An Adaptive Resonance Theory Neural Network (ART NN)-based fault diagnosis system: A Case Study of gas turbine system in Resak Development Platform

by

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Dissertation submitted in partial fulfillment of

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CERTIFICATION OF APPROVAL

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Approved by,

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Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK, MALAYSIA
MAY 2015

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

NGUYEN CHI CUONG

ABSTRACT

The project introduces a case study of a real gas turbine system in Resak Development Platform. There are two main objectives of this project. The first objective is aimed to achieve an online fault diagnosis model using Adaptive Resonance Theorem (ART) as a considered option to avoid potential faults happen during plant system and process. The second objective is focused on a solution to improve the maintenance plan for the gas turbine system to be more economical yet still maintaining its safety level.

Faults which are normally divided into three types which are hang faults, zero faults and drift faults are likely to happen at any time and anywhere during the process. Potential faults poses a danger to damage the plant facilities and assets as well as threating working personnel's lives in the plant, which hence badly affect the production efficiency of the plant as well as the safety and reliability of the plant. Therefore, having an early fault diagnosis system in the plant is of paramount importance in order to avoid those consequences. In this project, the first objective aims to develop a potential early fault diagnosis model in real time basis by adopting ART. Typically, fault diagnosis methods can be categorized into three main types which are quantitative model-based methods, qualitative models and search strategies and process history based methods. The obvious differences between these three methods lie on their approach into the fault diagnosis. ART is chosen among available methods due to its predictive power, fast reaction ability, incremental and stable learning aptitude. In order to carry out the fault diagnosis, data is first filtered and isolated into healthy and fault data. Healthy Data was then further grouped into six classes including three normal and three intermediate categories. Once the normal patterns were identified by analyzing the process every five data points and constructed using the six classes, they was compared with every 5-data-point set of input pattern to find the potential existing mismatch patterns.

Apart from that, the second objective of this project concentrated on finding a more cost-saving maintenance plan for the gas turbine system instead of sticking to standard six-month maintenance routine. This can be achieved by predicting the future data trend of the system using ART2 NN, RNN and EKF in order to extend the washing interval and identify the maximum air filter replacement period of the gas turbine.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND NOMENCLATURES

ART	Adaptive Resonance Theorem
EKF	Extended Kalman Filter
NMSE	Normalized Mean Square Error
ANFIS	Artificial Neuro Fuzzy Interference System
NARX	Nonlinear Autoregressive

CHAPTER 1: INTRODUCTION

1.1 Background

In the contemporary industrialization era, fault diagnosis has played a significant role in reducing the potential system breakdown and disaster threatening in loss of human lives and plant assets [1]. According to Merriam-Webster Online Dictionary [2], faults are defined as the responsibility for a problem, mistake or a bad situation. More specifically, a system fault relates to the deviation of the actual output value to its expected value due to the malfunction of the hardware, software bugs, operator's error and the network problems [3]. There are three possible types of fault considered in this system which are hang faults, zero faults and drift faults. In the processing plant, the probability of occurring fault is considerable due to equipment failures and sensors or actuators breakdown while working [4]. Hence, monitoring the process performance in real time basis to diagnose the potential abnormal conditions (known as faults [5]) is of paramount importance in order to ensure the safety, efficiency and reliability of the process [6] [7] [8] [9] [10]. This paper aims to develop an online fault diagnosis system for LM2500 Gas Turbine system in Resak Development Platform with the employment of adaptive resonance theory (ART) based neural network (NN) technique.

1.1.1 Fault Diagnosis

Two components of fault diagnosis are fault detection and fault isolation. On one hand, fault detection refers to the characteristic of abnormal conditions recognition without the necessity of knowing the core reasons [11]. On the other hand, fault isolation is ability to differentiate different fault types and their causes [11]. Such an early diagnosis of faults could not only prevent the process from being shut down which badly affect the economic performance but also protect personnel from potential dangers [10] [12] [13]. However, fault diagnosis is a challenging issue for all the researchers and engineers to solve due to different types of fault may happen in the process [14]. Different types of fault diagnosis which have been studied and applied into the industry, are normally divided into three main models which are quantitative model-based methods, qualitative models and search strategies and process history based methods [13] [15] [16].

1.1.2 LM2500 Gas Turbine Package

Nowadays, extensive usage of gas turbines in oil and gas industries has been found. Gas turbines are often used in those harsh environments and remote locations such as jungles, offshore platforms or FPSOs. LM2500 Gas Turbine package, which was invented by General Electric Aviation on 1960s, was initially used for marine applications as well as aircrafts and warships. Recently the increasing demands for low weight, high power engines in the oil and gas industry has led to GE developing a dedicated version for offshore use which is lighter and more compact. LM2500 Gas Turbine Package is an important component which is used both for electricity generation and direct driving compressor in Resak Development Platform. LM2500 Gas turbine engine consists of sixteen stage axial flow compressor which forms sixteen stage compressor high pressure-driven rotor of moving blades [17]. Annular-type combustor contains thirty fuel nozzles and two spark igniters. Turbine internal engine (motor and rotor) is cooled down by a flow cooling air bled from the compressor outlet [10] [17].

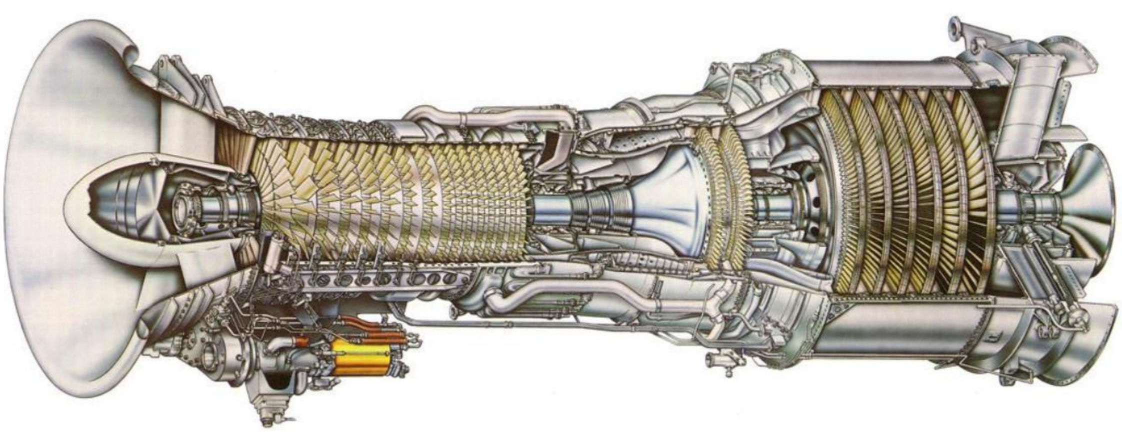


Figure 1: LM2500 Gas Turbine

Since LM2500 possesses a lot of components which increases the possibility of fault happening during process, General Electric has come out with GE Advanced Sensors and Monitoring & Diagnostics (M&D) with a system of various types of sensors installed to monitor the real time dynamic of all the components in the gas turbine. Designing an online fault diagnosis system by utilizing real time sensor readings is necessary and useful not only to prevent potential faults occur in specific but also to make full use of the complex RMD system to benefit for various other purposes.

Recognizing the potential to commercialize the idea, as a preliminary stage of the future end-product, this proposed model is simulated based on ART NN in order to quickly detect the potential faults, prevents the gas turbine from serious damages as well as considering some factors regarding maintenance issues due to user demands. In addition, by inventing a self-monitored and self-diagnosed model, this would be beneficial for user to be less independent to the manufacturer to reduce the actual maintenance cost.

1.2 Problem Statement

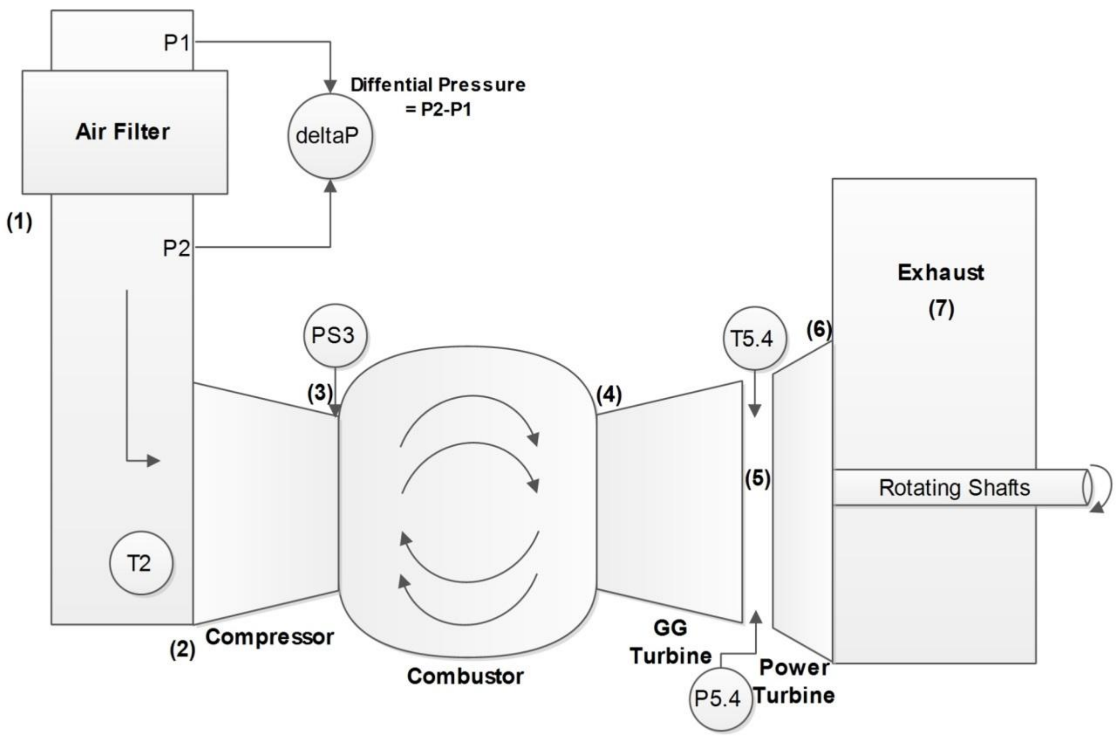


Figure 2: Simplified Diagram of LM2500 Gas Turbine

Throughout the project, it is expected to solve the following three (3) problems:

(1) Fault is likely to happen at any time or any places in the plant which leads to huge bad consequences.
(2) Air Filter is forced to replace every six months for safety purpose.
(3) Wash Interval is being set twice a year though it might be extended.

First and foremost, the first problem refers to the effects that a potential faults can cause to the system. Statistics shows beyond doubt that the economic performance of a system could be seriously jeopardized due to shutdown effect. Moreover, in the case of the plant explosion, safety of the working personnel as well as plant facilities and asset is extremely threatened. Hence, it is necessary for any plants to possess a fault diagnosis system in order to avoid faults' consequences. The LM2500 gas turbine system in Resak Development Platform is not an exception. Since there are many complex parts containing in the gas turbine, there is a high possibility that a fault might occur. Therefore, it is vital to have a real-time diagnostic system which can utilize the sensors readings from GE RMD system to detect and isolate the existence of potential faults.

Adding on the top of the first problem, last two problems (2 and 3) relate mostly to the economic issues. There is a fact that due to some certain safety levels, the manufacturer forces the user to obey strictly to some safety procedures. The LM2500 Gas Turbine is not an exception. For safety purposes, GE makes it compulsory for users to replace the air filter and wash the turbine every six months. Consequently, the user needs to allocate a fixed huge amount of money for this maintenance purposes though it is actually can be minimized by predicting the maximum acceptable period that an air filter can last as well as the maximum acceptable wash interval for the gas turbine in order to have a more economical maintenance plan while still ensuring the safety of the system.

The air filter replacement is related to the differential pressure (delta_P) between inlet and outlet of the air filtering system as illustrated from Figure 3. Replacing the air filter after every six months ensures the parameter delta_P will not go above the set limit to ensure the safety of the gas turbine. However, there is still an unknown period for the parameter delta_P to be kept in an acceptable safety limit which might increase the air filter replacement period to a longer time than its standard six months.

Similarly, the wash interval is dependent on the properties of some parameters such as Power Turbine Inlet Temperature (T5.4), Power Turbine Inlet Pressure (P5.4), Compressor Outlet Pressure (PS3) and Gas Turbine Compressor Efficiency (η). The routine bi-yearly washing procedure guarantees that those aforementioned parameters will not go beyond the safe operating limits. Nevertheless, it is possible to estimate the maximum interval between two consecutive washing times by estimate the maximum period that those parameters can drive before reaching the safe operating threshold.

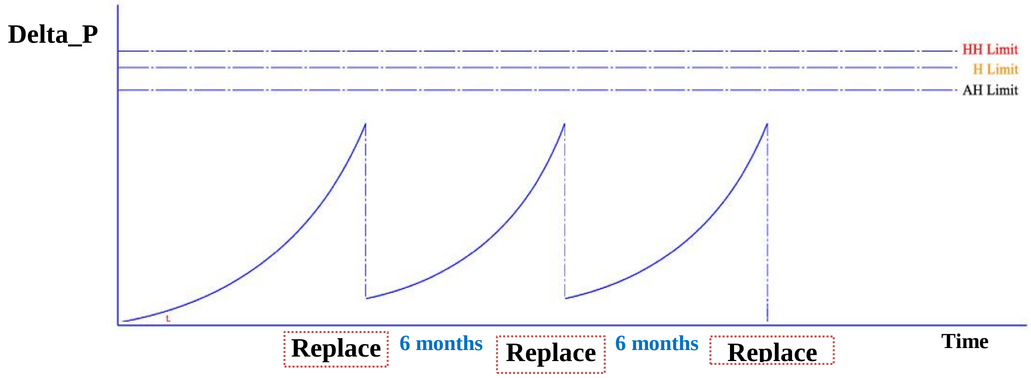


Figure 3: Changes of Delta_P due to air filter replacement.

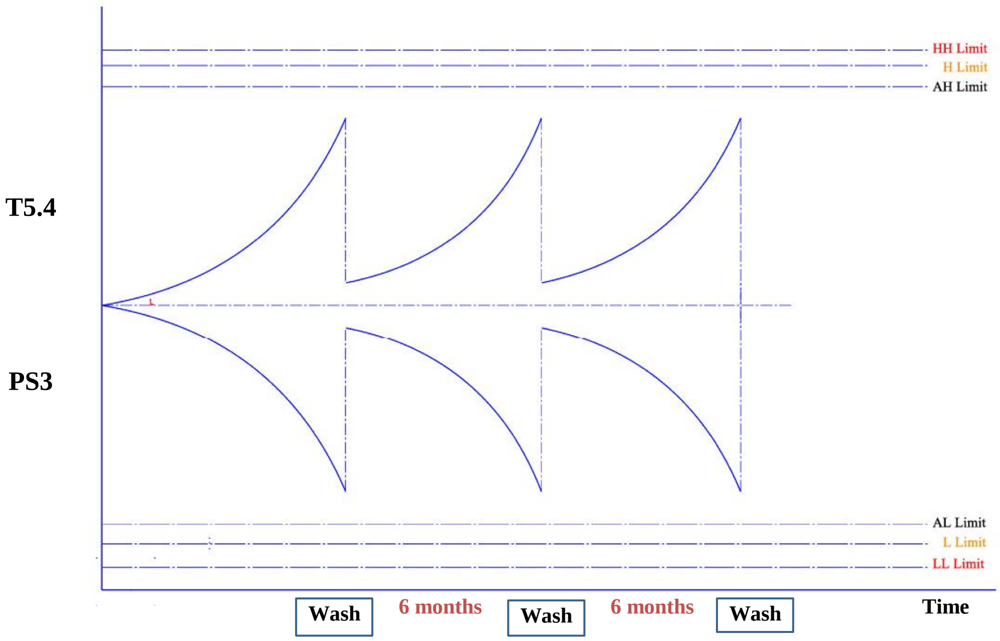


Figure 4 Changes of T5.4 and PS3 due to turbine washing process

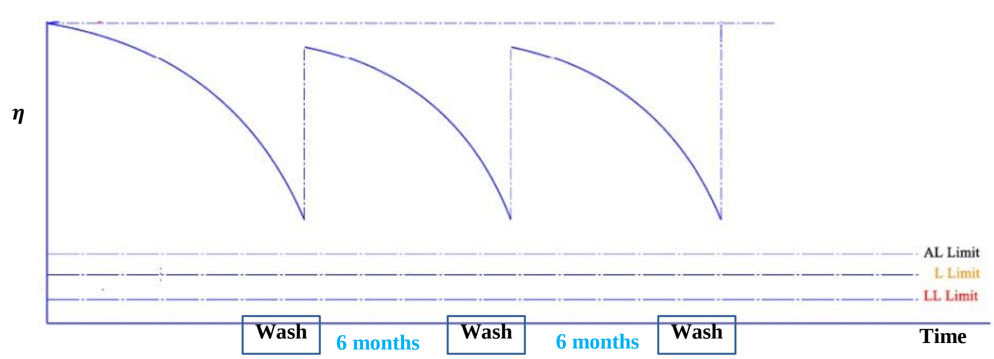


Figure 5: Changes of gas turbine efficiency ratio due to turbine washing process

The proposed online fault diagnosis model using ART NN is developed to find solutions for the above aforementioned three problems.

1.3 Objective

Throughout the project, the author hopes to achieve three key objectives as follows.

i. To develop an online based fault detection system for the gas turbine inlet system in Resak Development Project to avoid potential damage occurs.
ii. To determine the maximum wash interval based on gas turbine efficiency
iii. To determine the maximum period that a filter can last by monitoring the performance of Air inlet Differential Pressure

1.4 Scope of Study

The main focus of this project are to estimate the possible wash interval and air filter replacement period as well as developing the online fault diagnosis system using ART NN approaches. Based on a set of data recorded from the plant, the model is expected to be trained using ART NN in order to forecast the future trend of the data as well as the early existence of a potential fault.

The data obtained from the system was taken from the readings of several meters or sensors located in various parts of the gas turbine. In this project, six (6) sets of data from different parts of the main turbine are taken by the author to use as six (6) parameters for the model.

(1) Air Inlet Filter Differential Pressure (deltaP)
(2) Inlet Temperature (T2)
(3) Compressor Outlet Pressure (PS3)
(4) Power Turbine Inlet Temperature (T5.4)
(5) Power Turbine Inlet Pressure (P5.4)
(6) Compressor Discharge Temperature (T3)

Based on the above parameter readings data and the allowable operating range of each component, the system is trained to diagnose if there is abnormal behavior occur from these parameters which is the sign of the potential faults and also to predict the maximum wash interval and maximum air filter replacement period.

The expected deliverables of this project is a MATLAB model which carries three functions as below:

(1) Fault forecasting and cause identification.
(2) Maximum Wash Interval Estimations
(3) Gas turbine efficiency calculation and Maximum Air Filter Replacement period.

The prediction provided from this model is hoped to facilitate the respective personnel to have proper corresponding actions as well as bring up a solution for gas turbine's user to wisely spend the money for maintenance purpose.

CHAPTER 2 LITERATURE REVIEW AND THEORY

The objective of this chapter is to give readers an overview of fault diagnosis and provide the background of study in supporting the author to conduct the project. In this chapter, six (6) sections will be discussed. The first section which is overview of fault diagnosis summarizes several fault diagnosis techniques that have been researched by researchers and engineers worldwide recently. Next, another five (5) sections which are quantitative model-based methods, qualitative model-based methods, and process history based methods, methods comparison and ART development will be presented. The author will also explain the reasons why the author chooses to develop the project by using artificial neural network technique equipped with ART in sixth section.

2.1 Overview of fault diagnosis

One of the most critical and notable issue in industrial and automation system nowadays is the system reliability [10]. In fact, during working process, there is high probability that the system goes malfunctioned and system components might not operate well as the desired design. This could be due to the manufacturing defects or corrosion, late due maintenance, which may badly deteriorate the system performance, jeopardize the economic value due to potential plant shutdown and endanger lives of working personnel. Therefore, this issue has been taken into serious consideration by the industry in order to enhance the safety for both system and personnel by introducing several fault diagnosis techniques. The fault diagnosis methods were investigated in many researches and will be summarized in the following literature.

According to Stanley [11], there are various means of quantitative and qualitative methods, varying from simple technique such as alarm based on high and low, rate of changes, SPC (Statistical Process Control) to multivariable model-based approaches that can be used for fault detection. In addition, based on a three-part review research conducted by Venkat et al, fault diagnosis methods can be categorized into three main categories which are quantitative model-based, qualitative models and search strategies and process history based methods. Branches of each category will be demonstrated in the hierarchical chart shown in Figure 6.

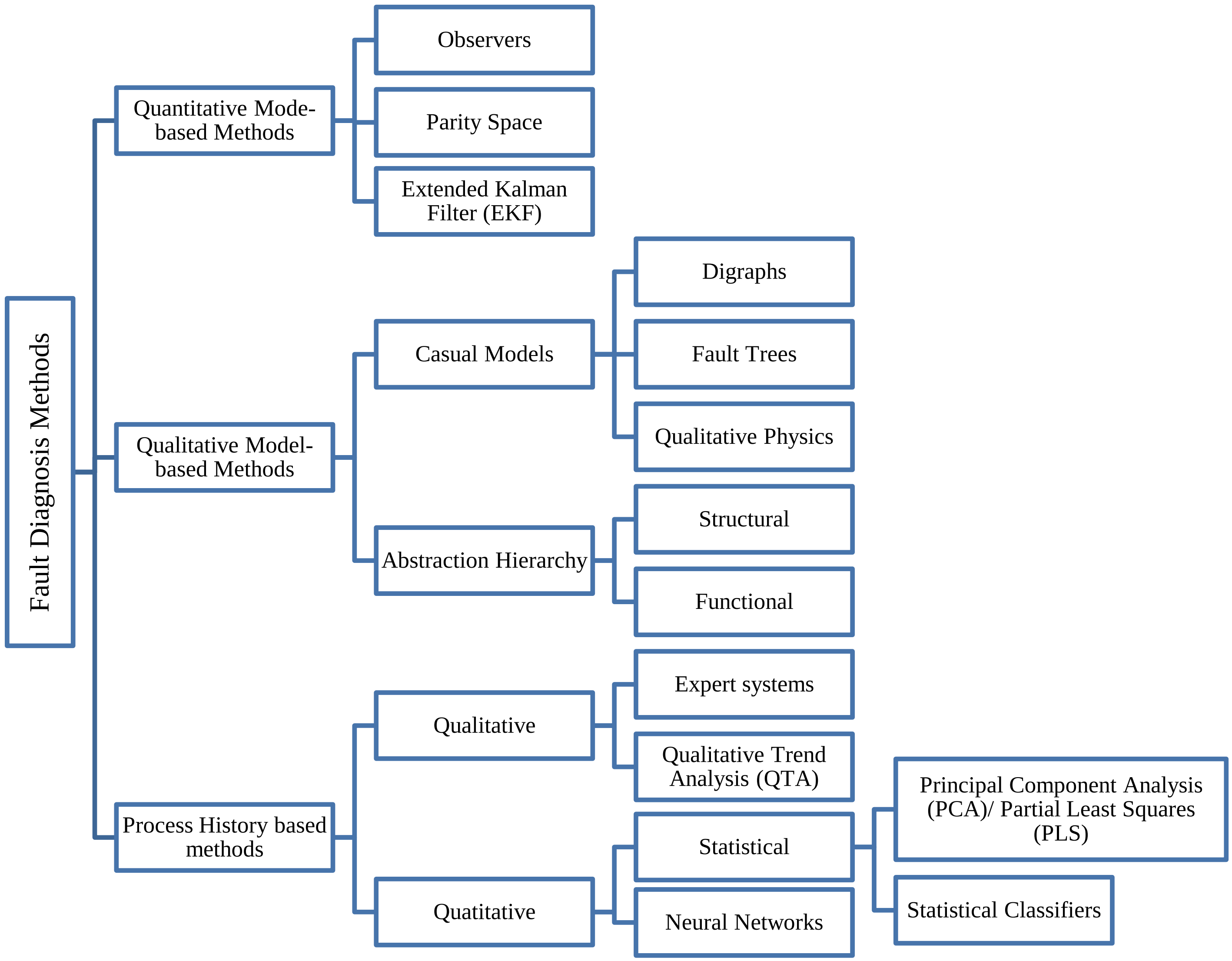


Figure 6: Hierarchical Chart of fault diagnosis methods. **[13]**

2.2 Quantitative model-based methods

Together with qualitative model-base methods, quantitative model-based methods are model-based fault detection techniques that have been used widely in the industry. Like most of the model-based fault detection methods, it consists of two steps which are the formation of residual (which is the system reflection of potential fault) of actual signal to the expected one and the fault presence detection process based on a set of decision rules. One of the most important concepts that quantitative model-based methods carry is the analytical redundancy [13].

Analytical redundancy refers to the functional dependency of the variables involved in the process and is usually express in term of multiple mathematical equations of the states, inputs and outputs. There are three most commonly used quantitative model-based methods. The first one is diagnostic observer method which is used for generating the residuals in order to identify several potential faults in the process. Its behavior and residual indication during normal and abnormal is summarized as the following Table 1 [12].

Table 1: Observer Behavior during normal and abnormal conditions

Conditions	Observer Behaviors
Abnormal conditions (fault occurs)	- Fault-insensitive observers develop small residuals which only reflect the unidentified inputs. - Fault-sensitive observers produce significant deviation resulting in large magnitude of residuals.
Normal condition (fault-free case)	- The process is followed strictly by observers and obtained residual from unknown inputs can be neglected.

Another method is the parity relation, which relates to the input-output relations or state-space model rearrangement in order to achieve the best fault isolation. In fact, the value of parity equation is zero during ideal steady state condition while s a non-zero value is obtained during the process which contains noises and errors from sensors and actuators (or so called faults) [13]. In addition, Extended Kalman filters, which is designed based on normal operating condition of the system to obtain the optimal state estimate. During the process, several disturbances in the plant reduce the accuracy of parameters which require the use of EKF to create a state estimator which produces the smallest estimation error. Its benefit into the proposed one step prediction model will be discussed later.

2.3 Qualitative model-based methods

In contrast to quantitative model-based methods which present the input-output relationships based on sets of mathematical equations, qualitative model-based methods use qualitative functions instead. Two main methods can be used as qualitative model-based which are qualitative casual models and abstraction hierarchies.

Qualitative casual model can be developed either by Digraph based causal models, fault trees models or qualitative physics models. Nowadays, cause-effect relationships can be expressed using the signed digraphs (or SDG). SDG is a graph which contains several directed arcs connecting nodes with attaching with positive or negative signs [15]. SDG has been proved as a very effective way to represent the qualitative models in the form of graphic and also used commonly as a fault diagnosis method. The second notable model is the fault tree model, which is developed based on digraphs model [18] with additional interesting feature of combining logics.

However, the fault trees models is highly prone to mistakes in various stages which cannot serves as an effective method for fault detection [15]. The last qualitative casual model used for fault diagnosis is the qualitative physics which can be approached by the derivation of qualitative equations from either confluence equations or ordinary equations (ODEs).

In addition, another considerable method of qualitative model-based methods is the abstraction hierarchies based on the decomposition. There are two most widely-used decompositions which are the structural models (which refer to the connection between units) and the functional models (which present the relationships between the system and the subsystems).

The idea of abstraction hierarchies approaches is that based on the hierarchical relationship between system and subsystem, the system can swiftly detect the failure if there are failures or malfunctions occurring in its subsystems. One of the most advantages of this method is its effectiveness in diagnosing large-scale fault and its easy integration to other techniques to locate the problems [15].

2.4 Process History-based methods

Unlike the model-based methods at which a quantitative or qualitative priori knowledge is needed, it is required a huge set of historical data in process history-based methods [16]. The data can be extracted, transformed and used as priori knowledge into the fault diagnosis system either by qualitative or quantitative approaches. There are two main methods used for the historical data extraction in the qualitative nature which are expert systems and quality trend analysis (QTA) methods. Brief description, advantages and disadvantages of these two methods is illustrated in the following Table 2.

Table 2 Qualitative feature extraction approaches

<table>
<tr><td colspan="2"></td><td>Expert systems</td><td>QTA</td></tr>
<tr><td rowspan="2">Description [16]</td><td>Basic components</td><td>- Knowledge acquisition
- Knowledge representation decision
- Knowledge coding
- Diagnostic reasoning inference procedure development
- Input-output interface</td><td>- Filtering
- Priori behavior</td></tr>
<tr><td>Objective</td><td>- Compose the standard solution to retrieve the process.
- Consider faults root as operator fault, equipment malfunction and disturbances.</td><td>- Events explanation
- Malfunction diagnosis
- Future prediction</td></tr>
<tr><td colspan="2">Advantages [16]</td><td>- Easy to develop
- Transparent reasoning</td><td>- Efficient data compression</td></tr>
<tr><td colspan="2">Disadvantages</td><td>- System-specific [19]
- Limited representation ability [19]</td><td>- Uneasy to implement</td></tr>
</table>

In addition, a qualitative feature extraction which considers the fault, occurring problem as the problem of recognizing the pattern can be divided into two main approaches which are statistical feature extraction from process data and artificial neural network based method. Statistical approach which relies on prior knowledge can be developed either by PCA/ PLS method or statistical classifier. PCA and PLS aims to portray the main trend by searching for factors that bring much lower dimension than the original set of data. PCA and PLS have been proved effective in the process industry throughout a lot successful researches worldwide. The methods are able to handle large numbers of process [20] [21] and nonlinearity in batch processes [22] [23] by integrating with some other methods such as neural networks, batch tracking and multi block PLS. Furthermore, Bayes classifier can be efficiently used for classical statistical pattern recognition framework.

Besides statistical feature extraction method, artificial neural networks have extensively used in the fault diagnosis system nowadays. Artificial neural network (ANN) is an interesting concept in order to imitate the brain functions into practical used system. An ANN which possesses the ability of supervised and unsupervised learning is organized in three separate layers as illustrated below. Each layer is constructed by multiple sets of interconnected nodes and between layers, there are various weighted connections.

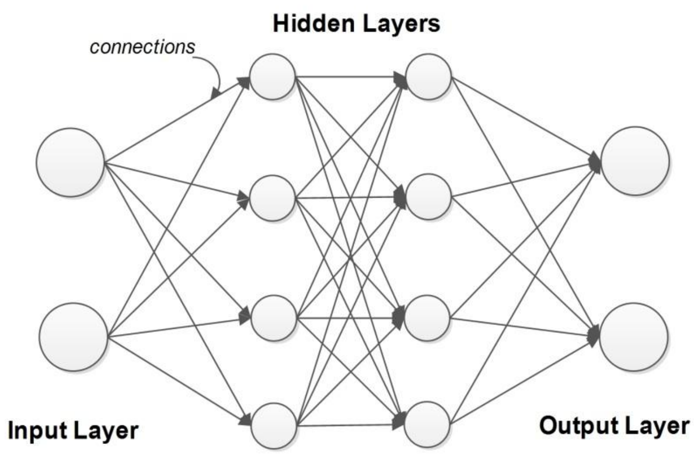


Figure 7: An illustrative example of ANN with its layers

There are several methods in order to improve the performance of ANN in fault diagnosis. The most conventional method used for ANN is the back propagation neural network (BPNN). The concept of BPNN is that through the process of forward of output signal and backward error propagation of weight adjustments and signal is forwarded, the supervised learning process is conducted.

By conducting BPNN, the differences between actual and expected results are expected to be minimized. Besides BPNN, ANN architecture equipped with ART has been widely researched. This particular topic will be discussed more details in section 2.6

2.5 Comparison of methods

Selection of methods used for fault diagnosis system is not a simple issue. An algorithm could solve one particular fault radically may not able to perform well in another fault situations [14]. A closed-up evaluation of pros and cons of each of three approaches will be conducted to help us have an objective view of each method.

Table 3 Overview of pros and cons of three fault diagnosis approaches

Approach	Advantages	Disadvantages	References
Quantitative model based	- Able to isolate faults. - Able to detect multiple faults	- Limited only in handling linear models - Involved in complicated mathematical quantitative model	[13] [16] [24]
Qualitative model based	- Able to determine fault paths. - Fast detection of fault areas	- Limited only in handling linear models - Condition-dependent	[15] [16]
Process history model based	- Robust - Involved in small amount of prior knowledge - User-friendly implementation ability since small portion of modeling is needed. - Able to detect noises quickly - Able to isolate faults	- Limited for quantitative model development. - Generation incapability outside training area - Unable to detect multiple faults - Limited distribution sampling of the class data - Unable to explain to root cause and adapt to different situations	[16]

Although, it can be obvious to acknowledge that process based method could be the most suited method to be applied in the industry due to its easy-to-implement ability and simple modeling and less prior knowledge required; however, selections of a method to apply for a specific system is very subjective and it is difficult for a single comprehensive method to solve complete the designing problem for the system. A set of ten most desirable characteristics that a fault diagnosis system should possess has been considered [13]. The following table 4 gives a brief description of each of ten desirable characteristics in the order regardless degree of their priorities.

Based on those standard requirements, it is possible to compare the advantages and disadvantages of each approach in order to select the most suitable method to apply for author's target model. Table 5 presents a comparison table of representative fault diagnosis methods from each of the three approaches based on the desirable characteristics criteria of a good diagnostic system as listed in table 4. Representative methods selected for the comparison are observer from quantitative model based methods; digraph and abstraction hierarchy from qualitative model based methods; expert systems, QTA, PCA and neural networks from Process history based methods. The symbols "check mark", "cross mark" and "star symbol" means satisfied, not satisfied and case-dependent satisfied accordingly. The first column numbering is based on the number order of characteristics shown in Table 4.

From the author's point of view, taking into consideration of designing an online fault diagnosis system, there are few important factors that require the target system to possess. They are quick detection and diagnosis; robustness; fault isolation ability; storage and computation; novelty identification ability and modeling requirement. Based on the analysis in Table 5, there are three options of method which are QTA, PCA and ANN. Although QTA is robust to different noises and more efficient into diagnosis compared to other two methods, its time consuming in customization and implementation make QTA might not suitable for the author's desired system. PCA, on the other hand is a time-invariant model, which might not be able to use in most time variant real processes. Unlikely, ANN contains an acceptable level of robustness and fast diagnosis and isolation ability, could be a considerable choice. Moreover, ANN with the employment of Adaptive Resonance Theory is promising to produce a real time system which can detect and isolate fault swiftly and adaptable to the changing situations due to its unsupervised learning ability.

Table 4 Desirable characteristics of a fault diagnosis system

No	Characteristics	Description
1	Quick detection diagnosis	The diagnostic system is required to be able to swiftly detect and diagnose the process faults.
2	Isolation Ability	The system should be able to differentiate several types of fault.
3	Robustness	Several abnormalities could happen require a good fault diagnosis system to be robust in order to ensure its performance drops gradually instead of falling sharply.
4	Novelty identification ability	The system is expected to detect if running process is normal or else determine the identification of abnormality cause.
5	Classification error estimate	One of a system's significant characteristics is the ability to ensure user about system reliability. This factor can be done by providing an early estimate on the classification error that might occur.
6	Adaptability	The diagnostic system should be change-adaptable.
7	Explanation facility	The diagnostic system should not only identify the abnormality causes but also provide the explanation on how these faults be formed and affected the current situation.
8	Modeling requirements	The diagnostic system should be easily modeled.
9	Storage and computational requirements	The diagnostic system is expected to balance out between less-complex algorithms and implementation possession and high storage required factor.
10	Multiple fault identification ability	The diagnostic system should be able to identify multiple faults.

Table 5: Comparison Table of different diagnosis methods **[16]**

	Observer	Digraph	Abstraction Hierarchy	Expert systems	QTA	PCA	ANN
1	☑	(*)	(*)	☑	☑	☑	☑
2	☑	☒	☒	☑	☑	☑	☑
3	☑	☑	☑	☑	☑	☑	☑
4	(*)	☑	☑	☒	(*)	☑	☑
5	☒	☒	☒	☒	☒	☒	☒
6	☒	☑	☑	☒	(*)	☒	☒
7	☒	☑	☑	☑	☑	☒	☒
8	(*)	☑	☑	☑	☑	☑	☑
9	☑	(*)	(*)	☑	☑	☑	☑
10	☑	☑	☑	☒	☒	☒	☒

2.6 ART Development

According to one the master in neural network field Stephen Grossberg, ART simulates several brain functions such as categorization, recognition and predictions based on a set of cognitive and neural theories [25]. The name of adaptive resonance comes from ART's ability to bring solution for the stability-plasticity dilemma by clearly explaining how a top-down attentive matching works. Particularly, a synchronous resonance state when there is an occurrence of good match, appear to exemplify an intentional focus and trigger its capability of driving fast learning of bottom-up recognition categories. In our changing world, ART has posed a significant impact to the industry due to its predictive power, fast reaction ability, incremental and stable supervised and unsupervised learning aptitude.

Since the first date ART be brought into the world up to now, ART has been developed itself throughout various forms [25]. The following Table 6 summarizes the some ART algorithms in recent researches.

Taking into consideration of designing an online fault diagnosis system, ART 2, which is a self-organizing, capable of dynamic, online learning network, shows itself the best suited solution for the system. Compared to several other ART algorithms such as BPNN, fuzzy NN, ART 2 produces effective solution for the stability-plasticity dilemma **[26]**. Moreover, compared to ART 1 NN, ART 2 NN is able to perform online supervised and unsupervised learning for set of not only binary but also analog input patterns while firmly keeping the old memory **[27] [28]**.

Moreover, Xu, Q., Meng, X., & Wang, N. **[28]** highlighted that the memory capacity of an ART 2 NN can proportional increase with the learning patterns. In addition, besides allowing an off-line learning process, ART 2 can be used in online learning and applying way concurrently due to the fact that these two processes are completely inseparable.

Table 6 Revolution of ART into engineering and technology world

Algorithms	Brief description	References
Default ARTMAP	Standard ART algorithm	[29] [30] [31]
ART 1	Only deal with arbitrary sequences of binary input patterns	[31]
ART 2	Upgraded version of ART 1 with ability of processing arbitrary sequences of not only binary input patterns but also analog input patterns.	[31] [32]
Fuzzy ARTMAP	Combination of ARTMAP with integration of fuzzy logic algorithm in order to produce more efficient algorithm.	[31] [33]
Distributed ARTMAP	Combination of distributed coding with fast, stable and incremental learning.	[34] [35]
ARTMAP Information Fusion	Ability to incrementally learn cognitive hierarchy of rules in conjunction with probabilistic, unfinished data	[36] [37]

CHAPTER 3 METHODOLOGY

The third chapter of the report aims to present how the project will be conducted. The author purposely divides the chapter into three sections which are development of modeling simulation, project process flow chart and Project Gantt chart. The first section's objective is to describe how the model will be constructed by using ART NN and simulation process. This section consists of four sub-parts which are data filtering, ART 2, the online Fault Diagnosis Model and the One Step Ahead Prediction Model. The third section explains how the project process will go methodically in the form of flow chart. The last section introduces the time frame allocated for each specific research activity throughout the academic semester in order to ensure the project is under control in timely manner.

3.1 Development of the model simulation

The proposed model development was conducted methodically through several stages as per the following figure 8.

3.1.1 Data filtering

The inputs to the proposed system which are sensor readings from components of the gas turbine first filtered in order to detect if data is healthy or abnormal. Three types of faults will be considered in this project which are hang faults, zero faults and drift faults.

Firstly, hang faults refer to situation when the reading is kept constant in consecutive time checkpoints. In this project, repetition of at least 60 same readings consecutively (readings are taken every minute) is considered hang fault. Second of all, zero faults are faults mostly caused by the malfunction of the transmitter. Consequently, zero readings are recorded over consecutive checkpoints. Lastly, drift faults relate to the situation when recorded readings show kind of deviation from the actual expected result. This abnormality could continue over consecutive checkpoints with possibility of higher deviation occur. A graphical illustration of these types of fault is presented as below Table 7. Sensor Readings of each parameter is also filtered based on its corresponding operating range set by the user for this particular instrumentation. Data which falls beyond the operating range will be considered as outliers [12]. The operating range for each of parameter is displayed in Table 8.

The data is first filtered to isolate hang faults, zero faults and outliers. The remaining no-fault data is treated as healthy data will be inputted into the process system.

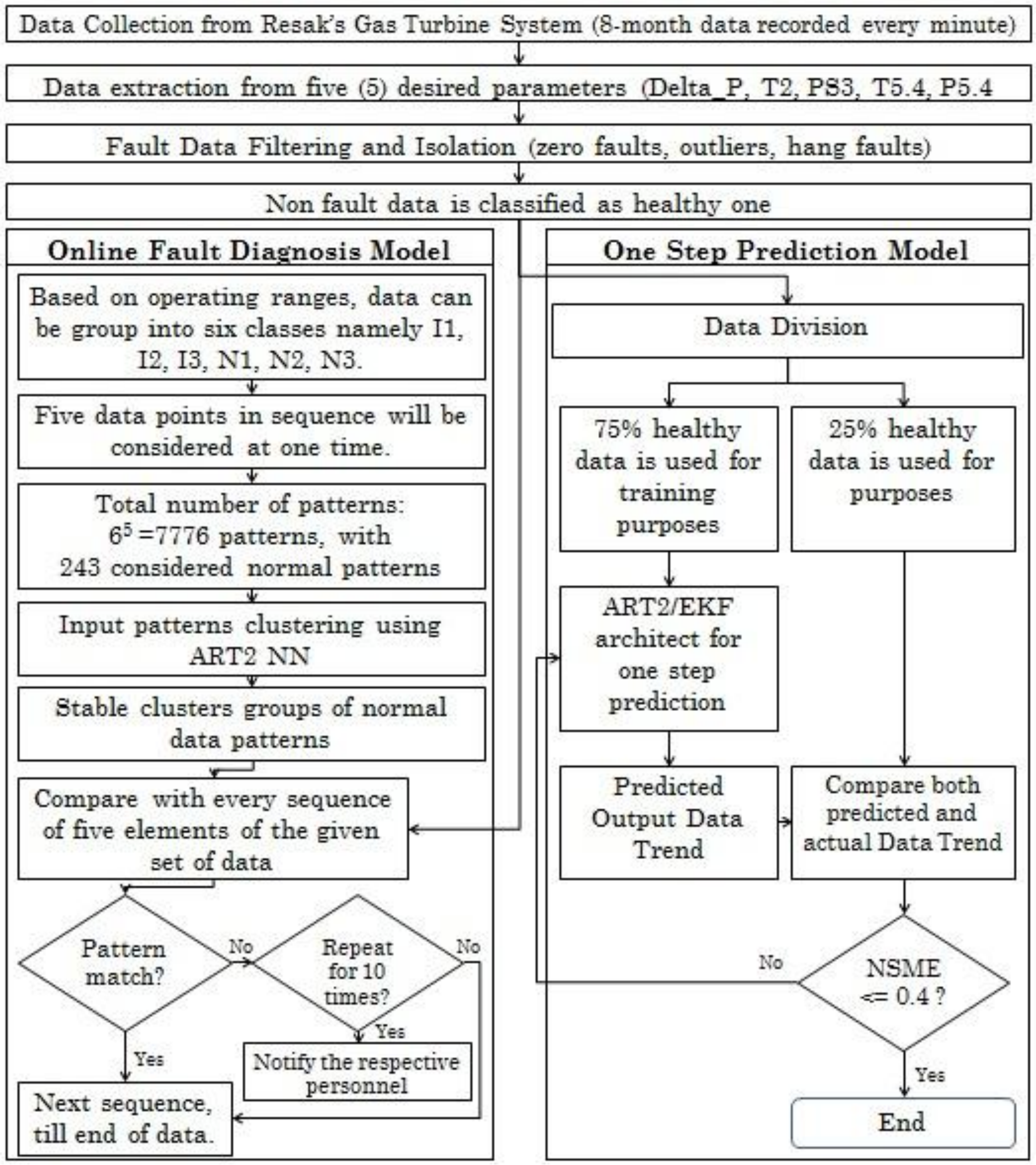


Figure 8 Block Diagram of the proposed model

Table 7: Three potential types of faults in plant process

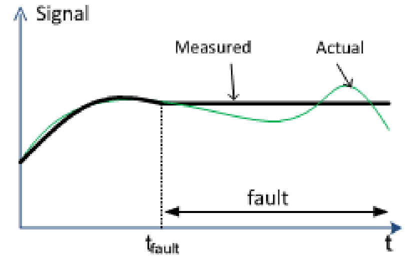
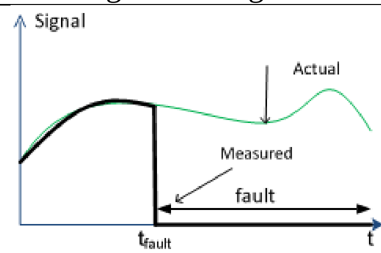
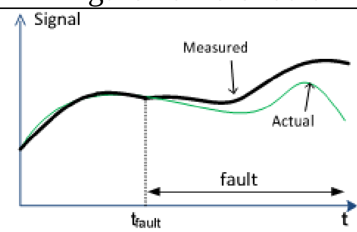
Fault Type	Fault Trend
Hang Fault	 Figure 9 Hang fault
Zero Fault	 Figure 10 Zero fault
Drift Fault	 Figure 11 Drift fault

Table 8: Operating Range

Parameter	**Tag No.**	**Unit**	**Low Limit**	**High Limit**
Air Inlet Filter Differential Pressure (delta_P)	PDT1253	mBar	0	AH = 7; H = 10; HH = 15
Inlet Temperature (T2)	TT1000	DegC	0	90
Compressor Outlet Pressure (PS3)	PT1004	Bar	AL = 10; L = 9.5; LL = 9	40
Power Turbine Inlet Temperature (T5.4)	TE1007	DegC	0	AH = 810; H= 838; HH= 857
Power Turbine Inlet Pressure (P5.4)	PT1035	Bar	AL = 2; L=1.7; LL = 1.2	8
Gas Turbine Compressor Efficiency		%	AL=75,L=70;LL = 75	95

3.1.2 ART 2 Algorithm

ART 2 NN architecture consists of two main subsystems which are attentional subsystem and orienting subsystem. The Figure 12 shows a typical architecture of an ART 2 NN.

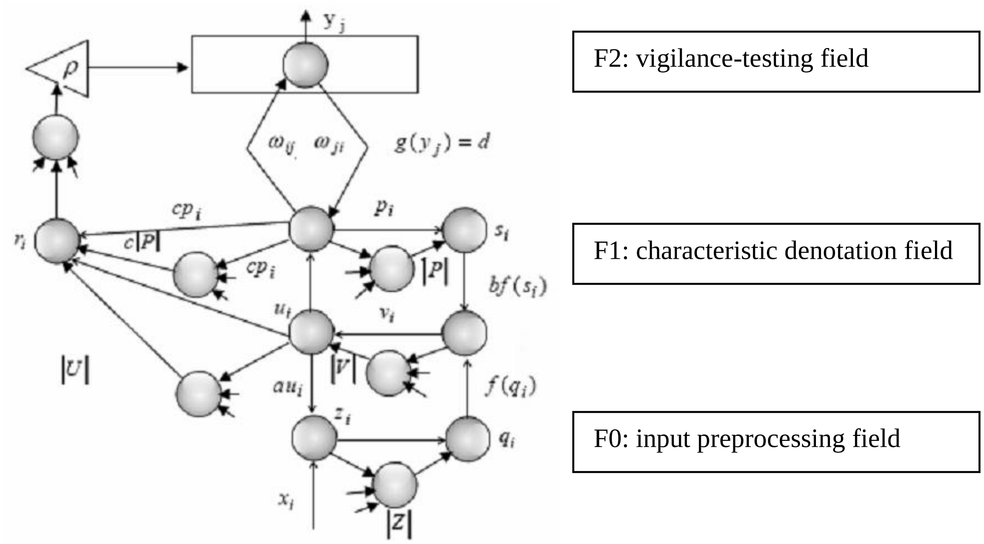


Figure 12: ART 2 NN Architecture

The basic concept of ART is based on the functions of its two subsystems. The attentional subsystem's responsibility is to select the best matching pattern upon a set of competitive rules from all the pattern prototypes. The pattern is obtained after preprocessing of the analog or binary input data. Unlikely, orienting subsystem's task is to conduct among all the selected patterns the similarity vigilance-testing. As if the result is passed, this subsystem will trigger resonance learning, and then adjust the weight vectors accordingly. However, in case the result is failed, the current node will be abandoned and another pattern will be searched. After all these, if no pattern matches the input pattern, a new output mode will be created to represent the input pattern.

The most significant session in any NN is the learning of NN since the learning involves in the calculations of weight vectors and the clustering of variety of patterns which describe the fault effects. Unlike other ANN methods, ART 2 learning mode is unsupervised. The unsupervised learning mostly refers to the recognition and cluster storage of patterns [38]. The core principle of ART 2's unsupervised learning mode is the competitive learning mechanism [28].

It can be seen from Figure 11 that there are two interconnected field/ layers F1 and F2 in ART2 architecture. While F1 layer is used as characteristic representation layer, F2 is so called the category representation layer.

Dimension of input vector decides the number of nodes in the F1 layer while a node in F2 layer represents a category given by its bottom-up and top-down weight, which are the Long Term Memory (LTM) of the neural network. In the case of new categories occur or arrive, nodes in F2 will vigorously be created and the coarseness of the categories is given by a vigilance parameter [39].

Numbers of operations on the input pattern are performed in F1 layer such as normalization and feature extraction. The pattern code is transmitted from F1 layer to the F2 layer through the bottom-up weights. The winner is declared as the node in F2 who has the bottom-up weights that best match with the F1 pattern and its top-down weights are then transmitted back to the F1 layer. Once the stabilization of the resonance between F1 and F2 has reached, the reset assembly compares the F1 pattern code and the input vector.

The winning F2 node is inhibited if the resemblance between the F1 pattern code and the input vector is too low and a new node in F2 representing the new category will be created. The winning node in F2 possesses the largest inner product of its weights and F1 pattern code and the adaption of weights which develops based on set of differential equations will only be performed with the winning node.

Lastly, the reset functions are done by using a clever angle measure between the input vector and the F1 pattern code [39].

The ART2 algorithm used in this project is presented more details step by step as below Table 9 [28] [39].

Table 9 Equations demonstrate ART 2 algorithm

Step	Function	Action and Effect
1	Initial Configuration	a = 10, is a constant parameter to improve the contrast. b = 10, is a constant coefficient of F1 upper layer output's normalization c = 0.1, is a constant coefficient of F1 upper layer output d = 0.9, is the feedback parameter from F2 to F1 e = 0, is the Q-layer parameter. Noise inhibition threshold: $0 \leq \theta \leq 1$ Surveillance Parameter: $0 \leq \rho \leq 1$ F1 layer's Error tolerance parameter (ETP): $0 \leq ETP \leq 1$ Top-down weight: $\omega_{ij}(0) = 0$ Top-down weight: $\omega_{ji}(0) \leq \frac{1}{(1-d)\sqrt{M}}$ Set sub-layer and payers outputs to zero value Set cycle counter to 1
2	An Input vector is applied into the sub-layer Z of the F1 layer.	Output of this layer z_i : $z_i = x_i + a.u_i$ (1)
3	Q sub-layer propagation (q_i) (normalization of z_i)	$q_i = \frac{z_i}{e+\lVert z \rVert}$ (2)
3	Middle layer (V) F1, v_i output calculation , s_i is the normalization of p_i (see (8))	$v_i = f(q_i) + bf(s_i)$ (3) Note that: in the first cycle, the value of s_i is zero. After that, small signal filter nonlinear function f(x) can be calculated using: $f(x) = \begin{cases} \frac{2\theta x^2}{(x^2+\theta^2)}, & 0 \leq x \leq \theta \\ x, & x > \theta \end{cases}$ (4)
4	Output signal from middle layer U of F1 calculation, u_i.	$u_i = \frac{v_i}{e+\lVert v \rVert}$ (5)
5	Upper layer P of F1 output propagation, p_i Assume L is the neuron number of max output of F2, L node of F2 is the winner node	$p_i = u_i + d\omega_{iL}$ (6) In case that network is in the first cycle (in initial configuration) or in case that F2 is inactive: $p_i = u_i$ (7)
6	S sub-layer propagation (s_i)	$s_i = \frac{p_i}{e+\lVert p \rVert}$ (8)
7	Error calculation and ETP comparison	$Error(i) = u_i - u*_i$ (9)
8	Repeat step 2 to 7 until F1 values stabilized	F1 layer is Stabilized if: $Error(i) \leq ETP$ (10)
9	Matching degree of STM and LTM is determined by R sub-layer output calculation.	$r_i = \frac{u_i+cp_i}{\lVert u \rVert + c\lVert p \rVert}$ (11)
10	Check for reset condition indication. If condition (12) is satisfied, *- Send a reset signal to F2* *- Mark any active F2 node as not enable for competition* *- Reduce cycle counter to zero, return to step (2)* If condition (12) is not obtained (no reset signal) and the *cycle counter is one,* *- Increase the cycle counter.* *- Proceed to step 11*	$\rho > (e + R), in\ which\ R = \lVert r \rVert$ (12)

	If condition (12) is not obtained (no reset signal) and the *cycle counter is greater than one,* *- Proceed to step 14, make sure resonance was established.*	
11	F2 layer input calculation	$t_j = \sum \omega_{ji} p_i$ (13)
12	Only the F2 winner node has non-zero output. Any node marked as non-capable by a previous reset signal doesn't participate in the competition	$g(t_j) = \begin{cases} d, t_j = \max(t_L) \\ 0, otherwise \end{cases}$ (14)
13	Repeat step 6 to 10	
14	Update the top-down and bottom-up weights of F2 layer winner node.	This can be updated quick learning equation: $\omega_{iL} = \frac{u_i}{1-d} = \omega_{Li}$ (15)
15	Input vector is removed and inactive F2 is restored.	
16	Input new input vector and return to step 1	

3.1.3 Online Fault Diagnosis Model

In order to solve the issue of likely happening faults during running process which can cause tremendous consequences, an online based fault diagnosis model in the gas turbine system is vital to be developed to avoid potential damage occurs.

The proposed online fault diagnosis model is constructed and can be seen in previous Figure 8.

Six engine parameters (input elements) from the main turbine which are Air Inlet Filter Differential Pressure (delta_P), Inlet Temperature (T2), Compressor Outlet Pressure (PS3), Power Turbine Inlet Temperature (T5.4), Power Turbine Inlet Pressure (P5.4) and Compressor Discharge Temperature (T3) will be used for the simulation. The first five (5) parameters can be obtained directly from the sensor readings while the Compressor Discharge Temperature (T3), which plays a major impact on HPC efficiency calculation, needs to be assumed due to the plant unavailability. Due to the fact that cannot be obtained directly from the sensor readings and upon this point of time, the sensor for T3 was not yet installed and commissioned, the value of T3 can be only estimated by using the ideal gas law. The definition of an ideal gas is the type of gas which has perfectly elastic collisions between atoms and molecules and none of the intermolecular attractive forces are existed. In this case, the gas inside the gas turbine is assumed as an ideal gas in order to simplify the calculation process.

Typically, three state variables are used to characterize an ideal gas, including absolute pressure (P), volume (V) and absolute temperature (T). The relationship between these variables might be deduced from kinetic theory and the characteristic equation for the ideal gas law is presented as follow.

$$PV = nRT \tag{16}$$

In which: - n = number of moles

- R = universal gas constant = 8.3145 J/mol.K

Assuming that the number of moles of the gas remains unchanged after going through the combustor and all the kinetic reaction happens inside the combustor (volume remains constant), hence it can be obtained that the ratio of pressure over temperature is kept the same from compressor discharge/outlet to Gas Generator (GG) inlet. The GG Inlet total pressure is notated as P2 and its value can be obtained from sensor readings directly.

$$\frac{nR}{V} = constant \Rightarrow \frac{P}{T} constant \Rightarrow \frac{PS3}{T3} = \frac{P2}{T2} \Rightarrow \frac{PS3}{P2} = \frac{T3}{T2} \tag{17}$$

Based on the operating ranges of each parameter, the author further categorizes and groups the data into six classes namely Intermediate 1 (I1), Intermediate 2 (I2), Intermediate 3 (I3), Normal 1 (N1), Normal 2 (N2) and Normal 3 (N3). Each parameter's classes will be presented in each of the follow tables 10-14.

Table 10: Parameter Limits for Delta_P

Parameter Class	Lower Limit (mBar)	Upper Limit (mBar)
Intermediate 1 (I1)	10	15
Intermediate 2 (I2)	7	10
Normal 1 (N1)	3	7
Normal 2 (N2)	1	3
Normal 3 (N3)	0.2	1
Intermediate 3 (I3)	0	0.2

Table 11: Parameter Limits for T2

Parameter Class	Lower Limit (DegC)	Upper Limit (DegC)
Intermediate 1 (I1)	75	90
Intermediate 2 (I2)	65	75
Normal 1 (N1)	50	65
Normal 2 (N2)	35	50
Normal 3 (N3)	20	35
Intermediate 3 (I3)	0	20

Table 12: Parameter Limits for PS3

Parameter Class	Lower Limit (Bar)	Upper Limit (Bar)
Intermediate 1 (I1)	35	40
Normal 1 (N1)	20	35
Normal 2 (N2)	10	20
Normal 3 (N3)	1	10
Intermediate 2 (I2)	0.5	1
Intermediate 3 (I3)	0	0.5

Table 13: Parameter Limit for T5.4

Parameter Class	Lower Limit (DegC)	Upper Limit (DegC)
Intermediate 1 (I1)	838	857
Intermediate 2 (I2)	810	838
Normal 1 (N1)	400	810
Normal 2 (N2)	150	400
Normal 3 (N3)	30	150
Intermediate 3 (I3)	0	30

Table 14: Parameter Limit for P5.4

Parameter Class	Lower Limit (Bar)	Upper Limit (Bar)
Intermediate 1 (I1)	5.5	8
Normal 1 (N1)	4	5.5
Normal 2 (N2)	2.5	4
Normal 3 (N3)	1	2.5
Intermediate 2 (I2)	0.5	1
Intermediate 3 (I3)	0	0.5

In this project, the assessment is conducted with every sequence of consecutive five data points at one time. The combination between six classes and five data points will produce a total number of $6^5 = 7776$ data patterns. Among six classes, there are three normal classes (N1, N2, N3), which produced 243 combinations of normal data patterns.

These normal patterns will be then treated as input vectors into ART2 NN Architecture in order to produce stable clusters groups of normal data pattern. The clusters are identified based on the similarities in patterns of all 243 normal patterns.

The output healthy data from the data filtering process is then compared with normal stable clusters in order to verify if the data contain potential faults. The comparison is conducted based on a similarity check of every sequence of five data points consecutively until the end of data. This similarity test is conducted by calculating Normalized Mean Square Error (NMSE) as following equation:

$$NMSE = \frac{1}{\sigma^2 p} \sum_{n=1}^{p} [y(n) - \hat{y}(n)]^2 \qquad (18)$$

In which: - $y(n)$: expected normal pattern value

- $\hat{y}(n)$: real input pattern value

- σ^2 : real sequence variance on the prediction interval

- p: number of testing data (here equals to 5)

The input pattern is considered matched with the normal cluster pattern when Normalized Mean Square Error, NMSE <= 0.1. In case a match is occur, the comparison will move on with the next sequence until the end of data.

This input pattern is considered unmatched with the normal cluster pattern when Normalized Mean Square Error, NMSE > 0.1. In this case, the unmatching counter which intially is zero, will be increased to 1 and the comparison will move on with the sequence. If the next sequence matches with the normal cluster pattern, the unmatching counter will be reset to zero, otherwise will be increased one unit. In the case that the unmatching counter is equal to 10, the possibility of having a fault is high and a notification will be sent to respective personnel to have proper corresponding actions to avoid fault incidents.

By monitoring each parameter in parallel, this preliminary diagnosis will also facilitate the fault tracing process for the engineers in order to identify the fault and have suitable actions to prevent the unfortunate incidents.

3.1.4 One Step A-head Prediction Model

The second model that is called one step a-head prediction is invented in order to forecast the future data trend of all the parameters to achieve the second and third objectives of this project which are determining the maximum wash interval and maximum sustaining period of an air filter. The proposed model is constructed and can be seen in previous Figure 8.

a. Gas Turbine Compressor Efficiency (η) Calculation

Apart from those six parameters, there is another input element - the gas turbine compressor efficiency (η), which is beneficial to determine the maximum wash interval, need to be taken into consideration.

The isentropic gas turbine compressor efficiency can be obtained using the following formula:

$$\eta = \frac{\left(\frac{PS3}{Atmospheric\ Pressure}\right)^{\frac{\gamma-1}{\gamma}} - 1}{\frac{T_3}{T_2} - 1} \tag{19}$$

In which: - Atmospheric Pressure = 760 mmHg or 14.696 psi or 101325 Pa

- $\gamma = \frac{C_p}{C_v} \approx 1.4\ (for\ standard\ air)$

Combining equation (19) and equation (17):

$$\eta = \frac{\left(\frac{PS3}{760mmHg * 0.00133322368bar/mmHg}\right)^{\frac{1.4-1}{1.4}} - 1}{\frac{PS3}{P2} - 1} = \frac{\left(\frac{PS3}{1.01325}\right)^{\frac{2}{7}} - 1}{\frac{PS3}{P2} - 1} \tag{20}$$

b. Recurrent Neural Networks

Recurrent network can be easily understood as the network whose output of some units can be the feedback input of other units [39]. Recurrent Neural Network (RNN) which possesses temporal processing and adaptive memories implementation capability [39] [40] [41], could play a beneficial role in implementing the real time prediction model. In this project, the area is being worked on related to signal prediction where time plays a dominant role. With capability of quickly learning to detect and generate temporal patterns by owning an internal feedback loop, RNN is helpful in order to predict the future data trend of gas turbine system's parameter. Among many RNN techniques, the RNN type that used in this project is described. Its architecture can be illustrated as the following figure 13.

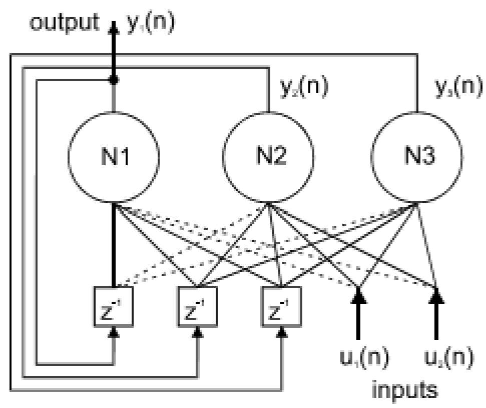


Figure 13: Recurrent Neural Network Architecture

The proposed RNN inspired from [39] consists of two layers which are processing layer and input-output concatenation layer. Suppose there are M inputs and N neuron, the RNN is connected with MN direct connections, N^2 feedback connections and several unit delay z^{-1} applied to the output vector. Let ω be the weight matrix with N (M+N) dimension, I be the input set, O be the output set. In addition, let $v_j(n)$ be the j neuron internal activity in the time instant t with $j \in B$.

$$v_j(n) = \sum_{i \in A \cup B} \omega_{ji}(n) u_i(n) \qquad (21)$$

In which ω_{ji} represents synaptic weights.

The j neuron output at the next input instant (next minute data) is given by:

$$y_j(n+1) = \varphi(v_j(n)) \qquad (22)$$

While assuming φ is the linear ramp function, the system dynamics can be described using equations (20) and (21).

c. Extended Kalman Filter based Training Algorithm

This modified version of Linear Kalman Filter can be used as an algorithm in real time basis for RNN to determine the weight matrix [39]. The EKF contains several equations in order to describe a recursive solution for the discrete value linear filtering problem [40] since by using EKF the non-linear part of the system can be linearized while still using the original Kalman filter in for linearized model.

In order to response, generate the temporal patterns for future reference; the RNN can be trained by using Extended Kalman Filter (EKF). The set of equations for EKF based neural training for RNN supporting this project from [39] will be described as follow.

Let $d(n)$be the desired output vector of size Bx1. Our aim is to find the $\omega(n)$ weights so that the differences between the neural network output and the desired output minimum in terms of quadratic error. The equations that govern the recurrent neural network operation are:

$$d(n) = h_n\big(\omega(n), u(n)\big) + r(n) \tag{23}$$

$$\omega(n+1) = \omega(n) \tag{24}$$

In which: - r (n) is the error measurement vector

- The non-linear function h (n) describes the relationship among the input u (n) and the weights w (n)

The training of previously presented RNN can be done using EKF algorithm through the following equations:

Equations for updating measurement:

$$K(n) = \frac{P(n\backslash n-1)H_n^T(n)}{H_n(n)P(n\backslash n-1)H_n^T(n)+R(n)} \tag{25}$$

$$\hat{w}(n\backslash n) = \hat{w}(n\backslash n-1) + K(n)[d(n) - h_n(\hat{w}(n\backslash n-1), u(n))] \tag{26}$$

$$P(n\backslash n) = \big(I - K(n)H_n(n)\big)P(n\backslash n-1) \tag{27}$$

Equations for updating temporal

$$\hat{w}(n+1\backslash n) = \hat{w}(n\backslash n) \tag{28}$$

$$P(n+1\backslash n) = P(n\backslash n) \tag{29}$$

In which: - $H_n(n) = \frac{\partial h_n(\hat{w}(n\backslash n-1), u(n))}{\partial \omega}$ (30)

- $h_n(.) = [h_1, h_2, \dots, h_M]$ are the M neural network outputs
- R (n) is the measurement error covariance matrix
- P is the state error covariance matrix
- $\hat{w}(n)$ is a state estimate (weights)
- K(n) is Kalman gain [42]

d. Constructing the model.

In order to fulfill the objectives, a combined ART2 NN and RNN which is equipped with EKF architecture are made. In the proposed architecture, the ART2 NN analyzes the input elements of the input-output pairs received and look for a category which is. If this similarity is sufficiently adequate, the LTM (Long Time Memory) weights relative to the category will be updated. The recurrent neural network RNNx connected to the category will be activated and the input-output pair is used in the supervised learning of this neural sub network. Combined method can be summarized step by step as follows:

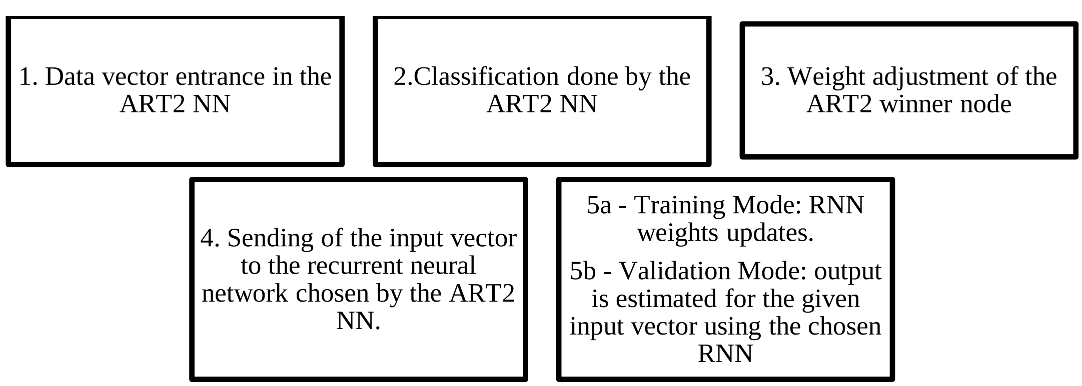


Figure 14 Proposed Architecture Operation Steps

The healthy data output from the data filtering process will be divided into two sub divisions. Three quarter of the data will be used for training purposes while the rest of 25% will be used as data validation. The training data will be inputted into the combined proposed model in order to conduct training and adaptively learning the input pattern so that it is possible for the combined system to provide the one step prediction using the combination of ART2, recurrent NN and EKF techniques. The predicted output data trend will be then compared with the validation data to determine the how much the predicted trend similar to the actual data by using NMSE formula. The process of learning and comparison will be continued until the resulted NMSE <= 0.4 is achieved.

3.1.5 Simulation Software

MATLAB will be used as the modeling tool for the target fault diagnosis system. The input data is saved in MS Excel file will be inputted into MATLAB Simulink and the results will be obtained from several probes.

3.2 Project Process Flow chart/ Project Activities

The project is conducted methodically as the project process flow chart shown in Figure 15. It is observed from the chart the entire project activities involved are presented generally in order to achieve the expected design. The project is started with the identification of problem statement, project's main objectives and scopes of study. The project is then continued with the background study and literature review in order to have sufficient knowledge topic-related and bring the author some ideas on how the algorithm will be formed. After that, the modeling simulation of the algorithm will be developed using MATLAB. All the simulated results are recorded before approaching to the final stage, which is result studies analysis.

3.4 Project Gantt chart

Compared to process project flow chart, Project Gantt chart is similar but the research activities are explained in more details with the timeline allocated. All the relevant activities to the project are listed in the correlation with time, displayed in table form. The Table 15 illustrates the project timeline with respected to number of weeks for completion to keep the project on track. Project milestones are indicated using the big RED DOT to show important achievements required to accomplish during the project.

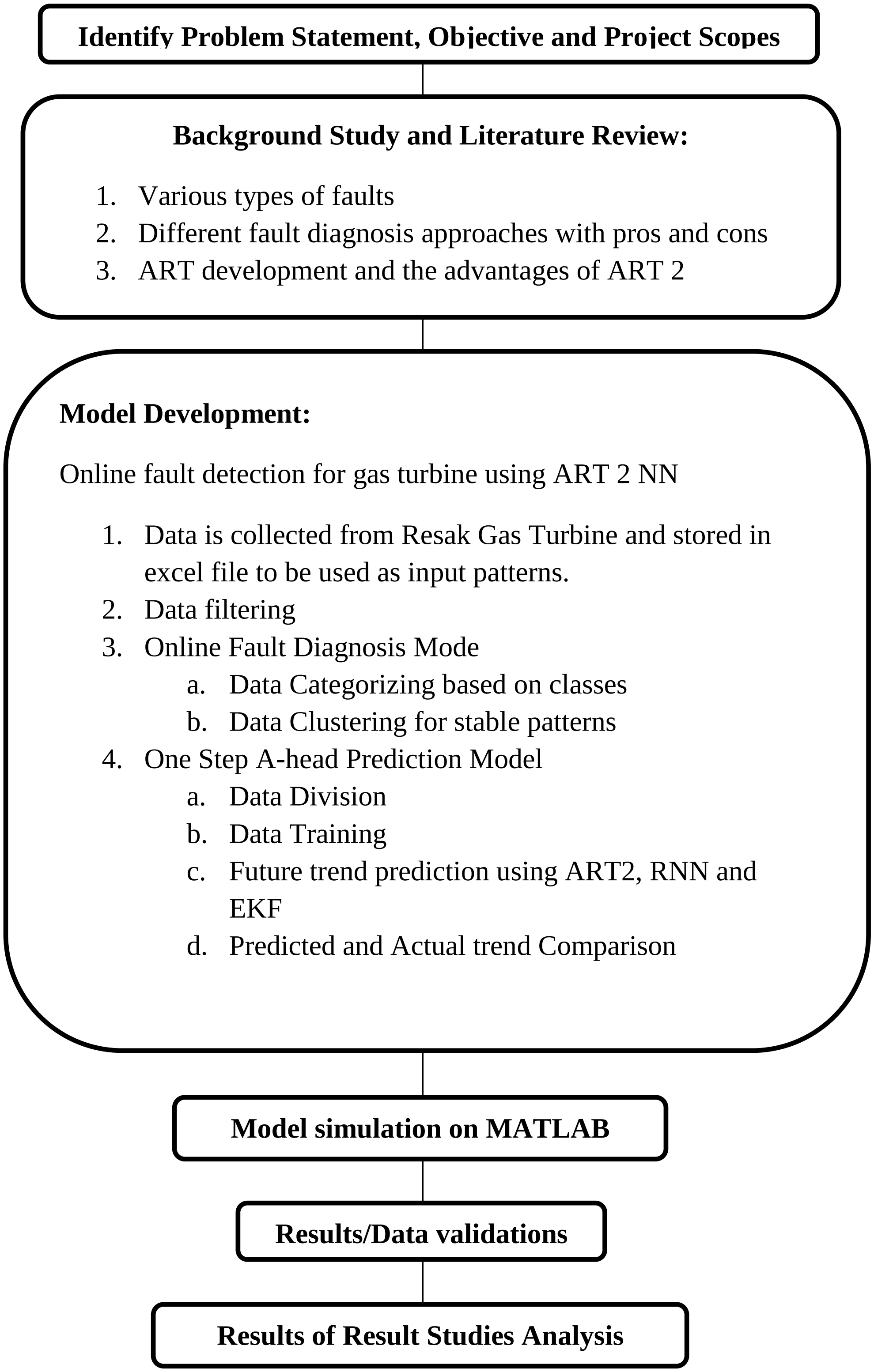


Figure 15: Project Process Flow Chart

Week number / Progress	FYP I														Semester Break	FYP II													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Topic confirmation																													
Background study / Lit. survey																													
Identify problem statement, project objectives & scopes of study						●																							
Familiarization of MATLAB Simulink software and Neural Network Toolbox																													
Data Collecting from Resak																													
Proposal Defense									●																				
Consultation from experts																													
Preliminary results – Data Filtering													●																
Interim Report														●															
Preliminary results – Learning Stage																			●										
Modal Simulating Compilation (comparison stage, wash interval and replacement period estimation)																									●				
Parametric result & sensitive graph analysis																											●		
Consultation from experts (Result and data validation)																													
Project presentation																													●

●: Key Milestone

Table 15 Project Gantt chart

CHAPTER 4 RESULTS AND DISCUSSION

Findings of this project will be presented and discussed in this chapter of the report. This section of the report contains of three main parts which are data filtering, online fault diagnosis model and one step ahead prediction model.

Firstly, in the data filtering section, the results of filtering and isolating abnormal data are discussed. A summary of three types of fault (hang faults, zero faults and drift faults) is given in Table 7.

Apart from that, the second section shows and discusses the results obtained from the online fault diagnosis model including data clustering and pattern comparison. Six classes were created for each parameter, which are Intermediate 1 (I1), Intermediate 2 (I2), Intermediate 3 (I3), Normal 1 (N1), Normal 2 (N2) and Normal 3 (N3). Stable clusters for normal pattern using ART 2 NN will also be displayed in this portion of chapter 4. On the top of these, the matching test between the stable normal data pattern and real input data pattern will be conducted in the basis of every five consecutive data point per sequence assessment. The NMSE results of all the comparison toward the end of data will be plotted to determine whether the system is healthy or contains potential for occurring faults.

In addition, the last part of this chapter is the results obtained after applying the one step ahead prediction model. Both graphs of the validation data trend and predicted data trend will be made for each of the participating parameters. Results of each parameter data trend comparison will also be tabulated together with results obtained from other similar methods yet applying to the same set of data. By achieve the lowest NMSE value, it can be concluded that by using the combination of ART 2 NN, RNN and EKF, it is possible to predict the future data trend for each parameter at an acceptable degree, which is possible to proceed with the maximum air filter replacement estimation. At the end, a plot for determining the behavior of the isotropic gas turbine efficiency value will be obtained in the effort to estimate the maximum wash interval.

Though there are three gas turbine (named L0657, L0658, L0659) at Resak Platform, the results will be shown in this chapter are obtained only gas turbine L0657.

4.1 Data Filtering

The raw data was recorded every minute from 00:01: 1st January 2014 to 03:04 12th August 2014 (data size is approximately more than 300,000 data points) and stored into several text files. These data need to be pre-processed by inputting into excel files for future easy modifications and calculations. Among numbers of parameters values in the text files, based on requirements, six sets of readings whose details are as below are taken:

Table 16 Six used Parameters Specifications from Raw Data

No.	Description	Tag	RM&D Tag	Tag Number	Notation (unit)
1	Turbine Air Inlet Filter Differential Pressure	T1_L102M4AI06PVA_NAME_VAL0_GT0657	FLD_097	PDT1253	Delta_P (mBar)
2	Inlet Temperature	VARCORE_MODT2SEL_VAL0_GT0657	T2	TT1000	T2 (DegC)
3	Compressor Outlet Pressure	T1_A106M4AI23PVA_NAME_VAL0_GT0657	PS3	PT1004	PS3 (Bar)
4	Power Turbine Inlet Temperature	T1_VARCORE_MODT54SEL_VAL0_GT0657	T48	TE1007	T5.4 (DegC)
5	Power Turbine Inlet Pressure	T1_IFACE_HDWRP54A_NAME_VAL0_GT0657	P48	PT1035	P5.4 (Bar)
6	GG Inlet Total Pressure	T1_A106I4AI05PVA_NAME_VAL0_GT0657	FLD_043	N/A	P2 (Bar)

When the parameter reading lies outside the operating range, it is considered as faults. They could be zero faults if the values are zero or they could be hang faults when there are at least sixty consecutive identical data values. Once the value is outside the operating range, either they are zero faults or hang faults or outliers. It can be clearly seen from the graph that there existed some period of time the values give NaN value which resulted from a hang connection or malfunction of the transmitter. Apart from that, there was a period, the user conducted shutdown plan, and hence the results obtained are constantly zero.

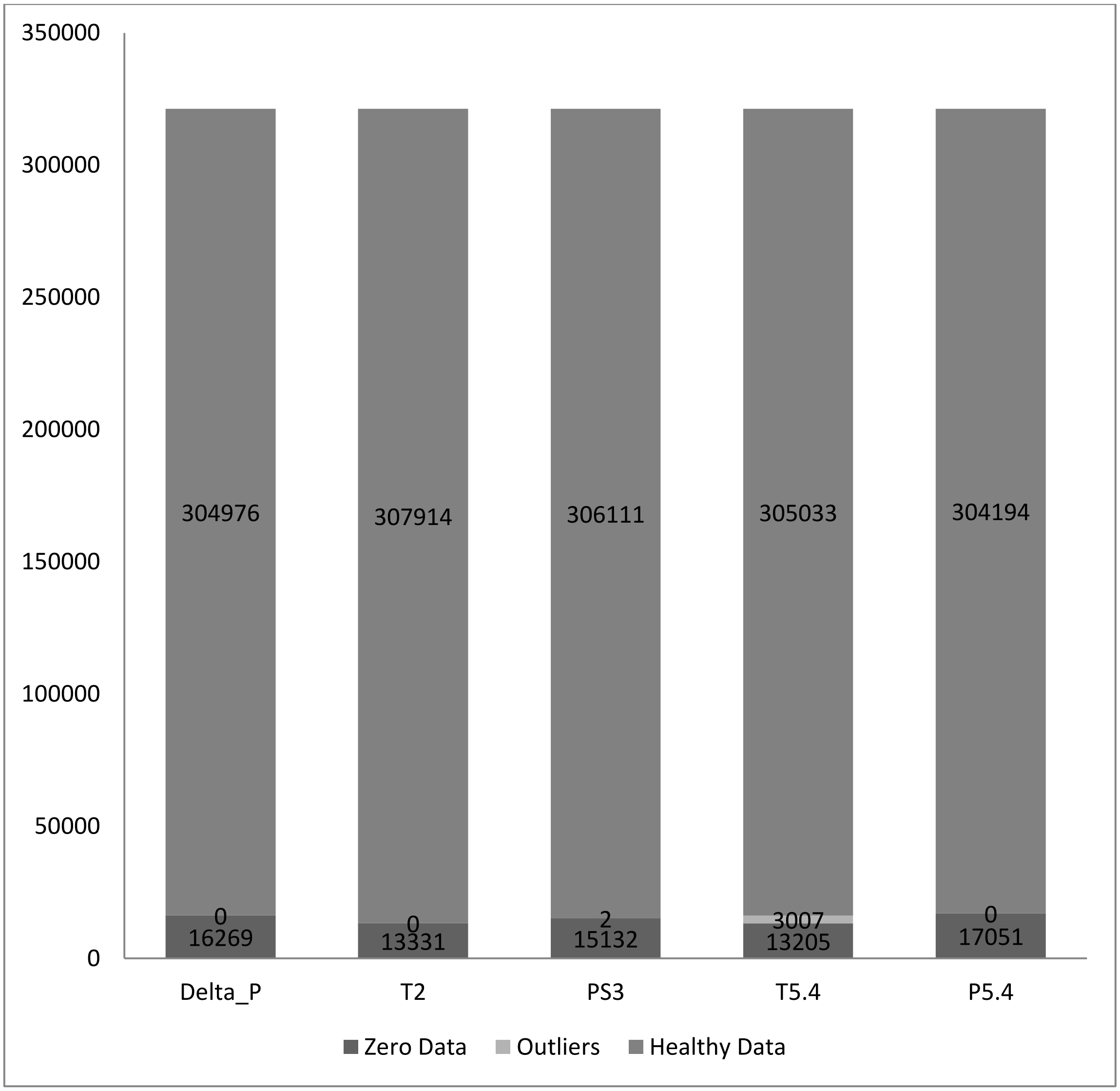


Figure 16: Fault Types Statistics of the gas turbine system

The above Figure 16 highlights the number of faults in each category of each parameter after scanning the whole input dataset. The sample data size whose contains every minute recordings of the gas turbine system in approximately 8 months is large with 321,245 data points in total.

In order to isolate and filter zero faults, the five parameter readings are scanned for the value of N/A or zero. It can be observe from Figure 16 that the percentage of transmitter faults identified was very around 4% to 5% over the total number of data points. All the five parameter sensor readings provide similar number of zero faults.

Adding on the top of that, in order to identify the hang faults due to transmitter malfunction, the five parameter readings are also scanned for a repetition of 60 consecutive same values, and it can be obtained that there are none hang faults happening during this set of data. The reason for this fact could be because that this RMD system has been newly installed and all the components or devices including transmitters and cables in this system are new and functioning in good conditions. Hence, the possibility of having a transmitter fault which resulting in hang faults is possibly low.

Apart from that, the search of outliers in the five parameter reading is also conducted. The reading values which lie beyond the operating range of each parameter will be considered outliers. It can be highlighted from the Figure 16 that the number of outliers identified in this particular case study is very small. This amount accounts approximately for less than 1% of the data. The outlier issue happens the most with Power Turbine Inlet Temperature T5.4 parameter (0.935%) and rarely occurs with small number of outliers for Compressor Outlet Pressure PS3 parameter (0.001%). There is none outliers obtained from the sensor readings installed for Turbine Air Inlet Filter Differential Pressure Delta_P, Inlet Temperature T2, and Power Turbine Inlet Pressure P5.4.

The detail percentage of each type of fault and healthy data for all the five parameter readings can be seen from the following table.

Table 17 Fault and Healthy Data Findings Distribution

	Size of Data (%)	Fault Data (%)	Suspected data (%)	Healthy data (%)
Delta_P	100	5.064	0	94.936
T2		4.150	0	95.850
PS3		4.710	0.001	95.289
T5.4		4.111	0.936	94.953
P5.4		5.308	0	94.692

4.2 Online Fault Diagnosis Model

In order to construct the online fault diagnosis model, it is compulsory to start with further categorize the healthy data into six different classes according to operating limits provided in Table 10-14.

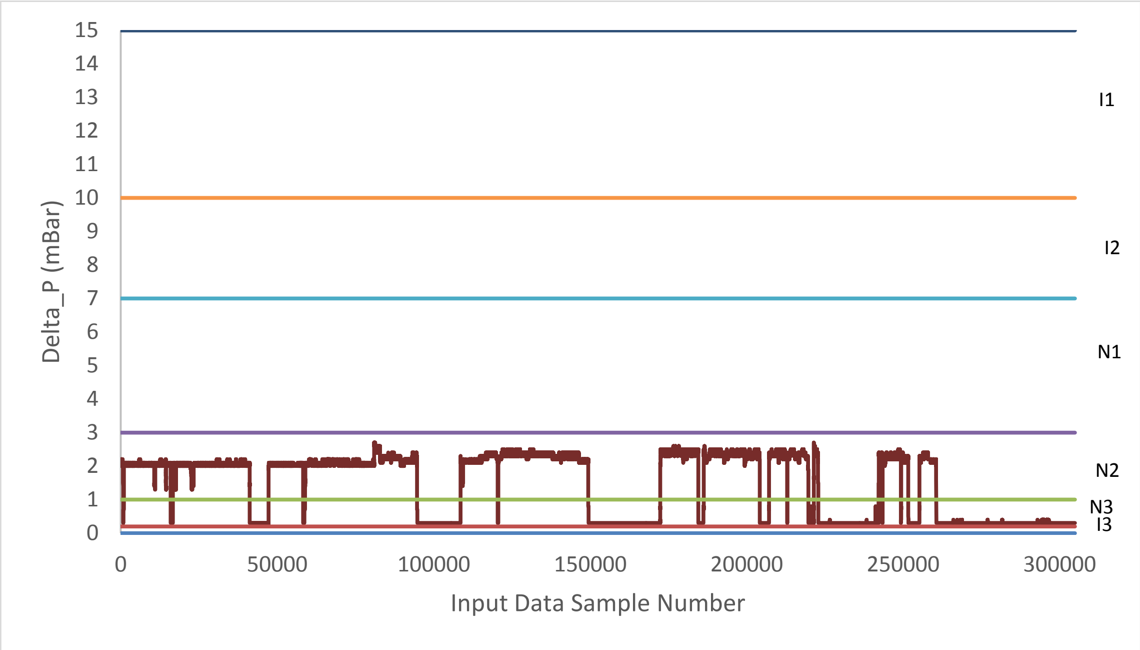


Figure 17: Delta_P Data Grouping according to classes

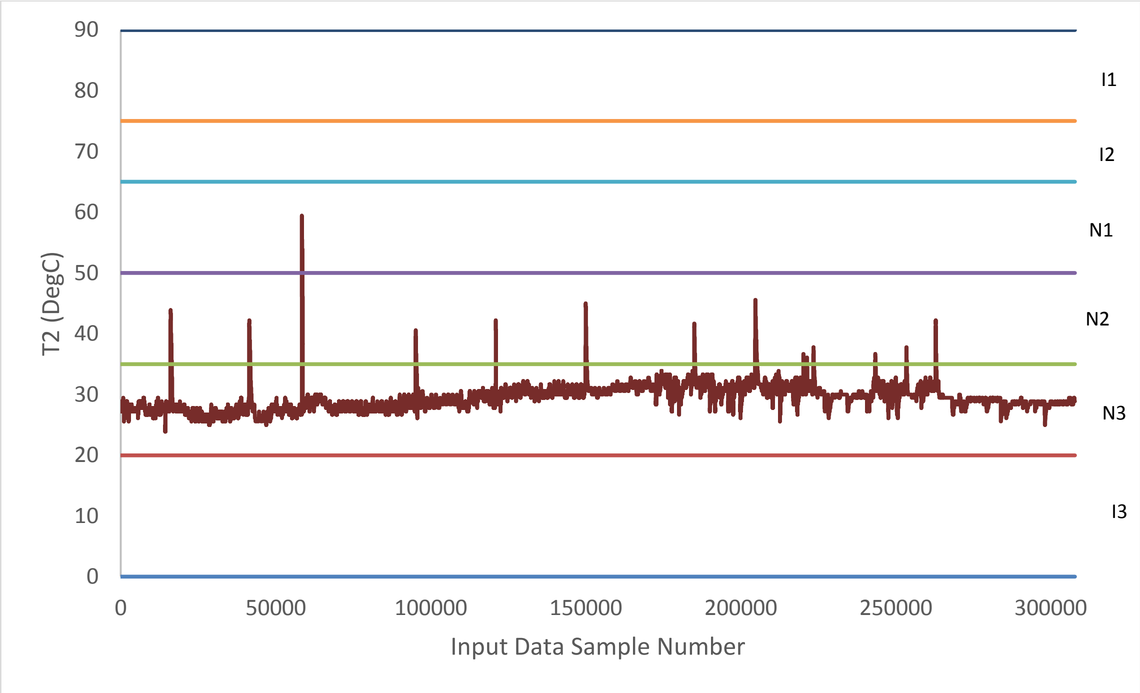


Figure 18: T2 Data Grouping according to classes

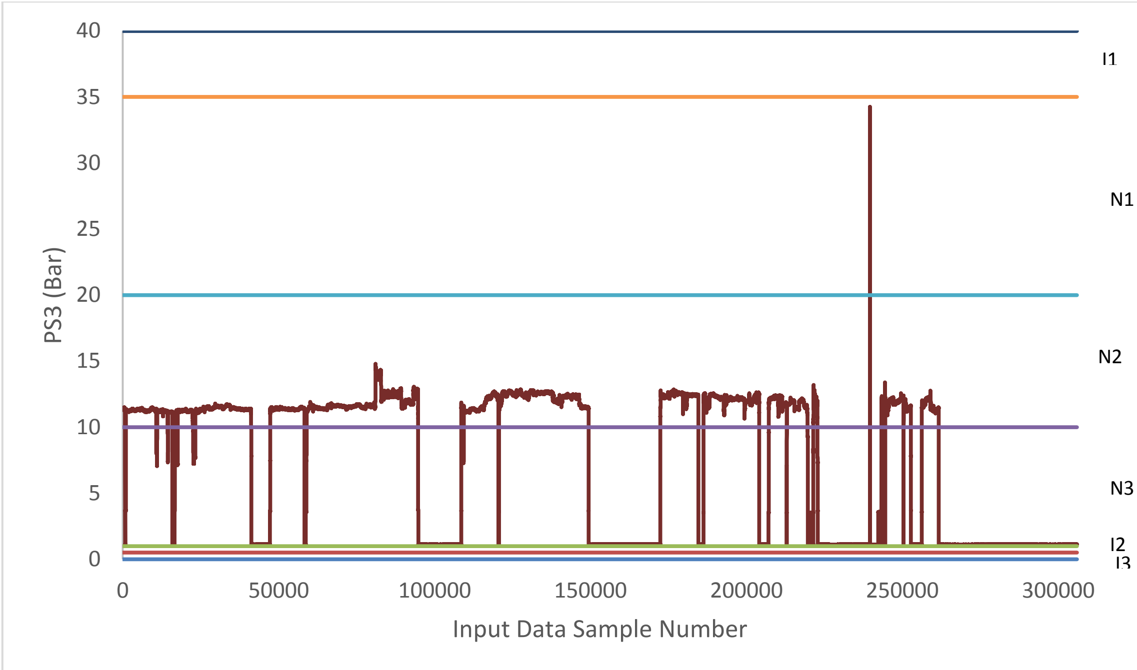


Figure 19: PS3 Data Grouping according to classes

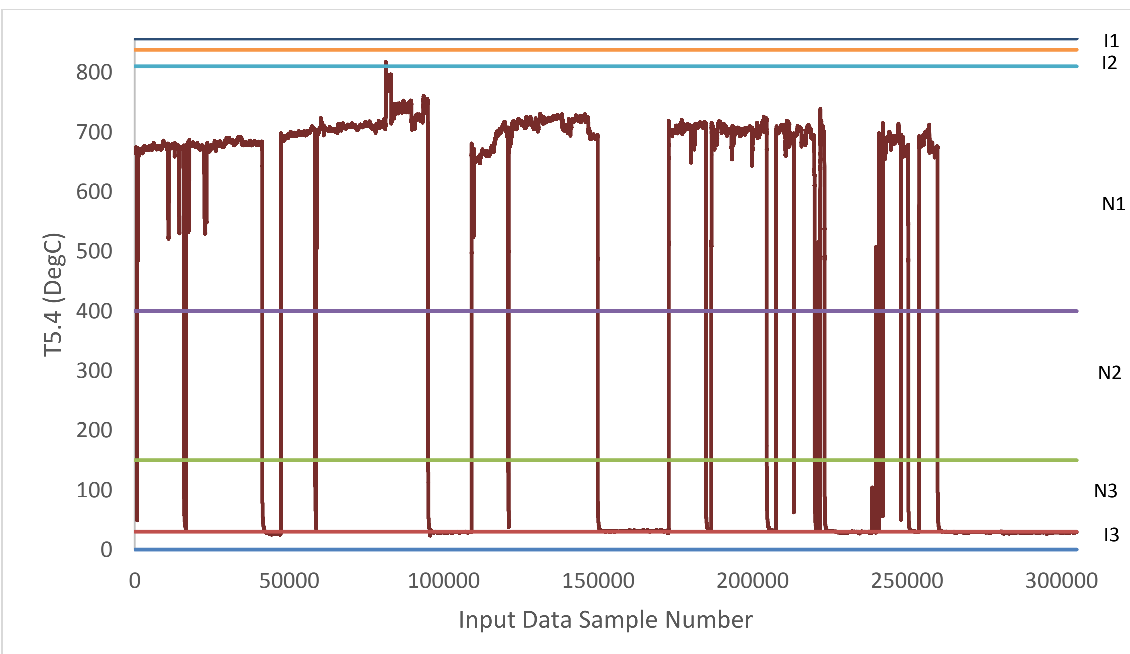


Figure 20: T5.4 Data Grouping according to classes

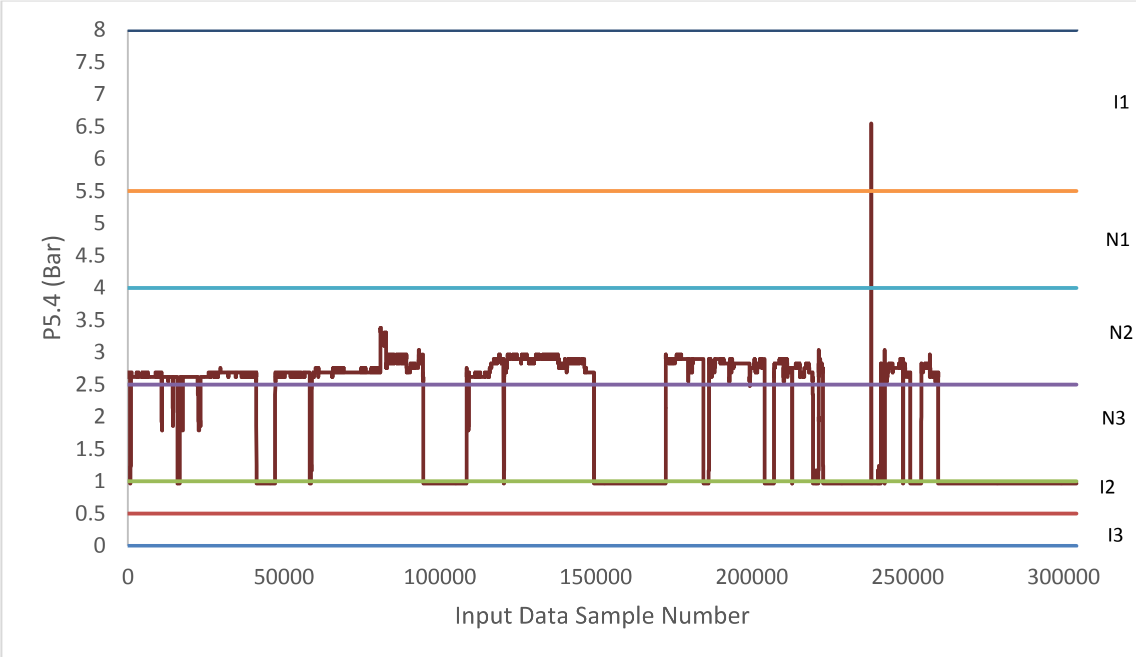


Figure 21: T5.4 Data Grouping according to classes

The above figure 17-21 present the data classification for five parameters. The classification is made into six groups of classes namely Intermediate 1 (I1), Intermediate 2 (I2), Intermediate 3 (I3), Normal 1 (N1), Normal 2 (N2), and Normal 3 (N3). The criteria for group the data into these six classes is based on each parameter's operating range and pre-defined range from the view of the author, which shall be seen in the Table 10-14.

The frequency for each class for all the five parameters Delta_P, T2, PS3, T5.4 and P5.4 were counted and presented in the following figure 22-26.

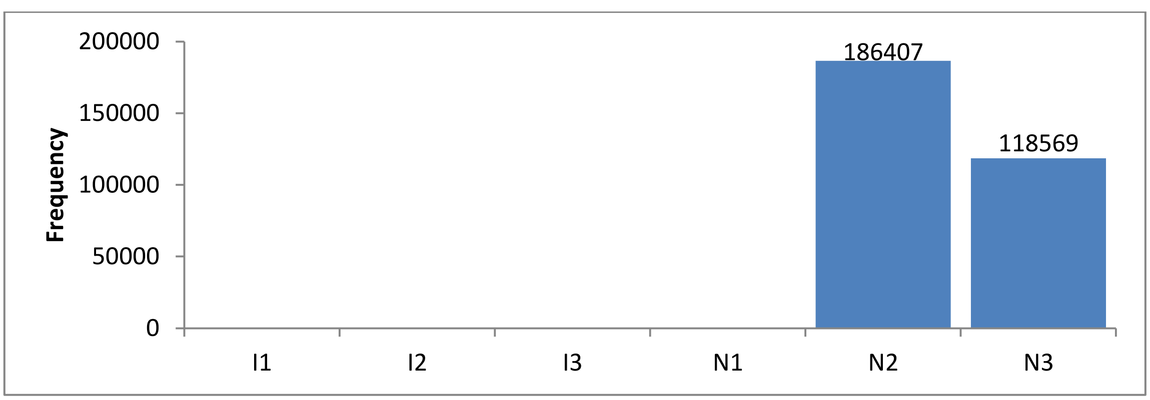


Figure 22: Frequency for each Delta_P Parameter Class

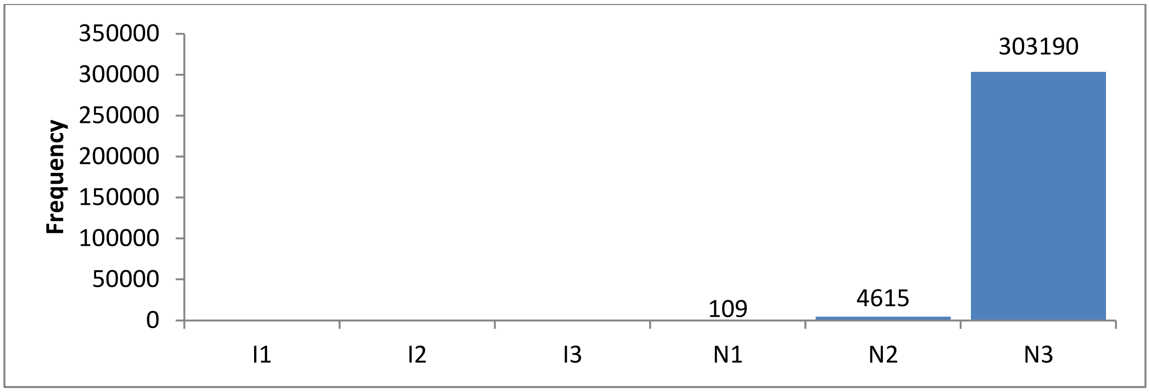


Figure 23: Frequency for each T2 Parameter Class

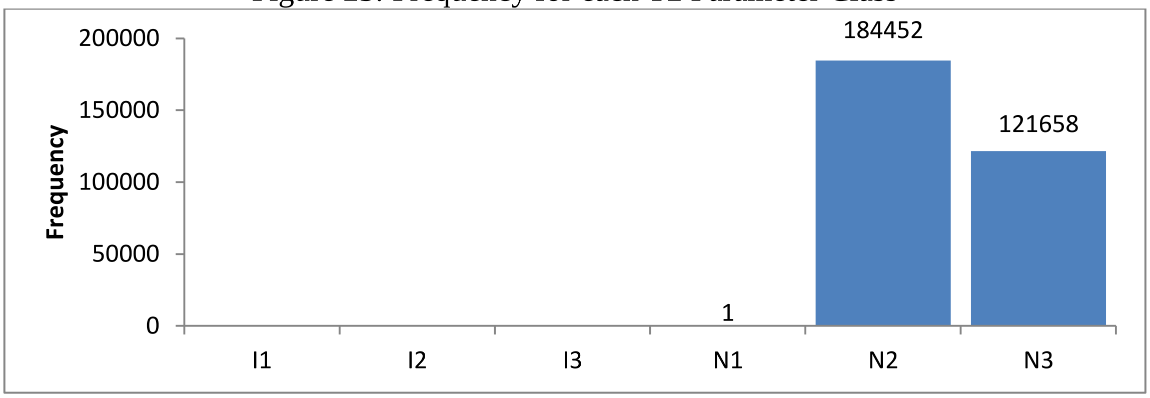


Figure 24: Frequency for each PS3 Parameter Class

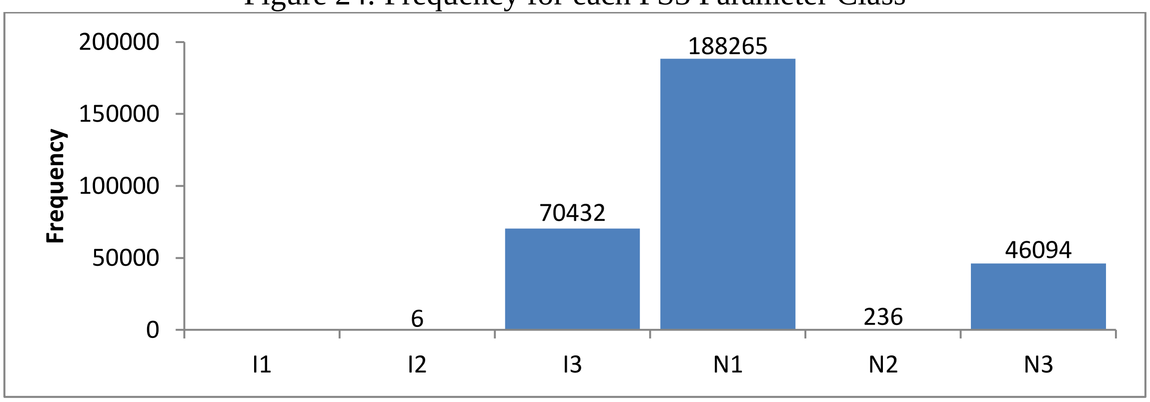


Figure 25: Frequency for each T5.4 Parameter Class

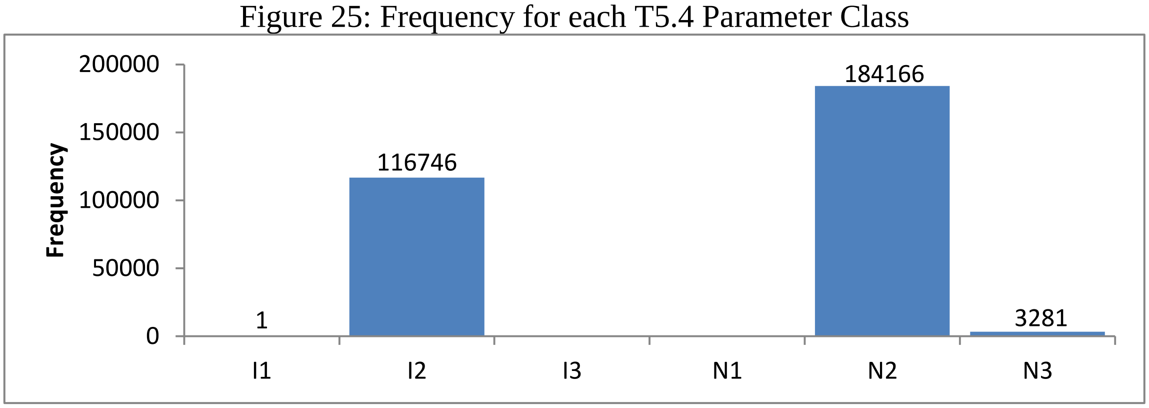


Figure 26: Frequency for each P5.4 Parameter Class

From the histogram of Air Inlet Differential Pressure (Delta_P) Parameter, it can be obtained that none of the recorded sensor readings falls into I1, I2, I3 and N1 classes but most the data points fall within N2 class (around 61.12% of the healthy data) and within N3 class (around 38.88% of the healthy data).

The histogram of compressor inlet temperature (T2) parameter shows that the majority of the healthy data lies within N3 class with a percentage of 98.47% of the total number of healthy data. The remaining 1.53% is shared by 4615 N2 class data points and 109 N1 class data points.

Apart from that, it can be seen from the histogram of Compressor Outlet Pressure (PS3) parameter that only one data point falls within N1 class. In addition, the frequency of data points falls into N2 class, like the one for Delta_P, accounts for the majority of the healthy data. It is shown that over 306,111 data points, 60% of it lies in N2 class while around 40% the rest of healthy data belongs to N3 class.

I1, I2 and I3 classes do not have any data points for PS3 parameter and T2 parameter.

Being different from the previous three parameters, the histogram of Power Turbine Inlet Temperature (T5.4) parameter displays a considerable number of data points registered with I3 class (23.09% of the healthy data). I2 class is also registered with 6 data points. Apart from that, most of the data points lie within N1 class with 61.72%. The N3 class and N2 class have a much small percentage of healthy data fall within with 15.11% and 0.08% respectively. There is zero data point registered with I1 class.

Lastly, in the histogram of Power Turbine Inlet Pressure (P5.4), it can be highlighted that a considerable amount of data points falls into I2 class (116,746 data points over total 304,194 healthy data points) while only one data point registered under I1 class and I3 class contains zero member on it. Like the results displayed for Delta_P and PS3, the histogram of P5.4 shows that the most of healthy data points are registered with N2 class with 60.54% while the rest of data (1.08%) falls into N3 class.

In overall, it can be obtained from the frequency histogram of all the five parameters that most of the healthy data outputting from data filtering process lies within Normal range condition (N1, N2 and N3) which can be resulted from the earlier stated fact that the RMD system is just being launched for less than 2 year and is being well maintenance every six months based on the safety procedure given by the gas turbine manufacturer.

The routine air filters replacement and turbine washing keeps the system running in normal condition most of the time. However, there are still a considerable amount of data falls into Intermediate range, which can be the potential threat or faults for the system.

As faults are likely to happen any time during the process, monitoring the system by keep an eye of all the parameters in order to ensure system safety in real time basis is highly required.

Since the health checkup for the system is evaluated in every sequence of five consecutive data points (Data Point 1 (DP1), Data Point 2 (DP2), Data Point 3 (DP3), Data Point 4 (DP4) and Data Point 5 (DP5) with the pre-determined six classes (I1, I2, I3, N1, N2 and N3), it is allowed to produce a total number of 6^5 = 7776 data patterns for each of the five parameters.

This result is calculated as the combination of 6 classes fit into 5 data points. Since the number of lines (7776 lines) is huge, the following table 18 does not show all the data patterns.

Table 18: Data Patterns

Data Pattern	DP1	DP2	DP3	DP4	DP5
1	I1	I1	I1	I1	I1
2	I1	I1	I1	I1	I2
3	I1	I1	I1	I1	I3
4	I1	I1	I1	I1	N1
5	I1	I1	I1	I1	N2
6	I1	I1	I1	I1	N3
7	I1	I1	I1	I2	I1
…	…	…	…	…	…
…	…	…	…	…	…
7769	N3	N3	N3	N2	N2
7770	N3	N3	N3	N2	N3
7771	N3	N3	N3	N3	I1
7772	N3	N3	N3	N3	I2
7773	N3	N3	N3	N3	I3
7774	N3	N3	N3	N3	N1
7775	N3	N3	N3	N3	N2
7776	N3	N3	N3	N3	N3

The normal data patterns are defined as those sequences of 5 data points that are registered only with either one of the three normal classes (N1, N2 and N3).

Among 7776 data patterns, hence, there are 3^5 = 243 normal data patterns.

The following table 19 does not show all the normal data patterns. A complete table of all the 243 normal data patterns can be seen in Appendix A.

Table 19: Normal Data Patterns

Data Pattern	DP1	DP2	DP3	DP4	DP5
4666	N1	N1	N1	N1	N1
4667	N1	N1	N1	N1	N2
4668	N1	N1	N1	N1	N3
4672	N1	N1	N1	N2	N1
4673	N1	N1	N1	N2	N2
4674	N1	N1	N1	N2	N3
…	…	…	…	…	…
6220	N2	N2	N2	N2	N1
6221	N2	N2	N2	N2	N2
6222	N2	N2	N2	N2	N3
6226	N2	N2	N2	N3	N1
6227	N2	N2	N2	N3	N2
6228	N2	N2	N2	N3	N3
…	…	…	…	…	…
7774	N3	N3	N3	N3	N1
7775	N3	N3	N3	N3	N2
7776	N3	N3	N3	N3	N3

These normal data patterns were then grouped together into clusters. The patterns that have the similar dynamic behavior will be grouped into the same cluster. This clustering process is done by using ART2 NN Architecture with the setting as presented in Methodology part, section 3.1.2. Some of the clusters are presented in the following Figure 27.

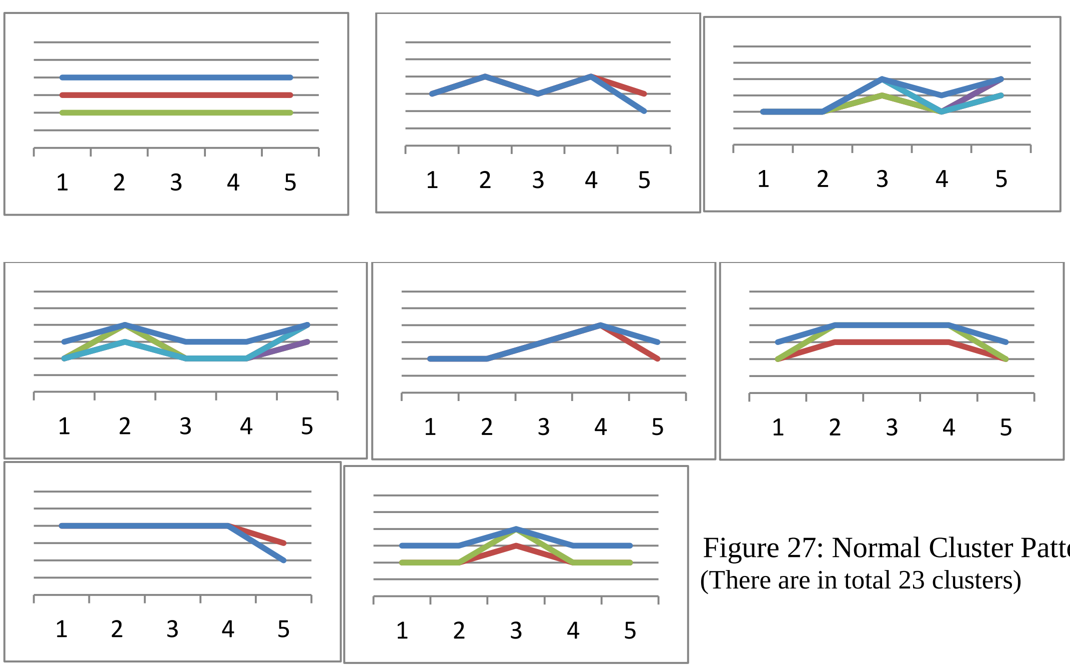


Figure 27: Normal Cluster Patterns
(There are in total 23 clusters)

The clustering patterns are then adaptively learnt by the model system by using unsupervised learning ability of ART 2 NN.

The healthy output data from the data filtering process will be then inputted into the model in order for the system to monitor the gas turbine system parameter behaviors. The five parameters are process in parallel to ensure that any fault incident happen at whichever of these five components will be identified immediately.

The health of the system is verified healthy or containing fault potential based on comparison of every five single consecutive data points between input healthy data patterns and normal cluster data patterns. If the comparison at any single 5-data point check produces the NMSE index fall below 0.1, that sequence is considered healthy.

In case the sequence comparison produces the value of NMSE greater than 0.1, in this case, the unmatching counter which intially is zero, will be increased to 1 and the assessment will continue with the next sequence of 5 data points. If the next sequence matches with the normal cluster pattern (NMSE <= 0.1), the unmatching coutner will be reset to zero, otherwise will be increased one unit. In the case that the unmatching counter is equal to 10, the possibility of having a fault is high and a notification will be sent to respective personnel to have proper corresponding actions to avoid fault incidents.

The following Figure 28-37 shows the results of NMSE of each of five parameters in first and last 500 minutes of the healthy input data.

The blue line shows the resulted NMSE index of the comparison between healthy input data pattern and normal cluster pattern in the first 500 minutes; while the red line shows the resulted NMSE index of the comparison between healthy input data pattern and normal cluster pattern in the last 500 minutes. The observations from these graph is described.

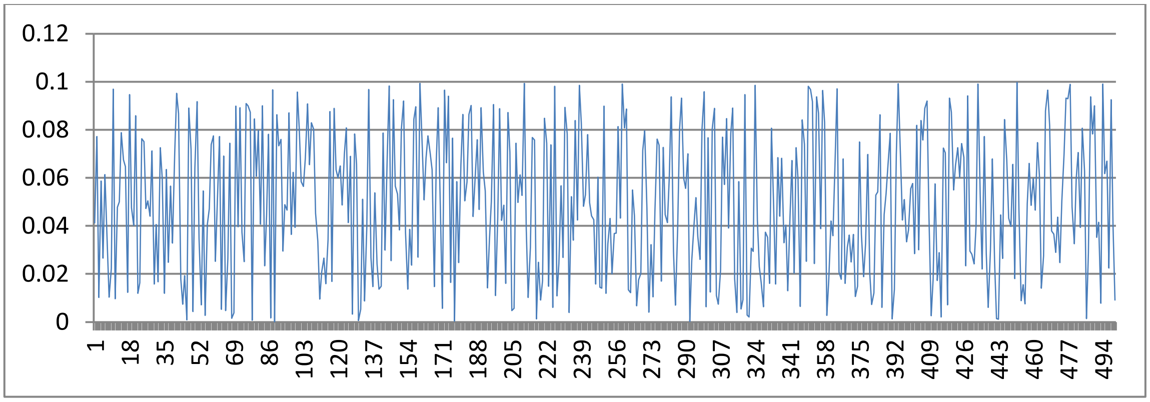


Figure 28: The NMSE calculation of the first 500 minutes comparison of Delta_P

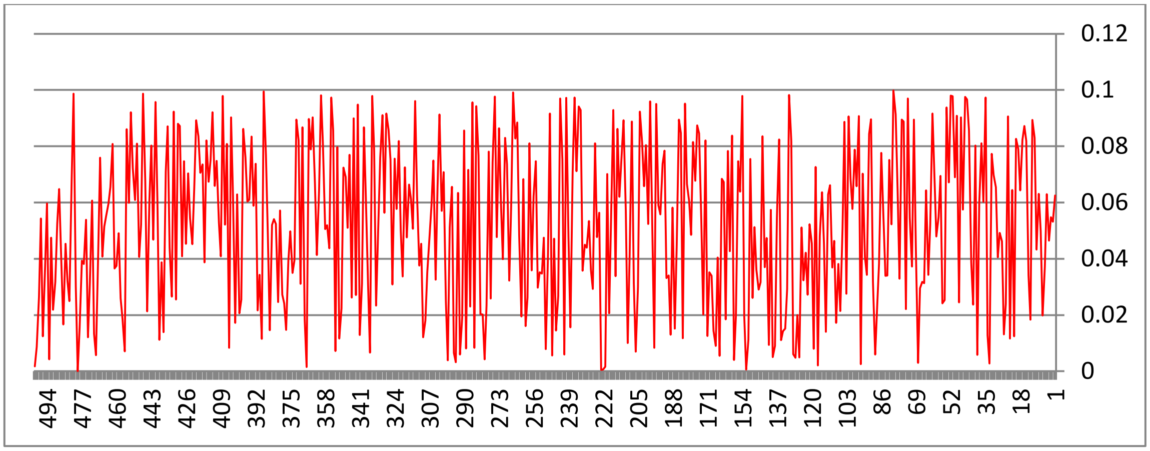


Figure 29: The NMSE calculation of the last 500 minutes comparison of Delta_P

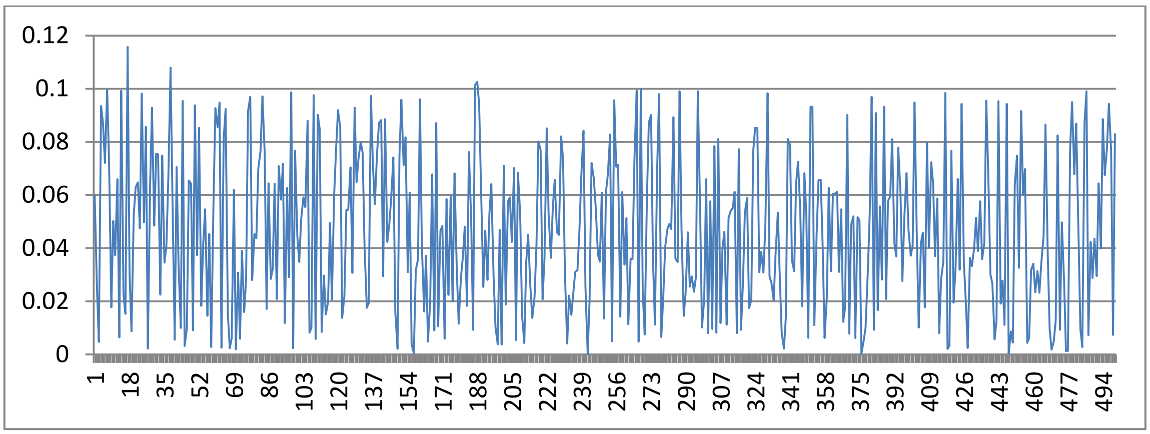


Figure 30: The NMSE calculation of the first 500 minutes comparison of T2

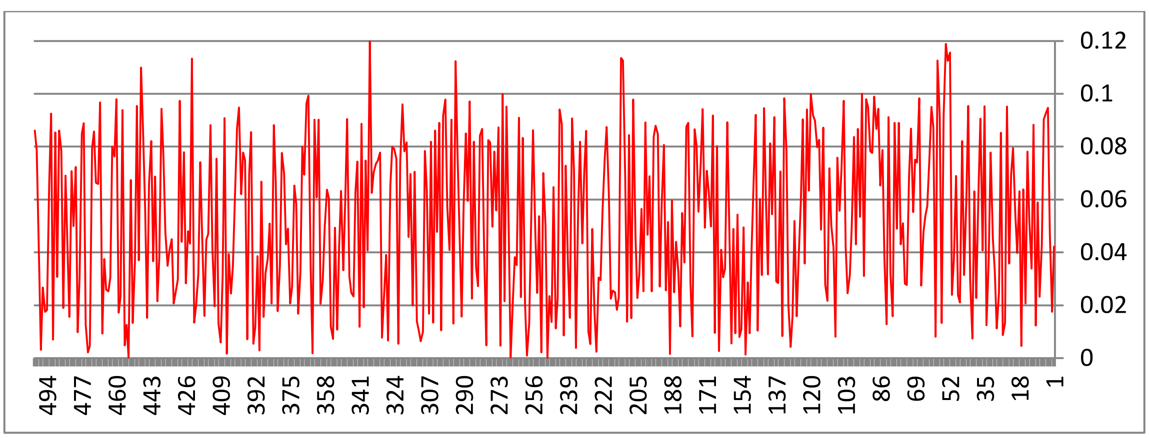


Figure 31: The NMSE calculation of the last 500 minutes comparison of T2

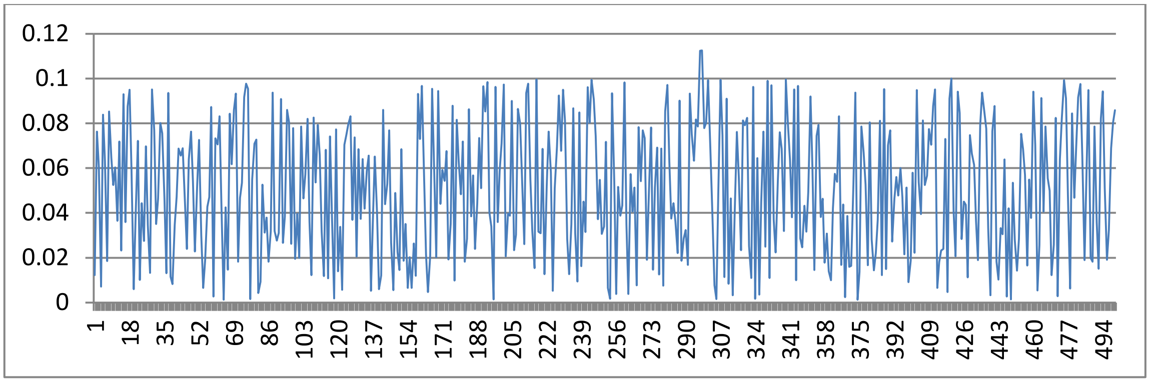


Figure 32: The NMSE calculation of the first 500 minutes comparison of PS3

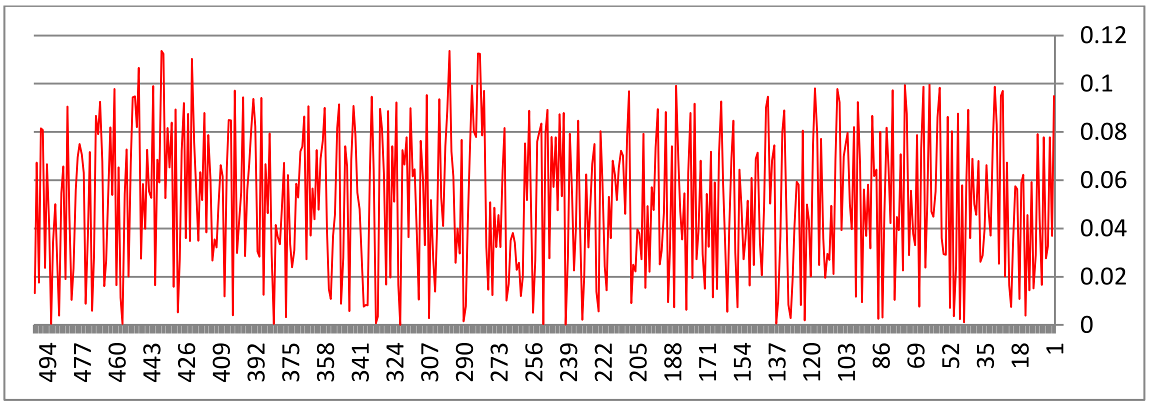


Figure 33: The NMSE calculation of the last 500 minutes comparison of PS3

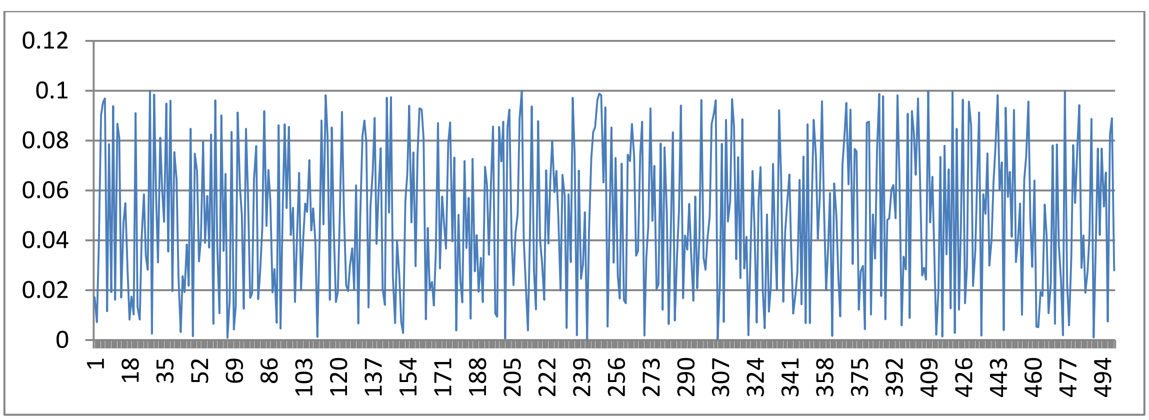


Figure 34: The NMSE calculation of the first 500 minutes of T5.4

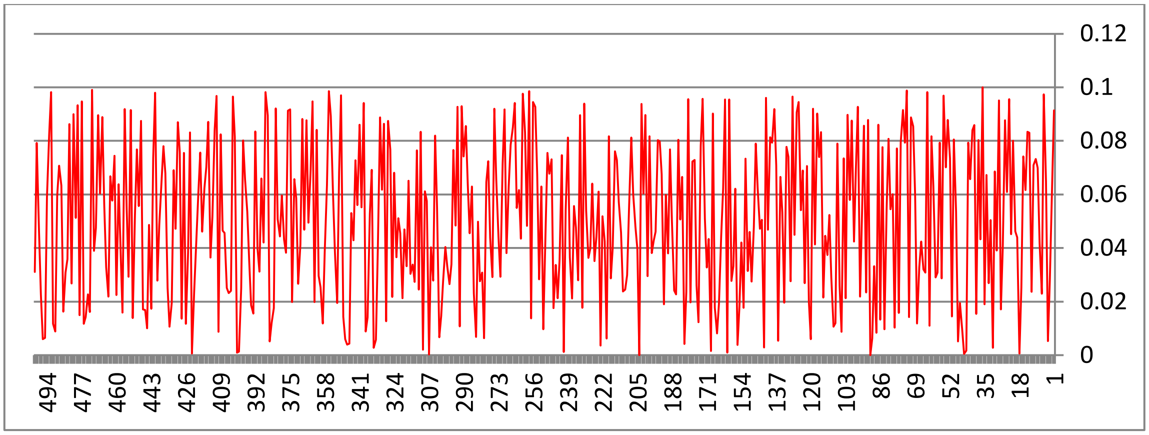


Figure 35: The NMSE calculation of the last 500 minutes of T5.4

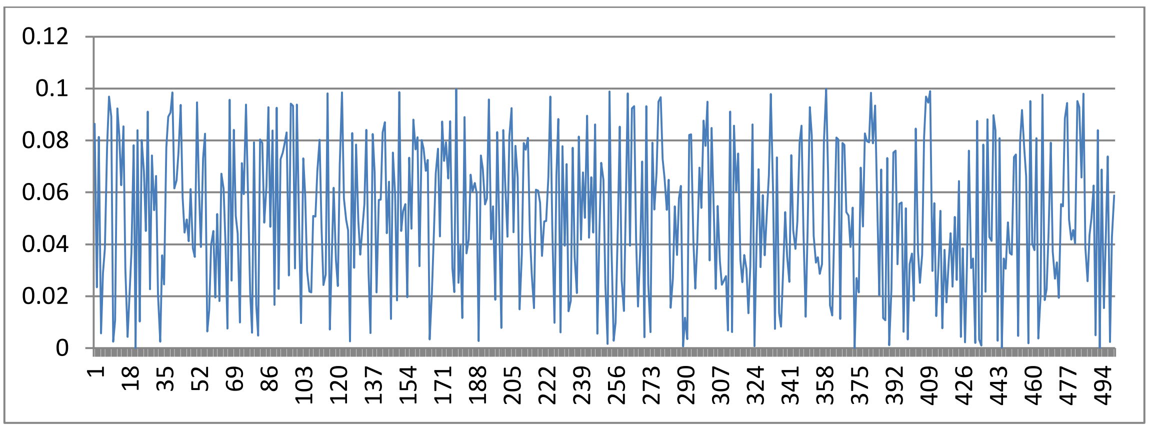


Figure 36: The NMSE calculation of the first 500 minutes of P5.4

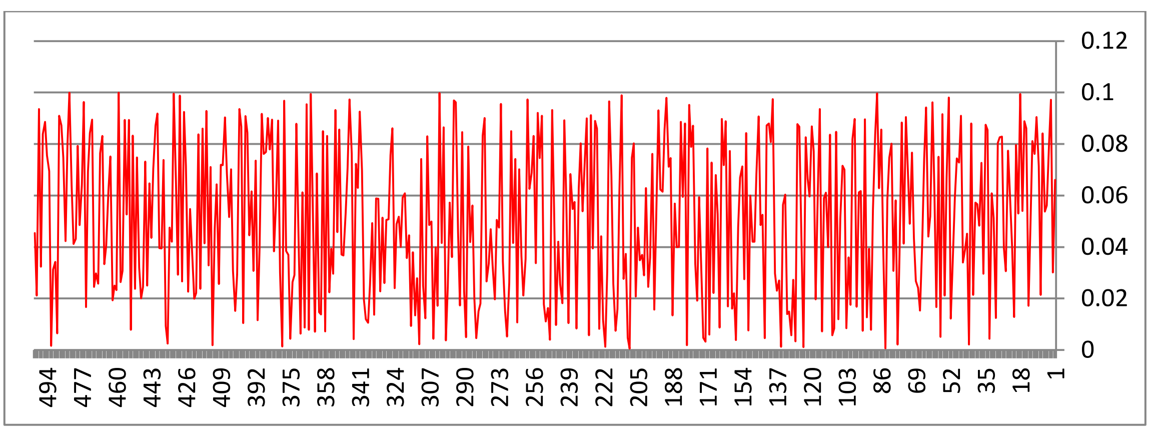


Figure 37: The NMSE calculation of the last 500 minutes of P5.4

Based on the observation from the graphs, it can be concluded that the given set of data from this particular case study is healthy for all the assessing components (Air Inlet Differential Pressure Delta_P, Compressor Inlet Temperature T2, Compressor Outlet Temperature PS3, Power Turbine Inlet Temperature T5.4 and Power Turbine Inlet Pressure P5.4). This is concluded based on the achieve NMSE indexes do not repeat the value greater than 0.1 for 10 consecutive times.

Apart from that, to be more specific, it is obviously obtained from the above graphs that the results for NMSE of Delta_P, T5.4, and P5.4 in both first and last 500 minutes are always below 0.1. This indicates that the set of input healthy data are matched with the stable cluster pattern, hence the data is healthy.

However, the result for NMSE of T2 and PS3 in Figure 30-33 contains some deviation from safe range of 0-0.1. At some particular time points, the NMSE index goes beyond the value of 0.1 which increase the un-matching counter. However, as the un-matching counter does not go up to the value of 10, the parameter still indicates a healthy result.

4.3 One step Ahead Prediction Model

This section of the chapter is dedicated towards the discussion of results obtained from the application of combined methods of ART2 NN, RNNs and EKF in the effort to predict the data trend of input parameters.

In order to determine the possible extended washing interval for the gas turbine, it is required to predict the future data trend of the parameter T5.4 and PS3 after the 6-month maintenance milestone and calculate the amount of time the trend can take to reach the safety threshold. This amount of time allows the user to be able to extend their washing interval to somehow reduce their maintenance cost instead of strictly obeying to standard 6-month washing interval suggested by the gas turbine manufacturer.

Apart from that, in order to determine the amount of time that the air filter replacement can be prolonged instead of being replaced bi-yearly, it is required to predict the future data trend for the isotropic gas turbine efficiency index. The calculation of the gas turbine efficiency index will be calculated based on the predicted data results of PS3 and P2.

The prediction of future data trend is produced by using the proposed one step a-head prediction model and its results will be presents as follow.

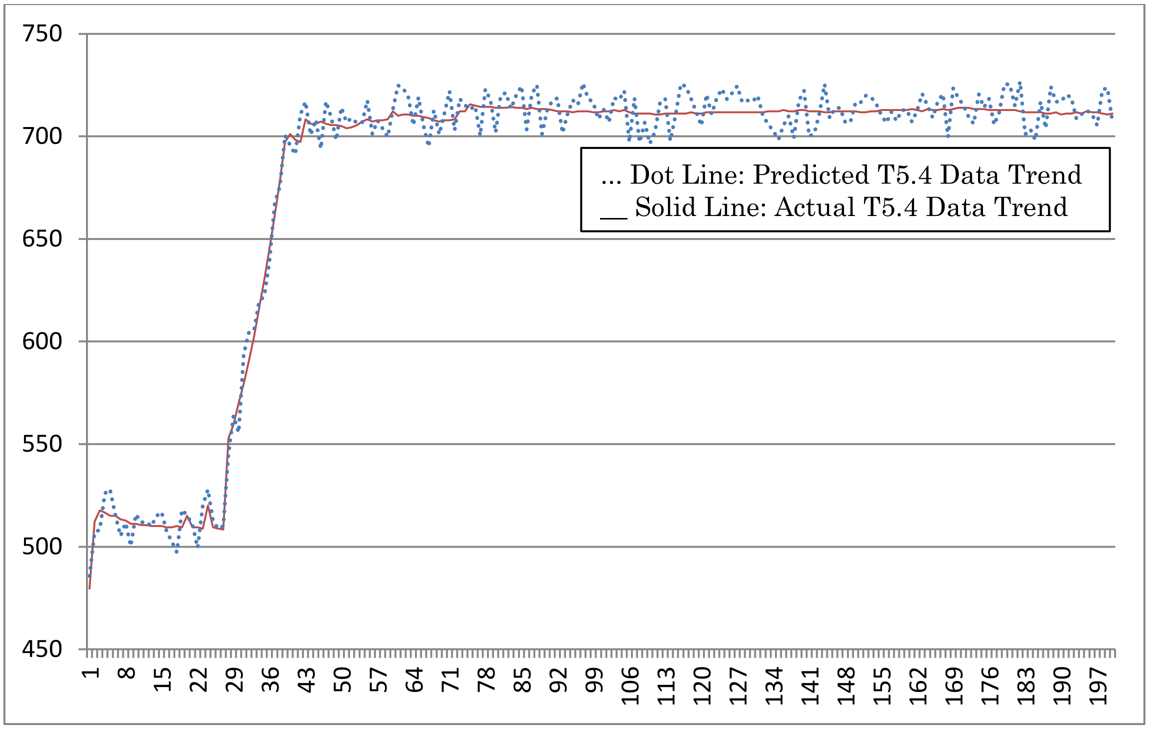


Figure 38: Predicted T5.4 Data Trend

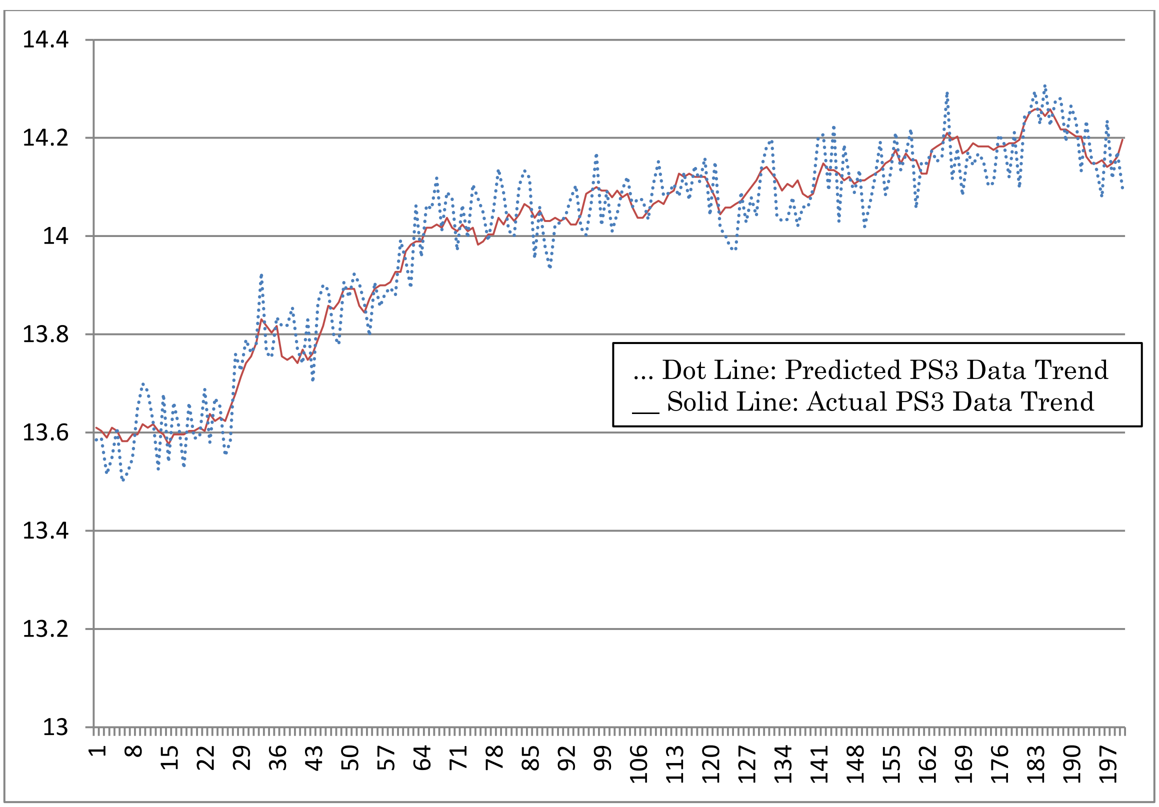


Figure 39: Predicted PS3 Data Trend

CHAPTER 5 CONCLUSION AND RECOMMENDATION

This research project aims to develop an online fault diagnosis system with the help of ANN NN. Throughout the completion of the project, the author expects to involve in multiple types of faults study and conduct background study for various fault diagnosis methods including quantitative model based method, qualitative model based methods and history based data methods. Among these main approaches, some of their advantages and disadvantages have been compared in order to find the most suitable model for the target system. Comparison is done using a set of expected characteristics that an ideal diagnostic system should possess. Moreover, a variety of ANN techniques have been analyzed based on the design criteria to identify the most appropriate ART algorithm to be equipped in the system. Lastly, an online fault diagnostic system equipping with ART 2 NN is formed and simulated to verify the results whether it is effective in diagnosing the potential faults occur. Apart from that, a better maintenance plan is suggested not only to maintain the safety level of the system but also to reduce the maintenance cost for the user. This report is mainly focused on the background studies, methodology development of the project as well as introducing a set of preliminary results obtained upon this point of time. Reading data obtained from a set of sensors installed in LM2500 Gas Turbine at Resak Development Platform was taken in order to input into the system as input data. The input data is then filtered to categorize into healthy and faulty data. Fault Patterns and Input Pattern learning processes will be conducted to help the system to learn the data input trend as well as the reference trend of fault. These two patterns will be then compared in order to detect the potential fault occurrence. Apart from that, by obtaining the trend of the input data, it is possible for the system to estimate the maximum time for each parameter to reach the safe operating threshold hence produce a better economical maintenance plan.

However, there were some limitations due to time constraint, lack of experience and knowledge. Therefore, further studies should enhance the research with an extent of time frame and improvement in term of background knowledge in order to further improve the model. In the next phase of the project, it is hoped to obtain results from learning stage and further improve the system to achieve required objectives.

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