ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

SENSOR VALIDATION AND FUSION FOR SYSTEM MONITORING

Ph.D. THESIS

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Department of Electrical Engineering

Electrical Engineering Programme

JANUARY 2022

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

SİSTEM GÖZETİMİNDE SENSOR DOĞRULAMA VE BİLGİ BİRLEŞTİRME

DOKTORA TEZİ

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Elektrik Mühendisliği programı

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OCAK 2022

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Date of Submission : 29 December 2021
Date of Defense : 31 January 2022

To my beloved parents,

FOREWORD

First of all, I sincerely thank to my supervisor Prof. Dr. Ş. Serhat ŞEKER who guided me with patience during my Ph.D. thesis and he supported me with his strong professional experience and his vision. I owe him a lot, because Without his expert guidance and support, writing this dissertation would have been impossible.

Also, I would like to present my thanks to Asst. Prof. Dr. Duygu BAYRAM KARA for her endless support in each step of my researches.

I am also enormously grateful to my thesis committee members, Prof. Dr. Emine AYAZ and Prof. Dr. Osman NURI UCAN, for their time to review the thesis, insightful critiques, and constructive suggestions.

The author would like to thank Prof. B. R. UPADHYAYA from Nuclear Engineering Department at the University of Tennessee Knoxville, USA, for permission to the use of the experimental data. Also, this study is supported by the Scientific Research Unit of Istanbul Technical University with the project ID: MDK-2018-41044, entitled as "Sensor Validation and Fusion for System Monitoring".

Last but not least, I wish to express a sense of gratitude and love to my kind parents for their support,strength, help and for everything.

January 2022

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TABLE OF CONTENTS

ABBREVIATIONS

ANN	: Artificial Neural Network
CM	: Condition Monitoring
DF	: Data Fusion
EKF	: Extended Kalman Filter
FD	: Fault Detectoin
HI	: Health Information
IFE	: Integrated Fault Evaluation
IM	: Induction Motor
KF	: Kalman Filter
KG	: Kalman Gain
Kurt	: Kurtosis
PSD	: Power Spectral Density
RMS	: Root Mean Square
SNR	: Signal to noise Ratio
STD	: Standard Deviation
SV	: Sensor Validation

SYMBOLS

F	: System matrix - state
G	: System matrix - input
H	: Observation matrix
kHz	: Kilo Hertz
kW	: Kilo watt
Q	: Process noise covariance matrix
R	: Measurement noise covariance matrix
u	: Input vector
v	: Measurement noise vector
w	: Process noise vector
x	: State vector
y	: Output vector

LIST OF TABLES

LIST OF FIGURES

SENSOR VALIDATION AND FUSION FOR SYSTEM MONITORING

SUMMARY

With the thesis, it will be feasible to bring state surveillance up to date with modern technologies and build a platform for scientific research. Through academic works, studies on this issue will give direction and solution partnerships to Turkey's industry. When a defect occurs in industry, it can harm the system, causing it to stop operating for a period of time or to perform inefficiently. Maintenance of the system results in increased expenses for business in certain scenarios. State monitoring methods are model-based tools that are commonly used in industries. During the rise of the fault, no error signal is created in these systems. To avoid this problem, detection and diagnosis are focused on the time between the onset of the fault and its discovery. As a result, an intelligent signal-based monitoring application for usage in an industrial system is required. The goal is to monitor the system and assess the status by merging and evaluating data from several sensors (data fusion). As a result, focusing on these topics will help us detect early faults before they cause system damage and lower maintenance costs.

In this thesis a data fusion technique is used for condition monitoring (CM) and fault detection (FD) of electrical motors (EM) utilizing Kalman filtering method. One of the most well-known data fusion approaches is Kalman filtering. It has difficult mathematics. The core mathematics of the kalman filter, on the other hand, is discussed here.

In this thesis, it is decided to employ the Kalman filtering method, which is one of the most well-known methods, for data fusion. As a result, in the next parts of this study, the Kalman filter is chosen as the major approach for data fusion application. Note that, there is no example of distinguishing the fault source in the literature utilizing a data fusion strategy powered by Kalman filtering. In other words, the application of FD and CM via data fusion using the KF technique is innovative in this thesis.

An EM data set is used as a case study, along with potential sensor and process problems. This technique also allows for sensor validation (SV) and fault tracking (either the sensor or the process). Two case studies are investigated in this thesis separately. The purpose of that, is to apply the proposed method on two types of signals with different characteristics, to demonstrate the capability of the suggested approach.

First case study is current signals which are received from two sensors with different biases and noises. In other words, biases and noises with varying characteristics are considered to be present in the sensors. Kalman filtering is used to calculate fused current information. Following that, the impact of measurement and process noises on the fused signal is discussed. consequently, the suggested method can distinguish if a sensor or a process is malfunctioning. Then, the fused and original signals are

compared in terms of spectral and statistical characteristics. To illustrate, related figures and tables are shown in following chapters. In mentioned tables you can find statistical data including mean square error, root mean square, standard deviation, mean value and kurtosis, correspondingly.

In addition, to perform SV, the Kalman gain is monitored to examine the influence of process and measurement noise. Kalman Gain eliminates the process defect. Following that, the defects in the sensors are identified using spectrum outputs such as power spectral densities and coherences. Finally, the defective sensor(s) are effectively removed.

Second case study is vibration signals which have stochastic characteristics. However, current signal has deterministic characteristics. Vibration signals indicating various aging stages of an induction motor are employed as the case study. For this conditions, an Integrated Fault Evaluation (IFE) approach is proposed. The suggested approach makes use of a data fusion algorithm that is further improved by the Kalman filter (KF). furthermore, IFE is accomplished using statistical and frequency domain features. The capacity of distinguishing between system aging and process issues is the study's most significant contribution. For this purpose, a health information (HI) rate is determined that can distinguish the influence of process noise and system age.

Three scenarios are developed and investigated individually using the IFE method. The first scenario is a measuring issue in which all sensors are defective. The second scenario is a sensor issue, in which one of the sensors is malfunctioning. The third scenario is a defective process with growing process noise as the system ages. It is attempted to distinguish between process noise and system aging in this case. The HI idea is provided for this aim.

The most significant aspect of the IFE strategy is HI. Because, as the process noise grows, the information about aging included in the fused signal is lost. A threshold must be specified to differentiate between process noise and system aging. Therefore, initially, two important factors are determined, and then the HI idea is created around those factors. The previously described threshold is extracted following detailed examinations and observations.

SİSTEM GÖZETİMİNDE SENSOR DOĞRULAMA VE BİLGİ BİRLEŞTİRME

ÖZET

Durum izleme yöntemleri, bakım planlaması için endüstride sık kullanılan model tabanlı araçlardır. Bu sistemlerde arızanın yükselmesi sırasında hata sinyali üretilmez. Model hata uyarıları vermeye başladığında, genellikle ilgili bileşenin değiştirilmesi veya onarılması planlanır. Elemanlar bozulmaya başladığında, tespit edilemediğinde ve performans gereksinimleri düşük verimlilikte devam ettiğinde süreç verimsiz hale gelebilir. Ayrıca bir arıza meydana geldiğinde, sistemin maliyeti daha yüksek olan bakıma ihtiyaç duyar ve sistemi bir süreliğine kesintiye uğratır. Bu sorunun önüne geçebilmek için arızanın başlangıcından belirgin hale gelene kadar olan süreçte tespit ve teşhis amaçlanır. Sonuç olarak, bu tez endüstriyel bir sistemde kullanılabilecek akıllı bir sinyal tabanlı izleme uygulaması üzerinde çalışacaktır. Amaç, farklı sensörlerden elde edilen verileri (veri füzyonu) birleştirerek ve değerlendirerek sistemi izlemek ve durumu tahmin etmektir.

Tezin amacı, akıllı izleme sistemindeki farklı sinyalleri değerlendirmek ve veri füzyonu yaparak sinyal tabanlı bir durum izleme sistemi kurmaktır. Böylece daha hızlı ve hassas bir takip ve tespit sistemi sağlanacaktır. Tezde bu füzyon verileri istatistiksel ve ileri sinyal işleme yöntemleri ile analiz edilecektir. Bu tezde akım, gerilim, titreşim, akustik gürültü vb. gibi çoklu sensörler kullanılarak elektriksel ve mekanik veriler elde edilebilir. İlk olarak sensörlerin sağlıklı veya arızalı olup olmadığını anlamak için sensörler doğrulanacaktır. Ardından, elde edilen veriler, sistemin durum izlemesi için veri birleştirme teknikleri kullanılarak manipüle edilebilir. Tezin kapsamı, EM'ler gibi endüstride sık karşılaşılan sistemler tarafından belirlenir.

Durum izleme ve sorun giderme literatürde bir veya iki basit sinyalden elde edilen bilgiler incelenerek yapılır. Durum izleme söz konusu olduğunda, tek bir sinyal kullanmak, mutlaka en iyi izleme ve arıza analizi sonuçlarıyla sonuçlanmaz. Ancak bu tezde, bir veri birleştirme algoritmasında iki veya daha fazla farklı sinyalin birlikte kullanılmasından bahsedilmiştir. Çalışma kapsamında yenilikçi sinyal işleme yöntemleri incelenecektir. Özellikle, veri birleştirmeye yönelik benzersiz yaklaşımlar hedeflenmektedir. Bu tezin benzersiz yönü, arızanın sisteme zarar vermesini önlemek için birden fazla izleme yöntemini bir arada değerlendiren ve erken arızayı tahmin eden akıllı bir algoritma ortaya koymaktır.

Bu tez ile durum izlemenin güncel teknolojilerle güncel hale getirilmesi ve bilimsel araştırmalar için bir platform sağlanması mümkün olacaktır. Akademik çalışmalarla bu konulardaki çalışmalar, Türkiye sanayisine yol gösterici olacaktır. Sonuç olarak her çalışma endüstriyel bir uygulamaya dönüştürülmelidir. Bu araştırma aynı zamanda bir asenkron motor kullanan herhangi bir endüstriyel uygulamaya da uygulanabilir. Ayrıca, uygun sinyalleri elde edebilen endüstride keşfedilen herhangi bir sistem önerilen tekniği kullanabilir.

Bu tezde, Kalman filtreleme yöntemi kullanılarak elektrik motorlarının (EM) durum izleme (CM) ve arıza tespiti (FD) için bir veri birleştirme tekniği kullanılmıştır. En iyi bilinen veri birleştirme yaklaşımlarından biri Kalman filtrelemedir. Zor olan matematiğine rağmen, Kalman filtrenin ana matematiğini burada anlatılmaktdır.

Bu tezde, veri füzyonu için en bilinen yöntemlerden biri olan Kalman filtreleme yönteminin kullanılmasına karar verilmiştir. Sonuç olarak, bu çalışmanın sonraki bölümlerinde, veri birleştirme uygulaması için ana yaklaşım olarak Kalman filtresi seçilmiştir. Kalman filtrelemesi kullanan veri birleştirme stratejisi literatürde arıza kaynağını ayırt etme örneği bulunmamaktadır. sonuç olarak, FD ve CM'nin KF tekniği kullanılarak veri birleştirme yoluyla uygulanması bu tezde yenilikçidir.

Bir elektrik motoru (EM) veri seti, potansiyel sensör ve proses problemleriyle birlikte vaka çalışması olarak kullanılır. Bu teknik aynı zamanda sensör doğrulaması (SV) ve arıza takibine (sensör veya proses) izin verir. Bu tezde iki vaka çalışması ayrı ayrı incelenmiştir. Bunun amacı, önerilen yaklaşımın kabiliyetini göstermek için önerilen yöntemi farklı özelliklere sahip iki tip sinyal üzerinde uygulamaktır.

İlk vaka çalışması, farklı bias ve gürültülere sahip iki sensörden alınan akım sinyalleridir. Yani, sensörlerde farklı karakteristiklere sahip biaslar ve gürültüler olduğu kabul edilir. Birleşik akım bilgilerini hesaplamak için Kalman filtrelemesi kullanılır. Bunu takiben, ölçüm ve proses gürültülerinin kaynaşmış sinyal üzerindeki etkisi tartışılmıştır. sonuç olarak, önerilen yöntem, bir sensörün veya bir işlemin arızalı olup olmadığını ayırt edebilir. Daha sonra kaynaşmış ve orijinal sinyaller spektral ve istatistiksel özellikler açısından karşılaştırılır. Bunu göstermek için, ilgili figürler ve tablolar aşağıdaki bölümlerde gösterilmiştir. Söz konusu tablolarda, mean square error, root mean square, standart sapma, mean value ve kurtosis gibi istatistiksel verileri bulunmaktadır.

Ek olarak, SV gerçekleştirmek için, proses ve ölçüm gürültüsünün etkisini incelemek için Kalman gain izlenir. Kalman gain, proses hatasını ortadan kaldırır. Bunu takiben, güç spektral yoğunlukları ve tutarlılıkları gibi spektrum çıktıları kullanılarak sensörlerdeki kusurlar belirlenir. Son olarak, arızalı sensör(ler) etkin bir şekilde kaldırılır.

İkinci vaka çalışması, stokastik özelliklere sahip titreşim sinyalleridir. Ancak, akım sinyali deterministik özelliklere sahiptir. Örnek olay olarak bir asenkron motorun çeşitli yaşlanma aşamalarını gösteren titreşim sinyalleri kullanılmıştır. Bu koşullar için, Entegre Hata Değerlendirmesi (IFE) yaklaşımı önerilmektedir. Önerilen yaklaşım, Kalman filtresi (KF) tarafından daha da geliştirilmiş bir veri birleştirme algoritmasını kullanır. ayrıca, IFE, istatistiksel ve frekans alanı özellikleri kullanılarak gerçekleştirilir. Sistem yaşlanması ve proses sorunları arasında ayrım yapma kapasitesi, çalışmanın en önemli katkısıdır. Bu amaçla, süreç gürültüsünün etkisini ve sistem yaşının etkisini ayırt edebilecek bir sağlık bilgi oranı belirlenir.

IFE yöntemi kullanılarak ayrı ayrı üç senaryo geliştirilmiş ve incelenmiştir. İlk senaryo, tüm sensörlerin arızalı olduğu bir ölçüm sorunudur. İkinci senaryo ise, sensörlerden birinin arızalı olduğu sorunudur. Üçüncü senaryo ise, sistemin yaşlanması ve process gürültüsün artması arasındaki farkı anlamak sorunudur. Bu durumda proses gürültüsü ile sistem yaşlanması arasında ayrım yapılmaya çalışılır. HI fikri bu amaç için sağlanmıştır.

IFE stratejisinin en önemli yönü HI'dır. Çünkü proses gürültüsü büyüdükçe, kaynaşmış sinyalde bulunan yaşlanma ile ilgili bilgiler kaybolur. Proses gürültüsü ile sistem yaşlanması arasında ayrım yapmak için bir eşik belirlenmelidir. Bu nedenle öncelikle iki önemli faktör belirlenir ve daha sonra bu faktörler etrafında HI fikri oluşturulur. Daha önce bahsedilen eşik, detaylı incelemeler ve gözlemler sonrasında çıkarılır.

1. INTRODUCTION

Sensor Fusion is the process of merging sensory input or data generated from sensory data to provide knowledge that is superior to what would be attainable if these sources were used separately [1]. Data fusion can also help with a variety of issues, such as noise and impending sensor failure. Even if none of these problems exist, sensor fusion can improve the system's accuracy and reliability. Particularly for high-performance operational systems such as helicopters, aircraft, space shuttles, and process control systems [2]. In order to improve system efficiency, sensor validation and data fusion can be utilized for system monitoring. If a defect is detected by the monitoring system, the sensor validation technique may be used to determine if the issue is caused by the system or the sensor itself. After the sensors have been validated, data fusion methods such as kalman filtering may be employed to monitor the system and improve its performance.

Data fusion has been approached in a variety of ways. Kalman filtering is one of these strategies. The Kalman filter is a famous fusion technique. It was first introduced by Kalman and Bucy [3, 4] in 1960, and it has been widely researched since then. To combine low-level redundant data, the Kalman filter is utilized.

Sensor information that is likely to be in error is removed in Bayesian estimation using consensus sensors [5], and the information for the other 'consensus sensors' is utilized to compute the fused value. The information from each sensor is represented as a probability density function, and the best way to fuse the data is to identify the Bayesian estimate that maximizes the consensus sensors' likelihood function.

Durrant-Whyte combines the corresponding probability distributions of each separate feature into a joint posterior distribution function using a multi-Bayesian technique, in which each sensor is treated as a Bayesian estimator. After that, a probability function of this joint distribution is maximized to produce the final sensory information fusion [6].

Durrant-Whyte developed a data fusion categorization based on the relationships between the input data sources in 1988 as well [7]. These relationships can be classified as (1) complimentary, (2) redundant, and (3) cooperative data, as shown in Figure 1.1:

1. complimentary: When the information supplied by the input sources reflects diverse portions of the scene and can thus be combined to acquire more full global knowledge, it is said to be complementary. In visual sensor networks, for example, input from two cameras with different fields of view on the same target is considered complimentary.

2. redundant: When two or more input sources give knowledge on the same target and may be fused to increase confidence, it is said to be redundant. Data from overlapping areas in optical sensor networks, for example, is deemed redundant.

3. cooperative: When supplied information is integrated to create new knowledge that is often more complicated than the original information, it is said to as cooperative. Multi-modal (audio and video) data fusion, for example, is considered cooperative.

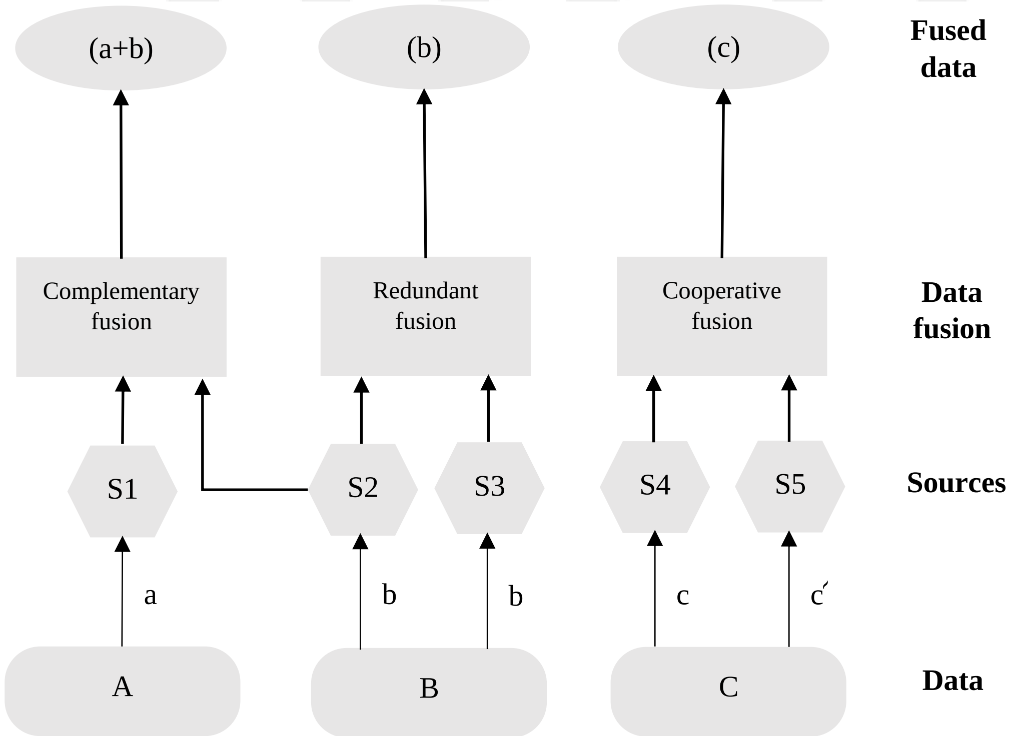


Figure 1.1 : Whyte's classification based on the relations between the data source.

The Dempster-Shafer technique is another data fusion or information fusion approach. This technique is based on Dempster [8] and Shafer's [9] mathematical theory, which generalizes the Bayesian theory. The Dempster-Shafer theory provides a framework for representing partial knowledge, updating beliefs, and a mixture of evidence, as well as allowing us to express uncertainty directly [10].

1.1 Purpose of Thesis

State monitoring methods are model-based tools often used in industry for maintenance planning. In these systems error signal is not generated during the rising of the fault. When the model starts to produce error warnings, it is usually planned for modification or repair of the component involved. The process can become inefficient as when the elements begin to deteriorate, can not be detected and performance requirements continue at low efficiency. Moreover, when a fault occurs, the system needs maintenance which has higher cost and interrupts the system for a while. In order to prevent this problem, detection and diagnosis are aimed at the period from the beginning of the malfunction until it becomes evident. As a result, this thesis will work on an intelligent signal based monitoring application that can be used in an industrial system. The aim is to monitor the system and estimate the situation by combining and evaluating the data (data fusion) obtained from different sensors.

The purpose of the thesis is evaluating the different signals in the intelligent monitoring system and establishing a signal based state monitoring system by making a data fusion. Thus a faster and more precise tracking and detection system will be achieved. In the thesis, these fusion data will be analyzed with statistical and advanced signal processing methods. In this thesis electrical and mechanical data can be obtained using multiple sensors such as current, voltage, vibration, acoustic noise and etc. First, the sensors will be validated in order to understand if sensors are healthy or faulty. Then, obtained data can be manipulated using data fusion techniques for condition monitoring of the system. The scope of the thesis is determined by the systems that are frequently encountered in the industry such as EMs.

State monitoring and troubleshooting are frequently done in the literature by examining the information obtained from one or two simple signals. When it comes to state monitoring, using a single signal does not necessarily result in the best monitoring and failure analysis results. However, in this thesis, it is mentioned that two or more different signals are used together in a data fusion algorithm. In the scope of the study, innovative signal processing methods will be examined. Particularly, unique approaches to data fusion are targeted. Unique aspect of this thesis is to set out an intelligent algorithm that evaluates multiple monitoring methods together and predicts premature fault in order to prevent the fault damaging the system.

1.2 Literature Review

In general, data/information fusion approaches may help with any activity that requires any sort of parameter estimate from many sources. In certain circumstances, the phrase information fusion relates to data that has already been processed, while data fusion refers to unprocessed data (obtained directly from sensors). These concepts also, can be utilized interchangeably as well. In this respect, information fusion is more semantically advanced than data fusion. Decision fusion, data combination, data aggregation, multi-sensor data fusion, and sensor fusion are some of the other terminologies used in the literature to describe data fusion.

The Joint Directors of Laboratories (JDL) workshop [11], correlation, and combination of data and information from single and multiple sources to achieve refined positions, identify estimates, and complete and timely assessments of situations, threats, and their significance".

The following well-known definition of data fusion was provided by Hall and Llinas [12]: "data fusion techniques combine data from multiple sensors and related information from associated databases to achieve improved accuracy and more specific inferences than could be achieved by using a single sensor alone".

In an essence, data fusion is the combining of numerous sources to acquire better information. Improved information in this sense refers to information that is less expensive, of greater quality, or that is more relevant. Data fusion approaches have been widely used in multisensor contexts to fuse and integrate data from many sensors; however, similar techniques may also be used to other domains, such as text processing. By combining data from numerous distant sources, data fusion in multisensor contexts aims to reduce detection error probability and increase dependability [13].

Data fusion approaches are divided into three groups, according to [2, 14]. These are the following:

- Probabilistic methods (Bayesian analysis of sensor values, Evidence Theory, Robust Statistics, and Recursive Operators).
- Probabilistic approaches (Least square-based estimation methods such as Kalman Filtering, Optimal Theory, Regularization, and Uncertainty Ellipsoids and Bayesian approach with Bayesian network and state-space models, maximum likelihood methods, possibility theory, evidential reasoning and more specifically evidence theory).
- Artificial Intelligence (Intelligent aggregation methods such as Neural Networks, Genetics Algorithms, and Fuzzy Logic).

A data fusion system for mobile robot navigation is provided in article [15], which uses extended kalman filtering and an aduptive fuzzy logic system. Instead of examining the signals separately, this method uses two signals that are blended together to better estimate vehicle position. This approach may also be used to monitor any system and precisely predict the system's future state.

A new Multi-Sensor Data Fusion (MSDF) architecture is introduced in article [16]. Kalman filtering is applied in order to improve the system's performance. In this work, a new multisensor based activity detection technique based on fuzzy logic fusion sensors to understand human behavior is suggested. The key advantages of this technology are the reduced computational requirements resulting from the fuzzy logic system's properties. This approach is also useful when there are many sensors measuring the same parameter, each of which is polluted with a different type of noise. This system may also be utilized for system state monitoring and defect detection in mechanical and electrical systems, in addition to human behavior identification.

A failure detection approach for planetary gearboxes based on multi-sensor data fusion is described in paper [17]. Since planetary gearboxes are not the same as fixed-axis gearboxes, problem detection procedures that work for fixed-axis gearboxes are invalidated. Multiple sensors deployed at different locations offer complementing information on the health state of systems as complicated as planetary gearboxes. Two planetary gearbox characteristics are employed to define the gear health conditions in this technique, and an adaptive neuro-fuzzy inference system is used to fuse all features from different sensors. As a consequence, two characteristics retrieved from planetary gearbox vibration signals are fused together, and problems in the planetary gearboxes may be recognized based on the fusion findings. In compared to alternative methods that use individual sensors, the suggested technique is far superior in terms of defect detection accuracy.

Two vibration signals are acquired using accelerometers fitted on two different parts of an induction motor (bearings and motor housing) for data analysis and feature extraction in paper [18]. These signals were evaluated using data fusion and signal processing methods in order to determine bearing deterioration.

A new defect diagnostic approach based on the merging of output data from two classifiers is proposed in paper [19]. The fault-related features recovered from a vibration signal are used in one classifier, while the fault-related features derived from a generator current signal are used in the other. The majority of existing fault detection systems were developed using only one sort of signal, such as current or vibration signals. In truth, sensors and the data collecting systems that go with them are susceptible to damage. Sensor failures are said to account for more than 14 % of all wind turbine failures [20]. A sensor failure might result in a false alert or the inability to diagnose faults. This problem may be overcome by combining data from many types of sensors to reduce the erroneous rate of defect diagnosis when data from a single sensor or type of sensors is used.

A Bayesian network (causal network) for the identification of a failure in a group of sensors is used in paper [21] to describe an algorithm for intelligent sensor validation in real-time contexts. The Bayesian network depicts all of the sensor's dependencies and independencies. The detection is carried out by evaluating the sensor's value in relation to the most relevant factors. Validating a sensor with a faulty one, on the other hand, leads in the discovery of a sensor problem. Furthermore, the Bayesian network separates the problematic sensor from the rest of the defective sensors.

For vibration monitoring of gas turbines, paper [22] proposes a sensor validation and system health reasoning approach that incorporates sensor signals from the primary sensor and those from accessible "sibling" sensors (see Figure 1.2).

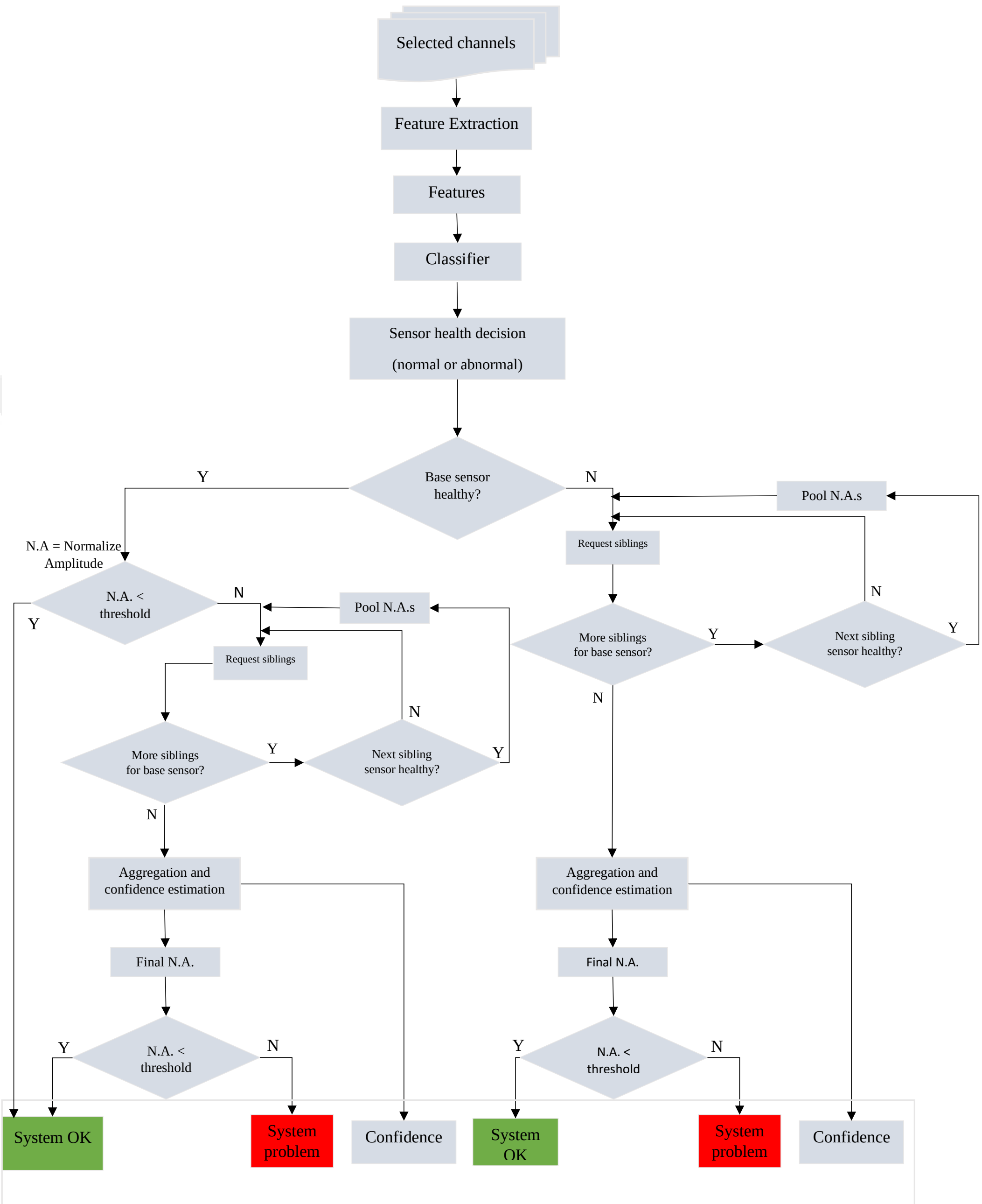


Figure 1.2 : Sensor validation and system health reasoning process map.

Because compressor blades and turbine buckets of gas turbines are prone to high cycle fatigue (HCF) failure, vibration monitoring is a significant concern during routine operation of gas turbine power systems, according to this article. As a result, it's critical to have trustworthy and precise vibration sensor data. In the suggested technique, certain sibling sensors are placed in a mechanically associated position to the location of primary sensors. When an abnormality in system health is suspected or the primary sensor is found to be faulty, information from accessible "sibling" sensors is dynamically combined.

Feature extraction is a critical component in detecting defective sensors. Feature extraction is the process of determining the properties of sensor data that may be used to differentiate between defective and healthy sensors. Due to data transmission size constraints, this work extracts only frequency features of the vibration signals. Sensor failure detection may be accomplished using a number of classifiers, ranging from statistics-based algorithms to those based on soft computing technologies. The rule-based decision tree was employed as the classifier since the specific challenge provided just a few samples and the requirement for a simple design with excellent readability.

1.3 Hypothesis

The study [23] describes optimum fusion kalman filtering weighted by matrices, diagonal matrices, and scalar. The authors demonstrate the great accuracy of the Covariance Intersection (CI) fusion kalman filter. Furthermore, this technique eliminates the need to calculate the cross-covariance matrix, lowering the computing cost [24]. This method's error covariance matrix P was compared to the other three approaches. Furthermore, a two-sensor linear system with delay may be transformed into a system without delay utilizing the measurement transformation technique.

The authors of article [24] have depicted a centralized optimum fusion estimator with the greatest accuracy in a linear minimal variance sense. The error cross-covariance matrix was produced in the same way as in study [25] in order to determine fusion weights. In addition, the CI fusion filtering approach was employed to reduce the calculation time. According to this study, centralized fusion filters are more accurate than distributed fusion filters, distributed fusion filters weighted by matrices are superior to CI fusion filters [23], and CI fusion filters are superior to local filters.

Multi sensor optimum information fusion technique weighted by matrix was also presented in article [26, 27]. The speed of calculations has been improved using two different methods: information fusion weighted by diagonal matrix (vector) and weighted by scalar. Finally, the optimal information fusion distributed kalman filters with two layers fusion structures have been given based on these methods for multi-sensor stochastic systems.

First, an optimum robust kalman type recursive filter was constructed in article [28]. The above-mentioned filter is then used to create a distributed weighted robust kalman filter fusion technique. The reason for this is because the best resilient kalman type recursive filter does not have a lot of calculations. For uncertain systems with several sensors, the distributed weighted robust kalman filter fusion technique was created. The sounds in this system are cross-correlated and auto-correlated over time. Two examples with simulation results have been shown at the conclusion.

The authors of article [25] created a distribution fusion filter that can be utilized in multi-sensor stochastic uncertain networked systems to handle transmission delay or data omission problems using an information fusion technique weighted by matrices. First, local optimum linear filters are produced using a novel suggested model with a reduced size state vector. The cross-covariance matrices of any two local filtering mistakes are then acquired in order to compute fusion matrices. The computational cost has been reduced in this research as a consequence of the strategy employed to create the local filters. Furthermore, the distributed fusion filter is more accurate [23, 25–29].

A review of distributed fusion estimated (DFE) techniques is presented in paper [29]. DFE algorithms were introduced in the first part. Section 4 also examines certain networked system phenomena (NSs). In comparison to centralized fusion, DFE algorithms exhibit poor accuracy, according to this article.

The study [30] proposes a unique multi-sensor ensemble kalman filter based on observation fuzzy support degree fusion (EnKF-FSDF). EnKF is a method for estimating powerful nonlinear systems that is also computationally efficient. When the estimated system has significant non-linear features or the noise characteristics are not Gaussian noise, the extended kalman filter (EKF) can diverge, whereas EnKF does not have this problem. EnKF, despite its advantages, has certain drawbacks. Depending on sensor accuracy, certain variations between the real observation noise and the observation modeling noise may occur due to unavoidable external disturbances in the practical engineering environment. The study proposes the unique EnKF-FSDF approach, which has the lowest error, to tackle this problem. In contrast to the methods provided in the study, the suggested technique has the lowest root mean square error (RMSE). Furthermore, the computations have been simplified.

In paper [31], a hybrid multisensor data fusion approach based on Rough Set (RS) and back propagation neural networks was developed (BPNN). The multisensor data fusion system's reliability and capabilities have been increased thanks to the RS-BPNN design. In this process, RS analyzes the input data and eliminates unnecessary or erroneous information from the database while keeping the relevant data. As a result, the crucial data is transmitted to NN, which has been trained using the back propagation process.

In paper [32], a defect detection approach for sensor fusion Kalman filtering is presented. A normalized innovation matrix has been developed in this technique, and the sensor information fusion kalman filter may be checked using the statistic of mathematical expectation of the spectral norm of the matrix to discover the defect in the kalman filter.

This research [33] provides a technique for unmanned aerial vehicle (UAV) attitude measurement during auto-landing. The fuzzy complementary kalman filter (FCKF) is used in this approach to combine data from IMU (Inertial Measurement Unit) and vision units. The state variables of the kalman filter are the mistakes in this approach, and a complementary filter is used to estimate the attitude. The complementary filter's gain has been increased using fuzzy logic in order to improve accuracy.

according to the literature review, it is clearly seen that there are lots of method for data fusion, however in this thesis it is decided to use Kalman filtering method, which is one of the famous methods, for data fusion. Hence Kalman filter is selected as the primary method for data fusion application in following sections of this work. To the best of the author's knowledge, there is no example in the literature of distinguishing the fault cause using a data fusion approach driven by Kalman filtering. in other words, FD and CM using data fusion through KF approach is a novelty used in this thesis.

First of all, two sensors which are measuring the same signal and are connected to an Induction Motor (IM) is assumed.

As the first case of study, the current signal is obtained from two distinct current sensors, which are disrupted by measurement and process disturbances. These signals are fused together to determine the impact and feasibility of disruptive noises. The source of the noise is determined, whether it is due to sensors or a process. In addition, the Kalman gain is monitored in order to investigate the process noise impact and obtain SV. As a consequence of its capacity to provide information about the error covariance matrix and the state vector, Kalman gain is recommended as a concise metric to identify changes in system behavior. moreover, KG eliminates the process problem and determines if the fault is caused by the system or the sensor. The SV program is then used to delete the malfunctioning sensor if the sensors are the cause of the error. Spectral analyses are used to detect the broken sensor in the SV application. To identify the malfunctioning sensor, the spectral features of the fused signal are compared to the real signal. Finally, the KG is recalled to determine which sensor is defective.

It is necessary to employ a signal with different characteristics such as vibration, in order to examine the performance of the suggested approach. Current signal has deterministic characteristics while the vibration signal has stochastic characteristics. Therefore, the second case study is vibration signal. Despite their extensive knowledge of FD and KF, the authors have yet to find data fusion via KF employing vibration signals in the literature.

In the next step, a data fusion technique driven by KF is suggested for the second case study. The case study is based on vibration signals collected on an IM for various aging conditions (seven conditions ranging from healthy to aged). Sensor Validation (SV), Fault Detection (FD), and Fault Source Identification (FSI) are all part of an Integrated Fault Evaluation (IFE) program. The FSI identifies if the failure is the result of a system, process, or sensors.

The suggested technique is divided into two steps; the first, examines the impact of measurement noise. Different noises reflect sensor information obtained from different sensors, and measurement data is replicated. As a consequence, applications for IFE and sensor validation (SV) are developed based on statistical and frequency domain features, with the goal of reducing the influence of measurement noise. Then, in the second step, process noise is thoroughly explored, which is a first in the literature. A health rating is proposed utilizing vibration signals in order to discriminate between process noise and system aging.

Please keep in mind that all of the current and vibration signals used in this thesis are real data.

2. MATHEMATICAL BACKGROUND

2.1 What Is Kalman Filter

The goal of filtering is to retrieve the necessary information from a signal while discarding everything else. A cost or loss function can be used to assess how effectively a filter fulfills this duty. Indeed, we may define the filter's purpose as the minimization of this loss function. The filter is built as a mean squared error minimizer, but an alternate derivation is also presented to explain how the filter connects to maximum likelihood statistics. Documenting this derivation gives the reader more information about the statistical structures within the filter [34].

2.2 Mean Square Error

The equation below is the main core of the most signals;

$$y_k = a_k . x_k + w_k \tag{2.1}$$

where y_k is the time-dependent observed signal, a_k is a gain term, x_k is the signal carring information, and w_k is noise. The ultimate goal is to calculate x_k. The error is defined as the difference between the estimate of $\hat{x_k}$ and x_k itself;

$$f(e_k) = f(x_k - \hat{x_k}) \tag{2.2}$$

The squared error function is an error function that has these features;

$$f(e_k) = (x_k - \hat{x_k})^2 \tag{2.3}$$

Finally the mean square error is:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(x_k - \hat{x_k})^2 \tag{2.4}$$

where n is the number of samples [34].

2.3 Maximum Likelihood

Utilizing maximum likelihood statistics, a more rigorous derivation may be built [34]. This is accomplished by redefining the filter's aim as identifying the $\hat{x}$ that maximizes the probability or likelihood of y.

$$Max[p(y|\hat{x})] \tag{2.5}$$

Considering the additional random noise is Gaussian with a standard deviation of σ_k, we get;

$$p(y_k|\hat{x_k}) = K_k exp(-\frac{(y_k - a_k\hat{x_k})^2}{2(\sigma_k)^2}) \tag{2.6}$$

where K_k is a normalisation constant. The maximum likelihood function of this is;

$$p(y_k|\hat{x_k}) = \prod_k K_k exp(-\frac{(y_k - a_k\hat{x_k})^2}{2(\sigma_k)^2}) \tag{2.7}$$

which leads to:

$$logp(y_k|\hat{x_k}) = -\frac{1}{2}\sum_k(\frac{(y_k - a_k\hat{x_k})^2}{2(\sigma_k)^2}) + constant \tag{2.8}$$

2.4 Kalman Filter Equations

Kalman defined his filter utilizing state space approaches, allows the filter to be employed as a smoother, filter or predictor. The capacity of the Kalman filter to estimate data, is proven to be a very valuable function. As a result, the Kalman filter is now used to solve a wide range of tracking and navigation issues. Another reason for its popularity is because defining the filter in terms of state space techniques simplifies the implementation of the filler in the discrete domain [34].

The Kalman filter (KF) model assumes that the state of a system at a time k evolved from the prior state at time $k-1$ according to the equation below. In other words, in the KF model, the pervious state of a system is used to calculate the next state by 2.9 [16, 23, 35]:

$$x_k = F.x_{k-1} + G.u_{k-1} + w_{k-1} \tag{2.9}$$

where x is the state vector, F is the state matrix, G is the input matrix, u is input vector and w is the process noise vector. The output vector also, can be obtained by the measurement and it can be expressed as a function of the state vector x as seen in Eq. 2.10;

$$y_k = H.x_k + v_k \tag{2.10}$$

where y is the output vector, H is the observation matrix and v is the measurement noise vector. Note that, w And v are normal distributed Gaussian noises with covariance matrix Q and R, respectively [16]. The variables in Eq. 2.9 and 2.10 are defined in the Table 2.1.

Table 2.1 : Dimentions and definitions of variables.

Variable	Description	Dimension
x	State vector	$n_x \times 1$
y	Output vector	$n_y \times 1$
u	Input vector	$n_u \times 1$
w	Process noise vector	$n_x \times 1$
v	Measurement noise vector	$n_y \times 1$
F	System matrix – state	$n_x \times n_x$
G	System matrix – input	$n_x \times n_u$
H	Observation matrix	$n_y \times n_x$

Note that in most of the applications the input matrix G and the observation matrix H, do not need to be square matrices. Output vector y can be obtained by measurement and it should be expressed as a function of the state vector x.

w_k contains the process noise terms for the state vector. The process noise is assumed to be a normal distribution Gaussian noise with covariance matrix Q [16].

v_k contains the measurement noise terms for each observation in the measurement vector. Like the process noise, the measurement noise is assumed to be zero mean Gaussian noise with covariance R [16].

The KF algorithm contains the prediction stage and the measurement updates. The equations of these stages are presented as below [16, 23, 35]:
Prediction stage:

$$\hat{x}_{k|k-1} = F\hat{x}_{k-1} + Gu_{k-1} \tag{2.11}$$

$$P_{k|k-1} = FP_{k-1}F^T + Q_t \tag{2.12}$$

Measurement update:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R_k)^{-1} \tag{2.13}$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(\hat{y}_k - H\hat{x}_{k|k-1}) \tag{2.14}$$

$$P_k = (I - K_kH)P_{k|k-1} \tag{2.15}$$

where $\hat{x}_k$ is predicted state vector, P_k is state error covariance matrix, K_k is Kalman gain matrix, $\hat{y}_k$ is measurement output and I is identity matrix. $\hat{x}_0$ and P_0 which are the initial state estimation matrix and the initial state error covariance matrix, respectively. First, the state vector $\hat{x}_k$ and the state error covariance matrix P_k are estimated in the prediction stage. Thereafter, the values of the Kalman Gain matrix K, predicted state vector and the state error covariance matrix are updated in measurement update stage.

2.5 Data Fusion Through Kalman Filtering

In fusion algorithm, assignment of the observation matrix H is very important. Observation matrix H maps the state vector into the output vector. Hence, in linear Kalman filter H matrix provides a linear transformation. H matrix indicates that which state variables are included and which are not. In addition, it illustrates dependence of the output vector to the state vector. For example, if the first and second states of a 3-dimensional state vector, are measured, H matrix should be selected as [35]:

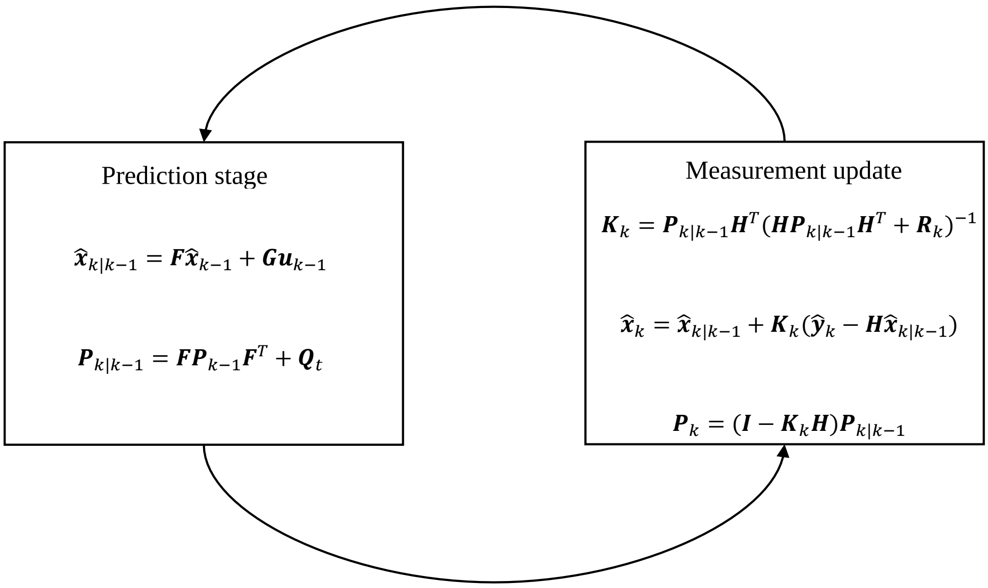
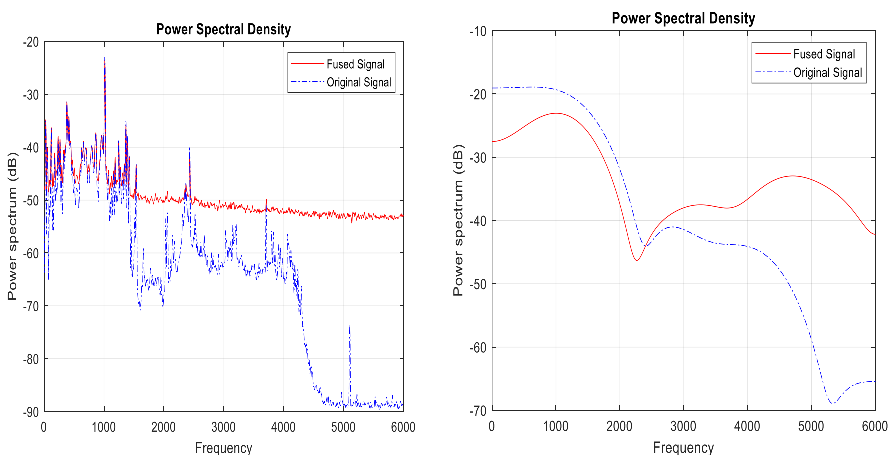


Figure 2.1 : Kalman filter prediction and measurement update stage.

$$H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{2.16}$$

$$y_k = Hx_k \Rightarrow y_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{2.17}$$



(a) (b)

Figure 2.2 : (a) Kalman algorithm with larg data (b) Kalman algorithm with small data points.

Furthermore, H matrix can be used for state combination which serves as a fusion tool. For example, in a system which the measured output depends on two states, the observation matrix is assigned as seen in Eq. 2.18, providing the linear combination of input states:

$$H = \begin{bmatrix} 1 & 1 \end{bmatrix} \tag{2.18}$$

$$y_k = Hx_k \Rightarrow y_k = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = x_1 + x_2 \tag{2.19}$$

Kalman algorithm satisfies small sample theory [36]. However, Kalman filter fusion algorithm may not work properly in small samples. Consequently, the fusion algorithm is run with different sized data. It is noticed that the algorithm does not succeed in small sized data. The outputs are given in the Figure 2.2 for a small sample (29 data points) and larger data.

3. THE FAULT ELIMINATION THROUGH KALMAN FILTER FUSION ALGORITHM USING CURRENT SIGNALS

In this chapter, fault elimination applications through Kalman Filter fusion algorithm is proposed. As a case study, an electrical motor (EM) data, with possible sensor and process faults, are employed. The proposed algorithm detects whether the sensor or the process is faulty. The current signals, obtained from two different sensors, are used. The sensors are assumed to be exposed to biases and noises having different characteristics. These deformed current signals are fused together through Kalman Filter algorithm and their convergence to the original signal is monitored. First, process fault is eliminated by Kalman Gain. Afterwards, the sensors faults are eliminated referencing spectral outputs such as power spectral densities and coherences. Lastly, the faulty sensor(s) is eliminated successfully.

3.1 Introduction

Kalman filter (KF) is a very popular recursive algorithm which is used in various applications. It basically approximates the future state of a process providing minimum error [37–39]. Also, KF is an attractive method for real time applications because of its optimality and simplicity [40]. It is usually employed for control applications as the state estimator [41] or for the sensorless control of electrical machines [42]. Reliability is another field that Kalman filtering is employed. In this context, it is used for fault detection (FD) purposes in complex systems. Since KF can deal easily with sensor or process disturbances, it is significantly efficient while the system is disrupted by random noises which is very common in FD [43, 44]. Sensor validation is also an application field by the nature of KF in terms of its ability of noise elimination.

In the literature, there are several studies on FD and SV of EMs supporting the case study introduced here. For example, in paper [43], the authors introduced a FD method based on KF for a linear dual motor system considering impact of sensor and system faults including random noises. Generally, a threshold is derived based on KF to determine the existence of fault. Similarly, in [44] a fine FD is accomplished for a DC motor through KF. The authors in paper [45] proposed an approach based on Extended Kalman Filter (EKF) to estimate the disturbance of the stator phase currents in an induction motor (IM). The extended model of the IM containing disturbances is employed in the study. Paper [46] represents a refined frequency domain based FD application for wind turbines employing KF as the frequency estimator. In paper [47] a model-based condition monitoring (CM) system supported by KF is proposed. It is designed as a real time monitoring estimating the rotor current, the harmonic content of the damper and field currents through EKF with a fault parameter defined by authors.

KF is also employed for data fusion purposes in applications like object tracking [48], navigation [49], diagnosis [50] and health estimation [51]. Various algorithms such as artificial neural network (ANN) [52,53], fuzzy logic [54] and support vector regression (SVR) [55] are used for sensor fusion applications. Comparatively, KF behaves more successfully in the presence of the noise [40]. Moreover, in reference [56] Kalman gain (KG) is used to demonstrate any alteration and degradation in the system. Hence, KG calculation can also be assumed as an effective measure for sensor validation (SV).

In a complex system including electrical, mechanical and digital components, it might be complicated to distinguish the origin of the fault. The fault might be caused by the sensor, by the process or by the system. In order to discriminate sensor faults, the SV ability of KF is benefited. Authors have not come across any study discriminating the source of fault either sensors or process via data fusion enhanced by KF in the literature. This paper presents a KF data fusion study discriminating the source of the faults. The advantages of the method which is utilized in this paper, is that data fusion through KF is much more reliable for SV, FD and discrimination the source of the faults. In reference [57], KF data fusion algorithm is applied on current signal, which has deterministic characteristic, for FD purpose. In reference [58], a new integrated fault evaluation (IFE) method using KF data fusion algorithm, is applied on vibration signals with different aging states. In paper [58], the vibration signal, which has stochastic characteristic, is employed to present the effectiveness of KF data fusion algorithm.

In this chapter, an electric motor condition monitoring application is introduced. Two current signals acquired form an induction motor are applied to fusion algorithm with various disturbing measurement and process noises. By the assessment of their burden under the impact of several noises, the origin of problem can be decided. First, the process fault is eliminated by KG and it is decided if the fault is originated by the system or the sensor. Then if the sensors cause the fault the SV application is executed to eliminate the faulty one. As the SV application, spectral analyses are employed to detect the damaged sensor. The spectral properties of the fused signal are compared with the actual signal to distinguish the faulty sensor. Lastly, the KG is recalled to decide the faulty sensor.

In Section 3.2 the experimental setup and data are shared. Section 3.3 introduces the strategy to follow researching the impacts of measurement and process noises. Finally, the paper is concluded at Section 3.4.

3.2 Installation of Fault Elimination and SV to The Experimental Setup

Identical current sensors are collected current signals from the supply line of a 5 HP induction motor which is loaded by a 3 kW, 1800 rpm dynamo-meter. The data is collected with NISCXI signal conditioning interface at the 12 kHz sampling frequency with 4 kHz cutoff frequency. The technical information about the test motor is mentioned in Table A.1 Appendix 1 [59].

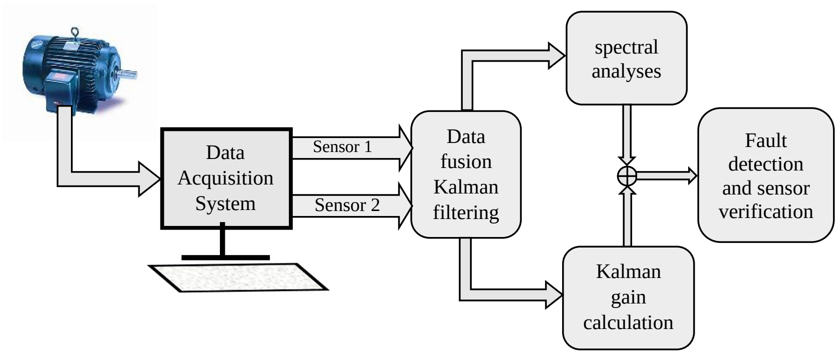


Figure 3.1 : Experimental setup and installation of fusion algorithm.

3.3 Sensor Fusion Application Through Kalman Filter for Fault Elimination

The fault elimination through KF Sensor Fusion method has two parts. The first one is the determination of process fault via KGs. Scenarios are created under the effect of variable process and measurement noises. By the calculation of KG for each scenario the process fault can be eliminated.

If the process is healthy, then measurement fault is focused. By the spectral analysis, the sensor faults can be detected easily. Thus the faulty sensor can be eliminated properly. In other word, sensor fault elimination is capable of distinguish the faulty sensor. By this point of view, it serves as a Sensor Validation application. The algorithm for the elimination process and SV is illustrated step by step through flowchart in Figure 3.2. The authors assume that there are two sensors with duplicated

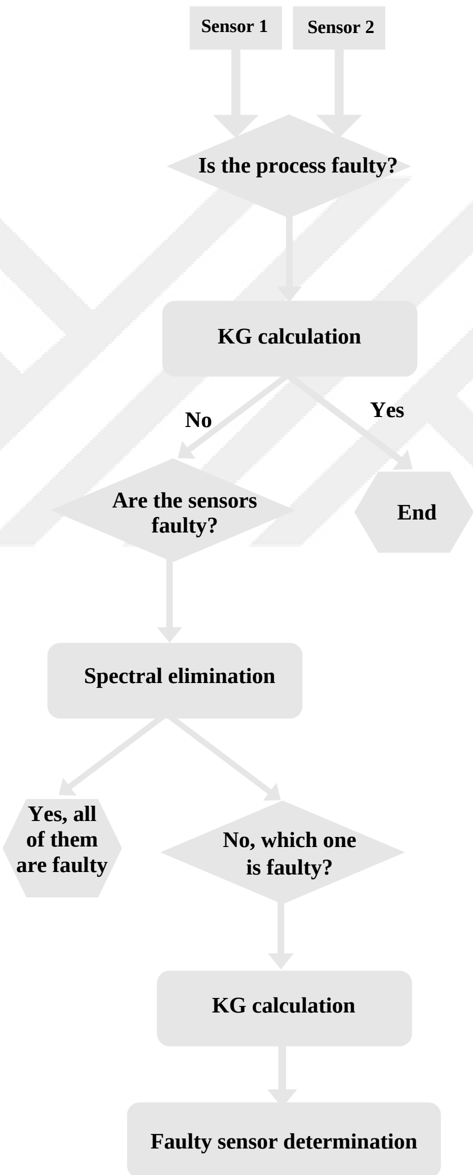


Figure 3.2 : Flow for Process fault elimination and sensor validation.

information including deformations such as process and measurement noises, offsets or unexpected phase difference and biases. By applying fusion algorithm on these current signals, KG is obtained. In order to eliminate the process faults, a decision strategy is adopted through the statistical results. If the process is faulty, it can be easily detected at this step.

The algorithm fuses the information of two sensors (x_1 and x_2) together via KF. Thereupon fused signal x_f and the sensor outputs (x_1 and x_2) are compared considering statistical and spectral properties and KGs. Discussing the impact of the process and measurement noises on x_f fault elimination and SV are achieved.

3.3.1 Elimination of process faults

KG monitoring is one of the best strategies to explore the estimation process and measurement noise impacts, which is new for the literature. In other words, KG is an important tool for detection of any alteration in the system. The following figures present the KGs under different process noises (Q) and measurement noises (R_1 and $R2$). R_1 and R_2 are the measurement noises corresponding defects on Sensor 1 and Sensor 2, respectively.

Figure 3.3 and 3.4 show the behavior of KG during the presence of the process and the measurement noises. These gains are calculated as a result of the KF sensor fusion algorithm. Figure 3.3 obviously shows that the KG tend to saturate when the process is noisy and the Sensor 1 and Sensor 2 are healthy.

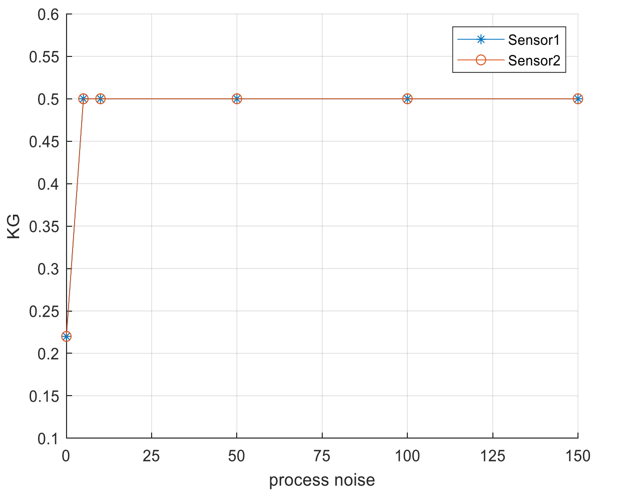


Figure 3.3 : Effect of the process noise variation on the KG of the sensors.

The process noise has same effects on both sensors. Consequently, Sensor 1 and Sensor 2 have similar behavior for the increasing process noise. On the other hand, Figure 3.4 presents the decay of KG with increasing measurement noise. According to Figure 3.4

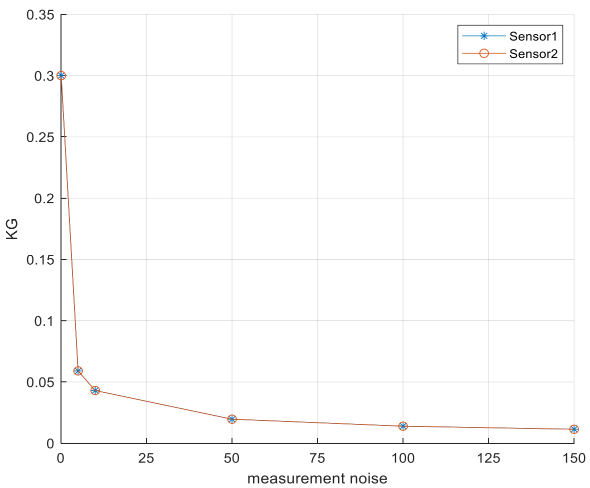


Figure 3.4 : Effect of the measurement noise variation on the KG of the sensors.

the measurement noise of the both sensors increase at the same time and KG's of the sensors decrease similar to each other. As a result, KG sorts out the existence of noisy sensor with its decreasing characteristics.

3.3.2 Elimination of faulted sensors

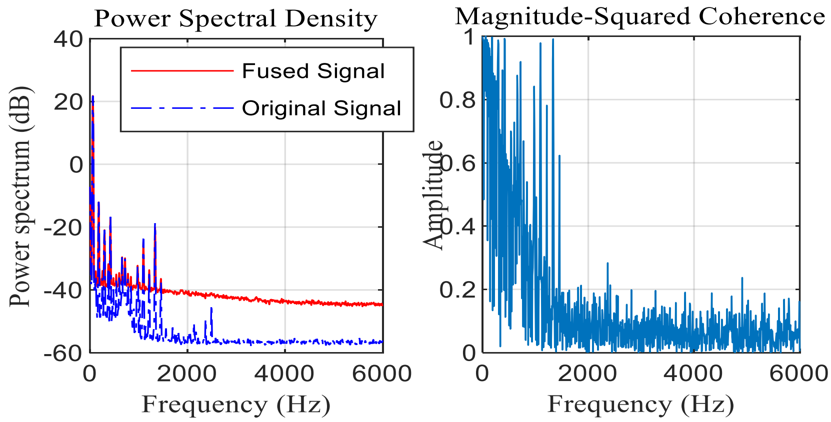
In order to eliminate the faulty sensor, spectral observations are executed. Sensor fault elimination application through KF fusion algorithm is significantly successful since it can decide if both of the sensors are faulty or not. Consequently, in case of the degradation of one sensor, it can detect the faulty one correctly.

Some cases are created to understand the success of KF fusion algorithm. These cases are listed at Table 3.1.

Table 3.1 : Possible cases for process and measurement noises.

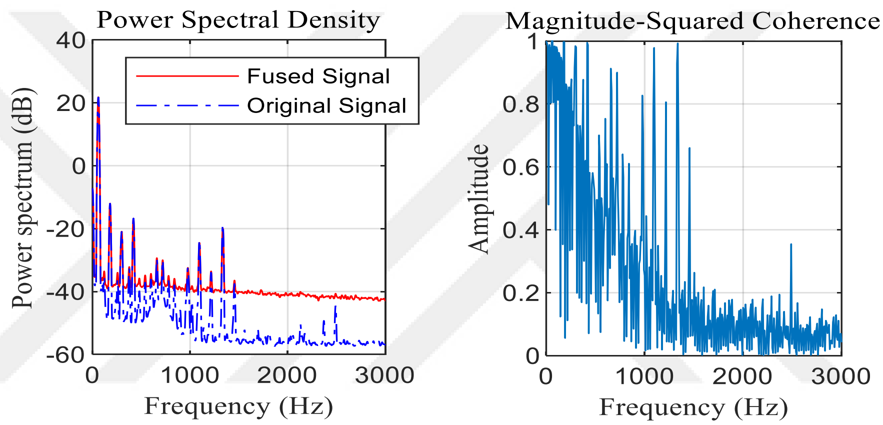
	Measurement noise	
	R1	R2
Case I	Fine	Fine
Case II	Noisy	Fine
Case III	Noisy	Noisy

Logarithmic Power Spectral Densities (PSD) and coherences of the fused and original signals for these cases are given in Figure 3.5 - 3.7.



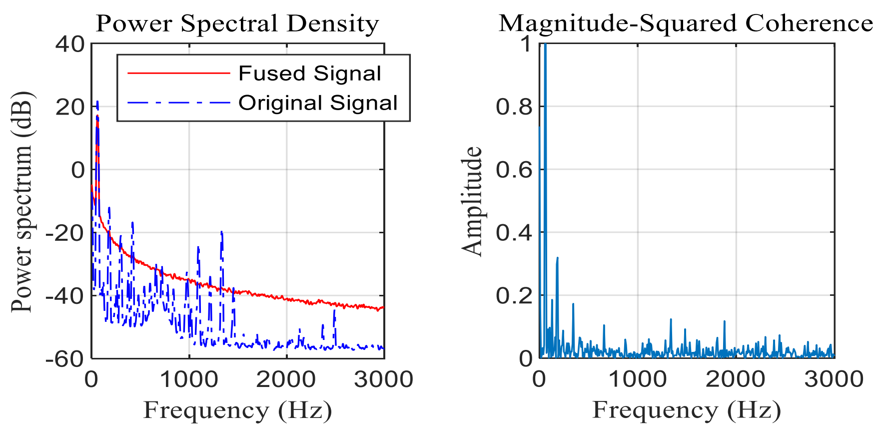
(a) (b)

Figure 3.5 : Spectral results for Case I (a) logPSD, (b) coherence.



(a) (b)

Figure 3.6 : Spectral results for Case II (a) logPSD, (b) coherence.



(a) (b)

Figure 3.7 : Spectral results for Case III (a) logPSD, (b) coherence.

Note that Case I is the reference test, where all sensors and the process are assumed in a healthy condition. The other cases are compared with the reference test. The

logarithmic PSD shows that components below 1.5kHz have significant amplitudes associated with the system characteristics. The remaining frequency components are filtered due to the nature of KF. The fusion algorithm have successfully estimated fundamental frequency and its harmonics. Supporting, the coherence of the fused and original signal outputs almost unity for the characteristic frequency region [0-1.5 kHz]. Another important finding is that the faulty sensor's measurement can be eliminated through KF fusion algorithm. In Case II only one sensor is faulty. Even if one of the sensors doesn't work properly, the fusion algorithm is able to omit it and estimate the actual signal with high resolution.
Case III is considered having both sensors faulty. When two sensors are damaged at the same time, the KF fusion algorithm is not able to estimate some spectral properties such as harmonics. The only dominant frequency is the fundamental one while coherence output supports this finding. In other words, if the fusion algorithm filters the harmonics then it can be concluded that both of the sensors are faulty. And also the coherence settles to zero. However, the coherence in fundamental frequency is at the maximum level. This indicates the success to determine the fundamental frequency but also the weakness on estimating the rest of the spectral features.

3.3.3 Determination of faulty sensor

The fault of all sensors can be detected through spectral methods. However, if only one sensor is damaged, then KG can be referable. The KG for each case is presented in Table 3.2 .

The table shows that the damage of a sensor can be named by the KG converging to zero. In other words, if the measurement noise of a sensor increases, KG of the sensor decreases impressively. Moreover, Figure 3.8 which is the graphical illustration of Table 3.2, presents variations of the KG's, when the measurement noises for sensors are different.

Table 3.2 : KG for all Cases.

	KG1	KG2
Case I	0.22	0.22
Case II	0.0004	0.83
Case III	0.0114	0.0114

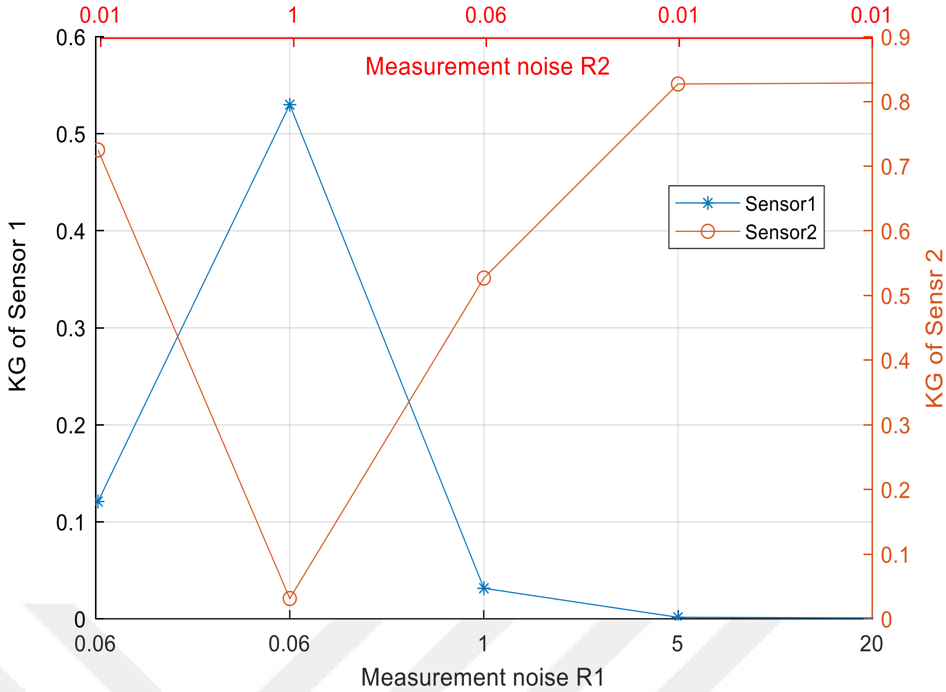


Figure 3.8 : KG variations during different measurement noises.

3.4 Conclusion

The sensor fusion through Kalman Filter method is presented here for fault elimination purposes. The method has two parts; the process fault can be detected by KG calculation. After the verification of process, measurement faults are focused. Cases are designed to evaluate the sensor fault variations. The spectral representations are used to evaluate the sensors for represented cases. It is shown that the KF Fusion algorithm responds very unique when both sensors are faulty. If only one sensor is faulty, then the KG is consulted again to execute a proper SV application and eliminates the faulty one. The important findings of the study are presented below:

• Process noise can be precisely eliminated by the KG monitoring.

• Kalman fusion algorithm behaves as a filter regarding its nature considering reference test.

• The prominent harmonics of the actual signal are accurately illustrated by the fusion algorithm.

• The fused signal converges to the reference (healthy) case, when only one of the sensors is faulty.

• Regarding spectral properties, the data fusion through KF algorithm distinguishes the faulty sensor or sensors. Furthermore, the algorithm eliminates the defective information received from the damaged sensors in spectra.

• According to the PSD analyses; although the fusion algorithm is not able to estimate spectral properties properly when the process is damaged, the fundamental frequency (60 Hz) is estimated accurately.

• By KG monitoring, the determination of faulty sensor is possible even if either one of the sensors is faulty.

• KG responds well to track the fault even if all the measured signals are faulty.

4. INTEGRATED FAULT EVALUATION USING VIBRATION SIGNALS

An Integrated Fault Evaluation (IFE) process is proposed in this chapter. It includes Sensor Validation (SV), Fault Detection (FD) and Fault Source Identification (FSI). The proposed algorithm employs data fusion algorithm enhanced by Kalman filter (KF). As the case study, vibration signals representing different aging states of an induction motor are used. The vibration data collected from two identical sensors with different measurement and process noises are achieved. Through the statistical and frequency domain characteristics, IFE is realized. The most prominent contribution of the study is the capability of distinction between the aging of the system and the process problems. For this aim, a rate representing the healthiness, which can discern the impact of the process noise and system aging, is calculated.

4.1 Introduction

Kalman filter (KF) which is initially proposed in 60's, first employed as state estimator thanks to its iterative nature [3, 60]. Then the algorithm is adapted to different applications such as target motion analysis [61], real-time thermal monitoring of an induction machine [62], etc. In the recent years KF raises its popularity as a fusion algorithm in many practical applications such as, remote sensing, object tracing, battle-field surveillance [63], etc. The major advantage of KF is the outstanding operation capability in real time applications through its robustness to high signal to noise ratios (SNR). Hence, this method is preferred widely as a fusion algorithm to be employed by multiple sensor information [40]. Moreover, as a result of filtering property of KF, fusion algorithms become very powerful for fault detection (FD) applications [44, 64, 65]. For example, in the reference [44], a KF-based FD technique is proposed for DC motors using residuals. In this paper, current and speed signals are assumed as state vectors. Variation between the real and the estimated states is indicated as residuals. The study also detects overload fault in presence of several uncertainties which are isolated successfully using KF. However, in reference [43], FD is achieved through residuals in linear dual motor system, despite the existence of noise. The residual signal is generated based on KF, then a threshold is determined to detect the sensor fault and actuator fault. Kalman filter is widely used in controller applications for electric machinery. It is usually employed as the observer algorithm. For example, in literature [66] a predictive direct torque controller is enhanced by KF which is used to estimate flux. KF is used as an estimator for secondary current and induced flux linkages of a linear IM [67]. By the estimation of KF a total least square EXIN neuron is trained as the observer. KF is also used for sensorless vector control for IMs. According to Boukhnifer et al. [68], a KF based fault tolerant control algorithm is proposed for an IM to eliminate the speed sensor failure. It is well-known that FD techniques can be applied using various types of signals for electric machinery. For example, in papers [69–72], phase current [73], angular velocity or temperature [74]. Vibration signal is widely used for FD applications in electrical machinery. Because of its stochastic nature, it is very favorable for both the statistical and spectral investigations [75–78]. Various types of failures such as bearing fault, rotor related faults and winding faults are mentioned in surveys to be detected through vibration signal [59]. Bearing faults is the most common fault in EMs, which can be detected easily either by the electrical or vibration signals [79–81]. Further, vibration signals carry lots of information on the bearing health of the EM that is why it is preferred for such mechanical faults [82]. Bearing FD using vibration signal is studied in the literature widely through various methods and algorithms [83–86]. For instance, Reference [87] uses vibration signals to diagnose bearing fault through an intelligent filter (adaptive linear neuron) by extracting features and running classification algorithms. Since the bearing fault arises between 2-4 kHz, in Reference [52], it is detected through a neural network which is trained by the coherence of vibration and stator current signals. On the other hand, FD through KF using vibration signal is very limited in the literature. For example, in Reference [88], first, the model of flux switching permanent magnet motor using electrical and mechanical equations is presented and then an observer system empowered by KF is designed to generate the residual function from predicted and measured vibration for FD and localization purposes. In spite of that much knowledge and application of FD and KF, data fusion through KF using vibration signals has not met by the authors in the literature. In this chapter, an application employing data fusion algorithm empowered by KF is proposed. Vibration signals acquired for different aging states on an induction motor (seven cases from healthy to aged) are employed as the case study. An Integrated Fault Evaluation (IFE) application is realized including Sensor Validation (SV), Fault Detection (FD) and Fault Source Identification (FSI). FSI determines whether the fault is originated by the system, process, or sensors. The proposed method has two major parts; the first part observes the effect of measurement noise. Measurement data is duplicated with different noises representing sensor information acquired from different sensors. As a result, IFE and sensor validation (SV) applications are proposed by observing the statistical and frequency domain characteristics aiming a contribution on impact of measurement noise. Then, in the second part, process noise is investigated deeply which is totally new for the literature. In order to distinguish the process noise and the aging of the system, a health rate is proposed through vibration signals. Section 4.2, accounts for the experiment with its outputs and data acquisition system. Section 4.3, presents a FD application utilizing data fusion through KF under different measurement noises. In section 4.4, a health rate is proposed to distinguish between the process noise and the aging in the system.

4.2 Experimental Setup And Data Acquisition System

The vibration data, is collected from an accelerated aging experiment having 7 cycles. At the end of the seventh cycle, the motor is completely defective. In this process, two methods are applied to achieve aging on the system. These are thermal-chemical aging (chemical) and electrical discharge machine (mechanical). In the chemical method the induction motor (IM) is exposed to severe thermal conditions. In the mechanical method, 30 V is applied to the shaft of the motor, to create a bearing fault. The experiment is verified on three identical 5 HP squirrel cage induction motors to validate the process. The test motors are loaded by a 3 kW, 1,800 rpm dynamo-meter, excited by 0-2 A, 0-200 V dc and loaded with 21.63 Ω resistance. The technical information about the test motors is mentioned in Table A.1 which exists in Appendix 1 [59]. The vibration data are acquired through NISCXI signal conditioning interface. They are also, sampled with 12 kHz sampling rate. The antialiasing filter which is utilized in the DAQ system is NISCXI-1142 eight-order elliptic low pass filter with 4 kHz cutoff frequency, -80 dB stop band and 135 dB/octave roll-off [59, 89].

Table 4.1 : Basic statistical properties of aging cycles.

Aging cycles	I. Means	II. Std Dev	Variances
Initial	0.0016	0.1135	0.0129
Cycle 1	0.0014	0.1553	0.0241
Cycle 2	0.0012	0.2082	0.0433
Cycle 3	0.0013	0.2894	0.0837
Cycle 4	0.0009	0.3275	0.1073
Cycle 5	0.001	0.3548	0.1259
Cycle 6	0.0005	0.4147	0.172
Cycle 7	0.003	0.604	0.3648

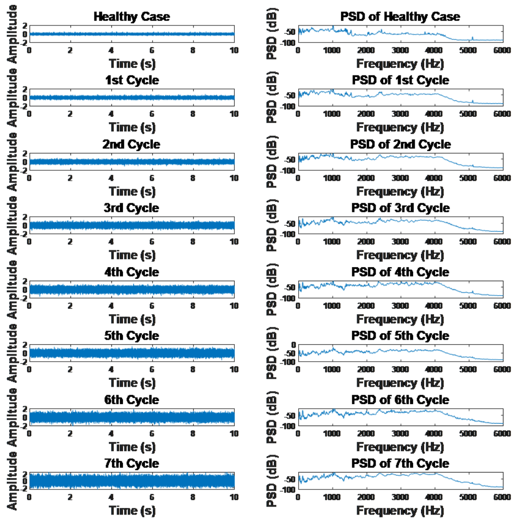


Figure 4.1 : Time and frequency domain representations of the vibration signals.

Statistical properties for each aging cycle are presented in Table 4.1. Moreover, time domain and spectral representations of the all signals are demonstrated in Figure 4.1. During the aging process, mean values do not vary, however, enormous changes are observed in standard deviations (Std Dev) and variances (Table 4.1). Consequently, the amplitude of the vibration signals in time domain increases in each cycle. Furthermore, the amplitudes of the frequency components between 2-4 Hz increase which indicates the bearing fault (Figure 4.1).

4.3 Integrated Fault Evaluation

Integrated Fault Evaluation (IFE) process can be presented in two section. The first one is SV and FD. Distinguishing the fault which is originated whether from the sensors or the system is an original contribution. It requires to observe both statistical - spectral

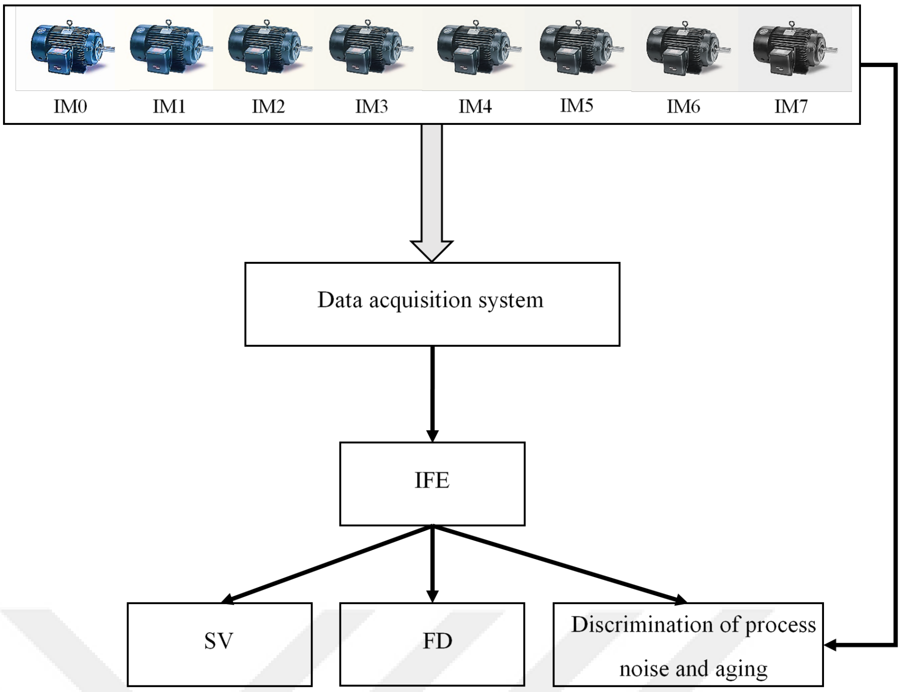


Figure 4.2 : The flowchart of the study.

properties of the sensor outputs. For this reason, the proposed algorithm cannot be mention as a simple FD operation which relies on a signal only. For a system with two different sensor information, fusion algorithm supported by KF is used to eliminate the faulty sensor. By this way, the possibility of fault for the sensors is deducted.

The second part is focused on the distinction of process fault and system fault. Since the process fault also increases the variance and standard deviation, so it can easily be confused with aging dynamics. This kind of discrimination study is very original and unique for the literature. The schematic seen in Figure 4.2 summarizes the flow of the study and in Figure 4.3 the pseudo code is presented. Authors have presented a KF fusion study with current signals [57]. The SV is executed using statistical analysis while FD is done through the spectral analysis. The current signal's deterministic nature does not permit any further interpretation like aging or the determination of health status for the system. However, in this thesis, through the stochastic nature of vibration signals, Kalman algorithm provides more information to use different tools. Statistical, spectral investigations are supported with coherences to succeed SV and FD. Additionally, discrimination of process problems and aging becomes possible by the defining a rate representing healthiness.

1.	Begin
2.	Get the vibration signal
3.	Making the process noise vector
4.	Making the measurement vectors
5.	Obtain the output of the sensor 1 including the measurement noise and bias
6.	Obtain the output of the sensor 2 including the measurement noise and bias
7.	Add the process noise
8.	Begin Kalman filter loop • Initialize the state vector • Estimated state vector • Guess for initial state • Initialize state error covariance matrix • Start calculation loop: • Predict the state vector • Predict the state error covariance matrix • Measurement update stage: • Calculate the Kalman gain matrix • Update the state vector • Update the state error covariance matrix
9.	End the loop and go to step 8
10.	Calculation of statistical values • Calculate mean square error • Calculate root mean square error • Calculate Mean value • Calculate standard deviation • Calculate kurtosis
11.	Obtain power spectral density • Plot spectral of original signal • Hold on • Plot spectral of the fused signal
12.	Plot Coherence between fused signal and original signal
13.	SV and FD using step 10 to 12
14.	End

Figure 4.3 : The pseudo code for the algorithm.

4.3.1 Sensor validation and fault detection through data fusion supported by Kalman filter

The purpose of this section, revealing the sensor performance and to detect the aging while one or all sensors are damaged. In other words, SV and FD are achieved together. For this aim, various measurement noises are applied to sensors for different aging cycles. In addition, FD is supported by the sensor fusion algorithm which is empowered by KF. The flow for the method is illustrated step by step in Figure 4.4.

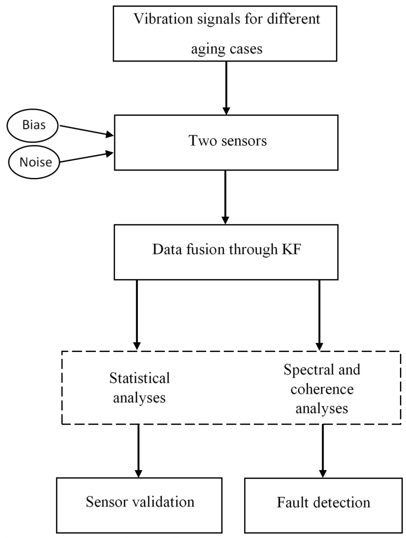


Figure 4.4 : DF through KF algorithm for FD and SV applications.

Table 4.2 : Detailed information on the scenarios.

Scenarios	Simulation Aim	Definition	Action
1st	Measurement problems	Faulty (noisy) sensor outputs are dealt.	The measurement noise of all sensors is increased equally.
2nd	Sensor problems	Only one of the sensors is assumed to be faulty	The measurement noise of one sensor is increased only.
3rd	Faulty process (Aging)	The noise is originated from the process (either electrical or mechanical	The measurement noise is kept minimum while the process noise is increased.

In fusion algorithm, the original signal (x) can be obtained from sensors with or without noise. Regarding Eq. 2.19, the fused signal is x_f while the first and second sensor information are x_1 and x_2 . In order to create the process and measurement noises, authors assume that there are two sensors with duplicated information including deformations such as offsets or unexpected phase differences and biases. According to the proposed method, the outputs of the sensors; x_1, x_2 are fused together by KF supported FD algorithm. Thereupon, FD is actualized by evaluating the statistical and spectral properties of the fused signal x_f and the sensor outputs.

For fusion algorithm, two vibration sensors with measurement noises (as biases +b and –b) are considered. Then, the fused signal x_f, which is assumed to estimate the original signal, is obtained through fusion algorithm. Three different scenarios are planned to be applied on vibration signals for each cycle. Scenarios and their aims are given in Table 4.2.

Each scenario is executed for the first (healthy case), third and seventh aging cycles (aged case). Statistical and spectral results of them are investigated. Tables 4.3, 4.4 and 4.5 present the statistical analysis of the collected and the fused signals for three different aging cycles respectively. In these tables, Q represents the process noise, while R_1 and R_2 represent the measurement noises which associate Sensor 1 and Sensor 2, respectively. Furthermore, MSE_1 and MSE_2 are mean square errors, RMS_1 and RMS_2 are root mean square error between fused signal and the output of the sensor 1 and 2, respectively. In the tables below, std_{x_1}, std_{x_2}, std_{x_f} are standard deviations; Mx_1, Mx_2, Mx_f are mean values; $Kurt_{x_1}$, $Kurt_{x_2}$,$Kurt_{x_f}$ are kurtoses of x_1, x_2 and x_f, respectively. $K_{x_1}$and K_{x_2} are Kalman gain of the first and the second sensor, respectively. In these tables Test #0 is supposed as the reference test associated with a system with minimum measurement and process noises.

First and second scenarios are applied to the data and given in Tables 4.3, 4.4 and 4.5 . When the measurement noises of two sensors are increased equally, the error values remain constant even in third and seventh aging cycles. Moreover, the Kalman gains (KG) for the sensors decrease with higher measurement noises. In the second part of the tables, which present the results of the second scenario, it is assumed that only one of the sensors is faulty. The mean values of the fused signal converge to the signal which is obtained from the healthy sensor. Furthermore, the standard deviation of the fused signal remains constant because the algorithm eliminates the faulty sensor. However, the kurtosis scales up, while, the difference between the noises of the sensors increment. In addition, the KG of the faulty sensor decreases distinctly. According to the tables, monitoring KG is very useful for detecting measurement noises. However, by the aging of the system KG does not alter, hence, it is not suitable for neither aging detection nor FD.

Table 4.3 : Statistical properties of the first aging cycle (healthy case) vibration signal under measurement noises.

Test	R_1	R_2	Q	Kx_1	Kx_2	MSE_1	MSE_2	RMS_1	RMS_2	$Stdx_1$	$Stdx_2$	$Stdx_f$	Mx_1	Mx_2	Mx_f	$Kurtx_1$	$Kurtx_2$	$Kurtx_f$
1st Scenario																		
#0	0.01	0.01	0.005	0.31	0.31	25	25	5	5	0.17	0.17	0.12	5	-5	0	3	3	3
#1	0.02	0.02	0.005	0.25	0.25	25	25	5	5	0.19	0.19	0.12	5	-5	0	3	3	3
#2	0.04	0.04	0.005	0.19	0.19	25	25	5	5	0.24	0.24	0.12	5	-5	0	3	3	3
#3	0.08	0.08	0.005	0.15	0.15	25	25	5	5	0.31	0.31	0.12	5	-5	0	3	3	3
#4	0.16	0.16	0.005	0.11	0.11	25.14	25.14	5	5	0.42	0.42	0.12	5	-5	0	3	3	3
#5	0.32	0.32	0.005	0.081	0.081	25.3	25.3	5	5	0.58	0.58	0.13	5	-5	0	3	3	3
#6	0.64	0.64	0.005	0.058	0.058	25.6	25.6	5	5	0.81	0.81	0.15	5	-5	0	3	3	3
#7	1	1	0.005	0.048	0.048	25.9	25.9	5.1	5.1	1	1	0.16	5	-5	0	3	3	3
2nd Scenario																		
#8	0.1	0.005	0.001	0.017	0.35	90.7	0.23	9.5	0.5	0.34	0.14	0.093	5	-5	-4.5	3	3	107
#9	0.5	0.005	0.001	0.004	0.356	98.5	0.017	9.93	0.13	0.72	0.14	0.093	5	-5	-5	3	3	139
#10	1	0.005	0.001	0.002	0.357	100	0.01	10	0.1	1	0.14	0.093	5	-5	-5	3	3	143
#11	0.005	0.1	0.001	0.347	0.017	0.23	90.8	0.5	9.5	0.14	0.34	0.093	5	-5	4.5	3	3	20
#12	0.01	0.2	0.001	0.263	0.013	0.24	90.85	0.5	9.5	0.15	0.46	0.084	5	-5	4.5	3	3	28
#13	0.01	0.4	0.001	0.266	0.007	0.072	95.5	0.27	0.97	0.15	0.64	0.084	5	-5	4.7	3	3	35.8

Table 4.4 : Statistical properties of the third aging cycle vibration signal under measurement noises.

Test	R_1	R_2	Q	Kx_1	Kx_2	MSE_1	MSE_2	RMS_1	RMS_2	$Stdx_1$	$Stdx_2$	$Stdx_f$	Mx_1	Mx_2	Mx_f	$Kurtx_1$	$Kurtx_2$	$Kurtx_f$
1st Scenario																		
#0	0.01	0.01	0.005	0.31	0.31	25	25	5	5	0.31	0.31	0.23	5	-5	0	3	3	3
#1	0.02	0.02	0.005	0.25	0.25	25	25	5	5	0.33	0.33	0.2	5	-5	0	3	3	3
#2	0.04	0.04	0.005	0.19	0.19	25	25	5	5	0.36	0.36	0.18	5	-5	0	3	3	3
#3	0.08	0.08	0.005	0.15	0.15	25	25	5	5	0.41	0.41	0.16	5	-5	0	3	3	3
#4	0.16	0.16	0.005	0.11	0.11	25.2	25.2	5	5	0.5	0.5	0.15	5	-5	0	3	3	3
#5	0.32	0.32	0.005	0.081	0.081	25.35	25.35	5	5	0.64	0.64	0.15	5	-5	0	3	3	3
#6	0.64	0.64	0.005	0.058	0.058	25.7	25.7	5	5	0.85	0.85	0.16	5	-5	0	3	3	3
#7	1	1	0.005	0.048	0.048	25.9	25.9	5.1	5.1	1	1	0.17	5	-5	0	3	3	3
2nd Scenario																		
#8	0.1	0.005	0.001	0.017	0.35	90.84	0.27	9.5	0.5	0.43	0.3	0.16	5	-5	-4.5	3	3	14.6
#9	0.5	0.005	0.001	0.004	0.356	98.5	0.052	9.9	0.23	0.76	0.3	0.16	5	-5	-4.9	3	3	18.8
#10	1	0.005	0.001	0.002	0.357	100	0.044	10	0.2	1	0.3	0.16	5	-5	-5	3	3	19.4
#11	0.005	0.1	0.001	0.347	0.017	0.27	90.84	0.5	9.5	0.3	0.43	0.16	5	-5	4.5	3	3	4.8
#12	0.01	0.2	0.001	0.263	0.013	0.28	90.9	0.5	9.5	0.31	0.53	0.13	5	-5	4.5	3	3	7
#13	0.01	0.4	0.001	0.266	0.007	0.12	95.66	0.34	9.8	0.31	0.7	0.13	5	-5	4.7	3	3	8

Table 4.5 : Statistical properties of the seventh aging cycle (aged case) vibration signal under measurement noises.

Test	R_1	R_2	Q	Kx_1	Kx_2	MSE_1	MSE_2	RMS_1	RMS_2	$Stdx_1$	$Stdx_2$	$Stdx_f$	Mx_1	Mx_2	Mx_f	$Kurtx_1$	$Kurtx_2$	$Kurtx_f$
1st Scenario																		
#0	0.01	0.01	0.005	0.31	0.31	25	25	5	5	0.62	0.62	0.38	5	-5	0	3	3	3
#1	0.02	0.02	0.005	0.25	0.25	25.15	25.15	5	5	0.62	0.62	0.32	5	-5	0	3	3	3
#2	0.04	0.04	0.005	0.19	0.19	25.22	25.22	5	5	0.64	0.64	0.26	5	-5	0	3	3	3
#3	0.08	0.08	0.005	0.15	0.15	25.3	25.3	5	5	0.67	0.67	0.21	5	-5	0	3	3	3
#4	0.16	0.16	0.005	0.11	0.11	25.4	25.4	5	5	0.73	0.73	0.18	5	-5	0	3	3	3
#5	0.32	0.32	0.005	0.081	0.081	25.6	25.6	5	5	0.83	0.83	0.16	5	-5	0	3	3	3
#6	0.64	0.64	0.005	0.058	0.058	25.8	25.8	5	5	1	1	0.16	5	-5	0	3	3	3
#7	1	1	0.005	0.048	0.048	26.25	26.25	5.12	5.12	1.17	1.17	0.17	5	-5	0	3	3	3
2nd Scenario																		
#8	0.1	0.005	0.001	0.017	0.35	90.99	0.43	9.5	0.65	0.68	0.61	0.23	5	-5	-4.5	3	3	5.47
#9	0.5	0.005	0.001	0.004	0.356	98.74	0.2	9.94	0.46	0.93	0.61	0.23	5	-5	-4.9	3	3	6.4
#10	1	0.005	0.001	0.002	0.357	100.13	0.2045	10	0.45	1.17	0.61	0.23	5	-5	-4.9	3	3	6.7
#11	0.005	0.1	0.001	0.347	0.017	0.43	91	0.65	9.5	0.61	0.68	0.24	5	-5	4.5	3	3	3.4
#12	0.01	0.2	0.001	0.263	0.013	0.47	91.1	0.7	9.5	0.61	0.75	0.18	5	-5	4.5	3	3	4
#13	0.01	0.4	0.001	0.266	0.007	0.31	95.84	0.56	9.8	0.6	0.87	0.18	5	-5	4.76	3	3	4.46

The spectral density results and coherences (Figures 4.5 - 4.10) illustrates more supporting features. Note that, Test #0 in Table 4.3 is the reference test for healthy system (1st cycle). It does not contain significant amount of measurement and process noises. Figures 4.5 and 4.6 are the reference figures for spectral representation of each aging cycle. They demonstrate the ability on estimating dominant frequencies of the proposed sensor fusion application.

Figure 4.7(c) and Figures 4.9(b-c) clearly demonstrate that, in spite of the defected sensors, the fused signal is able to detect the aging indications which are noticeable between 2-4 kHz. Moreover, as a result of Kalman algorithm filtering characteristics, the data fusion supported by KF can eliminate the faulty sensor. Thus, the faulty sensor becomes distinguishable. As regards, when only one of the sensors is damaged or faulty (Figure 4.9), the fused signal converges to the original signal and calculating an accurate estimation.

In order to support spectral findings, coherences between the fused signal and the original signals are also shared in Figures 4.6 , 4.8 and 4.10 for different tests. According to the figures, when the system is aged, the coherence of the fused signal with the original one grows in the 2-4 kHz frequency range. In addition, when all of the sensors are damaged (Figure 4.8), the coherence decrease in the lower frequency range.

As a consequence, in spite of the existence of the faulty sensors, the source of the faults (either one sensor or all sensors) can be easily identified. Thus the SV is executed very successfully. Moreover, since the KF fusion algorithm imitates the frequency components between 2-4 kHz, FD can be performed simply. To sum up, the outputs of the spectral and the statistical analyses justify each other.

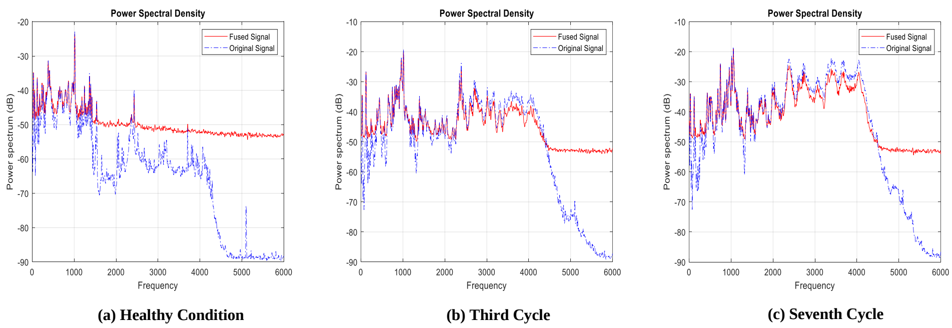
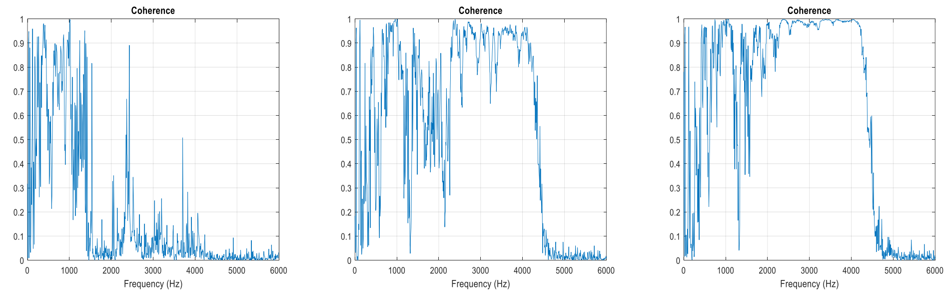
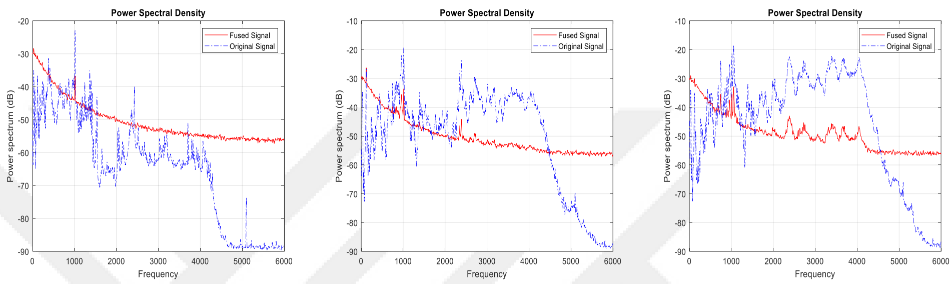


Figure 4.5 : Spectral results of Test #0 (The reference test) for different aging cycles.



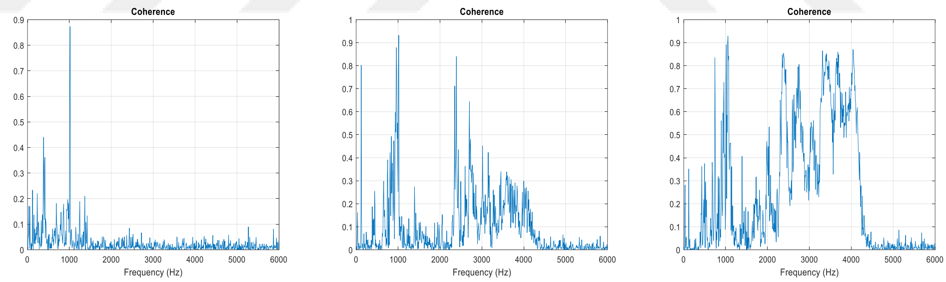
(a) Healthy Condition (b) Third Cycle (c) Seventh Cycle

Figure 4.6 : Coherences of the reference test for different aging cycles.



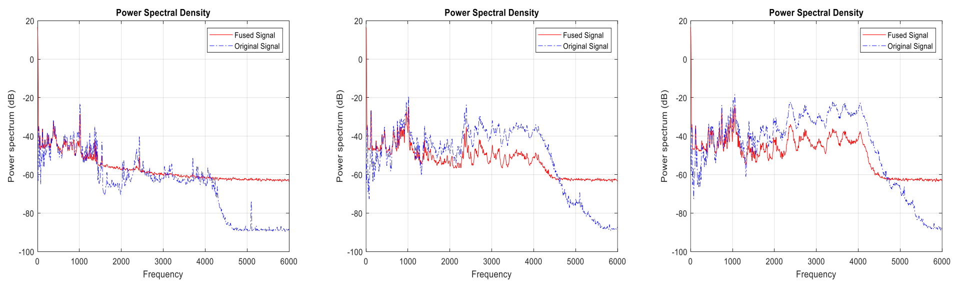
(a)Healthy Condition (b) Third Cycle (c) Seventh Cycle

Figure 4.7 : Spectral results of Test #7.



(a)Healthy Condition (b) Third Cycle (c) Seventh Cycle

Figure 4.8 : Coherences of Test #7.



(a) Healthy Condition (b) Third Cycle (c) Seventh Cycle

Figure 4.9 : Spectral results of Test #13.

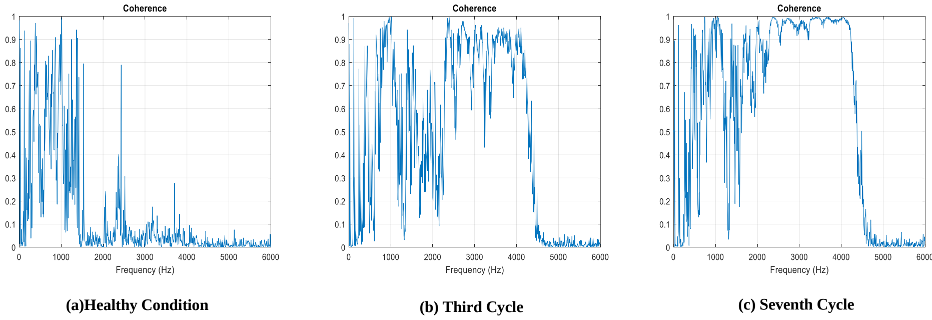


Figure 4.10 : Coherences of Test #13.

4.3.2 Fault detection under severe process noise

In the third scenario, in order to observe the effect of the process noise, authors apply various process noises for each aging cycle. The statistical and spectral results related to the healthy condition, third and seventh cycles are presented here also under the impact of process noise.

Tables 4.6 - 4.8 demonstrate that the process noise (Q) has a significant effect on the standard deviations of the measured signals and the fused signal. Process noise influences similarly on the both sensors and the fused signal. Consequently, the errors remain constant while the standard deviation increases equally. Moreover, impact of aging is detectable on the standard deviation values. Under the significant process noise, the Kalman gain of all sensors saturate to the same value (0.5).

Figures 4.11 and 4.12 illustrate the spectral and coherence analyses, respectively. The fused signal does not show any information expect for the very dominant frequency components for different aging cycles, as seen in Figure 4.12. There exists some limited information about aging in seventh cycle since these components are dominant. However, if the process noise increases more and more, the information about the aging which exist in the fused signal, is vanished.

Figure 4.12 represents a better perspective about the fault component of the system (aging indications). The amplitude of the frequency components between 2-4 KHz increases. Consequently, the fault is detected through coherences, while the process noise is dominant. Nevertheless, to obtain a relationship between the process noises and the aging cycles, a health information is proposed in the next section.

Table 4.6 : Statistical properties of the first aging cycle (healthy case) vibration signal under process noise.

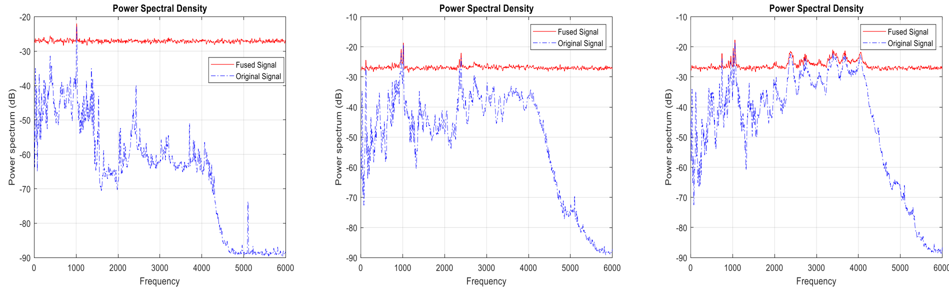
Test	R_1	R_2	Q	Kx_1	Kx_2	MSE_1	MSE_2	RMS_1	RMS_2	$Stdx_1$	$Stdx_2$	$Stdx_f$	Mx_1	Mx_2	Mx_f	$Kurtx_1$	$Kurtx_2$	$Kurtx_f$
#1	0.005	0.005	0.005	0.36	0.36	25	25	5	5	0.15	0.15	0.12	5	-5	0	3	3	3
#2	0.005	0.005	0.01	0.41	0.41	25	25	5	5	0.17	0.17	0.14	5	-5	0	3	3	3
#3	0.005	0.005	0.02	0.44	0.44	25	25	5	5	0.19	0.19	0.17	5	-5	0	3	3	3
#4	0.005	0.005	0.04	0.47	0.47	25	25	5	5	0.24	0.24	0.22	5	-5	0	3	3	3
#5	0.005	0.005	0.08	0.48	0.48	25	25	5	5	0.31	0.31	0.3	5	-5	0	3	3	3
#6	0.005	0.005	0.16	0.492	0.492	25	25	5	5	0.42	0.42	0.41	5	-5	0	3	3	3
#7	0.005	0.005	0.32	0.496	0.496	25	25	5	5	0.58	0.58	0.57	5	-5	0	3	3	3
#8	0.005	0.005	0.64	0.498	0.498	25	25	5	5	0.81	0.81	0.81	5	-5	0	3	3	3
#9	0.005	0.005	1	0.498	0.498	25	25	5	5	1	1	1	5	-5	0	3	3	3

Table 4.7 : Statistical properties of the third aging cycle vibration signal under process noise.

Test	R_1	R_2	Q	Kx_1	Kx_2	MSE_1	MSE_2	RMS_1	RMS_2	$Stdx_1$	$Stdx_2$	$Stdx_f$	Mx_1	Mx_2	Mx_f	$Kurtx_1$	$Kurtx_2$	$Kurtx_f$
#1	0.005	0.005	0.005	0.36	0.36	25	25	5	5	0.3	0.3	0.25	5	-5	0	3	3	3
#2	0.005	0.005	0.01	0.41	0.41	25	25	5	5	0.31	0.31	0.27	5	-5	0	3	3	3
#3	0.005	0.005	0.02	0.44	0.44	25	25	5	5	0.33	0.33	0.3	5	-5	0	3	3	3
#4	0.005	0.005	0.04	0.47	0.47	25	25	5	5	0.36	0.36	0.34	5	-5	0	3	3	3
#5	0.005	0.005	0.08	0.48	0.48	25	25	5	5	0.41	0.41	0.4	5	-5	0	3	3	3
#6	0.005	0.005	0.16	0.492	0.492	25	25	5	5	0.5	0.5	0.49	5	-5	0	3	3	3
#7	0.005	0.005	0.32	0.496	0.496	25	25	5	5	0.64	0.64	0.63	5	-5	0	3	3	3
#8	0.005	0.005	0.64	0.498	0.498	25	25	5	5	0.85	0.85	0.85	5	-5	0	3	3	3
#9	0.005	0.005	1	0.498	0.498	25	25	5	5	1.04	1.04	1.04	5	-5	0	3	3	3

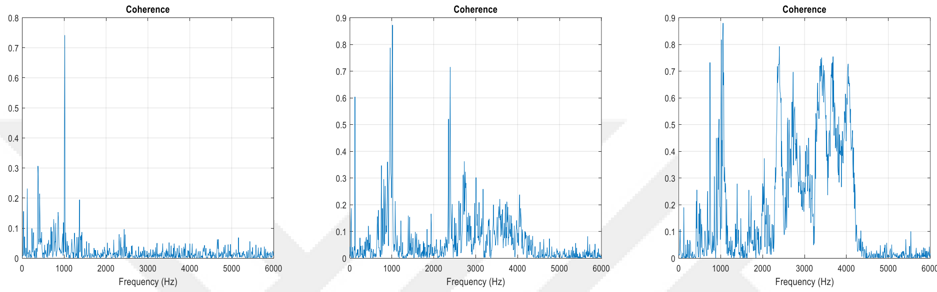
Table 4.8 : Statistical properties of the seventh aging cycle vibration signal under process noise.

Test	R_1	R_2	Q	Kx_1	Kx_2	MSE_1	MSE_2	RMS_1	RMS_2	$Stdx_1$	$Stdx_2$	$Stdx_f$	Mx_1	Mx_2	Mx_f	$Kurtx_1$	$Kurtx_2$	$Kurtx_f$
#1	0.005	0.005	0.005	0.36	0.36	25	25	5	5	0.6	0.6	0.4	5	-5	0	3	3	3
#2	0.005	0.005	0.01	0.41	0.41	25	25	5	5	0.62	0.62	0.51	5	-5	0	3	3	3
#3	0.005	0.005	0.02	0.44	0.44	25	25	5	5	0.62	0.62	0.56	5	-5	0	3	3	3
#4	0.005	0.005	0.04	0.47	0.47	25	25	5	5	0.64	0.64	0.6	5	-5	0	3	3	3
#5	0.005	0.005	0.08	0.48	0.48	25	25	5	5	0.67	0.67	0.65	5	-5	0	3	3	3
#6	0.005	0.005	0.16	0.492	0.492	25	25	5	5	0.73	0.73	0.71	5	-5	0	3	3	3
#7	0.005	0.005	0.32	0.496	0.496	25	25	5	5	0.83	0.83	0.82	5	-5	0	3	3	3
#8	0.005	0.005	0.64	0.498	0.498	25	25	5	5	1	1	1	5	-5	0	3	3	3
#9	0.005	0.005	1	0.498	0.498	25	25	5	5	1.17	1.17	1.16	5	-5	0	3	3	3



(a)Healthy Condition (b) Third Cycle (c) Seventh Cycle

Figure 4.11 : Spectral results under severe process noise (Test #9) for each aging cycle.



(a)Healthy Condition (b) Third Cycle (c) Seventh Cycle

Figure 4.12 : Coherences under severe process noise (Test #9) for each aging cycle.

4.4 Health Information Calculation

The health information (HI) is proposed considering two purposes.

1. To distinguish the process noise from the aging:

   This topic is totally new for the literature. The problem in the system might be caused by the system itself (as aging) or the sensors (as measurement noises) or the remaining system components (as process noise).

2. To provide an accurate FD under process noise:

   As the nature of the algorithm, with the raise of the process noise, a proper and correct FD becomes impossible. Because of that a threshold is presented to specify the possible maximum level of the process noise which allows an accurate FD.

For these aims, two parameters are defined to illustrate the effect of the different process noises on each aging cycle. The calculated parameters (K and P) are given in Table 4.9 and Table 4.10 .

Table 4.9 : K factor values for the different process noises on each aging cycle.

Cyc \ Q	0.01	0.02	0.04	0.08	0.16	0.32	0.64	1	1.5	2	2.5	3	3.5	4	4.5	5	10
Cyc1	2.6	3.6	4.5	5.9	7.7	8.3	10.2	11.7	12.3	12.6	13.2	12.8	14.1	13.9	14.3	14.3	14.8
Cyc2	1.2	1.3	1.54	1.78	2.1	2.44	2.7	2.9	3.3	3.3	3.63	3.63	3.63	3.63	3.63	3.63	3.63
Cyc3	1.04	1.14	1.26	1.4	1.7	1.78	2.1	2.2	2.4	2.4	2.5	2.7	2.7	2.7	2.7	2.7	2.7
Cyc4	0.99	1.1	1.2	1.43	1.72	1.9	2.2	2.5	2.7	2.9	3	3.15	3.3	3.5	3.5	3.5	3.7
Cyc5	0.94	1.01	1.1	1.2	1.33	1.43	1.7	1.8	1.93	1.95	2.12	2.12	2.3	2.2	2.2	2.2	2.4
Cyc6	0.9	1.02	1.14	1.3	1.56	1.75	2.1	2.3	2.5	2.6	3	2.8	2.9	3	3.2	3.1	3.56
Cyc7	0.93	1.01	1.06	1.2	1.25	1.4	1.5	1.75	1.8	1.83	2	2	2	2.15	2	2.24	2.2
Cyc8	0.92	0.97	1.01	1.05	1.1	1.2	1.3	1.35	1.45	1.5	1.55	1.62	1.67	1.66	1.74	1.72	1.95

Table 4.10 : P factor values for the different process noises on each aging cycle.

Cyc \ Q	0.01	0.02	0.04	0.08	0.16	0.32	0.64	1	1.5	2	2.5	3	3.5	4	4.5	5	10
Cyc1	1.3	1.5	2.1	2.6	3.5	5	6.8	8.56	10	11.7	14.6	14	14.8	17	17.7	21.3	26.1
Cyc2	1.1	1.2	1.5	2	2.5	3.25	5	5.8	7.2	8.1	10.3	10.7	10.6	12.5	13	13	17.8
Cyc3	1.01	1.07	1.23	1.43	2.3	2.7	3.5	4.7	5.65	7	7.35	7.23	8.76	9	10.1	9.6	13
Cyc4	0.96	1.02	1.2	1.4	1.8	2.2	3.1	3.8	4.6	5.3	5.8	6.45	7.1	7.25	7.25	7.25	10.8
Cyc5	0.86	0.96	1.08	1.3	1.6	2	2.4	3.1	3.7	4.25	5.23	5.25	5.67	6.1	6.7	7.2	10
Cyc6	0.85	0.99	1	1.27	1.5	1.86	2.4	3	3.45	4.1	4.5	5.4	5.1	5.57	5.8	6.3	9.3
Cyc7	0.8	0.94	1	1.11	1.3	1.7	2.1	2.4	3	3.06	3.5	3.75	4.2	4.45	4.8	5.5	7.46
Cyc8	0.85	0.93	1	1.13	1.24	1.43	1.6	1.93	2.25	2.6	3	3.1	3.6	3.7	3.62	3.6	6.1

K factor is the signal to noise ratio (SNR) while P factor is the peak to peak (P2P) value of the fused signal over the original one. Figs. 4.13 and 4.14 are graphical representations of the Table 4.9 and Table 4.10, respectively. Note that, in these tables Cyc_i represents i^{th} Cycle.

According to Fig. 4.13 and Fig. 4.14, K factor goes to the saturation while P factor raises with the process noise increment. Furthermore, in each aging cycle, the amplitude of both factors decrease. However, these factors are not practical individually. Hence, the following statement (Eq 4.3) is proposed in this study which is called as health information (HI). Table 4.11 represents HI values for each aging cycle under various process noise levels.

$$K \triangleq \frac{SNR(Fused\ signal)}{SNR(Original\ signal)} = \frac{SNR(x_f)}{SNR(x)} \tag{4.1}$$

$$P \triangleq \frac{P2P(Fused\ signal)}{P2P(Original\ signal)} = \frac{P2P(x_f)}{P2P(x)} \tag{4.2}$$

$$HI \triangleq \log(\frac{K}{P}) \tag{4.3}$$

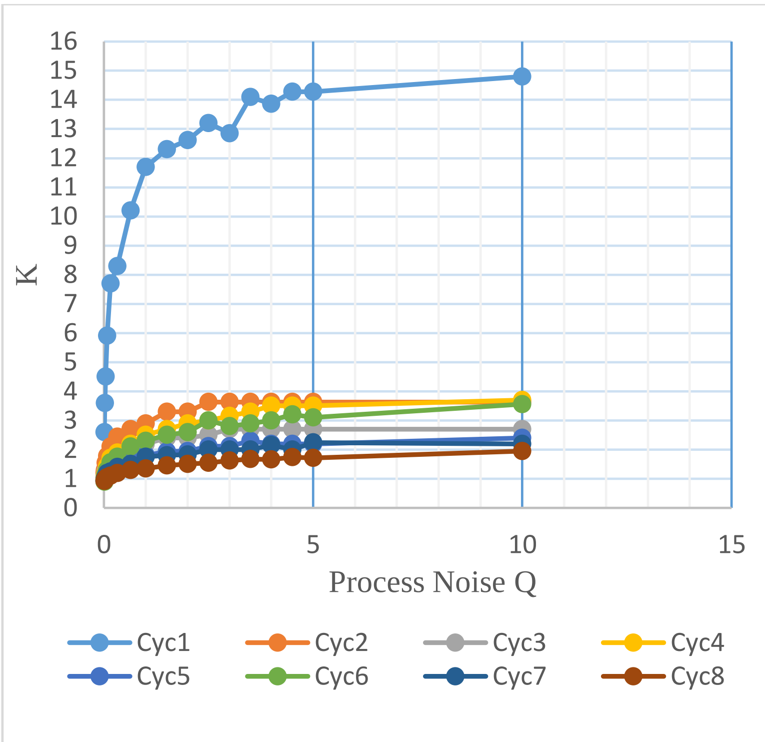


Figure 4.13 : Table 4.9 graphical representation, K factor.

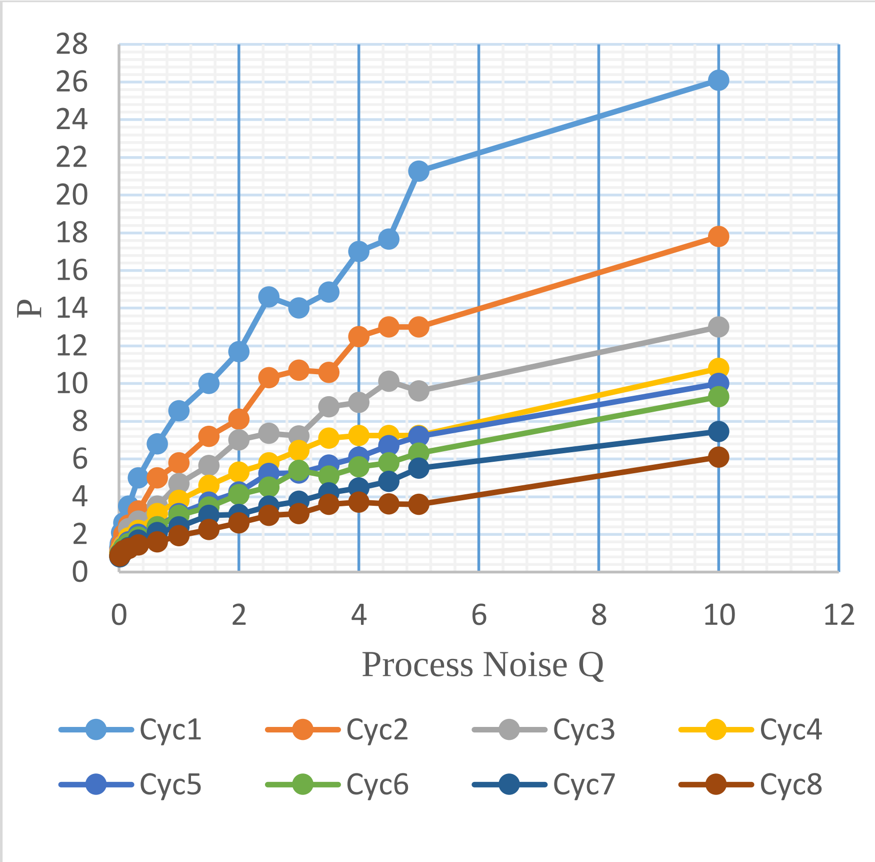


Figure 4.14 : Table 4.10 graphical representation, P factor.

Fig. 4.15 gives better perspective on HI. The rate of HI drops down when the process noise grows. The authors noted that, a threshold is required to discriminate the aged system and a system with process noise. This threshold is needed to comprehend the behavior of the system and distinguish the aging of the IM while the process noise is high. When the spectral interpretation for the fused signals are investigated deeply, some natural thresholds are acquired. It is noted that there are some intervals in which the process noise caches aging. Under low levels of process noise, the aging can be clearly seen on the PSD. However, the higher process noise prevents to detect the aging. Consequently, it is seen that while HI is lower than -0.3, process noise becomes dominant over aging. The regions for dominants process noise are shown in Table 4.11 with grey shaded. The intervals which are identified to interpret HI are listed below;

Table 4.11 : HI values for the different process noises on each aging cycle.

Cyc \ Q	0.08	0.16	0.32	0.64	1	1.5	2	2.5	3	3.5	4	4.5	5	10
Cyc1	0.36	0.34	0.22	0.18	0.13	0.09	0.03	-0.045	-0.045	-0.022	-0.097	-0.097	-0.17	-0.24
Cyc2	-0.05	-0.07	-0.12	-0.27	-0.3	-0.34	-0.39	-0.46	-0.47	-0.47	-0.5	-0.55	-0.55	-0.7
Cyc3	-0.01	-0.13	-0.18	-0.22	-0.32	-0.38	-0.47	-0.47	-0.43	-0.5	-0.5	-0.57	-0.55	-0.68
Cyc4	0	-0.022	-0.065	-0.15	-0.18	-0.23	-0.26	-0.28	-0.31	-0.34	-0.32	-0.32	-0.32	-0.47
Cyc5	-0.036	-0.081	-0.15	-0.15	-0.24	-0.28	-0.35	-0.4	-0.4	-0.4	-0.44	-0.48	-0.52	-0.62
Cyc6	0	0.01	-0.03	-0.06	-0.11	-0.14	-0.2	-0.17	-0.28	-0.25	-0.27	-0.25	-0.3	-0.42
Cyc7	0	-0.018	-0.09	-0.15	-0.14	-0.22	-0.23	-0.23	-0.27	-0.32	-0.32	-0.38	-0.39	-0.52
Cyc8	-0.03	-0.05	-0.075	-0.09	-0.15	-0.22	-0.24	-0.28	-0.28	-0.32	-0.36	-0.32	-0.32	-0.5

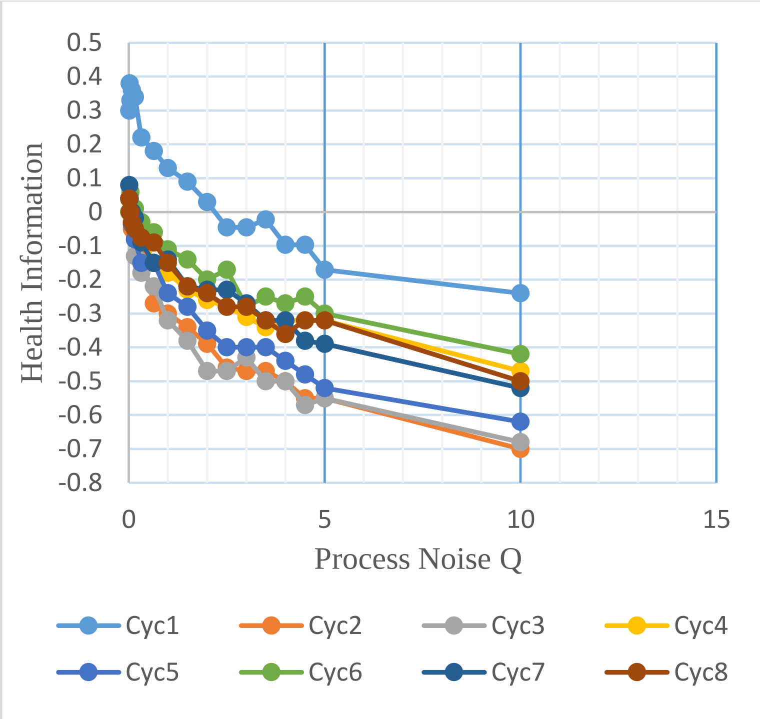


Figure 4.15 : The graphical representation of Health Information.

1. If $HI > 0.3$, the system is healthy and the process noise is not dominant.
2. If $-0.3 \leq HI \leq 0.3$, although the process noise increases, the aging indications (fault frequencies) can be detected through the fused signal. However, in this region, the PSD and coherence analyses are required for an accurate decision.
3. If $HI < -0.3$, the process noise is very dominant, hence, the fused signal is not able to indicate the proper information about system.

4.5 Conclusion

In this study, a data fusion application supported by KF for IFE is proposed. It integrates SV and FD operations in addition to the discrimination of process noise and aging. Vibration signals which are obtained through an accelerated aging process are used in this study. At the first step, the sensors are validated (SV) supported by statistical and spectral analyses. It is demonstrated that FD is also possible through the proposed method regarding the nature of Kalman filter. Then, the effect of the process noise on the fused signal is studied while the system is aged. At last, a health rate is proposed to distinguish the aging while process noise exists. According to the results, the following statements are listed as a conclusion:

• An IFE including SV and FD is possible through the proposed technique.

• According to the spectral illustrations, when one sensor is damaged, the proposed method eliminates it. Thus, the fused signal is not affected by the defected sensor.

• When any sensor is damaged, KG drops down significantly.

• When the process is noisy, KG saturates to a constant value.

• In the presence of damaged sensor, the fused signal can detect the frequency components between 2-4 kHz in each aging cycle. Thus, this property renders FD possible.

• Calculating the coherence between the fused and the original signals is the easiest way for FD.

• A health rate can be defined referring the mathematical characteristics of the fused and original signal.

• Some thresholds can be defined for HI indicating if the system and process is healthy or not.

Consequently, the results which are presented in this paper, prove that data fusion through KF is a powerful and novel technique which is extremely reliable for evaluating the system under various effects such as aging, measurement and process noises.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 General Conclusion

In terms of practical concerns, it's critical to determine whether or not the sensors are healthy. If one or more sensors are defective, we will be unable to determine the condition of the system, and all measurements and computations will be incorrect. As a result, SV plays critical role in the CM and FD processes.

As a result, it is clear that the suggested method (data fusion through KF) in this study, is an effective strategy for FD, SV, and CM for several types of signals, whether stochastic or deterministic.

First of all, the sensor fusion approach using the Kalman Filter is discussed here for error removal. The approach is divided into two sections; the process defect may be discovered using KG calculation. Following process verification, measurement errors are targeted. The cases are intended to analyze sensor fault variations. The sensors are evaluated using spectral representations for represented instances. When both sensors are malfunctioning, the KF Fusion algorithm replies in a highly unique way. If just one sensor is malfunctioning, the KG is consulted once again to conduct an appropriate SV application, which removes the risky one.

Secondly, a data fusion application enabled by KF for IFE is proposed. It applies SV and FD procedures to the detection of process noise and aging. In this investigation, vibration signals collected through an accelerated aging process are utilised. The sensors are validated (SV) in the first step, which is verified by statistical and spectral analysis. It is proved that FD is also conceivable due to the nature of the Kalman filter using the provided technique. The influence of process noise on the fused signal is then investigated while the system ages. Finally, a health rate is developed to differentiate aging in the presence of process noise.

In comparison to other studies, linear Kalman Filter which has simple mathematical computations is used for vibration signal in this study, while in paper [45] Extended kalman filter which has complex mathematics is used. Moreover, KG application is used for SV application which is easy and totally new in literature. The proposed method is easily applicable in practical issues of industry.

In surveys, there are a variety of SV and FD approaches such as references [22, 77]. They could be easier. The suggested approach, on the other hand, is extremely precise, due to its multi-functional capability.

5.2 Practical Application of This Study

With this thesis, it will be feasible to bring condition monitoring up to date with current technologies and to provide a platform for scientific research. Through academic efforts, studies on this issue will give guidance and solution collaboration to Turkey's industry. As a result, each study should be transformed into an industrial application. This research also, can be applied to any industrial application that employs an induction motor. Furthermore, any system discovered in industry that can obtain suitable signals can employ the proposed technique.

It is possible to give the following examples to the mentioned systems:

- Electro-mechanical energy conversion systems with and without driver (Motors)
- Power transformer
- Small power plants

When a problem occurs, the system requires maintenance, which is more expensive and causes the system to be unavailable for a period of time. To avoid this issue, detection and diagnosis are focused on the time between the onset of the defect and the appearance of the problem. As a result, this thesis worked on an intelligent signal based monitoring application that can be used in an industrial system. The aim is to monitor the system and estimate the situation by combining and evaluating the data (data fusion) obtained from different sensors.

5.3 Recommendation For Future Studies

The next step in the study's future is information fusion. Two signals with distinct features, such as vibration and current, can be combined using the proposed method. In other words, data fusion through a kalman filter will be utilized to fuse a current signal with a vibration signal. Because the signals have diverse characteristics, this will be a significant issue. The fused signal will then be used for FD, CM, and state predictions.

Furthermore, another research that might be conducted in the future is merging more than two signals using the same technique. If this occurs, this technique will be generalized for all practical applications in the future, which will have a significant impact on industrial cases and will result in an evolution in FD and CM implementations.

As demonstrated in this study, the suggested approach works extremely well on signals of varying characteristics; also, the kalman filter is one of the finest strategies for data fusion due to its filtering features. As a result, the aforementioned objectives will be readily attained.

In enhancing accuracy and create a powerful algorithm for more complicated systems, the author also recommends combining data fusion and information fusion using the Kalman filter with the artificial neural network (ANN) method as the future study.

Another idea for future work is to make the approach practicable. The appropriate device should be developed, to employ the suggested approach in industrial applications.

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APPENDICES

APPENDIX A.1 : The data of tested motor.

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Table A.1 : The nameplate of the test motor.

Property	Technical Information
Motor Type	Premium Efficiency Motor
Manufacturer	US Electrical Motors Division of Emerson Elec. Co. St. Louis, MO
Model Number	7965 B
Power	5 HP
Phase	3
Speed	1750 rpm
Frame Number	184T
Frame Type	TCE
Voltage	230/460 V
Current	13/6.5
Service Factor	1.15
Frequency	60 Hz
Power Factor	0.825
Efficiency	90.20%
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

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PUBLICATIONS, PRESENTATIONS ON THE THESIS:

- **S. Mousavi**, D. B. Kara, and S. S. Seker, “Integrated Fault Evaluation Through Fusion Algorithm Supported by Kalman Filter,” Trait. du Signal, vol. 37, no. 6, pp. 975–987, Dec. 2020, doi: 10.18280/ts.370610.
- **S. Mousavi**, D. Bayram, and S. Seker, “Current Data Fusion Through Kalman Filtering for Fault Detection and Sensor Validation of an Electric Motor,” in 2019 International Aegean Conference on Electrical Machines and Power Electronics (ACEMP) and 2019 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM), 2019, pp. 155–160, doi: 10.1109, ACEMP-OPTIM 44294.2019.9007202.
- **S. Mousavi**, D. Bayram, and S. Seker, "Fault Elimination Through Kalman Filter Fusion Algorithm," is under review in Electrical Engineering journal.

OTHER PUBLICATIONS AND PRESENTATIONS:

- Fuat Kucuk, **Sadra Mousavi**, “Development of a Novel Coaxial Magnetic Gear” ELMA 2017, Sofia, Bulgaria, 1-3 June 2017.
- **Sadra Mousavi**, Behnam Feizifar, Emel Onal, “A Wide-Range Model for Surge Arresters: Verification Analysis” CPESE 2017, Berlin, Germany, 25-29 Sept. 2017.
- A. Allahyari, **S. Mousavi** and D. Nazarpour, "Analysis of Different Rotor and Stator Structures in Order to Optimize Two-Phase Switch Reluctance Motor Torque Characteristics," 2019 10th International Power Electronics, Drive Systems and Technologies Conference (PEDSTC), Shiraz, Iran, 2019, pp. 28-33.