSD* $> Y_{threshold_hor}$, as shown in Figure 4.5.

The linear models divide the two dimensional Euclidian space (E^2) into 4 sub-spaces (regions). These regions are seen in Fig 4.5. In Regions (1), (2) and (3), the spectral variations almost correspond to each other. Region (3) includes the high frequency components indicating the aging within the motor.

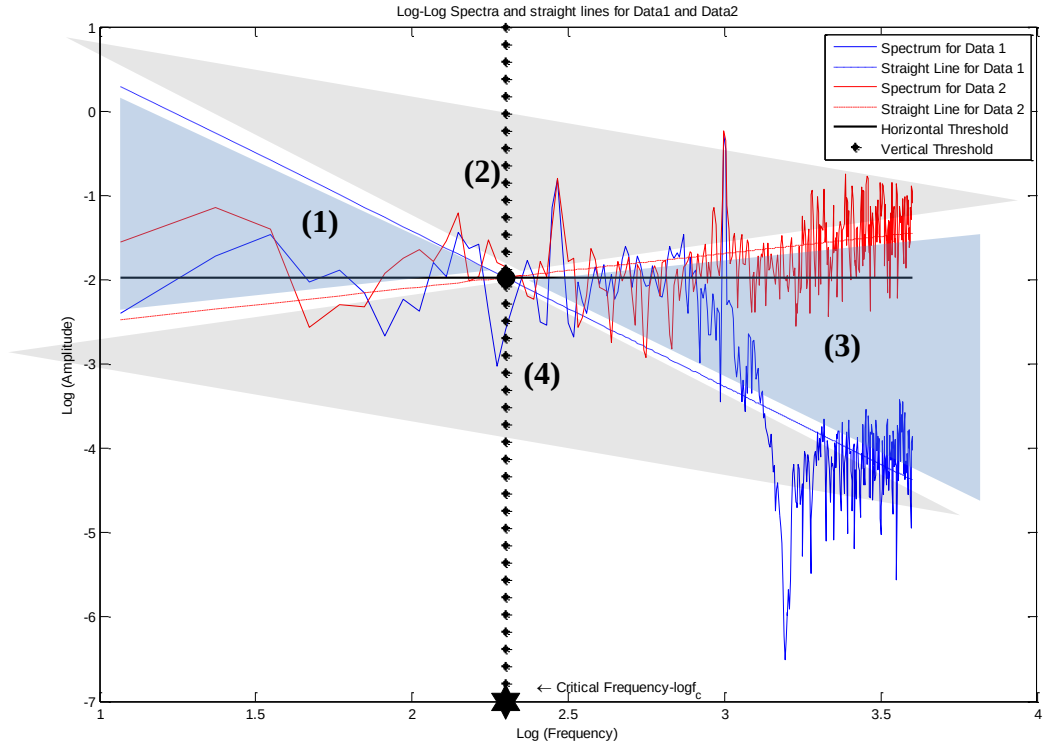


Figure 4.5 : Intersection of linear models and vertical-horizontal thresholds for vibration monitoring.

In order to observe the aging, Region (3) should be investigated in detail. To resolve this, three different sub-regions are defined in Region (3) as seen in Figure 4.6. They constitute some geometric shapes like Triangle O_1AB (ΔO_1AB), Triangle O_1CD (ΔO_1CD) and Trapezoid $CDAB$ ($\square CDAB$). The relationship between these regions are given in Equation 4.9.

$$\Delta O_1CD \subset \Delta O_1AB$$

$$\square CDAB \subset \Delta O_1AB$$
(4.9)

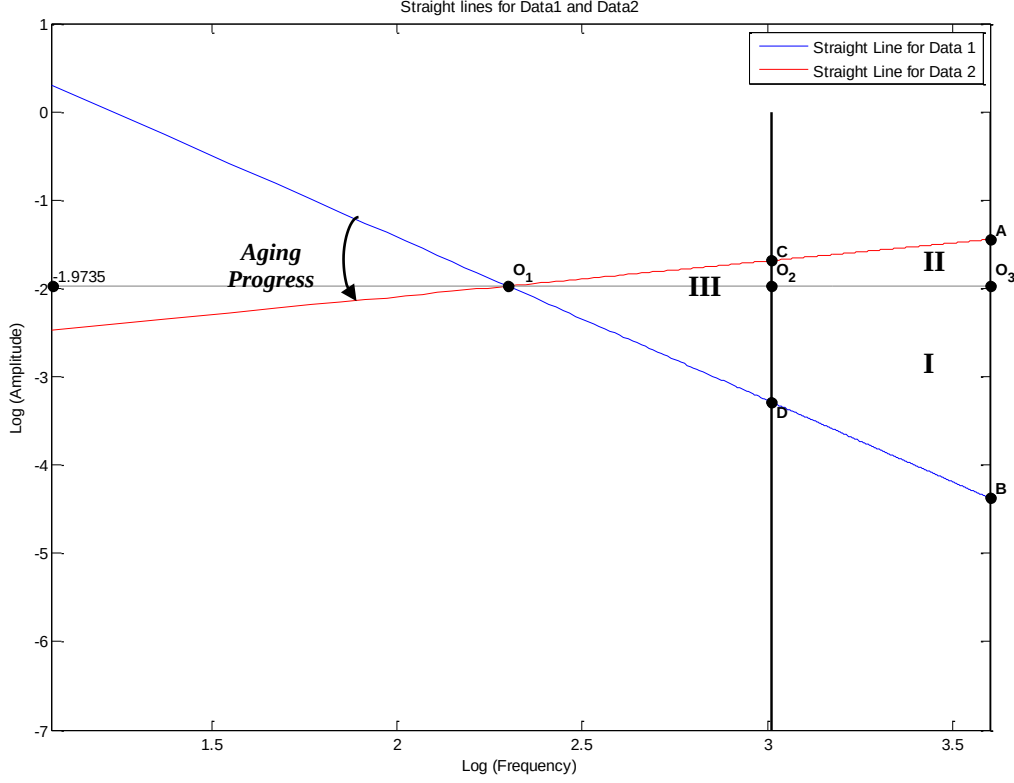


Figure 4.6 : Representation of aging regions on artificial data.

The ΔO_1AB is defined as the general aging triangle involving all frequency components, corresponding to aging. In other words, all possible trends are expected to be located in ΔO_1AB . The ΔO_1CD (Sub-Region III) is the envelope which begins with the critical frequency and ends with divergency frequency (between 200 Hz and 1023 Hz corresponding 2.29 and 3.01 on the logarithmic axis, respectively). It is a convex hull defined in the convex region ΔO_1AB . The $\square CDAB$ includes high frequency components located between divergency and boundary frequency (between 1023 Hz and 4000 Hz corresponding 3.01 and 3.6 on the logarithmic axis, respectively). This frequency band is associated with aging frequencies. So, focusing on $\square CDAB$ makes sense to evaluate the situation of the motor. $\square CDAB$ can be observed in two parts as Convex hull-I and Convex hull-2.

Convex hull-I is a defined space where following expression is valid:

$$Y_{threshold_hor} \geq Y \geq Y_1(logf) \quad (4.10)$$

Convex hull-II is a defined space where following expression is valid:

$$Y_2(logf) \geq Y \geq Y_{threshold_hor} \quad (4.11)$$

All possible trends are expected to be inside the aging triangle ΔO_1AB and Convex hull-III. If any random situation of the motor can be projected to $|AB|$ as a state indicator then the health of the system can be estimated using this projection.

State points, which are encountered in Convex hull-I, can be interpreted as non-aged cases. Degree of health can be identified using (4.12) for this hull.

$$Degree\ of\ Health = \frac{\|Euclidian\ metric\ to\ \overline{O_2O_3}\|}{\|\overline{BO_3}\|} \quad (4.12)$$

State points, which are encountered in Convex hull-II, can be interpreted as aged cases. The degree of aging can be identified using (4.13) for this hull.

$$Degree\ of\ Aging = \frac{\|Euclidian\ metric\ to\ \overline{O_2O_3}\|}{\|\overline{AO_3}\|} \quad (4.13)$$

Through these finding, the aging evaluation becomes an angle based rating.

4.2.2 Spectral trending with experimental data and its geometric interpretation

In Figure 4.7 the logarithmic spectra of experimental data are shown. In order to see the correspondence of two cases, the PSD calculation is done with a low number of FFT (1024). As seen in Figure 4.7, PSDs diverge after 1580 Hz which corresponds to 3.2 on the logarithmic axis. The amplitudes of high frequency components increase with aging as seen near 1580 Hz. The measurement system has an anti-aliasing filter (low pass filter), with a 4 kHz cut off frequency. So the PSD plot has a boundary on the frequency axis at 4 kHz, which corresponds to 3.6 on the logarithmic axis.

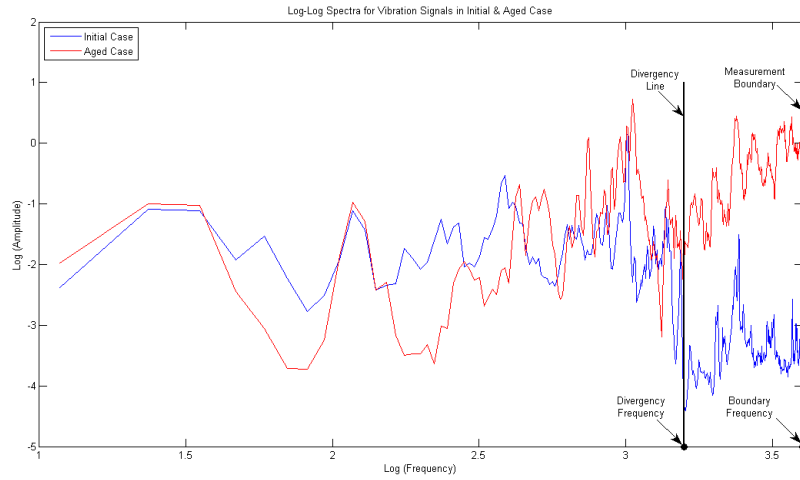


Figure 4.7 : Plots of the logarithms of the vibration PSDs.

To emphasize the difference between the two situations, logarithmically interpreted PSDs and associated linear models are given in Figure 4.8. The PSD calculations for trending operation are done with the highest number of FFT (65536). During the aging process, the slope's sign of the linear model changes from negative to positive. Thus, the sign of the slope can be used as an indicator of the aging.

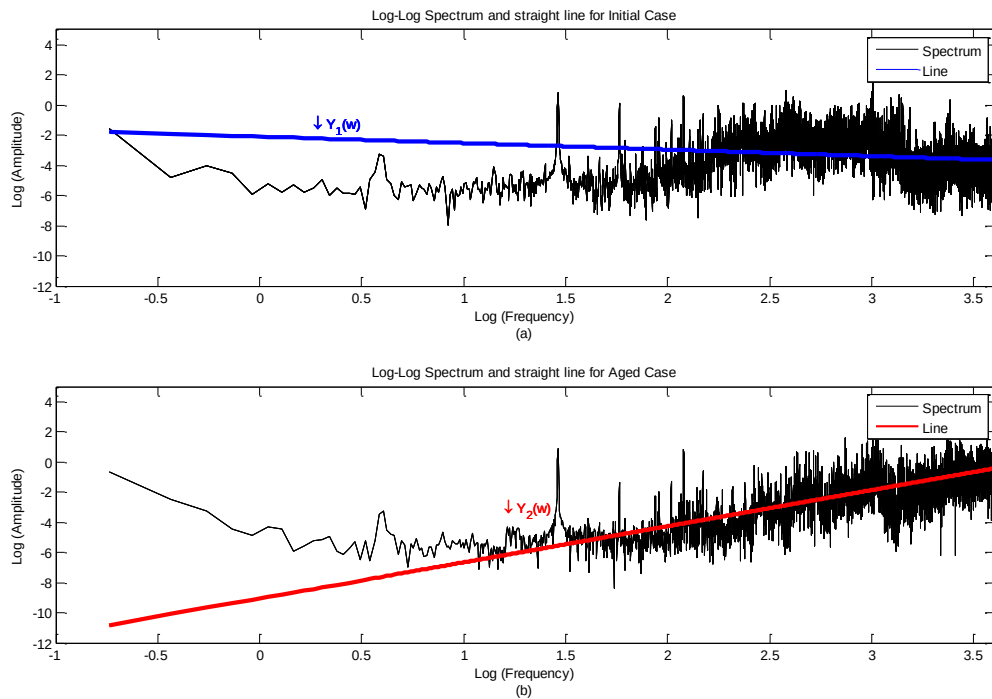


Figure 4.8 : Logarithmically interpreted PSDs and the corresponding linear fit.

The intersection coordinates are important considering the refined monitoring region. The (4.5), (4.6), (4.7) and (4.8) are also admissible for the experimental data.

The linear models split the two dimensional Euclidian space (E^2) into 4 regions as seen in Figure 4.9. In Region-1 and Region-2, the variations almost correspond to each other. Region-4 indicates low amplitude - high frequency information of the initial case, however it is not a valuable information for aging evaluation. Region-3 includes the most important information about the aging of electric motor. This information is based on the high frequency components that are the results of aging.

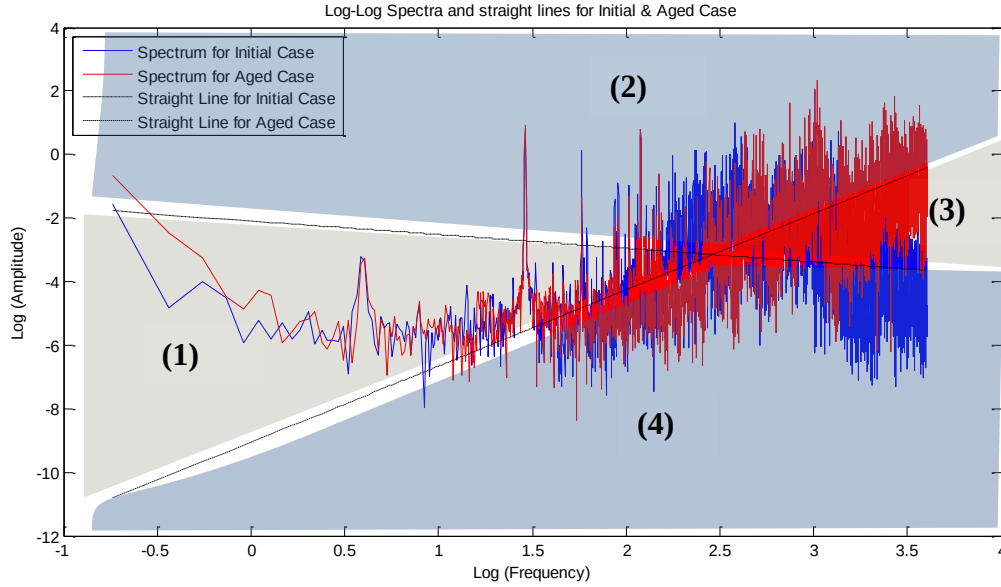


Figure 4.9 : Intersection of the fitted straight lines and vertical and horizontal thresholds for vibration monitoring.

Under these basic calculations, the novelty brought by this study may be seen in the definition of the threshold represented in the frequency domain ($\log f_c$) for the aging process. Thus, the required condition for vibration monitoring of an electric motor is given as $\log f > \log f_c$, and *logarithmic amplitude of PSD* $> Y_{threshold_hor}$, as shown in Figure 4.10.

Region-3 seen in Figure 4.9 has vital importance as defined in artificial data. Sub-regions (convex hulls) and their relationships (4.9) are also admissible here.

The ΔO_1AB is the aging envelope which is defined as the general aging triangle involving all frequency components, corresponding to aging as seen in Figure 4.10. The ΔO_1AB constitutes a CR including all possible trends and contains 3 CHs. The ΔO_1CD (CH-III) forms the region which begins with the critical frequency and ends with divergency frequency (between 292 Hz and 1585 Hz corresponding 2.4651 and

3.2 on the logarithmic axis, respectively). The $\Delta CDAB$ includes high frequency components located between divergency and boundary frequency (between 1585 Hz and 4 kHz corresponding 3.2 and 3.6 on the logarithmic axis, respectively) referring to severe aging frequencies. $\Delta CDAB$ is the most important CH which is observed in this study.

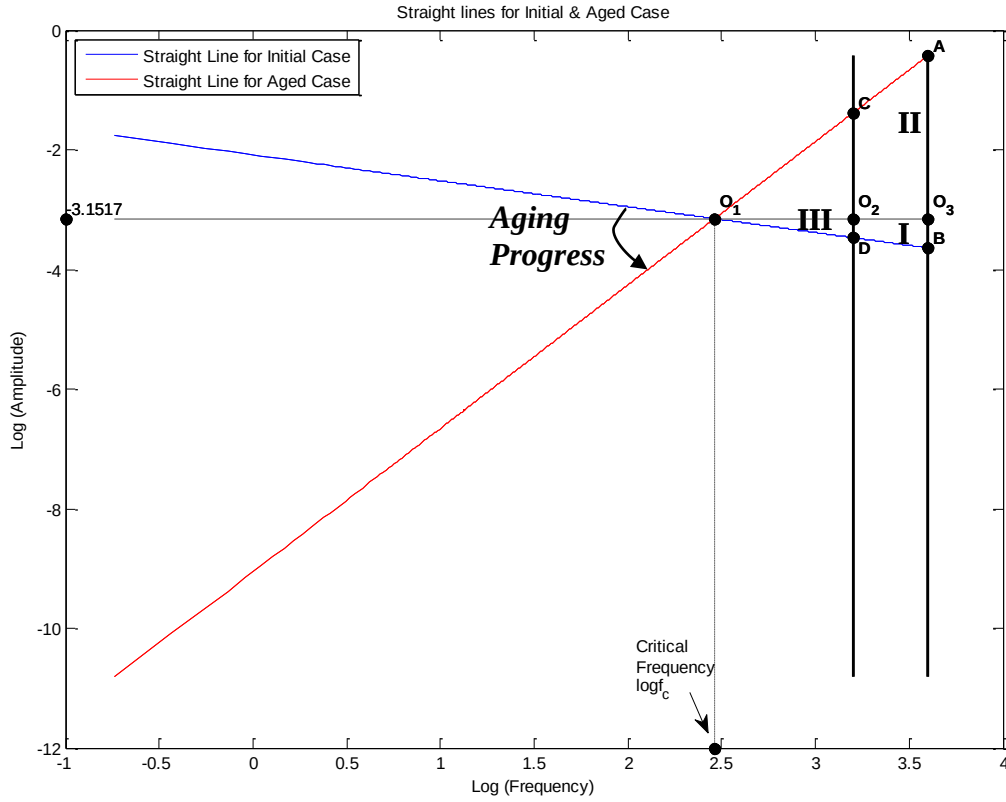


Figure 4.10 : Representation of aging regions.

$\Delta CDAB$ can be observed in two parts.

Convex hull-I is a defined space where the following expressions are valid:

$$\begin{aligned}
 \text{Log(Amplitude)} &\leq -3.1517 \\
 \text{Frequency} &\geq 1585 \text{ Hz} \\
 Y_{\text{threshold_hor}} &\geq Y \geq Y_1(\log f)
 \end{aligned}
 \tag{4.14}$$

Convex hull-II is a defined space where the following expressions are valid:

$$\text{Log(Amplitude)} \geq -3.1517
 \tag{4.15}$$

$$Frequency \geq 1585 \text{ Hz}$$

$$Y_2(\log f) \geq Y \geq Y_{threshold_hor}$$

It is obvious that all possible trends will take place within Convex Region-3 for that problem (between the linear representations of initial and aged cases). There are several probable situations which can be encountered in the aging envelope during the aging process. These situations can be represented by some random state points. State points which identify the motor status can be interpreted using these convex hulls. Some random state points and the trends, to which they belong, are shown in Figure 4.11.

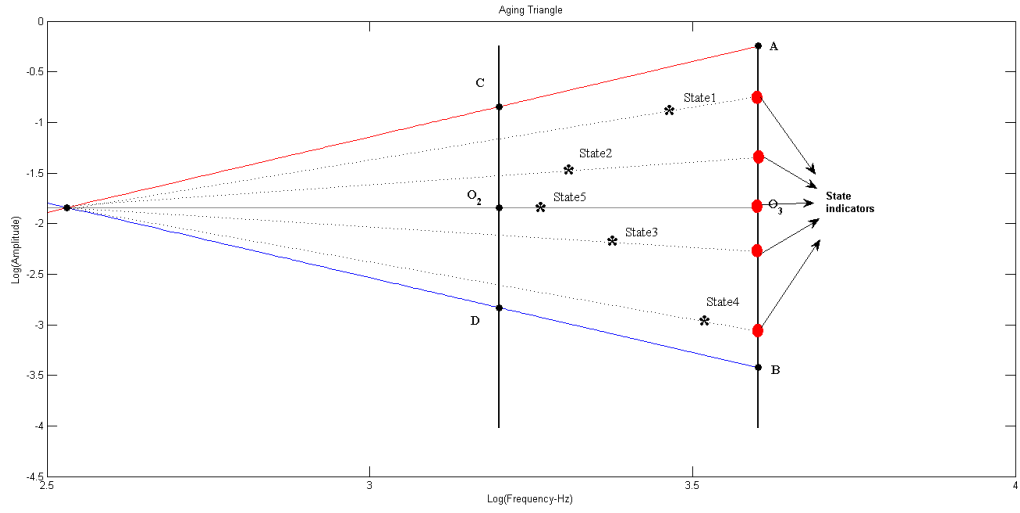


Figure 4.11 : State points defined in sub-regions I and II.

Since each aging case is represented by a unique trend, all states on the trend must have the same degree of health or degree of aging. Any state point on the trend should be represented by its projection point on the measurement boundary. Hence the measure of the aging can be shown by a metric ratio. The projection points are named as state indicators in Figure 4.11. Thus the condition of the system can be given by the help of Euclidian metrics in these convex structures. These metrics are calculated considering the distance defined between the projections of the state point and $Y_{threshold_hor}$. The condition of the system can be rated by the degree of health and degree of aging. For the state points, which are encountered in CH-I and CH-II, (4.12) and (4.13) are admissible.

In accordance with these estimations, Table 4.2 depicts an interpretation of the results shown in Figure 4.11. The evaluation is executed using the convex hull to which the state indicator belongs. If the state is within Convex hull-I, it is obvious that the state is healthy, so the measure of health should be calculated. In order to define the health situation $\frac{\|Euclidian\ metric\ between\ state\ indicator\ and\ O_3\|}{\|BO_3\|}$ is considered.

The situation degree may be decided as low, medium or high health considering the degree of health is less than 30% , between 30 - 60%, more than 60%, respectively. If the state belongs to Convex hull-II, the state is defined as aged. And the measure of aging is calculated according to $\frac{\|Euclidian\ metric\ between\ state\ indicator\ and\ O_3\|}{\|AO_3\|}$. The

aging degree may be decided as low, medium or high aging considering the degree of aging is less than 30% , between 30 - 60%, more than 60%, respectively. If the ratio is zero (such as State 5), then the situation is neither healthy nor aged; therefore this state is interpreted as a transition case between the healthy and aged cases. Using these directions, the state points can be classified as healthy or aged. Furthermore, they can also be rated and graded [79].

Table 4.2 : Situation for random states.

	State 1	State 2	State 3	State 4	State 5
Convex hull	II	II	I	I	Transition
Situation	Aged	Aged	Healthy	Healthy	Transition (Neither Healthy nor Aged)
Degree	High Aging	Medium Aging	Low Healthy	High Healthy	Zero

As an application of PSD trending operation, the trends of the all aging cycles are obtained. For this purpose, the logarithmic spectra is calculated and given in Figure 4.12. The corresponding trends for each aging cycle are given in Figure 4.13 as well.

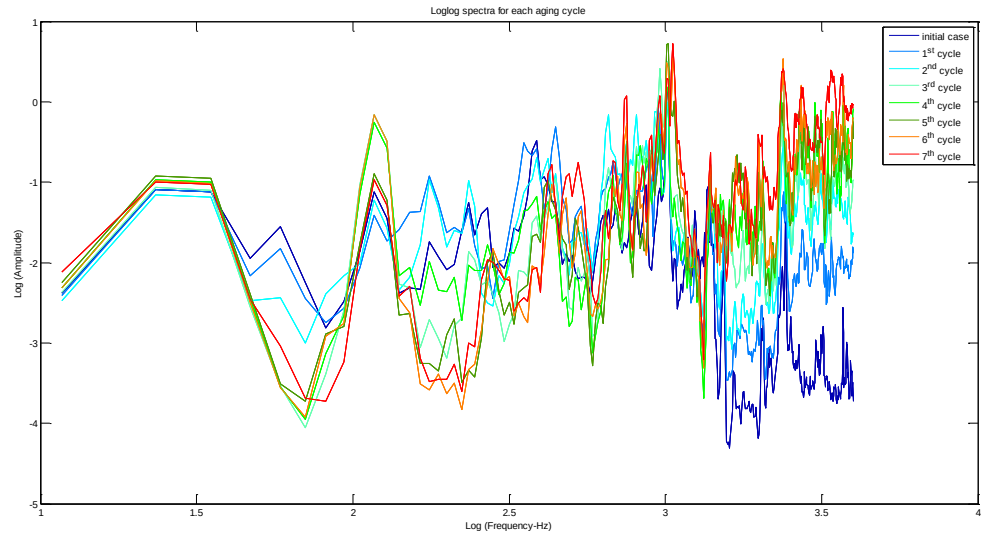


Figure 4.12 : Logarithmically calculated PSDs of aging cycles.

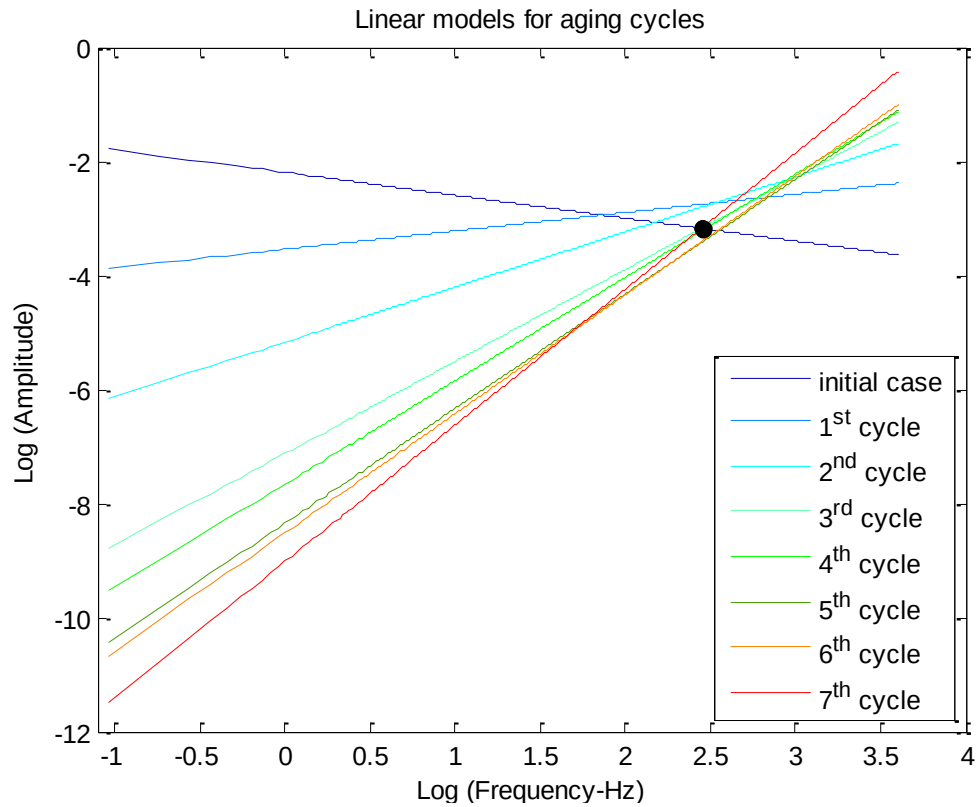


Figure 4.13 : Linear models for logarithmically interpreted PSDs of all aging cycles.

Ideally all trends are expected to intersect at the same point ideally but they do not. Because of the experimental errors, some offsets are noticed. The slopes of the trends are given in Table 4.3, where it can be seen that the slope changes for each aging cycle. Monitoring the value of the slope is a very simple way of understanding the condition of the motor.

The slopes of the trends are changing between -21.8383 and 67.2504 degrees which means that the aging situation can be rated within that interval. As mentioned earlier, the aging evaluation becomes an angle based rating. In these circumstances, the degree of aging and health can be reinterpreted as in Equations 4.16 and 4.17.

Trends, which are encountered in Convex hull-I, can be interpreted as non-aged cases. For this hull, degree of health can be identified using (4.16) as a percentage.

$$\text{Degree of Health} = \frac{\text{Angle of the trend}}{\text{Angle of the healthiest case}} \quad (4.16)$$

Trends, which are encountered in Convex hull-II, can be interpreted as aged cases. For this hull, the degree of aging can be identified using (4.17) as a percentage.

$$\text{Degree of Aging} = \frac{\text{Angle of the trend}}{\text{Angle of the most aged case}} \quad (4.17)$$

Table 4.3 : Aging situation for cycles based on PSD trending.

Aging Cycles	Slope	Convex Hull	Situation	Degree of Health or Aging
Initial case	-21.838	I	Healthy	1
1 st Aging cycle	17.818	II	Aged	0.264
2 nd Aging cycle	43.994	II	Aged	0.654
3 rd Aging cycle	58.172	II	Aged	0.865
4 th Aging cycle	61.077	II	Aged	0.908
5 th Aging cycle	63.527	II	Aged	0.944
6 th Aging cycle	64.339	II	Aged	0.956
7 th Aging cycle	67.250	II	Aged	1

4.3 Contribution of the Spectral Trending Method

In this section of the study, the aging progress of an induction motor is observed through the vibration signatures. The vibration signals are represented via linear trends based on PSD. Using these trends, growth of aging within a motor is observed, a new monitoring strategy is improved and a simple aging indicator is introduced. Then a health rating concept is defined for any random state of the induction motor.

As mentioned earlier, trends are linear models which form a 2D Euclidian space. And this space is used to define a convex region by a measurement limit in the frequency domain. Through this the Aging Region concept is introduced. General condition monitoring is refined to a smaller scale using some properties of the Aging

Region. Vertical and horizontal thresholds are defined to evaluate emerging faults and to increase the effectiveness of vibration monitoring. The intersection points of the trends are accepted as the sublimit of the required condition monitoring. During the aging investigation of the induction motor, there is no need to monitor the whole frequency plane. It is sufficient to monitor the regions defined below:

$$(\log f > \log f_c) \cap (\logarithmic \text{ amplitude of } PSD > Y_{threshold_hor})$$

It is obvious that using the critical (intersection) point is a feasible approach to refine the condition monitoring strategy of the motor. The intersection point, upper and lower boundaries of condition monitoring (CM) planes and CM areas are given in Table 4.4. As seen on the table, changing the condition monitoring region provides advantage.

Table 4.4 : Usual and refined condition monitoring areas.

Intersection point	Upper and lower bounds of the CM plane	Condition monitoring area		Gain of the method
$[i_x, i_y]$	$[x_{min}, y_{min}]$ $[x_{max}, y_{max}]$	<i>Usual</i>	<i>Refined</i>	
$[2.465, -3.151]$	$[-1.038 -11.5]$ $[3.599, -0.438]$	51.29	3.076	16.67

It is noticed that the slope of the trend increases with aging. In addition, the sign of the trend's slope changes from negative to positive in some trending applications. In other words, the value and the sign of the slope can be used to identify and evaluate the aging. So, any change in the slope is accepted as a very simple way of understanding the condition of the motor. This may also help to reschedule the maintenances as an additional benefit to general condition monitoring.

With this method, the degree of aging and degree of health are introduced as a health rate, as well. A consolidated plot of degree of health and degree of aging can be seen in Figure 4.14. The plot shows that the fading of health begins after the 2nd cycle.

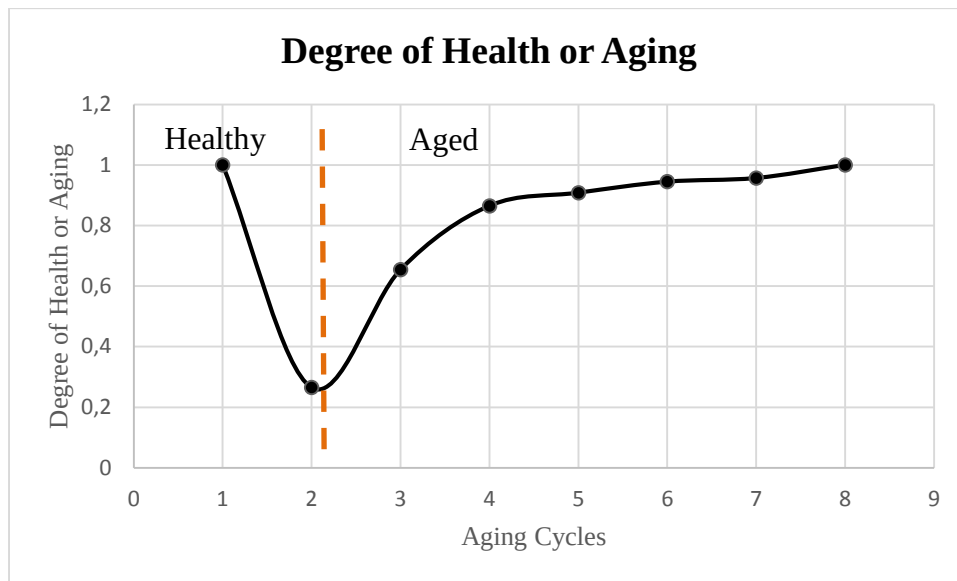


Figure 4.14 : Evaluation of the health situation for each trending application.

As a summary of this section; the progress of aging within a motor is observed by the trending method. A new monitoring strategy is proposed by the intersection point's coordinates. Slopes of trends lines are defined as a simple aging indicator. Then a health rating concept is defined by the degree of health and degree of aging definitions.

5. FEATURE EXTRACTION USING ALGEBRAIC SUMMATION

The vibration signal of an induction motor is likely to have a non stationary nature, as there are lots of rotating elements and their rotational frequencies modulate the fundamental frequency of the system [40]. Even though spectral tools are powerful for observing vibration signals, time-frequency techniques are also used frequently. For that reason, wavelet transform is employed in this study.

In this section, the motor cases which are named as healthy are examined for detecting any potential fault. According to the trending application, the initial case of the experiment is the only healthy case. The initial case of the motor is not 100% healthy in reality. However, it is assumed healthy in order to rate the other cycles related to the initial case. To find out potential faults, the redundancy property of the stationary wavelet transform is used. It is explained that SWT creates redundant coefficients following the decomposition process. The proposed detecting method reconstructs the signal by preserving the redundancy of these coefficients. This redundancy amplifies all existing small fault indications and makes them noticeable.

In this section of the study, the proposed reconstruction operation is given in detail. The method is improved using artificial vibration data. Algebraic summation operation is investigated in terms of redundancy. Then, the method is applied to the initial case data which is the unique healthy case of the experiment. Through this, fault frequencies, which cannot be monitored with PSD of the original signal are noticed after algebraic summation. The physical meaning of these frequencies are discussed, as well. At the end of this section, algebraic summation is employed with the aim of investigating the monitoring boundaries of motor.

5.1 Undecimated Reconstruction Approach: Algebraic Summation

Undecimated reconstruction approach proposes an algebraic summation before the decimation operation. By cancelling the decimation, the redundancy provided by the up-sampling (interpolation) operation is stored. A block diagram is shown for this

operation in Figure 5.1. The result of algebraic summation is given by $x'_{undecimated}$ where $x(n)$ is the original signal. As mentioned before, $h(n)$ filters are the low-pass filters and the convolution of the signal with $h(n)$ gives the approximation, and the convolution of the c_n coefficients with the wavelet function gives the details. The reconstruction operation is done by the summation of all details and the last approximation. Because of the fact that the up-sampling operation is executed during the production of every level, the coarser level contains more redundancy compared to a finer level. This means that the advantage of redundancy is more noticeable on coarser levels. On the other hand, coarser levels associate with the low frequency region of the signal's frequency band. That is why on $x'_{undecimated}$ signal the low frequency information is amplified by redundancy.

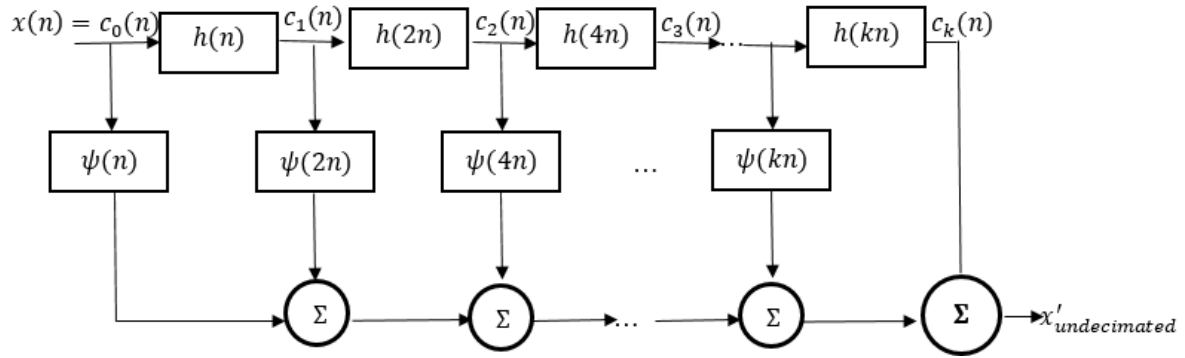


Figure 5.1 : Block diagram for algebraic summation operation.

The redundancy of SWT is originated by the up-sampling operation executed during the decomposition. This operation leads to a redundancy within the signal. As mentioned before, the algebraic summation aims to preserve this redundancy, so it cancels the down-sampling operation of the regular reconstruction algorithm. The representative schematic for the algebraic summation can be seen in Figure 5.2.

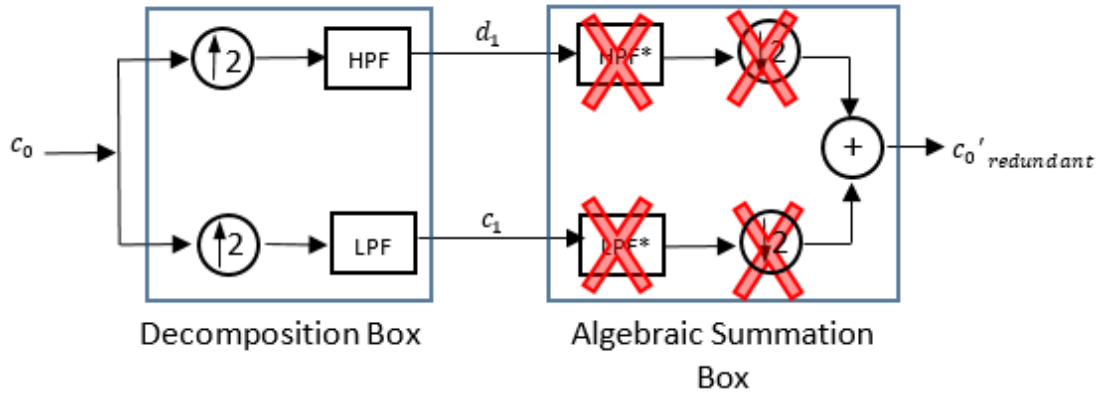


Figure 5.2 : Schematic for stationary wavelet decomposition and algebraic summation (for only one decomposition level).

Here, the coarser level contains more redundancy compared to a finer level. The more coarse level is obtained by high level decomposition, the more redundancy is gained. If a 2 level SWT decomposition is applied, the signal is up-sampled for only 2 times, or a 7 level SWT decomposition means that the signal is up-sampled for 7 times, handling the low frequency region at each decomposition. The advantage of redundancy is more noticeable on the 7 level of decomposition around the low frequency region. It can be concluded that advantages of redundancy are more noticeable on coarser levels. On the other hand, coarser levels associate with the low frequency region of the signal's frequency band.

To show this fact, the artificial data is utilized, it is decomposed and algebraic summed for several levels. The maximum level of decomposition is determined by the fundamental frequency of the system. The fundamental frequency of the system is the rotational frequency which is assigned as 29 Hz during the production of artificial data. The maximum decomposition level is assigned as 7 so that only the last approximation contains the rotational frequency.

The time domain and frequency domain responses for algebraic summed versions of Data 1 are presented for different decomposition levels in Figure 5.3 and 5.4. As been mentioned previously, Data 1 is the artificial healthy case representation of a motor.

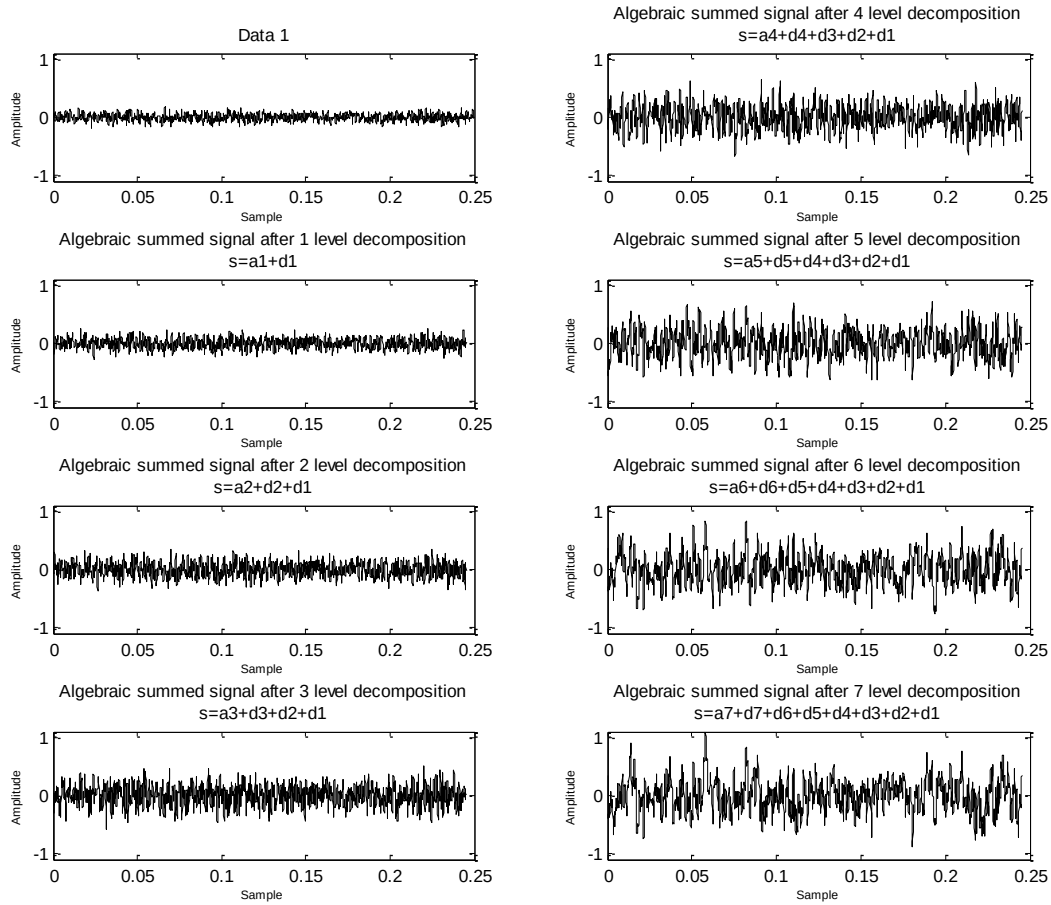


Figure 5.3 : Time domain representation of Data1 and its algebraic summed versions for various levels.

As a result, following the highest decomposition level, namely 7 level of decomposition, the amplification of the reconstructed (algebraic summed) signal is sufficiently large due to the redundancy.

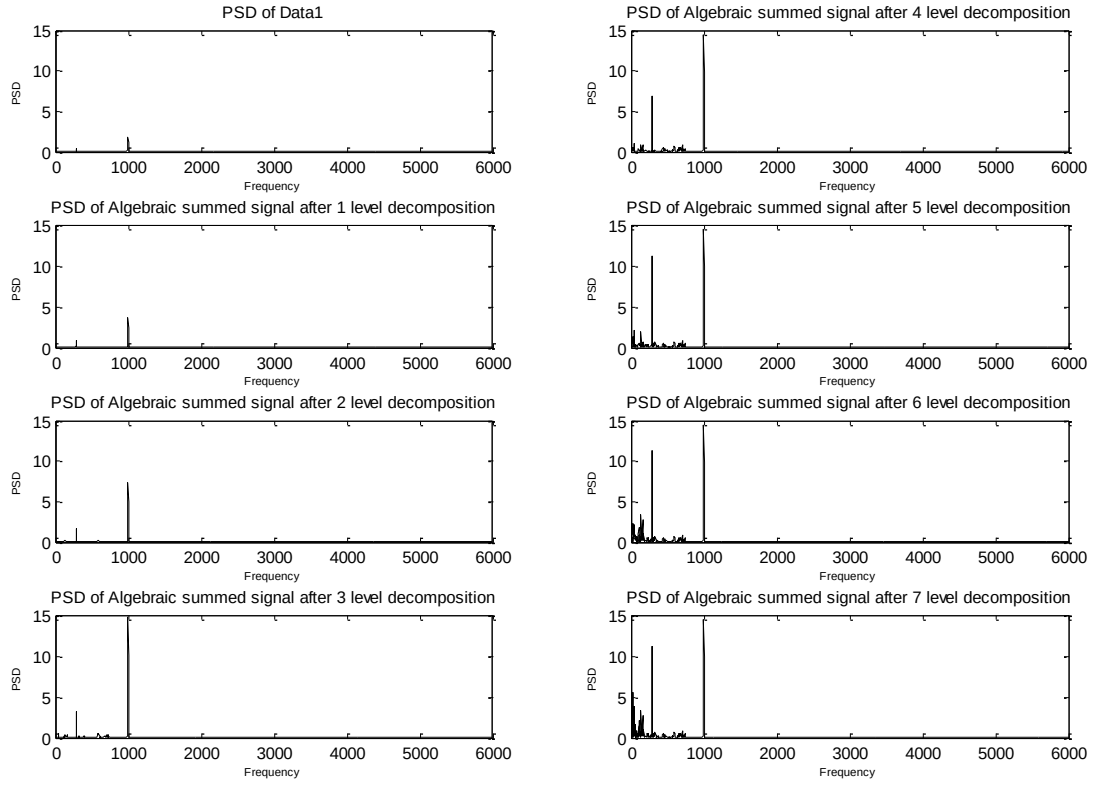


Figure 5.4 : Frequency domain representation of Data1 and its algebraic summed versions for various levels.

The redundancy can be seen as the amplitude information in time domain representation. Frequency domain representation provides some low frequency amplifications that are not possible to notice without algebraic summation. The cumulation of redundancy is observed through the low frequency range while the decomposition level increases. To show this property, reconstruction errors for every decomposition level are given in Figure 5.5.

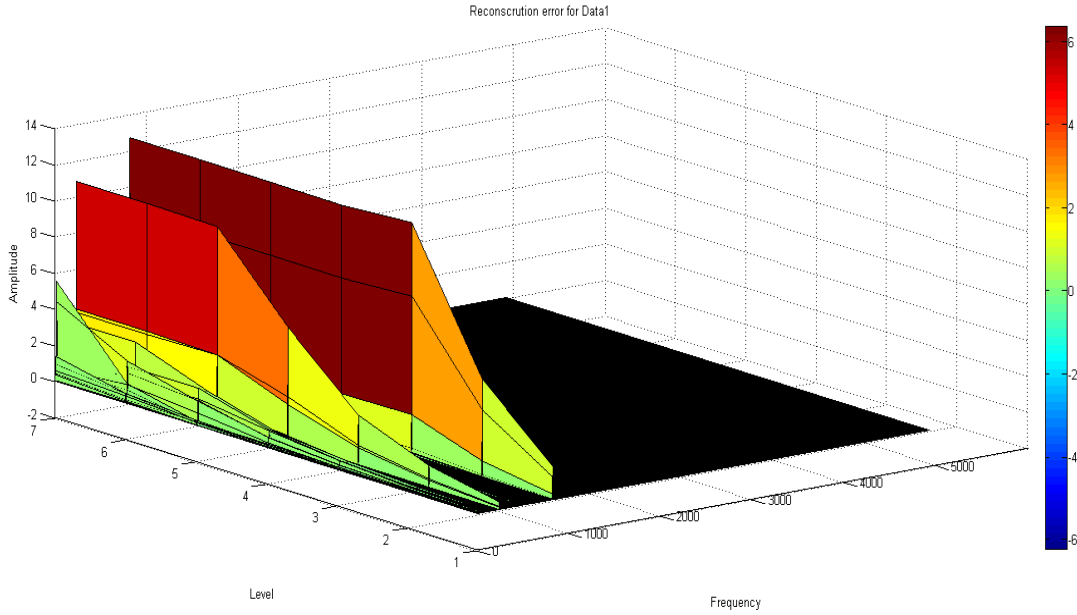


Figure 5.5 : Frequency domain representation of reconstruction errors of algebraic summed Data 1 for various levels.

Data 1 is an artificial signal and there are some frequencies which are deliberately embedded to the data. These are 29, 290, 1000, 137, 105 and 157 Hz components. They exist within Data1 in small amplitudes. In order to create an aging effect, these components are amplified while Data2 is produced. To show the success of the algebraic summation, the frequency domain representation is reproduced with these important frequencies in Figure 5.6 and Figure 5.7. It is seen that algebraic summation amplified these frequencies successfully. Figure 5.7 proves that the method is capable of recognizing all of the fault frequencies well. It detects all of the deliberately embedded frequencies easily.

Here, fault frequencies which were not distinguishable at the healthy case became recognizable. Thus the algebraic summation operation can be interpreted as an early fault detection method.

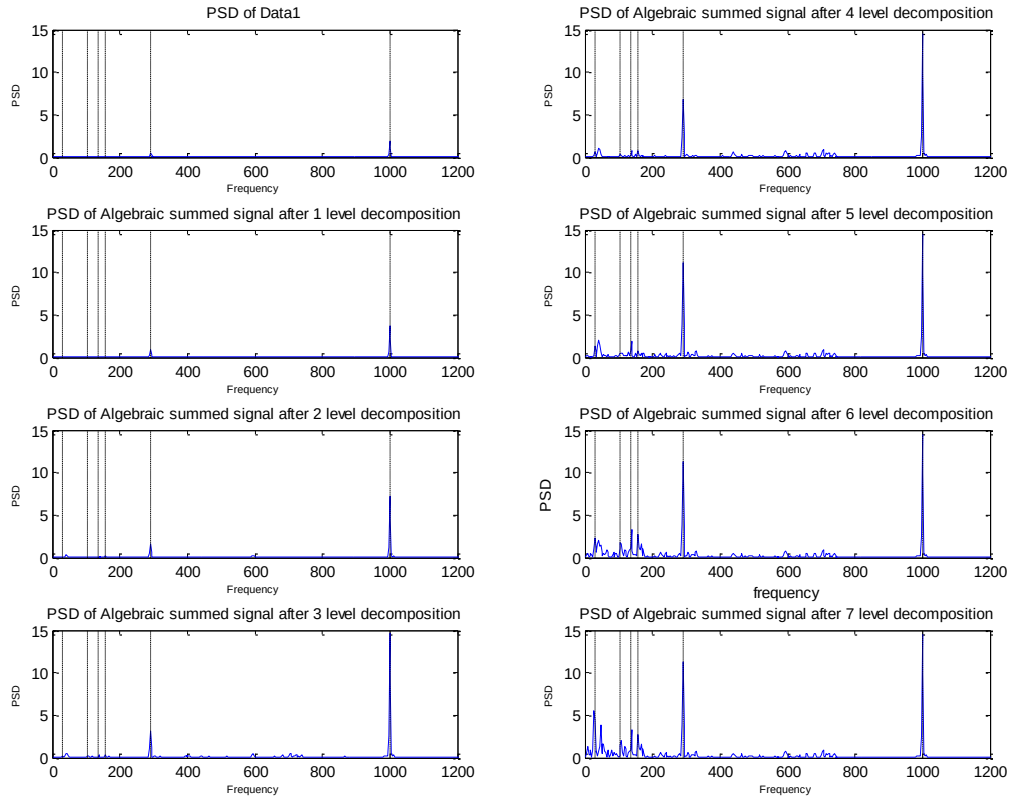


Figure 5.6 : Frequency domain representation of Data1 and its algebraic summed versions with embedded frequency components.

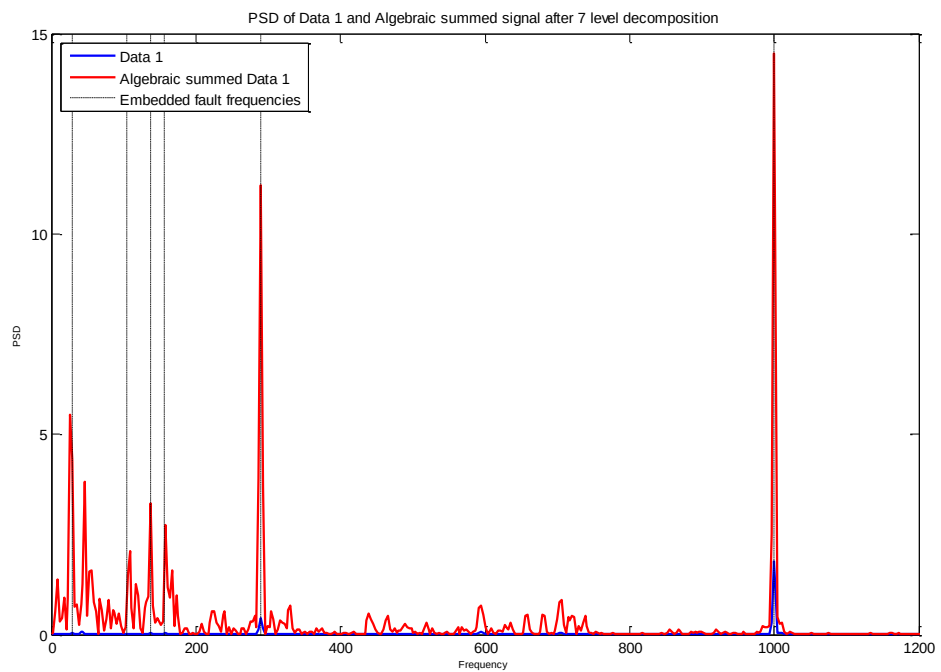


Figure 5.7 : Frequency domain representation of Data1 and its algebraic summed versions after 7 redundant decompositions with embedded frequency components.

The same observations are executed for Data 2 as well. The time domain and frequency domain responses for algebraic summed versions of Data 2 are presented for different decomposition levels in Figure 5.8 and 5.9. As mentioned previously, Data 2 is the artificial faulty case representation of a motor.

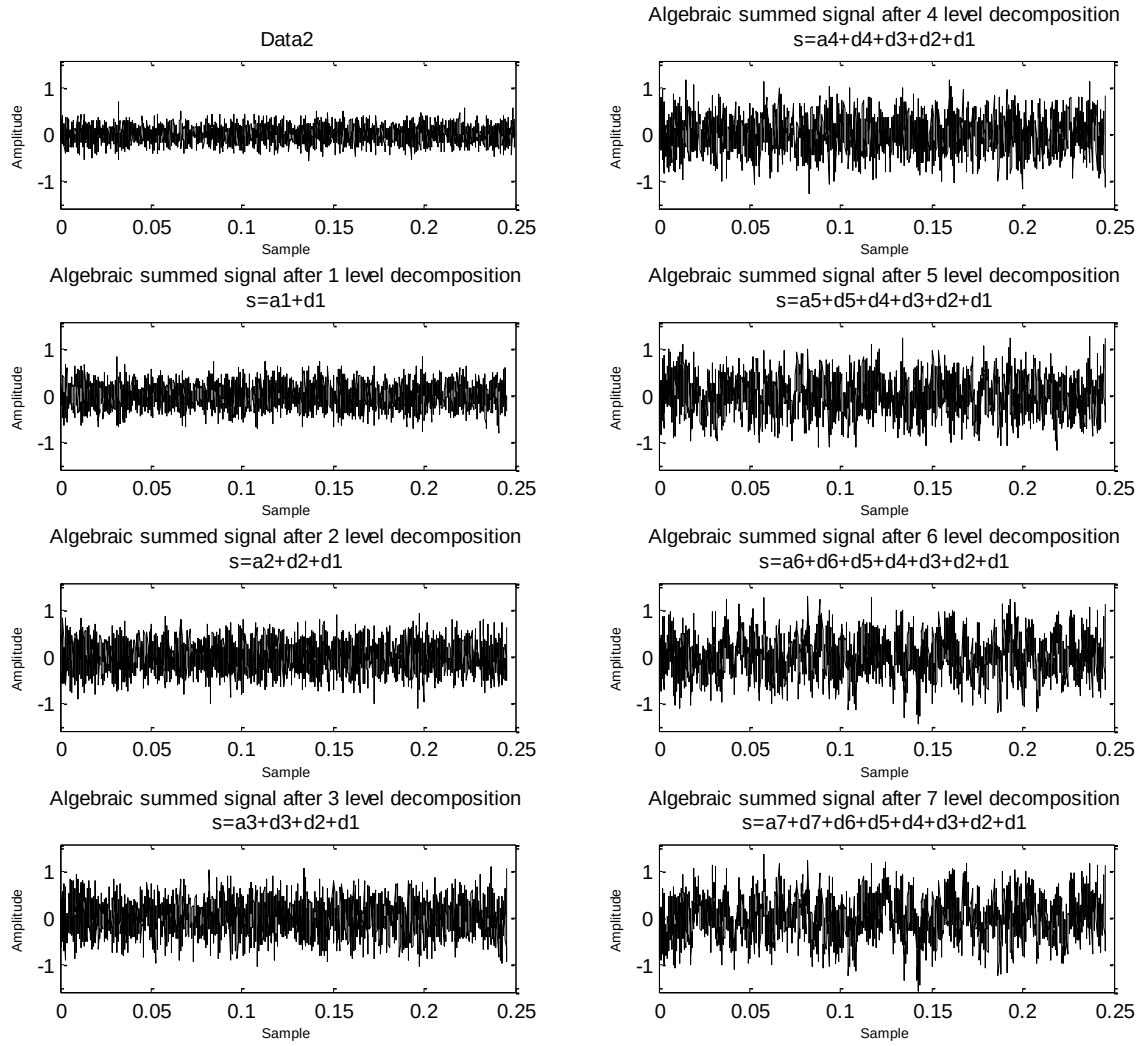


Figure 5.8 : Time domain representation of Data2 and its algebraic summed versions for various levels.

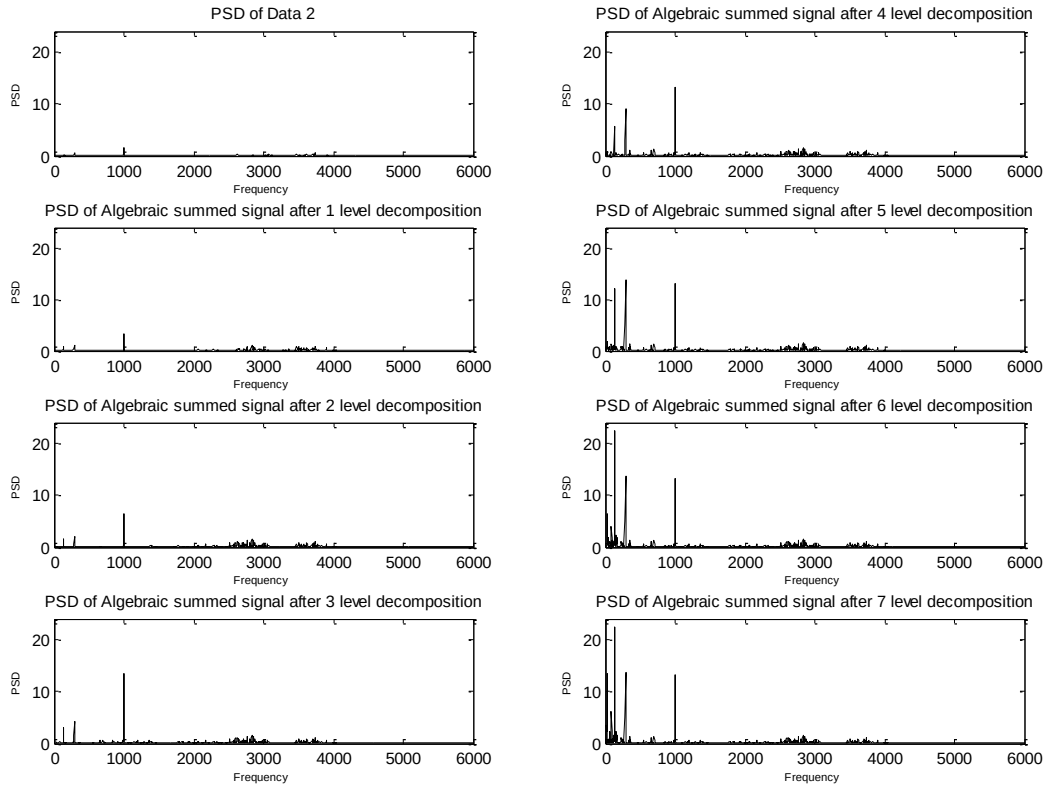


Figure 5.9 : Frequency domain representation of Data2 and its algebraic summed versions for various levels.

The same findings are also observed here; the redundancy can be observed in terms of an amplitude increment in time domain representation, and also, the low frequency part of the spectra is enriched by redundancy. The cumulation of redundancy is observed through the low frequency range while the decomposition level increases. To show this property, reconstruction errors of every decomposition level are given in Figure 5.10.

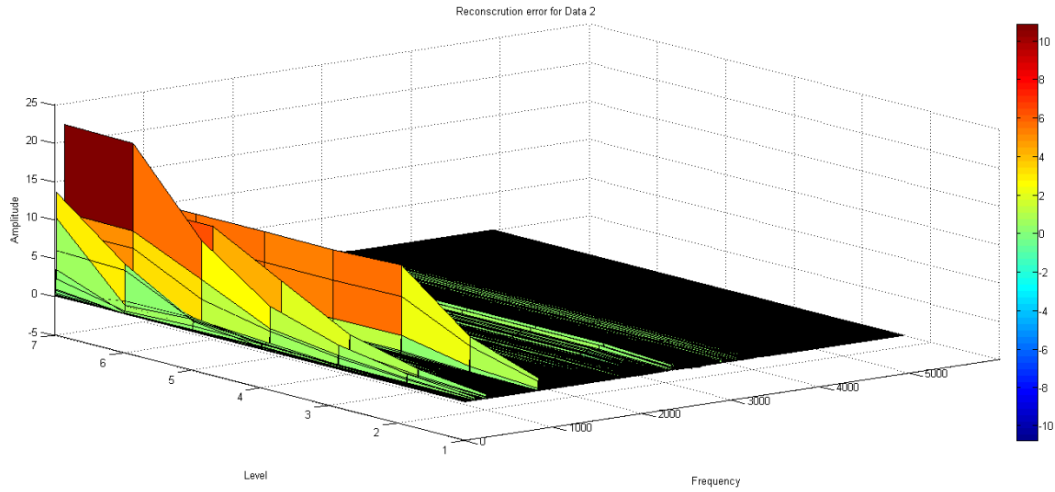


Figure 5.10 : Frequency domain representation of reconstruction errors of algebraic summed Data 2 for various levels.

Intentionally embedded frequencies (29, 290, 1000, 137, 105 and 157 Hz) are common in Data1 and Data 2. In addition to the common frequency components, Data 2 includes high frequency noises. In order to simulate the aged situation, embedded fault frequencies are amplified while Data2 is produced. To show the achievements of the algebraic summation, the frequency representation of Data 2 is reproduced with these important frequencies in Figure 5.11 and Figure 5.12. It is seen that algebraic summation amplified some these frequencies. Figure 5.12 shows that the method is capable of recognizing 5 of the fault frequencies.

On the other hand an already aged motor does not need an early fault detection algorithm. It might be useful to utilize another fault detection method proposed in the literature to find out the failure type for this motor. In order to do this, it is necessary to focus on the high frequency region of the spectrum. For this, the redundancy effect can be used. For example in Figure 5.9, algebraic summation following 1 or 2 levels of decomposition facilitate the observation of existing high frequency faults.

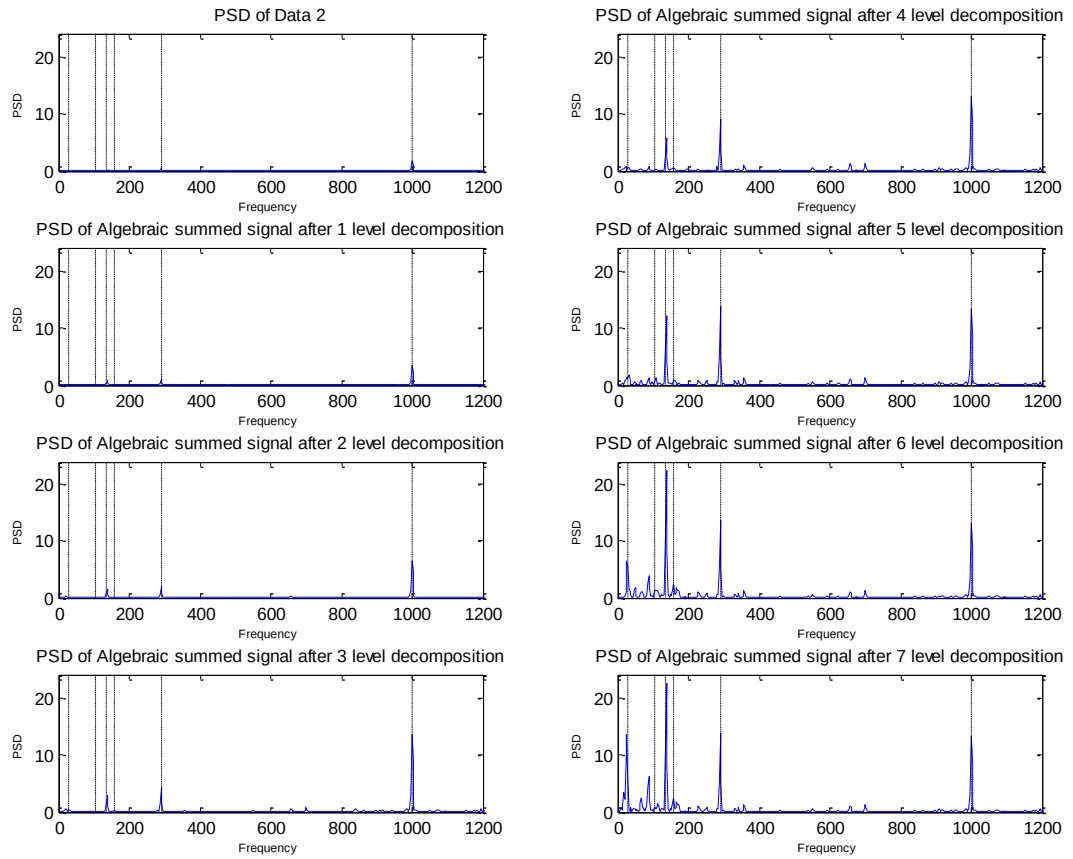


Figure 5.11 : Frequency domain representation of Data 2 and its algebraic summed versions with embedded frequency components.

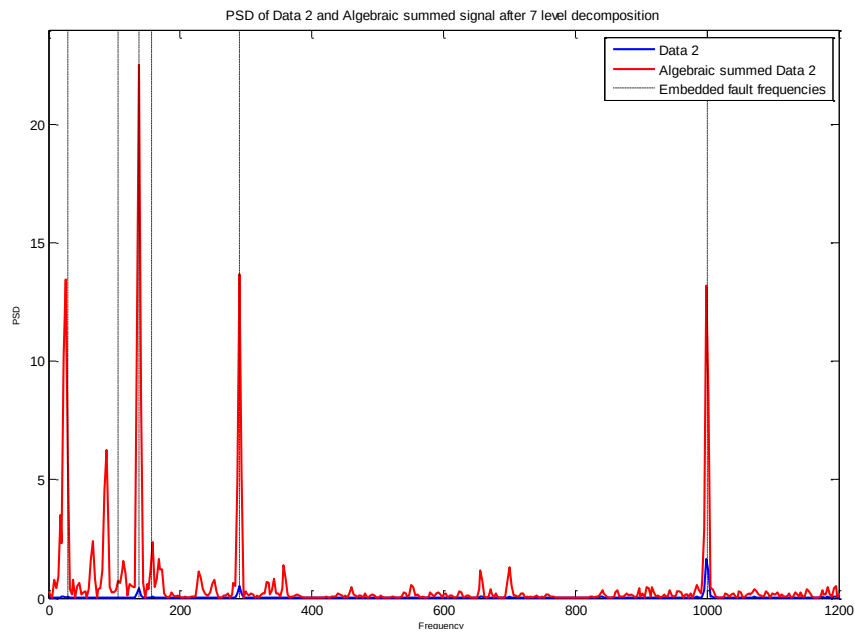


Figure 5.12 : Frequency domain representation of Data 2 and its algebraic summed versions after 7 redundant decompositions with embedded frequency components.

In summary, it can be seen that the algebraic summation operation amplifies fault frequencies that were added on purpose. The observation of fault frequencies are more successful on Data 1 compared to Data 2 with algebraic summation following 7 levels of decompositions. It can be concluded that healthier cases need high level decomposition where aged case data does not.

These investigations show that algebraic summation is a very powerful method for early and sensitive fault detection.

5.2 Feature Extraction on Experimental Data

In this study, the fundamental frequency of the system is the rotational frequency of the motor which is 29.03 Hz. The decomposition level for ideal feature extraction operation is chosen as 7, as only seven level decompositions can locate the fundamental frequency to the last approximation. The feature extraction method is applied to the initial case data because this case is the unique case named as healthy. The PSD of the algebraic summed healthy case signal after 7 SWT decompositions can be seen in Figure 5.13.

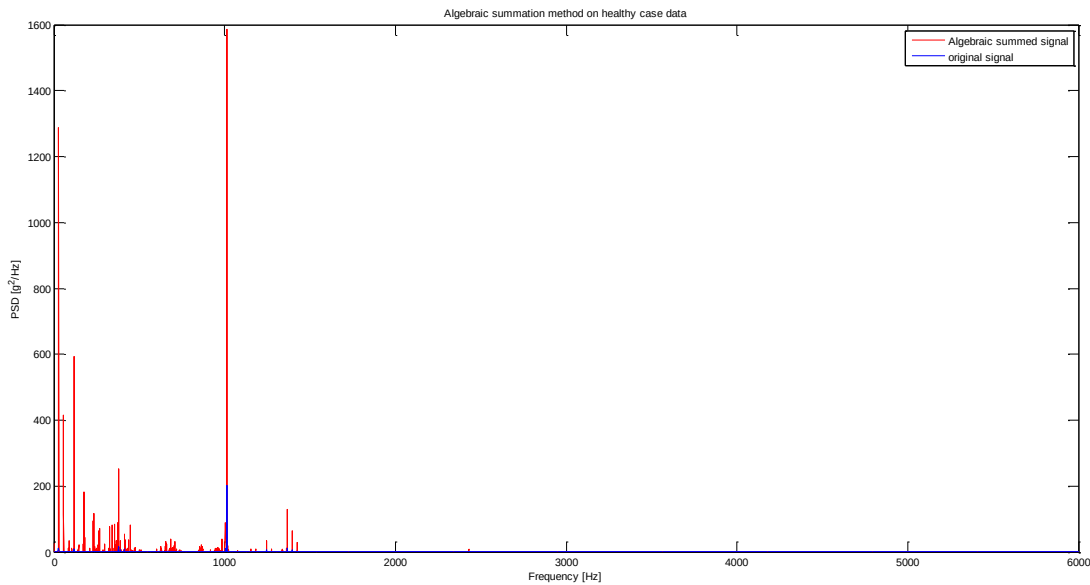


Figure 5.13 : PSD of algebraic summed healthy case signal after 7 SWT decompositions.

It is obvious from the figure that the low frequency components which are not visible have been added to the spectra. The frequency components above the threshold are

taken into consideration. The threshold is defined by 8% of the maximum amplitude in the spectra. These frequencies are shown in Figure 5.14.

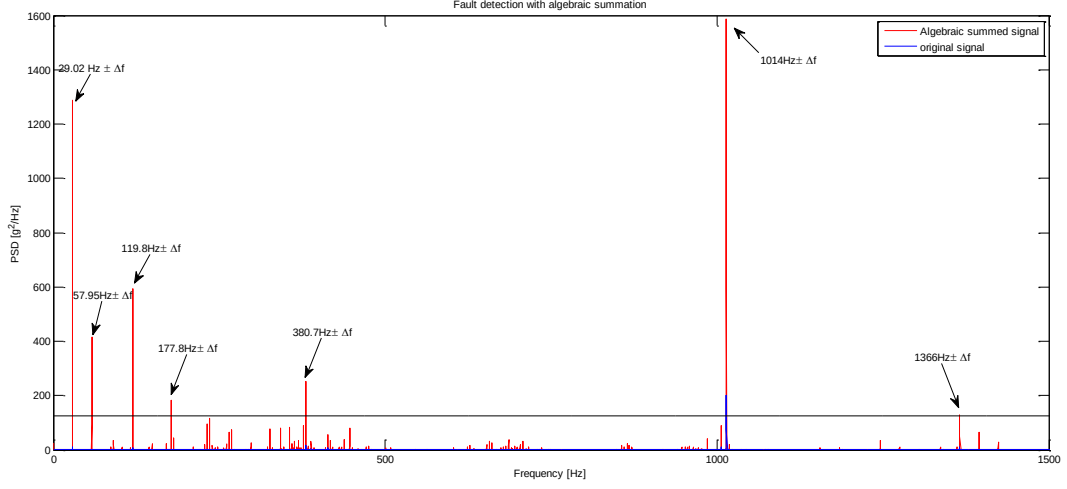


Figure 5.14 : Fault detection through healthy case vibration data.

These frequencies are associated with eccentricity frequencies of this motor. Eccentricity is a common problem encountered in electric motors. It can be described as the uneven air gap distribution. Windings cannot induce even magnetic fields with uneven air gap distribution in the motor. Uneven fields produce uneven magnetic forces on rotating parts, which may be interpreted as torque pulsations. As a result of this fact, the motor comes upon unexpected mechanical stress. The frequency of the eccentricity is given in (5.1) where f_e is the supply frequency, k is any positive integer, s is the slip of the motor, p is the number of poles and f_{rm} is rotor frequency in Hertz [60, 112, 113]. This expression is applicable on current signals however previous studies show that there is a strong coherence between current and vibration signals. These frequencies are the reflection of eccentricity frequencies within the vibration signal [112].

$$f_{ecc} \cong f_e \left[1 \mp k \left(\frac{1-s}{p/2} \right) \right] \cong |f_e \mp k f_{rm}| \quad (5.1)$$

The frequency components seen in Figure 5.14 closely approximate to eccentricity frequencies for $k=-1, 0, 2, 4, 11, 33$ and 45 associate to following eccentricity frequencies 30.9 Hz, 60 Hz, 118 Hz, 176 Hz, 379.3 Hz, 1017.9 Hz, 1366.3 Hz.

The algebraic summation amplifies the fault frequencies and makes them distinguishable. This method is very useful to discover small fault indications from the healthy case of the system. These frequencies are expected to become dominant and cause a failure mode in the motor, in the future. From this point of view, the algebraic summation provides a sensitive and early detection for electric motors.

5.3 Extended Aging Region with Algebraic Summation

The algebraic summation operation preserves the redundancy deliberately. This redundancy also changes the spectral content also. This operation amplifies the fault indications on purpose. Such an application changes the trends of the cases, as well. Trends of healthy and aged cases and their algebraic summed versions after 7 level decomposition are shown in Figure 5.15. As seen in the figure, the aging region changes with algebraic summation due to the fact that algebraic summed versions are amplified versions of the signal, in terms of fault frequencies, benefiting from the redundancy. Thus, the proposed method accelerates the observation of aging effects within the motor.

In order to keep the aging region (Region 3) convex, the angle between trends should be less than 180° . In other words the trend of the faultiest case should have a slope less than 90° . Thus, 90° can be assigned as the catastrophe limit for a motor. The angle between the initial and final cases also increases with redundancy as seen in Figure 5.15. In spite of the increment, the angles are below the catastrophe limit. From this point of view, this mathematical approach is highly esthetical, in terms of determining condition monitoring boundaries.

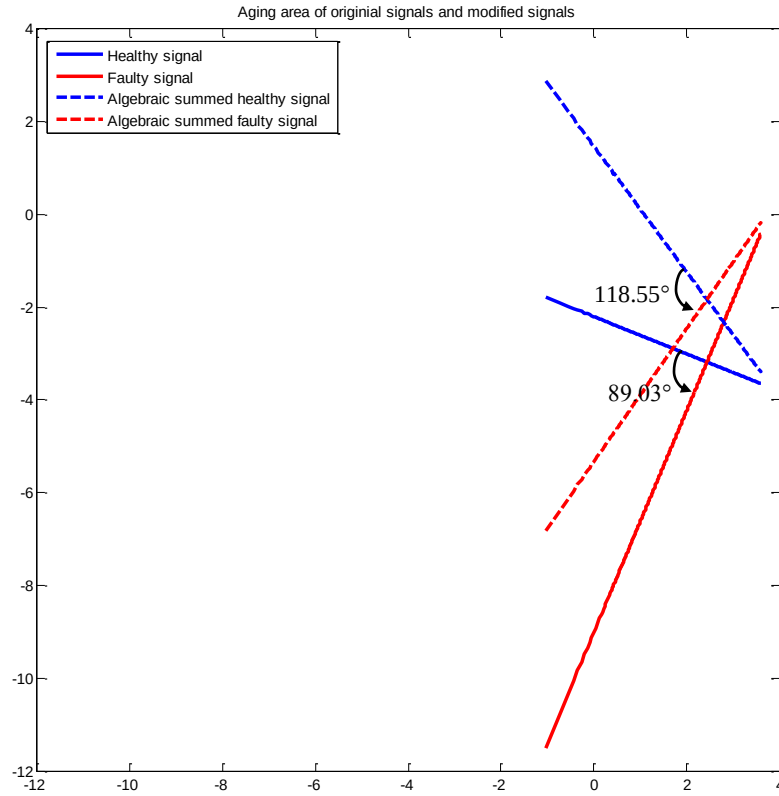


Figure 5.15 : Changing of aging regions with algebraic summation.

5.4 Contribution of the Algebraic Summation Operation

In this section a sensitive fault detection approach is developed for the motor cases which are named as healthy. The approach observes the data for identifying any potential fault. In order to develop the method, artificial data has been used as the content of the data is known. The method was successful on finding the fault frequencies with small amplitudes. The approach can be accepted as a suitable detection tool for any healthy case of an electric motor. Thus, a fault detection approach is defined using the advantages of the redundancy property of SWT and it is named as algebraic summation.

The aim of the algebraic summation operation was amplifying the anomalies and fault frequencies on purpose. By this, the fault frequencies are expected to become more noticeable. Stationary Wavelet Transform up-samples the data during the decomposition process. Then down-sampling operation is needed with the aim of preserving the stability of signal energy. Algebraic summation conserves the redundancy regardless of preserving the stability of the signal energy.

The fault detection approach is improved on artificial data and then applied to experimental data. The initial case of the motor is assigned as the only healthy case of the motor by trending application. Because of this, fault detection is executed on the initial case data only. It is noticed that the algebraic summation enriches the low frequency region of the spectra. Nevertheless, some components, which are not noticeable on PSD of the original signal, are added to spectra. After the required investigation, it is found out that these frequencies closely approximate eccentricity frequencies of the motor.

The accelerated aging experiment was focused on creating bearing aging. Because of this, the electrical discharge machining is applied to the motor. However, if such an action would not be taken, it is obvious that the motor would suffer eccentricity in its future, as the indications of eccentricity already exist at the initial case data.

The algebraic summation operation progresses the aging mathematically by amplifying fault frequencies. In other words, it changes the signal in terms of frequency domain properties. It is clear that the trend of the algebraic summed signal is different from the original one. In that manner, an extended condition monitoring region is defined. Increasing the aging may lead the system to a catastrophic state. By defining the convex region, the catastrophe boundary is implied. Thereby, the boundaries of possible aging is assigned philosophically.

6. CONCLUSION

This study presents an integrated condition monitoring and early fault detection approach for induction motors using vibration signals. Induction motors are backbones of industrial processes. Their failure may cause interruptions of systems and result in huge financial losses. Because of this fact, their condition monitoring is commonly-held through various signals. It is known that the vibration signal is highly informative in terms of mechanical and electrical problems. For that reason, the vibration signal is widely preferred in diagnostic studies.

Numerous techniques are applied to vibration signals in order to detect faults. Basically, the amplitude of vibration is employed to estimate the general condition of the motor. Fault frequencies associated to specific faults can also be calculated and these frequencies can be monitored regularly. These methods are not always practical and feasible for all applications. In this study, the aging situation of a motor is evaluated using the spectral properties of vibration signals and an early fault detection approach is proposed. The overall method is developed on artificial data and tested on experimental data.

The aging experiment, which is given in detail in Section 3, has been run in the Nuclear Engineering Department of University of Tennessee – Knoxville (UTK). The aging experiment was conducted by the Maintenance and Reliability Center as a part of a bigger experiment investigating the fault detection of induction motors used in the industry. The aging process is created using two different aging actions in seven aging. These actions are electrical discharge machining (EDM) and chemical-thermal aging actions. EDM is employed due to the fact that bearing faults are the most common failure type in induction motors. On the other hand, chemical and thermal stresses are inevitable for all electric motors and these two actions ensure the aging of the induction motor in several cycles.

The study consists of two parts as classification and analysis; the classification part decides if the motor may be classified as healthy or not, while the analysis part

executes a fault detection on healthy motors in order to spot even the smallest fault indications. Thus the study introduces an integrated condition monitoring and fault detection method for electric motors.

The classification part proposes a spectral based trending method which is very simple, reasonable and applicable. The aging does not suddenly occur, it progresses and grows in time. From this point of view, observing its progress has a vital importance in order comparing and rating the situation of the motor.

Following the classification part, the decision of whether the motor is healthy or not is made. If the motor is not healthy, there are plenty of methods to identify existing faults. However if it is healthy, there might still be some very small fault indications. These indications might get stronger in time and cause failures, so it is useful to be aware of their existence. In order to make them noticeable, a fault detection approach is developed using the redundancy property of SWT. Through this the analysis part suggests an early and sensitive detection algorithm.

In order to realize the spectral trending operation, the PSD of vibration signals are calculated logarithmically and then a straight line is fitted to trend the data. The method is developed on artificial data and then it is approved on experimental data. The comments and findings are listed as below:

- It is noticed that the health and aged cases' trends have different slopes. The slope of the trend changes from negative to positive with the growth of aging. It is established that a positive slope is an indication of aging. Thus a very effective aging indication is easily introduced.
- The linear models create a plane and this plane becomes a convex region by the measurement boundary. It would be possible to define any metric in a convex region, so it can be interpreted as a region to rate the situations.
- It is noticed that the initial and the final cases' trends form a triangle with the measurement boundary. All the possible aging cases of the motor are expected to be within this triangle.

- The vertical and horizontal thresholds are defined to catch the rising faults and enhance the condition monitoring quality. By these thresholds, the condition monitoring target is determined. It is concluded that monitoring the overall whole frequency plane is not necessary anymore.
- In order to find out the thresholds, the intersection points of the trends for the initial and the final cases are used. By these thresholds, the condition monitoring region comes down to a smaller scale. The condition monitoring region, required for aging identification, has been decreased 16.67 times.
- Observing the experimental data which has 7 aging cycles, shows that the slopes are changing consecutively. When the overall process is examined it is possible to discover either the beginning phase or the growing phases of aging.
- Due to the convex region, it is possible to rate the situations of the motor cases by referencing the initial or final cycles' trends.
- The aging region concept and health rating can be used to reschedule and plan the maintenance of the motors.

In the analysis part of the study, the healthy cycle is observed for distinguishing any potential faults. In the real world, a motor newly bought from the producer is never 100% healthy. Some manufacture related faults or defects might exist and they could appear in time. The method is developed on artificial data because the content of artificial data is known. The aim is to expose the frequencies which are implanted during the generation of the artificial data. As the method succeeded, it is tested on experimental data as well to find the potential faults. The detection method is an algebraic summation operation cancelling the down sampling operation defined for perfect reconstruction. In other words, the redundancy provided during decomposition is conserved on purpose.

The comments and findings are listed below:

- Every decomposition provides redundant information and the algebraic summation operation does not permit to remove this redundancy. So higher the decomposition level, more redundant is the information piled up in the

low frequency region. In other words, the algebraic summation, with higher decomposition levels, cumulates the redundancy through the low frequency region.

- The aged cases may use the redundancy to point out the existing faults around the high frequency region. For that purpose, low level decomposition can be done and high frequency information can be interpreted by means of redundancy. However, healthy cases need more decomposition levels in order to take advantage of redundancy.
- In this study, the maximum level of decomposition is chosen as 7 so that only the last approximation contains the rotational frequency. It is seen that 7 level decomposition is enough to detect the intentionally embedded frequencies in the artificial data.
- It is noticed that the method is more successful on Data1 (associated with the healthy case) compared to Data 2 (associated with the faulty case). For Data 1, all of the spectral information is defined below 1000 Hz and the algebraic summation amplifies this region strongly. On the other side, Data 2's spectral information is spread through the overall spectra. However, the algebraic summation for the high decomposition level only amplifies the low frequency components.
- The algebraic summation is applied to the experimental healthy case data. Some frequency components are amplified strongly. It is noticed that these frequencies are associated with eccentricity frequencies of the motor. These components are expected to become stronger eventually. Because algebraic summation which causes to redundancy in signal reconstruction procedure of SWT. Thus, the algebraic summation can be interpreted as an advance and perceptive detection approach.
- Following 7 level decomposition and algebraic summation, the trends of the cases also change. The angle between the cases geometrically increase. The physical meaning of this is that; the proposed method accelerates the aging effects unnaturally.

- In theoretical manner, the catastrophe limits are set as 90° considering the convexity of the region. In other words, the slope of the straight line must be less than 90° . Thus the maximum possible aging limits are set philosophically as catastrophe limits.

Considering the findings listed below, the study proposes a simple and easy aging indication and introduces a new monitoring strategy using the convex region approach which is totally new in this area. Through this, the health of the motor becomes a ratable concept. In addition to this, a new detection method is defined using the redundancy property of SWT. Additionally, the catastrophic aging boundaries are represented through convexity, inspiring the algebraic summation. These contributions are highly noteworthy regarding efficient and practical condition monitoring as well as an early feature extraction approach.

Besides these novelties the study is very implementable for industrial applications. It might bring a new perspective to maintenance engineering. Monitoring the progress of aging can be used as a very useful tool for critical fields which require high safety of operation. The study can be developed to be a predictive maintenance system, rescheduling and optimizing the maintenance. On a larger scale, either geometric interpretation of trends or redundancy based fault detection methods can be utilized in any engineering field interested in monitoring and diagnostics.

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APPENDICES

APPENDIX A

In this section the hardware used in the experiment are given with required technical details. The dissertations of Erbay [80] and Ayaz [81] include more detailed information about the experiment. In this section the nameplate information of test motors and dynamometer and the technical information of the accelerometers are given.

A.1. Technical Information of Dynamometer

A DC generator is used to load the electric motor during the performance tests. The dynamometer is a DC generator 3kW, 1800 rpm named LSC 132 MC7. Universal coupling is used on test bed. The excitation of the generator is supplied with 0-2A and 0-200VDC. In order to load the generator 21.63 Ohm resistance is used.

A.2. Technical information of the test motors

The test motors used in the experiment are all identical and their nameplates can be found in Table A.1.

Table A.1 : Nameplate of test motors.

Property	Technical Information
Motor Type	Premium Efficiency Motor US Electrical Motors
Manufacturer	Division of Emerson Elec. Co. St.Louis, MO
Model number	7965B
Power	5 HP
Phase	3
Speed	1750 rpm
Frame number	184T
Frame type	TCE
Voltage	230 / 460 V
Current	13.0 / 6.5
Service factor	1.15
Frequency	60 Hz
Power factor	0.825
Efficiency	90.2%
NEMA design	B
Insulation class	F
Enclosure	TE
Maximum ambient temperature	40°C
LR KVA code	J
Duty	Continuous
Maximum KVAR	1.4
Shaft end bearing type	6206-2Z-J/C3
Drive end bearing type	6206-2Z-J/C3
ID number	Z08Z177R190F

A.3. Technical information of accelerometers

The vibration information is collected by 6 high bandwidth accelerometers from different locations. Specifications of the high bandwidth accelerometers can be found in Table A.2.

Table A.2 : Specifications of high bandwidth accelerometers.

Property	Technical Information
Sensor type	High frequency industrial accelerometer
Manufacturer	Industrial monitoring instrumentation3425 Walden Av. Depew, NY
Model number	323B01
Sensitivity	100mV/g ± 5
Measurement range	$\pm 50g$
Resolution	0.0002g
Frequency range	144-480000 cpm $\pm 5\%$ 102-600000 cpm $\pm 10\%$ 48-9000000 cpm ± 3 dB
Mounted resonant frequency	40 kHz
Amplitude linearity	$\pm 1\%$
Transverse sensitivity	$\leq 5\%$
Shock limit	5000g pk
Temperature range	-54 to 121°C
Settling time within $\pm 1\%$ of output bias	5 seconds
Discharge time constant	≥ 0.2 seconds
Spectral noise	4.0 $\mu g/\sqrt{Hz}$ (10 Hz) 1.2 $\mu g/\sqrt{Hz}$ (100 Hz) 0.4 $\mu g/\sqrt{Hz}$ (1kHz)
Case isolation protection	RFI/ESD
Broadband electrical noise	200 μg (1-10kHz)
Mounting thread	10-32 female
Sensing element structure	Ceramic/shear
Power supply	Model 482A05 I.C.P. power supply

CURRICULUM VITAE



Name Surname: Duygu Bayram
Place and Date of Birth: İstanbul, 14.09.1983
Address: Telli kavak sok. Çallı Apt. No.20/6 Erenköy, İstanbul.
E-Mail: bayramd@itu.edu.tr
B.Sc.: 2006, Istanbul Technical University,
Electrical Engineering Department
M.Sc.: 2009, Istanbul Technical University,
Electrical Engineering M. Sc. Program

Professional Experience:

Research Assistant May 2007–February 2015
Istanbul Technical University
Electrical Engineering Department
Electrical and Electronics Faculty

Visiting Researcher January 2013 – July 2013
University of Tennessee - Knoxville
Nuclear Engineering Department
Reliability and Maintainability Research Group

PUBLICATIONS/PRESENTATIONS ON THE THESIS

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