Robust Fault Diagnosis by GA Optimisation with Applications to Wind Turbine Systems and Induction Motors

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Abstract

This investigation focuses and analyses the theoretical and practical performance of a dynamic system, which affords condition monitoring and robust fault diagnosis. The importance of robustness in fault diagnosis is becoming significant for controlled dynamic systems in order to improve operating reliability, critical-safety and reducing the cost often caused by interruption shut down and component repairing. There is a strong motivation to develop an effective real-time monitoring and fault diagnosis strategy so as to ensure a timely response by supervisory personnel to false alarms and damage control due to faults/malfunctions. Environmental disturbances/noises are unavoidable in practical engineering systems, the effects of which usually reduce the diagnostic ability of conventional fault diagnosis algorithms, and even cause false alarms. As a result, robust fault diagnosis is vital for practical application in control systems, which aims to maximize the fault detectability and minimize the effects of environment disturbances/noises.

In this study, a genetic algorithm (GA) optimization model-based fault diagnosis algorithm is investigated for applications in wind turbine energy systems and induction motors through concerns for typical types of developing (incipient) and sudden (abrupt) faults. A robust fault detection approach is utilized by seeking an optimal observer gain when GA optimisation problems become solvable so that the residual is sensitive to the faults, but robust against environmental disturbances/noises. Also, robust fault estimation techniques are proposed by integrating augmented observer and GA optimisation techniques so that the estimation error dynamics have a good robustness against environmental disturbances/noises. The two case studies investigated in this project are: a 5MW wind turbine model where robust fault detection and robust fault estimation are discussed with details; and a 2kW induction motor experimental setup is investigated, where robust fault detection and robust fault estimation are both examined, and modelling errors are effectively attenuated by using the proposed algorithms. The simulations and experimental results have demonstrated the effectiveness of the proposed fault diagnosis methods.

Acknowledgements

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Finally, I would like to acknowledge all my supervisory team and those who supported me morally during my research and survival period to accomplish this work.

Declaration

No part of this work has been submitted elsewhere in support of an application for another degree or qualification, or any other university, or institute of learning, or industrial organisation. The content of this proposal is all my own work except referenced to the different in the text. I declare the word count of this thesis is 31,150 words.

Name: Sarah Omolara Odofin

Signature:

Date:

Dedication

This work is dedicated to God Almighty who has Alpha and Omega it and also to Mrs Margaret Taiye Odofin, Dr (Mrs) Titilayo Alice Ode, not forgetting Naijapals for their love, support and moral contributions throughout this journey.

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Glossary of Symbols

$\|\cdot\|$	Standard norm for matrices/ norm of dedicated matrix
K	Gain matrix of the observer
W	Weighted matrix
J	Fitness function
Ψ	Set of parameters/ variables
λ	Eigenvalue (pole placement) of a system
Λ	Arranged eigenvalues of a system / the tradition of closed-loop
ω	Angular frequency
ω_d	Frequency of dominant uncertainty
ω_f	Frequency of the fault concerned
A, B, C, D	Matrices of the plant
$\bar{A}, \bar{B}, \bar{C}$	Augmented system matrices with appropriate dimensions
$\bar{n}$	Estimation of the augmented state vector
$\bar{K}$	Augmented observer gain
R	Space of real numbers vectors
H_∞	H-infinity robust control or estimation performance
$\|H\|_\infty$	Norm of Transfer function matrix *H(s)* in H_∞ space
$\|H\|_{s=j\omega}$	Norm of Transfer function matrix *H(s)* at argument of $s = j\omega$
3Φ	Three phase
Σ	Summation of all matrices

Glossary of Abbreviations

FD	Fault Diagnosis
FDI	Fault Detection and Isolation
FFT	Fast Fourier Transform
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
CA	Critical Analysis
RPN	Risk priority numbers
NASA	National Aeronautics and Space Administration
DDF	Disturbance dominant frequency
CM	Condition Monitoring
DDF	Disturbance dominant frequency
OB	Observer
RFD	Robust Fault Diagnosis
RFDO	Robust Fault Detection Observer
TFM	Transfer Function Matrix
UIO	Unknown Input Observer
AFDI	Actuator fault detection isolation system
WT	Wind Turbine
IM	Induction Motor
SCADA	supervisory command and data acquisition
FE	Fault Estimation
FT	Fault Tolerant
GA	Genetic Algorithm
LMI	Linear matrix inequality
IM	Inductor Motor
PID	Proportional Integral derivative

Chapter One: Introduction

"To improve is to change; to be perfect is to change often".–

Winston Churchill

1.1 Basics of Fault Diagnosis

Modern industrial dynamic control systems are becoming more complex, sophisticated and expensive, which provides the driving force for the ever rising demand to continually improve the system reliability, safety operation, product quality and reduce the cost caused by shut-down time and component repairing. These concerns are not generally relevant to safety-critical systems such as aircraft, nuclear reactors power stations, chemical plants etc. The costs of sudden abnormal changes in a dynamic controlled system could be extremely severe in regard to environmental impact, financial loss, numerous and serious accidents. As a result, the use of condition monitoring (CM) and fault diagnosis (FD) techniques is essential for recognizing abnormal circumstances in the system, which is the driving force behind the extensive research into FD over the last four decades. In order to improve the availability of the dynamic, system reliability and reduce the cost of repairing and maintenance in controlled systems, effective fault detection and diagnosis (FDD) systems are necessarily to be integrated with modern industrial automation processes/systems.

The term 'fault' implies that an abnormality exists at an initial moment nevertheless there is a need for early fault diagnoses even at its inception period in order to avoid any critical concerns. It is evident that early warning of emerging faults can save the system from failure, operational interruption and unanticipated emergency. Hence, FD is a major necessity when planning suitable maintenance and for the avoidance of severe accidents. The design of FD also considered as fault detection and isolation (FDI) has received much attention since 1970s, great contributions and an extensive diversity of methods have been suggested and developed in solving some of the sensitivity, stability as well as problems of robustness [1]-[4]. Traditionally, in the control systems community the term FDD *describes a monitoring technique for detecting all possible unexpected changes in the normal healthy working operation of a process system, by identifying the existence of faults, determining the location and analysing their tolerance capacity*. The monitored health of a dynamic system can respond to practical abnormal changes by utilizing early fault detection, fault isolation and fault identification, so that the system operating personnel can take appropriate measures to avoid further damage to the system, and sustain some functionality with tolerated system performance degradation. There have been fruitful results for early detection, fault isolation, and identification of fault. There are and still exist different tools for early detection of faults, isolation of faults, and the identification of their severity of faults in systems which will be later discussed in the next chapter.

With their rapid development there is an increasing need for modern control systems to keep on operating reliably in satisfying crucial functions in the event of system faults leading to the idea that fault-tolerance could determine the success of FDI. Unexpected components failure could cause the system to be less tolerance which could be risky to the system. However, the goal of fault tolerance is to sustain the system's working operation as well as give the operational staff enough time to repair the system or to determine on a different measure to prevent catastrophes.

FDI methods/techniques are based on the redundancy of hardware or software (so called analytical redundancy). Firstly, the standard method is known as physical (hardware) redundancy demanding at least double arrangements of physical redundant devices, nevertheless the challenge of this approach is the use of additional hardware to back up the system which makes the method costly as well as resulting in extra load and physical equipment space worries. Secondly, analytical redundancy operates using a mathematical model to replicate the real system's performance. From the perspective of modelling, analytical model-based FDI approaches require either quantitative models using measured variables of the monitored process or a qualitative blueprint (knowledge from experts to express the system). In quantitative modelling, the plant is expressed in respect of the available mathematical relationship between input and output variables, where the modelling errors must be overcome during control and monitoring design. In a qualitative model, these relationships of the input/output variables are expressed explicitly, often being based on knowledge from experts or data-based training analyses are assumed as regards to preceding information about the model.

1.2 Basics of Model-Based Fault Diagnosis

Model-based fault diagnosis can basically be explained as the assessment of consistency between the actual process and the model output, which is called the residual, as the fault indicator. Model-based fault diagnosis is on no occasion dependent on the model which represents the healthy systems and processes. It is noticed that the parameters of the system may fluctuate along the process when the characteristics of the uncertainties are unknown, then the system cannot be modelled accurately. In other words, modelling errors are unavoidable, which brings a challenge for model-based fault diagnosis techniques. In real-world dynamic systems case, disturbances, noises, and modelling errors are unavoidable, therefore there is a need to reduce the rate of false alarm posed by these uncertainties and also, improve the success rate of early fault detection by overcoming the adverse effects of the uncertainties. Therefore, an effective FDD system must be sensitive to faults but robust against modelling errors, disturbances, and noises. Previous approaches to FDD generally include quantitative, qualitative and intelligent computing based approaches. In this study, quantitative model-based fault diagnosis methods are combined for overcoming the modelling uncertainties challenges, thus reducing the false alarm rate, generally caused by unknown characteristics of environmental disturbances, and prevent the missing of fault signals.

It is evident that the difference between a real system and the modelled system could cause complications in FD, which may positively establish false/missed alarm and corrupt the FD system performance, and even lead to total failure of the FD. Real-time parameter perturbations are major influences that can reduce the control and monitoring performance of industrial systems/processes, and the consequence of modelling errors needs to examine in the context of FD theory. Many efforts have been made to solve this problem by using optimisation methods [3]-[7]. However, the investigation is still ongoing for developing novel robust fault diagnosis practices and their applications to a variety of industrial systems.

In fault diagnosis detector, there is a trade-off between improving the sensitivity to the faults and reducing the sensitivity to the uncertainties. Therefore, the optimisation technique is a natural choice for solving this trade-off problem. The main aim of this thesis is to develop novel robust fault detection, and fault estimation techniques for systems subjected to process disturbances, measurement noises, and modelling errors, as well as to investigate their applications to wind turbine systems and induction motors.

1.3 Motivation and Justification

FD is a vital tool for real-time industrial monitoring and malfunction diagnosis, which aims to improve system reliability, availability, and safety operation, to also, reduce the cost due to the unexpected shut-down and unscheduled repairing and maintenance. Fault diagnosis is used to determine when and where a fault occurs so that a timely alarm can be provided. For a model-based fault diagnosis method, the diagnosis performance has to be dependent on the rejection ability of the fault diagnosis scheme against such sorts of uncertainties, as modelling errors, process disturbances and measurement noises, such as frequently unavoidable in practical engineering systems. There are two typical faults in industrial processes, that is, the incipient, and abrupt fault. In this study, the two typical types of faults will be both examine. It is noticed that incipient faults might have a small influence on residuals so therefore, it is more challenging to detect the incipient type of faults. The uncertainties may prevent the faults being recognized in the residual, which can cause a fault to be missed or false positives alarms. As a result, it is vital to improving the uncertainty rejection ability to distinguish the fault effects from the disturbance effects in the design of fault detection algorithm. In this study, a novel robust fault detection algorithm is developed by attenuating the signals associated with dominant faults at specified frequencies subject to an optimisation framework. It is evident the disturbance attenuation ability would be improved if the dominant disturbances are minimized. In addition, the faults such as actuator faults and sensor faults could occur simultaneously within the monitored period. It would be challenging to detect all of them by using a single fault detector due to the effects of uncertainties, and the differences of the input and output signals in magnitudes. Multiple faults are also to be investigated in this study.

Along with fault detection, and fault isolation, it is also important to determine or estimate the severity of faults in components. Such a technique is called fault identification. In this study, a novel fault identification technique called fault estimation is to be developed. By using the proposed fault estimation technique, the dynamic system states, and the faults concerned are to be reconstructed, which lays a foundation for advanced control and decision making. The fault tracking ability against the uncertainties is also the key challenge for developing an effective fault estimation technique. Genetic Algorithm (GA) is a popular optimisation tool, which could find a global optimum solution, GA avoids the need to establish gradients of the cost functions, it is easier to use, for solving various optimisation problems with multiple objectives, and even for complex dynamic systems. In this study, GA optimisation algorithms are utilized to seek optimal gains of the fault detector and fault estimators for achieving optimal robust performance for both fault detection and fault reconstruction. The case studies of the research are concentrated on a wind turbine energy conversion system, and an induction motor system.

1.4 Research Aim and Objectives

This research work is aimed to develop novel fault detection and fault reconstruction approaches with applications to wind turbine systems and induction motors for improving system operation reliability and safety operation by overcoming the effects of the uncertainties (including modelling errors and process/measurement uncertainties). To achieve the aim above, the research objectives of this study are outlined as follows:

1. To review the state of the art of the fault diagnosis techniques and their applications.
2. To investigate robust fault detection techniques such that the fault detection indicator can achieve an optimal performance by enhancing the effects from the faults signals, but attenuating the influence of modelling errors, process disturbances and measurement noises.
3. To discuss the multi-fault detection problem under disturbances environments.
4. To investigate the fault reconstruction problem by integrating an augmented system approach with the GA optimisation technique.
5. To investigate the case study for wind turbine systems by using both robust fault detection and robust fault estimation techniques.
6. To investigate the case study for induction motors by using both robust fault detection and robust fault estimation techniques.

1.5 Thesis Organisation

This thesis is arranged into seven chapters. Following the general introduction from **Chapter One**, gives general introduction overview interest of study.

Chapter Two reviews the state of the art of the model-based fault diagnosis. This section enlightened the non-technical audience on true monitoring of a healthy dynamic system and review of various investigation techniques of faults diagnosis.

Robust model-based fault detection is discussed in **Chapter Three**, where an algorithm is addressed by integrating the dominant disturbance frequency checking method (frequency spectral analysis) and the genetic algorithm optimisation for seeking an optimal gain of the fault detector.

In **Chapter Four**, robust model-based fault estimation is investigated, where the augmented observer is designed to simultaneously estimate the system states and faults, where GA is utilized to find the optimal gain of the observer by minimizing the estimation error against modelling errors and environmental disturbances/noises.

Case study for wind turbine system is investigated in **Chapter Five**, where robust fault detection for wind turbine systems and robust fault estimation for wind turbine systems are both discussed. A state-space mathematical model of 5MW wind turbine system is used with a rotational speed of 10m/s.

The second case study is investigated in **Chapter Six**, where uses the real-data of an AC induction motor collected in **Chapter Six**, uses the real time data of an AC induction motor collected in the experimental setup to verify the proposed methods.

Finally, in **Chapter Seven**, key contributions and achievements of the research are summarised and concluded, as well as potential works in the future are remarked.

1.6 Original Contributions – Uniqueness of the investigation

Throughout the progress of this study, new ideas has been research and investigated:

1. To discuss GA-based robust fault detection problems for systems with multiple faults so that the residual (fault indicator) is sensitive to the faults, but robust against uncertainties.

2. To propose novel fault estimation techniques by integrating the augmented system methods and GA optimisation approaches so that the abrupt faults and incipient type of faults can be effectively reconstructed. Fault estimation can give the size, shape and type of the faults, which can provide valuable information for the advanced systems control and management.

3. To investigate the case study of the robust fault detection and robust fault estimation problem for a 5MW wind turbine conversion system.

4. To investigate the case study of the robust fault detection and robust fault estimation problem for a three-phase inductor motor.

5. To use the Fourier transform approach to obtain the frequencies of the dominant disturbance components, where are then utilized in GA optimisation for seeking an optimal gain for fault detectors and fault estimators. This integration leads to novel robust fault diagnosis algorithms.

6. In the GA optimisation, the selection of the cost functions is an original contribution leading to a multiple-objective optimisation problem for seeking optimal fault detectors and fault estimators.

1.7 List of Publications, Awards and Reports

Publications

[1] Odofin S. O., Kai S., Gao Z. and Liu X., "Robust Actuator Fault Detection for an Induction Motor Via Genetic-algorithm Optimisation" 2016 IEEE 11th Conference on Industrial Electronics and Applications ICIEA 2016

[2] Liu X., Gao Z. and Odofin S.O. Robust fault estimation for stochastic nonlinear systems with Brownian perturbations, IEEE 11th Conference on Industrial Electronics and Applications ICIEA 2016

[3] Odofin S.O., and Sowale, A, (2016), Regenerator Losses in Free Piston Stirling Engines' International Conference on Leadership, Innovation and Entrepreneurship. 20-22 April 2016, Dubai, UAE.

[4] Odofin S.O., and Sowale, A, (2016), Genetic Algorithm Systems for Wind Turbine Management' International Conference on Leadership, Innovation and Entrepreneurship. 20-22 April 2016, Dubai, UAE.

[5] S. Kai, Z. Gao and S.O. Odofin "Robust sensor fault estimation for induction motors via augmented observer and GA optimisation technique," *IEEE International Conference on Mechatronics and Automation*, Beijing, pp.1727-1732, August 2015.

[6] S. O. Odofin, S. Kai and Z. Gao "Robust fault estimation in wind turbine systems by using GA optimisation," *IEEE Conference on Industrial Informatics*, Cambridge, pp.580-585, July 2015.

[7] S. O. Odofin, S. Kai and Z. Gao "Robust fault diagnosis for wind turbine systems subjected to multi-faults," *International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering*, vol.9, no.2, pp.220-225, February 2015.

[8] S.O. Odofin, S. Kai, Z Gao and Z. Ghassemlooy, “Simulation study of fault detection and diagnosis for wind turbine system”, *15th Annual Postgraduate Symposium on the Convergence of Telecommunications, Network and Broadcasting*, Liverpool, June 2014.

Research Related Awards

- Naijapals Scholarship, 2013-2015
- IEEE Student Travel scholarship awarded by IEEE Industrial Electronics Society, 2015
- Northumbria PGR Conference Travel Bursary, 2015

Poster Presentation

[1] S. O. Odofin, Z. Ghassemlooy, S. Kai, and Z. Gao. “Fault Diagnosis for Wind Turbine Energy System”. Poster presentation Northumbria conference, 2014

[2] S. O. Odofin, and Z. Gao, “Investigation of Fault Diagnosis for Wind Turbines”. Pechakucha presentation. Northumbria University, 2014

[3] S.O. Odofin, and Z. Gao, “Fault Diagnosis Improvement for Wind Turbines”. Poster presentation. Northumbria University, 2015

Oral Presentation

[1] S. O. Odofin, and Z. Gao “GA Optimization based robust fault diagnosis for wind turbine energy system”. February 2015

[2] S. O. Odofin, and Z. Gao “Observer-based Robust Estimator for Wind Turbine System”, 2014. Presented in Optical communication and research group. (OCRG)

[3] S. O. Odofin, “Observer design for wind turbine based by genetic algorithm”. Power Energy Society, Newcastle University. 2014

[4] S. O. Odofin, “Condition Monitoring of Wind Turbine System Using Artificial Intelligent Algorithms”, 3MT. Organized by postgraduate school. 2015

Reports

[1] S. O. Odofin, “Wireless Sensor-Based Condition Monitoring for Wind Turbine Energy System” (Initial proposal Approval 2013)

[2] S. O. Odofin, “Model-Based Fault Detection and Diagnosis For Wind Turbine Energy system”, 1st year Annual Progression.

[3] S. O. Odofin, “GA Optimization Based Robust Fault Diagnosis For Wind Turbine Energy System”. 2nd Year Annual Progression Report 2015

Chapter Two: Fundamentals of Fault Diagnosis

“Diagnosis is not the end, but the beginning of practice”.

Martin H. Fischer

2.1 Introduction

Diagnosis is a modern Latin word from Greek which simply means *distinguish* that is interpreted as recognizing the nature and source of an element or distinguishing any form or nature of problem. The act of distinguishing the existence of syndrome from its signs or symptoms all started in the health sector, with doctor and patient relationships. The process of describing the identification of a condition symptom, could basically illustrate the background of the real nature and cause of an unhealthy circumstance that could result to criticality. *Diagnosis can provide an accurate picture of a true system condition and indicates healthier decisions or identifies the nature of a root problem through logical analysis of the history or background.* The derived judgement facilitates the generation of data from which valuable information about the problem can be extracted as these questions are raised: who has piloted to the problem? What it is? And in what way can the problem be communicated across to others, what way it will be treated and what the outcome result might be [8]. Diagnosis is aimed at defining the causes of the automatically monitored or observed system with malfunction symptoms or signals through perception and investigation. Diagnosis scheme could be carried out through offline or online analysis based on knowledge gained from the observer or monitoring procedure, gathered from historical information or in respect to the define root causes of problem.

2.2 Background of Fault Diagnosis

One of the traditional techniques of early diagnosis is the Failure Mode, Effects and Criticality Analysis (FMECA) which is a means of measuring reliability costing / design approach to observe the possible failure conditions inside a system and particular device, to compromise the issues on system and devices operation. Individually possible failure operations or methods are standardized to be influence on assignment of device/people safety. FMECA is comprised of two distinct analyses, Failure Mode and Effect Analysis (FMEA) and the Criticality Analysis (CA).

In the 1940's, American military was the first to introduce FMEA as a detection tool to improve and, assess effects/roots of all possible faults during Apollo missions [9]. In order to document system design, distinguish error, define the severity of failure, cost implication, as well as to determine systems reliability and control effect of equipment failure for war performance. National Aeronautics and Space Administration (NASA) in 1960 was the first to implement, identify and recognise the step by step fault supervision procedures of FMEA as a forward practical technique to evaluate, decide, design process and determine all possible failure in systems. NASA employed FMEA approach to determine any potential failures or accidents that can occur, and to control the actions to avoid the conditions that may lead to failures. In 1974, the Navy established *MIL-STD-1629* with the practice of FMEA and in 1970's, the automotive industry was motivated by the liability costs to employ FMEA tool of which the benefits of applying the tool to lower the danger associated to imperfect condition.

The purpose of FMEA is to explore the effects of systems failure operation and to identify conforming to the amount of each possible failure. The failure mode was described as ways or methods that could fail to achieve their predicted function estimated for health management. FMEA drive is to inspect possible failure approaches, designed operations to avoid breakdown and regulate the influence of these failures on a product with a valuable tool for analysing and preventing process problems before they occur [9]-[13]. This action is implemented to apprehend possible technical dangers in order to take challenge capacity to on those risks to reduce the chance of failure, where uncertainty is identified could continually sustain to regulate failure. FMEA has been applied to analyse risk assessment via various multidiscipline, when improperly executed, FMEA wastes time, is debatable, could be inconsistent, unsuccessful and at its worst direct the operator analyst in wrong directions. Risk priority numbers (RPN) is the phase of FMEA process, to find / measure / analyse the risk related with possible problems recognized in FMEA. RPN considered at the aim of possible causes of failure severity, occurrence and detection, though the information for occurrence ranking, evaluating and CA is severity rankings according to the shared effect of severity, chance of incident and detection. Deciding the potential failure modes, based on severity of the failure mode which aimed at emerging an active quality control system, prevention methods and design process control (protection of customers) to improve high value and reliability of product. The rapid development of modern automatic control technology, the automotive industry in 1970 adopted FMEA technique to classify changes using predictive maintenance tools and a failure in the system. Some of the significance diagnosis is as shown in Figure 2.1

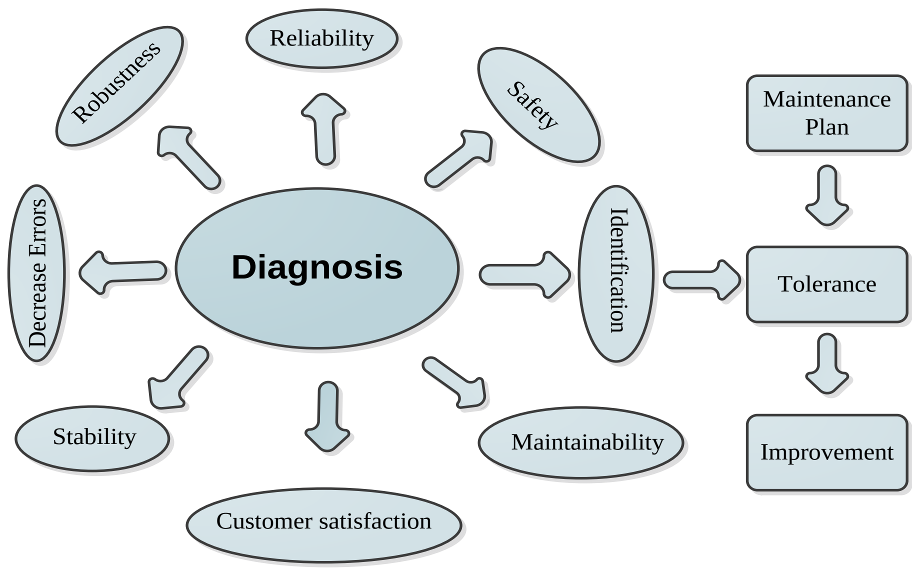


Figure 2.1: Justification for diagnosis

Currently, one of the most serious concerns surrounding the design of automatic systems are the *reliability* due to the system complications, cost, environmental impact, availability and the security of automation amount of practical processes are continuously growing.

In process, of modern control system, the often used diagnosis system is to monitor the movement of a specific signal and actively sorting out a measure when the signal attained a given threshold (point). There is a growing need for online supervision to increase the reliability of safety critical system as explained by the proposal of the detection filter, which produce error signals indicating the position of a change or failure in a system. However, the need to guarantee plant safety and availability, at the same time preventing expensive maintenance during plant interruption can provide awareness of the system condition, which tolerates an appropriate given maintenance plan to be instigated. Beard-Jones revealed a proposal to create a filter model proficient at detecting a considerable quantity of diverse changes or failures in the visible dynamics of a system [14]-[15]. This initiated the state-of-the-art in the model-based techniques, which allows a true on-line condition maintenance plan to be implemented. Practical algorithms are designed as well as on-line to produce any desired closed-loop poles for the controllable portion of the system due to feedback reorganisation problem [16].

2.3 Overview of Fault Diagnosis Techniques

An overview of FD technology is discussed in this chapter and it makes a sustainable corresponding access to industrial technology. Though the growing request for a sophisticated safety-critical, availability to increase reliability and reduce the costs of maintenance as well as component repairing has motivated a comprehensive investigation of FDI as in the early 1970s. FDI is still emerging and continues to advance, as a key and profitable measure of modern control, and agreeable results as been stated extending from physical hardware redundancy, analytical redundancy to algebraic knowledge and artificial intelligence. In a simple summary, *Fault is known* as *any error that may cause a failure to happen or any sudden deterioration of any part of the system*. Fault is an abnormal condition that is responsible for changes in the behaviour of a system of an unpermitted deviation of at least one normal property of the system from the satisfactory, typical standard condition. This could be a sudden unexpected change which is extended to failure of a component or a state within the system which leads to irregular form of deterioration or initial failure. Fault may not necessarily affect the current system performance but might lead to failures if proper measure is not put in place and even to breakdowns in the systems, so therefore, there is need to be diagnosed as soon as possible. Hence, fault is often considered as the primary stage of failure recognition. *FD is a monitoring scheme that is used to detect faults in a controlled system, diagnose its location, type, size and the nature about the irregular working parts in the system.* FD is a vital factor of an observant control system, which consists of the three detailed properties:

i. **Fault Detection:** Identifying when fault happens in the system
ii. **Fault Isolation:** To determine the location of a faulty place in a system.
iii. **Fault Identification:** To decide the type, size and the nature of the fault

FD characteristics can be considered in the diagram as shown in Figure 2.2.

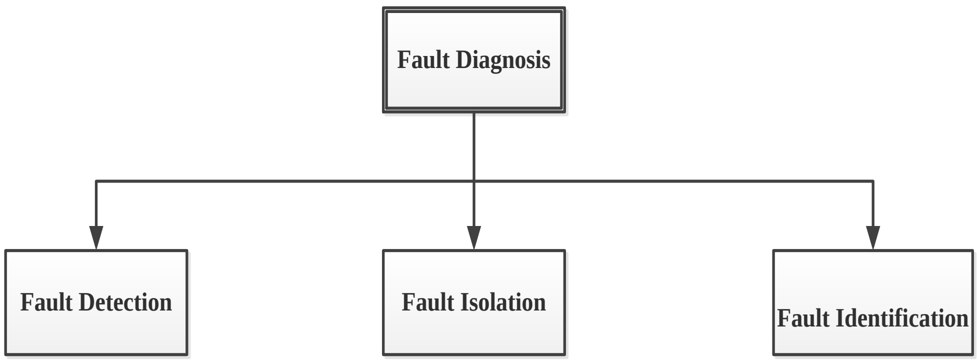


Figure 2.2: Framework of Fault diagnosis

2.3.1 Model-Based of Fault Diagnosis

The Failure diagnosis could be further explained into model-based and information driven, both could be analytical at the same time, but the data driven are statistical and artificial intelligence while the model-based could be both quantitative and qualitative methods. Fault, also known as unpredicted changes that may be acceptable at current level, failure or physical breakdown of a system operation while failure describes the entire breakdown of a system element. Potential premature faults may be beneficial to reveal abnormality that need to be investigated at an acceptable point, to avoid any severe concerns. Information interruption requires extensive testing to confront the challenges of modern control system. Motivated by rising more advanced safety and rapid improvement of modern automated system, diagnosis has been considered comprehensively. The diagnosis techniques could be qualitative, quantitative, real and systematic steps of identifying prospective difficulties, which can be allocated into practices to reduces substitute failure such as conventional FMEA, hardware (physical) and analytical (functional) redundancy as shown in Figure 2.3.

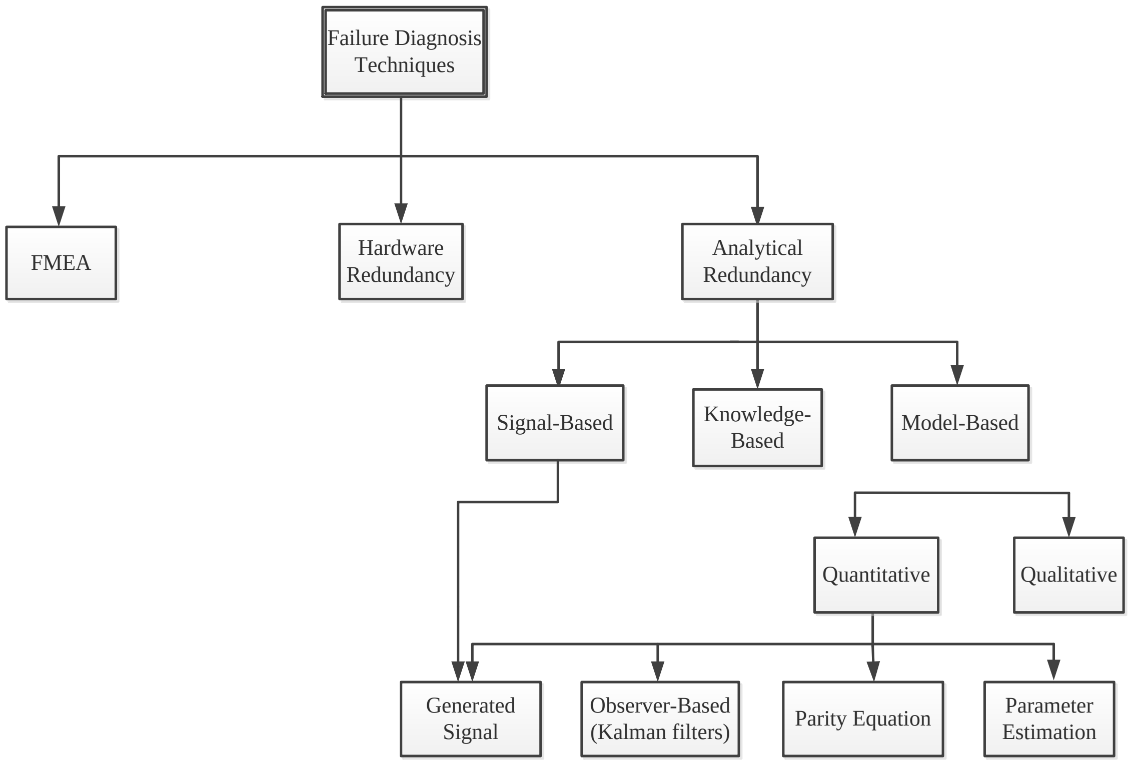


Figure 2.3: Description of failure diagnosis

In the field of analytical redundancy, model-based makes use of a (quantitative) mathematical representation of the monitored method to get related information on fault diagnosis instead of additional hardware components to recognised FD algorithm [17]-[18]. Monitoring of fault information in a system, a scale can be set as a basis to define the boundary of the abnormal changes. One of the model-based benefits is that no extra hardware components are required in order to recognise FDI system of which is always executed in software on the control computer system.

Such process consists of the following three main methodologies which have been developed:

- Parameter estimation method based on system identification [6] [19][20]-[23]
- Parity relation method [24]-[29]
- Observer/filter-based method [2] [5] [30]-[31] and [32]-[38]

The properties of the following stated statistical based approaches will further be discussed in this section.

2.3.2 Traditional Hardware fault diagnosis scheme

Inspired by the increasing request for sophisticated safety and rapid growth of modern control systems, fault diagnosis normally acknowledged as FDI has been studied extensively, since early in the 1970s. The study of FDI has been fast cumulative lot of attention globally in both principle and applications [2]. One of the traditional classifications of FDI is based on parallel extra hardware redundancy as a physical duplication which uses multiple components in a system. The matching hardware components which are employed to improve systems reliability, usually for a standby practice. The use of various excess equipment applications is universal with digital “fly-by-wire” aeronautical AIRBUS 320 example (which is known as a kind of twin engine airliner) and its results [39] also as in nuclear reactors control systems. The FDI issues with hardware, additional equipment redundant is relatively at a high cost, due to extra space needed to accommodate the excess equipment and maintenance cost thus the applications of this scheme is only restricted to a number of key components. The degradation of system value could be either swift or slow fault performance. Diagnosing fault in the plant component is spotted if the output of the component is changed from the set of additional hardware component as demonstrated in Figure 2.4. The main advantage of this system is its high reliability and the precise location of the fault. The tradition of exact hardware effects on the additional expenses likewise mainly carried out offline, hence the application of this scheme is only limited to a quantity of basic components [17].

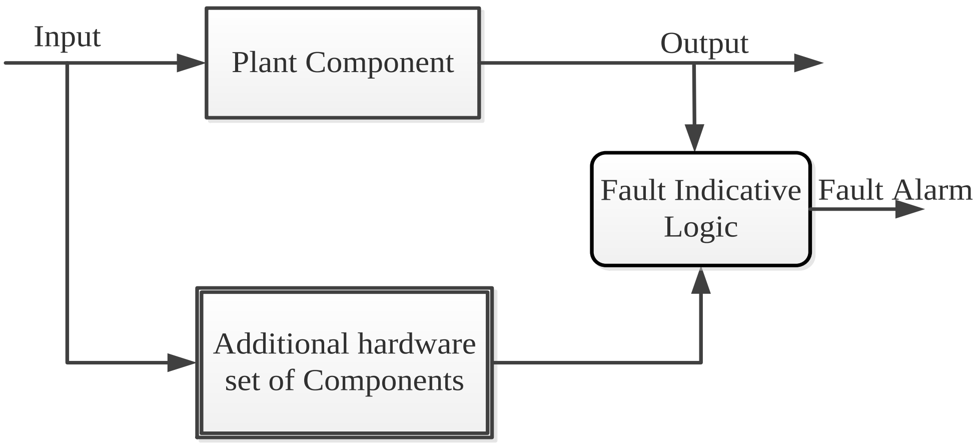


Figure 2.4: Representation of Hardware Redundancy

Hence, faults can be well-known by their performance, identity, location, arrangement, size, nature and magnitude. The traditional hardware system requires designed with additional physical equipment and challenges the complication of hardware backup expenses and capacity to shelter the equipment.

2.3.3 Analytical (systematic) fault diagnosis scheme

The knowledge of switching from hardware to analytical redundancy, invented by Beard [40] in 1971, uses matrix algebra mathematical model-based concept to describe failure detection of a physical linear systems property. Failure detection observers or filters producing residuals indicator for FDI was suggested. The notion of the analytical system is to assess the real system behaviour for reliability with a model which no additional hardware is allowed in analytical structure and the actual system is being remodelled in a state space model and monitored via online software. Analytical back-up or redundancy applies the reliability between the unpredictable alarm signs to acknowledge any case of abnormality. Compared to the hardware redundancy systems, in the outline of the software redundancy idea the plant component model will be in matching to the real plant component and be motivated by the same plant component inputs. It is rational to assume that the duplicate plant component provided by the plant component model will monitor the corresponding real plant component variables in the healthy operating states and indicate an apparent abnormality in the system. In order to obtain information about resulting changes, an evaluation of the real output signals with their estimates delivered by the plant components model will then be made.

The reconstructed system is expected to be working normally in an occasion of fault-free operating mode parallel to the real system but when there is an obvious change in the monitored system by a fault signal in the system sending an alert to be detected by fault indicator as shown in Figure 2.5a. On-line diagnosis is usually a mixture of qualitative and quantitative approaches to identify faults as earlier revealed.

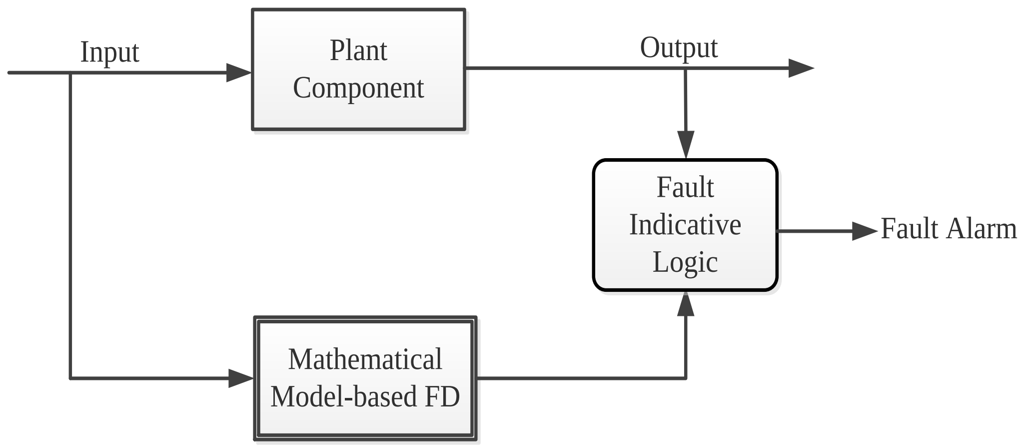


Figure 2.5*a*: Representation of Analytical Redundancy

The analytical model-based methods are the techniques to substitute hardware redundancy with a developed prototype which is applied in the software [17]. Quantitative or qualitative method explains the effective and reliability of the plant component process's behaviour with modelling method. The behaviour of a plant system is defined by its solution path or its frequency response. To monitor reliability in analytical redundancy is generally realized through an assessment between controlled (measured) signals with its estimation, which is produced by a mathematical model of the considered systems plant. Figure 2.5b gives a clear comparison between traditional hardware and model-based analytical fault diagnosis.

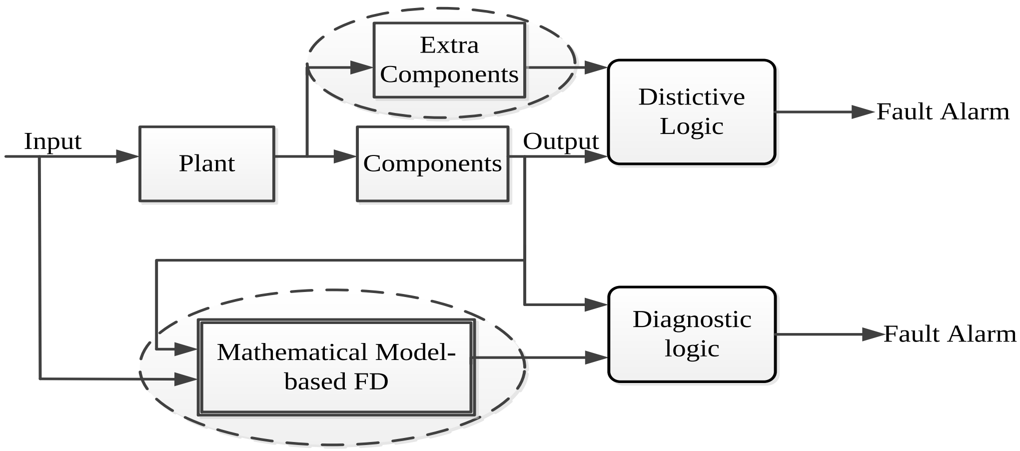


Figure 2.5*b*: Comparison in traditional hardware and analytical software back-up system

The benefit of model-based analytical over traditional *hardware* system is that no extra hardware components are required in order to recognize fault diagnosis scheme. Model-based FD system can be executed during computer process operating control by *software*. There has been collection of approaches proposed in the literature, established on the use of analytical mathematical model of the system in research and contributions to automation control concept. There are three online analytical (software) or systematic redundancy methods is predominantly methodised into three which are; signal processing based, model-based methods and knowledge-based methods which help to modernise the on-line process performance.

A. The signal processed based (SPB) method

This simply allows the demonstration of a physical, descriptive, abstract to be generally selected as signals from the system to give enough information on potential failure notice as in Figure 2.6a. Faults can be identified by choosing symptoms from the signals. This process involves earlier information about the relationship among symptoms from the signals and unexpected changes. Utilizing a mathematical model with the aid of frequency or time domain, it is assumed that signals can carry positive information about faults that can help to identify and detect any changes that occurred. Standard indicators of SPB are magnitude of a time domain function, or spectral frequency analysis, Fourier transforms are representative of function in frequency domain which is predominantly designed for the monitoring of states at given conditions. SPB notion is to give a good chance of fault validity test established on physical laws that would provide information about faults but are limited in their effectiveness in identifying early fault that could occur in a dynamic system [17]. Abnormalities from the standard performance have to be spotted by systems of abnormal changes recognition, the SPB method is principally described for condition monitoring at the constant state.

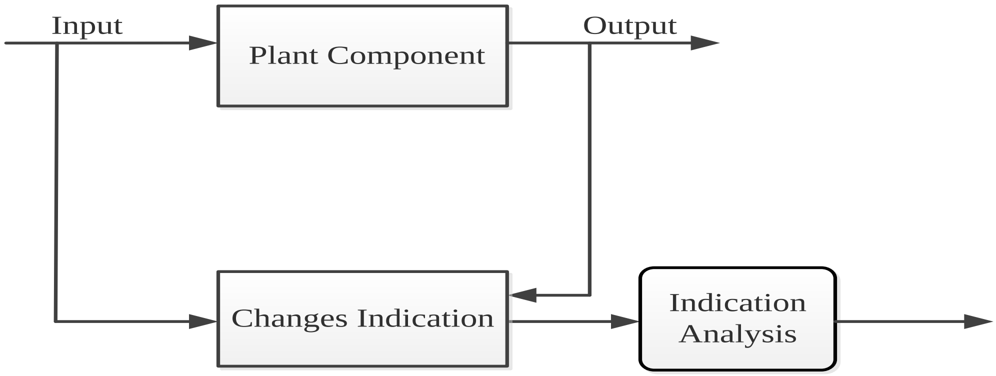


Figure 2.6*a*: Description of signal processed based validity method

B. Knowledge based techniques

Knowledge based approach (KBA) is kind of approach for collection of data to facilitate failure diagnosis information to sustain the whole condition stage and defined reports of developments to assist the advance reprocess of the information together during analysis which introduce computing intelligence. Gathering knowledge, responsibility information provides effective strategy for health management progress could be classified by historic data-driven based and identified by symptom based and qualitative model-based. The essential features of this knowledge established on gathering of true data, rules or information to deal with the ability to detect the fault condition and predict the behaviour of a system on previous performance or base on information that relates from knowledge established of the system. KBA makes employs traditional previous history and artificial intelligence methods in problem solving to support human judgment, knowledge and achievements act to model-based diagnosis [41]. KBA in the background of diagnosis proficient systems or in combination with a human professional is only achievable way by breaking the acquired knowledge into parts of well-defined facts, rules taken from behaviour of professionals. There was a later outline tool of fuzzy models as a different way to organise decision making which allows direct use of human normal intellect concept to make sound practical judgement as well as neural knowledge network to generate error residual, valuation and possibly indicate a possible cause. Diagnosis based on knowledge started around the 1980s, which was achieved established on the assessment of on-line observed information in terms of a set of instructions, knowledgeable by professionals from ancient knowledge. The ability to purpose under indecision, and the proficiency to explain the results provided. Some of the industrial applications are the supervisory control and data acquisition (SCADA) system and smart meters which are normally mounted in nowadays industrial computerization schemes, important to a great quantity of information accessible [59]. Knowledge based method requires information of the method by investigating the information history or difficult systems that cannot be model in contrast the model-based that requires mathematical mode of the observed process. These connected with both data from professional and human knowledge, mostly appropriate for large system whose model is difficult to get, alternative historical method information is available.

C. Model-based Techniques

The development of a model-based method, that makes use of mathematical models (which could be quantitative or qualitative) to mimic the healthy system behaviour and the reliability difference of the real system and the model to detect faults and symptom signals. Model-based FD employs previous information of the system to develop analytical mathematical models that can, in proper sequence, be used as conditions to estimate the current information. A good model has been achieved at a good condition the important of this method is residual generation which usually measures the predictability of the systems. The consistency is typically deliberated as residuals which represent symptom / indicator signal. *The residual is the function of time defined by the mathematical difference between the measured output variables process and the output estimated predicted model signal* also known to be *fault indicator*. All model-based approaches employ model of the observed system to generate an indicator alarm or sign. During the healthy working operation condition of the system, the residual is consider to be zero at fault free occasion, but in the event of fault, the indicator signal (residual) become slightly different from zero. Thus, model-based fault diagnosis *states the valuation of faults in a system from the observation of input/output available system measurements with previous information represented by the system's mathematical model, via residual quantities generation and their investigation.* To manage the behaviour of a healthy system thus, there is constantly inconsistency between the real system and the mathematical mimic model being monitored to identify faults.

2.3.4 Model-Based Justification

The concept of model-based re-construction of the system plant detailed the mathematical representation of dynamic systems in the real work and was distinguished by Jones in 1973 [3], [17]-[18]. The increase of calculation influence makes it likely to use systems description for suitable parameter model to real data. Hence, the representation of dynamic modelling for fault detection has gained more interests from both theoretical research and practical applications. Many data-driven techniques construct on the consistent handled data, which have been used in assigned model description and condition monitoring that could take significant time and expertise assistance of engineers and plant staff operators' prior accurate diagnoses of faults [42]-[46]. This approach is questionable to be active when a vital amount of faults can happen with parameter variation in practice.

The papers [47]-[49] investigated the time domain methods for estimating discrete models. In the 1980s, maximum record suggested review papers [26], [50]-[59] correspondingly, give a decent framework of recent model-based FDI techniques. In 1999, a unified background of model-based FDI was available in a book which exposed the foundational knowledge of model-based FDI. Fault detection is basically on generating a signal and comparing the physical measurements provided by the associated system model via the observer gain that is used to increase system stability as well as the accuracy of the system assessment. Residual-based is a kind of fault indicator that gives an alarm for possible present faults, which reveals failure condition or provides fault alarm of a supervised system and likewise gives a vital indication for an effective FD. For a faultless system, the reference model also calculates the system output precisely but if there is a fault, the output of the reference model differs from the real system output. A residual-based algorithm is a good tool for an active fault detection which normally holds a restricted capacity for fault estimation due to lack of access to the main plant component. Hence, a residual signal carries the most vital communication for an effective fault diagnosis [17] which reveals the probability of faults conditions and a decision rule (based on threshold testing) to determine if any faults have occurred on the monitored system as typically shown in Figure 2.6b. The modern standard technique phases of model-based was originally described by [3] as residual generation and decision-making (plus residual estimation). The state-of-art in the subject of FDI is still pretty new and presently getting substantial attention in the conventional engineering field and still open for knowledgeable contributions.

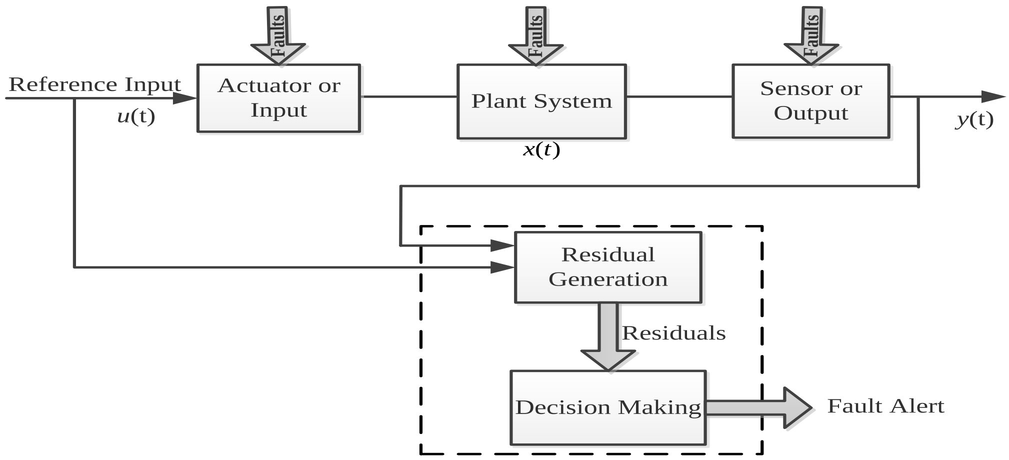


Figure 2.6*b*: Framework of model-based fault diagnosis

Residual generation can also be studied as an extensive of fault indication test whose input and output description behaviour are modelled as a technique for identifying faults information from the system. Faults in the controlled systems may be from an input (actuator) or output (sensor) signals or could within the plant system. Some researchers have been proposing new approaches in improvement of residual healthiness. The abstract model of the residual generation is to provide signal that carries information about any changes in the system and the location where there is abnormality. Meanwhile, it is frequently impossible to model a practical system accurately without interference of unknown disturbances and existence of uncertainties which often corrupt the fault message information generated by the residual signals. Model-based fault diagnosis is concerned with on-line monitoring of a normal working operation of a system. The context of residual evaluation, presents the signal processed-based (SPB) structures which is incorporated to the newest development technology for fault diagnosis. Among a number of estimation systems, the geometric methods proposed by Jones which was stated as "norm-based costing" (evaluate, compare and test) are the most standard which are regularly functional to succeed best support processing of the residual produced by an observer. These two costing systems, which typically produce guaranteed boundary that concerns all potential system uncertainties, disturbances and the changes in the system. Beyond the boundary specifies a fault in the process model that will announce an alarm signal as a fault indicator.

The analytical quantitative model-based started in the early 1970s, FDI tradition is considered into three main principles approaches: parity space, OB and parameter estimation techniques.

2.4 Parity Space Relation Model Approach

Parity state space model makes use of the knowledge about the model to improve the fault performance of the system. This also gives a derivative chance of scheming inappropriate diagnosis physically comparable to the OB model with unlike design ways. Parity is based on correct checking investigation of computation consistency of the monitored plant variable system, expressed in order to find the minimum for a quadratic form of a matrix [60]-[63]. The change of the system calculations focuses at separate diverse faults to improve their decision. Parity was first used to check the error reliability of a computer software and digital logics systems before it was later applied to FD as an indicator to point out the presence of failure in components of a system [3]. This approach was functional FDI to get tolerant information of quantities with error bound technique which was proposed to check and isolate the consistency of the redundant set of measurements, also to systematic residual problems [55]. However, this method was autonomously proposed by various authors among which are [26], [27] [49] and [58] recommended a parity relation design method in the discrete-time concern.

2.5 Observer-Based Approach

Luenberger was the first to discover the output of a system as an observer (motoring scheme) for deterministic system in 1964 and 1971 which has been widely employed extensively in various divisions of engineering and science for stable systems [34]. The diagnosis of observer system could be classified as regulatory system [37], [63] and [65] although Kalman filters (observer) proposed for unreliable (stochastic) system calculations [3]. OB modelling is an active system mainly via an online software device that permits provided an estimation of the unreachable states variables of a system is pragmatic. The basic idea of an observer is to substitute or replace the development model, which delivers a reliable estimate of the process output as well as provide design freedom for the designer to realize the anticipated behaviour. An observer is an active system that uses the actual available inputs and outputs (measurements) of a system to provide an online estimation of the unmeasured state variables [37] and [66]. The key idea of generation of residuals, and over the last two decades robustness has being the state-of-the-art concern. Basically an observer is an accurate online closed-loop dynamic system that uses the available quantities inputs and measured outputs to provide an estimation of the state variables that are not presented to be measured. The OB is a feedback matrix that motivates the detectability, handling of multiple faults and state estimation. The basic block diagram of Luenberger observer with precisely considered feedback gain matrix are as shown in Figure 2.7*a* & Figure 2.7*b*. This method allows output estimation errors to have indicator properties connected with some identified fault directions.

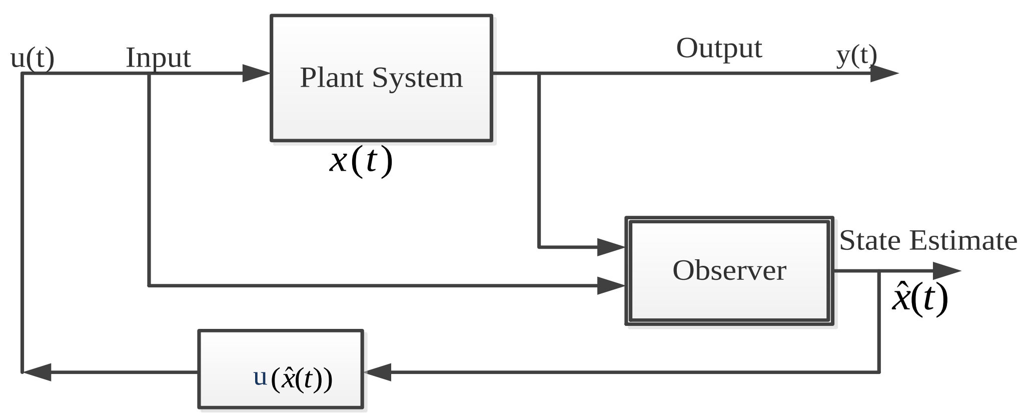


Figure 2.7*a*: Block diagram of an observer

The observer evaluate the real plant components, modifies the behaviour of a system in a desired way and compare it with the estimated signals, The observer uses general output residual signals to calculate the behaviour of the system from archived observations. Beard-Jones suggested failure detection observer, however, the robustness against uncertainties was not considered. Most researchers proposed this approach to improve fault robustness with respect to process parameter changes and unknown input signals entering the system. Among the accepted scheme for robust fault diagnosis (RFD) observer is to approach uncertainties express as differentiate disturbances label as unknown inputs and decouple it from residual thereby making it robust against model uncertainties (unknown inputs). [37] was the first that applied Luenberger observers for FDI and various sensor fault isolation schemes was later suggested by [63] - [71]. While the broad review in [68] recognized the place of observer-based techniques in model based FDI, by linear and non-linear observers with some demonstrated practical cases.

The Plant system original condition state is unidentified, while the observed state estimate is chosen randomly. Fault detection system is based on the plant system output error. Hence to determine the difference between the plant system state and the observed state estimate is considered to produce an error signal. The generated error; $x(t) - \hat{x}(t)$ is predictable to be zero or minimise to be nearly zero which is then used as a feedback signal into the observed system [69]. There is a certain sufficient amount of design freedom of benefits and challenges in the choice of an observer allow the eigenvalues of K to be dynamically freely chosen.

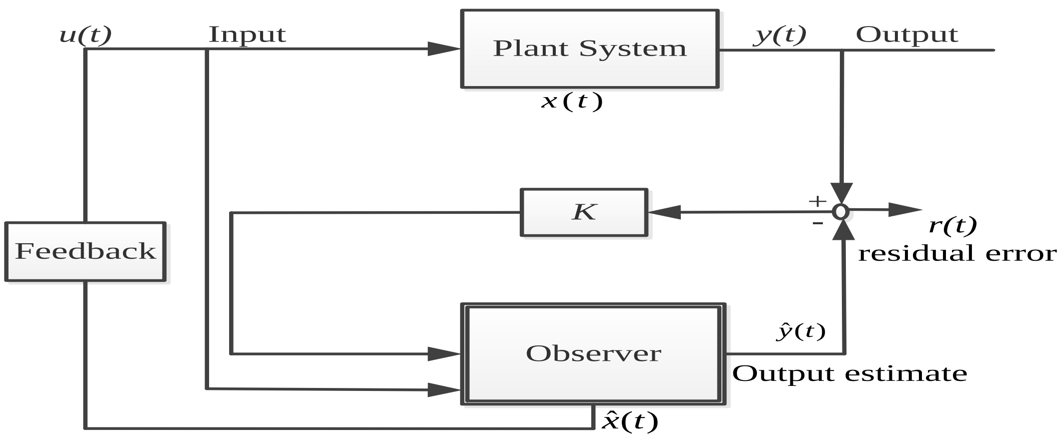


Figure 2.7*b*: Structure of Plant System Observer

The Plant system observer model is arranged such that K symbolizes the observer gain which is chosen as the observation error is reduced, this could affect the dynamic behaviour of the state estimate and hence the state error. The function of the feedback is to minimize the observation error to zero or approximately zero (at stable state) and through it the output of the observed system is fed back as an input of the plant system. Mathematically, we defined the observation error as $e(t) = x(t) - \hat{x}(t)$.

Fault detection model is developed if and only if the system (A, C) is observable, this promises the ability to choose K which assist to assign the eigenvalues of $A - KC$ randomly to detect a unidirectional fault [52]. In summary a linear state space with input and output relationship of single-input-single-output and multiple-input-multiple-output will be consider with transfer functions.

The linear system must have an equilibrium point of zero "0", and is stable if the eigenvalues of matrix A lies in the left-hand complex equation. To monitor a system, the system must be observable. The linear system is observable if the rank of its observability matrix is equal to n

$$\varphi_* = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix} \tag{2.1}$$

That is, where rank $\varphi_* = n$. Therefore, one can find a matrix K such that $(A - KC)$ is stable. The observer theory can produce the estimate of the state which can be further utilized for observer-based feedback controller design. Moreover, the observer can also give the estimate of the system output, which can be used to compare with the real-time output of the system process for the purpose of real-time monitoring and fault diagnosis. On-line monitoring tools not only provide early warning of plant malfunction (including loss of safety, environmental degradation, poor economy, etc.), but also information as to how to minimize maintenance schedule costs. Precise diagnostic information must be generated quickly to protect the plant / system from interrupted shut down and provide human operators with appropriate process status information to help take correct decisive actions not only when faults become serious but also when faults are developing and difficult to detect (also called incipient faults). It is clear that the application of supervised on-line diagnosis schemes can be profitable in terms of a decrease in service costs.

2.6 Parameter Estimation Model Approach

Parameter estimation (PE) technique is based on the assumption that faults are revealed in the physical system parameters identification. This approach is vital in precisely defining system behaviour through mathematical models such as algebraic likelihood sharing functions, parametric dynamic models. PE method develop balanced parameter report of an object, which is aimed at judging the position of an object or model data. Commonly, the total number of changes or achievement information is used to estimate the parameters of a particular system. This method was first shown clarified by [71]-[74] and has since been worked on to demonstrate the process of FD using estimation of unmeasurable process parameters and state variables, with up to date practical expansion [7] and [76]. The approach is that parameters of real development predictably use PE techniques to detect faults and the results processed are related with the parameters of the position model achieved originally under fault-free circumstances. Any significant difference indicates a change in the plant component and is often deduced as a fault illustrated in Figure 2.3.3. This approach is achieved based on the assumption that system parameters are changed when faults occur laterally with the total number of errors related with the evaluations and allow normal computation of errors. This technique was initially measured to resolve the performance of premature fault finding and analysis for serious systems which is fit for real operation in control applications, particularly in the framework of the modern industrial developments about calculating [77] and [78]. Since time delay has no limit, parameter estimation is problematic due to straight calculation of parameter estimate is impossible because of large amount of computation and physical parameters do not distinctively match to model correctly. To calculate the loss function error has to be reduced by mathematical optimization techniques since, the more computation is required as determination is much bigger and online real-time application is normally impossible. Furthermore, this approach combines parameter identification and experimental process knowledge whose performance is greatly dependants on the signal-to-noise ratio (SNR). Due to the immeasurability of real disturbance in the high-gain observer methods, disturbance estimates are needed for PE. The estimation of uncertainties involved in the observer makes the time delay has no limit which is problematic.

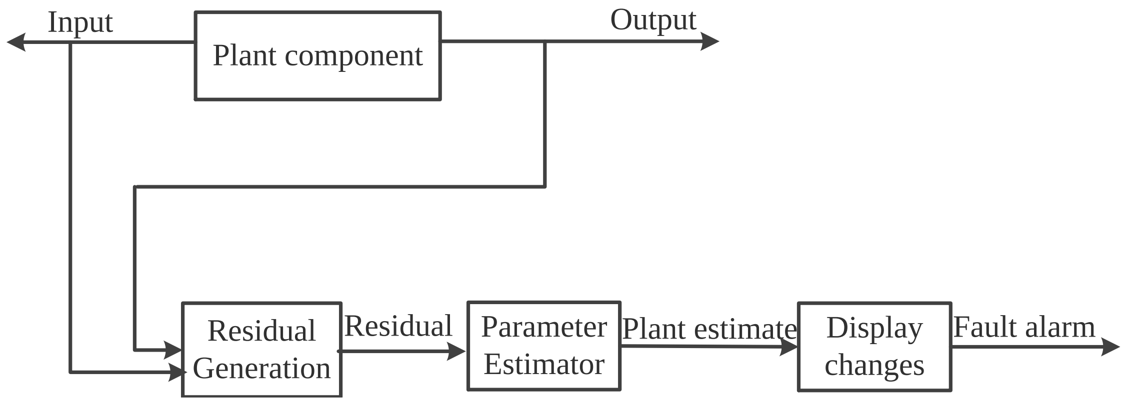


Figure 2.8: Representation of parameter estimate approach [17]

The outline of parameter estimation is performed on-line with the residual incorporated into the observer for fault diagnosis [17].

2.7 Significant Issues in residual generation of FDI

Model-based background pictured the true nature of the on-condition monitoring, of FDI state-of-the-art which discovered the contributed ideas of researchers' views to advances residuals generation by optimization analytical observers to monitor the system performance. Though the model-based system for residual generation has been predictable as an active method for FDI, but the essential issue of inevitable uncertainty modelling has remained entirely difficult. The emerging advancing applications of FDI, generally driven, by the demand for reliability, maintainability, availability and safety for controlled systems to be robust. There is constant need to frequently avoid high expensive at the event of plant respite period in the modern automotive industry. The difficulty concerning FDI schemes reliability is the uncertainty modelling as stated in the inductor session is unavoidable in real practical industrial systems. The scheme of an operative and reliable FDI system should be consider in modelling uncertainty during faults sensitivity detectability. Residual generation and errors are known as crucial problems in FD robustness, as assuming it is not observe properly in the presence of uncertainties, some fault information could be lost and degradation of the signal performance. Expected deterioration, is inevitable practically to happen in a model of a normal healthy working operation of a system possible due to the gap between the real system and the model system. The consequence of modelling uncertainties mostly caused by parameter differences, process noise and nonlinearities could downgrade the performance of system majorly triggering poor reliability of FDI schemes. Hence, the concern is vital in the robustness of model-based FDI theory and the clarification of this issue in practically applicability and significance of robustness has been extensively acknowledged by industry and academia. To conquer the problems of uncertainties received by any model as earlier stated in Chapter One, a model-based FDI has to be made effective, reliable and robust governing the importance of in FDI methods. The theory of robust FD is to measures the robustness and sensitivity of faults, firstly by the define performance index as a model of transfer function matrices (TFMs), then parameterise as a pole assignment method, eigenstructure Assignment parametrises the feedback gain matrix with eigenvalues and a set of free parameters, in addition to the benefits, also gives design freedom and randomly assigns the closed loop poles to desired places [4], [57], [79] and [80] and lastly optimize to solve the proposed concerns.

The nature of model-based FDI is the construction of residuals, and the robustness has become the main problem of observer (filter)-based approaches [24]. As one of principal methodologies, robust fault detection has been developed more than two decades [2]-[4], [19] and [57]. The following detection methods are briefly summarized in [9], [52], [53], [63] and [81]. The model-based FDI practice requires a high mathematical precision account of the observed system in order to monitor the performance of uncertainties which is extremely allocated by a signal-to-noise ratio (SNR) [18]. The system can be developed to be less sensitive to uncertainty modelling a right accurate model is not essentially required. The healthier model signifies the improve system dynamic performance of the FDI accuracy.

2.8 Summary

This section presents the fundamentals of diagnosis, the various ways it was briefly outlined, the revised past techniques for identifying faults like FMEA which is done offline naturally as a reliability engineering activity, which is independent of current conditions or faults that were studied. Diagnosis is done to determine one or more root causes of problems and to obtain evidence of changes based on observable symptoms / signals. Looking at the on-line diagnosis based on sensor information with signal fault which led to the concept of fault diagnosis overview was defined with the three overall basics tasks of defining fault diagnosis. The traditional physical hardware redundancy via the degradation of system, signal-based process can identify faults by intellectual symptoms from the generated signal which provides faults information. The model-based analytical way of diagnosing faults by mathematical model was also introduced, whereby the model-based is further considered and studied by parity space model approach, Luenberger observer-based and parameter estimation model approach. A common design for failure diagnosis in a system has been presented and a relation to methods based on propositional logic as indicated. Finally, the analytical-redundancy was further extended to knowledge based where the health management is achieved by human facts, understanding, evaluation and acknowledged history. The information is recognised by qualitative based methods which are an interpretation of the totally observed, adequate understanding of the behaviour and the cause that manage such performance and symptom based like a change present in the condition of a system. Some earliest work on dynamic observers has been done, but the attentions have been mostly on robustness in model-based fault diagnosis which has been a key issue in fault diagnosis community. Observer-based robust fault detection dynamic system has received much attention during the last years and brief major challenges of FDI were introduced. Different variations and techniques were also discussed and it was concluded that there still exists the requirement to come up with a better technique such that uncertainties and parameter perturbation need to be dealt with. Now, in the subsequent chapters of this study, newer modified methods will be proposed and explained investigating for quality of residual bank on the FD success, also, the dynamic model-based fault information will be further investigated.

Chapter Three: Robust Observer Based Fault Detection Approach

"An error doesn't become a mistake until you refuse to correct it".

O.A Batista

3.1 Introduction

An overview of the observer-based robust fault detection technology (OBRFDT) is presented in this chapter to give critical appraisal of contributed methods related to the subject of study. Over the years many approaches have been proposed for achieving robustness which has being one of the key issues in fault diagnosis community. The fast rising for dynamic system is becoming complicated and management are innovatory to improve the overall critical safety reliable conditions. Most researchers' concise uncertainties as disturbances functional on the system [7], marked out the effect of modelling faults on FDI behaviour [77] which was the first to challenge the robustness increase in observer-based FDI method. Inappropriately, modelling errors often lead to a poor degradation in the system performance. Nevertheless, disturbances and modelling errors are predictable in complex industrial system, for these reasons it is vital to improve the robustness in fault diagnosis system. The central of observer-based (OB) FD is the generation of residuals, and the robustness being contributing to be the attractive issue in the last two decades. Amongst the methods contributions to robustness in modern control-based robust fault diagnosis is the residuals generation which are the differences between model predictions and measured outputs, here, the uncertainties and faults often disturb the residual. Hence the design decision, in this situation impacts to become challenging to be distinguish. So, there is need to maintain a healthy operational system to have a good FD robustness that will be sensitive to various typical type of faults irrespective of any natural disaster and uncertainties that might practically act on the real system [3].

3.2 Background of Robust Fault Detection

In the simple terms, robustness issues have generally gained a considerable attention with various operational methodologies. Over the years, neural networks as an ideal estimated means for management of non-linear complications was suggested to overcome problems in predictable stable-state systems for handling nonlinearity that is it is not effective in indicating linear systems. There is petite to be achieved by practicing neural networks to linear time-constant systems. Neural networks are properly intended at developments that are inaccurate, complicated, nonlinear and indeterminate. This can be used in several of techniques to challenge fault diagnosis issues for non-linear dynamic systems. It may be effective to use for only system outputs to identify faults for some stationary systems, but this is not the case for detecting faults in dynamic systems because the change in system inputs can also affect unpreventable types of the system outputs. This approach is suitable for non-linear system, which makes it not very dynamic in describing linear system and could be complicated as well as also inefficient to apply to a linear system [38].

To challenge robustness problem, one of the general acceptable technique to handle modelling uncertainties as a characteristic of unknown input observer (UIO) which simply means to decoupled uncertainties from residual signal according to [30]. UIO is a remarkable way for explaining robust fault diagnosis, which has received much attention during the last three decades [78]-[79]. More researchers have facilitates de-coupling of disturbances to be accomplished by using UIO and lots of contributions has also been made [3], [80]-[84] which are extended to nonlinear systems and [82] or alternately eigenstructure approaches. Some of the theory for UIOs is that the unknown input distribution matrix has been given significance, while some of the hypothesis is that decoupled disturbances, in the situation of the distribution matrix for model uncertainties is usually anonymous. The presence circumstances for comprehensive decoupling have been originated in the UIO approach [31], [85]- [87], through eigenstructure assignment approach by Patton [88] - [90], properly. The complete disturbance decoupling, still, might not be potentially possible, in some events, because the absence of design freedom. It also noticed that most conventional UIO techniques are under the assumption that unknown inputs can be completely decoupled [91]. Nevertheless, this assumption cannot always be met in some practical systems. Additionally, it may be difficult due to the impact of fault performance to be detached alongside. If the satisfactory state of comprehensive decouple is not encountered, an estimated method would be hired. In this condition, the residual is not entirely decoupled from disturbances, nevertheless has a small sensitivity to disturbances and high sensitivity to faults.

Another concept to achieved disturbance decoupling design is by frequency domain design investigation method known as H_∞ norm optimization techniques index [62],[92] suggested to increase the robustness of frequency and [93] which are excellent in handling resolved bounded disturbances caused by modelling uncertainties with some robustness promise FD.

Whose objective was to reduce the influence of disturbances and modelling errors on the estimation error and successively on the residual using optimally robust fault detection observers for creating analytical redundancy. Some complex frequency optimization process was suggested to design robust FD. H_2 norm (also known as Kalman observer for optimal design built on stochastic noise model with recognized power spectrum output) [94], but this approach is very complex to parameter changes or unknown disturbances while some proposed to achieve robustness objective by using optimization approach to minimize disturbances to its minimal using performance index in regards to the norm of transfer function matrices (TFMs). Some gave a mixed approach of H_2/H_∞ [95]-[96] discourse to support the model uncertainty considering to improve tradeoff of observation and attenuation performance and H_-/H_∞ [97]-[102] were also recommended, H_- norm is for enhancement impact of faults by maximising the minimum TFMs cost of fault sensitivity. The problems with H_∞ norm complication which requires calculation of the whole frequency range $[0,\ \pi]$ and to definite the particular value of a matrix which makes the computation problem too heavy for the optimization algorithm to evaluates the objective function. Also, the other disadvantage of this approach is best at the poorest event occurrence which mostly produced by the system plant and not by exterior disturbance frequency for providing the most basic performance guarantee. Though, the present record of ORFD designs are proposed in both continuous and discrete-time domain or based on H_∞ [18], and [100]. The frequency domain robust FDI is unsuccessful in dealing with modelling errors though it can challenge disturbances and fault issues and the serious challenge is absence of design software as well as due to bandwidth selection that avoid comprehensive approval of this method.

An observer is likely to be robust to disturbance, if the performance index is optimized at the disturbance frequency relatively to the nastiest incident mostly determined by the plant. The conventional H_∞ optimisation method was to clarify the Algebraic Riccati Equation [100]-[102] which consider integrating modelling uncertainty into standard optimization problem. This best observation issue was advised to be explained with the aid of a prescribed linear matrix in equations (LMIs) [94], [99] and [103] as a convex optimization tool, this method was successful in the simultaneously in view of disturbance robustness and fault sensitivity. However, the subject of dealing with modelling uncertainty is yet to be investigated fully. Alternative method is frequency dependent weighting functions practice as in [104]. Preventing guaranty of worst case, the performance index is recommended by switching TFMs H_∞ norm will require the evaluation of disturbance frequency with a mathematical matrix norm. With the parametric eigenstructure to parameterise and optimise by minimising the performance index having a measure of the effects of both disturbance and faults over a specified range [102] and [104] in the event where the decoupling conditions is not met. Another suggestion on how to explain the FDI robustness problem is a mathematical illustration for defining modeling uncertainties is required. Numerous outlines to characterize modelling uncertainties from many causes as additive disturbances with an estimated distribution matrix [105]-[107], [51], and [91], based on decoupling condition method for robust FDI, the practical operation of fault is complex. One of the contributions is assumption that disturbance matrices are identified, but the theory is not effective for most practical system. [27] and [105] have some outcomes to lead off for applied practical application of robust FDI approach. Frequently, the eigenstructure assignment has concerned more debate in parameterisation, because the observer gain matrix and the performance index (stated in terms of TFMs) can simply expressed explored in a certain eigenstructure system with align of eigenvalues (poles) and secure free parameters [90] and [100]. Then, many iterative accepted optimisation algorithms, such as gradient search [75], Genetic Algorithms [107] - [118] are used to find the optimal gain filter matrix in order to further attenuate uncertainties.

3.3 Design Idea of Robust Observer-Based Fault Detector

The basic theory is to degree the robustness and sensitivity by an appropriate performance index and then improve it. The idea of decoupling the impacts of residual on model uncertainties explains the difficulty of FDI robustness of which lots of work has been broadly contributed to this subject [29]-[34], [28], [39] and [40]. Sensor faults have direct impacts on the measurement outputs, therefore the sensor faults would not be so difficult to be detected by using the residual (fault indicator). Many results on sensor FDD are available in the literature, e.g., see [80]-[82]. The proposal of robust actuator fault detection isolation system (AFDIS) as confirmed in a chemical process system [38] and [83]. Robust element FDI method was also suggested by [36]-[37] using observation approach to solve uncertainties which is simply comparable to UIO. However, actuator faults have unplanned impacts on the measurement outputs; therefore, it is more challenging to detect actuator faults from the residual More contributions were also made on AFDIS, nevertheless, the robustness concern was not considered in this case [46] and [87]. According to [80], approach robustness problem and also elimination of disturbances effects on residuals are performed with inflexible conditions applied to the open-loop which is also often not practicable. On the other hand, performance index is measured suitable for robust residual design which reveal a justification for both faults sensitivity and consequence of modeling uncertainty. Gathering, this theory, [13]-[14] calculated the strategy of optimal parity relations by assuming an improved performance index which is the relationship of the modeling uncertainty response consequence to that of fault sensitivity. Though, the modelling uncertainty account was measured to be bounded, while the unknown input (or disturbance) explanation which is difficult to represent in an extensive choice of uncertain situations without any modification and approximation. This inadequate factor was as a result of applied application matching in a simple academic application or model situation.

Based on the existing background and inspiration briefly stated in chapter one and chapter two, the observer-based continuous time fault detection design via eigenstructure assignment and GA optimization will be investigated in this study to achieves a better performance than other methods. Generally these indicators are defined in a practical type of behaviours representing abrupt also known as step and incipient faults recognized as ramp (bias or drift), respectively. Figure 3.1 illustrates the scheme of model-based fault detection for systems subjected to faults (e.g., actuator faults $f_a(t)$, sensor faults $f_s(t)$, and parameter faults $f_c(t)$ and disturbances (e.g., input disturbances $d_a(t)$, process disturbances $d_c(t)$ and measurement disturbances $d_s(t)$.

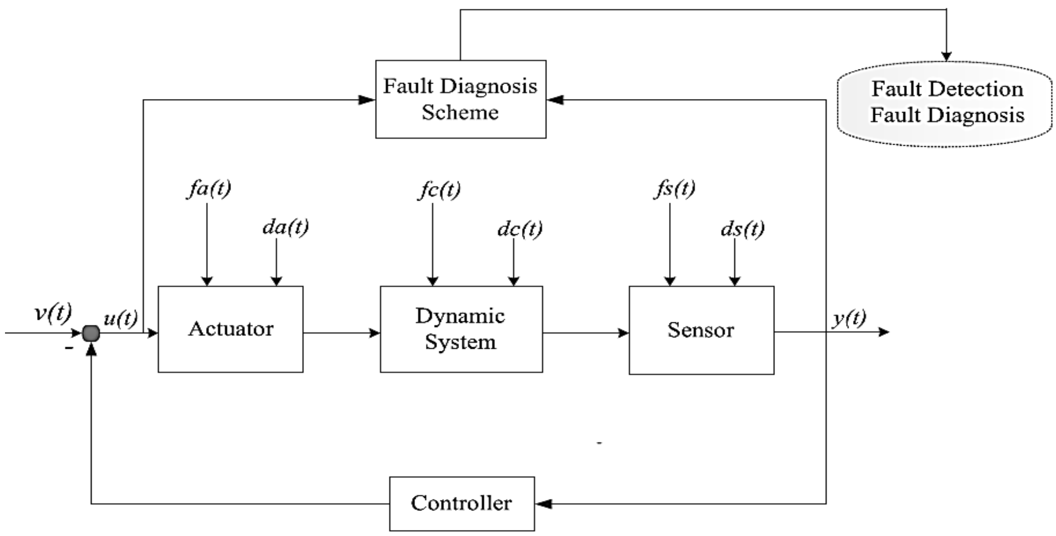


Figure 3.1: Scheme of model-based fault diagnosis

Consider a general case of a dynamic system degraded by disturbances, actuator and sensor faults in a continuous state spaces linear system:

$$
\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_a f_a(t) + B_{da} d_a(t) \\ y(t) = Cx(t) + D_s f_s(t) + D_{ds} d_s(t) \end{cases} \tag{3.1}
$$

where $x \epsilon \Re^n$ is the state vector, $u \in \Re^m$ is the system control input, $y \epsilon R^p$ is the measurement output; A, B, C are known matrices of appropriate dimensions; $f_a \in \Re^{k_a}$ and $f_s \in \Re^{k_s}$ represents actuator and sensor fault vector, B_a , D_s are the distribution matrices of the actuator fault and sensor fault, respectively; $d_a \in \Re^{l_a}$ and $d \in \Re^{l_s}$ represent input and output disturbance vector, B_{da} and D_{ds} are the distribution matrices of input and output disturbances.

Let

$$
f(t) = \begin{bmatrix} f_a(t) \\ f_s(t) \end{bmatrix}, d(t) = \begin{bmatrix} d_a(t) \\ d_s(t) \end{bmatrix},
$$

$$
B_f = [B_a \quad 0_{n \times k_s}],\ D_f = [0_{p \times k_a} \quad D_s],
$$

$$
B_d = [B_{da} \quad 0_{n \times l_s}], D_d = [0_{p \times l_a} \quad D_{ds}].
$$

Therefore, the system (3.1) can be rewritten as

$$
\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = Cx(t) + D_f f(t) + D_d d(t) \end{cases} \tag{3.2}
$$

The scheme of the observer-based fault detection filter is shown in Figure 3.2.

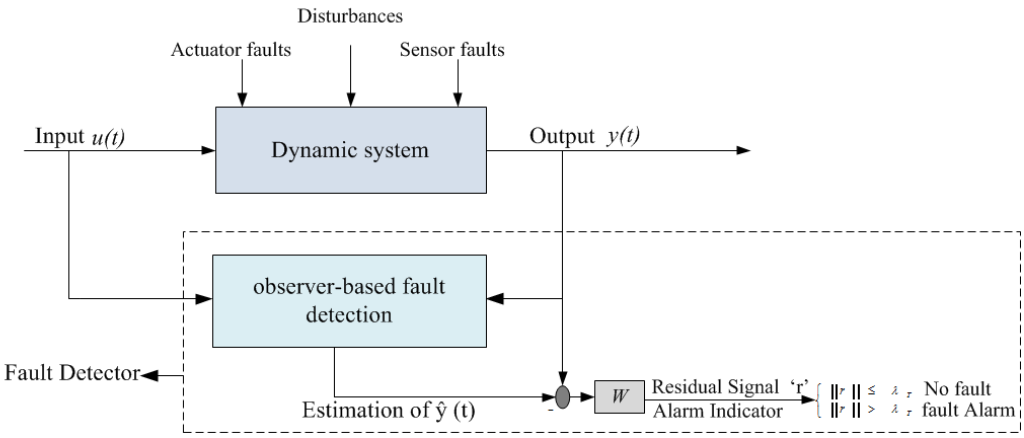


Figure 3.2: Scheme of observer-based fault detection filter

From Figure 3.2, one can see the measureable input and output are used to construct an observer-based fault detector, which can give the estimate of the system output of the real-time dynamic process. The residual is defined as the weighted term of the difference of the real-time output and estimated output. If the residual signal is zero (disturbances are not considered) or less than a threshold value λ (under disturbances/noises environment), the system is healthy. Otherwise, If the residual signal is not zero (disturbances are not considered) or larger than a threshold value λ (under disturbances/noises environment), the system is faulty, giving an alarm.

However, to design an observer-based fault detector shown by Figure 3.2 is the task of the session.

The observer-based fault detection filter can be described as:

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K(y - \hat{y}) \\ \hat{y}(t) = C\hat{x}(t) \\ r(t) = W\big(y(t) - \hat{y}(t)\big) \end{cases} \tag{3.3}$$

where $\hat{x}(t) \in \Re^n$ is the estimate of the state $x(t)$, $\hat{y}(t) \in \Re^m$ is the estimate of the system output $y(t)$; *the residual signal is the weighted difference between the real output* $y(t)$ *and the estimated output* $\hat{y}(t)$, defined by $r(t) = W(t)\big(y(t) - \hat{y}(t)\big)$.

Letting $e(t) = x(t) - \hat{x}(t)$, and using (3.2) and (3.3), one has the following form:

$$\begin{cases} \dot{e}(t) = (A - KC)e(t) + \big(B_f - KD_f\big)f(t) + (B_d - KD_d)d(t) \\ r(t) = W\left[\Big(Ce(t) + D_f f(t) + D_d d(t)\Big)\right] \end{cases} \tag{3.4}$$

For simplicity, one chooses $W = I$, here. Taking the Laplace transform for (3.4), one has

$$r(s) = H_d(s)d(s) + H_f(s)f(s) \tag{3.5}$$

where

$$\begin{cases} H_d(s) = C(sI - A + KC)^{-1}(B_d - KD_d) + D_d \\ H_f(s) = C(sI - A + KC)^{-1}\big(B_f - KD_f\big) + D_f \end{cases} \tag{3.6}$$

where $H_d(s)$ denotes the transformation matrix of disturbance $d(s)$, $H_f(s)$ is the transfer matrix of the fault $f(s)$. In order to make the estimation error dynamics (or the dynamics of the fault detection filter) stable, the eigenvalues of $A - KC$ should be stable, that is, all the eigenvalues of $A - KC$ should locate at the open half-complex plane.

It is noted that the residual signal in (3.5) is corrupted by both the faults signal and disturbances signal. Therefore, the key task is how to distinguish the effects of the faults from the influences of the disturbances. In other words, the desirable residual should be robust against disturbances, but sensitive to the faults. In order to achieve this, the observer K should be solved satisfying the following optimal index:

$$J = \frac{\|H_d(s)\|_{s=j\omega_d}}{\|H_f(s)\|_{s=0}} \tag{3.7}$$

In (3.7), ω_d is the frequency of the dominant disturbance component, which can be obtained by using signal processing method; for instance, one can observed by using the Fourier Transform Analysis on the output signal of the healthy system. The faults concerns are incipient faults (represented as ramp signals) and abrupt faults (represented by step signals), which are two typical faults in engineering practices. As a result, the frequency of the fault can be assumed to be zero. By solving the above optimal problem, one can obtain an optimal fault detection filter so that the residual is robust against the dominant faults, but sensitive to the concerned abrupt faults and incipient faults. More specifically, the subsequent criteria should be achieved:

- Stability: The eigenvalues of $A - KC$ should be assigned to located at the open, left-half complex plane.
- Robustness: To improve the robustness against dominant disturbances by minimizing $\|(sI - A + KC)^{-1}(B_d - KD_d) + D_d\|$ when $s = j\omega_d$.
- Sensitivities: To improve the sensitivity to the faults by maximizing $\|C(sI - A + KC)^{-1}(B_f - KD_f) + D_f\|$ when $s = j0$.

where the operator $\|\cdot\|$ represents the Frobenius transfer function matrix norm.

It is noted that K is the matrix to be establish, therefore it is not straightforward to solve the optimal problem described by (3.7). A natural idea is how to transfer the optimization problem for seeking an optimal K into an optimisation problem for considering a set of scalars, which will be addressed in the next sub-session.

3.4 Eigenstructure Assignment Techniques

During the last the 20 years, several authors have advanced robust residual generators design using the eigenstructure assignment to parameterise, of which some left eigenvectors of the observer are allocated equal-sided to the disturbance distribution guidelines which simply implies that the residual can be made robust against disturbances. The eigenstructure assignment is a technique used to allocate the entire eigenstructure (eigenvalues and eigenvectors) of a linear system through feedback control law, which is selected to give the parameterization of the gain matrix K according to [80]. This means the pole assignment method, of which eigenstructure assignment parametrises the feedback gain matrix with eigenvalues and a set of free parameters, which assigns the closed loop poles arbitrarily to desired places. One of the benefits of employing the parametric eigenstructure design is that the eigenvalues can be detailed in determining the position of poles prior to vital residual responses. Here, the eigenstructure assignment method is chosen to give the parameterization of the gain matrix K driven by [53], [79] and [123].

The multi-objective function is used to minimize the objective function because it is dual problems of robustness and sensitivity that needs to be solved. This method was originally proposed and has been more contributed practically by Patton *et al*. of which other researchers also considered the left observer eigenvectors assignment to appropriately achieve robustness. This technique illustrates the continuous time or discrete-time robust fault detection observer and system TFMs to have design freedom by a free set of closed-loop poles as lot of literature has revealed it. Eigenvalue assignment techniques in the system matrix of observer dynamics design to arbitrarily assign the eigenvalues of $(A - KC)$ poles to assign places λ_i by choosing an appropriate observer matrix $K \epsilon \Re^{n\times p}$ to satisfy certain additional performance indices [4], [86], [88], [92], [100], [119]-[126]. The observer gain matrix K in (3.2) and the TFMs $H_d(s)$, $H_f(s)$ [104] applied to optimization algorithm essential to be firstly parameterised.

The mathematical expression of the relationship among eigenvalues, eigenvectors and the observer gain can be shown as:

$$(A - KC)^T v_i = \lambda_i v_i \tag{3.8}$$

where $A - KC$ is the system matrix of the observer dynamics, λ_i is the ith eigenvalue of the system matrix $A - KC$, and v_i is the corresponding of $\lambda_{i.}$ The observer poles can be either real or complex-conjugate. It is assumed to have both n_r real poles: $\lambda_i(i = 1,2, \dots \dots, n_r)$, and n_c pair of complex-conjugate eigenvalues: $v_{j,re} \pm jv_{j,im}(j = 1, \dots \dots, n_c)$. It is evident that:

$$n_r + 2n_c = n, \tag{3.9}$$

The reformation of the observer gain K can be addressed by considering both real eigenvalue case and complex conjugate eigenvalue case as follows.

A). Real eigenvalue case

Assume one has n_r real eigenvalues among the observer eigenvalue. As defined in (3.10), v_i is the ith right eigenvector of $(A - KC)^T$ corresponding to the ith eigenvalue λ_i of $(A - KC)^T$, that is, $(A - KC)^T v_i = \lambda_i v_i$. One can obtain

$$v_i = -(\lambda_i I - A^T)^{-1} C^T w_i \tag{3.10}$$

$$w_i = K^T v_i \tag{3.11}$$

where $i = 1, 2, \cdots, n_r$.

B). Complex-conjugate eigenvalue case

Assume one has n_c pair of complex-conjugate eigenvalues. $v_{j,re} + jv_{j,im}$ represents the jth right eigenvector of $(A - KC)^{\mathrm{T}}$ corresponding to the jth eigenvalue $\lambda_{j,re} + j\lambda_{j,im}$ of $(A - KC)^T$. It is evident that

$$(A^T - C^T K^T)\left(\mathrm{v_{j,re}} + \mathrm{jv_{j,im}}\right) = \left(\lambda_{\mathrm{j,re}} + \mathrm{j}\lambda_{\mathrm{j,im}}\right)\left(\mathrm{v_{j,re}} + \mathrm{jv_{j,im}}\right) \tag{3.12}$$

which is equivalent to:

$$\begin{cases} \left(\lambda_{\mathrm{j,re}}\mathrm{I} - A^T\right)\mathrm{v_{j,re}} - \lambda_{\mathrm{j,im}}\mathrm{v_{j,im}} = -C^T K^T \mathrm{v_{j,re}} \\ \lambda_{\mathrm{j,im}}\mathrm{v_{j,re}} + \left(\lambda_{\mathrm{j,re}}\mathrm{I} - A^T\right)\mathrm{v_{j,im}} = -C^T K^T \mathrm{v_{j,im}} \end{cases} \tag{3.13}$$

From (3.13), one can obtain

$$\begin{bmatrix} v_{j,re} \\ v_{j,im} \end{bmatrix} = -\Gamma_j^{-1} \Omega_c \begin{bmatrix} w_{j,re} \\ w_{j,im} \end{bmatrix} \tag{3.14}$$

where $\mathrm{j} = 1, 2, \cdots, n_c$, and

$$\begin{cases} w_{j,re} = K^T v_{j,re} \\ w_{j,im} = K^T v_{j,im} \end{cases} \tag{3.15}$$

$$\Gamma_j = \begin{bmatrix} \lambda_{j,re} I - A^T & -\lambda_{j,im} I \\ \lambda_{j,im} I & \lambda_{j,re} I - A^T \end{bmatrix}, \tag{3.16}$$

$$\Omega_c = \begin{bmatrix} C^T & 0 \\ 0 & C^T \end{bmatrix}. \tag{3.17}$$

Let

$$W = \left[w_1 \cdots w_{n_r}\, w_{1,re} \cdots w_{n_c,re}\, w_{1,im} \cdots w_{n_c,im}\right] \in \Re^{p \times n} \tag{3.18}$$

$$V = \left[v_1 \cdots v_{n_r}\, v_{1,re} \cdots v_{n_c,re}\, v_{1,im} \cdots v_{n_c,im}\right] \in \Re^{n \times n} \tag{3.19}$$

According to (3.11) and (3.15), one has

$$W = K^T V \tag{3.20}$$

leading to

$$K = [WV^{-1}]^T \tag{3.21}$$

As a result, seeking an optimal K can be transformed to searching a set of optimal scalar parameters:

$$\{\lambda_1, \cdots \lambda_{n_r}, \lambda_{1,re}, \cdots, \lambda_{n_c,re}, \lambda_{1,im}, \cdots, \lambda_{n_c,im}, w_1 \cdots w_{n_r}\ w_{1,re} \cdots w_{n_c,re}\ w_{1,im} \cdots w_{n_c,im}\} \tag{3.22}$$

3.5 The Cost Function for Optimisation

The cost function can be formulated as follows:

$$\frac{\|H_d(s)\|}{\|H_f(s_0)\|} = \frac{\|(sI-A+KC)^{-1}\bar{B}_d+\bar{D}_d\|}{\|C(s_0I-A+KC)^{-1}(B_f-KD_f)+D_f\|} \tag{3.23}$$

where $s_0 = j\omega_f$, $s = j\omega_d$, i; ω_f is the angular frequency of the fault signal. The concerned fault signal (abrupt fault and incipient fault) is low-frequency signal, therefore, ω_f is chosen as zero in this study. ω_d is the frequency of the dominant uncertainty (e.g., modelling error, process disturbances), which can be obtained by using Fourier transform analysis.

Minimization of the cost function (3.33) indicates to maximize the effects from the fault signals, but minimize the effect from the disturbances. As a result, the cost function (3.23) can be used to produce a robust optimal design K for the observer-based fault detector.

From (3.21), $K = [WV^{-1}]^T$, where W and V can be determined by the set of the scalar parameters:

$$\Theta = \{\lambda_1, \cdots \lambda_{n_r}, \lambda_{1,re}, \cdots, \lambda_{n_c,re}, \lambda_{1,im}, \cdots, \lambda_{n_c,im}, w_1 \cdots w_{n_r}\ w_{1,re} \cdots w_{n_c,re}\ w_{1,im} \cdots w_{n_c,im}\} \tag{3.24}$$

As result, the matrix K in the cost function can be replaced the scalar parameter set denoted by (3.24). There is a variety of optimisation methods can be used to solve (3.23). In this study, Genetic algorithm (GA) will be utilised.

3.6 Genetic Algorithm (GA)

Genetic algorithm (GA) is a stochastic optimization method for solving constrained and unconstrained problems based on natural selection that is a process that inspires biological evolution. Algorithm is known as a precise procedure of guidelines on how to execute a task / a highly effective method for problem solving. GAs is a search algorithm based on the system of natural selection and natural genetics, that is a non-linear search evolutionary optimization algorithms motivated by the biological (natural) methods of natural selection and survival of the fittest mainly for optimising models. This universal philosophy is employed to solve the robustness concern in model-based FD. To tentatively find the effective cost or locate the main practicable best performance solution of a physical/behavioural representative by optimisation techniques is known as GA. GA is an Artificial Intelligence (*AI*) for solving extensive collection of problems naturally based on searching rule to exhibit robust quality anticipated search set which guide the design process [123].

3.6.1 Overview of GAs

GA is employed to search a dominant global optimal population solution to complex problem which combine Charles Darwin philosophy of survival of the fittest approach to reduce the unhealthy features of weak survivor and casually exchange information. Recently advanced tolerant soft computing method in artificial intelligence, GA was inspired by Darwin's philosophy of natural selection by the survival of the fittest and evolution. The theory of GA was first published in 1975 by Holland [109]-[113] who was the first founder to experimentally mimic the observed process in natural evolution in the field of GA inspired by Darwin's Adaptation in Natural and artificial systems to solve optimization problems. The application was successfully implemented by Goldberg in 1989 [114] and lot of research and applications were reported in the last two decades [115]-[119]. The principle of "survival of the fittest" is effective in each generation in respect to the fact that only the fit chromosome (population) only adapt to the environmental influences where there is potential to distribute their hereditary formation to next generation. In the natural genetics, genes are represented as chromosomes that express the physical features of individual's specific values of parameters. Traits of individuals are passed to next generations by GA operator that would later be discuss in this section. Another thought of applying the optimization purposes are the minimization of consequence respect to the modeling uncertainty and the maximization of fault sensitivity. Collectively the applied principle is comprehensive as a multi-objective optimization (considered as more than one problem) which is explained by establishing a "*mixed*" or compound goal optimization purpose problem.

3.6.2 Advantages of GAs

The multi-objective optimization is applied to minimise the dual optimization objective function of robustness and sensitivity through GA that was originally designed for natural selection. GAs is a useful tool that is capable of solving large complex problems which is apparently difficult to be solved using other traditional techniques. Today, study on GAs is comprehensive growing since early 1970 from computing to practical engineering and other branches of sciences where there is quest of optimization concern. Computer-based GA has been successful to model and described the evolution behaviour of fault analysis of observation concerns approach. GA is employed to search a paramount global optimal population solution to complex problem which combine Charles Darwin philosophy of survival of the fittest approach to reduce the unhealthy features of weak survivor and casually exchange information. GA avoids the cumbersome complexity requirement for calculation of cost function gradients. For the design problem presented in this section, the calculation of gradients is very complicated. Even the calculation of gradients is straight-forward, the GA procedure is less problem-dependent because the only problem-specific requirement is the ability to evaluate the trial solutions for relative fitness. Another benefit of GA is that it increases the possibility of finding the global optimum. GAs constitutes a parallel search of the solution space, as opposed to a point-by-point search in gradient-descent methods. By using a population of trial solutions, the GA can effectively explore many regions of the search space simultaneously, rather than a single region. This is one of the reasons why GAs is less sensitive to local minima. This is especially important when the cost function is not smooth, e.g. the maximal singular value functions used in this paper. Finally, GAs manipulate representations of potential solutions, rather than the solutions themselves, and consequently do not require a complete understanding or model of the problem. Multi-objective is a GA technique employed as a decision making tool to represent, define or solving to improve inconsistent of more than one objective functions simultaneously.

3.6.3 Flow Chart of GA Optimisation and Design Procedure

The binary GA is the most commonly used where the variables are changed into bit numbers with the encoding of the values of chromosome (gene) parameters operating in the population. GA operates with an initial random population using a stochastic operator to determine the global optimum for the solution to a given problem. The local optimum can be determined using other optimization methods like calculus based methods. The vital knowledge in GA is to exchange a set of population from initial random places to a global minimum point. GAs further adopts probabilistic standard operation in the investigation procedure, and they can usually predict better optimisation performances for challenging, irregular and multi-model tasks. To produce a new population with better individuals, the GA modifies population of individual solutions repeatedly. Although their nature distinctiveness and flexibility application abilities makes it stand out amongst other optimization method, that promise GA to potentially find the global solution, though, this is employed for attenuating external disturbances and model uncertainties they frequently determine a satisfactory (acceptable) relatively rapidly realization. The structure flow chart of GA is shown below in accordance to solving FD complex issues [3].

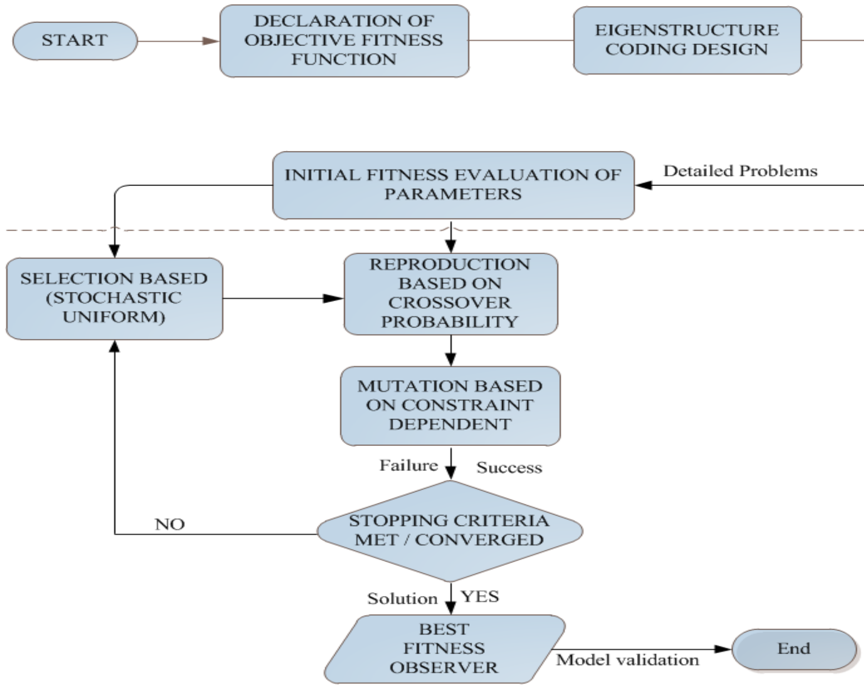


Figure 3.3: The computational structure of GA optimisation

The optimization explanation process comprises of a set of parameters of participant element which forms the vectors that represent the variables of GA in each chromosome of the population and helps to determine the design of the state-feedback gain K. GA is used to search for a suitable parameter set and also employed as an optimisation natural solution technique for solving the trade-off problem. GA algorithm is used to search a set of optimal scalar parameters, where the GA optimization tool is convenient for utilization under Matlab software platform. The GA can be run by using Matlab optimization toolbox, whose running procedure can be described as follows:

1) ***Representation:*** The primary parameter element of a GA is the gene, which in natural setup decides the specified distinguishing of an individual, such as hair colour gene is determined by the physical model description i.e., matrix formation of various chromosomes representation of individual population describes a parameter that is to be optimised. The parameter set is characterised by eigen-structure assignment coding system transformed to searching a set of optimal scalar parameters that is acceptable by gatool GA solver. The total sum of the parameters is defined as $\alpha = n + n \times p$ [122]. Parameters are represented as the number chromosomes that make up the population. The chromosome code population or parameters to be optimised as described in the form of (3.24).
2) ***Health Evaluation**:* The costing assessment is essential in GA, the link of individual with the location provides a quantity of its capability that GA uses before reproduction is taken place [117]. This fitness amount is used to define the sum of offspring that will be created to form a detailed chromosome. This is an assessment stage which helps to define the objective fitness of the current population by providing two input arguments which is declared as the dual problems of disturbance robustness and faults sensitivity.

$$J_1 = \|H_d(s)\|_{s=j\omega_d} \Rightarrow \qquad \text{Min}$$
$$J_2 = \left\|H_f(s)\right\|_{s=0} \Rightarrow \qquad \text{Max}$$

Therefore, the cost function is $J = \frac{J_1}{J_2}$ ⇒Min, which is the same as defined in (3.23).

3) ***Selection:*** The algorithm frequently selects individuals chromosomes based on best fitness values determined by objective function. This operator compromise, the trade-off between the global solution and convergence speed. The selection is carried out by probability stochastic uniform (random chance related to increase in convergence). This operator avoids the best parameter set from loss during iteration and also boosts the convergence rapidly. The best chromosomes which are the fittest survived are selected randomly selected for the parents of the reproduction operation meaning the specific function that the algorithm uses to selected parents in the function field are comparably related to the survival of the fittest “Only the fit survive the struggle”.

4) ***Reproduction:*** Choosing the parents from current population for the next generation, determine how the GA produces children at each generation. This stage allows GA to make apply survival-of-the-fittest scheme [3]. A heathier solution is generated with better fitness value via optional choice of parameter to provide a consistency in its probability choice with an increase in convergence speed. The key genetic operators are as follows.

Recombination: recombines each chromosome to produces new chromosomes from earlier generation features but the new chromosome do not occurs in the previous generation. The crossover operator creates new chromosome with a regular ideals parents. In normal development, recombination and reproduction happen in the same period of which individual are arbitrarily selected from population. Crossover is the mating process, in which a position along the chromosome is arbitrarily selected that dissects the two parent chromosomes into two sections, which are then exchanged. The new offspring population are embraced of a diverse section from each parent and thus inherit genes from the two parents. Here the accurate chromosome is passed to the next generation for crossover fraction whose default is selected in *gatool* as scattered to increase chance of survival giving room for more opportunity, which replaces current chromosomes with the children to form next generation. Priority chance of survival is given to the healthy chromosome or healthier chromosome of which the crossover helps to recombine survival parents in order to produce new offspring, the offspring is generated by mutation.

Mutation: The second operator in the reproduction process employed to avoid finding local solutions to problems which is inspired by the chance initial random population do not hold all of the information necessary to solve the global problem. Exploring many regions of the search space simultaneously, rather than a single region helps to introduce changes in each generation. The mutation function is defined as the constraint dependent of which are limited to the left-half complex plane to concentrate on the stability conditions. A constraint dependent is chosen as defined in the constraint function to ensure the poles are rightly place within the eigenvalues as in (3.15) and (3.16). Global solution is always suggested in the optimization process, but if a quick convergence happens then the solution achieved could be localised minimum or maximum solution. Furthermore, it is possible that the individuals that produce no offspring may have had some information that is crucial to the solution therefore, there is need to input new information into the population. Mutation presents the random selection of variables to change the value of some physical parameters in the chromosome. Mutation rate of 0.2 set in the solver, is used which slows down the convergence process, to ensure global solution is obtained.

Elitism: The elitist approach repairs possible source of loss by replication the best member of each individuals in the current generation with the best fitness values into the subsequent generation, which makes best individuals to automatically survive to the next generation. The elitist improve the performance of GA, increase the speed of convergence as well as find the local minimum individual due to the supremacy of best survival. This is the greatest member of the population that are weak to produce an offspring in the next generation. The elitism approach could increase the speed of control of a population by a strong individual, alternatively it helps to improve GA performance.

5) ***Stop Check:*** When the optimal results convergence, the algorithm terminate if the stopping conditions are reached or a generation is beyond the set perimeter, alternatively return to health (fitness evaluation) to continue the evolution. The stopping principles guarantee that at least one minimal solution is found which could be: Generations, time limit, fitness limit, stall generations, stall time limit, function tolerance, nonlinear constraint tolerance.

3.7 Summary

In this chapter, robust observer-based fault detection filter is addressed by integrating eigenstructure assignment method and GA optimisation technique. The design procedure of the GA optimization for seeking K can be summarized as follows.

- Set the sizes of the population and generation.
- Set the parameters to be optimized in form of (3.24).
- Set the cost function in form (3.23).
- Set the constraint such that the observer system matrix $A - KC$ is stable, that is, all the real parts of the eigenvalues must be less than zero, in every iteration.
- GA runs until the stop condition is satisfied.

The addressed robust fault detector is designed to be sensitive to the faults but robust against disturbances. Therefore, the faults can be effectively distinguished from the disturbances. In the optimisation design, the dominant disturbance is minimized at the specified frequency, which can be observed from the Fourier Transform Analysis. The addressed methods will be applied to the case studies for wind turbine systems and induction motor systems in the following chapters.

Chapter Four: Robust Observer Based Fault Estimation Approach

"Our goal is to show that you can develop a robust, safe manned space program and do it at an extremely low cost".

Burt Rutan

4.1 Introduction

In distinction to the prior chapter three, that demonstrates robust fault detection to seek optimal observer gain such that residual signal is sensitive to faults, but robust against disturbances. The robustness issues of FD still requires to be further investigated due to the continuous increase in industrial system complications and cost triggered by less tolerance for performance corruption and safety risks, which poses a need to improve fault diagnosis performance. The advanced fault diagnosis technique is the fault reconstruction or called fault estimation, which can provide more information about systems like the size, shape and types of faults. Therefore, fault reconstruction (or fault estimation) can be utilized to assess the strict degree of the monitored faults. This kind of faulty information is paramount for control and management to take proper measures of further damages and apply tolerant control actions.

Fault Estimation (FE) employs model-based approach of industrial processes or applied practical systems to give the estimation of all likely faults. The effect of uncertainties on an observer can be amplified unavoidably however the conventional approach cannot adequately achieve the system performance. There is need to attenuate the effect of modelling error in order to improve the performance of the system and reduce the big experimental worries in realising a reliable robust FE via models of the industrial practices. Fault *estimation is defined as a technique to estimate or modernise the size, type and shape of faults, which can provide more information on the nature of the faults and facilitate the fault-tolerant (FT) design*. Fault estimation is a kind of fault diagnosis method that gives estimation of possible fault and provides the estimate of the state at the same time using available input and output. Noticing that environmental disturbances are unavoidable, therefore how to improve the robustness of FD system against disturbances/noises has been a key issue in FD community. The principle of the robust fault estimation technology (RFET) state-of-the-art observers is to construct an augmented system by presenting the alarmed fault as an extra state, and the comprehensive state vector which is subsequently predictable, and also essential to the estimates of the disturbed fault signal together with innovative system states. Therefore, the sophisticated (inventive) observers are also named as simultaneous state and fault observers.

4.2 Literature Review of Fault Estimation Techniques

A variety of fault estimation/reconstruction methods have been developed to improve the efficient and reliability of FT design for early detection of developing faults such as adaptive system [127]-[132] methods based on linear matrix inequality (LMI) approach to solve the considered parameters. The steadiness analysis of the closed-loop control system in the presence of unknown faults and modeling errors was first proposed by [133]. The accommodation of faults was [128], the system design reduces this assumption by allowing the bounded to be unidentified explicitly, and the scheme uses an adaptive bounding method where the bounded is estimated online. The adaptive for informing the neural network error that could raise as a consequence failure of the online estimation to contest the fault function precisely, even with optimal weights and bounding estimate, as well as the design of the corrective control function to avoid unpredictably in the presence of a fault. The closed-loop stability of the suggested fault accommodation scheme was strictly recognised with Lyapunov concept to reshape technique focus to abrupt faults [129] and [134]. The drawback of adaptive fault diagnosis system in relation to precision, tracking error delay original estimate which could cause missed alarm and speed to reach the performance condition/convergence error leading to reduced transient performance, to achieve the rigid limitation by explaining the designed parameters. Fast adaptive fault estimation (FAFE) approximator was later proposed to increase the speediness, guarantee an acceptable dynamical steady state performances of fault estimation of which LMI algorithm technique was investigated to effectively solve the designed parameters [131] and [135]. The system is exposed to either model uncertainty or external disturbance is discussed in detail and a modification to the adaptive diagnostic algorithm is proposed to enhance its robustness which is limited in application to real systems. Moreover, [129] suggested linear quadratic control to improve the system performance behaviour and system steadiness. The sliding mode approach was introduced more than 60 years ago with growing research contribution to be known as one of the competent tools to design robust controllers due to low sensitivity to elimination of inevitability of strict disturbances modelling and variations in plant parameter behavior for a dynamic plant operating under uncertainties environments [132]. Sensor and actuator faults have been deliberated for robust fault reconstruction techniques for linear parameter varying (LPV) systems based on sliding mode observers by LMIs to minimize the impact of uncertainties and size manipulation on moral fault reconstruction performance [135]. In [136]-[138], the sliding signal is permitted to interrupt in the existence of faults/failures in the system. Some latest contributions [139]-[140] and principally [141]-[142] use the robustness materials of sliding modes to contribute getting information about the 'size' and 'shape' of the faults and fault detection. This is reached through reconstruction of the faults by investigating the 'extra output error injection' signals that are essential to continue sliding at the existence of faults. [143] discussed that systems where repetition is not available, the reconstruction of faults can be advantageous particularly for sensor fault progressive device complications. The outline of the design process based on the exposition and developments in the previous section observer to handle variations in the operating condition shows faults has been reconstructed with satisfactory accuracy. Sliding mode does not depend on plant dynamics, but often resolute by systems output parameter "*C*" [144] of which the observer is designed using LMIs. The nonlinear dynamics in a linearized plant which are presumed to be an agent of uncertainties of which could motivate some variations which could provoke false alarm interference leading to poor performance therefore, the overall performance needs further improvement in terms of highlighting the sensitivity and robustness. The renovation performance is accomplished by enhancing the plant conditions with the observed output measurements that are liable to faults [135]. Another proposed technique allowed complete decoupling of bounded noises as well as estimation of measurement noises, input disturbances and system states simultaneously with the concept of derivative and proportional gain designed observer to change a multivariable system with measurement noises to an augmented descriptor system. Control community has suggested Proportional Multiple Integral Observer (PMIO) for state-space systems with unknown input disturbances are only states estimators, and cannot give the estimation of unknown disturbances [145]-[148]. This method along with the modified proportional and integral derivative (PID) observer tolerates decouple of the measurement noise completed [149]-[150]. The LMI with Lipschitz constraint robust filter was applied to a nonlinear descriptor system to concurrently modernize the uncontrolled fault signal [127] and other approaches in [151] and [152]. Also, descriptor system reduces the input bounded disturbances but nevertheless, little efforts were suggested on robust fault estimation for unbounded faults and disturbances there is room for improvement of this approach. Augmented system observer and high gain design method is one of the novel robust observers to simultaneously, predict faults time results, modernize fault signals and provides estimate of the states at the same time using available input and output which is more efficient than other estimation approach [134]. It is of interest to continuously improve the efficient of the related progressive observer systems that are beneficial both for estimating measured unpredictable advancing faults (PI and PMI observers), gradual changing parameter faults (adaptive observers), actuator faults with simulating (sinusoidal) waveforms (sliding mode observers), and high-frequency sensor faults (descriptor system approaches) [51].

The above observer methods can be combined (incorporated) uninterruptedly to deal with applied concerned set up complications. Comparatively, in [143], integral observer, sliding observers, and adaptive observers are integrated to renovate sensor faults for satellite control systems. In [148], PI observer and descriptor observer techniques are incorporated to evaluate the parameter faults for aero engine systems. Considering the strength of combined methods to tackle robustness would be evaluated in this section.

4.3 Fault Estimation via Augmented System Approach

Dynamic system corrupted by faults and disturbances is described as follows:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = Cx(t) + Du(t) + D_f f(t) + D_d d(t) \end{cases} \tag{4.1}$$

where $x(t)\epsilon\Re^n$ is the state vector, $u(t)\epsilon\Re^m$ is the system control input, $y(t)\epsilon\Re^p$ is the measurement output, $d(t)\epsilon\Re^l$ is the disturbance vector, and $f(t)\epsilon\Re^k$ is the fault vector.

As the incipient and abrupt faults are considered in this study, the second-order derivative of the fault vector should be zero, that is,

$$\ddot{f}(t) = 0. \tag{4.2}$$

In terms of (4.1) and (4.2), the augmented state-space system can be constructed as follows:

$$\begin{cases} \begin{bmatrix} \dot{x}(t) \\ \ddot{f}(t) \\ \dot{f}(t) \end{bmatrix} = \underbrace{\begin{bmatrix} A & 0 & B_f \\ 0 & 0 & 0 \\ 0 & I & 0 \end{bmatrix}}_{\bar{A}} \underbrace{\begin{bmatrix} x(t) \\ \dot{f}(t) \\ f(t) \end{bmatrix}}_{\bar{x}} + \underbrace{\begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix}}_{\bar{B}} u(t) + \underbrace{\begin{bmatrix} B_d \\ 0 \\ 0 \end{bmatrix}}_{\bar{B}d} d(t) \\ y(t) = \underbrace{\begin{bmatrix} C & 0 & D_f \end{bmatrix}}_{\bar{C}} \begin{bmatrix} x(t) \\ \dot{f}(t) \\ f(t) \end{bmatrix} + Du(t) + D_d d(t) \end{cases} \tag{4.3}$$

Let

$$\bar{x}(t) = \begin{bmatrix} x^T(t) & \dot{f}^T(t) & f^T(t) \end{bmatrix}^T \tag{4.4}$$

$$\bar{A} = \begin{bmatrix} A & 0 & B_f \\ 0 & 0 & 0 \\ 0 & I & 0 \end{bmatrix} \epsilon \Re^{\bar{n} \times \bar{n}} \tag{4.5}$$

$$\bar{B} = \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix} \in \Re^{\bar{n} \times m}, \bar{B}_d = \begin{bmatrix} B_d \\ 0 \\ 0 \end{bmatrix} \in \Re^{\bar{n} \times l}, \tag{4.6}$$

$$\bar{C} = [C \quad 0 \quad f] \epsilon \Re^{p \times \bar{n}} \tag{4.7}$$

$$\bar{n} = n + 2k. \tag{4.8}$$

Therefore, the system (4.3) can be written as:

$$\begin{cases} \dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{B}_d d(t) \\ y(t) = \bar{C}\bar{x}(t) + Du + D_d d(t) \end{cases} \tag{4.9}$$

For system (4.9), one can construct an observer in the following form:

$$\dot{\hat{\bar{x}}}(t) = \bar{A}\hat{\bar{x}}(t) + \bar{B}u(t) + \bar{K}(y(t) - Du(t) - \bar{C}\hat{\bar{x}}(t)) \tag{4.10}$$

where $\hat{\bar{x}}(t) \epsilon \Re^{\bar{n}}$ is the estimate of the augmented state $\bar{x}(t) \epsilon \Re^{\bar{n}}$; and $\bar{K} \epsilon \Re^{\bar{n} \times p}$ is the state-feedback (observer) gain to be designed.

Let

$$\bar{e}(t) = \bar{x}(t) - \hat{\bar{x}}(t), \tag{4.11}$$

The estimation error dynamics is governed by the following equation:

$$\dot{\bar{e}}(t) = (\bar{A} - \bar{K}\bar{C})\bar{e}(t) + (\bar{B}_d - \bar{K}D_d)d(t) \tag{4.12}$$

As a result, the design goal is to design $\bar{K}$ to make (4.12) asymptotically stable when $d(t) = 0$; and reduce the effect from the disturbance to the residual signal in (4.13) when $d(t) \neq 0$.

Existence condition of the observer:

In order to make $(\bar{A} - \bar{K}\bar{C})$ stable, the sufficient condition of the pair $(\bar{A}, \bar{C})$ is observable, that is,

$$\bar{n} = n + 2k = rank \begin{bmatrix} sI - \bar{A} \\ \bar{C} \end{bmatrix}, \text{for any complex number } s. \tag{4.13}$$

It is noted that,

$$n + 2k = rank \begin{bmatrix} sI - \bar{A} \\ \bar{C} \end{bmatrix} = rank \begin{bmatrix} sI_n - A & 0 & -B_f \\ 0 & sI_k & 0 \\ 0 & -I_k & sI_k \\ C & 0 & D_f \end{bmatrix}$$

$$= \begin{cases} rank \begin{bmatrix} sI - A \\ C \end{bmatrix} + 2k, & s \neq 0, \\ rank \begin{bmatrix} A & B_f \\ C & D_f \end{bmatrix} + k, & s = 0. \end{cases} \tag{4.14}$$

If the pair $(A,\ C)$ is observable, $rank \begin{bmatrix} sI - A \\ C \end{bmatrix} = n,$ (4.15)

Assumption

Supporting conditions (4.15), can derive that the pair $(\bar{A}, \bar{C})$ is completely observable, as in (4.13) and (4.14) implies that

$$rank \begin{bmatrix} sI - \bar{A} \\ \bar{C} \end{bmatrix} = \bar{n}. \tag{4.16}$$

Therefore, the observer gain $\overline{K}$ can be found so that $(\bar{A} - \overline{K}\bar{C})$ is asymptotically stable. The next task is how to design gain $\overline{K}$ to attenuate the effect from the disturbance $d(t)$. If an effective observer (4.10) can be designed, the estimates of the state and fault can be given as follows:

$$\begin{cases} \hat{f}(t) = [0_{k\times\bar{n}} \quad 0_{k\times k} \quad I_{k\times k}]\hat{\bar{x}}(t) \\ \hat{x}(t) = [I_{\bar{n}\times\bar{n}} \quad 0_{\bar{n}\times k} \quad 0_{\bar{n}\times k}]\hat{\bar{x}}(t) \end{cases} \tag{4.17}$$

The design of the augmented observer can be depicted by Figure 4.1.

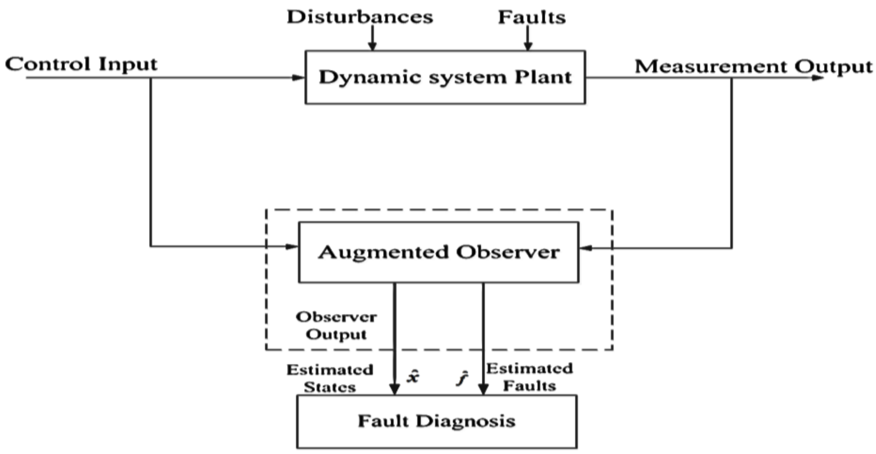


Figure 4.1: Diagram of augmented observer

4.4 Eigenstructure Assignment for Seeking Optimal Observer Gain

The eigenvalues of the observer can be real or complex-conjugate. Assume that there are $\bar{n}_r$ real eigenvalues λ_i ($\mathrm{i} = 1,2,\cdots,\bar{n}_r$) and $\bar{n}_c$ pairs of complex-conjugate eigenvalues $\lambda_{j,re} \pm j\lambda_{j,im}$ $(j = 1,2,\cdots,\bar{n}_c)$, and $\bar{n}_r$ and $\bar{n}_c$ satisfy the following relation:

$$\overline{n}_r + 2\overline{n}_c = \overline{n} \tag{4.18}$$

Real eigenvalue case:

Assume that v_i is the *i*th right eigenvector of $(\overline{A}^T - \overline{C}^T\overline{K}^T)$ corresponding to the *i*th eigenvalue λ_i of $(\overline{A}^T - \overline{C}^T\overline{K}^T)$, one thus has:

$$v_i = -\left(\lambda_i I - \overline{A}^T\right)^{-1} \overline{C}^T w_i \tag{4.19}$$

where

$$w_i = \overline{K}^T v_i. \tag{4.20}$$

Complex-conjugate eigenvalue case:

Assume that $v_{j,re} + jv_{j,im}$ is the *j*th right eigenvector of $(\overline{A}^T - \overline{C}^T\overline{K}^T)$ corresponding to the *j*th eigenvalue $\lambda_{j,re} + j\lambda_{j,im}$ of $(\overline{A}^T - \overline{C}^T\overline{K}^T)$. It is evident that

$$\left(\overline{A}^T - \overline{C}^T\overline{K}^T\right)\left(v_{j,re} + jv_{j,im}\right) = \left(\lambda_{j,re} + j\lambda_{j,im}\right)\left(v_{j,re} + jv_{j,im}\right) \tag{4.21}$$

which is equivalent to:

$$\begin{cases} \left(\lambda_{j,re}I - \bar{A}^T\right)v_{j,re} - \lambda_{j,im}v_{j,im} = -\bar{C}^T\bar{K}^T v_{j,re} \\ \lambda_{j,im}v_{j,re} + \left(\lambda_{j,re}I - \bar{A}^T\right)v_{j,im} = -\bar{C}^T\bar{K}^T v_{j,im} \end{cases} \tag{4.22}$$

Define:

$$A_j = \begin{bmatrix} \lambda_{j,re}I - \bar{A}^T & -\lambda_{j,im}I \\ \lambda_{j,im}I & \lambda_{j,re}I - \bar{A}^T \end{bmatrix}, C_c = \begin{bmatrix} \bar{C}^T & 0 \\ 0 & \bar{C}^T \end{bmatrix}, \tag{4.23}$$

$$\begin{cases} w_{j,re} = \overline{K}^T v_{j,re} \\ w_{j,im} = \overline{K}^T v_{j,im.} \end{cases} \tag{4.24}$$

Therefore, from (4.22)-(4.24), one can obtain:

$$\begin{bmatrix} v_{j,re} \\ v_{j,im} \end{bmatrix} = -A_j^{-1} C_c \begin{bmatrix} w_{j,re} \\ w_{j,im} \end{bmatrix}. \tag{4.25}$$

By integrating the two cases (real eigenvalues and complex conjugate eigenvalues), one can define the following two vectors:

$$W = \left[w_1 \ \cdots w_{n_r} \ w_{1,re} \ \cdots \ w_{n_c,re} \ w_{1,im} \ \cdots \ w_{n_c,im}\right] \in \Re^{p\times\bar{n}} \tag{4.26}$$

$$V = \left[v_1 \ \cdots v_{n_r} \ v_{1,re} \ \cdots \ v_{n_c,re} \ v_{1,im} \ \cdots \ v_{n_c,im}\right] \in \Re^{\bar{n}\times\bar{n}} \ . \tag{4.27}$$

In terms of (4.20) and (4.24), one can calculate the augmented observer gain as follows:

$$\overline{K} = [WV^{-1}]^T. \tag{4.28}$$

4.4.1 Cost Function

The transfer function of (4.12) can be given as follows:

$$e(s) = (sI - \bar{A} + \overline{K}\bar{C})^{-1}(B_d - \overline{K}D_d)d(s). \tag{4.29}$$

In order to minimise the influences from the disturbance d, the observer gain $\overline{K}$ should meet the following performance index:

$$\text{minimize}\ J(\overline{K}) \tag{4.30}$$

where,

$$J = \|(sI - \bar{A} + \overline{K}\bar{C})^{-1}(B_d - \overline{K}D_d)\|_{s=j\omega_d} \tag{4.31}$$

where ω_d is the dominant frequency of the disturbance.

Based on Session 4.4, the gain $\overline{K}$ can be obtained from a set of scalars:

$$\psi = \left\{\lambda_1, \cdots \lambda_{n_r}, \lambda_{1,re}, \cdots, \lambda_{n_c,re}, \lambda_{1,im}, \cdots, \lambda_{n_c,im}, w_1 \ \cdots w_{n_r} \ w_{1,re} \ \cdots \ w_{n_c,re} \ w_{1,im} \ \cdots \ w_{n_c,im}\right\} \tag{4.32}$$

Therefore the cost function (4.30) can be reformulated as follows:

$$\text{minimize}\ J(\psi) \tag{4.33}$$

4.4.2 Design for GA Based Robust Fault Estimator

The design procedure of seeking optimal $\overline{K}$ can be outlined as follows.

- **Population Representation:** Many coding techniques have been suggested, like gray coding, and binary bit strings. The total number of the parameters to be optimized is $\psi = \bar{n} + \bar{n} \times p$, and the set of the parameters is defined as (4.32).
  - **Fitness Evaluation:** The fitness function is defined as (4.33).
  - **Constrains:** The eigenvalues of the $(\bar{A} - \overline{K}\bar{C})$ are ensured to be stable.
  - **Selection:** Same as chapter three, In order to search the area of concern effectively for a global result occurs, many regions of the search space is explore randomly, rather than a single region. This operator is responsible for randomly stochastic uniform search (selects some solutions from the population by repetitive random sampling, helps to select potential useful solutions for recombination) to filter for the better fitness values survival.
- **Reproduction:** The algorithm selects the individual parameters that have better fitness values as parents to breed children at each fresh generation to make random changes in the individual population. The process of recombining the survival to generate value of parents. This create a kind of diversity, the selected parent (parameters) must ensure the system $\bar{A} - \overline{K}\bar{C}$ lies within the eigenvalues plane, the selected parent (parameters) which must ensures the system are placed in the open, left complex plane hand lies within the eigenvalues plane, mutation is a kind of change introduced randomly to a single parent. The repetition of the population of super chromosomes copied to the next generation.
- **Stop:** The global minimum point is reached, where the stopping conditions determine the end of the algorithm is terminated when the number of generations exceeded, otherwise return to ***FITNESS FUNCTION*** to continue the evolution.

4.5 Summary

By integrating augmented system approach, eigenstructure assignment method and GA optimisation technique, a novel fault reconstruction method is proposed. The frequency of the dominant disturbance can be obtained from the signal processing technique (Fourier Transform and analysis), which enhance the disturbance attenuation ability. As a result, the proposed GA based fault estimation technique is a hybrid fault diagnosis technique by synthesising model-based method and signal processing method. The proposed methods will be applied to the case studies of wind turbine systems and induction motor systems.

Chapter Five: Wind Turbine Technology and Fault Diagnosis

"The future is green, sustainable and renewable energy".

Arnold Schwarzenegger

Windmills have been a significant evolution from mill grinding, sawing wood, water pumping mostly by the Persians in the middle east to modern power technology [153]. Fossil fuels have created alternative energy sources which were relatively cheap but has some increasing concerns on global warming and environmental hazards and contain a high measurement of carbon. The traditional fossil fuel resources are becoming exhausted out with presently 11 billion tonnes been consume every year, and fuel importation are at a top, from statistic fossil fuels will run out soon with reserves predictable or become costly to be genuinely afforded and continuously affecting severe environment impact [154].

Fossil fuels are gradually exhausting at a quicker rate with the negative effect on the environment. There is the need for an overthrow of fossil fuels energy values getting its scarcity limit with renewable energy resources which contributed importantly as part of the world's power production which is considered in this study. Most Power production around Europe continues its exchange of fossil fuel oil, coal and gas respectively with knowledge continuing to neutralize more than it installs. In order to create a sustainable system, this implies a significance fact to keep the energy going forever into the future, to significantly reduce greenhouse gases like carbon dioxide and lasting energy predictability as well as energy security. As a result, renewable energy technology refers to as clean sources of energy, with far trivial environment effect than the fossil fuel traditional energy will be of interest in this study.

5.1 Introduction- Review of Wind turbine renewable energy

Wind energy has become the world's promising, nature of clean and fastest growing renewable energy source with the high market impact which increases as well as contributing to world's power production with an unlimited energy source. Lots of contributions have been made to support wind turbine renewable energy sources that have many advantages over the traditional fossil fuels. The European wind power installed capacity has reached a volume of 320 GW and wind energy contributes currently about 4% of the world's power demand. The new figure of installed capacity in the European Union is 128.8 GW of almost 120.6 GW onshore and nearly 8 GW offshore [155]. The normal annual growth amount of wind turbine installation is about 30% in the past ten years, with annual growth of about 37.1%.

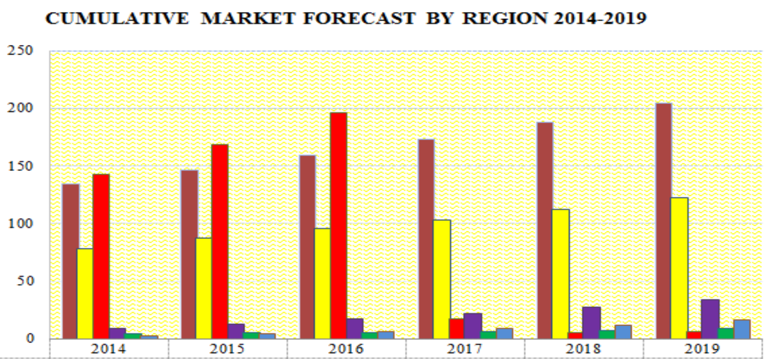
By the end of 2020, it is expected that this number will rise to above 1,260,000 MW, which will be satisfactory for 12% of the global electricity production supply to give the industry a new boost. The European Union (EU) installed capacity achievement since 2014 has increased by 14.8GW to 910.1 GW with wind energy power increasing by 11.4 GW benefit of electricity generation analysis of 14.1% [155]-[156]. The healthy growth of US wind target power installation capacity is 712 GW by 2020 of about 20% power generation [157]-[168] for offshore placement. The global market for wind renewable energy continues to grow as technologies is more environmentally friendly with a total worldwide installation capacity of 2000 GW by 2030 with supplied of about 19% of global electricity [159] and [160].

Accelerated growths of standard renewable energy have potentially boosted the number of installation in the market. Wind turbines (WT) have been a significant role in the origination of cleaner energy in the UK, the knowledge obligating substantiated over the last 20 years. The technology is swiftly emerging industrial area and large turbines like 6MW are being created both offshore and onshore. The worries over environmental variations and energy safety rise, faulty components emerging concern in renewable energy schemes that can cause a high loss in energy production as well as possible damage of the turbines.

Arnold Schwarzenegger orientation on green sustainability future is simply to increase the environmental safety, security, reliability fit for the function of energy supply and to moderate addiction on traditional oil and other fossil fuels. WT have been reserved to play a vital role in the generation of clean energy in the UK, known as one of the substitute energy sources and are estimated to produce energy with very little interruptions. Though, in the past, as the wind turbine life, the impact of a resourceful assessment or components state valuation has increased extremely. The issues that arise with the WT production are the high cost of production often causes losses in offshore farms with complexity that requires sophisticated strategies. Though, availability may fall below 60% of offshore WT due to considerable interruption frequently caused by high incidences of components failure that could decrease the reliability and increase the cost of maintenance [161] and [117]. These are costly tasks as for example the cost of replacing the gearbox accounts for about ten percent of the wind turbine construction and installation cost, which eventually results in an increase in energy production cost. This is one of the driving forces to detect developing faults of WT at an early stage in order to ensure adequate measure taken to avoid any further costs and also enhance reliability. This chapter briefly presents the basics interest on environmental variations, reliability and an account of growing concerns in renewable energy systems and how best to constantly increase working operation by reducing performance degradation.

5.2 Market Forecast

It has remained a substantial increase in power energy directive due to global economic and industrial expansions. Successively, the increasing market growth will be between Asia and Europe till 2018, where Asia will rapidly begin to pull out of the market gradually. The international wind turbine markets economy led by Asia, Europe, and North America are said to the amount by 33.5GW in 2019, innovative markets begin to make an actual change in the next five years. Brazil is expected to move up to 3rd or 4th position in the yearly market ranks over a subsequent couple of years, and interrupt into the top ten in positions of increasing installations as initial as the end of 2014. South Africa is lastly attracting, and this will expectantly lead to a mini-boom in Southern and Eastern Africa in the next five years. The actual rough estimate is that Saudi Arabia, with its determined goal of up to 50 GW of solar and the wind by 2030; and Russia, around is primary signs that it might begin to exploit its huge wind assets in the nearest future [159]. The growing market will lead to additional expansion which will further reduce the cost of a wind turbine to be able to contest with other conventional power production like fossil fuels. The increasing growth of WT market prediction for 2014-2019 is shown below in Figure 5.1.



	2014	2015	2016	2017	2018	2019
Europe	134	146.5	159.5	173	188	204
North America	78.1	87.1	95.1	103.1	112.1	122.1
Asia	142	168	195.5	17	5.4	6
Latin America	8.5	12.5	17	22	27.5	33.5
Pacific	4.4	4.9	5.4	6.4	7.4	8.4
Middle East & Africa	2.5	4	6	9	12	16

Figure 5.1: The Cumulative Market forecast by Region 2014-2019 [159]

There is a continuing increase growth in the yearly wind turbine installed global size, thereby making it have a prospect in the nearest future (e.g., see Figure 5.2).

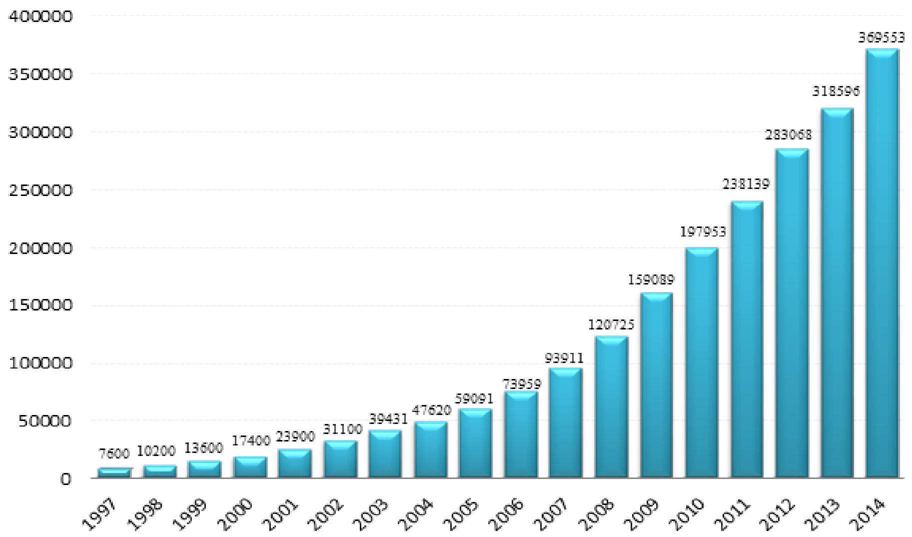


Figure 5.2: The annual global chain installed wind power capacity from 1997 to 2014 [161]

There is an annual market growth of 44% that is authorised 50GW made a history in 2014 which is a sign of market recovery after the previous slowdown in past years. The total cumulative installed since 2014 according to Global wind Energy council is about 369,553 MW. Statistics shows that the United Kingdom, Denmark, Germany, Belgium, PR China, Netherlands, Sweden, Japan, Finland, Ireland, Korea, Spain, Norway, Portugal and the United States is leading the world in Offshore wind installation. The cumulative demand of energy is of acute significance for the world economic growth and environmental protection.

5.3 Modern Wind turbine Aerodynamics Description

The wind is triggered by the communication of the patchy heating of the atmosphere with the irregular outside part of the earth, and the earth's cycle. The Wind can produce both mechanical and electricity power. In the case of electricity, the wind drives the blades of a wind turbine, and the kinetic energy generated from the rotating motion is changed to mechanical energy. The mechanical power is then used to drive a generator that produces electricity that is useful in homes and industries [162]. Wind turbines convert kinetic energy to mechanical power which induces electricity that describes the process of electricity energy generation whose purpose is to reduce greenhouse gas. The contemporary wind turbine is a three-blade horizontal/vertical generating axis, in which the produced energy is in response to the obtainable wind. Horizontal axis wind turbine (HAWT) topology whose rotation is parallel to the ground includes the following subsystems (see Figure 5.3).

- Rotor: This consist of blades and supporting hub
- Drive Train: This includes shafts, gearbox, mechanical brake and the generation
- The tower and the foundation: Supports the rotor and the drivetrain.
- The nacelle and the main structure: This includes yaw and wind turbine housing.
- The machine controls: This includes the sensor (Speed, position, temperature, current, voltage etc.), Controller (mechanical mechanism, computers and electrical circuits), Actuators (Motors, pistons, solenoids and magnets)
- Other equipment includes electrical cables, switchgear, transformer, ground support equipment, interconnection equipment, and feasibly electronic power converters.

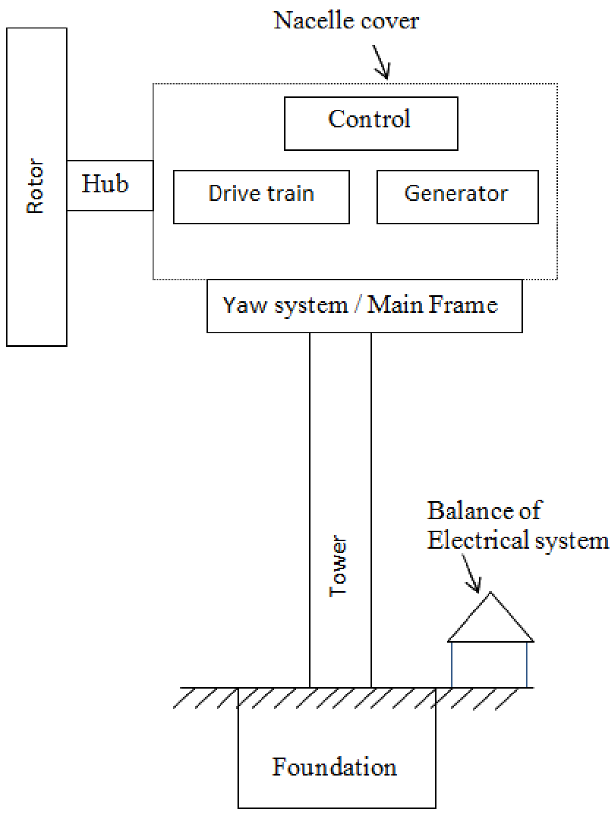


Figure 5.3: Main components of a horizontal axis of wind turbine [149]

The design is based on a variable speed that can integrate a pitch parameter piece which involves turning the blades about their sideways horizontal axes which is known as pitching the blades to control the power removed by the rotor. This makes the turbine operate at perfect tip-speed ratios over a larger range of wind speeds so as to collect the concentrated energy from wind, it supply power at a continuous voltage and frequency while the rotor speed varies and finally it controls the active and reactive power [163]. The turbines generate power by using the natural influence of the wind to drive the doubly fed induction generator. The wind turbine consists of four models which are: The wind energy is transformed into mechanical energy through rotation of the blades by the wind. Blade and pitch systems drive train, generator/ converter, and controller. By pitching the blades or by controlling the rotational speed of the turbine relative to the wind speed, we can change the aerodynamics of the turbine and hence we can control this mechanical energy. The role of the drive train is to increase the rotational speed from the rotor to the generator. The generator torque can be controlled by the converter as well as the rotational speed of the DFIG. The doubly fed induction generator (DFIG) is a design based on induction generator which is fully coupled with a converter that converts the mechanical energy to electrical energy. DFIG technology permits extracting determined energy from the wind for small wind speeds by improving the turbine speed while reducing mechanical pressures on the turbine through gusts of wind. This makes the generator generate electricity with a full converter coupling to stabilized; however, at this system near, the difference is small between a full converter and a doubly fed induction generator. The output rotor speed, the generator speed, and the pitch positions of all blades are measured with two sensors. Both these generator types are variable-speed and pitch-controlled turbines [164]. The normal wind turbine model consists of some subsystems, including blade and pitch systems, drive train, generator and converter, and controller. The standard wind turbine model consists of some like the blade and pitch systems, drive train, generator/ converter and controller as shown in the model arrangement of wind power energy generation (see Figure 5.4).

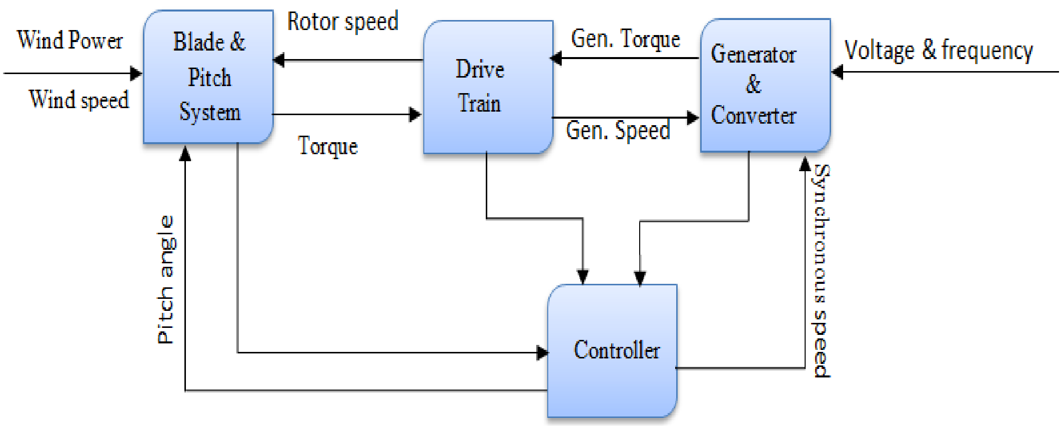


Figure 5.4: Principle of the wind turbine model [163]

Blade pitch subsystem is to possess the rotor speed ineffective restrictions as the wind speed changes which convert the wind energy into rotational energy and pitch, the input power of the turbine is controlled. The drive train normally comprises a gearbox and generator doubly-fed induction generators are extensively used technology in wind turbines [165]. In a full-scale conversion drivetrain, the wind turbine gearbox is protected because the generator is not connected directly to the grid and therefore exposed changes in the grid that can generate extreme pressure on the drivetrain. A vastly proficient key that also affords healthier power value to the grid, the full converter solution has a redundant converter system that offers security in case of a disaster. To aid the urgent need of industrial reliability in order to stay improves.

5.4 Challenges of wind turbine technology

5.4.1 Cost

The request for wind power continues to grow as the best advanced and cost-effective source of renewable energy, the actual cost of wind turbine project is around 69% of the entire development cost. The economics rates of wind energy project fluctuate subject on the scale, location and connection requests. Various models have been advanced for exploiting generated wind power, reducing the turbine cost and raising the effectiveness and reliability. The global analyst report says there is predictable rise in maintenance outflow of wind turbines from $9.25billion in 2014 to $17 billion in 2020 [166]. The table below shows power in numbers collected by Element Energy Saving Trust, it is possible that wind energy will become competitive with gas power generation [167].

Turbine size	**Basic Cost per turbine**	**Feed-in-Tariff generation rate (£/kWh, current)**
Building-Mount Micro (2.5kW)	£10,000	£0.27
Micro (6kW)	£20-28,000	£0.27
Small (20-50kW)	£50,000-£125,000	£0.24
Medium (100kW -500kW)	£ 250k-320k	£0.22
Medium (850kW -1.5MW)	£1.4-1.8 million	£0.09-£0.19
Large (2-3MW)	£2.7 -3.1 million	£0.05-£0.09

Table 5.4: Statistics of Element Energy Saving Trust

5.4.2 Environmental concerns

Wind power is noticed as an environmental friendly which could have a huge impact on the climate change, eco emission environment, nevertheless, it is not completely emission-free. Emissions are indirectly produced based on fossil fuel used for exploration of the material and transport of equipment leads to consumption of energy resources.

Environmental concern over the use of predictable sources of wind turbine renewable has reached a disturbing time, therefore substitutes causes are the ecological future prospect. Though wind power plants have relatively little impact on the environment compared to fossil fuel power plants, there is some concern over the interferences that distract the power energy. Wind speed is one of the most important influence affecting the turbine performance, fluctuations in wind speed could results to chaotic turbulence predominantly caused by contact with the earth's outside part or motion from the blades, which could be disturbance triggered by humid structures and current effects which could cause air masses to move abruptly as a consequence of variations in temperature and henceforth density of air. Most of these social problems have been resolved or greatly reduced through technological development or by properly siting wind plants. As highly expected power generation in the next future, there are concerns on how to distinguish between real uncertainties hazards around the system that would have less effect on the normal working condition of the wind turbine. Early interception of a reliable to an effective technique to monitor the activities around the system could reduce the amount of unnecessary emergency in the system and hence boost the conditions of the monitored parameters significantly to the success of energy production. With the fact that there is industrial request target to increase in demand for modern dynamic systems to be safe, reliable, efficient, to substantially reduce the cost to the consumers on utilities which make it one of the most affordable electricity power [168].

5.4.3 Repairs and Maintenance

Wind power has the potential contribution to the future of power energy among the current repairs approaches, for predictive and preventive techniques to support wind turbines to reach availability and less expensive energy. Decreasing the operation and maintenance (O&M) costs and filtering reliability have developed the top significances in WT repairs methods. The trends of how to reduce operation and maintenance (O&M) cost is researchers concerns to guarantee the low repairs, availability period and minimizing the costs of maintenance and repair. The idea of expenses in wind industry was the growing stage of wind turbines and the failure of electric system sensors and blade/pitch components. Therefore, the expansion greatly advanced WT designs proposed to improve availability, the request of reliable and cost-effective condition monitoring (CM) techniques that motivate monitoring a particular parameter to offers an effective method to realize this goal. CM is a device generally active for the early finding of faults/failures so as to reduce interruption and maximize efficiency, which is also considered as a comprehensive process for defining the complete operational health of the WT often used for the rotating parts. The key function of a successful CM system should be to provide a reliable warning of the presence of a fault within the WT system and furthermore to identify the location and severity of the condition. This method of monitoring is fit for design purpose, parameter state in order to predict failure or identify substantial changes to control the best point between corrective and planned maintenance schemes [169] and [170]. The wind turbines are normally planned to function for about of 20-30 years according to some study [171]. The chance that an unsuccessful component will be reinstated to operational effectiveness within a given period of time when the repair is carried out in agreement with recommended measures. The method to optimize the maintenance of components which degradation can be classified according to the severity of the damage. Maintenance for these components can often be based on different condition-based maintenance (CBM) strategies for uninterrupted monitoring which are economically justifiable. The scrutiny practices are employed to identify early developing of incipient faults and to decide any needed maintenance assignments ahead of failure to ensure system reliability and to improve from interruptions [172]-[176]. A major issue of WT is the relatively cost of O&M which often increases maintenance costs which could cause poor reliability that could reduce the availability thereby triggering shut-down and component repairing. The operating functional time-based maintenance is assumed that the fault behavior of WT is estimated. Basically, three fault outlines define the features state of WT. The bathtub curve shown in Figure 5.5 illustrates the notional fault rate against process lifetime in a process system [171] where $r < 1$ represents a decreasing fault speed, $r = 1$ represents a constant fault proportion which implies normal working condition, and $r > 1$ denotes a cumulative fault level..

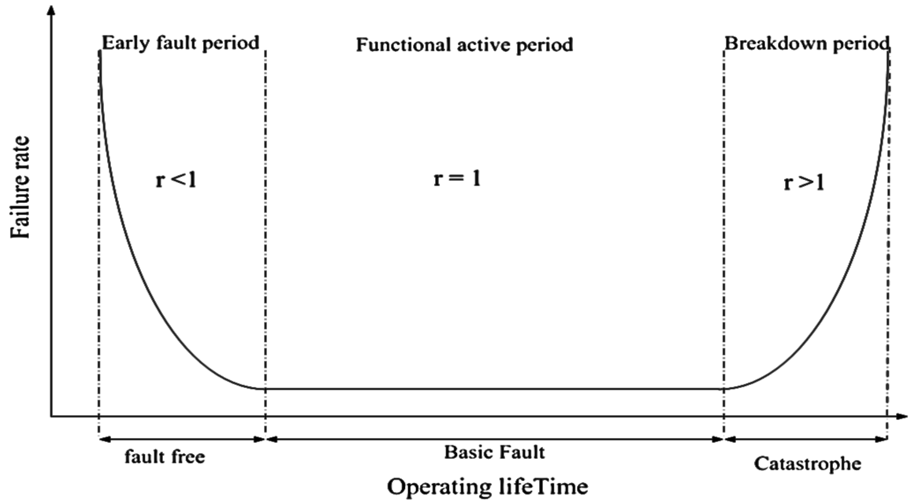


Figure 5.5: The technical reliability analysis of the fault in bathtub [171]

The fault presented in the curve above, the early fault free rate is the first part of the curve where fault period is decreasing also known as infant mortality failures. The middle section is referred to as a basic fault which is also the useful life, which assumed that fault exhibit a constant fault. The final part of the curve defines the catastrophe and is expected that failure/fault rate increases as a wear out current mechanisms.

5.4.4 Failure Rate

The desired rate and act developments could be reached with state-of-the-art variations in current designs that integrate original improvements in resources, plan methods, device approaches, and industrial processes. The fixed cost of a wind power project is subject to the straight principal rate. The capital cost can be classified into Wind turbines (includes blades, tower, and transformer) to be 64% which is expensive of the wind farm, Groundwork 16%, Grid Construction 11%, Planning, and Miscellaneous to be 9%. Most failures were linked to the electrical system followed by sensors and pitch/blades components [177] (see Figure 5.6).

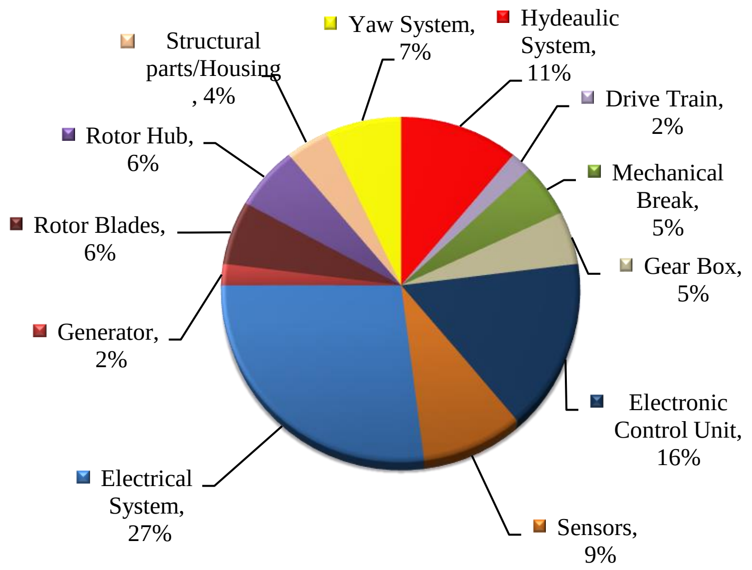


Figure 5.6: The component failures of wind turbine system [177]-[178]

The total percentage of failures is shown above instituting the huge influence of a component / parameter failure on wind turbine reliability. The prospective unexpected changes in component could affect the repair cost, hazards and performance of the component failure on WT reliability, this focus on the availability as presented in [171] that revealed about 75% of the yearly interruption is triggered by about 15% of the average failure rate and downtime per component in WTs. The assessment with the Electrical system repairs, Electronic control unit, Hydraulic system and sensor device that are majorly subjected to high failure rates, requiring so often repairs, maintenance and possibly extra redundancy. In the wind turbine, the sensor has as key unbiased to identify in prior any destruction of the wind turbine nacelle components, in order to allow the proposal of operative and precisely upkeep operations and repairs. In this network, the secured data from the sensor device are sent to a control system, from where the plant state can be constantly observed. Likewise, this method increases the value of the upkeep and maintenance process as well as prevents unwanted extra interruptions of the plant. The highest mechanical fault rate and the assessments, which have to be achieved, will be defined. Furthermore, it will be obtainable state-of-art assessment performances and technologies in the wind turbine sector [171]. As the request for wind energy is growing quickly precisely, it is essential to guarantee a good excellence of the power supplied and an improved temporary permanence of the wind farm, so that the wind farm can overwhelm the variations triggered by the error as rapidly potentially. The wind turbines need to operate reliably at all times, despite the possible occurrence of faulty system components and sensors to achieve the purpose of the system, which one of them is availability. Fault detection avoids catastrophic failures by making possible for scheduled maintenance to keep the turbines running, improvement in the reliability of wind turbines would both greatly reduce the amount of interruption considerable of the present and high maintenance expenses [179]-[180]. Therefore, the design of fault diagnosis and accommodation techniques is a crucial step in achieving reliable operations of wind turbines. The expenses of wind turbine repairs can be lessened by emerging wind turbines that need less planned and principally non-organised service and has less interruption by failure. This is essential particularly for offshore wind farms where the fee related to O & M is sophisticated and where climate circumstances may avert repairs upkeep for an extended time. The analysis to moderate O & M expenses is the answer that affords us the prospect of generating power, possibly with some deprivation in the performance, subsequently, failure has happened till the subsequent planned check. The control system is of high importance for detection, isolation and accommodation of faults in wind turbines since it has access to information from the different components of the wind turbine. Early stage engineering, monitoring, and maintenance are vital to keeping turbines available to generate energy and improve performance. Control systems are combined into all turbines to permit them to function unattended and device an uninterrupted optimisation of power performance. Comprehensive Supervisory Control and Data Acquisition (SCADA) controller systems monitor, data collection, reporting, coordinate the operation to original and shut down turbine operator are employed in all commercial wind farms and which are economically justifiable. They collect data from individual turbines and from substations. Often there are meteorological masts that are also used to gather wind data for the site. A high level of understanding has been developed, allowing optimisation of both wind farm design and operation [181]-[184]. A comprehensive investigation by monitoring engineers with the aim of diagnosing the fault is their core values. Plant operator's key importance is observing for alarms are reliable so that they can take assured action with regard to warning power downtime or shutting down a turbine to escape severe or risk failure happening. This point is the relationship between CM and diagnostic systems where CM leads to the diagnosis. A competent scheme to moderate O & M costs is initial and precise fault detection and diagnosis (FDD).

5.5 Fault Detection for wind turbine technology

The concepts of fault detection and diagnosis are a condition monitoring system that monitors to detect on-line fault performance of the rotating dynamic system and diagnose irregularities to provide information about the irregular working parts of the dynamic system [184]. To continuously ensure reliable working process of the modern control system in WT, avoid abnormal event progression, reduces productivity losses and system breakdown which means, dangerous faults are not acceptable and must be spotted earlier before they truly occur. Though, the condition for soft (incipient) faults is very small of which is nearly invisible to be seen. Small faults progress gradually to cause severe impact on the system. An initial onset warning of soft faults can provide sufficient information the operator and interval to take proper actions to avoid any severe concern on the system. Unknown disturbances always exist in the practical environment, which could cause false alarms. There is the need to design a robust optimal fault detection observer to make the residual sensitive to faults but robust against disturbances. A UIO was intended for detection of sensor faults around WT drive train with the assumption that UIO can be completely decoupled. Nevertheless, this theory cannot always be met in some practical events, additional motivation has been positioned on the electrical change system in the WT with some relevant examples in [185].

5.5.1 Types of faults in a controlled systems

Model-based FD system is practical primarily with on-line fault diagnosis, in which the analysis is supported during system working operation. The model-based FD requires the system obtainable input and output information when the system is in operation [186]-[187]. The modeled faults considered are the sensor, actuator and process faults in the different fragments of the wind turbine.

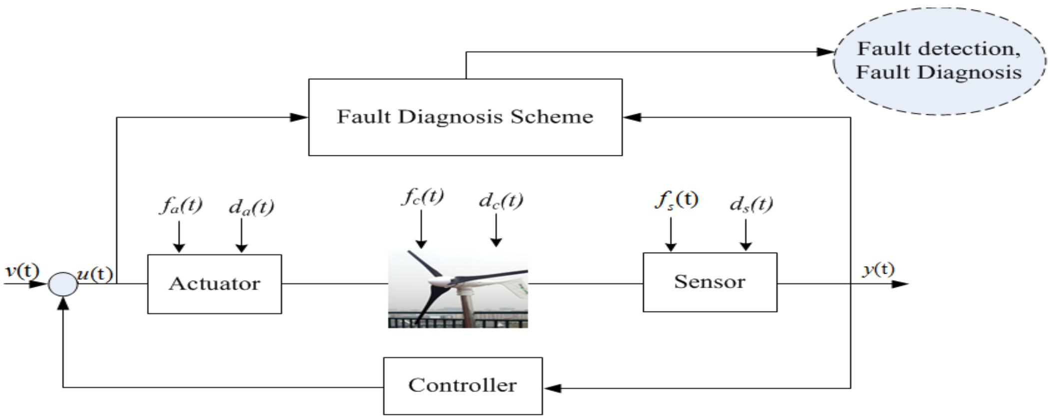


Figure 5.7: Types of faults in a control system

Figure 5.7 illustrates the scheme of the WT model-based fault diagnosis, where v(t) is the reference command, u(t) is the control input, y(t) is the measured output. The symbols d_a(t), d_c(t), d_s(t) are the input disturbances, process disturbances (due to the modelling errors and parameter variations), and sensor disturbance; and f_a(t), f_c(t) and f_s(t) are the actuator fault, process fault (or called parameter fault) and sensor fault, respectively. In this study, we focus on actuator faults and sensor faults in types of incipient faults and abrupt faults.

5.5.2 Wind Turbine System Model

A 5MW wind turbine system model corrupted with system faults and disturbances can be represented in the form:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = Cx(t) + Du(t) + D_f f(t) + D_d d(t) \end{cases} \tag{5.1}$$

where $x(t) \epsilon \Re^n$ is the state vector, $u(t) \epsilon \Re^m$ is the system control input, $y(t) \epsilon \Re^p$ is the measurement output, A, B, C, D are known matrices of appropriate dimensions; $f(t) \in \Re^k$ represents the fault vector, B_f, and D_f are the fault distribution matrices; $d(t) \in \Re^l$ is the disturbance vector, and B_d and D_d are disturbance matrices. The system parameter matrices of the wind turbine system are given below [178]:

$$A = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \frac{-1}{n_g} & 0 & 0 \\ 0 & \frac{K_s}{J_T} & \frac{-C_s}{J_T} & \frac{C_s}{J_T n_g} & 0 & 0 \\ 0 & \frac{K_s}{J_G n_g} & \frac{C_s}{J_G n_g} & \frac{-C_s}{J_G n_g^2} & 0 & 0 \\ 0 & 0 & 0 & -i_q & \frac{R_s}{\sigma L_r} & (\omega_s - \omega_m) \\ 0 & 0 & 0 & \frac{i_d + L_m u_{sq}}{L_s \omega_s} & -(\omega_s - \omega_m) & \frac{R_r}{\sigma L_r} \end{bmatrix} B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{J_T} & 0 & 0 & 0 \\ 0 & 0 & \frac{-1}{J_G} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\text{C=} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{-\sqrt{3} n_p L_m V_s K_c}{\sigma L_r L_s \omega_s} \end{bmatrix} \quad D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \text{ where } K_c = 0.8383. \tag{5.2}$$

The symbols of the 5MW wind turbine model are defined in Table 1 [178], where the wind turbine is operating at wind speed of 10 m/s.

Table 5.5: Symbols of 5MW wind turbine Parameters [178]

DESCRIPTION	SYMBOL	DESCRIPTION	SYMBOL
Turbine Inertia	J_T	Leakage coefficient	σ
Gearbox ratio	n_g	Stator current	i_d, i_q
Generator inertia	J_G	Pitch angle	β
Torsional stiffness	K_s	Desired pitch angle	β_d
Torsional damping	C_s	Mechanical torque	T_{wt}
Synchronous speed	ω_{s}	Electrical torque	T_e
Stator resistance	R_s	Control torque	T_e^c
Rotor resistance	R_r	Control rotor voltages	v_{dr}, v_{qr}
Stator inductance	L_{s}	Wind turbine speed	ω_{wt}
Rotor inductance	L_{s}	Generator speed	ω_{m}
Mutual inductance	L_m	Stator voltage	
		Gearbox ratio	

The states x, inputs u and output y, of the wind turbine model are defined as:

$$x = \begin{bmatrix} \beta \\ \theta_K \\ \omega_{wt} \\ \omega_{m,} \\ i_{dr} \\ i_{qr} \end{bmatrix} = \begin{bmatrix} \text{pitch angle} \\ \text{angular speed position} \\ \text{wind turbine speed} \\ \text{generator speed} \\ \text{d - axis rotor current} \\ \text{q - axis rotor current} \end{bmatrix} \text{ Refers to the entire system health state condition}$$

$$u = \begin{bmatrix} \beta_d \\ T_{wt,} \\ T_e^c \\ v_{dr} \\ v_{qr} \end{bmatrix} = \begin{bmatrix} \text{pitch angle} \\ \text{wind turbine torque} \\ \text{electrical control torque} \\ \text{active control rotor voltages} \\ \text{reactive control rotor voltages} \end{bmatrix} \text{ Predictive or known input value of the WT}$$

$$y = \begin{bmatrix} \beta \\ \omega_{wt} \\ \omega_m \\ T_e \end{bmatrix} = \begin{bmatrix} \text{pitch angle} \\ \text{wind turbine speed} \\ \text{generator speed} \\ \text{electromagnetic torque} \end{bmatrix} \text{ WT output}$$

5.5.3 Robust Fault Detection for WT

For the wind turbine model (5.1), the observer-based fault detection filter can be described as:

$$\begin{cases}\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K(y - \hat{y}) \\ \hat{y}(t) = C\hat{x}(t) + Du(t) \\ r(t) = W\big(y(t) - \hat{y}(t)\big)\end{cases} \tag{5.3}$$

where $\hat{x}(t)$ is the estimated state, $\hat{y}(t)$ is the system output estimate; the residual signal, denoted by $r(t)$, is the weighted difference between the real output state of the wind turbine system $y(t)$ and the estimated output $\hat{y}(t)$. For brevity, we choose $W = I$ in this study.

Let,

$$e(t) = x(t) - \hat{x}(t). \tag{5.4}$$

In terms of (5.1) and (5.3), one has

$$\begin{cases}\dot{e}(t) = (A - KC)e(t) + \big(B_f - KD_f\big)f(t) + (B_d - KD_d)d(t) \\ r(t) = Ce(t) + D_f f(t) + D_d d(t)\end{cases} \tag{5.5}$$

Therefore, the residual of the equation can be expressed by frequency domain model:

$$r(s) = H_d(s)d(s) + H_f(s)f(s) \tag{5.6}$$

where,

$$H_d(s) = C(sI - A + KC)^{-1}(B_d - KD_d)d(s) + D_d \tag{5.7}$$

$$H_f(s) = C(sI - A + KC)^{-1}\big(B_f - KD_f\big) + D_f \tag{5.8}$$

It can be perceived from (5.6) that, due to the existence of disturbances, the residual would not be zero even at the event of fault free. The upshot of disturbances behaviour could cause a missed or wrong alarm. Hence, the key goal of the robust fault detection design is to seek an optimum observer gain $'K'$ to attenuate disturbances influence and to enlarge fault. If the residual signal is less than a threshold value (e.g., under disturbances/noises environment), the system is healthy. Otherwise, the system is faulty, giving an alarm.

In terms of Chapter 3, GA-based fault detection filter design method can be summarised as follows:

Algorithm 5.5: GA-based fault detection filter design

- Set the sizes of the population and generation.
- Set the parameters to be optimized in form of (3.24), that is,

$$\Theta = \{\lambda_1, \cdots \lambda_{n_r}, \lambda_{1,re}, \cdots, \lambda_{n_c,re}, \lambda_{1,im}, \cdots, \lambda_{n_c,im}, w_1 \cdots w_{n_r}\ w_{1,re} \cdots\ w_{n_c,re}\ w_{1,im} \cdots\ w_{n_c,im}\} \tag{5.9}$$

- Set the cost function in the form of (3.23), that is,

$$\frac{\|H_d(s)\|_{s=j\omega_d}}{\|H_f(s_0)\|_{s_0=j0}} = \frac{\|(sI-A+KC)^{-1}(B_d-KD_d)+D_d\|_{s=j\omega_d}}{\|C(s_0I-A+KC)^{-1}(B_f-KD_f)+D_f\|_{s_0=j0}} \tag{5.10}$$

where ω_d is the frequency of the dominant disturbance, and the frequency of the fault concerned is chosen to be zero.

- Set the constraint such that the observer system matrix $A - KC$ is stable, that is, all the real parts of the eigenvalues must be less than zero, in every iteration.
- GA runs until the stop condition is satisfied. The optimal Θ_* is thus obtained, that is,

$$\Theta_* = \{\lambda_{1*}, \cdots \lambda_{n_{r*}}, \lambda_{1,re*}, \cdots, \lambda_{n_c,re*}, \lambda_{1,im*}, \cdots, \lambda_{n_c,im*},$$

$$w_{1*} \cdots w_{n_r*}\ w_{1,re*} \cdots\ w_{n_c,re*}\ w_{1,im*} \cdots\ w_{n_c,im*}\} \tag{5.11}$$

- The optimal K_* is thus calculated by

$$K_* = [W_*(V_*)^{-1}]^T, \tag{5.12}$$

$$W_* = [w_{1*} \cdots w_{n_{r*}}\ w_{1,re*} \cdots\ w_{n_c,re*}\ w_{1,im*} \cdots\ w_{n_c,im*}] \in \Re^{p\times n} \tag{5.13}$$

$$V_* = [v_{1*} \cdots v_{n_r*}\ v_{1,re*} \cdots\ v_{n_c,re*}\ v_{1,im*} \cdots\ v_{n_c,im*}] \in \Re^{n\times n} \tag{5.14}$$

$$v_{i*} = -(\lambda_{i*}I - A^T)^{-1}C^T w_{i*}, \quad i = 1, 2, \cdots, n_r \tag{5.15}$$

$$\begin{bmatrix} v_{j,re*} \\ v_{j,im*} \end{bmatrix} = -{\Gamma_{j*}}^{-1}\Omega_c \begin{bmatrix} w_{j,re*} \\ w_{j,im*} \end{bmatrix}, \qquad \mathrm{j} = 1, 2, \cdots, n_c \tag{5.16}$$

$$\Gamma_{j*} = \begin{bmatrix} \lambda_{j,re*}I - A^T & -\lambda_{j,im*}I \\ \lambda_{j,im*}I & \lambda_{j,re*}I - A^T \end{bmatrix}, \tag{5.17}$$

$$\Omega_c = \begin{bmatrix} C^T & 0 \\ 0 & C^T \end{bmatrix}. \tag{5.18}$$

- Apply the observer-based fault detection filter in the form of (5.4), that is,

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K_*(y(t) - \hat{y}(t)) \\ \hat{y}(t) = C\hat{x}(t) + Du(t) \\ r(t) = y(t) - \hat{y}(t) \end{cases} \tag{5.19}$$

5.5.4 Simulation Results for Robust Fault Detection

To illustrate the proposed robust fault detection filter and robust fault estimation observer approach on sensor and actuator scenarios, the model is simulated based on 5MW continuous-time wind turbine system as illustrated above. The investigation is carried out on Matlab/Simulink platform. The optimization is demonstrated on gatool toolbox in Matlab environment to operate the genetic algorithm method of typical abrupt and ramp types of faults are considered in this simulation.

There are two match approaches to design observer gain "K", the first method is GA and the second method is place command function in Matlab. Considering the possibility and the error in the simulation, it is needed to simulate the parameters with two main types of faults, step and ramp signal. Disturbance is defined as a sine wave, with the process disturbance injected to the 5MW wind turbine system is defined as follows:

$$d(t) = 0.001\sin(12\pi t) \tag{5.20}$$

A. Robust Fault Detection For Sensor Faults

The Multi-objective optimization problem is to attenuate the robustness to disturbance and enlarge the sensitivity to faults. Scenario One: For system (5.5), consider sensor fault only by letting $B_f = 0$, while $D_f = I$. The frequency of the disturbance is $\omega_d = 12\pi$. The sensor faults considered are abrupt faults and incipient faults, and the frequency of the faults is chosen as zero. In is noticed that $n = 6$ and $p = 4$, thus the number of parameters to be optimized is $\alpha = 6 + 6 \times 4 = 30$. Following the GA-based fault detection filter design algorithm (see Algorithm 5.5), one can obtain the optima fitness value (see 5.8) and the resulting optimal observer gain.

$$B_f = \qquad D_f = \begin{bmatrix} I \\ 0 \\ 0 \end{bmatrix} \begin{matrix} \text{Sensor fault} \\ \text{Actuator fault} \\ \text{Process fault} \end{matrix} \quad B_f = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad D_f \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

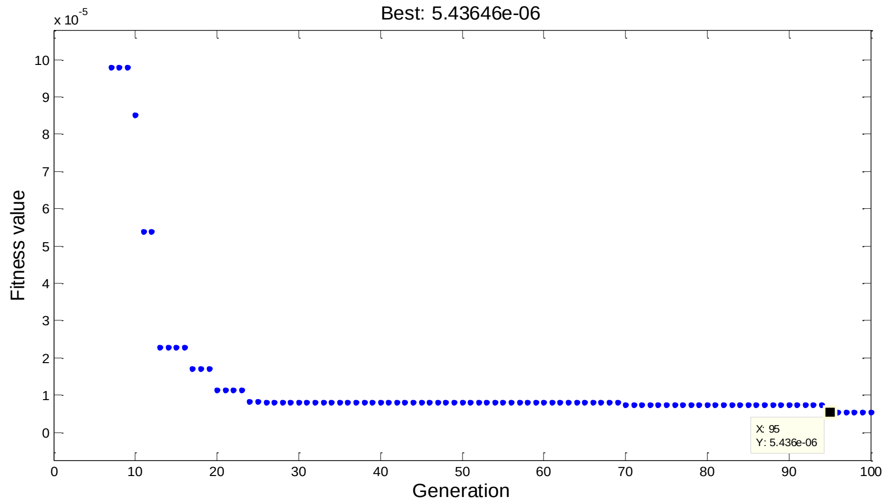


Figure 5.8: The sensor best fitness value by using GA optimization

The computed generated optimal observer gain is

$$K_{GA} = \begin{bmatrix} 3.8163 & 0.7756 & -2.9272 & -0.0001 \\ 1.0936 & -1.8260 & -2.5665 & 0.0001 \\ 5.6920 & 9.6210 & 13.5782 & -0.0001 \\ -0.0019 & 0.0033 & 0.0047 & 0.0000 \\ -0.1719 & 0.2932 & 0.4138 & -0.0046 \\ 3.2818 & -5.6739 & -8.1987 & -0.0002 \end{bmatrix}. \tag{5.21}$$

A1). Single incipient sensor fault detection

Considering individual single faults

(a) Pitch angle sensor fault

$$f_{sensor1} = \begin{cases} 0.1t + 0.001sin(0.1t) & t \geq 10 \\ 0 & t < 10 \end{cases} \tag{5.22}$$

(b) Wind turbine sensor fault

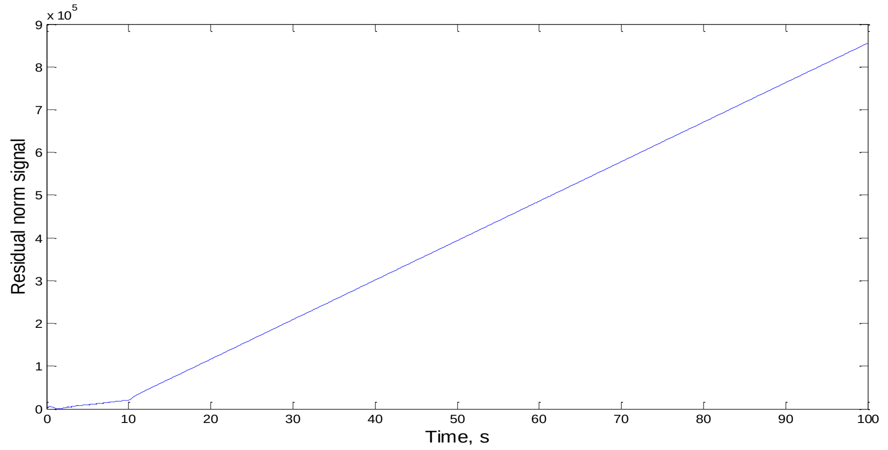
$$f_{sensor2} = \begin{cases} 0.1t + 0.001sin(0.1t) & t \geq 20 \\ 0 & t < 20 \end{cases} \tag{5.23}$$

(c) Generator speed sensor fault

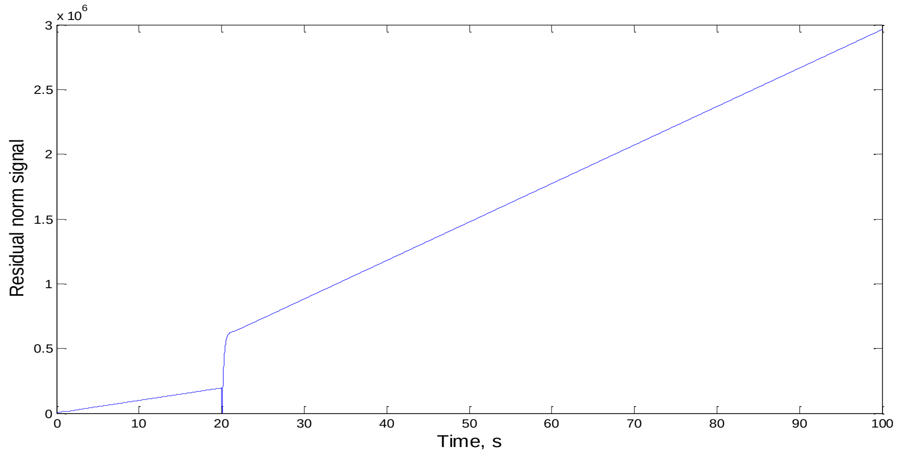
$$f_{sensor3} = \begin{cases} 0.1t + 0.001sin(0.1t) & t \geq 30 \\ 0 & t < 30 \end{cases} \tag{5.24}$$

(d) Electromagnetic torque

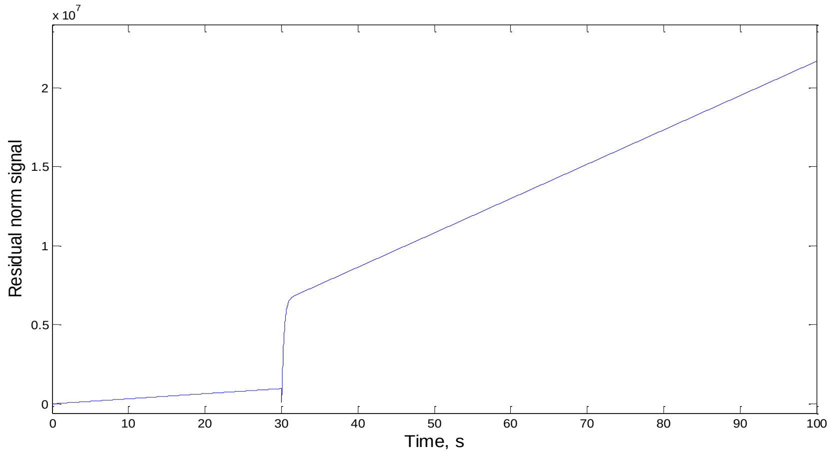
$$f_{sensor4} = \begin{cases} 10t + 0.001sin(0.1t) & t \geq 40 \\ 0 & t < 40 \end{cases} \tag{5.25}$$



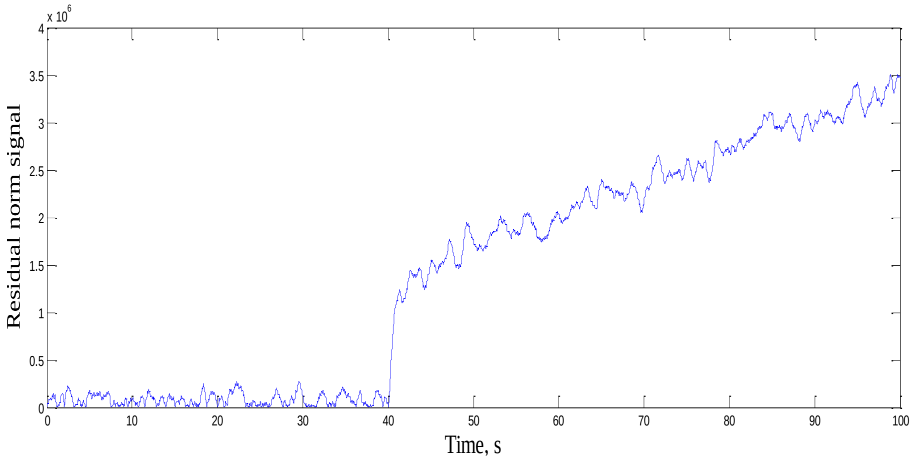
(a) Fault detection for the pitch angle incipient sensor fault



(b) Fault detection for the wind turbine speed incipient sensor fault



(c) Fault detection for the generator speed incipient sensor fault



(d) Fault detection for the electromagnetic torque incipient sensor fault

Figure 5.9: Single incipient sensor fault detection by using GA-based fault detector

According to Figure 5.9, it can be clearly seen that the the first three sensor faults pitch angle sensor fault, wind turbine speed sensor fault, and generator speed been successfully detected repectivley at 10s, 20s and 30s. However, the electromagnetic torque sensor fault occuring at 40s is not clearly detected, although the change at 40s can be seen if the figure is zoomed in. It seems to be reasonable as the amplitude of the steady electromagnetic torque is around 50000 so that a ramp fault with a small gradient is challenging to be detected. When one increases the gradient of the fourth sensor fault, that is, electromagnetic torque sensor fault, it is evident that the detabablity should be increased. For instance, the electromagnetic torque sensor fault is modified as follows:

$$f_{sensor4} = \begin{cases} 100t + 0.001sin(0.1t) & t \geq 40 \\ 0 & t < 40 \end{cases} \qquad (5.26)$$

The residual norm for the wind turbine system subjected to the electromagnetic torque sensor fault is shown by Figure 5.10. One can see the fault decribed by (5.26) has been successfully detected.

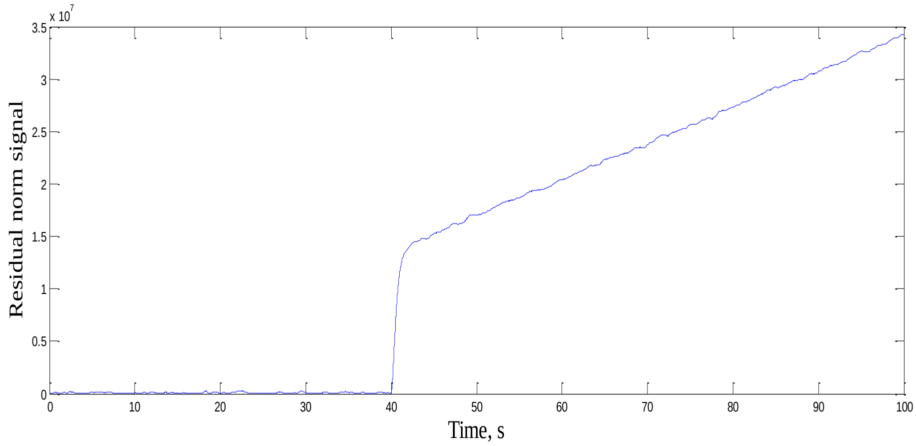


Figure 5.10: Incipient fault detection of the electromagnetic torque sensor

A2). Detection of multiple incipient sensor faults

Now one assumes the four sensor faults occur sequentially at 10s, 20s, 30s and 40s, respectively. The first, second and fourth sensor faults are given respectively by (5.23), (5.24) and (5.27), and the third sensor fault is given as follows:

$$f_{sensor3} = \begin{cases} 10t + 0.001sin(0.1t) & t \geq 30 \\ 0 & t < 30 \end{cases} \tag{5.27}$$

The residual is shown by Figure 5.11.

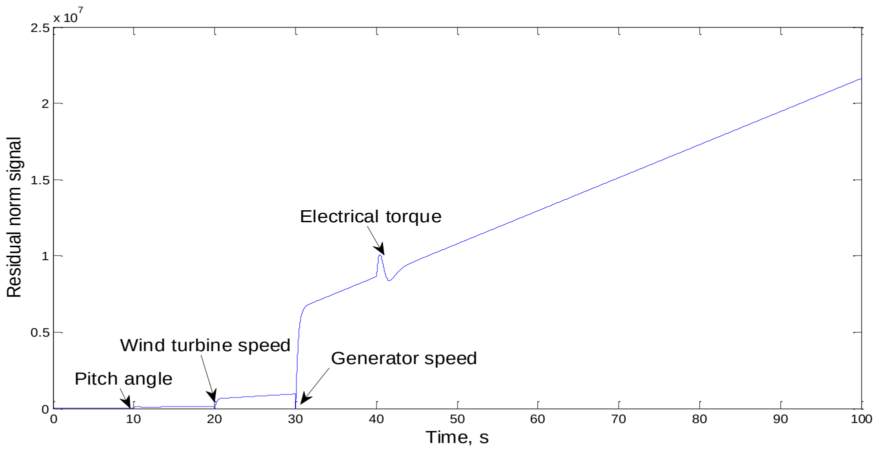


Figure 5.11: Multiple sensor fault detection: GA-based approach

From Figure 5.11, one can see the residual has shown the changes respectively at 10s, 20s, 30s and 40s. In other words, the four sensor faults have been successfully detected.

A3). Single abrupt sensor fault detection

The abrupt faults of the four sensors are assumed to be as follows:

(a) Pitch angle sensor fault

$$f_{sensor1} = \begin{cases} 0.1 + 0.001 sin(0.1t) & t \geq 10 \\ 0 & t < 10 \end{cases} \tag{5.28}$$

(b) Wind turbine sensor fault

$$f_{sensor2} = \begin{cases} 0.1 + 0.001 sin(0.1t) & t \geq 20 \\ 0 & t < 20 \end{cases} \tag{5.29}$$

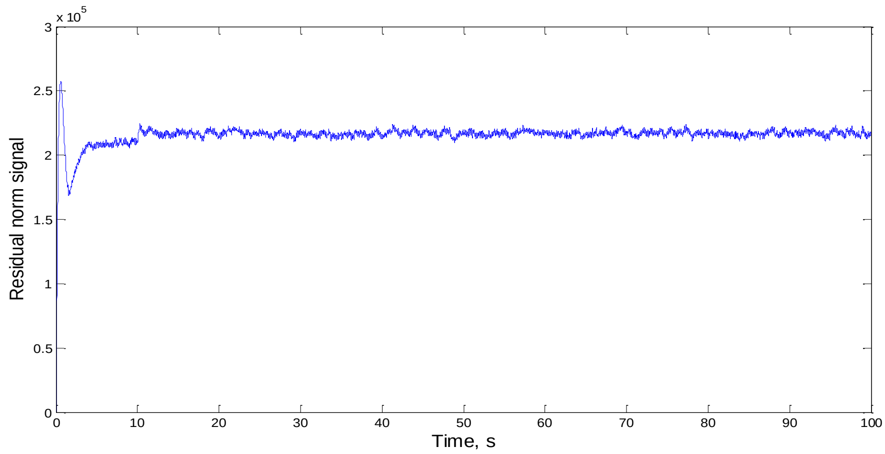
(c) Generator speed sensor fault

$$f_{sensor3} = \begin{cases} 0.1 + 0.001 sin(0.1t) & t \geq 30 \\ 0 & t < 30 \end{cases} \tag{5.30}$$

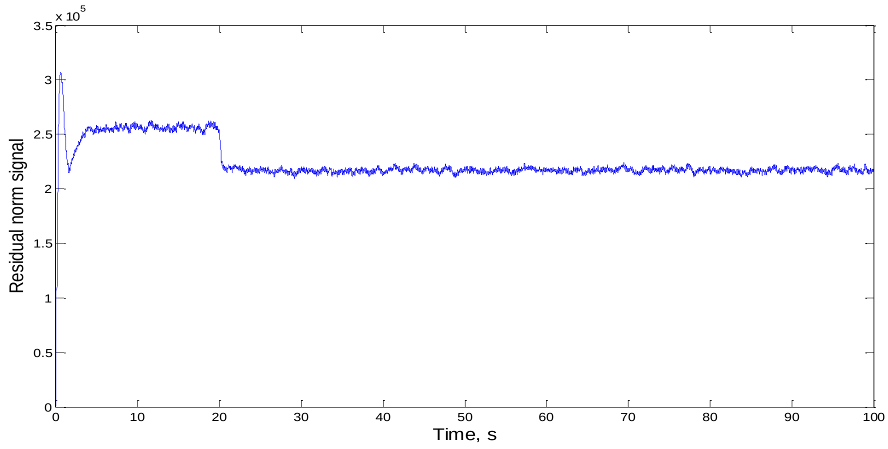
(e) Electromagnetic torque

$$f_{sensor4} = \begin{cases} 0.1 + 0.001 sin(0.1t) & t \geq 40 \\ 0 & t < 40 \end{cases} \tag{5.31}$$

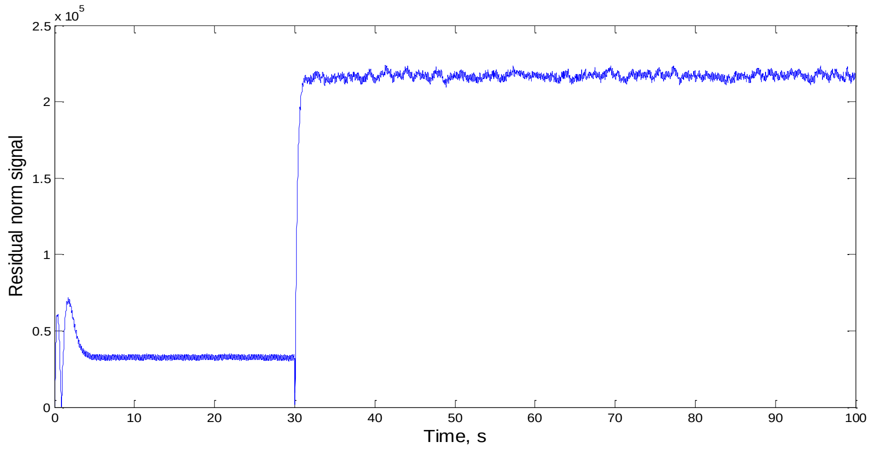
For single abrupt sensor fault, the residuals are shown by Figure 5.12. One can see the residuals have successfully catched the signal changes respectivley at 10s, 20s, 30s and 40secs.



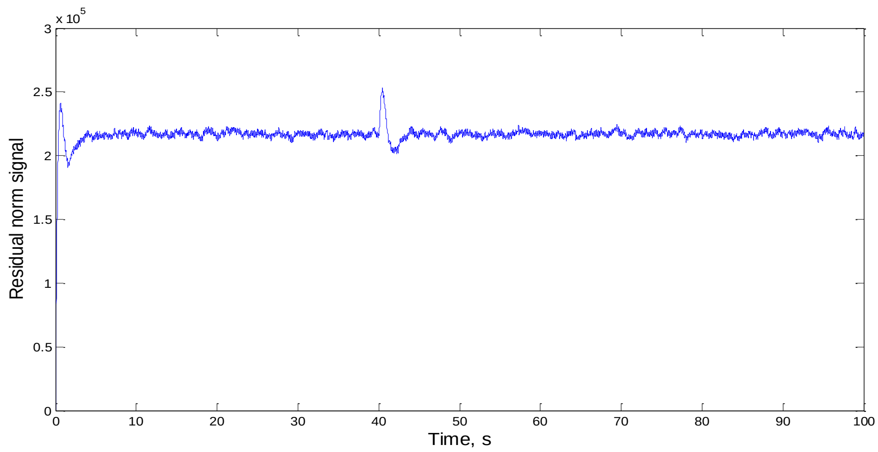
(a) Fault detection for the pitch angle abrupt sensor fault



(b) Fault detection for the wind turbine speed abrupt sensor fault



(c) Fault detection for the generator speed abrupt sensor fault



(d) Fault detection for the electromagnetic torque abrupt sensor fault

Figure 5.12: Single abrupt sensor fault detection by using GA-based fault detector

A4). Detection of multiple sensor faults with comparisons

One supposes the four sensor faults described by (5.28)-(5.31) sequentially occur at 10s, 20s, 30s and 40s respectively. In order to make the comparison, one also designed observer-based fault detection with the conventional pole-assignment method without considering disturbance attenuation. The place command function is used to assign poles to the set of $p = \{-2, -3, -4, -5, -6, -7\}$ leading to the observer gain as follows:

$$k_{PLACE} = \begin{bmatrix} 0.0004 & -0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0986 & 2.9480 & -0.0000 \\ -0.0000 & 0.0014 & 0.0001 & 0.0000 \\ 0.0000 & 0.0001 & 0.0060 & -0.0000 \\ -0.0000 & -0.0000 & 2.4992 & -0.0000 \\ -0.0000 & -0.0000 & 0.0017 & 0.0000 \end{bmatrix} \tag{5.32}$$

By using GA-based fault detection filter and pole-assignment based fault detection filter, the residuals are shown by Figure 5.13. One can see the pole-assignment based fault detection filter can only detect the abrupt fault occurring at 30s, but failed to detect the faults happening at 10s, 20s and 40s. On the contrary, the GA-based fault detection filter can successfully detect all the four sensor faults respectively happening at 10s, 20s, 30s and 40s. Therefore, GA-based fault detection has shown a better fault detection ability.

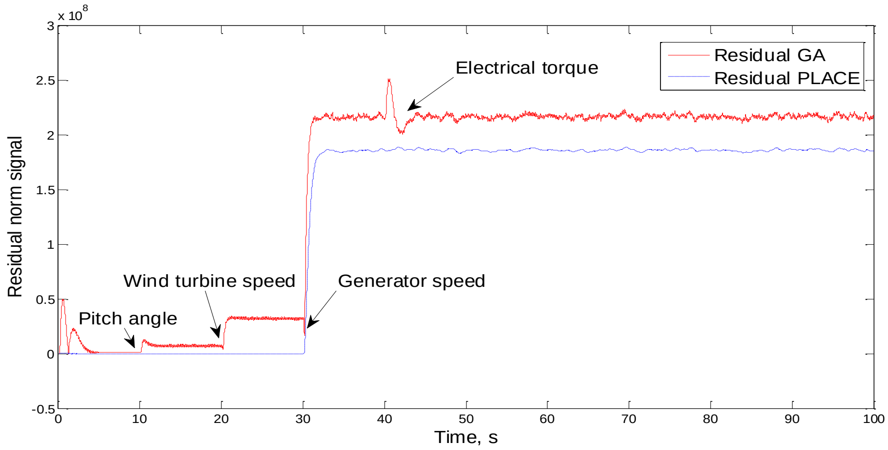


Figure 5.13: Multiple abrupt sensor fault detection

Now we can look at the multiple incipient faults again in order to compare with the pole-assignment based fault detection method. The incipient sensor faults are defined by (5.22)-(5.25). The residuals are shown by Figure 5.14. One can see the pole-assignment method only can detect the incipient faults occurring at 30s, but failed to detect the faults happening at 10s, 20s and 40s. However, the GA-based fault detection filter can successfully detect the incipient faults occurring at 20s, 30s and 40s, although the change at 10s is not shown very clearly. As a result, the GA-based fault detection filter has shown better fault detection ability comparing with the pole-assignment based fault detection filter.

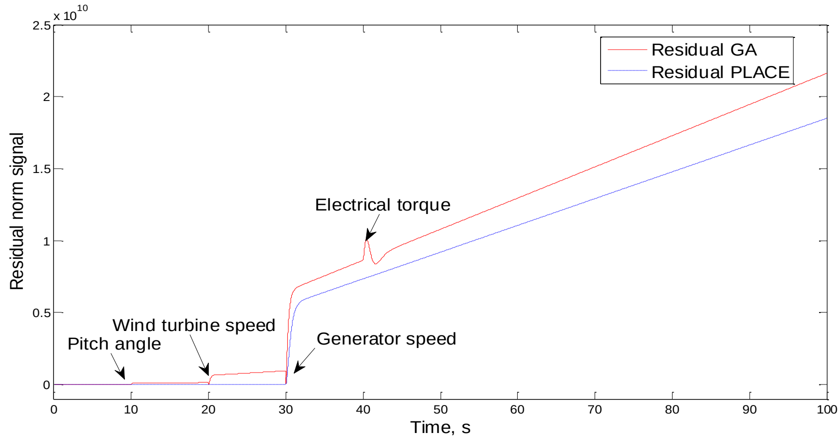


Figure 5.14: Multiple incipient sensor fault detection

B. *Robust Fault Detection For Actuator Faults*

Let us consider actuator faults only, that is, $B_f = B$, and $D_f = 0_{4\times4}$. Set the sizes of the population and generation are both 100. Use the GA-based algorithm (see Algorithm 5.5), one can obtain the optimal fitness value (see Figure 5.11) and the corresponding optimal gain.

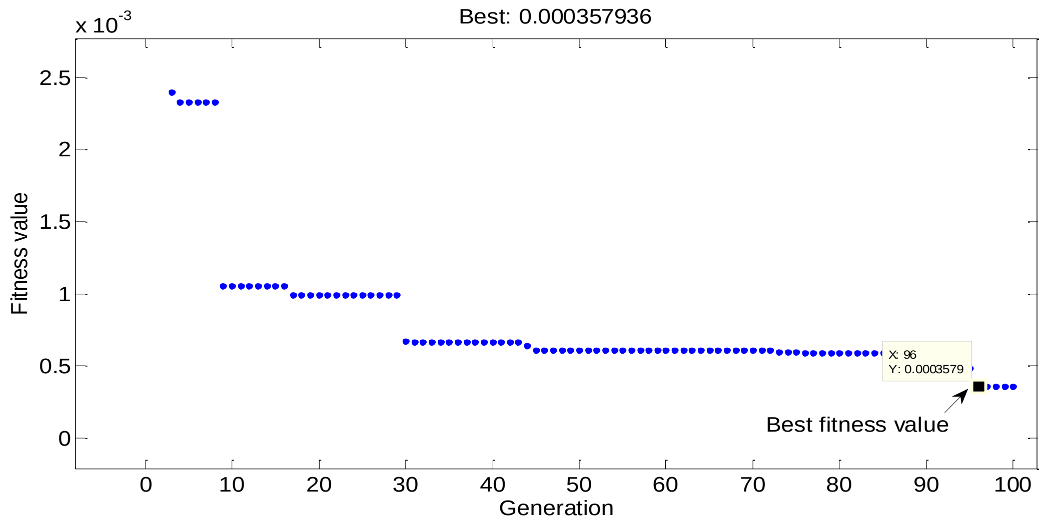


Figure 5.15: Fitness value via GA optimization: actuator faults

The optimal observer gain is given as follows:

$$K_{GA} = \begin{bmatrix} 18.578 & 0.4928 & -8.1870 & -0.0000 \\ 1.2270 & -0.7439 & -1.2515 & 0.0000 \\ 0.6116 & 20.1506 & -3.18 & -0.0000 \\ 0.0011 & 0.0108 & -0.0027 & 0.0000 \\ 0.1304 & 1.2904 & -0.33303 & -0.0046 \\ -0.8895 & -9.1475 & 2.2002 & -0.0006 \end{bmatrix} \quad (5.33)$$

The five abrupt actuator faults are defined as follows:

(a) Pitch angle actuator fault

$$f_{actuator1} = \begin{cases} 0.01 + 0.001sin(0.1t) & t \geq 10 \\ 0 & t < 10 \end{cases} \quad (5.34)$$

(b) Wind turbine torque actuator fault

$$f_{actuator2} = \begin{cases} 10^5 + 0.001sin(0.1t) & t \geq 20 \\ 0 & t < 20 \end{cases} \quad (5.35)$$

(c) Electrical control torque actuator fault

$$f_{actuator3} = \begin{cases} 0.01 + 0.001sin(0.1t) & t \geq 30 \\ 0 & t < 30 \end{cases} \quad (5.36)$$

(d) Active control rotor voltage actuator fault

$$f_{actuator4} = \begin{cases} 0.01 + 0.001sin(0.1t) & t \geq 40 \\ 0 & t < 40 \end{cases} \quad (5.37)$$

(e) Reactive control rotor voltage actuator fault

$$f_{actuator4} = \begin{cases} 0.01 + 0.001sin(0.1t) & t \geq 50 \\ 0 & t < 50 \end{cases} \quad (5.38)$$

The five incipient actuator faults are defined as follows:

(a) Pitch angle actuator fault

$$f_{actuator1} = \begin{cases} 0.01t + 0.001sin(0.1t) & t \geq 10 \\ 0 & t < 10 \end{cases} \quad (5.39)$$

(b) Wind turbine torque actuator fault

$$f_{actuator2} = \begin{cases} 10^5t + 0.001sin(0.1t) & t \geq 20 \\ 0 & t < 20 \end{cases} \quad (5.40)$$

(c) Electrical control torque actuator fault

$$f_{actuator3} = \begin{cases} 0.01t + 0.001sin(0.1t) & t \geq 30 \\ 0 & t < 30 \end{cases} \tag{5.41}$$

(d) Active control rotor voltage actuator fault

$$f_{actuator4} = \begin{cases} 0.01t + 0.001sin(0.1t) & t \geq 40 \\ 0 & t < 40 \end{cases} \tag{5.42}$$

(e) Reactive control rotor voltage actuator fault

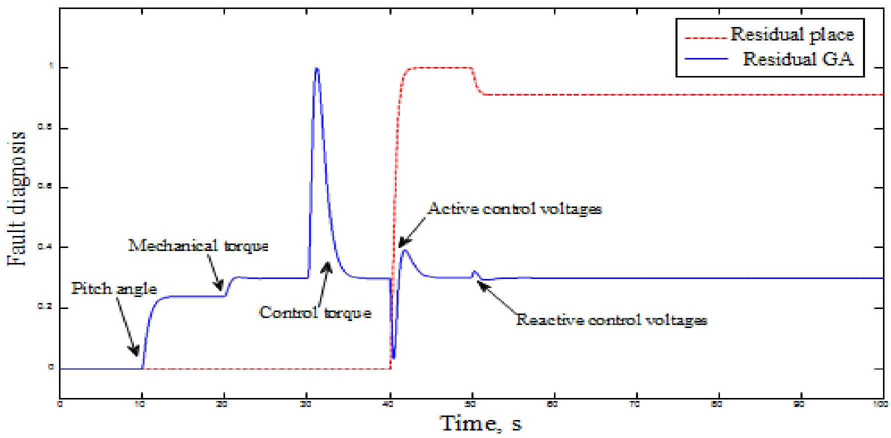
$$f_{actuator4} = \begin{cases} 0.01t + 0.001sin(0.1t) & t \geq 50 \\ 0 & t < 50 \end{cases} \tag{5.43}$$

It is noticed that the coefficients of the second control input are one million times smaller than the coefficients of the other input signals, therefore the second actuator fault is extremely difficult to detect. As a result, the second actuator fault can only be detected with a sufficiently large size (Here, one can choose 105 as the fault amplitude or gradient for the second actuator fault). Actually, in this case, the signal intensity (i.e, the product of the control coefficient and actuator fault signal) of the second actuator fault and those of the other actuator faults added to the system dynamics have the same order.

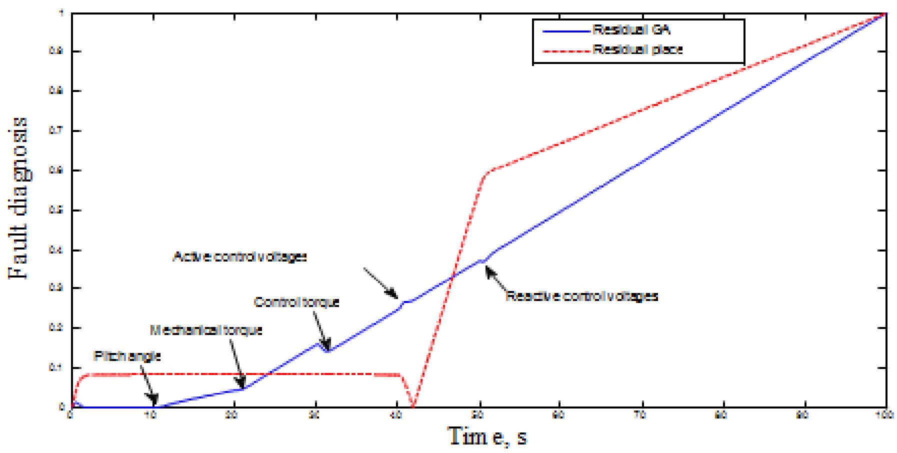
In order to make comparison, the pole-assignment based fault detection filter gain is also given by locating the poles to the set of p={$-3, -3.436, -1.42, -1.4, -1.205, -4.835$}:

$$k_{PLACE} = \begin{bmatrix} 0.0040 & -0.0000 & 0.0000 & 0.0000 \\ 0.0000 & 0.0986 & 2.9480 & -0.0000 \\ -0.0000 & 0.0014 & 0.0001 & 0.0000 \\ 0.0000 & 0.0001 & 0.0060 & -0.0000 \\ -0.0000 & -0.0000 & 2.4992 & -0.0000 \\ -0.0000 & -0.0000 & 0.0017 & 0.0000 \end{bmatrix} \times 10^3 \tag{5.44}$$

The residuals for the abrupt faults and incipient faults are shown in Figure 5.16. From Figure 5.16 (a), one can see the pole-assignment based fault detection filter can only detect the abrupt actuator faults occurring at 40s and 50s only. However, the GA-based fault detection filter can successfully detect all the five abrupt actuator faults sequentially happening at 10s, 20s, 30s, 40s, and 50s. In addition, from Figure 5.16 (b), the pole-assignment based fault detection method can detect incipient actuator faults happening at 40s and 50s, however, the GA-based fault detection approach can successfully the signal changes at 10s, 20s, 30s, 40s and 50s. Therefore, the GA-based fault detection method has a better fault detection performance compared with the pole-assignment based fault detection approach.



(a) Fault detection for abrupt faults



(b) Fault detection for incipient faults

Figure 5.16: Fault detection for multiple actuator faults

5.6 Robust Fault Estimation for Wind Turbine Systems

5.6.1 The design algorithm of the wind turbine system

Fault estimation can provide the size, shapes and types of the monitored faults and this kind of information is important for control/management centre to take proper actions to protect the system against potential further damages. Consider the wind turbine system subjected disturbance and faults in the form of:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = Cx(t) + Du(t) + D_f f(t) + D_d d(t) \end{cases} \tag{5.45}$$

where, $x \in \Re^n$, $u \in \Re^m$, $y \in \Re^p$, $d(t) \in \Re^l$ is the disturbance vector, and $f(t) \in \Re^k$ is the fault vector. The matrices B_f and D_f are known as fault entry matrices which represent the effect of faults on the system, B_d and D_d are known as disturbance entry matrices which represent the effect of disturbances on the system. A, B, C and D are known constant matrices of appropriate dimensions. For the abrupt and incipient faults, the second-order derivative of the fault should be non-zero piecewise function. However, in practical conditions, some oscillations are found in incipient and abrupt typical practical type of faults that could leads to some variations.

Certainly, it can be challenging to distinguish the influences of faults from the consequence of active environmental discrepancies on wind turbine system. Environmental disturbance could uncertainly reduce the performance of FD which could act as a source of false and missed alarms. So, there is need to study disturbance in wind turbine, in order to minimize the amount of false alarms in the system.Therefore, the considered fault f, i.e., $\ddot{f}$ is bounded [134]. In contrast to chapter 4, (4.2),

$$\ddot{f}(t) \neq 0 \tag{5.46}$$

Let

$$\bar{x} = \left[x^T \;\; \dot{f}^T \;\; f^T\right]^T \in \Re^{\bar{n}} \tag{5.47}$$

The augmented state space system can be written as follows:

$$\begin{cases} \dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{B}_d d(t) + \bar{G}\ddot{f}(t) \\ y(t) = \bar{C}\bar{x}(t) + Du(t) + D_d d(t) \end{cases} \tag{5.48}$$

where

$$\bar{x} = \begin{bmatrix} x \\ \dot{f} \\ f \end{bmatrix}, \quad \bar{A} = \begin{bmatrix} A & 0 & B_f \\ 0 & 0 & 0 \\ 0 & I & 0 \end{bmatrix}, \quad \bar{B} = \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix},$$

$$\bar{B}_d = \begin{bmatrix} B_d \\ 0 \\ 0 \end{bmatrix}, \quad \bar{G} = \begin{bmatrix} 0 \\ I \\ 0 \end{bmatrix},$$

$$\bar{C} = \begin{bmatrix} C & 0 & D_f \end{bmatrix}. \tag{5.49}$$

The augmented fault observer can be constructed as follows:

$$\dot{\hat{\bar{x}}}(t) = \bar{A}\hat{\bar{x}}(t) + \bar{B}u(t) + \bar{K}(y(t) - Du(t) - \bar{C}\hat{\bar{x}}(t)) \tag{5.50}$$

where $\hat{\bar{x}}(t) \epsilon \Re^{\bar{n}}$ is the estimate of the augmented state vector $\bar{x}(t) \epsilon \Re^{\bar{n}}$; and $\bar{K} \epsilon \Re^{\bar{n} \times p}$ is the observer gain to be designed.

Let

$$\bar{e}(t) = \bar{x}(t) - \hat{\bar{x}}(t), \tag{5.51}$$

The estimation error dynamics is governed by the following equation:

$$\dot{\bar{e}}(t) = (\bar{A} - \bar{K}\bar{C})\bar{e}(t) + (\bar{B}_d - \bar{K}D_d)d(t) + \bar{G}\ddot{f}(t) \tag{5.52}$$

The transfer function of (5.53) can be given as follows:

$$e(s) = (sI - \bar{A} + \bar{K}\bar{C})^{-1}(B_d - \bar{K}D_d)d(s) + (sI - \bar{A} + \bar{K}\bar{C})^{-1}\bar{G}(s^2 f(s)) \tag{5.53}$$

Hence, the cost function can be given as follows:

$$J = J_1 + J_2 \tag{5.54}$$

where,

$$J_1 = \|(sI - \bar{A} + \bar{K}\bar{C})^{-1}(B_d - \bar{K}D_d)\|_{s=j\omega_d} \tag{5.55}$$

$$J_2 = \|(sI - \bar{A} + \bar{K}\bar{C})^{-1}\bar{G}\|_{s=0} \tag{5.56}$$

Following Chapter 4, the sufficient condition for the matrix $\bar{A} - \bar{K}\bar{C}$ is stable is:
The pair $(A,\ C)$ is observable,

$$rank\begin{bmatrix} A & B_f \\ C & D_f \end{bmatrix} = n + k, \tag{5.57}$$

Based on the above and Chapter 4, the design procedure of the fault estimator for wind turbine system is summarised as follows.

Algorithm 5.6 GA-based fault estimator design

- **Check condition of observer:** Check whether (4.15) and (5.57) are satisfied. If yes, go to the next step; otherwise, stop the procedure.
- **Set the parameters to be optimized:** The total number of the parameters to be optimized is $\bar{n} + \bar{n} \times p$, and the set of the parameters is defined as (4.32).
- **Fitness Evaluation:** The fitness function is defined as (5.54).
- **Constrains:** The eigenvalues of the $(\bar{A} - \bar{K}\bar{C})$ are ensured to be stable.
- **GA running:** Run GA until one of stop condition is met.

5.6.2 Simulation study for wind turbine system

A. Fault estimation for multiple sensor faults

It is assumed that the first three sensor faults occur sequentially. In this simulation study, the disturbance is assumed to be the same as (5.20). By using Algorithm 5.6, one can obtain the optimal fitness value (see Figure 5.17).

The final evolutional optimal process can be displayed below.

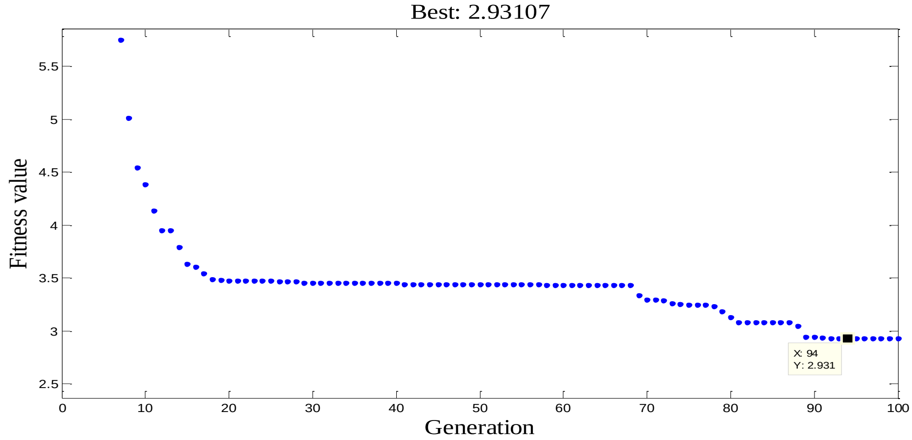


Figure 5.17: The evolutional final optimal process for sensor.

The optimal GA-based observer gain matrix sensor fault is calculated and verified as

$$\bar{K}_{GA} = \begin{bmatrix} -0.0037 & -0.0053 & 0.0071 & 0.0001 \\ -17.3390 & -26.8135 & -31.3327 & 0.3679 \\ -26.3733 & -32.7155 & -64.0829 & 0.2484 \\ -0.0283 & -0.0487 & -0.0720 & 0.0007 \\ -3.0730 & -6.5951 & -16.9141 & -60.2632 \\ 39.6491 & 247.8310 & 146.4340 & -5.1615 \\ 1.8789 & -0.8540 & -3.6742 & 0.0015 \\ -1.4823 & 3.1287 & -2.8359 & -0.0005 \\ 3.1459 & 1.5077 & 8.3643 & -0.0040 \\ 3.0748 & -0.4325 & -1.7292 & 0.0004 \\ 25.3790 & 36.4629 & 62.3357 & -0.2486 \\ 2.2416 & 1.1250 & 7.5367 & -0.0018 \end{bmatrix} \tag{5.58}$$

A1) Incipient sensor faults:

The first three sensor faults are assumed to be as follows:

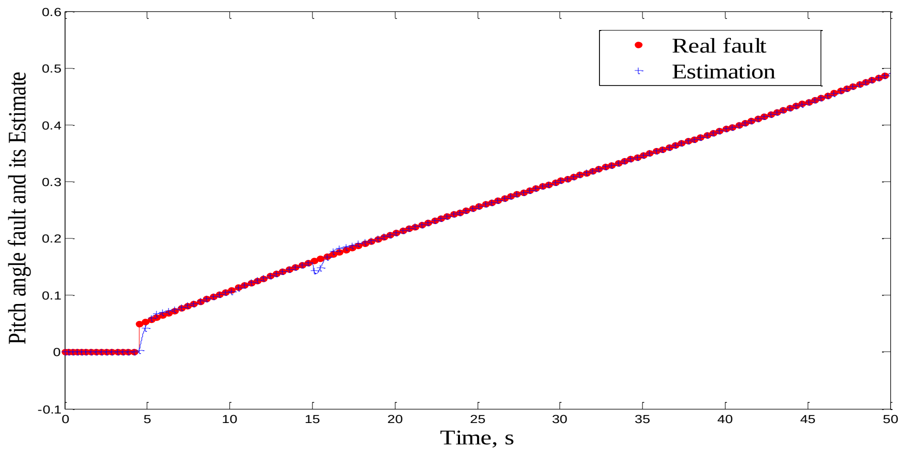
$$f_{s1.Ramp} = \begin{cases} 0.01t + 0.001sin(0.1t), & t \geq 4.5s \\ 0, & t < 4.5s \end{cases} \tag{5.58}$$

$$f_{s2.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \tag{5.59}$$

$$f_{s3.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 15s \\ 0, & t < 15s \end{cases} \tag{5.60}$$

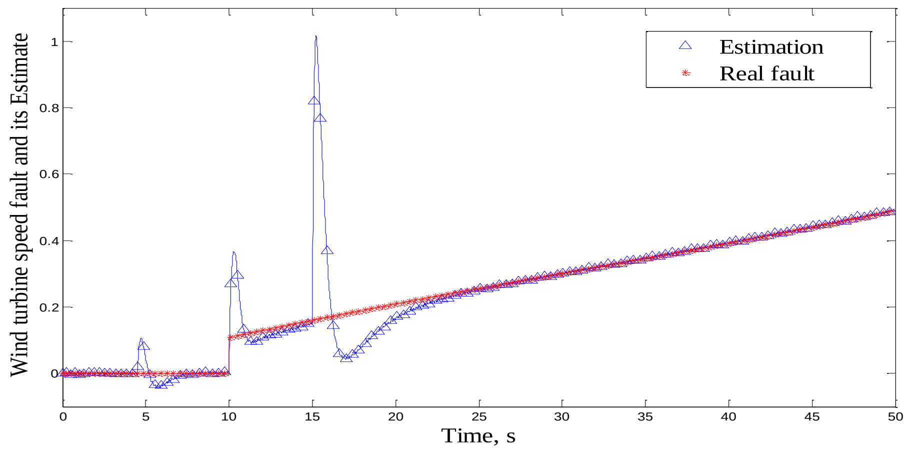
Wind turbines operate at a low frequency sensitivity of fault performance index to be maximized and the robustness disturbance frequency information is designed to attenuate the disturbance to its minimal. Figure 5.18 demonstrates the wind turbine parameters as stated in each curves displayed in the figure below with sensor faults with their estimations respectively, where the “red line” views the real fault signals, and the “blue line” signifies estimation. The proposed observer gain is calculated by GA with excellent estimation performance for abrupt / incipient faults and states.

The estimates of the three sensor faults above are depicted by Figure 5.18, which has shown that three sensor faults in the types of ramp signals are estimated excellently.

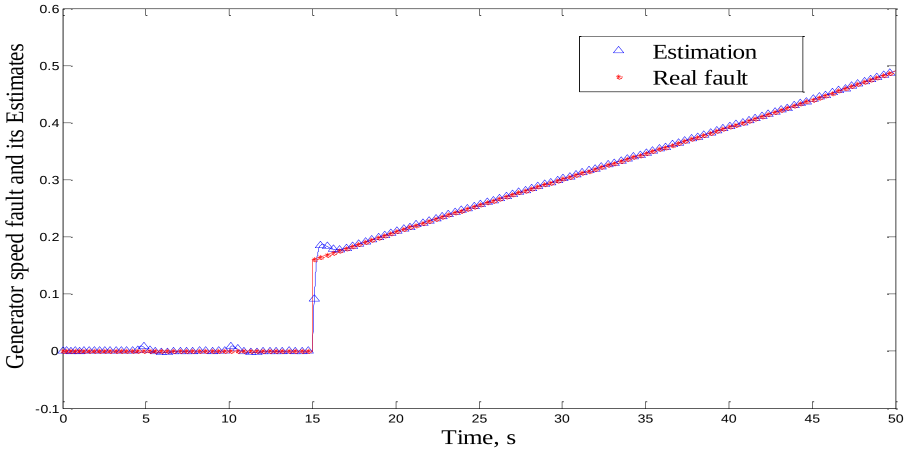


1

(a) The pitch angle and its fault estimation.



(b) The wind turbine speed and its fault estimation.



(c) The generator speed and its estimate

Figure 5.18: Sensor incipient faults and their estimate: WT

A2) The Abrupt sensor faults are well-defined as:

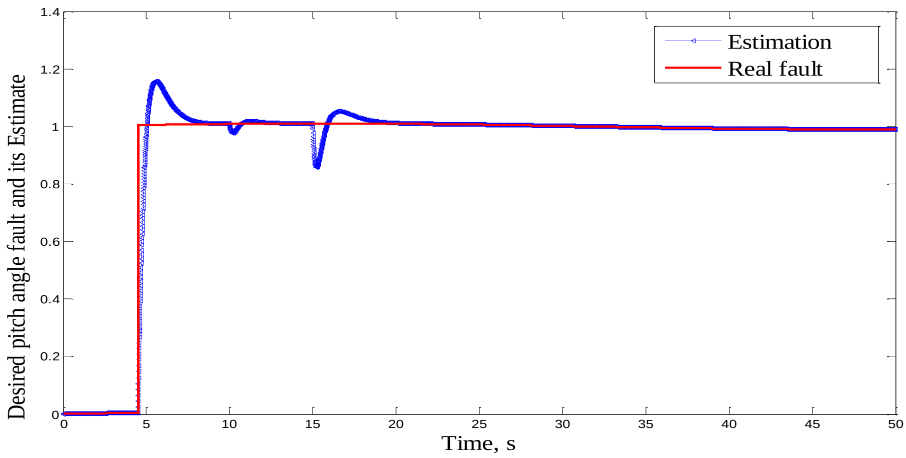
The first three abrupt sensor faults are assumed to be as follows:

$$f_{s1.step}=\begin{cases}1+0.001sin(0.1t), & t\geq 4.5s\\ 0, & t<4.5s\end{cases} \tag{5.61}$$

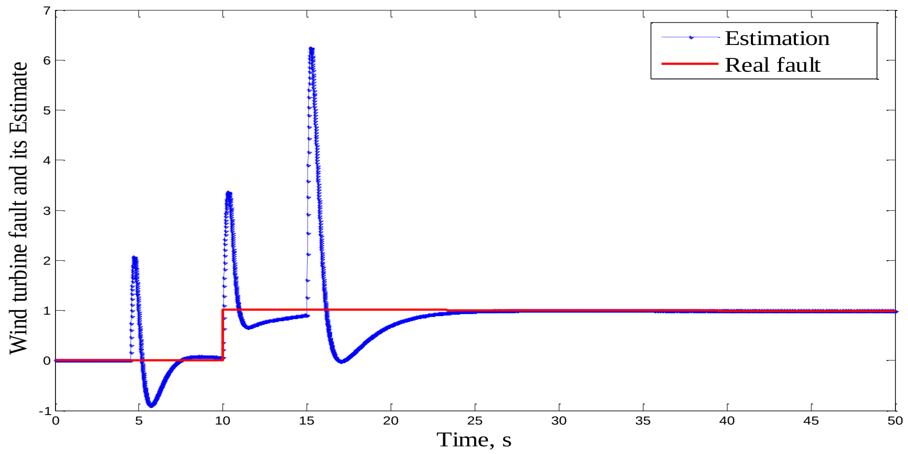
$$f_{s2.Step}=\begin{cases}1+0.001\sin(0.1t), & t\geq 10s\\ 0, & t<10s\end{cases} \tag{5.62}$$

$$f_{s3.step}=\begin{cases}1+0.001\sin(0.1t), & t\geq 15s\\ 0, & t<15s\end{cases} \tag{5.63}$$

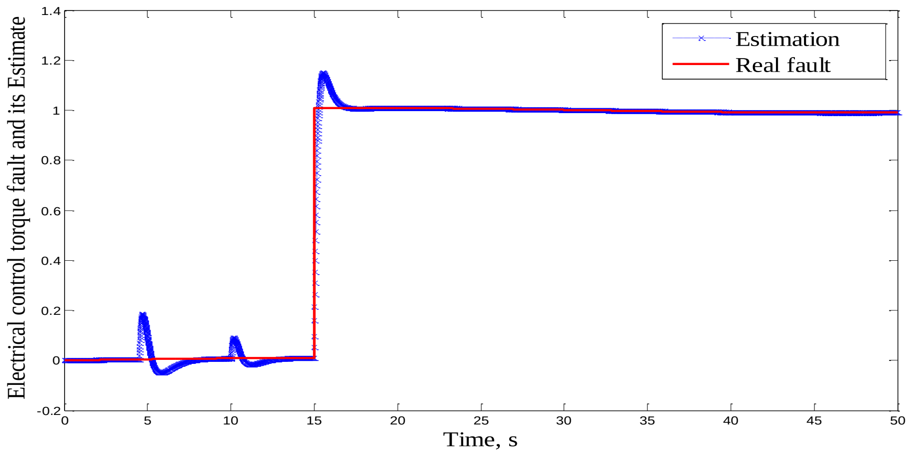
Figure 5.19 shows excellent tracking performance.



i) The pitch angle fault and its estimate



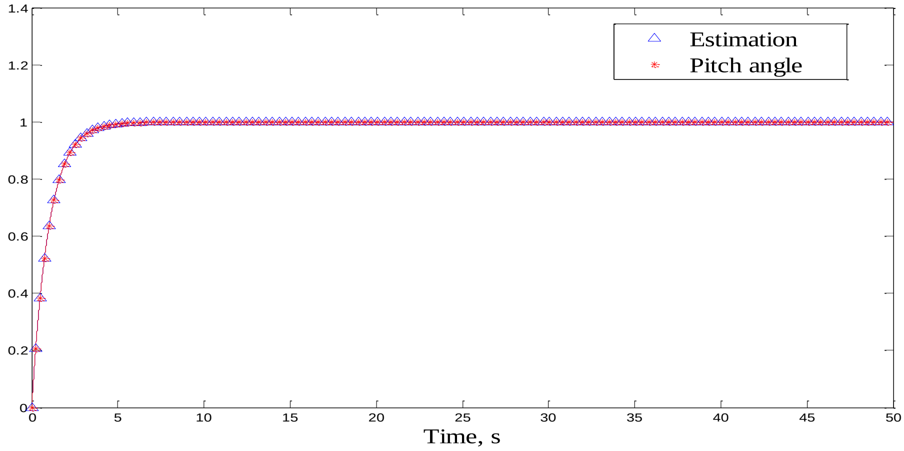
ii) The wind turbine fault and its estimate



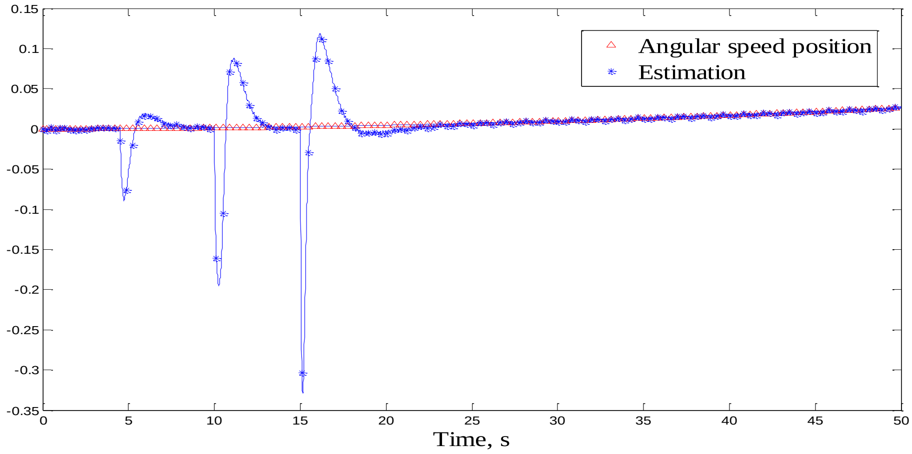
iii) The generator speed and its estimate

Figure 5.19: Abrupt (step) sensor faults and its estimate

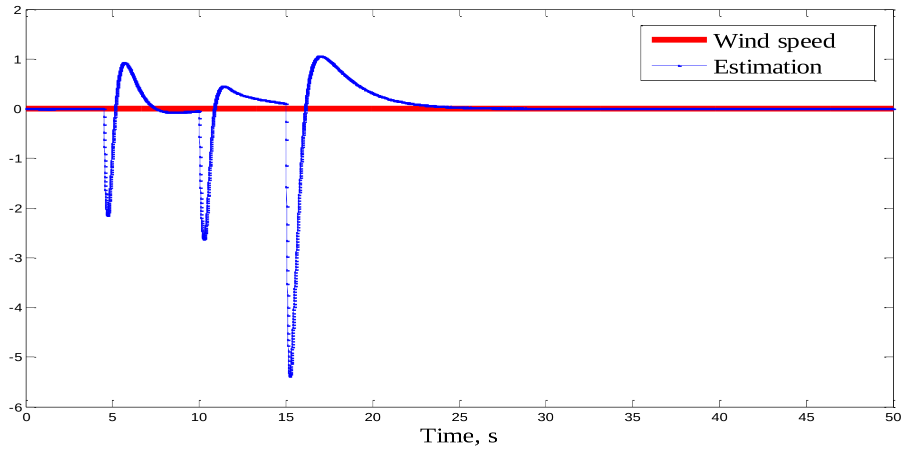
As the by-product, the estimates of the system states are also obtained, which are depicted by Figure 5.20. One can see the six states have been well estimated. The estimate of the state has been achieved with available input and output of the WT model.



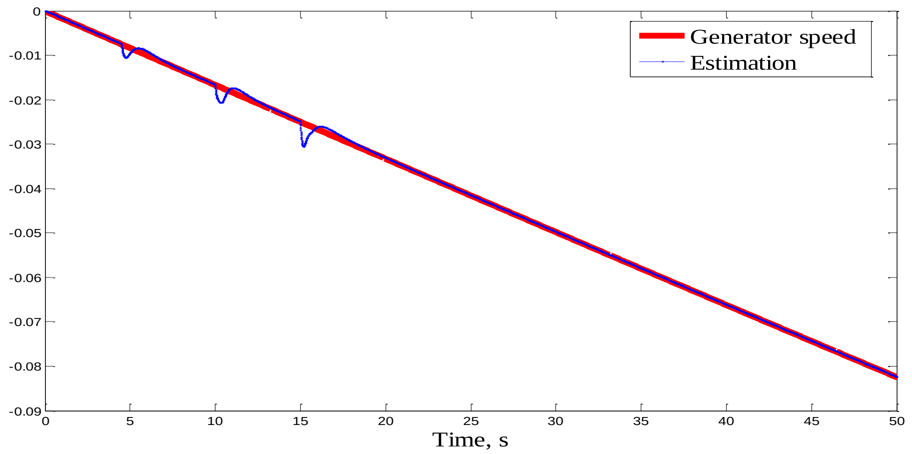
i) The pitch angle state and its estimates



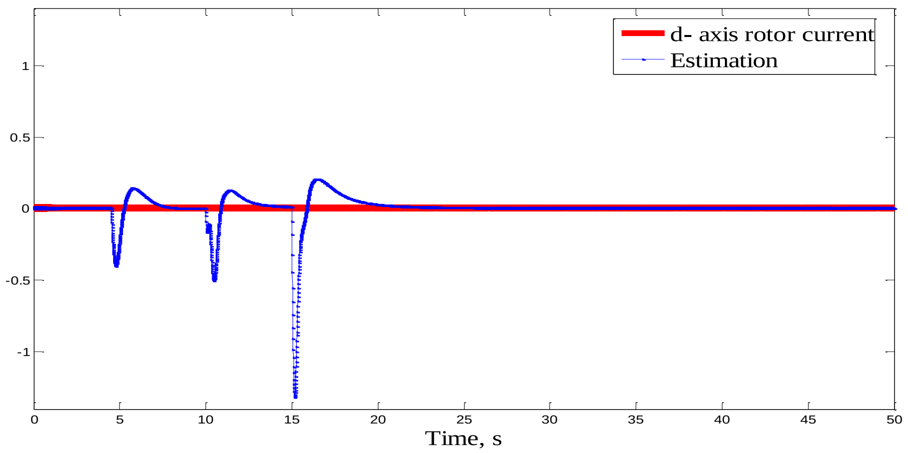
ii) The angular speed position state and its estimate



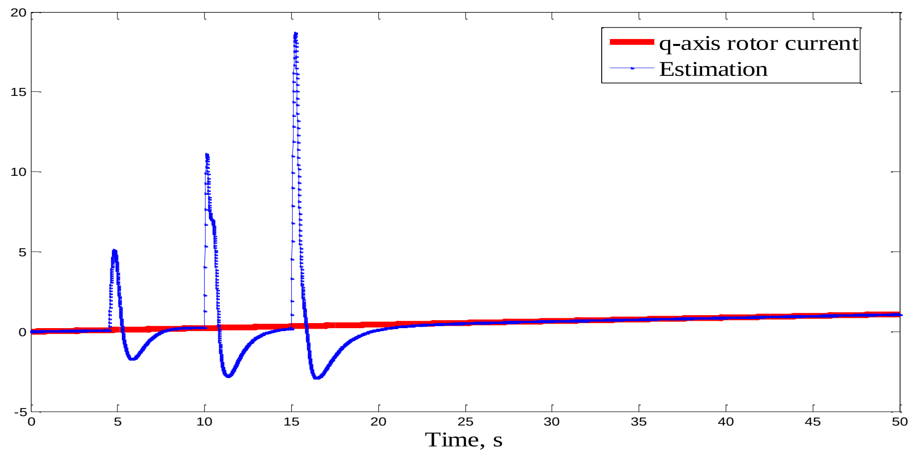
iii) The wind speed state and its estimate



iv) Generator speed state and its estimate



v) d-axis rotor current state and its estimate



vi) q-axis rotor current and its estimate

Figure 5.20: States x_{i-n} and its estimate

B. *Fault estimation for multiple Actuator faults*

It is assumed to have three actuator faults, which occur sequentially. By using Algorithm 5.2, the fitness value evolution curve is depicted by Figure 5.21. The optimal observer gain is given as:

$$\bar{K}_{GA} = \begin{bmatrix} 6.2288 & 1.6312 & -23.9501 & -0.0110 \\ 180.0053 & 56.8155 & -599.0632 & 0.2679 \\ 0.2264 & 5.8281 & 25.1646 & 0.0162 \\ 0.1156 & 0.0075 & -0.2835 & 0.0004 \\ 32.9596 & -9.7649 & 49.6414 & -60.2155 \\ -604.0544 & -689.3634 & 314.2205 & -4.8630 \\ 10.5965 & 4.6452 & -56.7652 & -0.0215 \\ 74.1747 & 40.5367 & -148.6501 & 0.2521 \\ 1.0190 & 7.2841 & 68.3764 & 0.0561 \\ 15.5997 & 5.4915 & -72.2895 & -0.0308 \\ 208.4218 & 95.1749 & -572.2227 & 0.4945 \\ 0.9594 & 11.2842 & 84.8977 & 0.0609 \end{bmatrix} \tag{5.64}$$

The actuator optimal observer gain reached by GA is shown below:

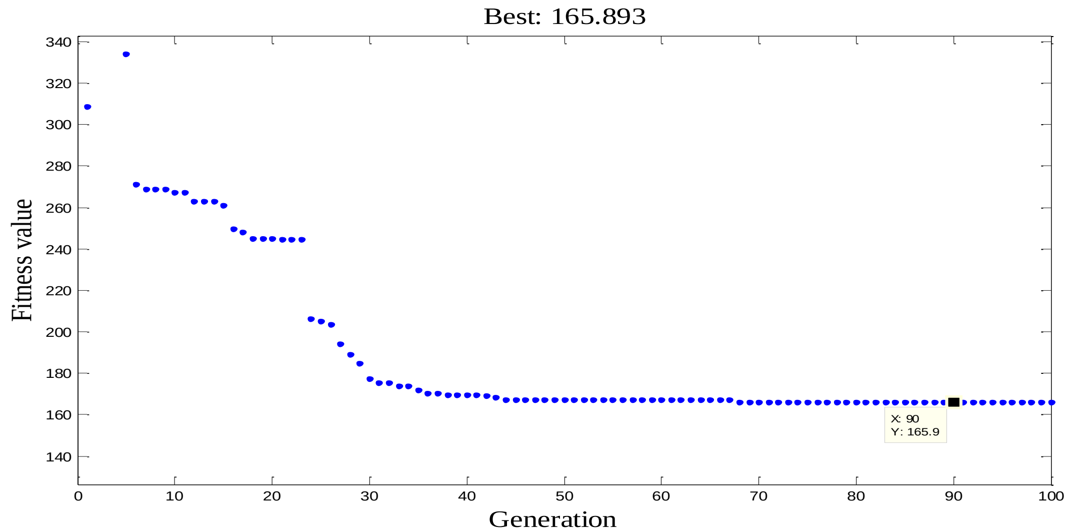


Figure 5.21: The fitness evolution by GA algorithm

The capacity of the proposed global optimum observer is modeled in the fault and its estimate. This shows a great improvement in the fault diagnosis technology.

A1) Actuator Incipient fault and its Estimate

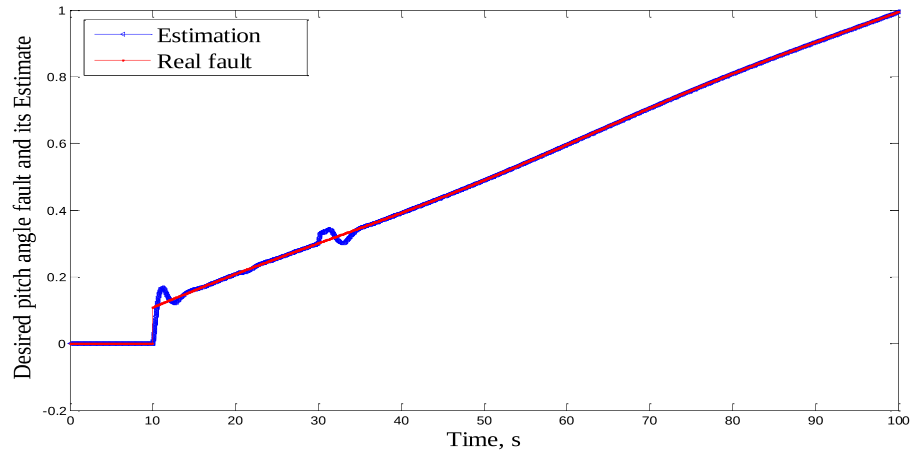
The first three actuator faults are assumed to be as follows:

$$f_{a1.Ramp} = \begin{cases} 0.01t + 0.001sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \tag{5.65}$$

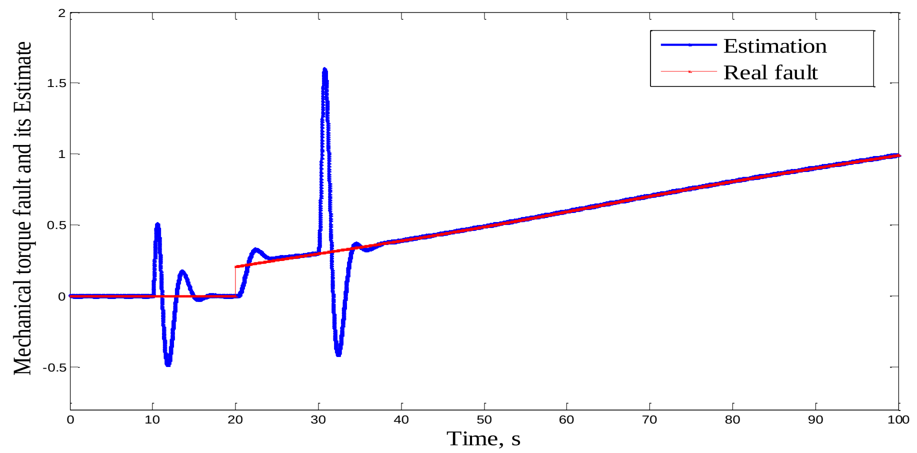
$$f_{a2.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 20s \\ 0, & t < 20s \end{cases} \tag{5.66}$$

$$f_{a3.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 30s \\ 0, & t < 30s \end{cases} \tag{5.67}$$

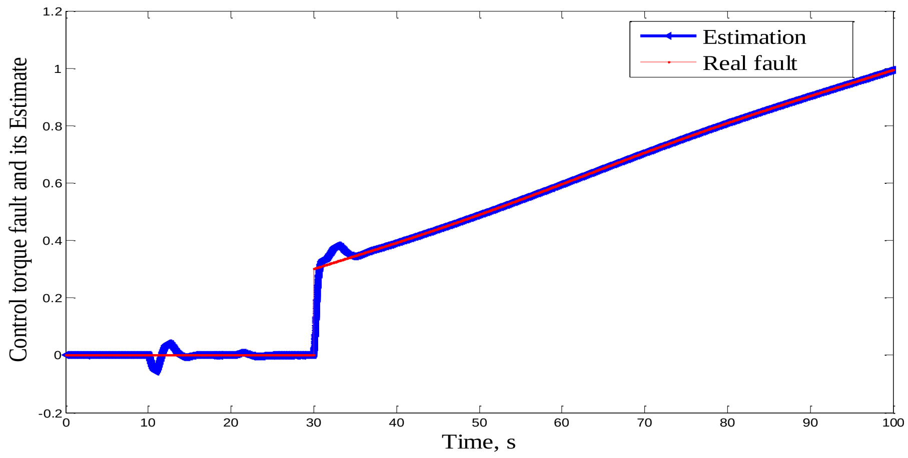
Figure 5.22 has shown the three actuator faults have been estimated satisfactorily.



a) Desired pitch angle and its estimate



b) Mechanical torque and its Estimate



c). Control torque fault and its estimate

Figure 5.22: Actuator incipient faults and its estimate: WT system

In this case, we aim to concentrate on the real fault and its estimate for actuator faults

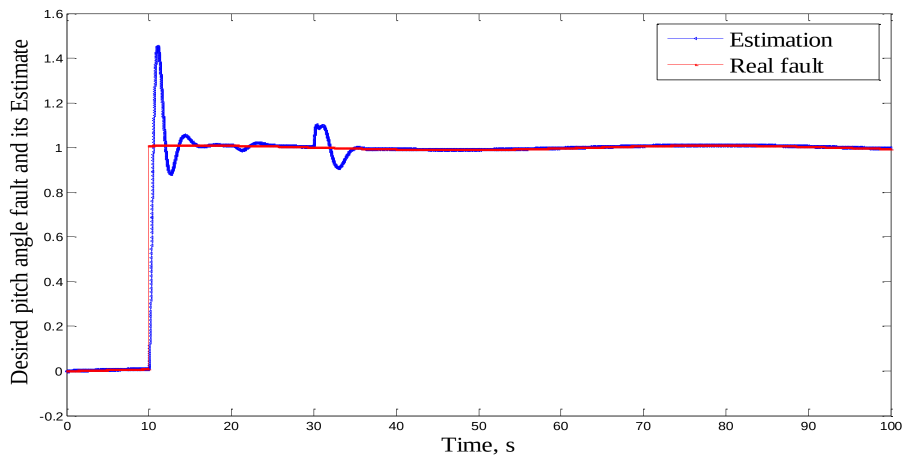
A2) Abrupt actuator faults and its Estimate

The first three actuator faults are assumed to in the following types:

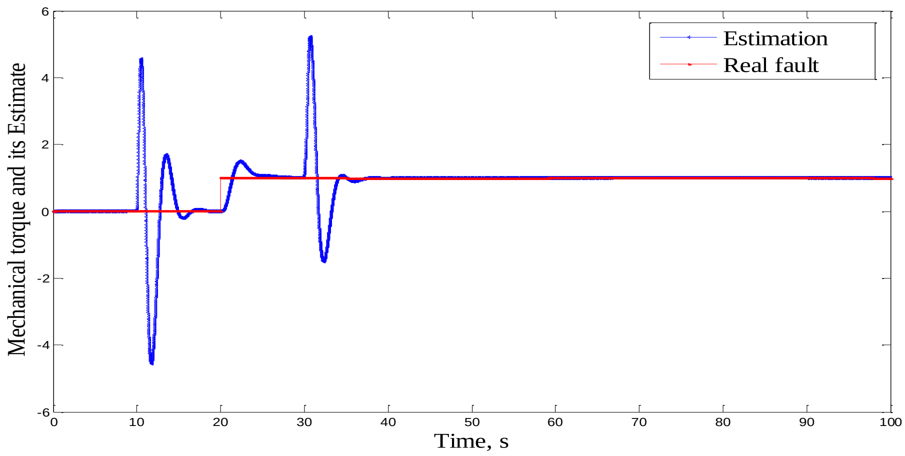
$$f_{a1.step} = \begin{cases} 1 + 0.01sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \tag{5.68}$$

$$f_{a2.step} = \begin{cases} 1 + 0.01\sin(0.1t), & t \geq 20s \\ 0, & t < 20s \end{cases} \tag{5.69}$$

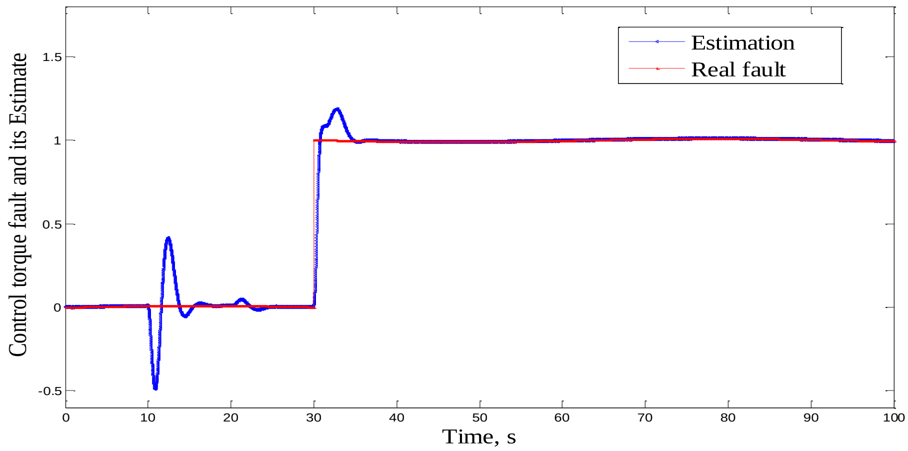
$$f_{a3.step} = \begin{cases} 1 + 0.01\sin(0.1t), & t \geq 30s \\ 0, & t < 30s \end{cases} \tag{5.70}$$



a) Desired pitch angle actuator fault and its estimate



b) Mechanical torque actuator fault and its estimate



c) Control torque actuator fault and its estimate

Figure 5.23: Step actuator faults and its estimate: WT system

Figure 5.23 has shown an excellent estimation performance for the abrupt actuator faults. The diagnosis displayed in Figure. 5.23 and Figure 5.22 displayed the real fault, its estimate and demonstrated the state of WT system where the red line thick represents the real state of the system and the blue lines are its estimated path, this shows how unique this method is in improving fault monitoring.

For the system with actuator faults as represented in step type of faults, it successfully shows the quick clear response to faults and its estimation with appropriate convergence quality. This technique can seek an optimal observer gain which minimizes the influences from the disturbances and the non-dominant fault components to the estimation error dynamics. There the proposed technique has shown good performance for the reconstruction of multiple sensor faults and multiple actuator faults.

5.7 Summary

In this chapter, an overview of wind turbine technologies has been presented, particularly with an introduction of the wind turbine global current cumulative market trends and analysis. Moreover, the challenges for wind turbine industries have been analysed, especially about system reliability and component fault rates. This has raised a strong motivation for the research on fault detection and fault diagnosis.

The contribution of this chapter is emphasised as follows:

- GA-Based robust fault detection algorithm for the wind turbine system is addressed by integrating observer-based fault detection filter technique, eigenstructure assignment method, and GA-optimisation approach. The simulation study has demonstrated that the residual can well detect the single fault or multiple faults as well as better disturbance attenuation achieved.
- GA-Based robust fault estimation algorithm for the wind turbine system is addressed by integrating augmented system technique, eigenstructure assignment method, and GA-optimisation approach. The concerned faults and system states can be effectively estimated. The simulation study has verified the proposed fault estimation technique has excellent fault/state tracking performance.
- The proposed fault detection and fault diagnosis methods can cover two typical faults in engineering practices, that is, abrupt faults and incipient faults, showing the reasonability and effectiveness of the used fault diagnosis techniques

Chapter Six: Fault Diagnosis for Induction Motors

"***Knowledge isn't life changing. The application of knowledge is.***"

Todd Stocker

6.1 Introduction

This chapter presents different simulation results in contrast to the previous chapters, where the proposed techniques are employed to solving robustness in WT model as discussed. The hybrid FD is also applied to the real application of Induction Machines (IMs) examples in order to validate the execution of robust FE approach. Current sensors of IMs would have faults or malfunctions due to the age, which may lead to wrong commands of the controller, causing system performance degradation and even dangerous situations. Likewise, voltage actuator faults will have indirect impacts on the measurement outputs; consequently, it is more challenging to diagnose actuator faults from the residual. Whose information is vital for fault-tolerant operation, in order to effectively enhance the tolerance capacity, there is the need to reconstruct the faults concerned and distinguish the impacts of the current sensor and voltage actuator faults from those of uncertainties. GA optimisation techniques are a natural solution for solving and diagnosis the trade-off problem that is practicable in this application. As a result, there is strong motivation to confirm the applied applicable of robust diagnose in voltage actuator and current sensor faults at the early stage which is a kind of necessary actions to be taken to avoid further damage, degradation of the IMs / serious situations besides facilitating fault tolerant design. In this study, a robust residual and an augmented observer are presented with various scenarios based to illustrate the performance of the proposed techniques.

6.2 Principle Element of IMs

IMs are electromechanical network machines operated in nearly all industrial applications for the conversion of energy from electrical to mechanical form which operates as a motor or generator but preferably used as motors. IMs are important components which are been generally employed due to their economical low cost, robustness, have low maintenance, moderately have high efficiency, reliability and excellent performance in most of the industrial automation systems applications. CM and FD of engineering plant have improved lately due to the general use of computerisation which resulting in decreasing of human- direct-machine contact to supervise the motor drive systems operation. The industrial demand for steady reliable operation is of great importance to the plant and machinery during the entire system longevity. Generally, at least two current sensors are necessarily deployed in order to obtain good performance in voltage source inverter-based induction motor drives [188]. However, current sensors may be subjected to faults, which may result in the deterioration of motor drive performance, poor safety, and reliability, and even the collapse of the system [189]-[193]. Changes in the measurement of current sensors could have unplanned influences on voltage actuators, IMs components in any system are subject to manufacturing faults, friction with the environment could cause performance degradations thereby reducing system reliabilities. The outcome of environmental disturbances is invariably inevitable, which motivates more concerns on how to enhance the robustness of FD system against disturbances which has been a key interest in FD community. In [194] an observer based residual generation and fault detection method was addressed on the basis of the mathematical model of the induction motor. Luenberger observers are used to generating residuals for stator and rotor current sensors to determine faulty position, as in [189], two parallel fault detection observers were applied to doubly-fed induction generators. Hence the investigation into sensor fault detection and diagnosis is very significant to the development of the global system performance. In applied dynamic systems, the residual signal is significantly affected by the system modeling error, parameter perturbation, and the unknown inputs disturbances/noises. Variations in sensor/actuator are one of the crucial elements in the fault diagnosis system of an induction motor due to the effect of trivial deflection which could lead to a missed or the false alarm action of the fault detection system, as well as affect the performance of IM's causing unreliable and poor critical safety system. Some researchers proposals are to eliminate the effects of disturbances on the residuals, this technique is practically impossible because of the strict conditions criteria that needs to be met [76]. More concepts have been proposed on how to decouple uncertainties by attenuating disturbances as much as possible by some optimization techniques [275] and [90].

However, as the responsibilities performed by machines nowadays developed gradually complex, enhancements were also requested in the field of fault diagnosis community, in order to facilitate fault tolerate. In practical systems, the residual signal is significantly influenced by the systems parameter perturbation, modeling error and the unknown uncertainties, whose outcomes are the sophisticated false or missed alarm amount of systems fault. For robustness in model-based fault detection problem, it is vital to make the residual signal robust against the disturbances, noises, and modelling errors which could result in improper anxiety. Therefore, there is a need to continuously propose an improvement approach to the global performance of the system theoretically by establishing using correct mathematical models to imitate the position and information of IMs. The fundamental focus of this study will be to improve the fault CM of induction accordingly, it is very significant to develop robust fault detection for IMs. In order to increase the fault diagnosis performance, in this section, the frequencies of the disturbances and modelling errors are known by using Fast Fourier Transformation (FFT)-based spectrum analysis. Then an eigenstructure assignment technique is approved which allocates the observer poles and GA optimization to optimize the performance.

6.3 The 3-phase (3Φ) IMs Fault Monitoring

The method presented in this notion is a IMs fault diagnosis monitoring technique critical for maintenance drives based on the air gap torque profile analysis, associated with machine learning importance is centred on cost investment and high reliability for safety motives. IM or asynchronous motor is a type of alternating current (AC) motor where power is supplied to the rotor by means of electromagnetic induction. Presently, asynchronous motors are extensively used in the industries, due to their robustness design and structure. Though, they could be affected by many types of faults as specified above, where the general works are motivated on AC motor's faults. Electric motor or generator is mostly active due to its machines speed of rotation, practical to voltage and frequency of the current source. The Capacity desires can be design to steady state or dynamic characteristics as well as speed control, electric braking, gearing, preliminary several effects can be achieved. The flow below shows the different types of machine drives that can be extensively used in the huge amount of domestic like motors and industrial applications.

Diverse kinds of electric motor are illustrated in Fig. 6.1 below [195]-[196]

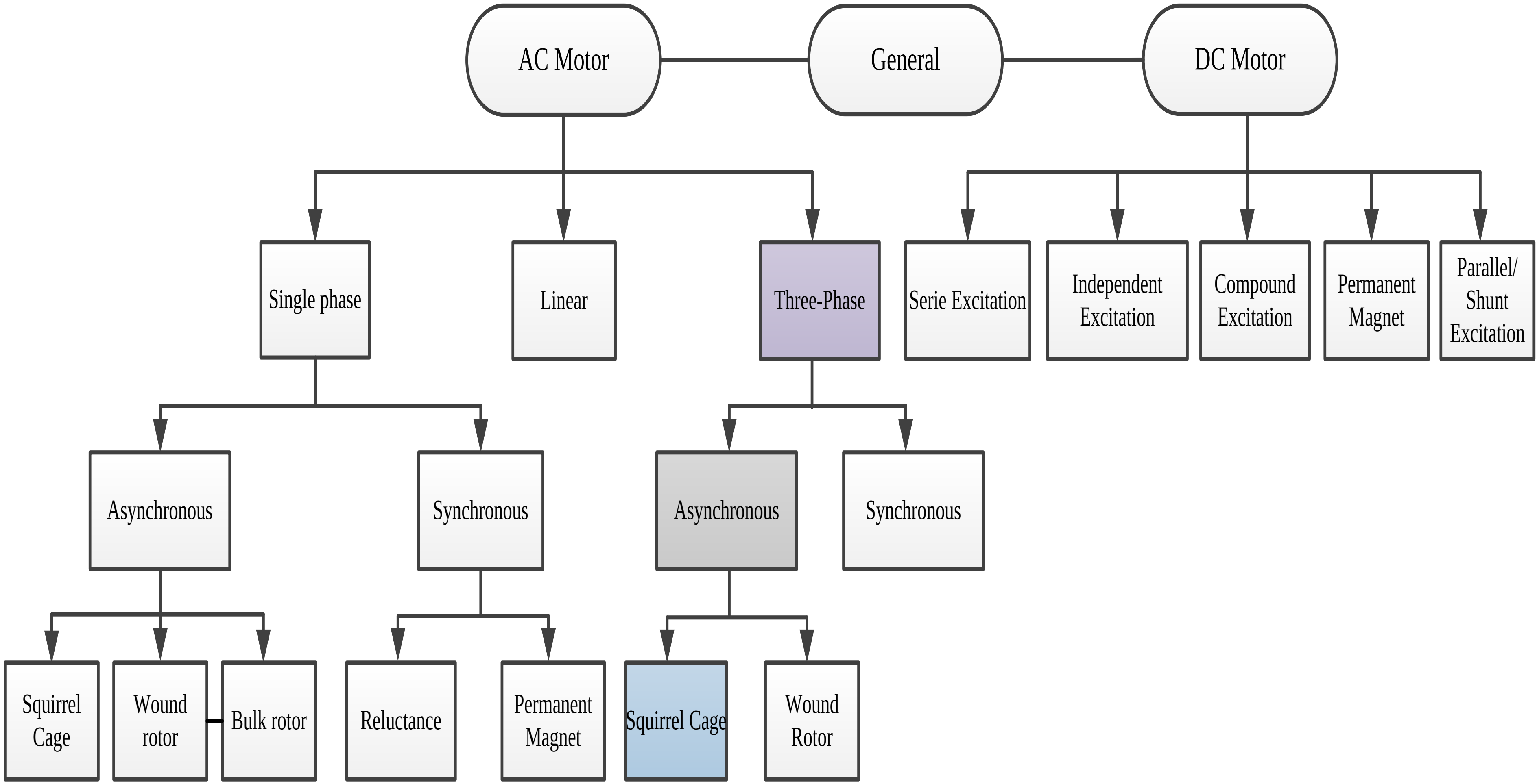


Figure 6.1: Types of electric motors

The highlighted 3Φ Induction asynchronous squirrel cage will be employed for the purpose of this study application to demonstrate the established RFD techniques on 3Φ induction machine performance.

6.3.1 Model of Three-Phase Induction Motors

A mechanical load was provided by a separately excited 2 kW DC generator of electrical parameters and variables are denoted to the stator and rotor, indicated by the mathematical principal symbols in the succeeding machine equations. The ABC model of stator and rotor measures are substantial nonlinear and complicated which is subjective to two-axis reference frame ($d - q$ frame) of which are normally represented in direct and quadrature ($d - q$) axis arrangement in order to improve the high order models for certain applications and to make modelling step easy for use. 3Φ AC motors, are contained of a stator, which generate the magnetic field, and a rotor, which is made to alternate (rotate) by the magnetic field that is induced from the current generated by the stator. Mathematical dynamic modelling of a 3Φ induction is usually done in the arbitrary rotating reference frame, from which other reference frames are realized of two commonly used reference frame that is the stationary reference frame and the synchronously rotating reference. According to dynamic models of AC machines [197] and [198] developed by several authors, a representation by two "phase magnitudes," known as $\alpha - \beta$ in the real-imaginary complex plane coordinates is employed to construct the model in state-space description equations is given by the next expressions.

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \tag{6.1}$$

where $x(t) \in \Re^n$ is the system state, $u(t) \in \Re^m$, and $y(t) \in \Re^p$ are the control input and measurement output respectively. Definitely, one has:

$$x(t) = [i_{s\alpha}(t) \quad i_{s\beta}(t) \quad i_{r\alpha}(t) \quad i_{r\beta}(t)]^T \tag{6.2}$$

$$u(t) = [u_{s\alpha}(t) \quad u_{s\beta}(t) \quad u_{r\alpha}(t) \quad u_{r\beta}(t)]^T, \quad y(t) = [i_{s\alpha}(t) \quad i_{s\beta}(t)]^T \tag{6.3}$$

In (6.1), *x* is the state vectors, *u* is the input vectors, *y* is the output vectors, ω_r is the rotor angular frequency, $i_{s\alpha}$ and $i_{s\beta}$ are $\alpha - \beta$ components of stator currents; $i_{r\alpha}$ and $i_{r\beta}$ are $\alpha -$

β components of rotor currents; $u_{s\alpha}$ and $u_{s\beta}$ are $\alpha\beta$ components of stator voltages; $u_{r\alpha}$ and $u_{r\beta}$ are $\alpha\beta$ components of rotor voltages. The coefficient matrices in (6.1) are defined by [199]:

$$A = \frac{1}{\sigma L_s L_r}\begin{bmatrix} -R_s L_r & \omega_r L_m^2 & R_r L_m & \omega_r L_m L_r \\ -\omega_r L_m^2 & -R_s L_r & -\omega_r L_m L_r & R_r L_m \\ R_s L_m & -\omega_r L_m L_s & -R_r L_s & -\omega_r L_r L_s \\ \omega_r L_m L_s & R_s L_m & \omega_r L_r L_s & -R_r L_s \end{bmatrix}, \tag{6.4}$$

$$B = \frac{1}{\sigma L_s L_r}\begin{bmatrix} L_r & 0 & -L_m & 0 \\ 0 & L_r & 0 & -L_m \\ -L_m & 0 & L_s & 0 \\ 0 & -L_m & 0 & L_s \end{bmatrix}, \tag{6.5}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{6.6}$$

In the induction motor system, $D = 0$, and $D_f = 0$, where 0 indicates the zero matrix with approximate dimensions. setting, $\sigma = 1 - L_m^2/L_r L_s$ is the leakage coefficient of L_s and L_r are correspondingly to the stator to stator and rotor to rotor of winding inductance respectively, L_m is the stator to rotor mutual inductance.

Application of the field oriented control (FOC) of IM drive results in the instant control of a high performance drive, for 3-Φ squirrel-cage induction motor, the FOC structure requires two phase voltage as input. So, at least two current sensors or two actuators are necessary to sense stator currents and same for actuator voltage faults. The two voltage actuators and current sensors are for the transform phase-A and phase-B, $\alpha - \beta$ model. The 3Φ stator voltages $u_{sA,}u_{sB}$ and u_{sC} reference frame is changed to $u_{s\alpha}$ and $u_{s\beta}$ and currents i_{sA}, i_{sB} and i_{sC} to $i_{s\alpha}$ and $i_{s\beta}$ as in three to two arrangement conversion are usually measured for employed of control drives as expressed in Clarke transform.

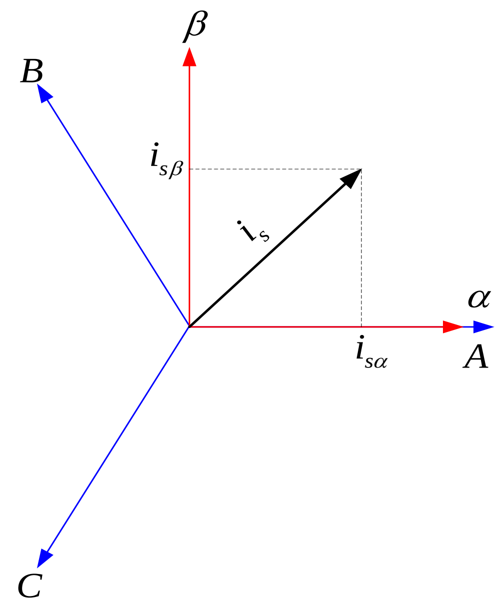


Figure 6.2: Reference frame (*A*,*B*,*C*) performance to (α , β) projection

The Clarke transform is applied from $u_{sA,}u_{sB}$ and u_{sC} reference frame to $u_{s\alpha}$ and $u_{s\beta}$ and i_{sA}, i_{sB}, and i_{sC} to $i_{s\alpha}$ and $i_{s\beta}$ illustrated as shown by [200] - [202].

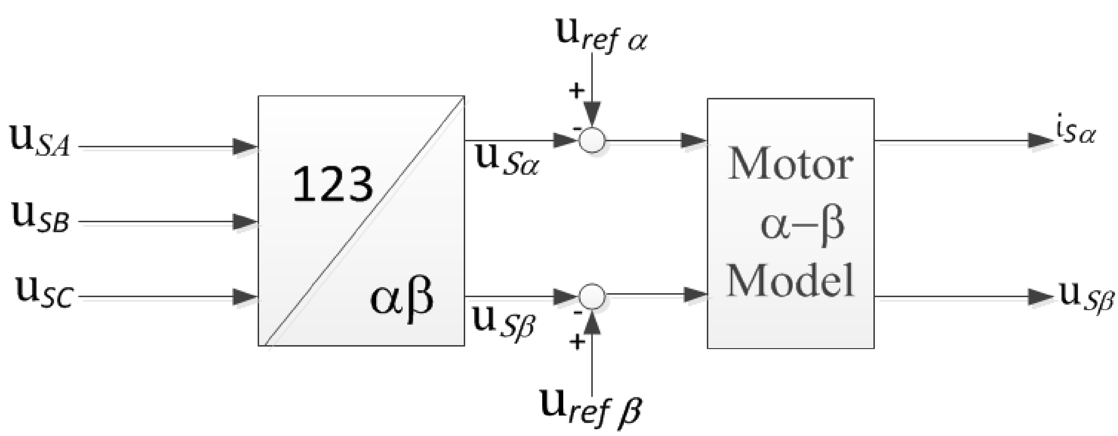


Figure 6.3: voltage-current space vector of 3Φ IM reference frame

For, the algebraic sum of 3-Φ voltage and current IMs i_{sA}, i_{sB} and i_{sC}, in a balanced system are zero, that is

$$i_{sA} + i_{sB} + i_{sC} = 0 \tag{6.7}$$

$$u_{sA} + u_{sB} + u_{sC} = 0 \tag{6.8}$$

Considering the voltage for the 3Φ converted to inverse Clarke transformation of phase-A, phase-B in $\alpha\beta$ reference frame and Clarke transform from i_{sA}, i_{sB}, and i_{sC} to $i_{s\alpha}$ and $i_{s\beta}$. The transformation is also basic in the distinctive event of stationary reference frame. The Clarke transform is shown as voltage in (6.9) and currents (6.10).

$$\begin{bmatrix} u_a \\ u_b \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} \tag{6.9}$$

$$\begin{bmatrix} i_{s\alpha} \\ i_{s\beta} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \frac{1}{\sqrt{3}} & \frac{2}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} i_{sA} \\ i_{sB} \end{bmatrix} \tag{6.10}$$

The set of parameters description of IM is defined in Table 6.1 below, where the 3Φ, 2 kW, 1-pole, wye (**Y**)-connected, squirrel-cage induction motor parameters are chosen for the simulation studies have the following:

Table 6.1: Description of IM physical parameters specifications

Physical Parameters of 3-Φ Motor	Definitions	Values and Units
R_r	Stator resistance	$2.564\ \Omega\ /ph$
R_s	Rotor resistance	$3.478\ \Omega/ph$
L_s	Stator inductance	$0.3454\ \Omega\ /ph$
L_r	Rotor inductance	$0.0418\ \Omega\ /ph$
L_m	Magnetizing inductance	$0.3329\ \Omega\ /ph$
ωr	Electrical angular velocity	$2850 * 2 * pi/60$
np	Number of magnetic pole pairs	1 p
Ts	Sampling time	0.1 seconds
f	Motor supply frequency	50 Hertz
$\sigma = 1 - L_m * L_m/(L_s * L_r)$	sigma	pu

Supposed a balanced sinusoidal 3-Φ system is in the reference frame (*a*,*b*,*c*) of which the induction motor as expressed in the two-phase reference frame ($d - q$) according to park transformation. In mathematical motor model of synchronously rotating reference frame with rotating speed ω_s, the mathematical (d– q frame) model of IM as indicated in (6.1) is obtained given the above mentioned load disturbance. The architecture 3Φ model observer based design corrupted with disturbances and faults is shown in Figure 6.4 below.

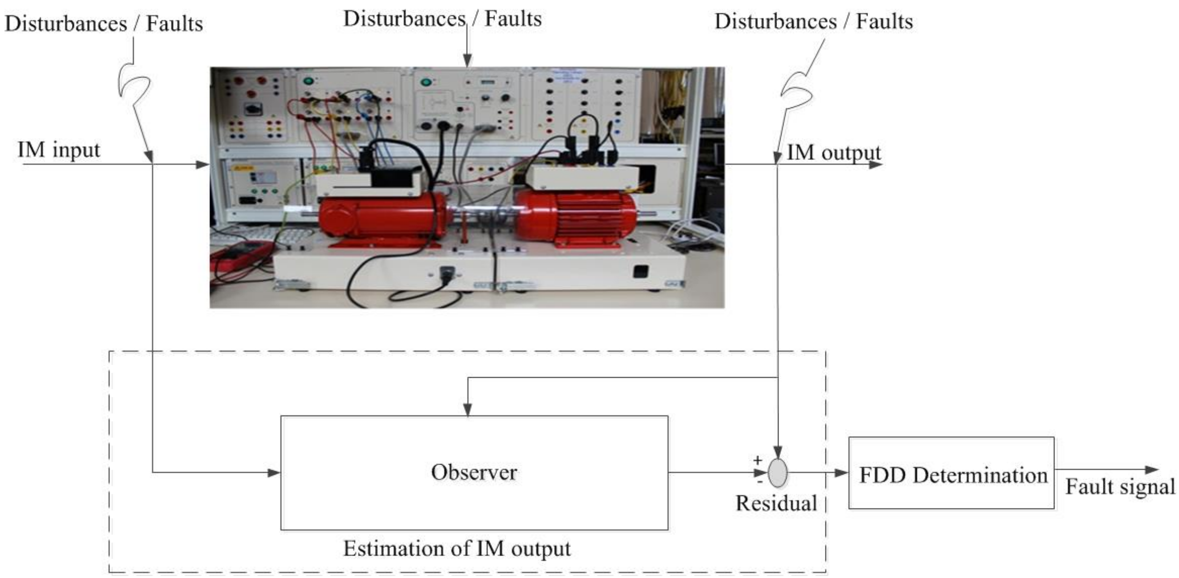


Figure 6.4: The architecture of robust observer-based IM.

Robust condition monitoring and fault diagnosis are important in the health monitoring and supervision for mechanical/electrical equipment. The purpose of this case study is to robustly monitor possible faults happening on sensors as well as actuators.

6.4 Application of Robust Fault Detection Approach

6.4.1 Robust Fault Detection Algorithm

Considering the following state-space form in a continuous corrupted system with modeling errors of known dominant disturbance frequencies (DDF) obtained by using Fourier Transform technique (FFT) to analyze the frequency spectral under fault free condition, the IM's mathematical model (6.1) can be expressed as:

$$\begin{cases} \dot{x}(t) = (A + \Delta A)x(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = (C + \Delta C)x(t) + Du(t) + D_f f(t) + D_d d(t) \end{cases} \tag{6.11}$$

where $x(t) \epsilon \Re^n$, $u \epsilon \Re^m$, and $y \epsilon \Re^p$ are respectively system state, control input and measurement output; $d \epsilon \Re^l$, ΔAx is the unknown bounded process disturbance, $\Delta A x(\mathrm{t})$ and $\Delta C x(\mathrm{t})$ are the modelling errors; $f \in \Re^k$ is the fault vector. While A,B, C, D, B_f, D_f, B_d and D_d are known constant matrices with appropriate dimensions.

For the system (6.11), the robust fault detection observer under concern can be constructed by:

$$\begin{cases}\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K(y - \hat{y})(t)\\ \hat{y}(t) = C\hat{x}(t) + Du(t)\\ r(t) = y(t) - \hat{y}(t)\end{cases} \tag{6.12}$$

$$\hat{y}(t) = C\hat{x}(t) + Du(t)$$

$$r(t) = y(t) - \hat{y}(t)$$

where $r(t)$ is the residual that is used as a fault indicator signal which alert when there is contradiction between the real system output and the estimated system output.

Let the estimation errors be $e(t) = x(t) - \hat{x}(t)$, can proceeds this form.

$$\begin{cases}\dot{e}(t) = (A - KC)e(t) + (\Delta A - K\Delta C)x(t) + (B_d - KD_d)d(t) + \left(B_f - KD_f\right)f(t)\\ r(t) = Ce(t) + \Delta Cx(t) + D_d d(t) + D_f f(t)\end{cases} \tag{6.13}$$

Let,

$$\bar{B}_d = [I_n \quad 0_{n\times p} \quad I_n \quad 0_{n\times p}],\ \bar{D}_d = [0_{p\times n} \quad I_p \quad 0_{p\times n} \quad I_p] \text{ and } \bar{d} = \begin{bmatrix}(\Delta A - K\Delta C)x\\ \Delta Cx\\ (B_d - KD_d)d\\ D_d d\end{bmatrix} \tag{6.14}$$

Taking the Laplace transform for (6.13), one has

$$r(s) = [C(sI - A + KC)^{-1}\bar{B}_d + \bar{D}_d]\bar{d}(s) + [C(sI - A + KC)^{-1}\left(B_f - KD_f\right) + D_f]f(s) \tag{6.15}$$

Denote

$$H_f(s) = C[(sI - A + KC)^{-1}\left(B_f - KD_f\right) + D_f] \tag{6.16}$$

$$H_d(s) = C[(sI - A + KC)^{-1}\bar{B}_d + \bar{D}_d] \tag{6.17}$$

The residual signal in (6.15) can be re-written as

$$r(t) = H_f(s)f(s) + H_d(t)\bar{d}(s) \tag{6.18}$$

The cost function can be given as follows:

$$J = \frac{\sum_{i=1}^{N}\|H_d(s_i)\|}{\|H_f(s_f)\|} \tag{6.19}$$

where $s_i = j\omega_{di}, i = 1, 2, \cdots, N$ and $s_f = j0$; ω_{di} is the frequency of the dominant uncertainty component.

Based on the above and following Chapter 3, one can give GA-based robust fault detector design algorithm as follows.

Algorithm 6.4: GA based optimization fault detection for Induction Motor

- Set the sizes of the population and generation.
- Set the parameters to be optimized in form of (3.24), that is,

$$\Theta = \{\lambda_1, \cdots \lambda_{n_r}, \lambda_{1,re}, \cdots, \lambda_{n_c,re}, \lambda_{1,im}, \cdots, \lambda_{n_c,im}, w_1 \cdots w_{n_r}\ w_{1,re} \cdots w_{n_c,re}\ w_{1,im} \cdots w_{n_c,im}\} \tag{6.20}$$

- Set the cost function in the form of (6.19).
- Set the constraint such that the observer system matrix $A - KC$ is stable, that is, all the real parts of the eigenvalues must be less than zero, in every iteration.
- GA runs until the stop condition is satisfied. The optimal Θ_* is thus obtained, that is,

$$\Theta_* = \{\lambda_{1*}, \cdots \lambda_{n_{r*}}, \lambda_{1,re*}, \cdots, \lambda_{n_c,re*}, \lambda_{1,im*}, \cdots, \lambda_{n_c,im*}, w_{1*} \cdots w_{n_r*}\ w_{1,re*} \cdots w_{n_c,re*}\ w_{1,im*} \cdots w_{n_c,im*}\} \tag{6.21}$$

- The optimal K_* is thus calculated by

$$K_* = [W_*(V_*)^{-1}]^T, \tag{6.22}$$

$$W_* = [w_{1*} \cdots w_{n_{r*}}\ w_{1,re*} \cdots w_{n_c,re*}\ w_{1,im*} \cdots w_{n_c,im*}] \in \Re^{p\times n} \tag{6.23}$$

$$V_* = [v_{1*} \cdots v_{n_r*}\ v_{1,re*} \cdots v_{n_c,re*}\ v_{1,im*} \cdots v_{n_c,im*}] \in \Re^{n\times n} \tag{6.24}$$

$$v_{i*} = -(\lambda_{i*}I - A^T)^{-1}C^T w_{i*}, \quad i = 1, 2, \cdots, n_r \tag{6.25}$$

$$\begin{bmatrix} v_{j,re*} \\ v_{j,im*} \end{bmatrix} = -\Gamma_{j*}{}^{-1}\Omega_c \begin{bmatrix} w_{j,re*} \\ w_{j,im*} \end{bmatrix}, \qquad \mathrm{j} = 1, 2, \cdots, n_c \tag{6.26}$$

$$\Gamma_{j*} = \begin{bmatrix} \lambda_{j,re*}I - A^T & -\lambda_{j,im*}I \\ \lambda_{j,im*}I & \lambda_{j,re*}I - A^T \end{bmatrix}, \tag{6.27}$$

$$\Omega_c = \begin{bmatrix} C^T & 0 \\ 0 & C^T \end{bmatrix}. \tag{6.28}$$

- Apply the observer-based fault detection filter in the form of (6.12).

6.4.2 Fourier Transform Analysis

Fourier transform analysis is carried out for one of the system outputs, which is shown by Figure 6.5, that displays the four dominant disturbances components, with frequecies at $f_{d1} = 48.37Hz$, $f_{d2} = 36.32Hz$, $f_{d3} = 32.27Hz$ and $f_{d4} = 25.71Hz$. The corresponding angular frequencies are $\omega_{di} = 2\pi f_{di}, i = 1, 2, 3, 4$.

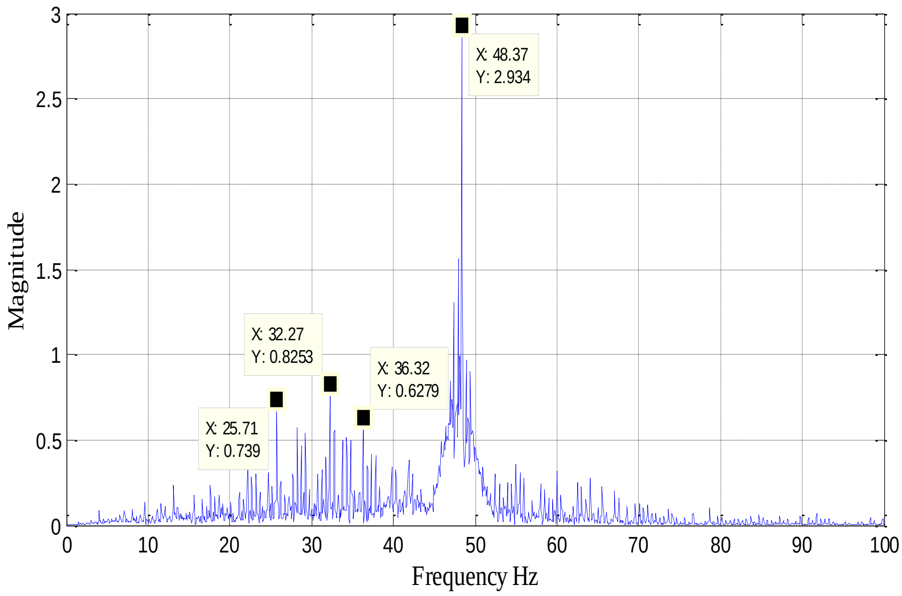


Figure 6.5: FFT frequency spectral of the DDF

6.4.3 Sensor Fault Detection

For sensor fault detection, one chooses $B_f = 0_{4\times 2}$ and $D_f = I_2$.

A. Sensor fault detection: single dominant disturbance frequency for GA optimisation

In this section, one chooses the main dominant disturbance frequency for GA optimisation. In other words, in the fitness function (6.19), $N = 1, s_1 = j2\pi \times 48.37 = j96.7\pi$ (dominant disturbance frequency) and $s_f = j0$ (fault frequency).

Setting the population size as 20, and the generation as 100, and using algorithm 6.1, one can obtain the best fitness value (e.g., see Figure 6.5).

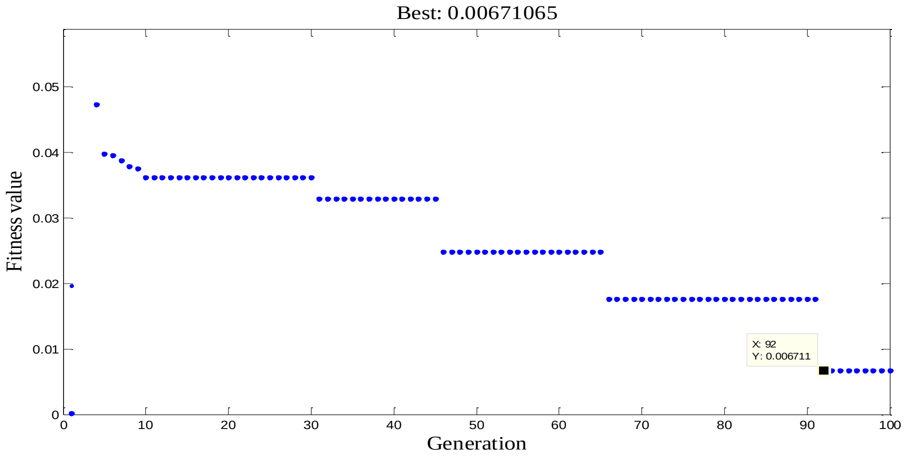


Figure 6.6: The best evolution output sensor by GA algorithm

The generated optimal observer gain $K_{GA} = 10^3 \times \begin{bmatrix} 0.2476 & 0.0827 \\ -0.9759 & -0.0526 \\ -0.2606 & -0.0913 \\ 1.0268 & 0.0523 \end{bmatrix}$. (6.29)

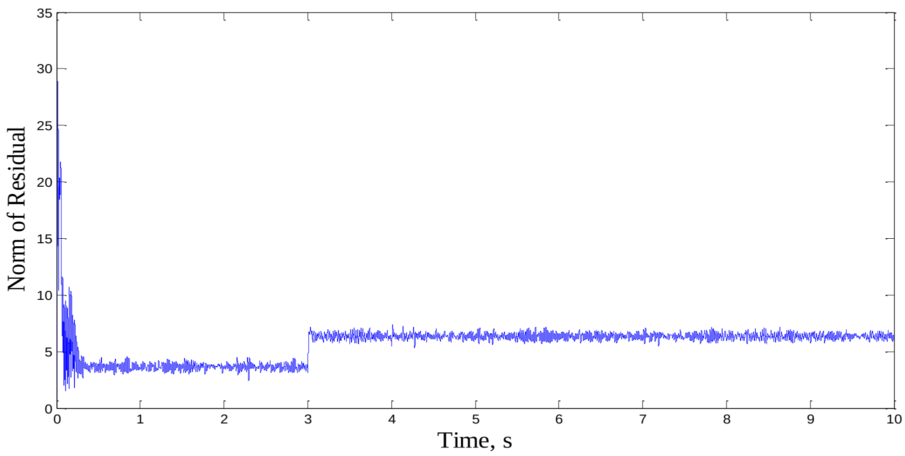
A1) Fault Detection for abrupt sensor faults

The two abrupt sensor faults are given as follows:

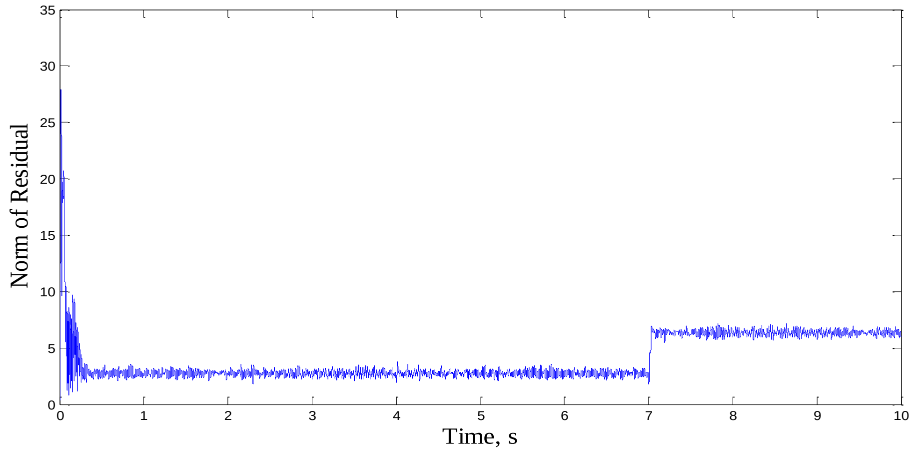
$$f_{s\alpha} = \begin{cases} 0, & t < 3s \\ 0.5 + 0.1\sin(10\pi t), & t \geq 3s \end{cases} \tag{6.30}$$

$$f_{s\beta} = \begin{cases} 0, & t < 7s \\ 0.5 + 0.1\sin(10\pi t), & t \geq 7s \end{cases} \tag{6.31}$$

When the sensor faults occur individually, the residuals are shown by Figure 6.6. One can see the residual changes caused by faults are successfully detected respectively at $3s$ and $7s$.



(a) Fault detection for the first sensor fault.



(b) Fault detection for the second sensor fault.

Figure 6.7: Norm of the residuals: individual abrupt sensor faults

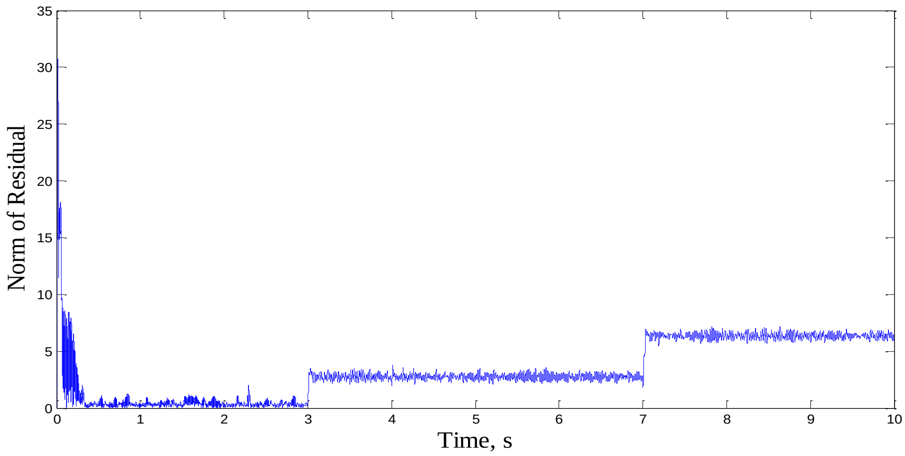


Figure 6.8: Norm of the residual: multiple abrupt sensor faults

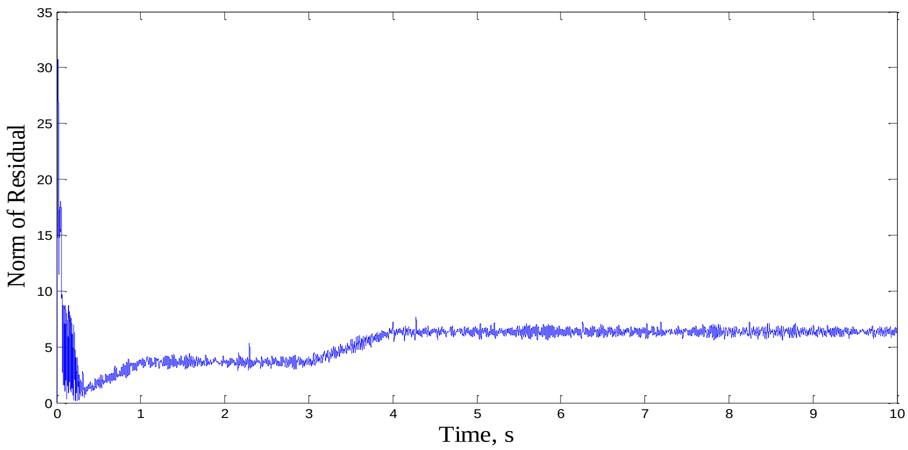
When the two sensor faults occur sequentially, the residual is shown by Figure 6.8, which has exhibited the two abrupt sensor faults have been detected successfully at 3s and 7s, respectively.

A2) Fault Detection for Incipient sensor faults

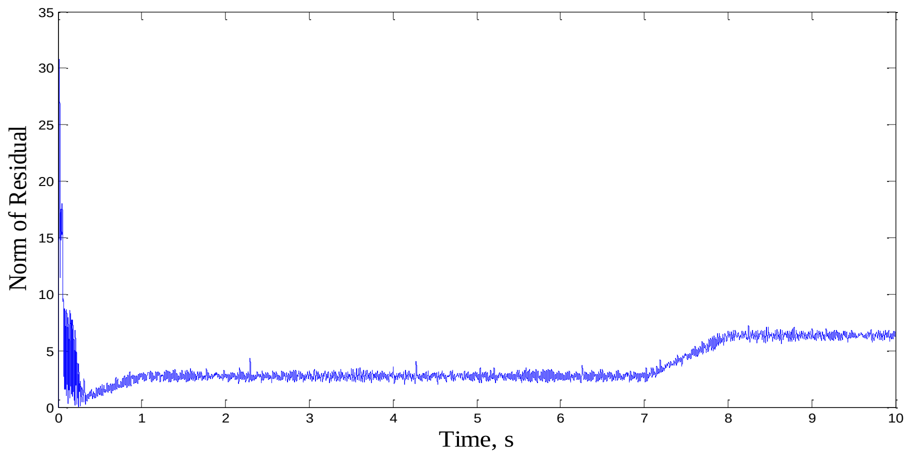
The incipient sensor faults are given as follows.

$$f_{s\alpha} = \begin{cases} 0,\ \mathrm{t} < 3\mathrm{s} \\ -0.5(\mathrm{t}-3) + 0.1\sin(10\pi\mathrm{t}),\ 3\mathrm{s} \le \mathrm{t} < 4\mathrm{s} \\ -0.5,\ \ t \ge 4s \end{cases} \tag{6.32}$$

$$\mathrm{f}_{\mathrm{s}\beta} = \begin{cases} 0,\ \mathrm{t} < 7\mathrm{s} \\ -0.5(\mathrm{t}-7) + 0.1\sin(10\pi\mathrm{t}),\ 7\mathrm{s} \le \mathrm{t} < 8\mathrm{s} \\ -0.5,\ t \ge 8s \end{cases} \tag{6.33}$$



(a) Fault detection for the first sensor fault.



(b) Fault detection for the second sensor fault.

Figure 6.9: Norms of the residuals: individual incipient sensor faults

The residuals are depicted by Figure 6.9. One can see two individual incipient sensor faults have been detected successfully at 3s and 7s. Actually, the shapes of the sensors faults are also visible from the residual.

When the two sensor faults occur sequentially, the residual is shown by Figure 6.10, which has exhibited the two incipient sensor faults have been detected successfully at 3s and 7s, respectively. The shapes of the two incipient sensors faults are also visible from the residual.

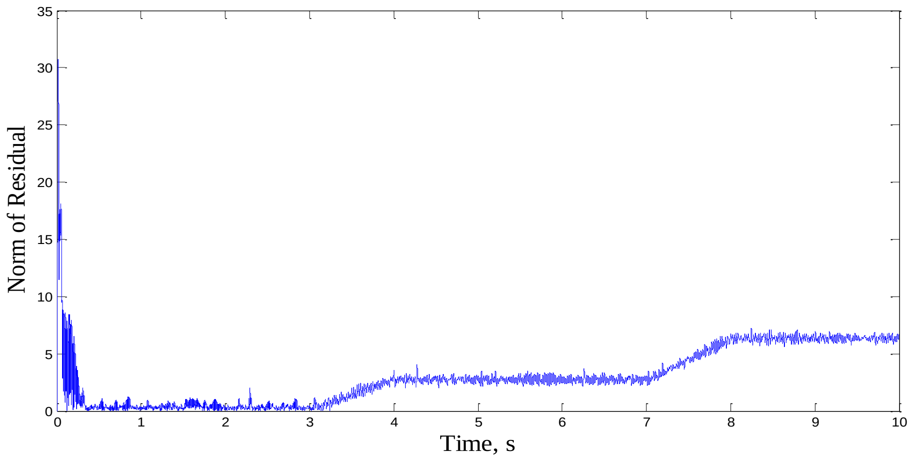


Figure 6.10: Norm of the residual: multiple incipient sensor faults

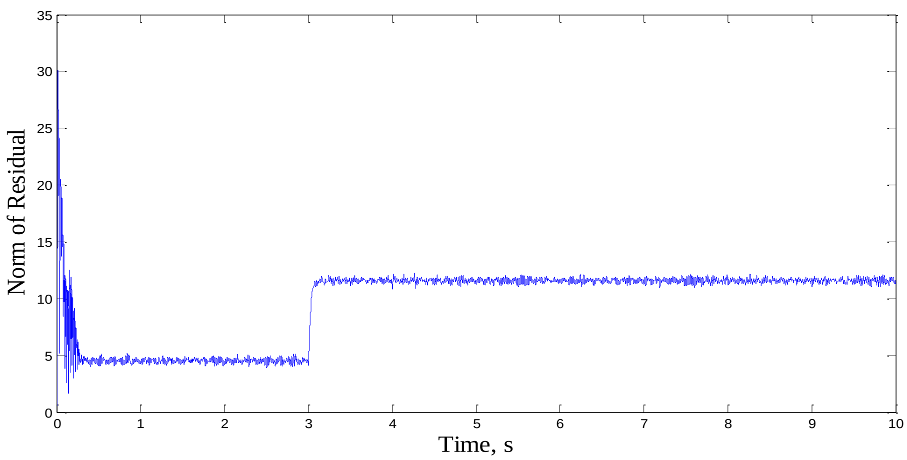
B. Sensor fault detection: multiple dominant disturbance frequencies for GA optimisation

In this study, one choose $s_1 = j2\pi f_{d1}$, $s_2 = j2\pi f_{d2}$, $s_3 = j2\pi f_{d3}$, and $s_4 = j2\pi f_{d4}$ where $f_{d1} = 48.37\ Hz$, $f_{d2} = 36.32\ Hz$, $f_{d3} = 32.27\ Hz$, and $f_{d4} = 25.71\ Hz$. Applying Algorithm 6.1, one can obtain an optimal observer gain K matrix as follows.

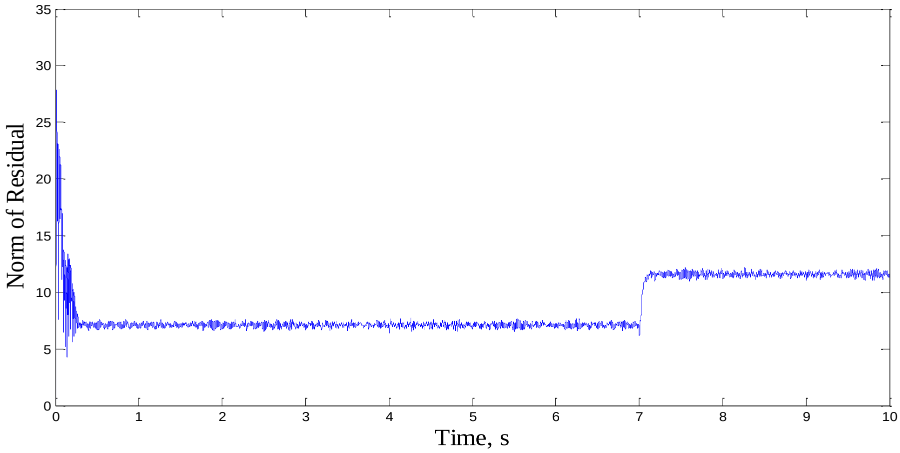
$$K = \begin{bmatrix} 24.2909 & -214.0628 \\ 401.1494 & -42.1104 \\ -43.7049 & 224.0126 \\ -403.8383 & 29.1124 \end{bmatrix} \tag{6.34}$$

B1) Fault Detection for abrupt sensor faults

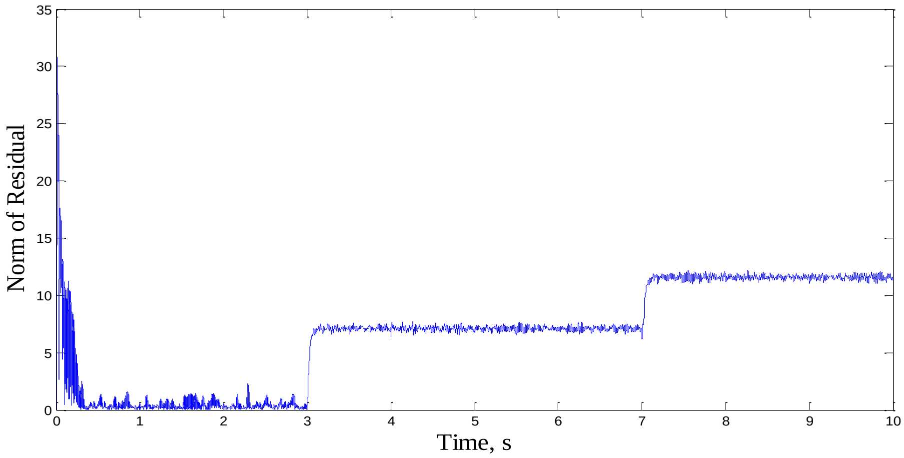
The residuals are exhibited by Figure 6.11, which has shown the faults occurring either individually or sequentially have been detected successfully. Compared with Figures 6.7 and 6.8, the multiple dominant disturbance frequencies optimisation has generated a better fault detection performance.



(a) Fault detection for the first sensor fault



(b) Fault detection for the second sensor fault

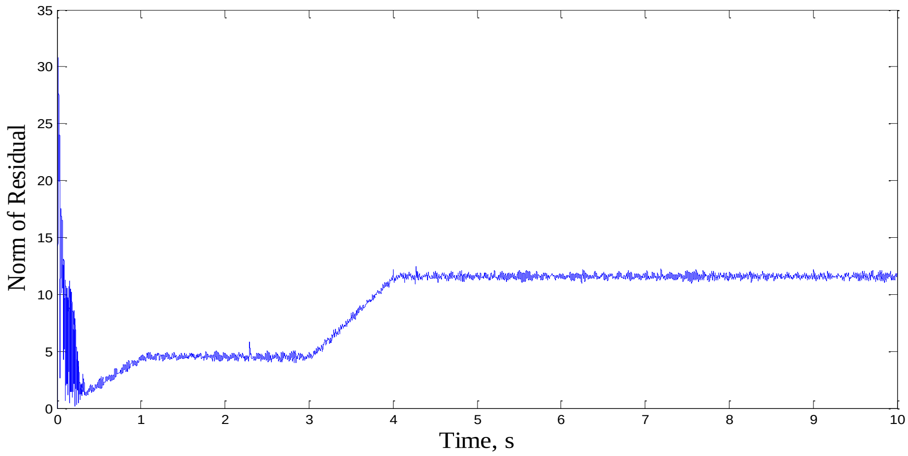


(c) Fault detection for the two sensor faults occurring sequentially

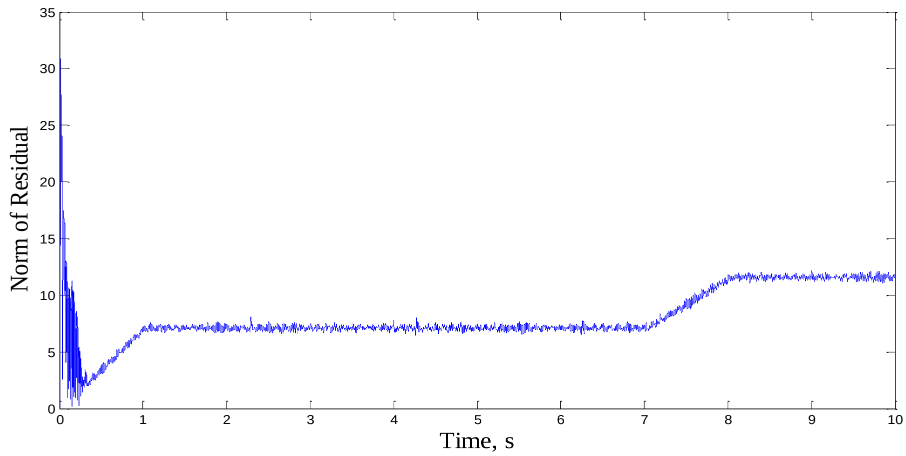
Figure 6.11: Norms of the residuals: abrupt sensor faults

B2) Fault Detection for incipient sensor faults

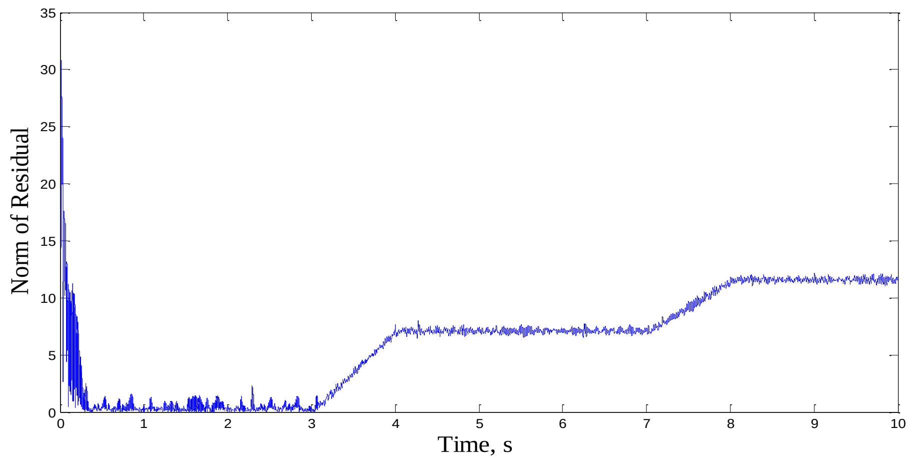
The residuals are exhibited by Figure 6.12, which has shown the faults occurring either individually or sequentially have been detected successfully.



(a) Fault detection for the first sensor fault



(b) Fault detection for the second sensor fault



(c) Fault detection for the two sensor faults occurring sequentially

Figure 6.12: Norms of the residuals: incipient sensor faults

Compared with Figures 6.8 and 6.9, the multiple dominant disturbance frequencies optimisation produced a better fault detection performance.

6.4.4 Actuator Fault Detection

For actuator fault detection, one chooses $B_f = B$ and $D_f = 0_{2\times 2}$.

*A. **Actuator fault detection: single dominant disturbance frequency for GA optimisation***

In this section, one chooses one dominant disturbance frequency for GA optimisation. In other words, in the fitness function (6.19), $N = 1$, $s_1 = j2\pi \times 48.37 = j96.7\pi$ (dominant disturbance frequency) and $s_f = j0$ (fault frequency). Using Algorithm 6.1, one can obtain the best fitness value (e.g., see 6.12).

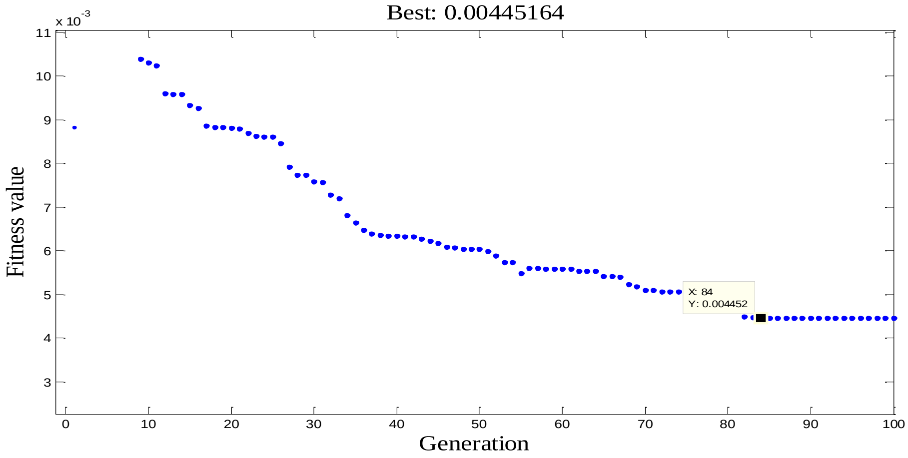


Figure 6.13: Evolution of the best performance index via GA

The optimal observer gain is given as follows:

$$K = \begin{bmatrix} -158.2412 & -153.7820 \\ 220.8111 & -136.6016 \\ 154.8895 & 159.4946 \\ -229.5844 & 131.6082 \end{bmatrix} \tag{6.35}$$

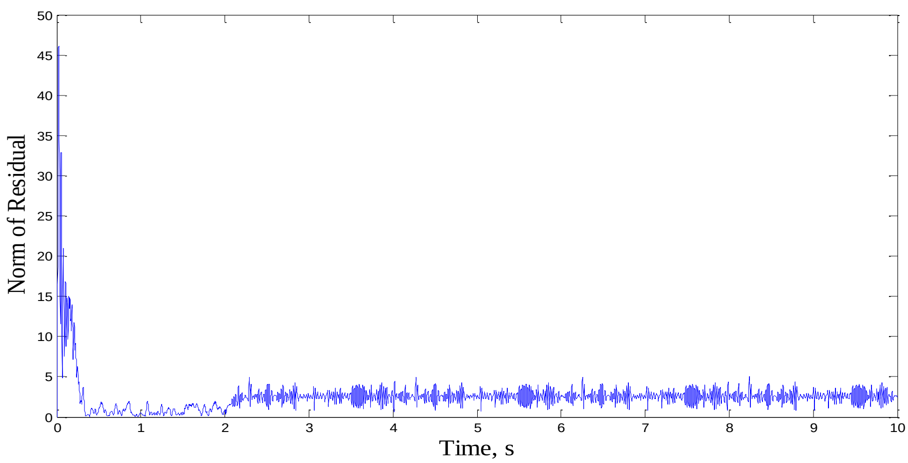
A1) Fault Detection for abrupt actuator faults

The two abrupt actuator faults are given as follows:

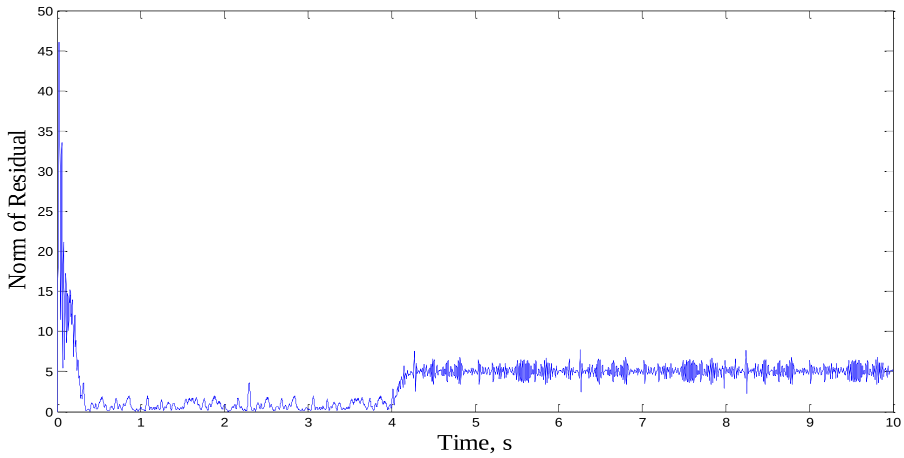
$$f_{a\alpha} = \begin{cases} 0, & t < 2s \\ 0.5 + 0.1\sin(10\pi t), & t \geq 2s \end{cases} \tag{6.36}$$

$$\mathrm{f}_{\mathrm{a}\beta} = \begin{cases} 0, & t < 4s \\ 0.5 + 0.1\sin(10\pi t), & t \geq 4s \end{cases} \tag{6.37}$$

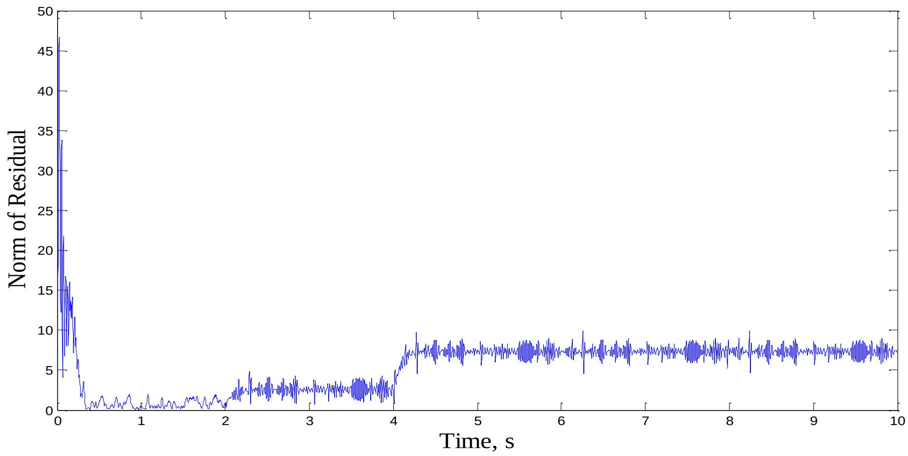
The residuals are depicted by Figure 6.14. One can see the residuals can successfully show the changes at 2s and 4s caused by the actuator faults.



(a) Fault detection for the first actuator fault



(b) Fault detection for the second actuator fault



(c) Fault detection for the two actuator faults occurring sequentially

Figure 6.14: Norms of the residuals: abrupt actuator faults

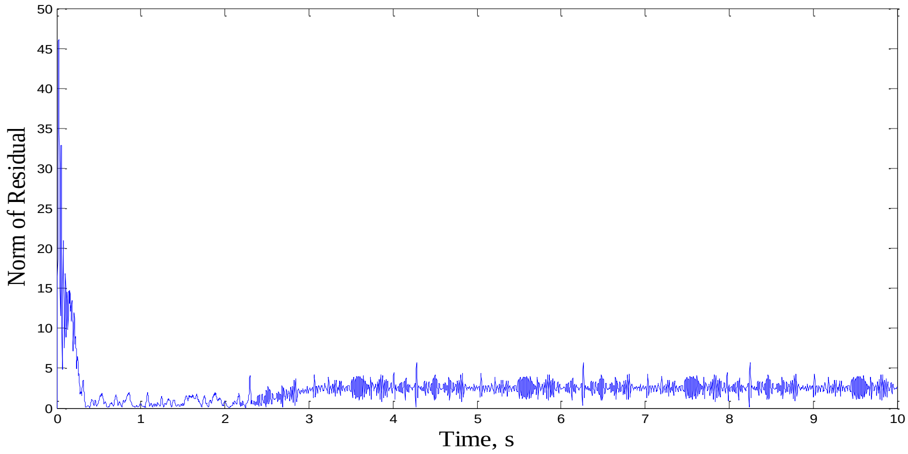
A2) Fault Detection for incipient actuator faults

The first and second actuator faults are given as follows:

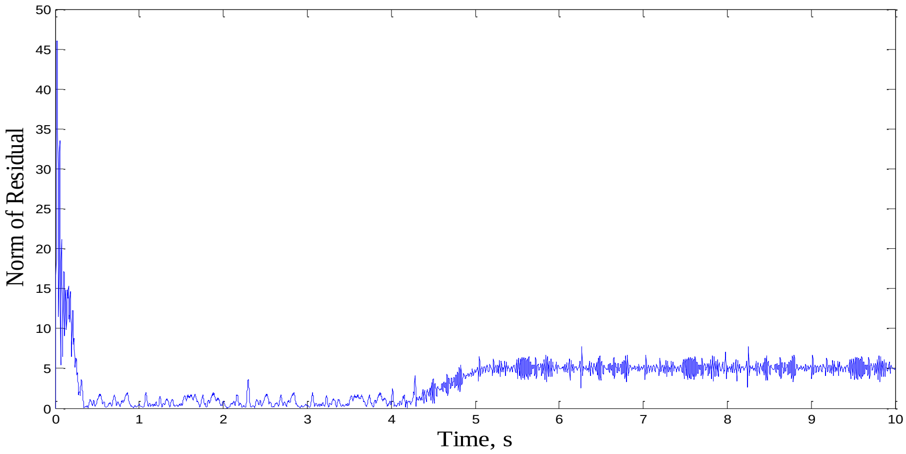
$$f_{a\alpha} = \begin{cases} 0, \ t < 2s \\ -0.5(t-2)\ , \ 2s \le t < 3\,s \\ -0.5, \quad t \ge 3s \end{cases} \tag{6.38}$$

$$\mathrm{f}_{a\beta} = \begin{cases} 0, \ t < 4s \\ -0.5t(t-4), \ 4s \le t < 5s \\ -0.5, \quad t \ge 5s \end{cases} \tag{6.39}$$

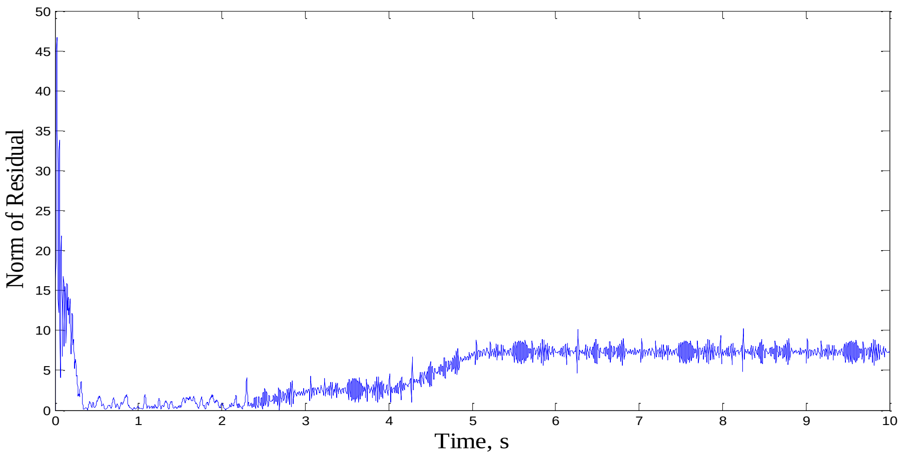
The residuals are depicted by Figure 6.15. One can see the residuals can successfully show some changes happen at 2s and 4s caused by the actuator faults. However, the changes are not very visible. It is evident that the abrupt actuator faults are more challenging to be detected compared with the abrupt actuator faults.



(a) Fault detection for the first actuator fault



(b) Fault detection for the second actuator fault



(c) Fault detection for the two actuator faults occurring sequentially

Figure 6.15: Norms of the residuals: incipient actuator faults

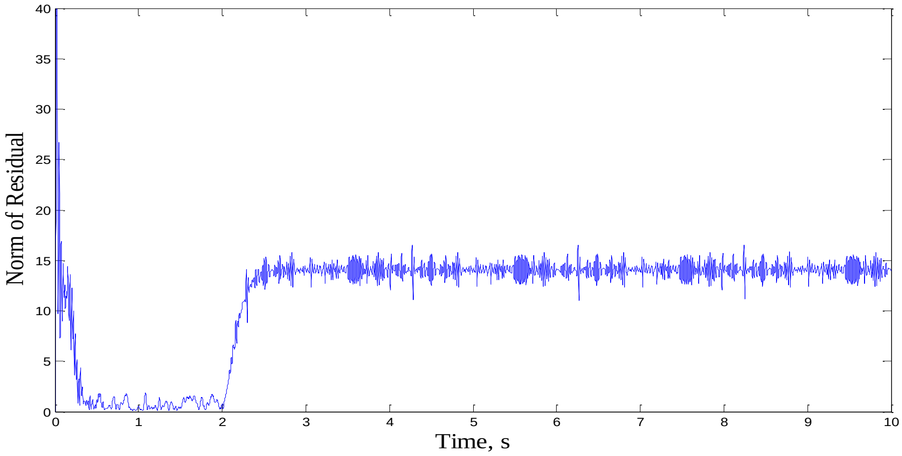
B. Actuator fault detection: multiple dominant disturbance frequencies via GA

In this case, one choose $s_1 = j2\pi f_{d1}$, $s_2 = j2\pi f_{d2}$, $s_3 = j2\pi f_{d3}$, and $s_4 = j2\pi f_{d4}$ where $f_{d1} = 48.37\ Hz$, $f_{d2} = 36.32\ Hz$, $f_{d3} = 32.27\ Hz$, and $f_{d4} = 25.71\ Hz$. Applying Algorithm 6.1, one can obtain an optimal observer gain K matrix as follows.

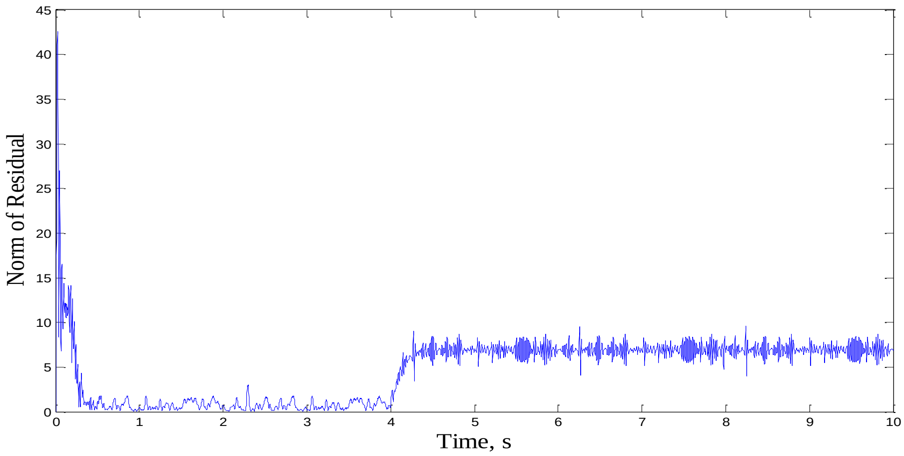
$$K = \begin{bmatrix} -161.3058 & -222.0471 \\ 197.1528 & -155.8353 \\ 157.2389 & 230.1410 \\ -205.0606 & 151.8913 \end{bmatrix} \tag{6.40}$$

B1) Fault detection for abrupt actuator faults

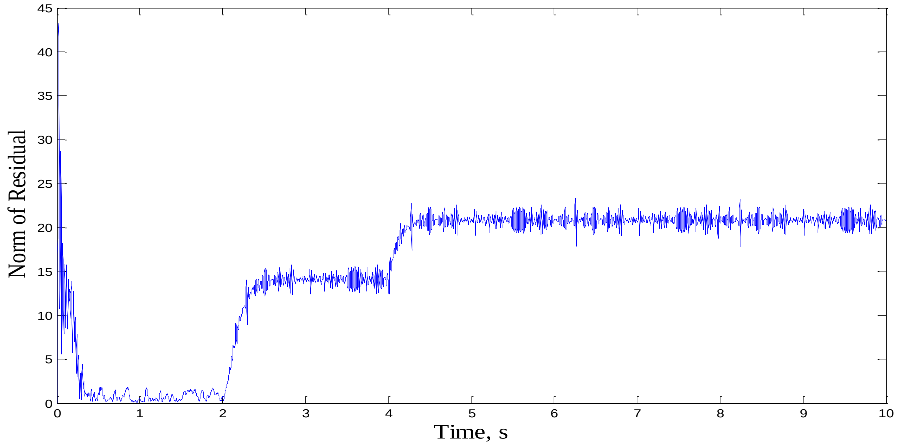
The residuals are shown by Figure 6.16. compared with Figure 6.14, the curve of Figure 6.16 is shows a better fault detection performance.



(a) Fault detection for the first actuator fault



(b) Fault detection for the second actuator fault



(c) Fault detection for the two actuator faults occurring successively

Figure 6.16: Norms of the residuals: multiple abrupt actuator faults

The curve of figure 6.17 achieves a better improved robust fault detection performance to figure 6.15.

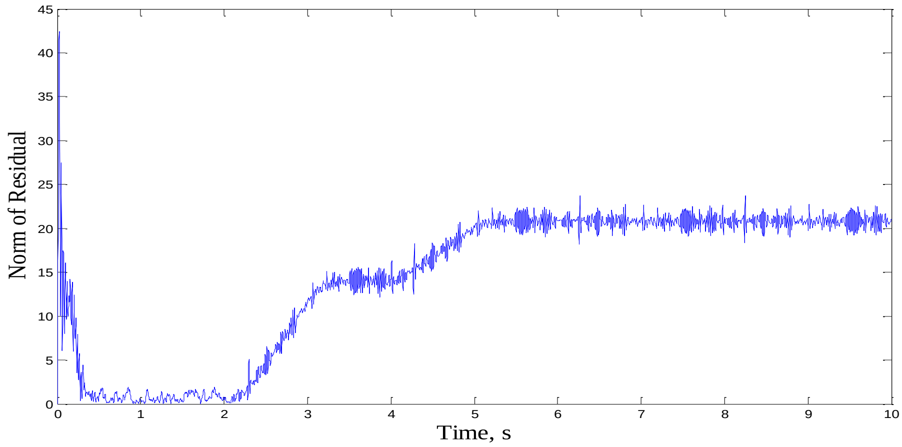


Figure 6.17: Norms of the residuals: multiple incipient actuator faults

6.4.5 Actuator and Sensor Fault Detection

Assume two actuator faults and two sensor faults occur sequentially. Therefore, $B_f = [B,\ 0_{4\times2}]$, and $D_f = [0_{2\times2},\ I_2]$. By using Algorithm 6.1, the optimal observer gain is given as follows:

$$K = \begin{bmatrix} -77.0130 & -187.2454 \\ 109.4329 & -191.6990 \\ 72.4737 & 195.2286 \\ -113.7875 & 188.4578 \end{bmatrix} \tag{6.41}$$

A) Abrupt faults

The four abrupt faults are defined as follows:

$$\mathrm{f}_{a\alpha}(t) = \begin{cases} 0, & \mathrm{t} < 1\mathrm{s} \\ 0.5 + 0.01\sin(10\pi\mathrm{t}), & \mathrm{t} \geq 1\mathrm{s} \end{cases} \tag{6.42}$$

$$f_{a\beta}(t) = \begin{cases} 0, & t < 2s \\ 0.5 + 0.01\sin(10\pi t), & t \geq 2s \end{cases} \tag{6.43}$$

$$f_{s\alpha}(t) = \begin{cases} 0, & t < 4s \\ 0.5 + 0.01\sin(10\pi t), & t \geq 4s \end{cases} \tag{6.44}$$

$$f_{s\beta}(t) = \begin{cases} 0, & t < 5s \\ 0.5 + 0.01\sin(10\pi t), & t \geq 5s \end{cases} \tag{6.45}$$

Figure 6.17 has shown two actuator and sensor faults have been detected successfully.

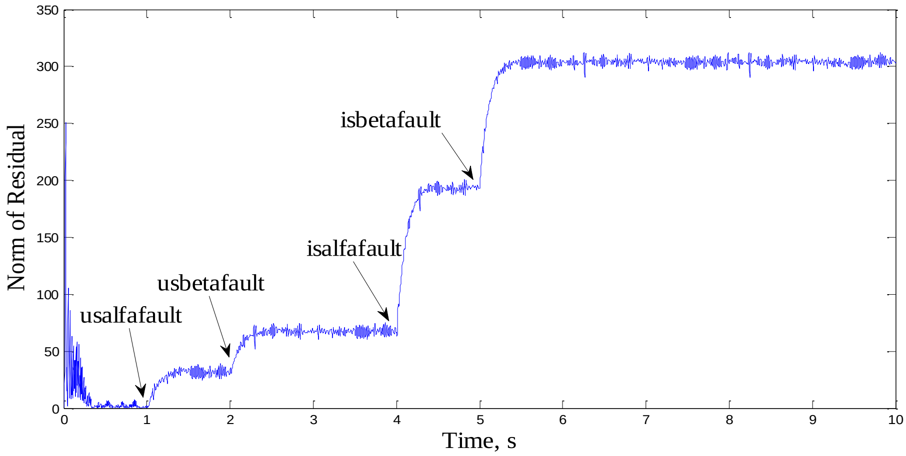


Figure 6.18: Actuator and sensor fault detection: abrupt faults

B) Incipient faults

The four incipient faults are defined as follows:

$$f_{a\alpha}(t) = \begin{cases} 0, & t < 1s \\ -0.5(t-1), & 1s \leq t < 2s \\ -0.5, & t \geq 1s \end{cases} \tag{6.46}$$

$$f_{a\beta}(t) = \begin{cases} 0, & t < 3s \\ -0.5(t-3), & 3s \leq t < 4s \\ -0.5, & t \geq 3s \end{cases} \tag{6.47}$$

$$f_{s\alpha}(t) = \begin{cases} 0, & t < 5s \\ -0.5(t-5), & 5s \leq t < 6s \\ -0.5, & t \geq 5s \end{cases} \tag{6.48}$$

$$f_{s\beta}(t) = \begin{cases} 0, & t < 7s \\ -0.5(t-7), & 7s \leq t < 8s \\ -0.5, & t \geq 7s \end{cases} \tag{6.49}$$

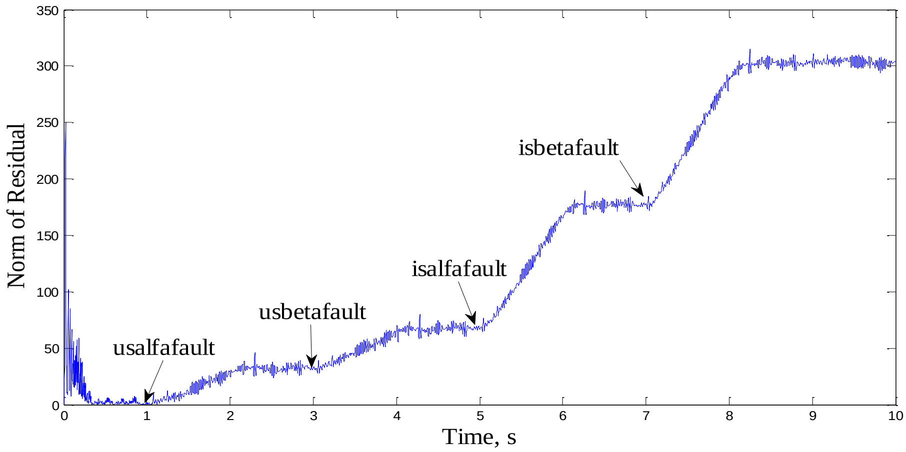


Figure 6.19: Actuator and sensor fault detection: incipient faults

Figure 6.18 has shown the successfully detectability of two actuator faults and two sensor faults. However, the detection performance of the incipient faults is not as good as that of the abrupt faults but is visible.

6.5 Robust Fault Estimation for Induction Motors

6.5.1 Fault Estimation Algorithm for Induction Motors

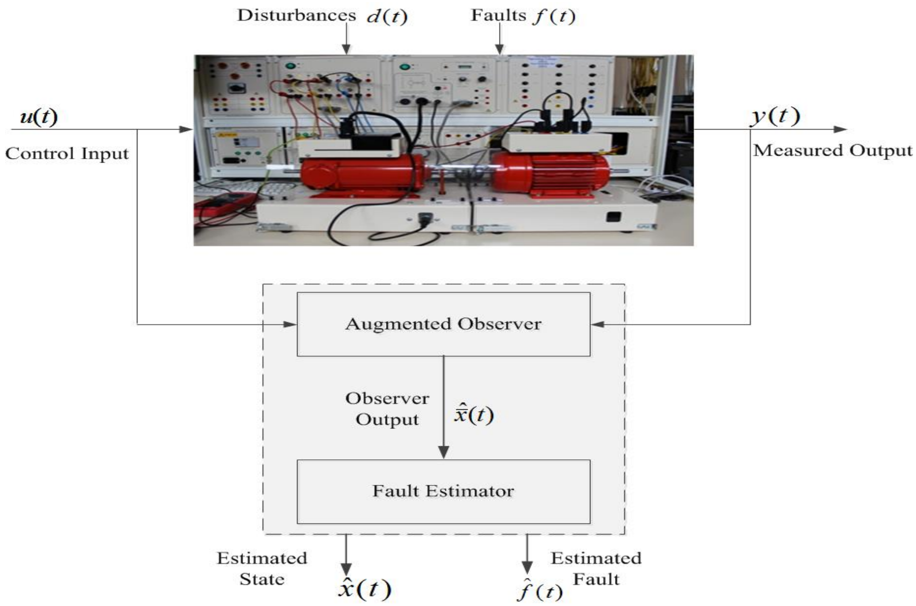


Figure 6.20: The scheme of fault detection for induction motors

Let

$$\bar{x}(t) = \left[x^T(t)\ \dot{f}^T(t)\ f^T(t)\right]^T \in \Re^{\bar{n}} \tag{6.50}$$

The induction motor model can be described by the augmented form as follows [203]:

$$\begin{cases} \dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{B}_d d(t) + \bar{M}(\Delta Ax(t)) + \bar{N}\ddot{f} \\ y(t) = \bar{C}\bar{x}(t) + Du(t) + D_d d(t) \end{cases} \tag{6.51}$$

where

$$\bar{A} = \begin{bmatrix} A & 0 & B_f \\ 0 & 0 & 0 \\ 0 & I & 0 \end{bmatrix} \in \Re^{\bar{n}\times\bar{n}}, \quad \bar{B} = \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix} \in \Re^{\bar{n}\times m} \tag{6.52}$$

$$\bar{C} = \begin{bmatrix} C & 0 & D_f \end{bmatrix} \in \Re^{\bar{p}\times\bar{n}}, \quad \bar{B}_d = \begin{bmatrix} B_d \\ 0 \\ 0 \end{bmatrix} \in \Re^{\bar{n}\times l} \tag{6.53}$$

$$\bar{M} = \begin{bmatrix} I \\ 0 \\ 0 \end{bmatrix} \in \Re^{\bar{n}\times n}, \quad \bar{N} = \begin{bmatrix} 0 \\ I \\ 0 \end{bmatrix} \in \Re^{\bar{n}\times k} \tag{6.54}$$

$$\bar{n} = n + 2k \tag{6.55}$$

An augmented observer is needed to be designed in the following form:

$$\begin{cases} \dot{\hat{\bar{x}}}(t) = \bar{A}\hat{\bar{x}}(t) + \bar{B}u(t) + \bar{K}\big(y(t) - \hat{\bar{y}}(t)\big) \\ \hat{\bar{y}}(t) = \bar{C}\hat{\bar{x}}(t) + Du(t) \end{cases} \tag{6.56}$$

where $\hat{\bar{x}}(t) \in \Re^{\bar{n}}$ is the estimation of the augmented state vector $\bar{x}(t)$, and $\bar{K} \in \Re^{\bar{n}\times p}$ is the observer gain to be designed.

Let $\bar{e}(t) = \bar{x}(t) - \hat{\bar{x}}(t)$. The estimation error dynamics is governed by the following equation:

$$\dot{\bar{e}}(t) = \big(\bar{A} - \overline{KC}\big)\bar{e}(t) + \big(\bar{B}_d - \bar{K}D_d\big)d(t) + \bar{M}\Delta Ax(t) + \bar{N}\ddot{f}(t) \tag{6.57}$$

Taking the Laplace transform, (6.57) becomes

$$\begin{aligned} \bar{e}(s) &= \big(sI - \bar{A} + \overline{KC}\big)^{-1}\big(\bar{B}_d - \bar{K}D_d\big)d(s) \\ &\quad + \big(sI - \bar{A} + \overline{KC}\big)^{-1}\bar{M}\Delta Ax + \big(sI - \bar{A} + \overline{KC}\big)^{-1}\bar{N}s^2 f(s) \end{aligned} \tag{6.58}$$

Define

$$H_d(s) = \big(sI - \bar{A} + \overline{KC}\big)^{-1}\big(\bar{B}_d - \bar{K}D_d\big)$$

$$H_{\Delta A}(s) = \big(sI - \bar{A} + \overline{KC}\big)^{-1}\bar{M}$$

$$H_f(s) = \big(sI - \bar{A} + \overline{KC}\big)^{-1}\bar{N}$$

(6.58) can be rewritten as in a compact form:

$$\bar{e}(s) = H_d(s)d(s) + H_{\Delta A}(s)\Delta Ax + H_f(s)s^2 f(s) \tag{6.59}$$

The cost function is given as follows:

$$J = J_1 + J_2 + J_3 \tag{6.60}$$

where,

$$\begin{cases} J_1 = \|H_d(s)\|_{s=j\omega_d} \\ J_2 = \|H_{\Delta A}(s)\|_{s=j\omega_{\Delta A}} \\ J_3 = \|H_f(s)\|_{s=j\omega_f} \end{cases} \tag{6.61}$$

ω_d is the frequency of the disturbance, $\omega_{\Delta A}$ is the frequency of the dominant modeling error, and ω_f is the frequency of $\ddot{f}(t)$.

Based on the above and following Chapter 4, the fault detection algorithm can be summarized as follows.

Algorithm 6.5: GA-based fault estimator design for induction motors

- **Check condition of observer:** Check whether (5.55) and (5.56) are satisfied. If yes, go to the next step; otherwise, stop the procedure.
- **Set the parameters to be optimized:** The total number of the parameters to be optimized is $\bar{n} + \bar{n} \times p$, and the set of the parameters is defined as (4.32).
  - **Fitness Evaluation:** The fitness function is defined as (6.60).
  - **Constrains:** The eigenvalues of the $(\bar{A} - \bar{K}\bar{C})$ are ensured to be stable.
  - **GA running:** Run GA until one of stop condition is met.

6.5.2 Sensor Fault Estimation for Induction Motors

A) Abrupt faults

In case of abrupt sensor faults, the faults are expressed as follows:

$$f_{s\alpha}(t) = \begin{cases} 0, \ \mathrm{t} < 2\mathrm{s} \\ 1 + 0.1\sin(10\pi\mathrm{t}), \ \mathrm{t} \geq 2\mathrm{s} \end{cases} \tag{6.62}$$

$$f_{s\beta}(t) = \begin{cases} 0, \ t < 4s \\ 1 + 0.1sin(10\pi t), \ t \geq 4s \end{cases} \tag{6.63}$$

In this case, there are two pulse disturbances d_{sA} and d_{sB} adding on the two current sensors, respectively, as follows:

$$d_{s\alpha} = \begin{cases} 0, \ t < 6s, \ t > 6.1s \\ 1, \ 6s \leq t \leq 6.1s \end{cases} \tag{6.64}$$

$$d_{s\beta} = \begin{cases} 0, \ t < 8s, t > 8.1s \\ 1, \ 8 \le t \le 8.1s \end{cases} \tag{6.65}$$

The constrains of the eigenvalues of $(\bar{A} - \bar{K}\bar{C})$ are defined as

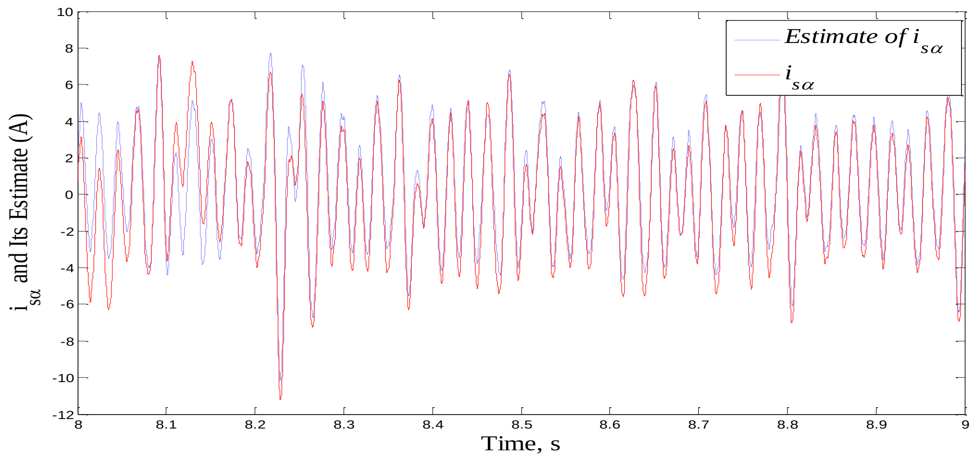
$$\begin{cases} -50 \le \lambda_i \le -10, i = 1,2,\cdots,6 \\ -50 \le \lambda_{j,re} \le -1, j = 1 \end{cases} \tag{6.66}$$

The disturbance frequency is $\omega_d = 0$, and the frequency of the dominant modelling error is selected as $s_1 = j2\pi f_{d1}$ where $f_{d1} = 48.37\ Hz$.

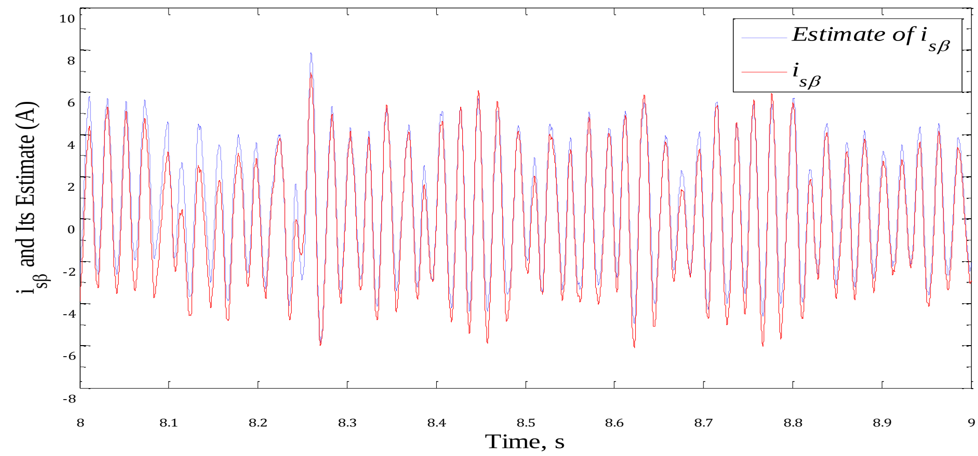
In addition, $B_f = 0_{4\times 2,}$ and $D_f = I_2$. Utilizing Algorithm 6.4, the optimal observer gain is calculated by gatool optimization solver in Matlab [204].

$$\bar{K} = \begin{bmatrix} -37.4733 & -297.2632 \\ 298.4003 & -28.1681 \\ 28.6670 & 305.2835 \\ -306.8077 & 19.1127 \\ -10.3557 & -71.4337 \\ 61.6486 & -9.6311 \\ -0.5475 & -8.4127 \\ 7.2380 & -0.3816 \end{bmatrix}. \tag{6.67}$$

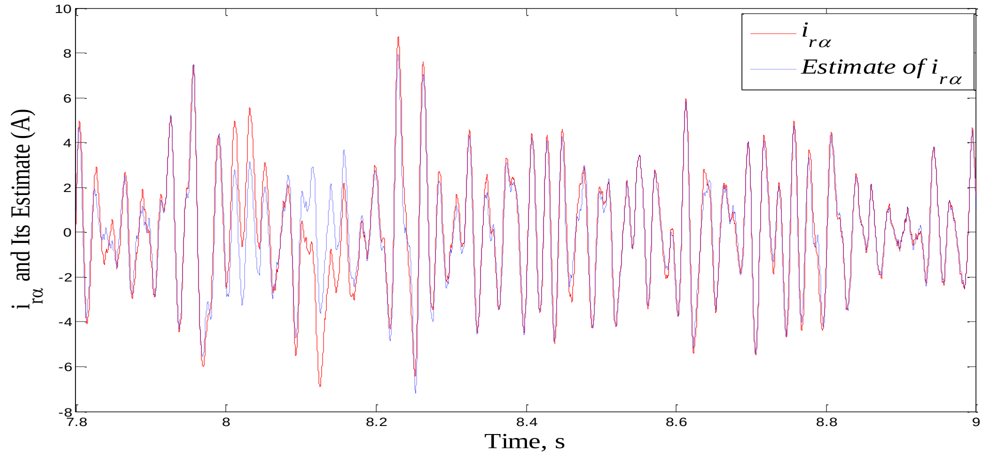
Figure 6.20 exhibits the state estimates of $i_{s\alpha}$, $i_{s\beta}$, $i_{r\alpha}$, and $i_{r\beta}$. The solid line represents the real state, and the dash line denotes the estimate. One can see the estimation performance is excellent.



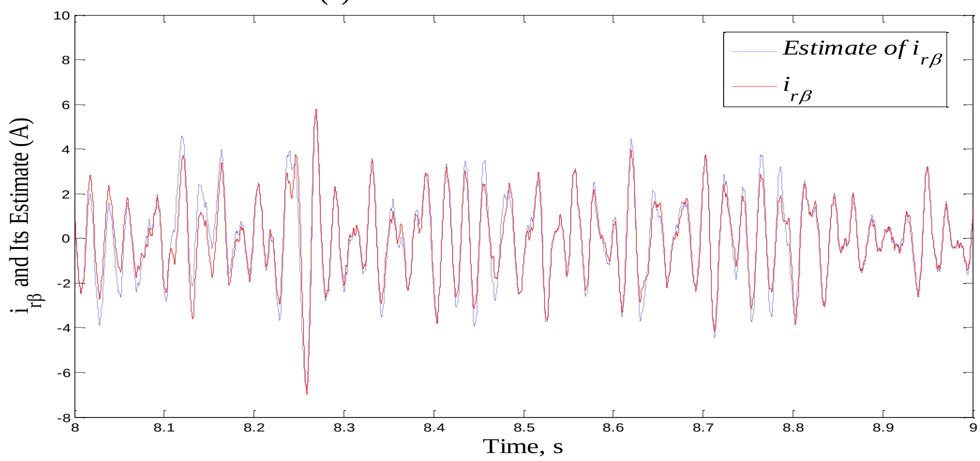
(a) The estimate of the first state



(b) The estimate of the second state



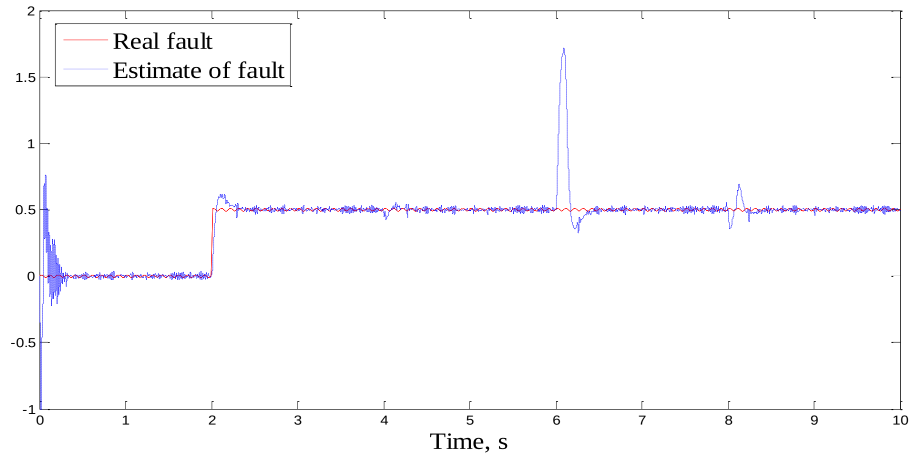
(c) The estimate of the third state



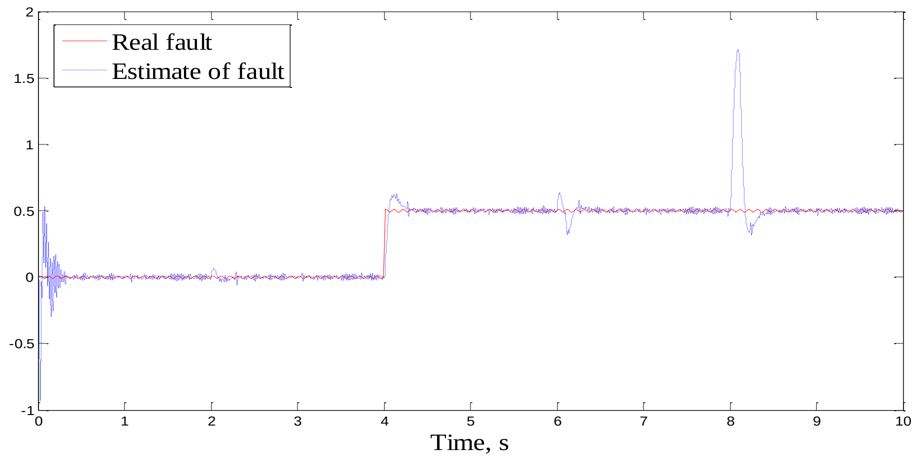
(d) The estimate of the fourth state

Figure 6.21: Estimate state of the induction motor

Figure 6.22 exhibits the estimates of the two abrupt sensor faults, which have shown excellent tracking performance.



(a) Estimate of the first sensor fault



(b) Estimate of the second sensor fault

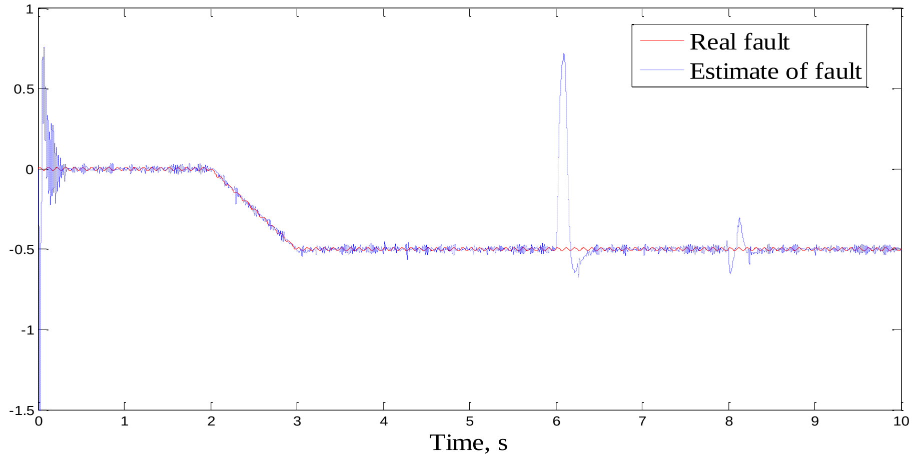
Figure 6.22: Abrupt sensor faults and their estimates

B) Incipient faults

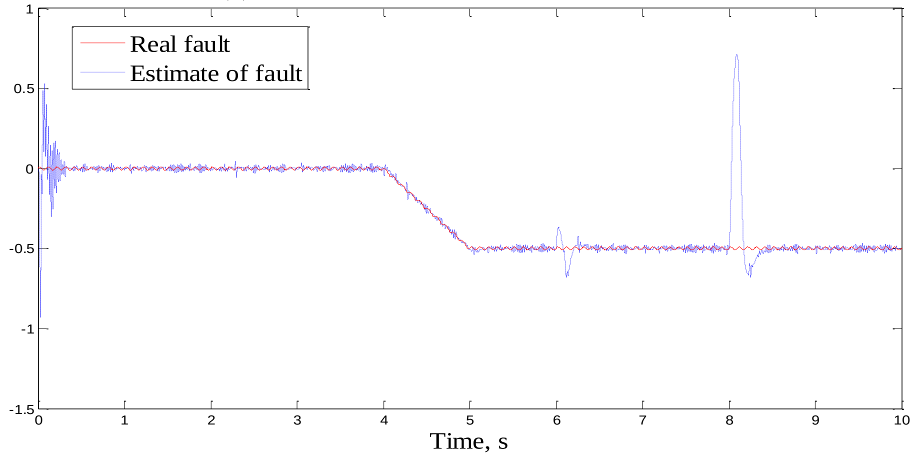
The two incipient faults are defined as follows:

$$f_{s\alpha}(t) = \begin{cases} 0, \;\; t < 2s \\ -0.5(t-2), \;\; 2s \le t < 3s \\ -0.5, \;\; t \ge 3s \end{cases} \quad (6.68)$$

$$f_{s\beta}(t) = \begin{cases} 0, \;\; t < 4s \\ -0.5(t-4), 4s \le t < 5s \\ -0.5, \;\; t \ge 5s \end{cases} \quad (6.69)$$



(a) Estimate of the first sensor fault



(b) Estimate of the second sensor fault

Figure 6.23: Incipient sensor faults and their estimates.

Figure 6.23, of the incipient sensor fault estimation performance is excellent.

6.5.3 Actuator Fault Estimation for Induction Motors

It is noted that $B_f = B,$ and $D_f = 0_{2\times 2.}$ The optimal observer gain is given as follows:

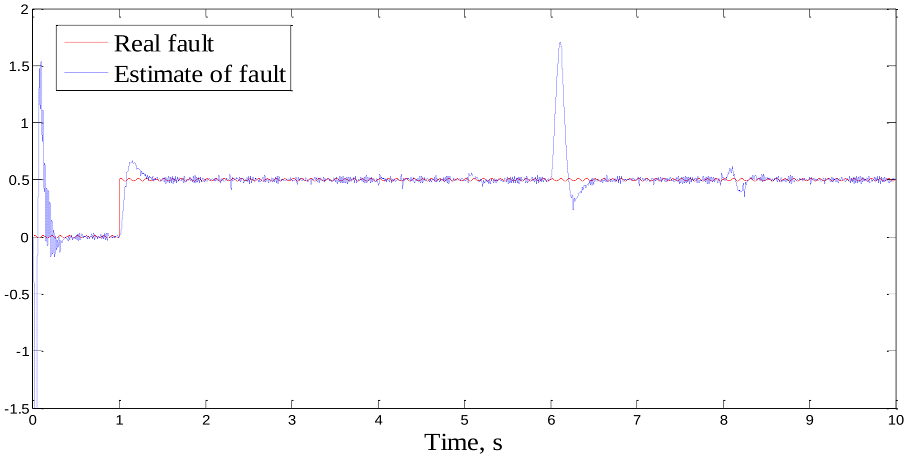
$$\bar{K} = \begin{bmatrix} -104.5257 & -138.2030 \\ 300.5068 & -138.2030 \\ 98.2343 & 300.4096 \\ -309.8830 & 133.1418 \\ 29.5166 & -77.6937 \\ 149.3106 & -14.4852 \\ 2.1320 & -8.3611 \\ 15.8218 & 0.2016 \end{bmatrix} \tag{6.70}$$

A) Abrupt faults

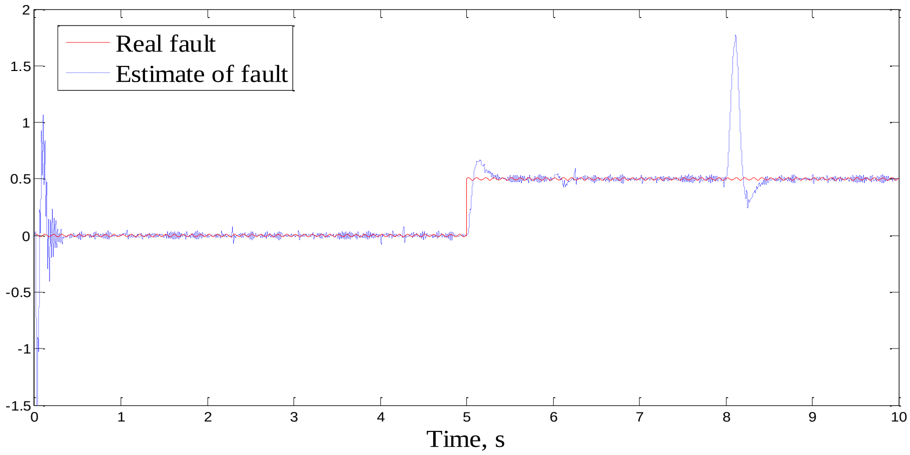
The first two actuator faults are defined as follows:

$$f_{a\alpha}(t) = \begin{cases} 0, \ t < 1s \\ 0.5 + 0.01sin(10\pi t), \ t \geq 1s \end{cases} \tag{6.71}$$

$$f_{a\beta}(t) = \begin{cases} 0, \ t < 5s \\ 0.5 + 0.01sin(10\pi t), \ t \geq 5s \end{cases} \tag{6.72}$$



(a) Estimate of the first actuator fault



(b) Estimate of the second actuator fault

Figure 6.24: Abrupt actuator faults and their estimates

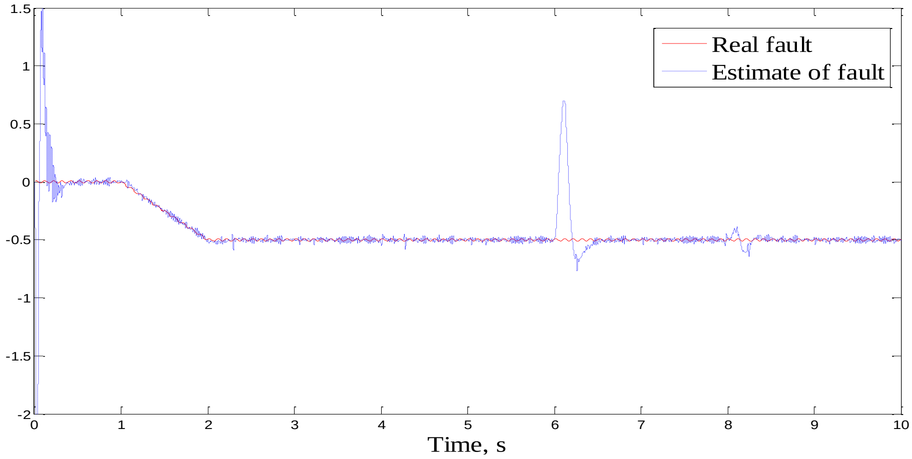
From 6.24, one can see satisfactory fault tracking performance.

B) Incipient faults

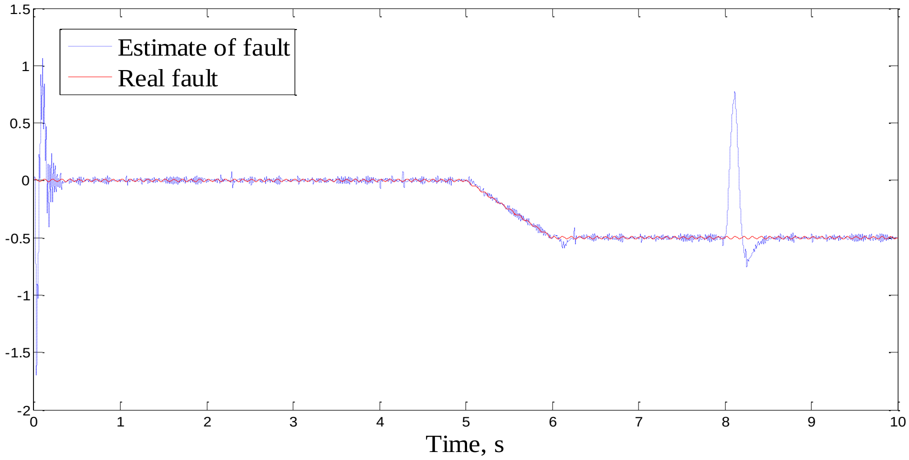
The first two actuator faults are defined as follows:

$$f_{a\alpha}(t) = \begin{cases} 0, \ t < 1s \\ -0.5(t-1), 1s \leq t < 2s \\ -0.5 + 0.01sin(10\pi t), \quad t \geq 2s \end{cases} \tag{6.73}$$

$$f_{a\beta}(t) = \begin{cases} 0, \ t < 5s \\ -0.5(t-5), 5s \leq t < 6s \\ -0.5t \ + 0.01sin(10\pi t), \quad t \geq 6s \end{cases} \tag{6.74}$$



(a) Estimate of the first actuator fault



(b) Estimate of the second actuator fault

Figure 6.25: Incipient actuator faults and their estimates

From 6.25, one can see satisfactory estimation performance of the actuator faults.

6.5.4 Fault Estimation for Both Actuator and Sensor Faults of Induction Motors

A) Faults in $u_{s\alpha}(t)$ *and* $i_{s\beta}(t)$

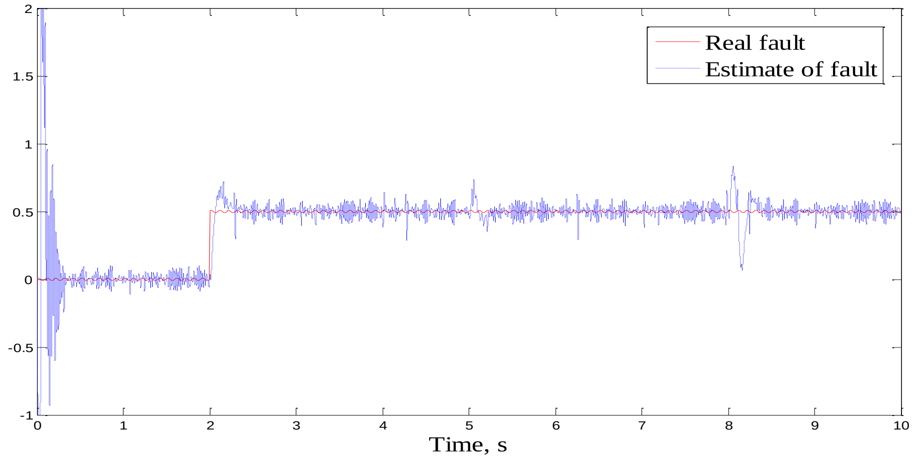
$$B_f = B_1 \tag{6.75}$$

$$D_f = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{6.76}$$

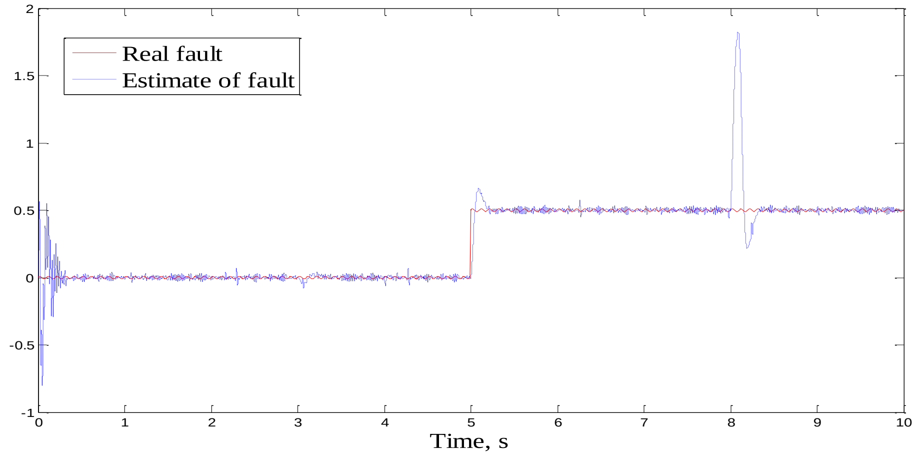
where B_1 is the first column of B.

By using Algorithm 6.4, one can obtained the optimal observer gain as follows:

$$\overline{K} = \begin{bmatrix} -77.1919 & -275.5043 \\ 257.2378 & -70.3514 \\ 71.0285 & 283.4563 \\ -264.9243 & 63.4019 \\ 99.4509 & -104.5106 \\ 35.7128 & 92.4866 \\ 12.1207 & -17.8838 \\ 5.1249 & 4.7266 \end{bmatrix} \tag{6.77}$$

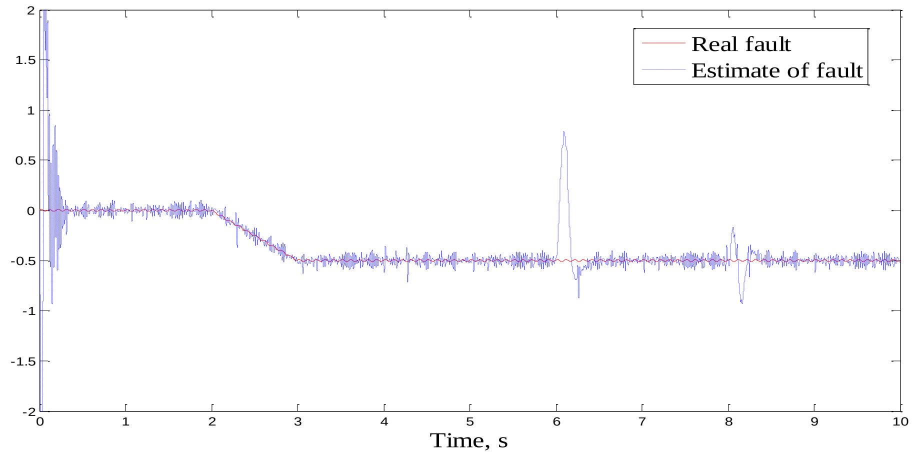


(a) Fault estimation of the first actuator fault

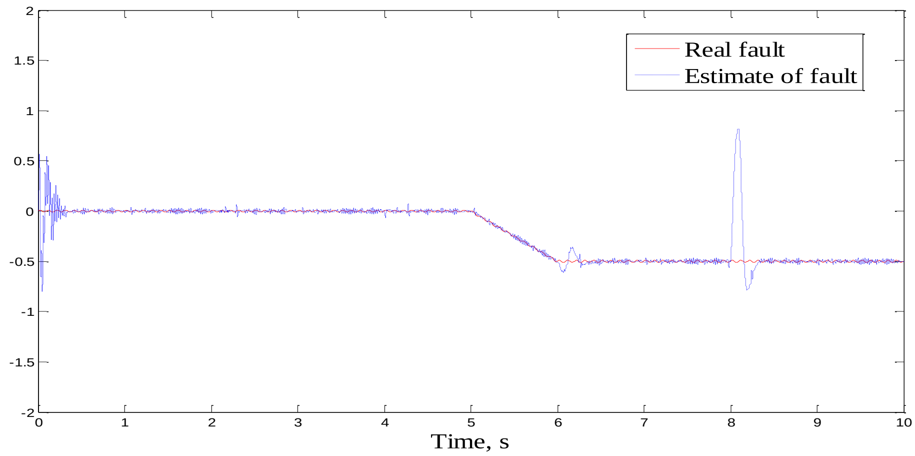


(b) Fault estimation of the second sensor fault

Figure 6.26: Estimates of the actuator and sensor faults $u_{s\alpha}(t)$ & $i_{s\beta}(t)$: abrupt faults



(a) Fault estimation of the first actuator fault



(b) Fault estimation of the second sensor fault

Figure 6.27: Estimates of the actuator and sensor faults $u_{s\alpha}(t)$ & $i_{s\beta}(t)$: incipient faults

In terms of Figures 6.26 and 6.27, the estimates of the first actuator fault and the second sensor fault show the satisfactory performance for either abrupt types of faults or incipient types of faults.

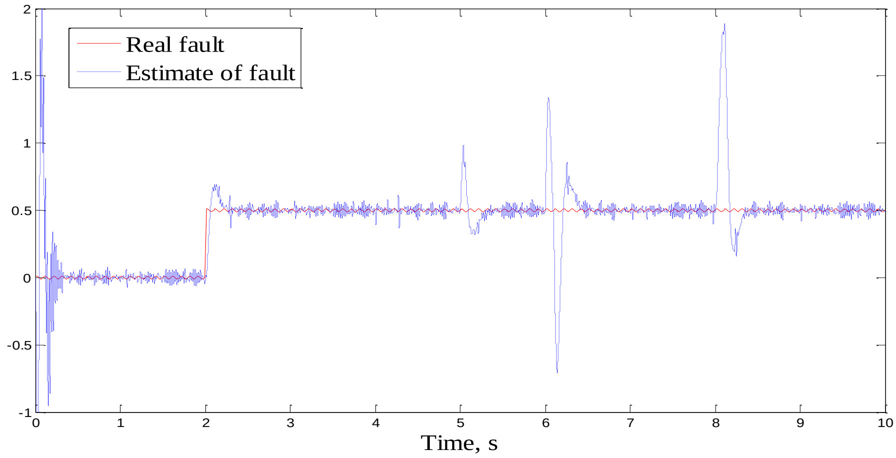
B) Faults in $u_{s\beta}(t)$ and $i_{s\alpha}(t)$

$$B_f = B_2 \tag{6.78}$$

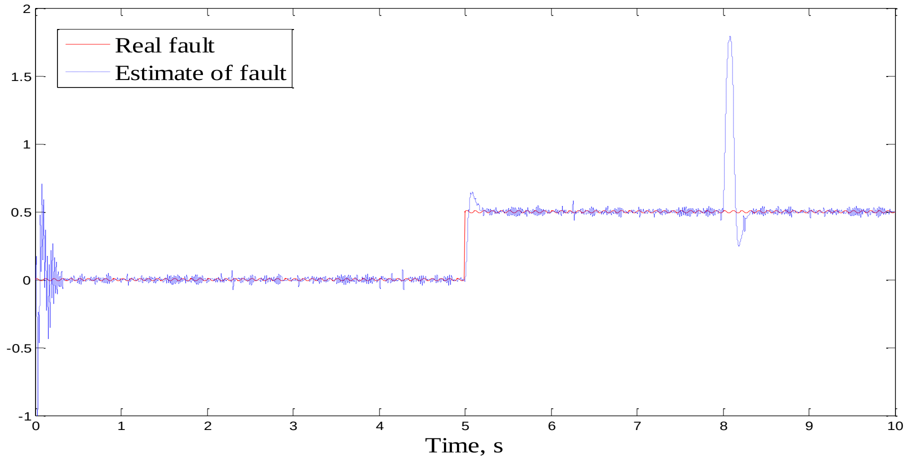
$$D_f = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{6.79}$$

where B_2 is the second column of B. By using Algorithm 6.4, the optimal observer gain is given by:

$$
\overline{K} = \begin{bmatrix} -96.4550 & -313.7909 \\ 313.1584 & -83.1312 \\ 89.4909 & 323.5390 \\ -322.8342 & 75.5862 \\ 128.8442 & -75.3598 \\ -20.8001 & -37.1141 \\ 15.8695 & -5.8731 \\ -1.3117 & -5.0143 \end{bmatrix} \tag{6.80}
$$

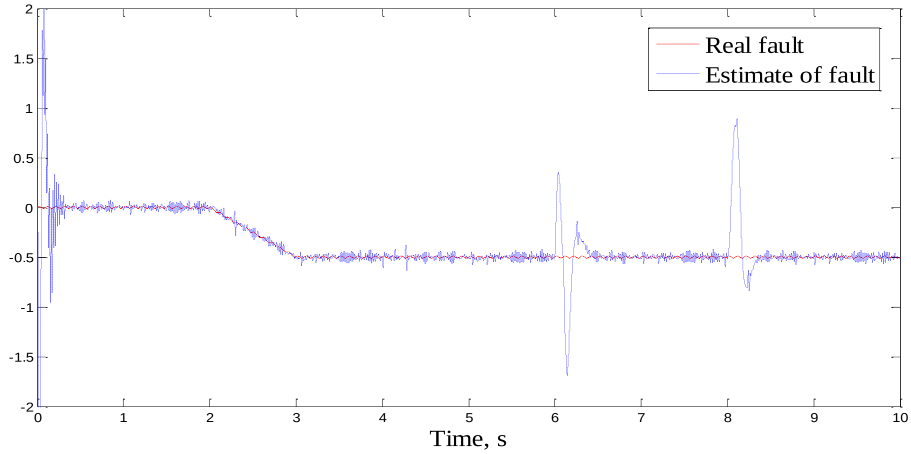


(a) Fault estimation of the second actuator fault

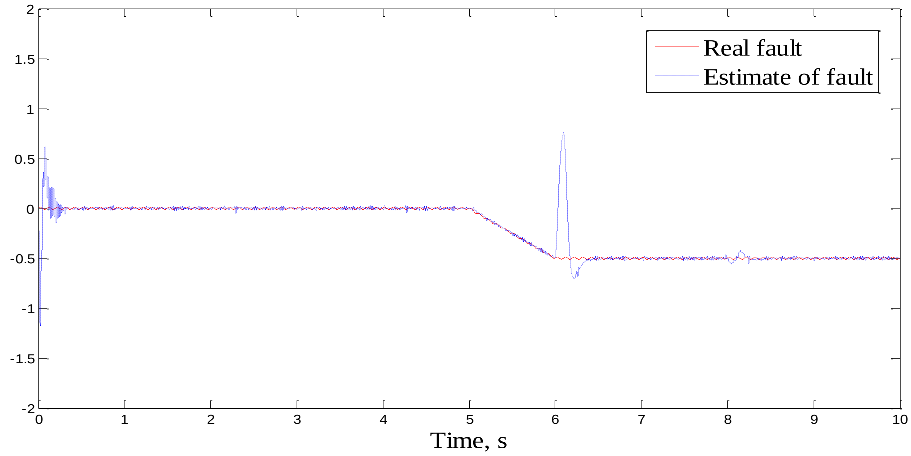


(b) Fault estimation of the first sensor fault

Figure 6.28: Estimates of the actuator and sensor faults $u_{s\beta}(t)$ *and* $i_{s\alpha}(t)$: abrupt faults



(a) Fault estimation of the second actuator fault



(b) Fault estimation of the first sensor fault

Figure 6.29: Estimates of the actuator and sensor faults $u_{s\beta}(t)$ *and* $i_{s\alpha}(t)$: incipient faults

According to Figures 6.28 and 6.29, the estimates of the second actuator fault and the first sensor fault show the satisfactory performance for either abrupt types of faults or incipient types of faults.

6.6 Summary

The contribution of this session is summarized as follows:

- Robust fault detection design algorithm is applied to fault detection for induction motor with individual sensor faults and actuator faults.
- Robust fault detection design algorithm is applied to fault detection for induction motors with multiple faults including actuator faults and sensor faults.
- By using multiple frequencies of the dominant uncertainty components for GA-based optimal observer gain design, fault detection performance has been improved significantly, which is an interesting contribution and novelty of this session.
- Robust fault estimation algorithm is addressed for the application of the fault estimation for induction motors with sensor faults.
- Robust fault estimation algorithm is addressed for the application of the fault estimation for induction motors with actuator faults.
- Robust fault estimation algorithm is addressed for the application of the fault estimation for induction motors with both actuator and sensor faults.
- The real-data from the experiment are used to validate the algorithms.

Chapter Seven: Conclusion and Future work

"Finally, in conclusion, let me say just this."

Peter Sellers
1925-1980

7.1 Conclusion

Fault diagnosis is an important research topic, which is motivated to improve system reliability and safety, and reduce the cost caused by unexpected faults. As a matter of fact, uncertainties arising from modelling errors, process, and measurement disturbances are unavoidable in practical engineering environments. These uncertainties have brought challenges for an effective fault diagnosis, which could cause false alarms or the failure to catch the signal changes when faults occur at an early stage. In this study, GA-based robust fault detection and fault estimation algorithms are addressed and applied to the two case studies, one involving a: wind turbine systems and other three-phase induction motors.

The contributions of this research are summarised as follows:

- The addressed fault diagnosis methods can effectively handle two typical faults in industrial systems: abrupt faults and incipient faults.
- The GA-based optimisation and eigenstructure assignment are integrated to determine an optimal observer-based fault detection filter so that the residual is sensitive to the fault, but robust against uncertainties.
- The frequency of the dominant disturbance is utilised to carry out optimisation, which is straightforward and would reduce the concern for seeking an optimal observer gain.
- The frequencies of the dominant uncertainties components are used for observer gain optimisation, which produces a better fault detection performance than one using a single dominant disturbance frequency.
- By integrating an augmented system approach and the GA-optimisation method, a novel fault estimation approach is developed, which can effectively simultaneously estimate system states and the faults concerns.
- The frequencies of the dominant uncertainties can be obtained by using a signal processing technique, such as, Fourier Transform Analysis. Combining with the model-

based fault diagnosis method and the signal processing technique, the developed method is in essence a form of hybrid fault diagnosis.

- Wind turbine energy conversion systems have dominated the renewable energy industry. The safety and reliability of wind turbine systems have received much attention during the recent years. The application of the GA-based fault detection and GA-based fault estimation to a 5MW wind turbine is investigated and addressed with details.
- An experiment is carried out using a 2kW three-phase induction motor, and the recorded real data is used for the verification of the GA-based fault detection and fault estimation algorithms.
- Simulation studies using Matlab/Simulink environment have demonstrated the effectiveness of the addressed GA-based fault detection and GA-based fault estimation algorithms.

7.2 Future Work

All the objectives stated in chapter one have been achieved. The devised algorithm is integrated with a variety of techniques, whose effectiveness has been demonstrated both in theory and in practice via the two case studies investigated. Due to the complexity of modern industrial systems, the addressed methods/algorithms would not cover all the scenarios in complex industrial processes. In the future, the following research topics would be encouraged.

- **Application to various engineering systems:** The addressed methods have been applied to two case studies: wind turbine systems and induction motors. It would be of interest to apply the addressed algorithms to other industrial systems such as photovoltaic systems and robotic systems etc.
- **Extension to nonlinear systems:** Nonlinearity generally exists in engineering systems. It would be of interest, but challenging to extend GA-based fault diagnosis method to a nonlinear system.
- **Robust fault tolerant control:** Another important topic is fault-tolerant control. It is of interest to apply GA optimisation technique to fault tolerant control so that the system would work in tolerant performance degradation even when a fault occurs.
- **Real-time implementation:** It is intended to apply the proposed GA-based fault diagnosis technique to a real-time implementation applied to a real industrial system.

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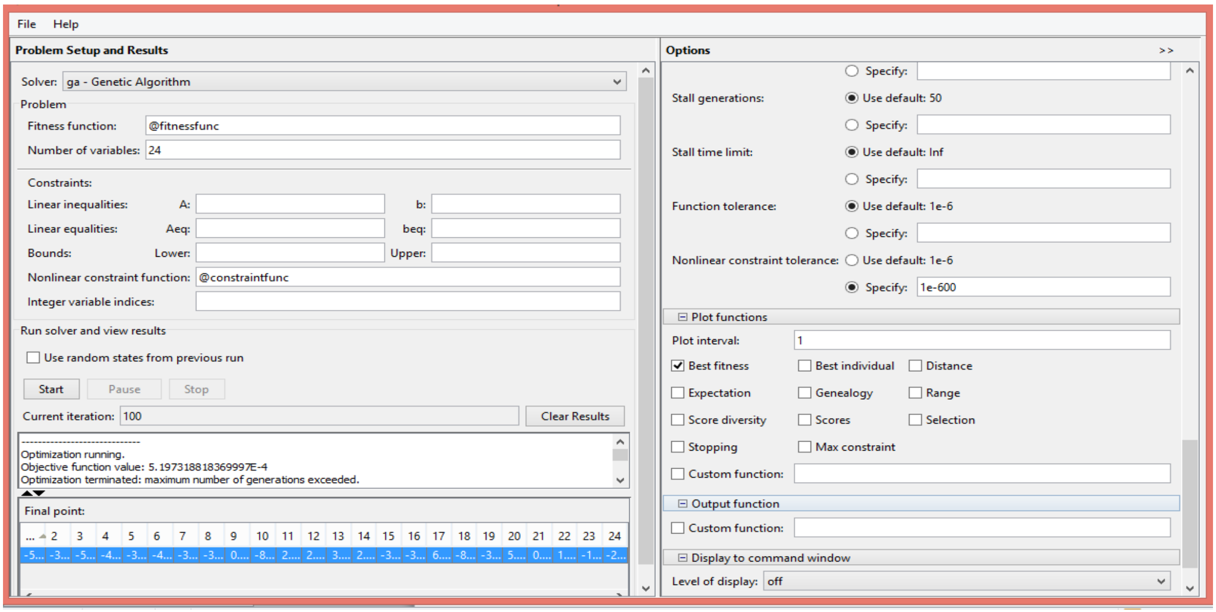
Appendices

Appendix A: Working Operation of Optimization Toolbox

The toolbox named *gatool* solver optimization toolbox is employed via Matlab for operating or to run the operation of GA problems. The idea of GA is to move a series of population of chromosome from initial random scores to a global value after some representation, selection, mutation and reproduction operations method. The evolutionary is iterated until a global solution is reached or until no better optimal observer value can be found. For the parameters from (6.20), $V \in \Re^{\bar{n}}$, $W \in \Re^{p\times\bar{n}}$, where $\bar{\mathrm{n}} = 8$, $p = 2$. The sum number of parameters is 24, and the nonlinear constraint function depends on the data.



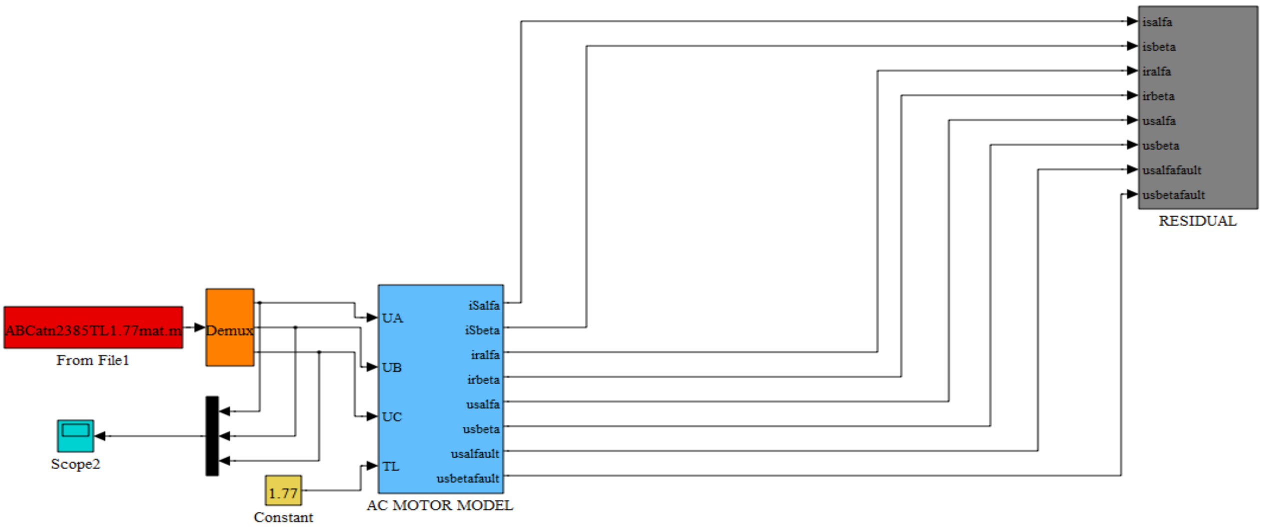


Figure A1: The Robust fault detection for IM Matlab/Simulink linear-time Model with actuator fts

Appendix B: 3 phase Induction Motor Test Rig

The three phase IMs condition performance gives a comprehensive information of real time data collected from experimental setup. The objective of this testrig is used to measure the 3 phase voltage and current performance of squirrel cage IMs, the data collected is employed to simulate the real data of the designed fault diagnosis.

The drive of this experimental work is to measure the three phase (3-Φ) AC squirrel cage IM 64-501 performance and capture from the PC computer (which control the torque/speed and record measured data) voltage and current generate the real data characteristics during the operation measure. Besides giving the graphical views to the user, MATLAB also give good analytical capabilities about the behavioral performance measurements on the IM experiments. The 3-Φ A.C IM squirrel cage dual voltage was connected to a dynamometer motor, the Armature current Dynamometer system consisting of a shunt DC machine 63-110 with a fitted 68-500 virtual instrumentation system. The mandatory connections with universal power supply of 60-105 to the motor control unit 68-411 which are torque and speed control panel connected to dynamometer test bed. 68-500 multi-channel Input/output panel connected to the AC motor in the $\mathbf{Y}$ and Δ connected configuration of stator windings determine and compare various steady-state/rotational speed (rpm) reference of $\omega_r^* = 249.63\ \mathrm{rad/s}$, at frequency of 50Hz. Constant load torque $T_L = 1.77\ \mathrm{N.m}$ of the motor characteristics operation under different loading conditions with 68-911 software for virtual instrumentation. The data collection system is real for voltage and currents via data recorder with a sampling frequency of 0.1 kHz of the personal computer (PC) with 68-911 software for virtual Instrumentation connected to the 68-411 Torque/Speed control panel. A mechanical load was provided by a separately driven excited 2 kW DC generator.

The 3Φ, 2 kW, wye (**Y**) connected, squirrel-cage induction motor parameters are chosen for the simulation studies.

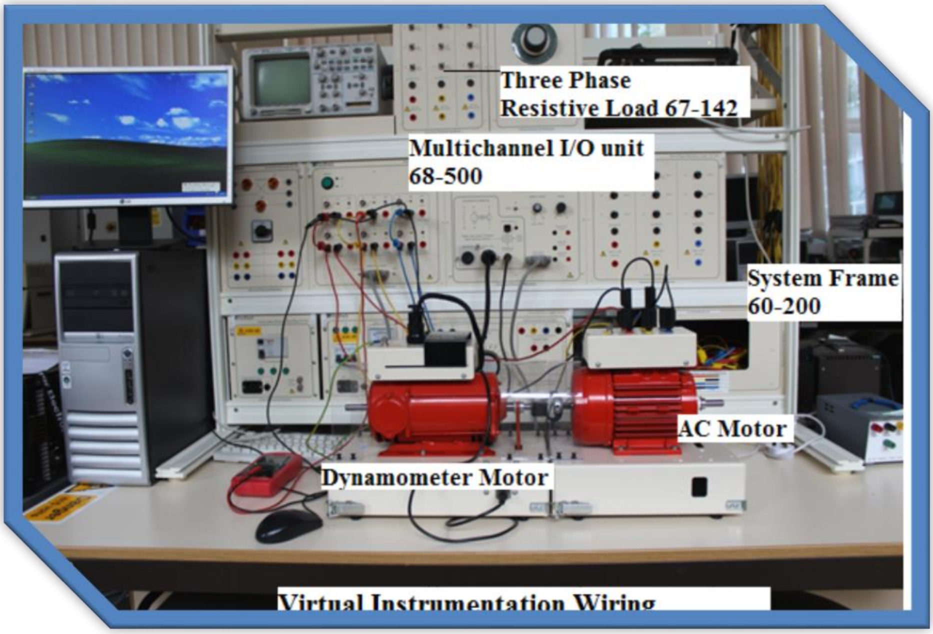


Figure B2: A photograph of Experimental setup

The procedure begins with to switch on the 60-105 circuit breakers, confirm that dynamometer is connected to the torque socket gently, set up as shown in the configuration above. Gradually increase the variable supply control until the line-to-line voltage is about 415V for **Y** connection and 240V for Δ connection of stator windings. This unit has voltage sensors, current sensors, an accelerometer, and an encoder. A card for the signal acquisition of six simultaneous analogical inputs is integrated in a PC of which a data acquisition system is important component of a dynamometer as for measurements and to store the generated voltage and current, in 3 phase AC files. The load torque is set to be zero and also turn slowly the variable supply control back to 0% to stop the machines. Switch off the universal power supply-60105 at the circuit breaker. The parameters measured squirrel-cage induction motor performance comparison under robust fault diagnosis conditions. The proposed approach allows continuous real time identifying monitoring of faults health.

Operation/ procedure of using the IMs

This text gives ***guidelines*** for the safe operation of the 3Φ IM performance test rig under.

Safety

- Ensure that the 3Φ power supply to your bench is switched on.
- Connect the motors to the power supply with cables, torque-speed control panel 68-411 and Multi-Channel Input / output panel (68-500) equipment.
- Confirm that the dynamometer is connected to the torque socket.

- Switch on the required feedback modules. Power it on by pressing the square switch in the centre of the control unit, the red LED will light up.
- Switch **ON** the PC computer and start the discovery software by National Instruments
- From the start windows, click on the *Electrical power and machines* to open up machines virtual instrumentation software 68-911.
- Then power **ON** the set up
- Double click and setup each virtual instrument as set-up the virtual instruments by double clicking on the each instrumentation to select the squared box as required.
- Ensure that the 3Φ power supply to your bench is switched **OFF** after the data collection.

SAFETY NOTE

Do not leave the 68-411 powered up with the test motor **NOT** rotating with a load demand. This will cause the dynamometer motor to overheat which may lead to perpetual accident.

Appendix C: Fault Estimation Simulink Of Wind Turbine Model

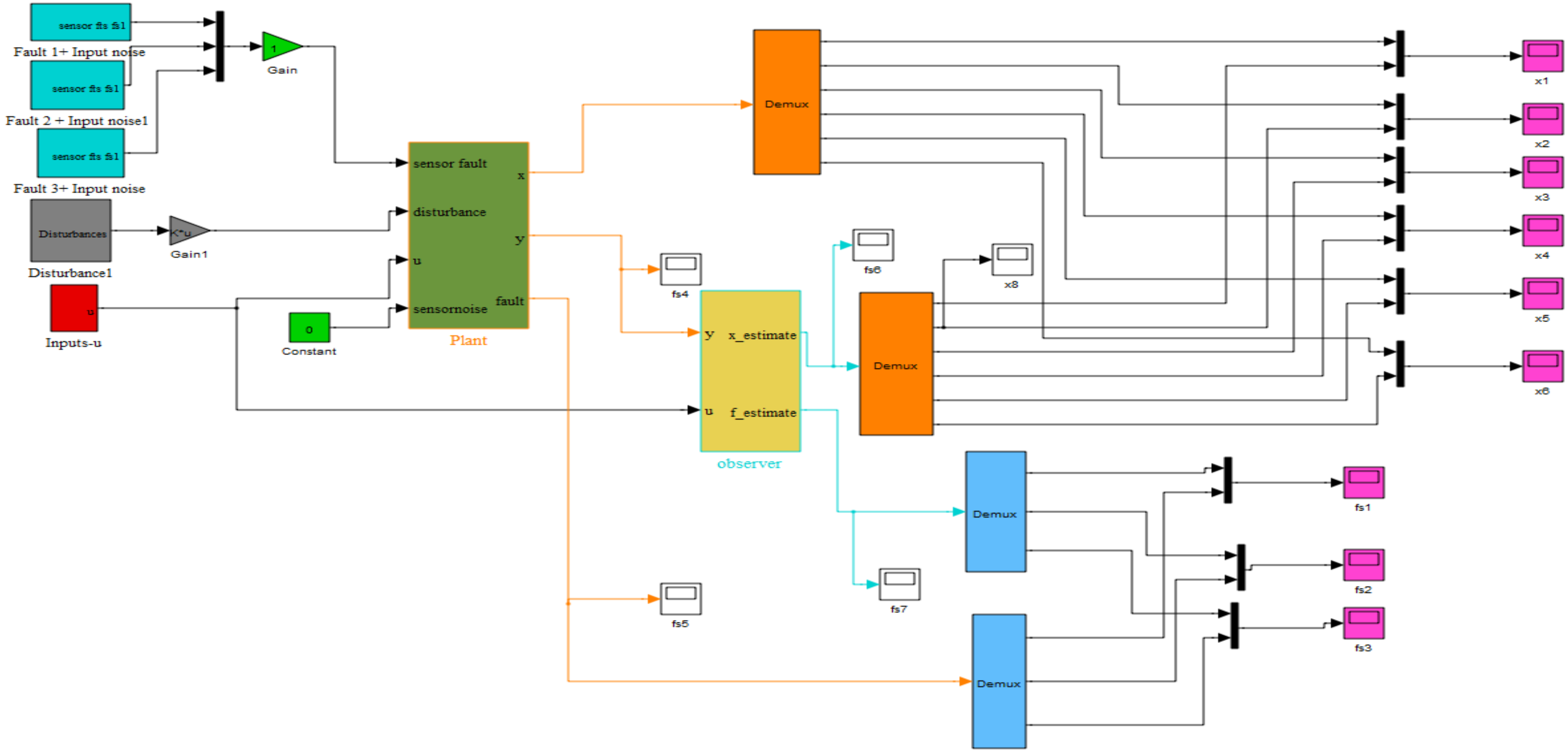


Figure C: The Robust fault Estimation Wind Turbine Matlab/Simulink Model

Appendix D: IM real-time Fault Estimation Matlab / Simulink Model

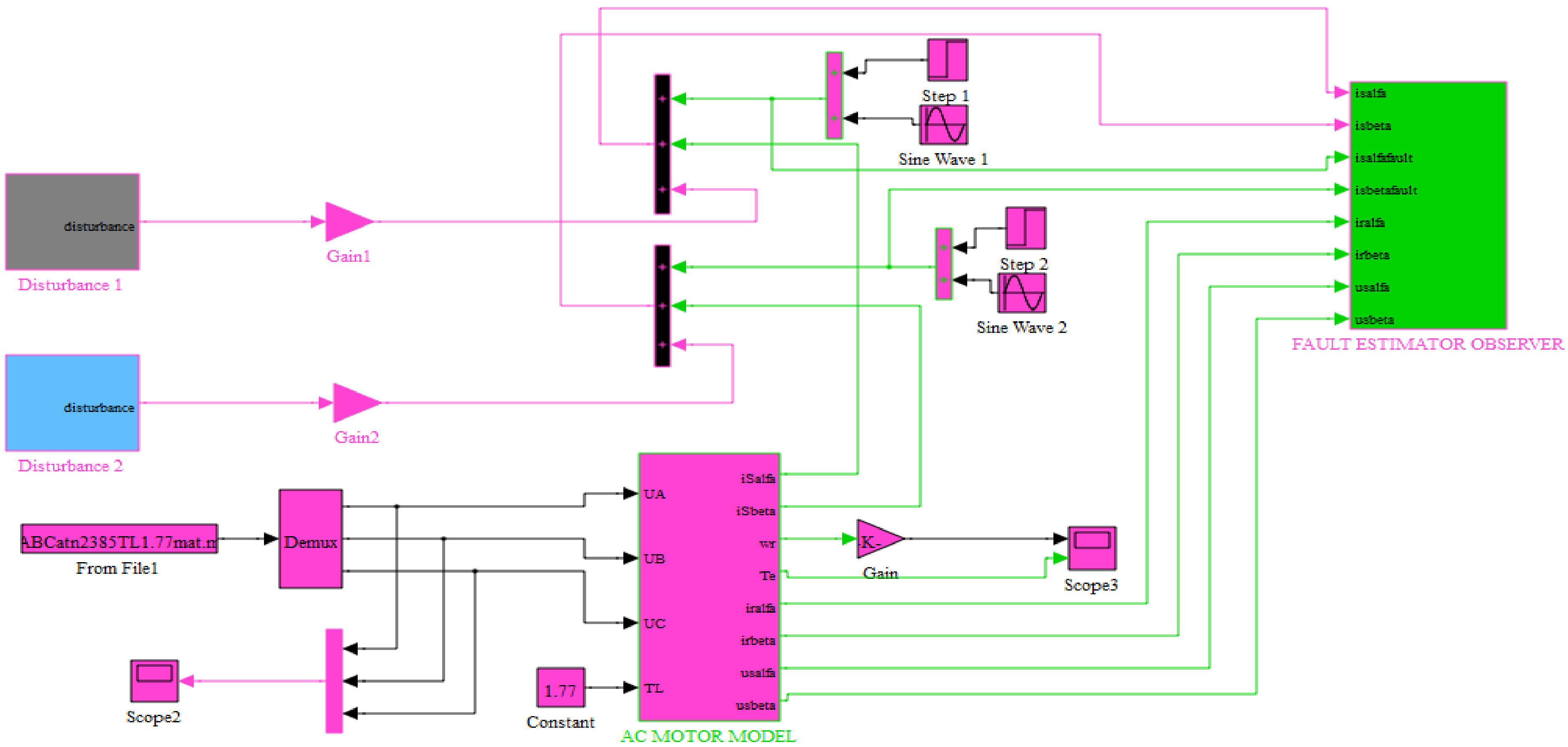


Figure B.2: The IM Motor Robust fault Estimation Matlab / Simulink Model

Appendix E. Coding in M-File

A. Fault Detection

```
global A
global B
global C
global D
global Bf
global Bd
global Bdbar
global Ddbar
global Df
global Dd
global M
global W
global K
global P
global k

%%%%%%%%%%%%%%%%%%%%%%%%%
np=1;
J=0.0131;%
Dfraction=0;%
Rs=3.478;
Rr=2.564;
Lm=0.3329;
Ls=0.3454;
Lr=0.3452;
Sigma=1-Lm*Lm/(Ls*Lr);
Ts=0.0001;%sample time
wr=2850*2*pi/60;%Ó¦

A=(1/(Sigma*Ls*Lr))*[-Rs*Lr wr*Lm*Lm Rr*Lm wr*Lm*Lr;-wr*Lm*Lm -Rs*Lr -wr*Lm*Lr
Rr*Lm;Rs*Lm -wr*Lm*Ls -Rr*Ls -wr*Lr*Ls;wr*Lm*Ls Rs*Lm wr*Lr*Ls -Rr*Ls];
B=(1/(Sigma*Ls*Lr))*[Lr 0;0 Lr;-Lm 0;0 -Lm];
C=[1 0 0 0;0 1 0 0];
D=zeros(2,2);
Bf=B;
Bd=eye(4,2);
Bdbar=[eye(4) zeros(4,2) eye(4) zeros(4,2)];
Ddbar=[zeros(2,4) eye(2) zeros(2,4) eye(2)];
Df=zeros(2,2);
Dd=eye(2,2);
EyeMaxtrix=eye(2,2);

M=ones(2,1);
```

B. Fault Estimation

```
%        Initialization             %

global A
global B
global C
global D
global Bf
global Bf1
global Bf2
global Bd
global Df
global Df1
global Df2
global Dd
global Abar
global Bbar
global Cbar
global Bdbar
global Nbar
global Mbar
global Kbar
global Kx
global Kf

np=1;
J=0.0131;%
Dfraction=0;%
Rs=3.478;
Rr=2.564;
Lm=0.3329;
Ls=0.3454;
Lr=0.3452;
Sigma=1-Lm*Lm/(Ls*Lr);%Â©
Ts=0.0001;%sample time
 wr=2850*2*pi/60;%
A=(1/(Sigma*Ls*Lr))*[-Rs*Lr wr*Lm*Lm Rr*Lm wr*Lm*Lr;-wr*Lm*Lm -Rs*Lr -wr*Lm*Lr
Rr*Lm;Rs*Lm -wr*Lm*Ls -Rr*Ls -wr*Lr*Ls;wr*Lm*Ls Rs*Lm wr*Lr*Ls -Rr*Ls];
B=(1/(Sigma*Ls*Lr))*[Lr 0;0 Lr;-Lm 0;0 -Lm];
C=[1 0 0 0;0 1 0 0];
D=zeros(2,2);
Bf=B;
Bf1=[B(:,1) zeros(4,1)];
Bf2=[B(:,2) zeros(4,1)];
Bd=eye(4,2);
Df=eye(2,2);
Df1=[zeros(2,1) Df(:,1)];
Df2=[zeros(2,1) Df(:,2)];
Dd=eye(2,2);

ZeroMaxtrix1=zeros(4,2);
ZeroMaxtrix2=zeros(2,4);
```

```
ZeroMaxtrix3=zeros(2,2);
ZeroMaxtrix4=zeros(2,2);
ZeroMaxtrix5=zeros(2,4);
ZeroMaxtrix6=zeros(2,2);
EyeMaxtrix=eye(2,2);
Abar=[A ZeroMaxtrix1 Bf2;ZeroMaxtrix2 ZeroMaxtrix3 ZeroMaxtrix4;ZeroMaxtrix5 EyeMaxtrix
ZeroMaxtrix6];

 ZeroMaxtrix7=zeros(2,2);
Bbar=[B;ZeroMaxtrix7;ZeroMaxtrix7];
ZeroMaxtrix8=zeros(2,2);
Bdbar=[B;ZeroMaxtrix8;ZeroMaxtrix8];

EyeMaxtrix=eye(4,4);
ZeroMaxtrix=zeros(2,4);
Mbar=[EyeMaxtrix;ZeroMaxtrix;ZeroMaxtrix];

ZeroMaxtrix1=zeros(4,2);
EyeMaxtrix=eye(2,2);
ZeroMaxtrix=zeros(2,2);
Nbar=[ZeroMaxtrix1;EyeMaxtrix;ZeroMaxtrix];
ZeroMaxtrix=zeros(2,2);
Cbar=[C ZeroMaxtrix Df2];


EyeMaxtrix1=eye(4,4);
EyeMaxtrix2=eye(2,2);
ZeroMaxtrix1=zeros(4,2);
ZeroMaxtrix2=zeros(2,4);
ZeroMaxtrix3=zeros(2,2);

Kx=[EyeMaxtrix1 ZeroMaxtrix1 ZeroMaxtrix1];
Kf=[ZeroMaxtrix2 ZeroMaxtrix3 EyeMaxtrix2];

P=[-0.1 -0.2 -0.3 -0.04 -0.5 -0.6 -0.7 -08];
kbar=place(Abar',Cbar',P)';
```

Fitness Evaluation

```
function fitness=fitnessfunc(x)
global A
global B
global C
global D
global Bf
global Bd
global Df
global Dd
global Abar
global Bbar
```

```
global Cbar
global Bdbar
global Nbar
global Mbar
global Kbar
global Kx
global Kf

%x=(1:24);

eigen1=x(:,1);%
eigen2=x(:,2);
eigen3=x(:,3);
eigen4=x(:,4);
eigen5=x(:,5);
eigen6=x(:,6);%
eigen1re=x(:,7);%
eigen1im=x(:,8);%


w1=x(:,9:10)';%
w2=x(:,11:12)';
w3=x(:,13:14)';
w4=x(:,15:16)';
w5=x(:,17:18)';
w6=x(:,19:20)';%
 w1re=x(:,21:22)';%
w1im=x(:,23:24)';%

AbarT=Abar';
CbarT=Cbar';
E=eye(8);%

v1=-inv(eigen1*E-AbarT)*CbarT*w1;%
v2=-inv(eigen2*E-AbarT)*CbarT*w2;
v3=-inv(eigen3*E-AbarT)*CbarT*w3;
v4=-inv(eigen4*E-AbarT)*CbarT*w4;
v5=-inv(eigen5*E-AbarT)*CbarT*w5;
v6=-inv(eigen6*E-AbarT)*CbarT*w6;%

 ZeroMaxtrix=zeros(8,2);
Cc=[CbarT ZeroMaxtrix;ZeroMaxtrix CbarT];

E=eye(8);
A1=[(eigen1re*E-AbarT) -eigen1im*E;eigen1im*E (eigen1re*E-AbarT)];
v1reim=-inv(A1)*Cc*[w1re;w1im];%

v1re=v1reim(1:8,:);
v1im=v1reim(9:16,:);

W=[w1 w2 w3 w4 w5 w6 w1re w1im];
V=[v1 v2 v3 v4 v5 v6 v1re v1im];
```

```
Kbar=(W*inv(V))';

E=eye(8);
s1=j*0;%for disturbance
s2=j*pi*2*48.37;%for deltaAx
3=j*0.5;%for fault

% OTHER DDF FROM FFT

s4=j*pi*2*36.32;
s5=j*2*pi*32.27;
s6=j*2*pi*25.71;
J1=norm(inv(s1*E-Abar+Kbar*Cbar)*(Bdbar-Kbar*Dd));%for disturbance
J2=norm(inv(s2*E-Abar+Kbar*Cbar)*Mbar);%for deltaAx
J3=norm(inv(s3*E-Abar+Kbar*Cbar)*Nbar*s3^2);%for fault
J=(J1+J2+J3);
fitness=J;
```

Constraint Function

```
function [c,ceq]=constraintfunc(x)

eigen1=x(:,1);%
eigen2=x(:,2);
eigen3=x(:,3);
eigen4=x(:,4);
eigen5=x(:,5);
eigen6=x(:,6);%

eigen1re=x(:,7);%
eigen1im=x(:,8);%

c(1)=eigen1;%
c(2)=eigen2;
c(3)=eigen3;
c(4)=eigen4;
c(5)=eigen5;
c(6)=eigen6;
c(7)=eigen1re;

c(8)=eigen1+30;%c(1)<=0,eigen1<=-0.1
c(9)=eigen2+30;
c(10)=eigen3+30;
c(11)=eigen4+30;
c(12)=eigen5+30;
c(13)=eigen6+30;
c(14)=eigen1re+20;

ceq=[];
```