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Predictive Maintenance of Critical Equipment for Floating Liquefied Natural Gas Liquefaction Process

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Predictive Maintenance of Critical Equipment for Floating Liquefied Natural Gas Liquefaction Process

by

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This thesis is dedicated to ***My Dear Parents***

for their impeccable love, guide, and support and throughout my entire life.

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DECLARATION

At no time during the registration for the degree of Master of Philosophy, has the author been registered for any other University award without prior agreement of the Graduate Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at University of Plymouth or at another establishment.

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Abstract

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Rabiu Mohammed Rabiu

Meeting global energy demand is a massive challenge, especially with the quest of more affinity towards sustainable and cleaner energy. Natural gas is viewed as a bridge fuel to a renewable energy. LNG as a processed form of natural gas is the fastest growing and cleanest form of fossil fuel. Recently, the unprecedented increased in LNG demand, pushes its exploration and processing into offshore as Floating LNG (FLNG). The offshore topsides gas processes and liquefaction has been identified as one of the great challenges of FLNG. Maintaining topside liquefaction process asset such as gas turbine is critical to profitability and reliability, availability of the process facilities. With the setbacks of widely used reactive and preventive time-based maintenances approaches, to meet the optimal reliability and availability requirements of oil and gas operators, this thesis presents a framework driven by AI-based learning approaches for predictive maintenance. The framework is aimed at leveraging the value of condition-based maintenance to minimises the failures and downtimes of critical FLNG equipment (Aeroderivative gas turbine).

In this study, gas turbine thermodynamics were introduced, as well as some factors affecting gas turbine modelling. Some important considerations whilst modelling gas turbine system such as modelling objectives, modelling methods, as well as approaches in modelling gas turbines were investigated. These give basis and mathematical background to develop a gas turbine simulated model. The behavior of simple cycle HDGT was simulated using thermodynamic laws and operational data based on Rowen model. Simulink model is created using experimental data based on Rowen's model, which is aimed at exploring transient behaviour of an industrial gas turbine. The results show the capability of Simulink model in capture nonlinear dynamics of the gas turbine system, although constraint to be applied for further condition monitoring studies, due to lack of some suitable relevant

correlated features required by the model.

AI-based models were found to perform well in predicting gas turbines failures. These capabilities were investigated by this thesis and validated using an experimental data obtained from gas turbine engine facility. The dynamic behaviors gas turbines changes when exposed to different varieties of fuel. A diagnostics-based AI models were developed to diagnose different gas turbine engine's failures associated with exposure to various types of fuels. The capabilities of Principal Component Analysis (PCA) technique have been harnessed to reduce the dimensionality of the dataset and extract good features for the diagnostics model development.

Signal processing-based (time-domain, frequency domain, time-frequency domain) techniques have also been used as feature extraction tools, and significantly added more correlations to the dataset and influences the prediction results obtained. Signal processing played a vital role in extracting good features for the diagnostic models when compared PCA. The overall results obtained from both PCA, and signal processing-based models demonstrated the capabilities of neural network-based models in predicting gas turbine's failures. Further, deep learning-based LSTM model have been developed, which extract features from the time series dataset directly, and hence does not require any feature extraction tool. The LSTM model achieved the highest performance and prediction accuracy, compared to both PCA-based and signal processing-based the models.

In summary, it is concluded from this thesis that despite some challenges related to gas turbines Simulink Model for not being integrated fully for gas turbine condition monitoring studies, yet data-driven models have proven strong potentials and excellent performances on gas turbine's CBM diagnostics. The models developed in this thesis can be used for design and manufacturing purposes on gas turbines applied to FLNG, especially on condition monitoring and fault detection of gas turbines. The result obtained would provide valuable understanding and helpful guidance for researchers and practitioners to implement robust predictive maintenance models that will enhance the reliability and availability of FLNG critical equipment.

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Nomenclature/Notations

Abbreviations

AI	artificial intelligence
ANFIS	adaptive neural fuzzy inference system
ANN	artificial neural network
ANN_FDM	artificial neural network time domain signal processing
ANN_FDM	artificial neural network frequency domain
BP	British petroleum
BV	bleed valve
C3MR	propane pre-cooled mixed refrigerant
CBM	condition-based maintenance
CNG	compressed natural gas
CNN	convolutional neural network
CT	compressor turbine
CWT	continuous wavelet transform
DBN	deep believe network
DMR	double mixed refrigerant
DNV	det norske veritas
EIA	energy information administration
FFT	fast fourier transform
FLNG	floating liquefied natural gas
F_N	false negative
F_P	false positive

FPSO	floating production storage and offloading
GG	gas generator
GT	gas turbine
HDGT	heavy duty gas turbine
HEFA	hydro processed ester & fatty acids
HHV	higher heating value
HMI	human machine interface
IGVs	inlet guide valves
LNG	liquefied natural gas
LSTM	long short time memory
ML	machine learning
MLNG	Malaysian liquefied natural gas
MTBF	mean time between failure
MTBO	mean time between outages
MW	mega watts
NN	neural network
OEM	original equipment manufacturers
OSA	open system architecture
PCA	principal component analysis
PdM	predictive maintenance
PFLNG	petronas floating liquefied natural gas
PSD	power spectral density
PT	power turbine
ReLu	rectified linear unit

RGB	red green and blue colours
RMS	root mean square
RNN	recurrent neural network
RUL	remaining useful life
SCADA	supervisory control and data acquisition
SMR	single mixed refrigerant
STFT	short time fourier transform
SVM	support vector machine
TDSF	time domain statistical features
T_N	true negative
T_P	true positive
WT	wavelets transform
XGB	extreme gradient boosting

Variables

C_P	specific heat in constant pressure (J/KgK)
C_V	specific heat in constant volume (J/KgK)
W_C	work for compressor (J)
W_t	work of turbine (J)
Wcyc	total output work (J)
Q_{23}	heat added to system (J)
M_a	mass of air (Kg)
M_f	mass of fuel (Kg)

N_2	nitrogen
γ	ratio of specific heat
η_{cyc}	efficiency
h	specific enthalpy kJ/Kg
x	fault vector
y	performance parameters
u	control input
v	ambient condition
P_{Gin}	nominal frequency (Hz)
P_R	pressure ratio
P_{GPU}	output power per unit (J)
V_{CE}	common signal
N	nominal speed
T_{FS}	fuel system manifold
E_{CR}	combustor reach delay
E_{TD}	delay between fuel combustion and measuring system
T_V	time constant of lag for container's volume
T_R	nominal temperature of the HDGT
D_{SH}	shield head diameter (cm)
L_{SH}	shield heal length (cm)
L_{SH}	shield head thickness (mm)
W	speed governor gain
T_G	speed governor time constant
${}_{max}F$	fuel demand signal maximum limit

${}_{min}F$	fuel demand signal minimum limit
K_{NL}	no load fuel consumption
b	valve positioner time constant
T_{FS}	fuel system time constant (s)
K_F	fuel system external feedback loop gain
T_{CR}	delay of combustion system (s)
T_{TD}	transport delay of turbine and exhaust system (s)
T_{CD}	compressor discharge lag time constant (s)
G_{SH}	radiation shield parameter
T_{SH}	radiation shield time constant (s)
T_{TR}	thermocouple time constant (s)
G_{TC}	temperature controller parameter

Chapter 1

Introduction

1.1 Background

Energy is the golden thread that connects economic growth, increases social equity and an environment that allows the world to thrive. Energy is the catalytic driver for global sustainable development. The world economy continues to grow especially with increasing prosperity in the developing world. Perhaps, increased in prosperity drives growth in energy demand (BP Energy Outlook, 2018). In short Increase in population in developing countries and rising income levels are the two key drivers of energy demand (Ha et al, 2013). With the world population increasing by around 1.7 billion to reach nearly 9.2 billion people in 2040 (BP outlook 2018) and 9.77 billion in 2050 (DNV Energy outlook, 2018), energy security is critical to the global economic growth. This prompts most of the emerging nations to be concerned with provision of viable secured energy to develop and sustain their booming economies. However, with this trend of greater demand for energy coupled with requirement for sustainability and environmental legislations, a cleaner and sustainable energy source is thenon-negotiable. Thus, natural gas is seen as a cleaner bridge to a renewable energy future andthe only fossil energy source which is projected to grow to 2050 (World Energy Council, 2017).

Natural gas is the cleanest burning fossil fuel with tremendous advantages over other energy sources. Natural gas is cheaper, cleaner with high energy value compared to other fossil fuels. Its sustainable burning feature led into a boost of its consumption all over the world. Thus, the demand of natural gas increases at 1.6% p/a which is much faster than either oil or coal (BP Outlook, 2018). The production of natural gas also increases by 6%/year from 2017 to 2020 compared to 4%/year from 2005 to 2015 (EIA outlook, 2018). The demand of oil as a major energy source will peak in the 2020s as shown in Figure 1.2 and will be taken over by natural gas as biggest energy source in 2026 as shown in Figure 1.1. This trend will continue up to 2050 whereby natural gas accounts for 25% of the global energy mix by 2050 as shown in Table 1.1. This unprecedented growth in natural gas demand is led by increases in industry and the power sector. Perhaps, almost 70% of the energy demand increase goes to power sector. (BP Outlook 2018). Therefore, the relevance of natural gas to meet world's energy need now and into the future is clear.

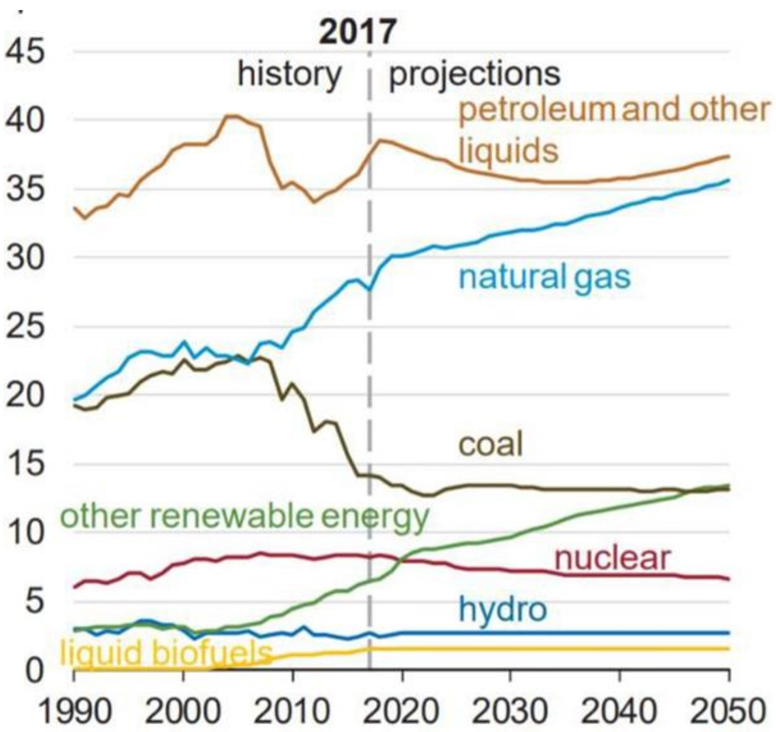


Figure 1.1: Energy Consumption by Fuel (EIA Energy Outlook, 2018) (Quadrillion British thermal units)

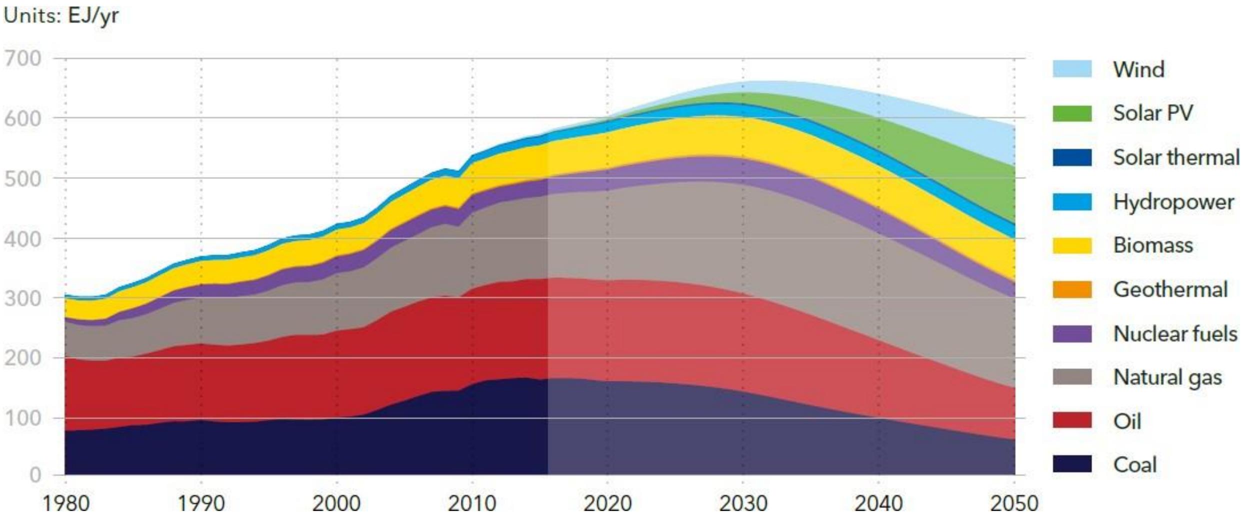


Figure 1.2: World primary energy supply by source (DNV Energy outlook, 2018)

Table 1.1: World primary energy supply by sources (EJ/yr) (DNV Energy outlook, 2018)

Energy Source	2016	2020	2030	2040	2050	Share in 2050
Coal	163	157	140	96	60	10%
Oil	168	169	164	130	86	15%
Natural Gas	140	150	182	179	149	25%
Nuclear Fuels	30	36	44	41	28	5%
Biomass	56	59	66	69	67	11%
Hydro Power	14	17	20	23	24	4%
Solar Thermal	2	2	3	3	4	1%
Solar PV	1	3	19	55	96	16%
Total	581	603	660	639	586	100%

Natural gas markets are mostly far away from production fields. Thus, prompt the need for transporting the gas from its producing field to the end-user. Transporting the produced gas is achieved via pipeline system or on-board ships as transformed compressed natural gas (CNG)or liquefied natural gas (LNG). The transformation process of both LNG and CNG helps to easy transportation and safe handling when pipeline transportation isn't feasible which increases their availability globally. Liquefied natural gas (LNG) is a natural gas which is converted and transformed to liquid form for ease of storage and transport. The transport of LNG involves three stages: **liquefaction**, **shipment,** and **regasification** (Eisbrenner et al., 2014). **Liquefaction** involves transforming the natural gas by cooling it to a temperature of $-160°C\,(-260°F)$. This cooling process shrinks the volume 600 times for easier and safer storage and shipment (Saavedra, 2017). **The shipment** of LNG is achieved with well-insulated storage ship tankers which transport it to the end user via pipeline distribution systems. However, prior to the pipeline distributions, LNG is restored back to its gaseous state through **regasification** process (Gowid et al., 2015). LNG is the most suitable among natural gas sources and identified by (Shell outlook, 2018) as the fastest growing gas supply sources as shown in Figure 1.3. The removal of carbon dioxide and other impurities during liquefaction also make LNG to be the cleanest form of natural gas (He et al., 2018).

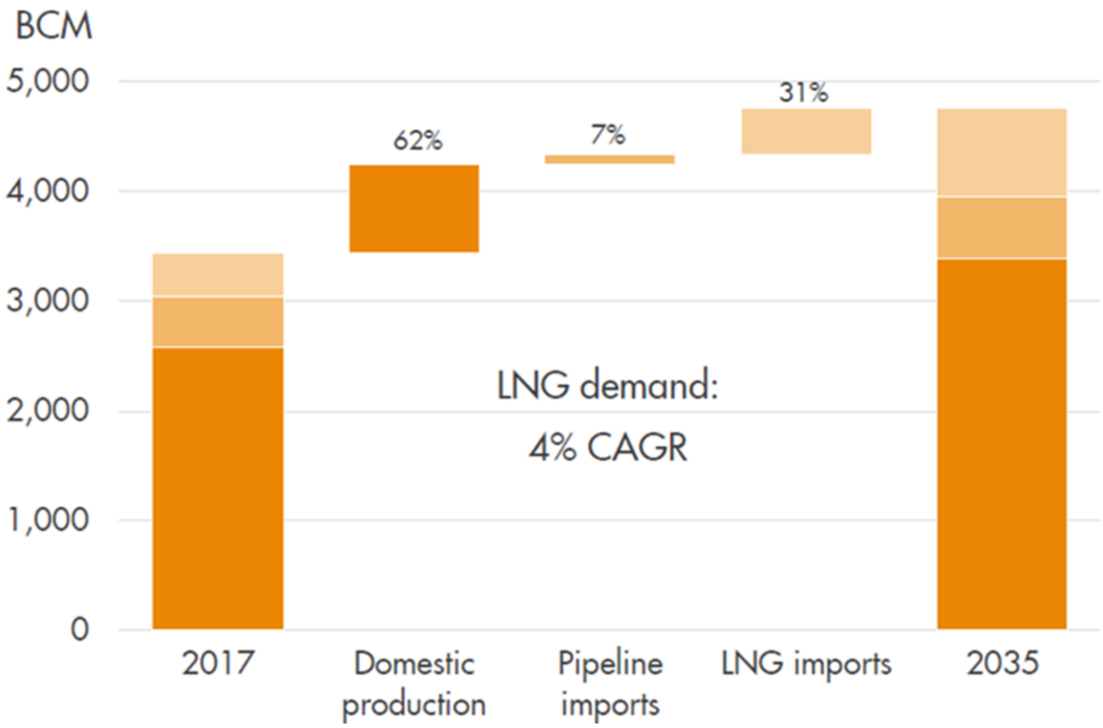


Figure 1.3: Global gas supply by sources (Shell LNG outlook, 2018)

Liquefaction is the most important unit in LNG process (Zainal-Abidin et al., 2011) which account for 30% to 40% of the overall cost of LNG production plant as stated by (Gowid et al., 2015) or up to 50% of the plant overall cost as reported by Usama et al. (2011) as shown in Figure 1.4. Various process configurations exist for liquefaction, but generally classified depending on the size and function as large base load, peak-shaving and small to medium scale plants (Mokhatab et al, 2014). The typical Floating LNG process plant is illustrated in Figure1.5. Over the past several years, siting of LNG plants is usually onshore. However, with increased in environmental regulations, higher project cost and increased in LNG and natural gas demand as well as maturity of offshore oil and gas applications, Floating LNG is seen as the new frontier for robust LNG production. FLNG offers potential cost saving up to 40% when compared to traditional onshore LNG facility (Gowid, 2016). Another key benefit of FLNG technology involves enabling access to abundant stranded offshore natural gas fields that were commercially difficult to be developed with conventional onshore liquefaction facility (Eisbrenner et al., 2014). Floating LNG concept solves many onshore production challengesassociated with demographic constraints and environmental safety regulations (Lee et al., 2014). In offshore applications, it also solves myriad gas handling challenges faced by offshoreoil and gas producers. High cost of associated gas reinjection and uneconomical long offset offshore pipelines left offshore oils and gas producers with only flaring option. However, withincreased strict marine and environmental regulations, flaring is no longer acceptable in manyregions. Hence, FLNG provides an alternative solution to handle offshore associated gas profitably and effectively (Saavedra, 2017). Therefore, FLNG is promising with many potential benefits compared with onshore LNG facility.

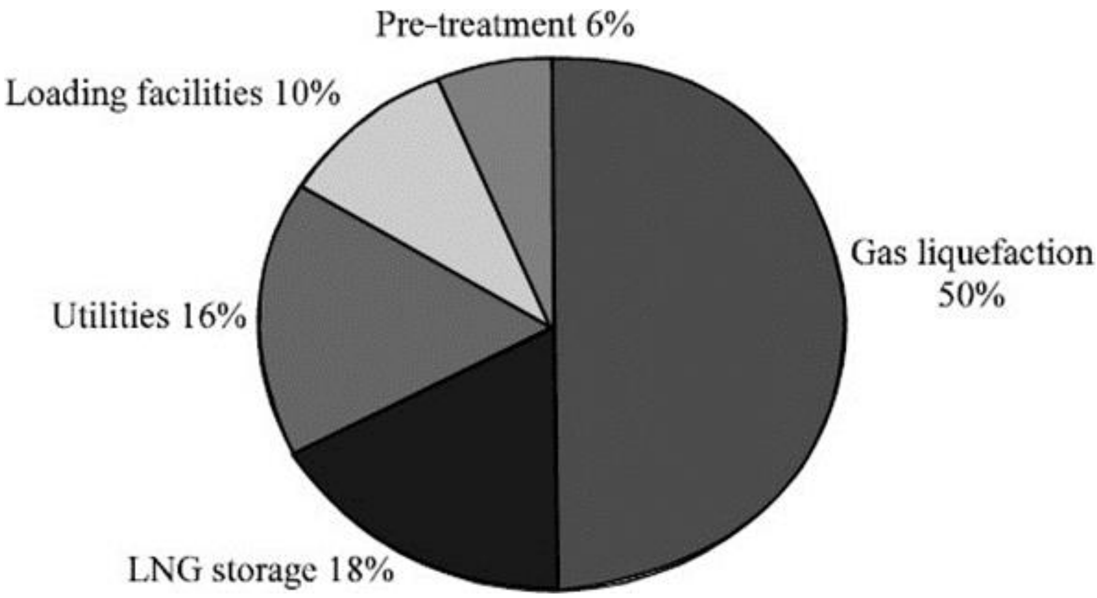


Figure 1.4: **Breakdown of liquefaction plant capital cost (Usama et al., 2011)**

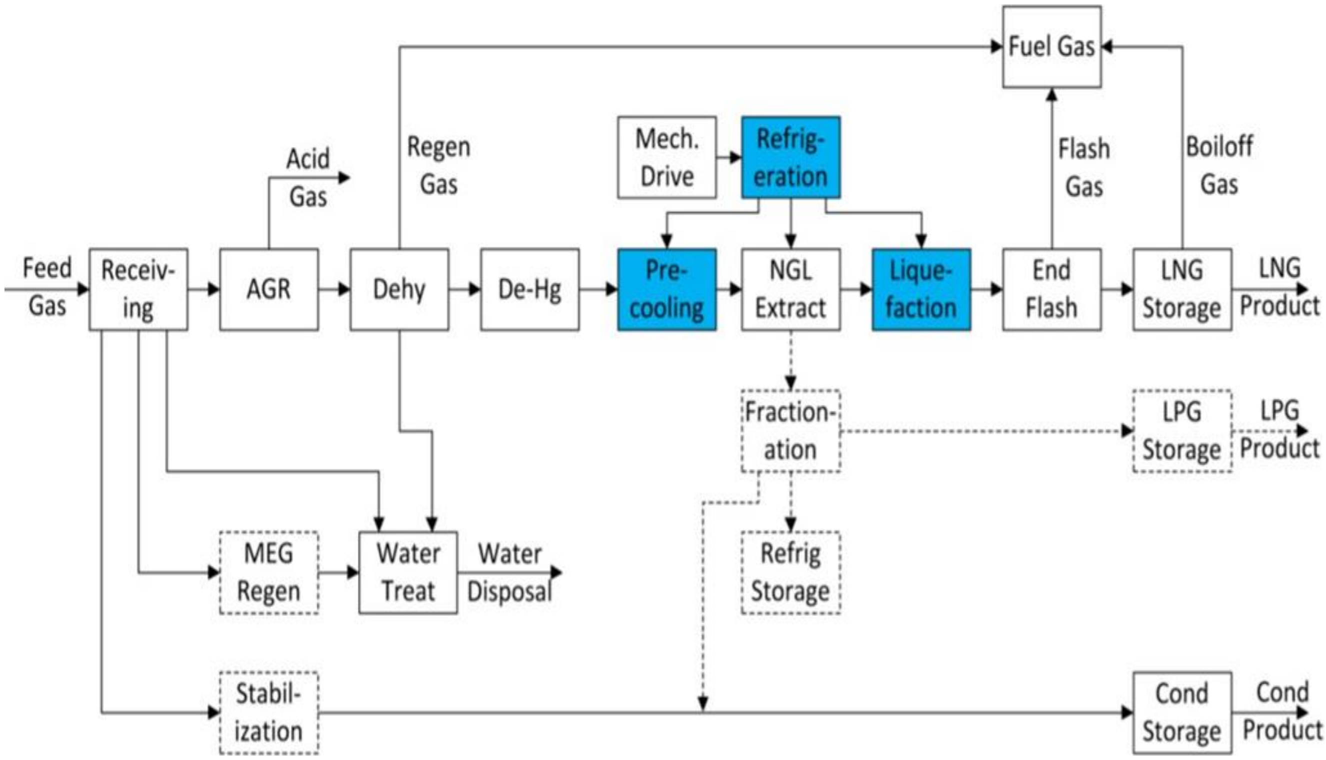


Figure 1. 5: FLNG Process Overview (Tierling and Attaway, 2017)

Considering the importance of liquefaction unit in LNG facility (50% of the overall cost), failure associated to this unit will significantly causes serious risk to the entire FLNG facility (Gowid et al., 2015). The study conducted by Forte et al. (2017) found liquefaction unit as most critical and major contributor of the FLNG downtime (30%) in the entire FLNG processfacility as shown in the Figure 1.6. Investigative research of the various failure root causes over 60 years of LNG plants operations identified various failure root causes of LNG facility as shown in Figure 1.8. The substantial plant failure is associated with mechanical failure ofequipment and storage which accounts for 47.1 of the entire plant’s failures. Materialscorrosion accounts for 17.6%, failure associated to human error accounts for 17.6, instrument and control error takes 5.9%, natural hazard accounts for 5.9% while the remaining 5.9% is associated with unknown factor. However, from Figure 1.8, it can be observed that 65% of the overall LNG failures can be associated with maintenance activities in the plant. Thus, implementation of stringent maintenance regime impacts significantly to improve plants reliability, availability and its profitability (Angelsen et al., 2006).

Since, major LNG plant's failure is associated with equipment, more attention will be required to identify critical equipment that contributes to the most of the plant's downtime. A such, compression equipment has the highest failure rate of the overall LNG process equipment (OREDA, 2009).LNG compression equipment consists of Compressors, Gas turbines, heat exchangers, pumpsand blowers (Gowid, 2016). However, most critical among this equipment in the liquefactionplants are refrigeration compressors and their drivers (Lee et al., 2014). Thus, their functionality, reliability and availability significantly affect the overall plant's performance andefficiency (Meher-Homji et al., 2011). In the research conducted by Benyessaad et al. (2016) observed most of the downtime among the FLNG liquefaction equipment comes from gas turbine with availability loss of 32% as shown in Figure 1.7. This indicates the critical of thegas turbine in the whole FLNG process facility and as such requires operators to give the highest maintenance priority to gas turbine.

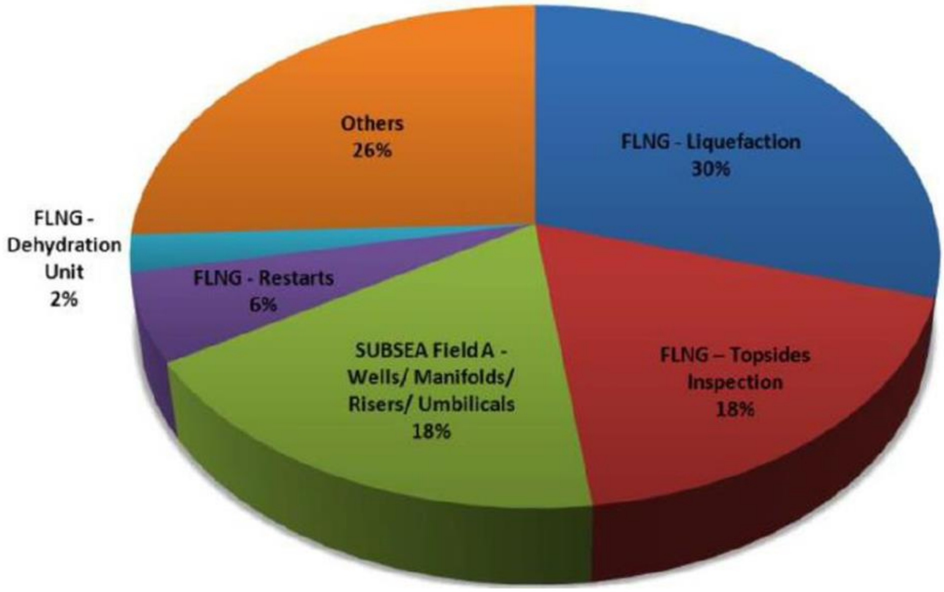


Figure 1.6: **FLNG system criticalities (Benyessad et al., 2017)**

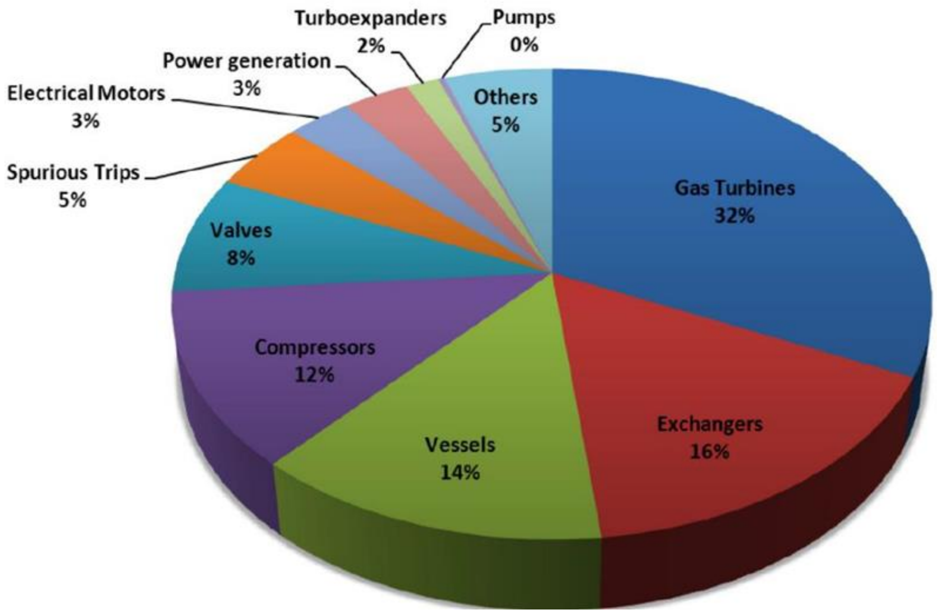


Figure 1. 7**:** FLNG equipment item criticalities (Benyessaad et al., 2016)

One of the key challenges of FLNG lies on the appropriate selection of refrigeration compressor driver (Kumar and Jang, 2017). Selecting the driver type with right configuration is significantly important and has a direct impact on the overall performance, efficiency availability as well as profitability of FLNG facility. As mechanical drive, gas turbines have been applied in many LNG plants especially the large trains. Gas turbines exist as heavy duty, industrial or aeroderivative. The Aeroderivative gas turbine are becoming popular and widely accepted in the LNG industry as mechanical drives (Ott et al., 2015). Aeroderivative have an improved efficiency which range between 41-44% compared to 30-38% efficiency of heavy-duty machines (Almasi, 2012). An extensive mechanical drive experience with aeroderivative (both offshore and onshore) demonstrated good availabilities even under hostile operating conditions. Site maintenance of aeroderivative is more complex, especially with engines typically being shipped to an authorized repair depot for service. Further, the high power to weight ratio of an aeroderivative engine is significantly important especially in the event a floating LNG facility being planned.

Unplanned downtime associated with equipment failure in both onshore and offshore oil and gas facilities substantially reduces the volume of product sales and decreases the revenue. Perhaps, both cost of downtime and maintenance are the major concern of Oil and Gas operators. In short, profitability of FLNG plant has a direct link with the applied maintenance strategy and reliability of the liquefaction plant (Gowid, 2016). This calls for higher reliabilityin liquefaction most critical equipment (gas turbine) especially offshore when taking into consideration that the FLNG facility is on sea with few or no spare parts due to weight and space constraints. Therefore, retaining a plant's reliability to an optimum level is the highest priority for FLNG process operation and production which can be achieved by adopting a robust maintenance approach to the process system and equipment. It is obvious that systems and equipment degrade and deteriorate over time irrespective of their design robustness. However, the equipment failure complied by NASA and US Navy (NASA, 2008) shows that only 18% of the failures are age related, while 82% of the equipment failures occurs randomly.This indicates that only 18% of the equipment failures can be detected prior to failure using

preventive or time-based maintenance practice alone. The remaining 82% requires more sophisticated maintenance strategies that incorporate a condition and predictive based component to enable early warning to diagnose the failure and be able to proactively predict failure in advance.

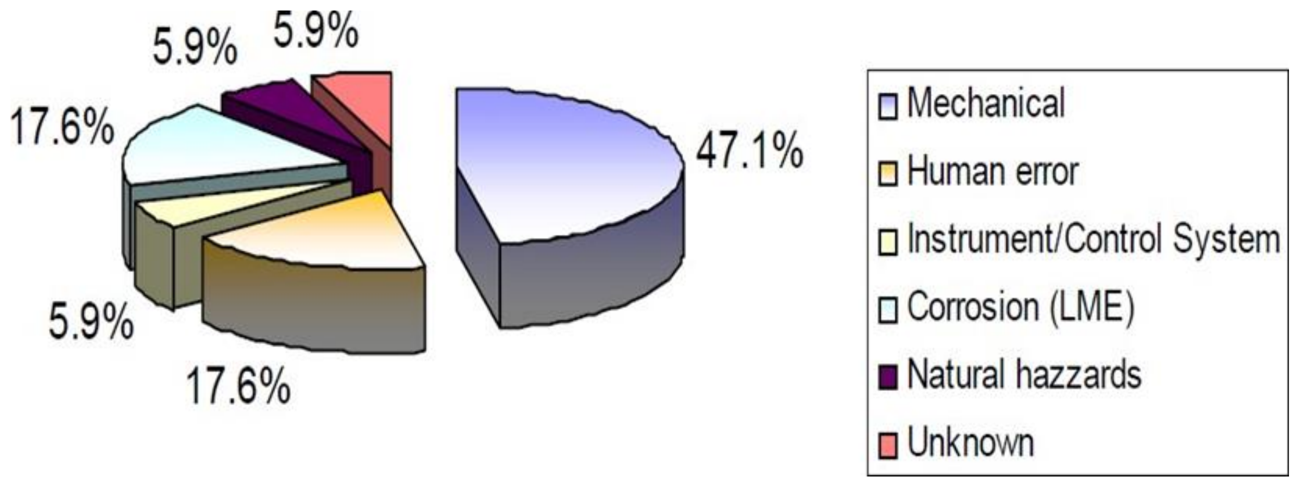


Figure 1.8: Distribution of failure root causes over 60 years of LNG/LPG operations (Angelsen et al., 2006)

Time-based preventive maintenance has been the recognised in oil and gas industry and widely adopted practice to improve for maintenance effectiveness as well as enhancing equipment reliability. It has been observed that the cost of maintenance incurred by rotating equipment using preventive maintenance is 30% less than the cost incurred from reactive maintenance. However, with recent advances in predictive maintenance program, operators have better opportunity to plan maintenance action to an equipment prior to the actual maintenance implementation. As such, predictive maintenance approaches offer more savings (50%) compared to cost of maintenance incurred from reactive maintenance (Moore, 2004).

Considering the criticality of gas turbine in FLNG process facility, it is vital to assign more robust maintenance regime that will enhances equipment reliability and availability. Predictive/Condition based Maintenance (CBM) is a maintenance program that recommend maintenance decision according to information obtained through condition monitoring process (Jardine et al, 2006). Thus, CBM is based on actual condition of the monitored equipment/machine. Therefore, the overall philosophy of CBM is a strategy that shift maintenance processes from fail and fix practice to prediction and prevention of failure (Tehanet al. 2017).

1.2 Motivation of the Research

The development and extension of the LNG into offshore industry is seen as a major improvement and a game changer in the utilisation of the world's energy resources (Benyessaad, et al., 2015). Floating LNG enables production and liquefaction, storage and transfer of LNG from gas fields at sea. FLNG innovations emerges from the technologies of both subsea andmarine facility of Floating Production Storage and Offloading (FPSO) as well as onshore LNG technology (Hwang et al., 2018). Oil andgas FPSOs are known with limited space, sensitive to motion, inherent difficulty towards providing maintenance support among others. As a new concept in the industry, FLNG is potentially recognised to be more dangerous than oil and gas FPSO, with topside liquefaction process more vulnerable and critical to safety (Lee et al., 2014). Perhaps, the topsides gas processes and liquefaction has been identified as one of the great challenges of FLNG, and itsprofitability strongly depends on reliability, availability, and maintainability of these process facilities.

The current most widely used maintenance methods such as breakdown and preventive maintenances used in offshore oil and gas operations are not sufficient to maintain critical FLNG equipment such as gas turbines. Gas turbine as mechanical drive is identified asmost critical with highest availability loss in FLNG process facilities (Benyessaad et al. (2016). The availability, reliability, high safety standard requirement as well as efficient operation of the engine is always the major concern of its users. On this basis, a swayfrom conventional maintenance approaches to more robust, reliable, and cost-effective maintenance is required.

More proactive and advance maintenance method (Condition-based maintenance), pave its way into oil and gas industry by combining multiple solutions, process reliability and system operating optimisation to achieve lowest operation risk as well as delivering the desired output (GE Digital Solutions, 2019). Also, efforts towards enhancing the performance of offshore plant maintenance methods with condition-based maintenance, drawn the attention of researchers. However, very few studies have introduced instances of the condition-based maintenance implementation in offshore oil and gas, with little focus on FLNG liquefaction equipment and non to its critical equipment (Aeroderivative Gas Turbine) as the time of writing this report.

Currently the research for the development of Condition-based maintenance in oil and gas industry is progressing, although it’s still a challenging area especially in the offshore applications. In short, the current approaches have limitations regarding methods and validations. Thus, this thesis introduces approaches and methodologies towards implementation of condition-based maintenance for critical equipment in floating LNG process, i.e., aeroderivative gas turbine.

1.3 Aims and Objectives

The main objective of this research is to address the challenge of failure and downtime in floating LNG critical equipment (Aeroderivative gas turbine) through the design and development of novel approaches and methodologies in modelling, simulation gas turbines based on physics-based techniques. Simulink-based gas turbine model is developed based on thermodynamic equations and mathematical analysis. Although, the simulated data lack detailed features required for the model and hence the utilisation of experimental data. Data-driven AI-based models were built to predict failures associated with gas turbines, especially when exposed to different fuels. These models shall be capable in detecting and predicting incipient failures in the equipment.

Given the results of the literature survey and the contents already discussed in this chapter, the following research objectives are made:

1- Development physics-based gas turbine model based on thermodynamics equations and state space mathematical analysis. Simulink model for gas turbine is developed to understand some dynamic and transient responses of the engine, especially when tuned to various operation conditions. The model output responses or output parameters generated based on input changes can be applied reliably for gas turbine diagnostics studies to predict engine's failures with a high accuracy.

2- Development of data driven AI-based models to reliably perform gas turbines failure diagnostics and predictions. The dynamic response behaviours of gas turbines critically change, when exposed to different types of fuels. A diagnostics-based AI models are constructed to classify gas turbine engine's failures associated with exposure to different types of fuels. The experimental time-series datasets obtained from gas turbine engine facility, represents system responses on exposure to different types of fuel. This data is used to model operating characteristics of gas turbine and its condition monitoring classification.

Feature extraction such as Principal Component Analysis (PCA) and signal processing-based tools are applied, to add more correlations to the dataset and extract good features for the model. Neural Network based model is used further to classify failures associated with different fuels used.

3- Simulate dataset through deep learning-based LSTM model, which extract features from the time series dataset directly, and further perform condition monitoring classification. The objective here is to compare the prediction performance and capability of deep learning-based model against conventional neural network-based model developed.

1.4 Contribution

This thesis is specifically focused on research on floating LNG (transition fuel) and application of digitalisation strategy to maintain the FLNG's critical asset. The thesis identified most critical asset that requires more research attention. In FLNG project, Industrial gas turbine is not compatible offshore, therefore Aeroderivative gas turbine is more preferred in offshore application. However, with limited literature on CBM implementation on FLNG Aeroderivative gas turbine. The thesis contributes in;

2- Surveying a comprehensive current state-of-the-art of predictive maintenance approaches on as turbine applied to floating LNG process. to underpin the appropriate method compatible for modelling and validation of the study.

3- Developing a physics-based model to simulate the operational characteristics of gas turbine, which will further applied on gas turbine condition monitoring studies. Although the model requires further analysis to fit for CBM.

4- Developing an intelligent model capable in detecting gas turbines failures. Data driven AI-based models are constructed with experimental dataset. The models built are efficient enough to predict engines failures, and enhances optimal operations, improve reliability and availability of FLNG critical asset (aeroderivative gas turbine). Therefore, thesis gives deeper understanding on how Predictive maintenance could drive efficiency, improve system reliability and availability of the new FLNG concept.

6- Part of this thesis has been presented at 20th Nigerian Oil and Gas Conference and Exhibition (20th NOG conference & exhibition, 5-7 July 2021). The paper presented is titled "***Predictive Maintenance of Critical Equipment for Floating Liquefied Natural Gas Liquefaction Process: Framework & Benefits***".

1.5 Outline of the Thesis

This study deals with modelling a predictive maintenance model for aeroderivative gas turbines. The entire contents provide new research basis and novel solutions in this area. The thesis is structured as follows:

The 1st Chapter commences with a general representation of background, motivations of the research, objectives of the study, thesis contributions and thesis outline structure.

The 2nd Chapter presents a comprehensive overview of the literature in the field of PdM of aeroderivative gas turbines. It covers the general concepts and design of an aeroderivative gas turbines, gas turbine maintenance in LNG process, condition-based maintenance of FLNG.

The chapter concluded with brief structural modelling architecture of aeroderivative gas turbine's Condition Based-Maintenance.

The 3rd Chapter briefly discuses modelling and simulations of gas turbines. It covers challenges and significance of gas turbine model in LNG process. Both white-box and black-box gas turbine models were treated, with brief introduction of grey-box gas turbines models. The theories and fundamentals for gas turbines modelling based on white-box model have been covered. The chapter concluded by establishing a case study for modelling and simulation of gas turbines. A Simulink gas turbine model is constructed based on the thermodynamic and energy balance equations in MATLAB environment, and the output responses were recorded for further PdM studies.

The 4th Chapter Presents modelling and simulation of gas turbines based on data driven modelling approach. An experimental time series dataset is used to classify anomalies associated with gas turbine's exposure to different fuels. Feature extraction tools such as PCA-based and signal processing-based are used to prepare the dataset by reducing its dimensionality and extracted good features for gas turbine diagnostics modelling. A model based on neural network is developed further to classify the gas turbine engine anomalies. Deep learning-based LSTM model is used to develop a diagnostics model for gas turbine. The overall models are tested and validated against unseen dataset, and performances of the models are compared.

The 5th Chapter represents the final chapter and covers overall conclusion of this research, discusses future work and area of possible improvements on aeroderivative gas turbines condition based-maintenance research work.

1.6 Summary

This chapter introduced a background development behind the growing influence of LNG as an energy mix and important fossil fuel in the energy transition. Then preceded the discussion on motivations for this research. The contributions of this thesis have been briefly explored. Finally, the chapter highlighted key objectives of the research work as well as study outline of the thesis.

Chapter 2

Literature Review

2.1 Concept of Floating Liquefied Natural Gas

While onshore LNG facility is a well-established mature process, the floating LNG is relatively new concept (Saavedra, 2017). Although, the concept of floating LNG has been studied since the mid- 1970s with very low progression until May 2011, when the Shell Oil company decided to develop floating LNG (Prelude) to be operated in the Timor Sea. Since then, many projects and research regarding FLNG continue to emerge progressively (Songhurst, 2016). As at the time of writing this thesis, only Petronas Floating LNG (PFLNG1) is commercially operating on the sea. PFLNG1 saw its first LNG drop in December 2016, first cargo in April 2017 followed by performance test in June 2017 (Su, 2018). Although Prelude made its way to the Sea, but the LNG commercial export hasn't yet started.

FLNG blends the technology of land-based LNG industry, offshore oil and gas industry and marine transport technology. The FLNG design architecture as defected in Figure 2.1 constitutes topside, storage mooring and turret systems. The topside mainly contains both process and liquefaction units. The raw natural gas from the subsea well is transferred to the topside via risers and turret. The process unit takes in the in raw natural gas and remove impurities (C02, sulphur etc.). The liquefaction compresses and transformed the gas into LNG which is then transferred into a hull for storage. The stored LNG is normally transferred to arriving LNG carriers through uploading equipment (Aronsson, 2012).

Given the availability of conventional onshore LNG, many questions will arise on why floating LNG are considered? Perhaps this translates to the key benefits of FLNG over the conventional

LNG facilities. Some of the advantages of FLNG over onshore LNG were observed by (Abe et al., 2018; He et al., 2018) as;

- Cost saving by eliminating subsea pipelines from the offshore gas fields to the shores.
- Cost saving opportunity by employing lower labour rates at shipyards as opposed to higher labour rate in the regions where onshore LNG projects are executed.
- Opportunity to develop and monetise stranded gas fields as well as the redeployment to another gas fields upon the production decline which save the operators from full sunk experienced with onshore plants due to mobility challenges.

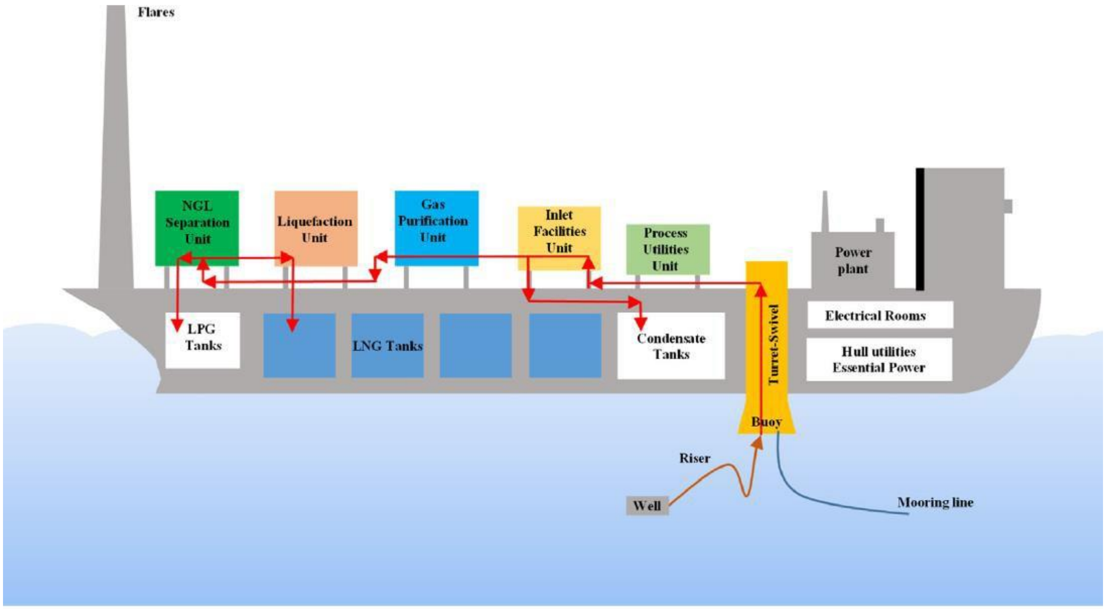


Figure 2.1: Typical FLNG layout (He et al., 2018)

Table 2.1: Selection of various liquefaction technologies (Eckhardt, 2010 and Lee et al.,2014)

Category	**Technology**	**Cascade**	**C3-MR DMR**	**SMR**	**N2 Expander**
Suitability to LNG FPSO	Equipment counts for liquefaction	50—65	45-65	40-55	12
	Process sensitivity to motion	Yes	Yes	Yes	No
	Ease of start-up/operation	Low	Low	Low	High
	Flexibility to feed gas changes	Medium	Low	Low	High
Safety issues	Storage of HC refrigerants	Yes	Yes	Yes	No
	Cryogenic equipment counts	High	High	Medium	Low
	Space requirement	High	High	Medium	Low
Efficiency	Thermal efficiency (% of HHV)	91%	92%	89%	84%
	Availability	Medium	Medium	Medium	High
	Specific investment	High	High	Medium	Medium

Selecting the right liquefaction process is critical to FLNG process. Various criteria have been adopted in selecting appropriate FLNG process architecture as presented in Table 2.1. Many researchers work have their specific interest on some process configurations depending on their preferences and requirements. Li and Ju (2010) considered performance parameters such as economic performance, layout, sensitivity to motion, suitability to different gas resources, safety and operability as well as accountability of for the liquefaction process to marine environment as selection criteria. In their study, the authors compared Propane pre-cooled mixed refrigerant (C3/MRC), mixed refrigerant cycle (MRC) and Nitrogen expander (N_2 Expander) liquefaction technologies for their suitability in processing associated offshore gas in South China Sea. The result obtained by the authors found N_2 Expander as the most suitableliquefaction process despite its setbacks regarding poor economic performance and higher energy consumption compared to the other two process technologies. Perhaps its size compactness, higher safety, less sensitivity to FLNG vessel motion and simplicity in operationsmakes it more preferred option for FLNG offshore applications.

Although some researchers like Li and Ju (2010); Gowid et al. (2015); and Lee et al. (2014) considered the possibility of adopting C3/MRC in the floating LNG applications due to its high efficiency and proven reliability which accounts for 66% of the total onshore LNG trains in 2013 as reported by WORLDLNG Report (2014). But recent studies found C3/MRC unfit for floating LNG application especially because the major technology driver for offshore applications considers weight and space as priority. Propane pre-cooled mixed refrigerant usekettle chillers and heat exchanger with large flammable liquid refrigerant inventories. As such the large footprint (space and weight) consumed by these pieces of equipment makes C3/MRC unfavourable for FLNG liquefaction process technology (Tierling and Attaway, 2017). This limits the selection to only Nitrogen expander (N_2 Expander), Single mixed refrigerant (SMR) and dual mixed refrigerant (DMR) as illustrated in Table 2.2. Nitrogen expander has been chosen as a liquefaction process for the first floating LNG on the sea (PFLNG1) and the selection criteria was reported by Ahmad et al. (2014).

On the bases of scaling capacity criteria, Castaneda (2015) and Tierling & Attaway, (2017) differs in selecting liquefaction technology for small and mid-scale capacity. Castaneda (2015) selection is shown in Table (2.2), while Table 2.3 illustrated the selection criteria forTierling and Attaway (2017). Therefore, regardless of the selection criteria followed, successof any FLNG application is tied to the liquefaction technology that is proven, reliable, space efficient and as well as simple to operate.

Table 2.2: **FLNG Liquefaction selection based on capacity (Castaneda, 2015)**

Capacity MTPA	**Liquefaction Technology**
<0.2	Expander process Nitrogen expander Feed Gas (Niche process)
2-3	Single Mixed Refrigerant PRICO SMR
>3	DMR

Table 2. 3: FLNG Liquefaction selection based on capacity

Capacity	Liquefaction Technology	Reason
Small scale	SMR	Footprint (Space & Weight)
Small-Midscale	N_2 Expander	Less sensitive to motion
Large scale	DMR	Higher efficiency and safety

2.1.2 Gas Turbine as FLNG Compressor Mechanical Driver

One of the key challenges of FLNG lies on the appropriate selection of refrigeration compressor driver (Kumar and Jang, 2017). Perhaps selecting the driver type with right configuration is significantly important and has a direct impact on the overall performance, efficiency availability as well as profitability of FLNG facility. Some considerable research work covered LNG equipment selection, with refrigerant compressor driver selection receivesmore attention in the publications. The compression driver options reviewed involves steam turbines, industrial gas turbines, aeroderivative gas turbine and electric motor. However, for applications that requires significant mechanical shaft power beyond 1 MW such as LNG compression, a direct drive arrangement prompt most suitable always. Gas turbine engine is a direct drive turbomachinery which is popular in oil and gas and chemical process industry. These industries use gas compressors, blowers/fans and pumps (Solar Turbines, 2011;Jansohn, 2013).

As mechanical drive, gas turbines have been applied in many LNG plants especially the large trains. Gas turbines exist as heavy duty, industrial or aeroderivative. Industrial gas turbine is the most widely used driver for refrigerant compressor over the last two decades. However, theheavy-duty industrial gas turbine has many setbacks that makes it unsuitable for FLNG applications. For instance, low thermal efficiency (30-38%), high specific fuel consumption, give rise to increased emissions and extensive maintenance requirements **(**Bardon, 2016). In addition, its constrained with limited speed range, and as such requires an auxiliary large variable speed motor for start-up, which requires more space on FLNG deck and additional cost. Hence, the concern on emission reduction, improved reliability and improved thermal efficiency of the refrigerant driver lead LNG operators to search for more sustainable, reliableand efficient driver (Almasi, 2012).

Aeroderivative gas turbine are becoming popular and widely accepted in the LNG industry as mechanical drives (Ott et al., 2015). They have an improved efficiency which rangebetween 41-44% compared to 30-38% efficiency of heavy-duty machines (Almasi, 2012). Improving plant efficiency centred around two areas which involves turbomachinery and cryogenic heat exchanger. However, considering the maturity of LNG liquefaction processes, little further tightening modification could be done to exchanger temperature approaches. Hence, that leaves two areas that significantly influences plant efficiency, i.e., refrigeration compressors and gas turbines drivers. However, harnessing improved efficiency throughrefrigerant compressors has little impact, especially given that their efficiencies are already inthe high 80s. Therefore, appropriate selection of gas turbine determines both thermal efficiency and carbon emission for the liquefaction turbomachinery. As such, improved efficiency and emission reduction are some key benefits of aeroderivative compared to industrial gas turbines(Habibullah et al., 2009).

Recently, aeroderivative gas turbine has been applied in LNG application in Darwin onshore plant, Australia. This is the first instance where aeroderivative gas turbine is applied to LNG operations and has been successfully operating from 2006 to date. However, given the little experiences of aeroderivative gas turbine mechanical driver in the LNG onshore, how compatible it is to fit into offshore LNG operations?

Several critical parameters are essential when selecting an appropriate refrigerant compressor driver for FLNG configuration. Some of these parameters were identified by Kumar and Jang (2017) as footprint size, weight, starting methodology, thermal efficiency, ease of operation, hazardous area "Ex" use, availability, impact on other system economics and operational advantage, marine environment use (marinization), operator comfort and life cycle cost. All these factors are critically important and drives the choice on appropriate selection criteria. However, more critical choice lies primarily on weight, footprint and serviceability at the offshore location as well as thermal efficiency. Aeroderivative gas turbines as developed fromaircraft jet engines acquired some unique features aircraft engines such as lightweight, fuel efficient, easily swapped in and out of service, and ability to quickly ramp the power up and down. Perhaps, these features made aeroderivative gas turbines suitable for mechanical or compressor drives for FLNG (Ott et al., 2015).

The selection of aeroderivative gas turbines to floating LNG applications has motivations that lies on its technical capabilities and commercial benefits. Couple with the challenges of offshore environment ranges from metocean conditions and logistics, an equipment with proven reliability, availability, maintainability, flexible operating conditions, efficiency, low emission and small footprint stands the most preferred choice. Aeroderivative gas turbine met these conditions compared to any other mechanical drive equipment in the offshore floating LNG applications.

2.2 Aeroderivative gas turbine Concept and design

The aeroderivative gas turbine are originated from aerospace industry as the prime mover of aircraft. The concept has been adapted to the electrical power generation industry by removing the bypass fans and addition of power turbine at the exhaust. Aeroderivative has an output power ranges from 2.5 MW to about 50 MW and efficiencies ranges between 35-45% (Boyce,2006; Doom, 2013). The architecture of aeroderivative gas turbine is characterised with multi-shaft design (two or three shafts). The power turbine sits on a separate shaft which allows the speed adjustment without the need a gearbox (Del Greco et al., 2018). The machine also consists of two basic components (an aircraft-derivative gas generator and a free-power turbine). The energy or gas horsepower is produced by gas generator which is a component derived from an aircraft engine and modified to burn industrial fuels. This component (gas generator) raises combustion gas products to conditions of around 45-75 psi (3-5 Bar).Conventional aircrafts engines have fan jet which are removed and replaced by some additionalcompression stages in front of the existing low-pressure compressor. In many cases, the axial flow compressor in aeroderivative gas turbine is divided into low-pressure and high-pressure sections. In those case, turbine is usually comprising of low-pressure turbine and high-pressure turbine which drive the corresponding sections of the compressor. The shafts of aeroderivativeengines are usually concentric. This significantly enables speed optimisation of the low- pressure and high-pressure sections. Hence, the power turbine is separated and mechanically uncoupled with the connections only via an aerodynamic coupling. In these cases, the turbines have three shafts with all operating at an independent speed (Boyce, 2006). Figure 2.2 depicted a typical aeroderivative gas turbine.

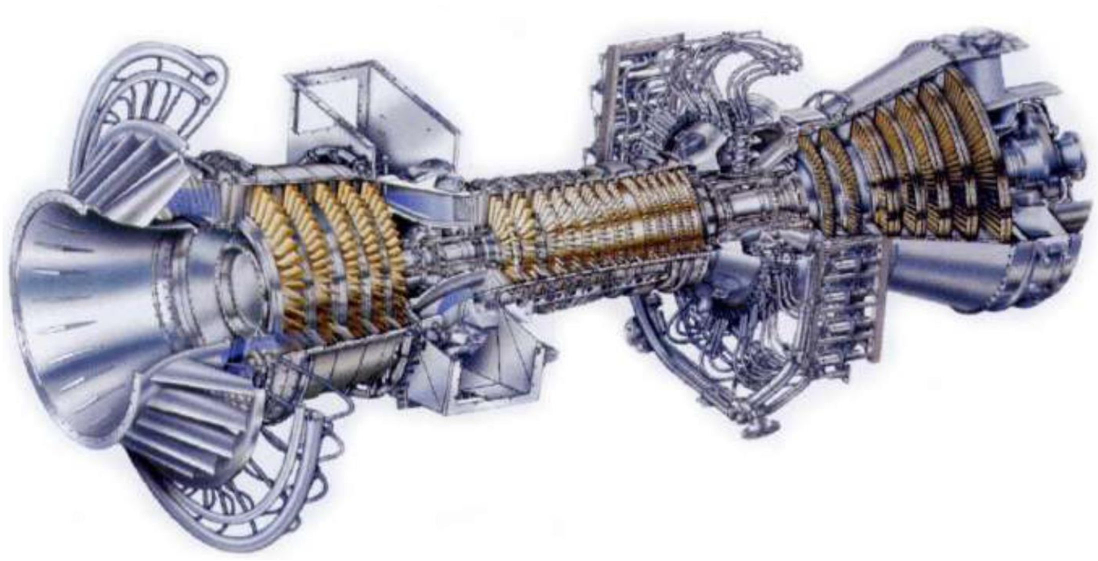


Figure 2.2: Typical Aeroderivative gas turbine LM 6000 (McMillian, 2013)

Like all gas turbines, Aeroderivative gas turbine follows Brayton Cycle. It takes in air and continues injection of fuel to create hot and pressurized gas flow which expands through the turbine. Then process begins by pressuring the incoming air by a compressor through its stages. This pressurisation compressed and heated the air which subsequently passed to the combustion chamber where chemical energy from the burning fuel adds more heat. The hot and pressurised air expands and follow through turbine blades to rotates the shaft that drives the compressor at the front of the engine and the cycle continues. The shaft is normally connected to either external generator for power generation or as a mechanical drive to refrigerant compressor or pumps. However, for efficient energy conservation, the remaining energy not used in driving the shaft can be captured in useful ways for various applications in the plant (Doom, 2013).

Various gas turbine Original Equipment Manufacturers (OEMs) design and develop various types of gas aeroderivative gas turbines for both power generation and mechanical drive applications. Some of the most popular aeroderivative gas turbine include GE (LM 2500 class& LM 6000 class) and Siemens SGT-A45 and SGT-65. LM 2500 has proven experience in marine ships propulsion and offshore oil production. Some research effort has been put to investigate some experience and lessons regarding the applications and operations of some aeroderivative gas turbine in offshore and marine environment. Spector and Cimino (1990) investigated 10 years' experience of GE LM 2500 gas turbines operating at North Sea offshoreplatforms. The study specifically focused on some operational experience, maintenance philosophy, reliability and some advantages of the engine given its record of over one millionhours of operation in North Sea at the time of the study. The evaluation of success and challenges of the LM 2500 operating experience revealed an unexcelled level of reliability and availability. Some recommendations were further given by the authors which aimed at enhancing reliability, availability and application flexibility of the LM 2500 engines in offshore applications. As such many developments has been occurred resulting to the evaluation of many versions of LM 2500 by its OEMs.

Recently Meher-Homji et al (2008) reviewed the operational experience of world's first aeroderivative gas turbines in LNG applications. The author discussed design, manufacture, testing, implementations as well as operational experience and lessons learnt from deploying aeroderivative into LNG application as a mechanical driver. The study discovered an overwhelming operational performance of the plant over two years operation. The result obtained by the study met all the expectation as well as exceeding the LNG production performance. Infurther investigation by Maher-Homji et al (2011), the authors conducted another study to evaluate four years operational experience. Design compatibility, maintenance implementationas well as debottlenecking activities were further investigated. Since installation, the plant has been successfully operated over 4 years as at time of the study. Likewise, the previous study, the authors reported that the expectations and production goals we met and exceeded. The debottlenecking activities that have been implemented by the plant has been well covered and extensively discussed by the authors. The over result success and failure discovered in these two studies is profoundly essential especially to many FLNG operators who deploys aeroderivative gas turbine into offshore floating LNG application with no experience in offshore liquefaction process. Figure 2.3 shows the aeroderivative gas turbine installed andoperated by Darwin LNG plant.

Figure 2.3: Aeroderivative gas turbine (LM2500+) being Installed at Darwin LNG Plant(Meher-Homji et al., 2011)

2.3 Maintenance in LNG Process

Machines/equipment suffers changes during its operating life due to deviations from its standard design state, leading to a reduction of its reliability and availability (Leturiondo, 2016). Faulty equipment poses the threat of a full breakdown or outage of the LNG plant. Likewise, equipment/ machines operating at wretched condition may not fail completely, but certainty their efficiency and output will be reduced. Hence, raises operating costs and impactproduction performance negatively (STI Group - Industrial, Midstream & Fabrication Services, 2015). However, with good maintenance practice, minor and major problems in LNG process plant could be detected before they escalate and poses negative consequences. Therefore, Maintenance is crucial towards assurance of machines health condition, which is equally essential to determine the optimum moment to replace or repair them (Leturiondo, 2016).

The maintenance works, inspection, refurbishments, and parts replacement are performed to keep equipment and systems efficient and operate within a tolerable design life. Maintenance can be regarded as a strategy and actions implemented during the plant's service life, requiredto ensured safe, reliable, and cost-effective operation of the assets. Thus, LNG plants performance strongly depends on availability and reliability of critical equipment/systems as well as their safe operation and cost effectiveness in maintaining them. Perhaps, the importanceof reliability improvements to make the LNG plants more competitive and profitable prompts the need for adopting sophisticated technology for inspection and maintenance optimisation (Angelsen et al., 2006) especially on critical LNG assets.

Similarly, one of the primary goals of adopting good maintenance at LNG plants/terminals is to improve and maintain safety levels. Although LNG itself cannot burn until it is mixed withair, and is unlikely to explode, but the presence of other potentially dangerous gases and compounds that are used in the refrigeration or re-gasification process could explode if mishandled or allowed to leak. Mishandle or leakage could be associated with faulty equipment and machinery, hence potentially leads to the risk and occurrence of explosion or of an accident (STI Group - Industrial, Midstream & Fabrication Services, 2015). Therefore, safety is another critical important factor for LNG process. In short, with unprecedented increase in LNG production value chain involving processing, transporting andconsumption, raises public concern on the environmental risk, safety and health associated withthe LNG. This has direct relation with the design, operation and maintenance of LNG facilities.

Some accidents have been recorded in LNG industry with consequential revenue damages, lossof lives and refutation. The first LNG accident occurred at Cleveland, U.S which injured 225 people and killed 131 people with huge damages in facilities and infrastructures. In 2003, An explosion occurred in Malaysian LNG plant (MLNG Tiga) train 8. No casualties or injuries were recorded, but the incidence raised public concern. Algerian LNG plant exploded in 2004,killed 27 workers and causes an estimated damage of $1 Billion. Another explosion for Algerian LNG plant occurred at Skikda town in 2005, which rendered 72 people injured with 28 casualties. Skikda accident was worst LNG accident since 1973 when the catastrophic explosion at Staten Island, U.S. claimed 40 lives (Angelsen et al., 2006). Most recent LNG accident was the Plymouth LNG explosion, occurred in 2014 at Plymouth Washington, U.S, which injured 5 people and claimed $69 million damage (Powell, 2016). More details regardingincidences of LNG accidents can be sourced from (Riley and Riley, 2016).

A review for over 60 years of LNG plant operations shows that the various root causes of incidences for LNG accidents reported are associated with mechanical failure of equipment and storage tanks, including brittle fracture account for 47.1% of the failures. Corrosion failuresrelated to operation of cold boxes and mercury liquid metal embrittlement, accounted for 17.6%. This indicates that about 65% of the major root causes can influenced by maintenanceand inspection activities. Hence, optimizing maintenance and inspection activities for criticalequipment such as gas turbine is necessary to improve the overall plant reliability, availability, and safety (Angelsen et al., 2006).

2.4 Gas Turbine Maintenance in LNG Process

2.4.1 Overview and Significance

Gas turbine equipment especially when operated in the cryogenic LNG process or offshore environment often runs under rigorous conditions. Subjecting this equipment to rigorous operating condition and harsh operating environment, exposes them to corrosion, erosion and wear. At the same time, day to day operations induces ageing-related factors that consequently leads to its deterioration and degradation. If these effects are not monitored well, they can leadto unexpected failure which significantly affects the performance, efficiency and productivityof the entire process plant. Consequently, this could also lead to large financial losses, imposeshealth and safety problems to the operating personnel on board and creates major environmental pollution. However, with improved equipment reliability and systemavailability, these effects will be mitigated. But can only be achieved by proper monitoring andinspections on the right equipment in the right location at the right time on the right informationthat guides in carrying out the necessary maintenance, modification, or replacement (Ratnayake, 2015).

The cost of maintenance and machine availability are two most important concerns to gas turbine equipment owners (Eggart et al., 2017). The need for maintenance is usually predictedon actual or impending failure depending on the plant's maintenance approach and strategy. Thus, FLNG plants performance strongly depends on availability and reliability of critical equipment/systems as well as their safe operation and cost effectiveness in maintaining them. Therefore, to ensure seamless operation of gas turbine mechanical driver with optimum availability and reliability, appropriate maintenance process scheme such as periodic inspection, repair, and replacement of parts, must be established and planned accordingly (Knorr and Jarvis, 1975).

Gas turbine components can be categorized into two, i.e. (i) those that require most frequent maintenance attention and (ii) those that involves long term maintenance consideration and planning. The gas turbine components that require the most careful attention are those relatedto combustion process, together with those exposed to the hot gases discharged from the combustion system, which are regarded as the combustion section and hot gas path parts. These components include combustion liners, end caps, fuel nozzle assemblies, crossfire tubes, transition pieces, turbine nozzles, turbine stationary shrouds, and turbine buckets. The other gas turbine parts that need long-term maintenance consideration and planning involves compressor rotor, turbine rotor, casings, and exhaust diffuser (GE Power Atlanta, GA, 2017).Therefore, to ensure seamless plant operations, a robust, efficient, and flexible maintenance strategy must be developed for both components with high maintenance frequency and those with long term maintenance requirements. This significantly improves the reliability and availability of gas turbine assets and, consequently decreases the number of unpredicted breakdowns, operating costs, and downtime. Thus, a successful implementation of the right maintenance scheme for gas turbine, is tied to proper inspection and planning. The maintenanceplanning for gas turbines depends on some factors as indicated in Figure 2.4. 1n short numerous trade-offs among environmental, technological, economic and operational factors help towards establishment of successful maintenance and operational strategy for gas turbineassets (Tahan et al., 2017 & Hoeft and Gebhardt, 1993).

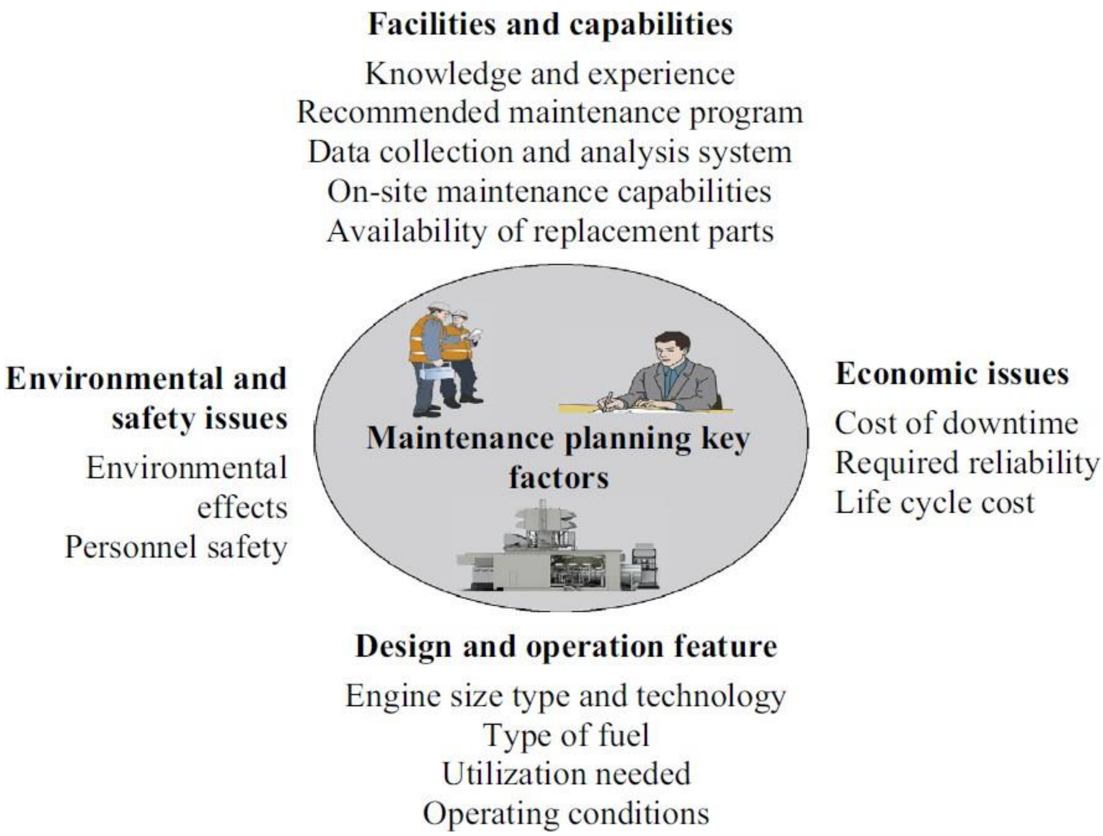


Figure 2. 4: Principal factors that affect gas turbine maintenance planning (Tahan et al.,2017, Hoeft and Gebhardt, 1993)

2.4.2 Types of Maintenance Schemes

The goals of FLNG operators are tailored towards safe operation without harming the personnel and safeguarding the ocean environment whilst generating revenue. These objectives are only achievable when right and appropriate maintenance policy has been implemented to critical equipment such as aeroderivative gas turbine. However, maintaining an equipment in offshore platform is one of the toughest challenges to the maintenance engineers. Various maintenance strategies have been applied in maintaining industrial equipment, depending on the established maintenance policy of the operator. Thus, there are three basic maintenance approaches as classified by (Niu, 2017) as;

- Breakdown or run to failure maintenance
- Preventive or time-based maintenance
- Predictive or condition-based maintenance

2.4.2.1 Breakdown Maintenance

The breakdown maintenance also known as unplanned maintenance strategy, is usually implemented to repair equipment only after the manifestation of defect, or total breakdown (fixit when breaks). In this maintenance approach, the equipment is allowed to run until a given component(s) fail. No prior efforts or action is taken to maintain the system/component as recommended by OEM until when its completely failed. In short breakdown maintenance practice failed to take into cognisance the stochastic nature of the system failure and plan for maintenance, until the ultimate breakdown. When equipment/machine breakdown, there couldbe a tendency for production disruption which may likely leads to the stoppage of the entire plant especially when critical equipment are involved (KARIBO, 2017). When the unit/component fails, an imperfect corrective maintenance is undertaken (Kouedeu et al., 2014), which involves replacing or repairing the failing unit. (KARIBO, 2017)

Breakdown maintenance usually occurs as an emergency and therefore requires a cost premium (Monks, 1996 and KARIBO, 2017). As such, adopting this maintenance practice is always associated with unscheduled downtime with severe consequences. It is important to note that, this type of maintenance scheme is not compatible with aeroderivative gas turbine, especially when operated in FLNG. Although some non-critical components in the FLNG process whose failure may not halt the production process, could be subjected to this type of maintenance approach. Figure 2.5 indicated the flow chart of breakdown maintenance processes.

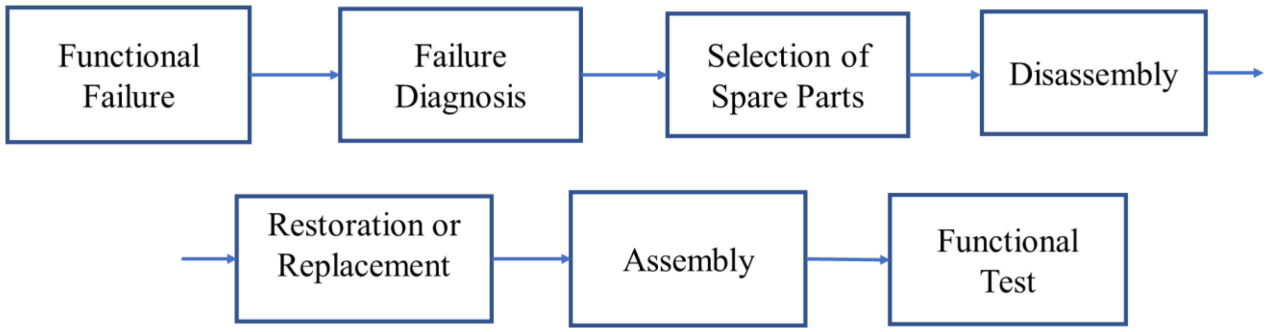


Figure 2.5: Breakdown or Unscheduled maintenance flow chart (Souza, 2012)

2.4.2.2 Preventive Maintenance

This is essentially implemented at a predetermined scheduled interval withthe aim in minimising the probability of failure and degradation (Kothamasu et al., 2006). Unlike breakdown type, the preventive maintenance strategy is planned, more effective and robust. As the name suggests, the maintenance is implemented prior to the equipment failure. This maintenance strategy enables more utilisations of resources compared to reactive. Its implemented using statistical information and operational experience to schedule successive overhaul to safeguard the equipment from unexpected failure. Successful implementation of this type of maintenance scheme helps in identifying potential areas of failure in an equipment/system, which by extension helps in avoiding unplanned breakdown and its consequence (KARIBO, 2017). This is succeeded by inspection, service and replacement of parts before they fail. Figure 2.6 shows the flowchart of Preventive maintenance. More details regarding preventive maintenance and its further classification could be found in Ben-Daya et al. (2009).

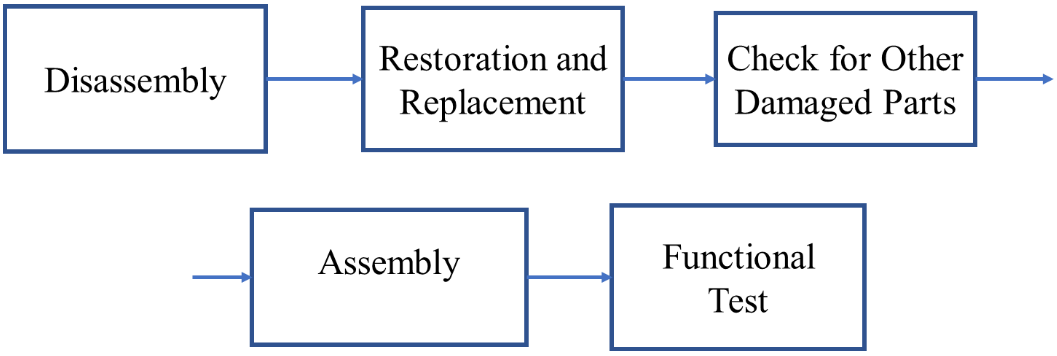


Figure 2. 6: Preventive Maintenance Flow Chart (Souza, 2012)

Preventive maintenance scheme is applied in LNG industry to maintain critical equipment like gas turbine and its components. This is achieved by undertaking routine and schedule servicing at certain intervals. Usually, the gas turbine engine or any other element is withdrawn from service at scheduled intervals to perform inspection or repair. Aeroderivative gas turbine normally has fast cooldown and less maintenance time, i.e., 20-48 hours changeout.Unlike Heavy duty type whose maintenance time is longer, i.e., 20-28 days changeout. This maintenance philosophy has been the practice and classic way to operate and maintain gas turbine engine in the past and even nowadays (Tomas, 2015 and Burke, 2011). Although despite its advantages over reactive type, yet preventive maintenance has some setbacks. It is often not cost effective especially given the possibility of replacing component (s) or elementswith substantial operating life left. Hence, increases the number of scheduled maintenance outages unnecessarily.

The scheduled maintenance intervals for gas turbine turbines are normally determined by the OEM according to the statistical analysis of the fleet, i.e., MTBF, MTBO, reliability, availability, among others. Other factors include design practices and safety considerations. The time-based maintenance schedule for aeroderivative gas turbine has been defected in Table 2.4.

Table 2. 4: Aeroderivative classic preventive maintenance schedule (Tomas, 2015)

Maintenance Activity	Operating Hours
Semi-annual (including BSI)	Every 400
Hot section repair (gas only)	Every 25,000
Maintenance Outage Hours	Every 50,000

It shall be noted that the Table 2.4 is obtained based on units that reflects typical operation with few starts and many hours per year (>6000 hrs). Some maintenance activities will be recommended according to starts (i.e., semi-annual at 450 starts)or event time (annual, semi-annual) for units with different operational profiles.

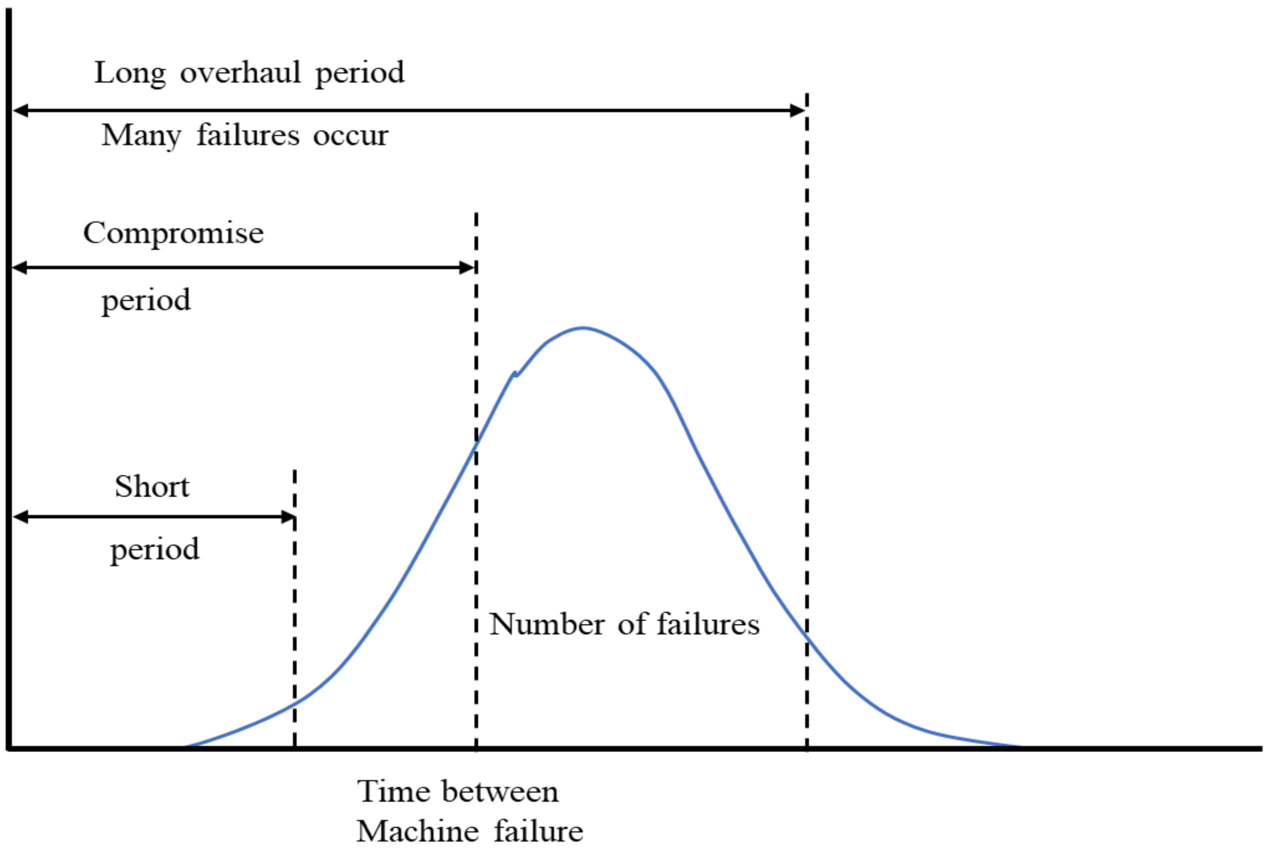


Figure 2. 7: Engine failures and overhauls intervals (Burke, 2011 and Tomas, 2015)

Figure 2.7 demonstrated how the maintenance interval is set. For instance, if the period is long, quite many events might occur. Conversely, when the window is too short, a large considerable amount of life is left in the engine and increases the maintenance outages. Thus, for optimal maintenance, the correct number is always a compromise (Tomas, 2015).

2.4.2.3 Predictive Maintenance

This maintenance philosophy involves scheduling maintenance only when functional failure is manifested and detected (Scheffer and Girdhar, 2004). The mechanical and operational conditions of the equipment are consistently monitoredwhich reveals the current state and health status of the asset. When an unhealthy trend is detected, appropriate correction action will be taken to mitigate the failure effect. This helps inavoiding unnecessary maintenance tasks by restricting maintenance action only on justifiable evidence of abnormal behaviours manifested from physical assets (Romesi and Li, 2013). Theflow chart for predictive maintenance is shown in Figure 2.8.

More capabilities could be herness by implementing predictive maintenance in the processes and manufacturing industries by minimizes failure risk, as well as enhances and maximises theuseful life of an asset. In addition, more lead-time window is allowed to purchase component that requires replacement. Thus, reducing the need for large inventory of spares, since the maintenance action is carried out only when needed. (Scheffer and Girdhar, 2004; Pektas and Pektas, 2018). Some of the values that could be harnessed by implementing PdM has been highlighted by Gang (2017) as;

- Return on investment: 10 %,
- Reduction in maintenance costs: 25–30 %,
- Elimination of breakdowns: 70–75 %,
- Reduction in downtime: 35–45 %, and
- Increase in production: 20–25 %.

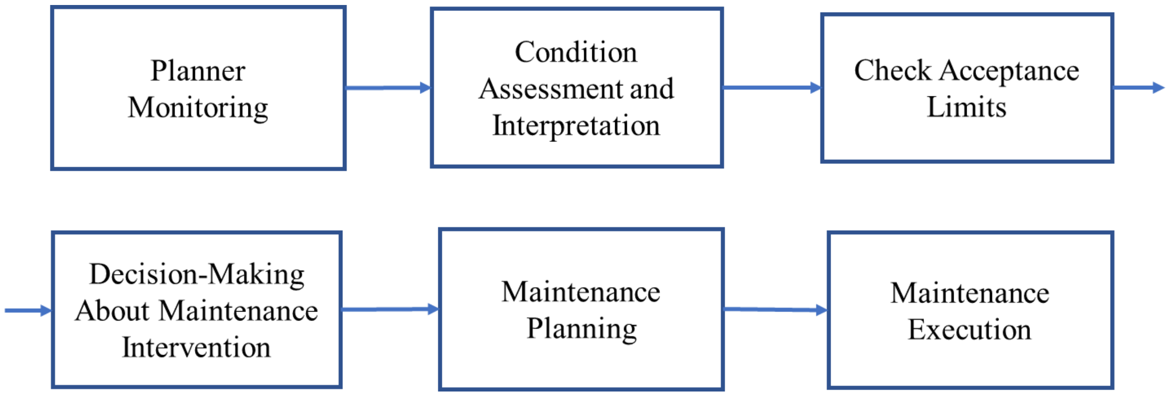


Figure 2. 8: Flow chart for predictive maintenance implementation (Souza, 2012)

Condition-based maintenance can be applied to any system, although the focus of this research work is based on FLNG Aeroderivative gas turbines. Implementing predictive/CBM on gas aeroderivative gas turbines requires some sequence of processes which will be explained in section 2.6.

2.5 General Maintenance Concepts of Aeroderivative Gas Turbine

The general philosophy in the industry for maintaining aeroderivative gas turbines involves three main concepts, i.e. On condition maintenance, minimize downtime and maximize on-site maintenance capability

2.5.1 On condition maintenance

Under this concept, gas turbine components or units are repaired or replaced only when it is required. Furthermore, this is the underlying concept of condition-based maintenance, which is the focus of this study. More details will be discussed in section 2.6.

2.5.2 Maximize on-site maintenance capability

Given the similarities between aeroderivative gas turbines and aircraft engines, the former leverages some design and maintenance features of the latter. Thus, based on these similarities, aeroderivative gas turbine maximize the on-site maintenance capabilities of aircraft as observedby (Tomas, 2015, Siemens, 2014 and GE, 2013);

- Modular design of the engine enables on-site exchanges for major components like High Pressure Turbine (HPT), without total engine disassembly. This permits component(s) exchanges whilst major overhaul work is conducted on the facility. Hence, reduces the turn time whist carrying out maintenance overhaul for the engine.
- Possession of borescope enable easy one-site Non-Destructive Testing and inspections on the engine. Hence allow access to impossible-to-reach area such as high temperature portions of the turbine without dismantling the engine.
- Some vital engine components such as controls, accessories (gearbox, seal etc) and sensors are externally oriented, and thus can be easily replaceable.
- Compressors are typically of split design. Blades can be easily repaired and replaced on site.
- The split design nature of engine allows on-site repair and replacement of compressor blades, stator vanes as well HPT blades easily

2.5.3 Minimize downtime

The characteristics design of aeroderivative gas turbine, and its lightweight feature enable quicker exchange on-site while conducting major overhaul (GE, 2013). The maintenance simplicity of aeroderivative gas turbine is one of the key benefits to LNG operators (Meher-Homji et al., 2018). The aeroderivative engine can be changed and quickly (GE, 2013), especially when the need for major overhaul arises, the gas turbine enclosure design allows easy removal, with the aid of preinstalled crane or removal cradles (GE, 2013). Sometimes, flange to flange engine can be replaced (for engine type such as LM6000) or the exchange of gas generator section in for engine with free power turbine like LM2500 (Meher-Homji et al.,

+

Figure 2. 9: Gas Generator Removal (Left) and Power Turbine Removal (Right) (Meher-Homji et al., 2011 and Meher-Homji et al., 2018)

2.6 Condition-Based maintenance of Floating LNG Critical Equipment

FLNG takes liquefaction technology into a floating production system to exploit stranded offshore gas. Floating LNG concept have been briefly introduced in section two, with critical units, appropriate process configurations as well as critical equipment for FLNG operations being identified. Uptime availability of the liquefaction process unit is the highest priority of LNG operators, its importance in LNG value chain as reported by Zainal-Abidin et al. (2011) accounts for 30-40% of the overall LNG production cost. However, maintenance priority shallbe directed to most critical equipment in the liquefaction plant. Gas turbines (Aeroderivative) as identified by Benyessaad et al. (2016) is the most critical equipment in FLNG liquefactionunit, accounting for (32%) failure criticality. Given such criticality, priority shall be given to this equipment in respect to maintainability, reliability, and its availability in the FLNG processunit. Scheffer and Girdhar (2004) highlighted how critical equipment could be identified in the process plant and recommends appropriate maintenance philosophy to be applied to them.As described by the authors, critical machines are costly, very expensive to repair and have a longer repairing time, and since they are expensive, keeping a spare standby equipment could be unprofitable.

On the other hand, better utilisation and operation of such critical equipment could saves energy and improve production. However, their failure can affect the entire plants' safety and their shutdown curtails the production process. Perhaps, with 65% of the overall LNG failures associated with equipment (Forte et al., 2017), the maintenance cost, reliability and availability of critical equipment are some of the most important concerns to the LNGoperators. As such, this makes a predictive maintenance (PdM) philosophy more suitable for critical equipment such as gas turbines in floating LNG (Scheffer and Girdhar (2004). PdM seemly provides a smooth operation of offshore platform by advanced maintenance prior to the occurrence of failure. It plans for more advanced intelligent maintenance actions and enables assess to degradation properties of facilitiesoperated in poor environment like offshore platforms (Hwang, 2015). This enables further quantification of health condition parameters of a system and/or its components that are continuously monitored whilst being in operation (Kothamasu et al., 2006).

The cost of maintaining gas turbines is significantly higher than its original purchase cost (Wanet al. 2018). For instances, SIEMENS version (V94.3A) gas turbine is estimated to cost 51,340,000 Euros based on its maintenance schedule in its 40 years life expectancy. This costis 17.8 times to its initial purchase cost, i.e. 2,867,000 Euros **(**Aminyavari, et al., 2016). Although maintenance is substantial part of gas turbines life cycle, but the enormous maintenance cost has been the major concern for the gas turbine users (Wan et al., 2018) for ages. For instance, Thompson et al. (1989) estimated the cost of typical marine gas turbine (LM 2500) ranges between $300,000 to $400.000. The general practice in maintaining for maintaining gas turbines is typically carried out in a prescheduled manner (preventive) with the arrangement usually determined by the OEM irrespective of the actual condition of the engine (Depold and Gass, 1999; Wan et al., 2018). This indicates that overhauls usually takeplace when the turbines are either in perfect conditions or in a failure state (Zaidan et al, 2015; Wan et al., 2018). On this basis, while its uneconomical to schedule maintenance for equipment in a healthy condition, also its very risky to allow maintenance window until the failed state has been reached. This left gas turbines operators with no alternative than implementing maintenance to the equipment only on actual condition of the equipment using PdM.

To meet the objectives of CBM implementation, the integration of various functional modules into a single architecture or framework is necessary. Several previous works in the academia proposed various CBM concept, frameworks, or architectures. Some of these architectures have been summarised by Hwang et al. (2018) as depicted in Table 2.5. However, the unifying standard architecture is Open Standard Architecture Condition- Based Maintenance (OSA-CBM) designed by Machinery information Management Open System alliance (MIMOSA) (Gouriveau et al., 2016). Based on ISO Standard (ISO13374-2, 2006) OSA (Open System Architecture) CBM consists of seven functional levels/modules as depicted in Figure 2.5. These functional levels/modules include **Data acquisition module** which provides the system with digital data acquired from equipment using sensors ortransducers**. Data Processing module** extracts the features that characterised presence of anomaly, initiation of degradation which represents the state of the monitored system. This is preceded by **Condition assessment module** which detects and compares real-time (extracted features) with some expected or known values**. A diagnostic module** further determines whether the monitored system or component is degraded or not, it also identifies the probablecauses of failure**. Prognostics module** depends on the data issued from diagnostics module which enable it to predict future state of the monitored system or component as well as estimating the time to failure or remaining useful life (RUL). The maintenance action or controlis recommended by **Decision Analysis module.** The system may likely function until certain operational mission has been accomplished, the maintenance decision window afterwards recommends appropriate action based on RUL estimates**.** Finally, information from all previous modules for online or further usage will be received by **presentation module.** This is presentation interface which can be build inform of Human Machine Interface (HMI).

Table 2. 5: Comparison of various system layers for CBM implementation (Hwang, 2018)

ISO 13374	**ISO 13374-1**	**OSA-CMB (Gouriveau et al., 2016)**	**Jardine et al. (2006)**	**Chen at al. (2012)**
Data acquisition	Data acquisition	Data acquisition	Data acquisition	Sensor & Data acquisition
	Data manipulation	Data processing/ Sensor module	Data processing	
Diagnostics	State detection	Condition assessment/Condition monitor		Condition monitoring
	Health assessment	Health assessment		Fault diagnosis
Prognostics	Prognostic assessment	Diagnostics module		Predicting RUL
Prognostics actions	Advisory generation	Prognostics module	Maintenance decision making	
Post-mortems	Presentation			Health management

2.6.1 Previous Related Work

The research regarding application of CBM in Floating LNG facility first appeared in Gowid et at. (2015). A comprehensive survey has been conducted by the authors to investigate the factors affecting the profitability of floating LNG. More interest on Floating LNG developments and promising viability of CBM strategy prompted Korean government to funda research project towards implementing CBM system in Floating LNG between 2013 to 2016.Cho et al. (2016) published the detailed research as well as the result obtained which focusedon investigating the prognostics approaches/techniques to estimate the next failure time of offshore floating LNG compressor. Advances in FLNG developments and lack of detailed methods and validated models of existing CBM concepts/functional modules as well as insufficient reference work towards implementing CBM in offshore plant, recently motivated Hwang et al. (2018) to conduct another comprehensive survey on implementation of CBM on Floating LNG applications. The summary of these research and corresponding PdM maintenance philosophy investigated have been outlined in Table 2.6.

The literatures clearly demonstrated the research gap regarding the application of predictive maintenance/condition-based maintenance on aeroderivative gas turbine used in FLNG. Thus, prompt the need for a comprehensive study to develop a concise approach that integrate all the major CBM components on aeroderivative gas turbine FLNG mechanical driver, according to the requirements of popular CBM architecture.

Table 2. 6: Most Prominent FLNG research works

Reference	Type	Input Data	Technique (s)	Target	Maintenance
Gowid et. al (2015)	Review Article	Nil	Model Based Signal Based Feature Selection Based	FLNG Compressor	Diagnostics Reliability
Cho et al. (2016)	Research Article	SCADA (Vibration)	Regression Markov Hybrid of both Regression & Markov	FLNG Compressor	Prognostics
Hwang et al. (2018)	Review Article with Case Study	Vibration	Reliability-Based Regression-Based Markov-Based Bayesian-Based	FLNG Compressor	Prognostics
		SCADA	CBM-Framework Bayes Classifier	FLNG Topside	
		OREDA	Monte Carlo Simulations	Unit/Module Inlet Facility Pre-treatment Liquefaction	Diagnostics

2.7 Condition Based Maintenance of Aeroderivative Gas Turbine Based on Open System Architecture

The literature on OSA-CBM architecture has been extensively covered by Thurston(2001) and Swearingen et al. (2007). Although more specific OSA-CBM framework on rotating equipment was investigated by Tahan et al. (2014). OSA-CBM framework is critical in achieving viable maintenance objectives as well as the successful implementation of both diagnostics and prognosis process modules (Tahan, et al., 2017). As such, on this basis, more effort would be given to address various techniques/components of OSA-CBM architecture that leads to the success of CBM of aeroderivative gasturbine in FLNG applications.

OSA-CBM framework is more unifying standard architecturefor the implementation of CBM, and therefore considered and adopted in this study. It's apparent that the concept of CBM involves sequence of activities as illustrated in Figure 2.10,whereby equipment deterioration information is collected as featured sensor data useful features are extracted with the aim system downtime by implementing an intelligent diagnostics and prognostics models (Tahan et al. 2014; Lee et al. 2006). Figure 2.10 shows the overall architecture of OSA-CBM for rotating machinery.

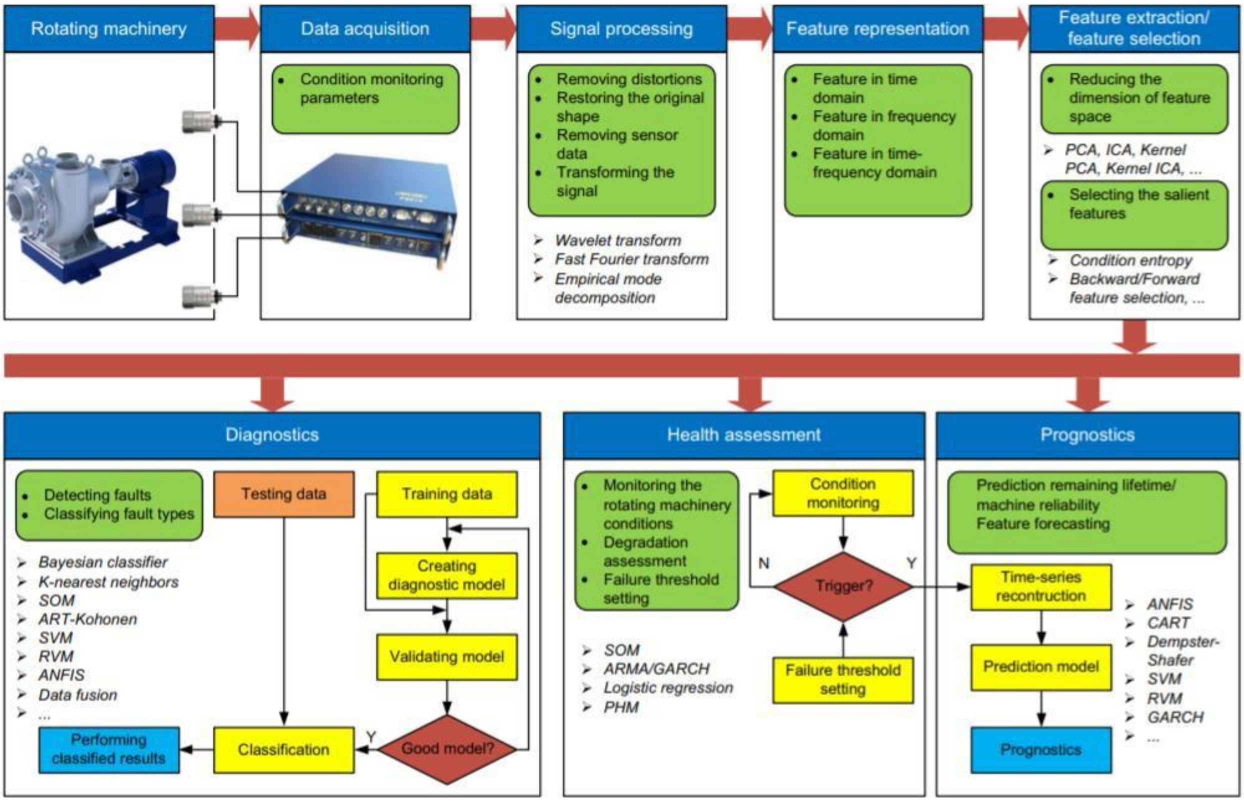


Figure 2. 10: The architecture of OSA-CBM platform (Tran and Yang, 2012)

2.8 Summary

This chapter presented a comprehensive overview of the literature regarding application of condition-based maintenance applied to aeroderivative gas turbine used as floating LNG mechanical driver. Basically, the onshore LNG facility is a well-established matured process, unlike floating LNG which is relatively new concept. Also, the offshore maintenance is more critical compared to land-based maintenance due to factors like accessibility and environmental conditions. With these constraints in mind, the chapter briefly introduced the state-of-the-art maintenance regime applied to the critical equipment in floating LNG process. The chapter begins by introducing the concept of FLNG, identifying appropriate liquefaction process designs as well as various liquefaction process drivers. Gas turbine was also identified the mostsuitable

FLNG liquefaction driver. On that basis, a review on its application on LNG industryhas been conducted, which give an insight for its limited application in LNG process plant bothonshore and offshore despite its capabilities.

Nevertheless, since ADGT is considered as most suitable for FLNG applications, the engine is expected to operate with highest reliability and availability with minimum breakdown. Therefore, appropriate maintenance is critical to the availability of ADGT. Hence, challenges

regarding maintaining equipment in an offshore environment were discussed. Various maintenance practices were briefly introduced, in which predictive maintenance is identified as most suitable to maintain ADGT in offshore applications such as FLNG. To implement CBM, various failure root causes were briefly explained. Then preceded by reviewing the state-of the-art techniques such as data acquisition, data processing, diagnostics and prognostics used for implementation of CBM.

Much previous research effort dealt with various aspects of CBM, yet there is still lack of research on the overall solution that integrate all the CBM functions as an entity especially in the offshore environment. Majority of the previous related work focused on some parts of CBM, either diagnosis or prognosis without proper integration of the framework or system architecture. This indicates the need for more integration of the function and modules required for the implementation of CBM as an entity. Until recently with a novel work conducted by (Hwanga, et al., 2018), there has been an insufficient framework or architecture that integrates various function of CBM module in an offshore O&M. However, although various equipmenthas been integrated in a framework that establishes CBM in the LNG FPSO, yet one of the most critical equipment in the FLNG process plant, i.e., liquefaction prime mover (Aeroderivative gas turbine) has not been considered in the studies.

Chapter 3

Gas Turbine Model and Simulation

3.1 Introduction

Aeroderivative gas turbine is essentially vital and critical to floating LNG performance and revenue generation. As mentioned in Chapter 2, FLNG plants performance strongly depends on availability and reliability of critical equipment/systems (aeroderivative gas turbine) as wellas their safe operation and cost effectiveness in maintaining them. As such, the cost of maintenance and machine availability are two most important concerns to gas turbine equipment owners (Janawitz et al., 2015). Hence, the need for a robust, effective and efficient maintenance program that will reduces the owner's cost whist increasing the equipment availability is necessary. However, for effective implementation of maintenance regime in a plant, the need for maintenance is usually predicted on actual or impending failureon the equipment, depending on the plant's monitoring approach and maintenance strategy adopted.

Condition based maintenance (CBM) help operators in meeting their production target by avoiding unnecessary maintenance actions and maintaining the condition of gas turbine components at an optimal level (Kaikko & Sarkomaa, 2003). Implementing an intelligent diagnostic system for gas turbines maintenance reduces excessive outages and costly component replacement unnecessarily, by calling for early corrective action before problems transforms to failures (Ajoko and Adigio, 2012). Various condition-based maintenance technologies have been developed for detection and classification of different engine faults. Among them is model-based approach, which uses first principles thermodynamics equations to predicts gas turbine's failures. This model is essential when the necessary gas turbine operational data or commercial diagnostic simulation software is not available. Thus, simulation model can be used for performance evaluation of gas turbines, withquest to reduce unplanned down time in the plant.

3.2 Objectives for Modelling Gas Turbines

Various objectives prompt analysts and practitioners to model and simulate gas turbine system. Perhaps, diagnostics and prognostics of engine, sensor validation, plant/system identification as well as overall system control model, forms the bases of GT modelling andsimulation. In addition, clarity of the modelling goals and objectives, leads to the development of a successful gas turbine diagnostics model. Some of these objective involves;

3.2.1 Monitoring the State

One of the purposes for creating gas turbine models is aimed at monitoring various states and condition of the system. This can be achieved using system's parameters such as temperatures, mass flow rate, pressure, and vibration etc. Therefore, condition monitoring is fundamental tool to predictive maintenance philosophy. Perhaps, condition monitoring on gas turbine engine detects anomaly condition of the system, identify, and isolate the faulty component on the system and evaluates a potential effect of the failed component to the entire system (Wanget al., 2011). State monitoring serves as essential tool that indicates potential failure in advanceand inform operators via warnings to take appropriate maintenance action (Clipton, 2006).

Robust health monitoring of the system is critical to the maintenance planning. Careful condition monitoring yield considerable benefits in reducing production lost, minimises maintenance cost and improve efficient and seamless operation of the gas turbine engine. Therefore, good monitoring through continuous controlled gas turbine through sensory parameters (temperature, pressure, vibration etc) and quantitative event information obtained from critical component of the engine guide operator's decisions. It also enhances operationalexcellence, minimises the risk of potential failure and significantly reduces maintenance cost. In short, good condition monitoring shall be robust to detect the current state of the system, diagnoses anomalies and predicts an incipient system's failure that has propensity in reducingsystem's performance, occurrence of undesired trips and lost in production and fatalities.

3.2.2 Fault Diagnosis and Isolation

Gas turbine model is useful in detecting fault and diagnosing system failure. Operators and researchers monitor engine health condition by performing diagnostics and prognostics using online/offline modelling and simulations. Perhaps, system failure can be predicted, detected, and prevented with the help of robust model. Diagnosis basically involves fault detection, isolation, and identification when it occurs (Jardine et al., 2006). Hence, diagnosis is vital toolin restoring GT engine to normal state thereby preventing critical loss or damage to the machines and humans. Modelling also enables operators when shifting maintenance strategy from active (preventive) to proactive (predictive) maintenance process (Lee et al., 2011). Perhaps, the underpinning objective of this study lies on identifying and integrating various methods for the successful implementation of fault diagnosis and isolation model for aeroderivative gas turbine.

3.2.3 Sensor Validation

Sensors plays an important role in monitoring and controlling industrial plants. Thus, monitoring and control process of plants considerably depends on accuracy and reliability of sensors. In general, sensor validation enhances reliability, availability, and operational cost effectiveness of plants. Considering the profound importance of sensor in vast industrial applications, considerable research effort has been made on sensors and sensor validation. Palme et al. (2011) performed a comprehensive study on sensor fault detection and isolation using black-box Artificial Neural Network model.

Sensor validation is critical to gas turbine model. Perhaps, as discussed in section 2.5.1, condition monitoring is essential to gas turbine availability, reliability, and maintainability. However, implementation of dependable diagnostics and prognostics models significantly depends on the robustness of data acquisition. Data is essential for monitoring equipment performance, and sensors plays a vital role in captures dynamics and performance characteristics of the system. The gas turbine condition parameters are usually acquired via

sensory devices attached, which generate voluminous data that can be used for predictive maintenance modelling purposes. Therefore, given the criticality of sensors on gas turbine condition monitoring, strengthening the validity, accuracy and reliability of data acquisition components especially sensors often improve the robustness of predictive maintenance implementation (Asgari, 2014).

3.2.4 Model Identification of Gas Turbine Engines

Identification of gas turbine engine tend to be a difficult task due to its nonlinear as well as system dynamic characteristics. Modelling essentially contribute to gas turbine system identification. System identification refers to the methodology for building mathematical models of dynamic systems given the measured system's input and output parameter. Although, it's worth noting that despite significant research effort regarding gas turbine systemidentification over past decades, accurate and reliable model for gas turbine is still requited for Model identification purpose (Asgari and Chen, 2016; Asgari, 2014).

3.2.5 Design of Control System

Gas turbine models may be constructed for designing or optimising control system for gas turbines (Asgari, 2014; Asgari and Chen, 2016). The control system is critical to gas turbine operations. For instance, the efficiency and safety requirement of gas turbine significantly depends on the robustness of its control system. Therefore, gas turbine model enables design simulation of GT control system (Shia and Chen, 2016). Gas turbine has different operational stages under different conditions that requires different functional controller. Generally, control system monitors and control system dynamics by comparing input and output of sensory parameters such that any deviation from desired performance will be corrected using feedback mechanism (Burns, 2011). Recently there have been significant interest and research advanceson gas turbine control. Seok, et al. (2017) recently proposed a noble advanced predictive control model for aircraft and power system gas turbine engine. The predictive model controlsand maximises system performance and enhances its control against anomalies and transient system dynamics variations.

3.3 Challenges and Significance of Gas Turbine Model in LNG Process

Gas Turbines are complex systems, with an array of different operational configurations and supporting infrastructures. This is prominent especially when compared with other rotating equipment's design type, number of components, number of shafts, and functional dynamic cycles (Forsthoffer, 2017). It is the most complex system among turbomachinery systems. (Kulikov and Thompson, 2005; Giampaolon, 2007 and Fourthoffer, 2011). The complexity of gas turbine machine could be associated with many numbers of components and subsystem ranges up to 20,000 or more. The sophistication and complexity during its design and development potentially leads to some reliability challenges when deployed into the field for operations. Thus, the engine will potentially expose to an incipient failures and deterioration over its operational life cycle (Loboda, 2010).

Gas turbine engine is critical to LNG process plant and many industrial applications. Hence, considering the profound role of gas turbine in process plants, substantial effort has been placed by researchers and original equipment manufacturers (OEM) in testing various design configurations and investigating the performance characteristics of the machine through modelling and simulations. Moreover, gas turbine simulators play an important role in understanding changes in engine performance, effects of ambient conditions, deteriorations, and overall machine health. Hence, insightful information obtained from simulator enhances inform decision on the gas turbine performance and operations (Razak 2007). Although, the complex dynamics of gas turbines make its modelling and control challenging and controversial. However, the quest for optimized models for different objectives and applications has been a strong motivation for researchers to continue to work in this area (Asgari, 2011).

3.4 Requirement for Gas Turbine Model in Optimising Engine Maintenance

Gas turbine model can be used to optimised plant maintenance. This can be achieved by taking into considering how the condition of the components affects the thermodynamic performanceof the engine. Usually, field operation of a gas turbine, exposes its components to some changesthat progressively deteriorate engine performance, when compared to new or overhauled engines. These degradations can be associated with several performance mechanisms such as fouling, erosion, corrosion, abrasion, and foreign object damage (Kaikko & Sarkomaa, 2003) or mechanically oriented mechanisms such as misalignment, unbalance, bearing defects, loose components and lack of lubrication (Tahan et al., 2017). The condition parameters can be usedto describe the degree of degradation. To develop a gas turbine model, both performance designpoint (DP) parameters of the engine and parameters obtained due to degradation (off design performance parameters) are essential. These parameters are applied in building a dynamic model of a gas turbine engine, using set of algebraic equations, that helps in explaining the steady-state features of the gas turbine thermodynamics, time delays, and a few relevant controls (Al-Dalwi and Vural, 2017).

Accurate implementation of the gas turbine model could help determining the condition of the components as well as estimating the cost effects associated with excess accumulation of unavoidable non-recoverable degradations of component(s) (ageing) (Kaikko & Sarkomaa, 2003). This generally assists in optimising maintenance process of the plant by determining the appropriate maintenance intervals through prognosis health management. Hence, increases availability and plant throughput.

3.5 Theory of gas turbines operations and Brayton Cycle

Gas turbine is an integral combination of steam turbine and internal combustion engine technologies that uses air and fuel to produce mechanical energy (Forsthoffer's, 2017). Thus,as internal combustion engine, it converts chemical energy from mixture of fuel and air as working fluid to mechanical energy (Asgari, et al., 2011). Figure 3.1 shows a typical single-shaft gas turbine with its major components (compressor, combustor, and turbine). The set of these components are usually referred to as engine core or gas generator (GG). Both compressor and turbine are connected by the central shaft which rotate them. The gas turbine system operates according to thermodynamic cycle known as Brayton cycle (Chapman et al., 2016), which describes the overall working principles of gas turbine engine (Asgari, 2011). The Brayton cycle is often represented on both pressure-volume diagram (pV diagram) and temperature-entropy diagram (Ts diagram) as illustrated in Figure 3.2 (a-b). The ideal process of Brayton cycle can be regarded as a thermodynamic cycle that consists of an isentropic and adiabatic compression of a gas, followed by heat addition at constant pressure, and extraction of energy which results in gaseous expansion. In general, Brayton cycle consistof two Isobaric (constant pressure) and two Isentropic (equal entropy) processes. The combustor system and turbine involves isobaric process, while compressor and turbineexpander form the isentropic process units (Boyce, 2006). Air is drawn and enters thecompressor at section 1 and get compressed through section 4 upon passing through compressor. The compression process squeezes the air molecules together which increases theinternal temperature of molecules as well as their pressure. Thus, the hot compressed air then enters the combustion chamber (combustor) at section 2 where it mixes with fuel and get ignited. The hot gases created from the ignited mixture are forced into the turbine at section 3 and causes them to spin. Hence, the turbine capture energy from expanding gas which causes the driving shaft to rotate. This drives the compressor as well as the gas generator mechanicaloutput such as alternators in power plant, larges compressors in LNG plants and pumps for various industrial applications.

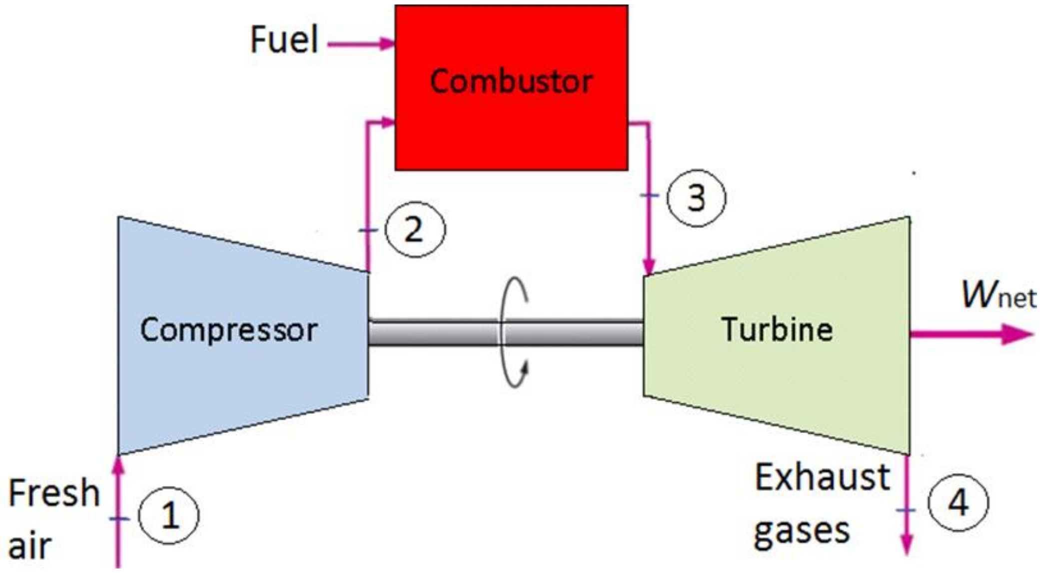


Figure 3.1: Typical single-shaft gas turbine (Asgari, 2014)

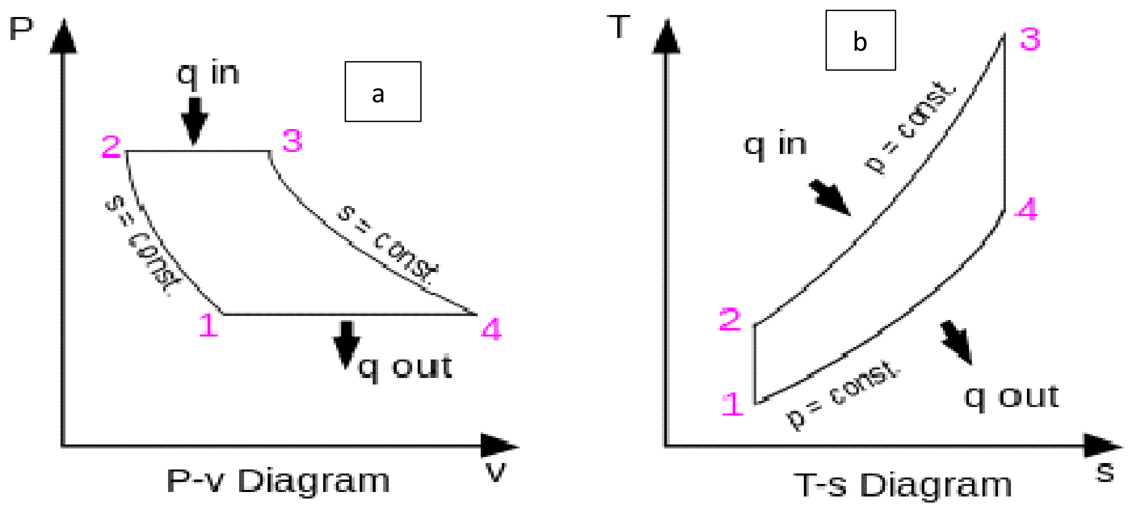


Figure 3.2: (a-b) Ideal Brayton cycle in pressure-volume and temperature-entropy frames (Asgari, 2014)

3.5.1 Gas Turbine Thermodynamics and Brayton Cycle

Modelling gas turbine engine requires an understanding of the two main essential components.In short, developing a successful gas turbine model depends on the understanding of total system thermodynamics and the component level energy, as well as flow equations. Inthermodynamic-based gas turbine model, the system modelling is based Brayton cycle that anchors the dynamic relationship between pressure, temperature, entropy, and enthalpy (Chapman et al., 2016). The flow equations are discussed by Boyce (2006)**.** They are based on simplified applications of the first law of thermodynamics to the air-standard Brayton cycle, with specific assumption that kineticand potential energy remained unchanged during the cycle processes. The basic equations are summarised below;

- Work for Compressor

$$W_c = \dot{m}_a (h_2 - h_1) \tag{3.1}$$

- Work of turbine

$$W_t = (\dot{m}_a + \dot{m}_f)(h_3 - h_4) \tag{3.2}$$

- Total output work

$$W_{cyc} = W_t - W_c \tag{3.3}$$

- Heat added to the system

$$Q_{2,3} = \dot{m}_f * LHV_{fuel} = (\dot{m}_a + \dot{m}_f)(h_3) - \dot{m}_a h_2 \tag{3.4}$$

- Overall cycle efficiency

$$\eta_{cyc} = (W_{cyc} / Q_{2.3}) \qquad (3.5$$

Equations 3.1-3.5 are the fundamental equation on which gas turbine physics-based modelsare driven from. that Brayton cycle efficiency depend on pressure ratio and turbine firing temperature. The underpinning linear relationship between pressure ratio and turbine firing temperature affects the overall cycle efficiency. Thus, increase in pressure ratio and turbine temperature increases the Brayton cycle efficiency. Although this cycle relationship is based on assumptions as highlighted by Boyce (2006) That;

$\dot{m}_a > \dot{m}_f$

c_p & c_v are constant and thus γ remained constant throughout the cycle.

Pressure ratio (r_p) remained the same in both compressor and turbine.

All components operate at 100% efficiency.

With these assumptions, the effect of ideal cycle efficiency as a function of pressure ratio for the ideal Brayton cycle operating between ambient and firing temperature can be deduced and expressed as;

$$\gamma_{ideal} = (1 - \frac{1}{r^{\frac{\gamma-1}{\gamma}}}) \qquad (3.6)$$

Table 3.1: Definition of parameters in equations (3.1 - 3.6)

Parameter	Symbol	Unit
Mass of air	m_a	kg
Mass of fuel	m_f	kg
Specific heat at constant pressure	c_p	$J/kg\ K$
Specific heat at constant volume	c_v	$J/kg\ K$
Ratio of the specific heat	γ	—
Specific enthalpies	$h_{1\text{-}4}$	kJ/kg
Cycle efficiency	η_{cyc}	—
Work done by turbine	W_t	J
Work done on the gas by compressor	W_c	J
Total work output by the cycle	W_{cyc}	J
Heat added to the system	$Q_{2,3}$	J

Therefore, Ideal Brayton cycle is represented in Figure 3.3 with stages;

1-2: Isentropic compression (Air compressor).

2-3: Constant pressure heat-addition (compressed air with fuel in combustion chamber).

3-4: Isentropic expansion (combustion products in turbine).

4-1: Constant pressure heat rejection (exhaust).

2s & 4s: These stages demonstrate ideal situation.

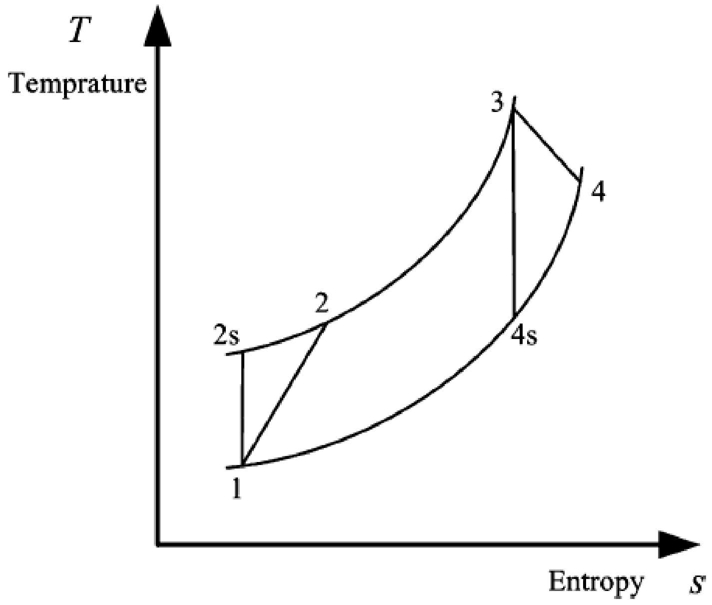


Figure 3.3: Ideal Brayton Cycle in Temperature-Entropy frames (Tavakoli et al., 2009)

Ideal representation of gas turbine cycle can be further extended to defect the actual operational gas turbine cycles applicable to industries. These cycles are categorised as;

Simple cycle (20-43%)

Regenerative cycle (30-45%)

Combine cycle (55-60%)

Simple cycle as shown in Figure 3.4a is highly flexible with low operating cost butconstrained with poor thermal operational efficiency which is associated with exhaust gas discharge to atmosphere. The direct exhaust discharge could be prevented and utilised to improve the efficiency of the turbine cycle. This is achieved by preheating the compressor discharge air in the exchanger before reaching combustor as shown in Figure 3.4b. The cycle efficiency is also enhanced when gas exhaust is diverted to heat recovery steam generator (HRSG) to driver steam turbine or generate heat for plant heating processes. This process is known as combine cycle and is capable in enhancing efficiency up to 60% (Boyes 2006).

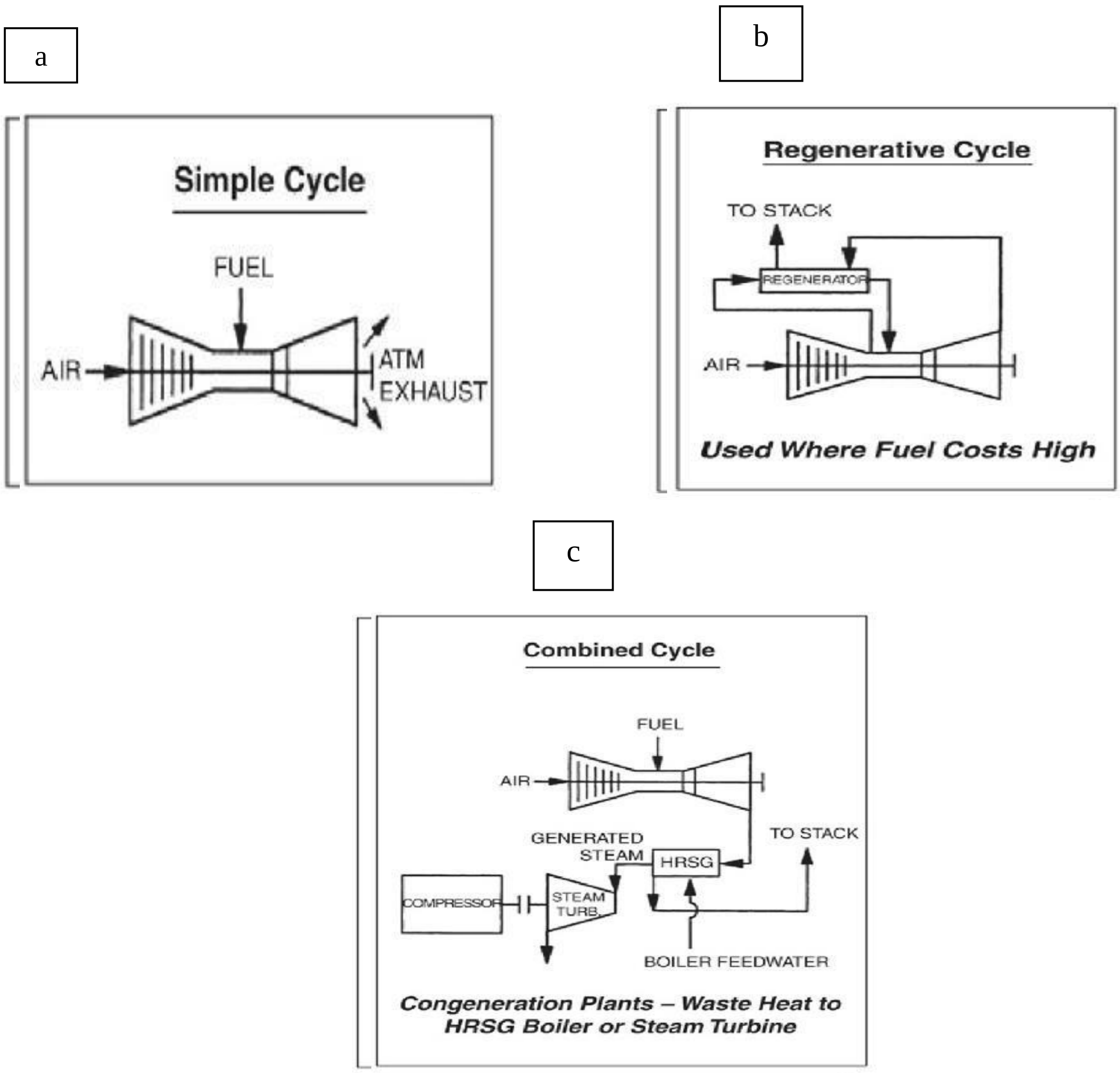


Figure 3.4: (a-c) Gas turbine Simple cycle, Gas Turbine regenerative cycle, and Gas Turbine combine cycle (Boyce, 2006)

3.5.2 Modelling and Simulations of gas turbines

Understanding the characteristics behaviour of gas turbine system is easily achieved byanalysing operational data obtained using various sensors attached to the physical gas turbine system. Yet industrial data is expensive, difficult to obtain due to data censorship and security.Conversely, gas turbine behaviour analysis could be achieved through laboratory experiments. However, performing experiments on real system by stripping its components could bechallenging and associated with rigorous fatigue, reliability challenges, error and damages. These constraints make it difficult and too dangerous and expensive to perform experiment on real systems. Alternatively, simulations can be done on model system to understand the effect of design characteristics and performance behaviour of simulated real system (Fritzson 2012).Gas turbine is normally modelled and simulated to achieve various objectives and purposes. Depending on the desired objective, researchers simulate gas turbine model for condition monitoring, fault detection and diagnostics studies. Some model the engine to understand a robust performance optimisation and system control, design configuration or validation of sensor configurations. Thus, clarity on modelling objectivity is the key towards obtaining goodengine model (Asgari et al., 2016).

Model represent a system behaviour given some independent input variable and dependant variables. Modelling basically is a process that produces a representation of a system. Model is an important representation of a system behaviour, hence it's an approximation of working principles of system of interest. Modelling techniques produce a model that enable analyst to evaluate and predict system's behaviour and effect s some changes using input variables. Model is built using first principles or set of relevant mathematical equations that defect systemdynamics. Furthermore, model's operation and performance evaluation is achieved by simulation technique. Thus, simulation enables analysts to obtain a robust model of the system through reconfiguration and experimentation until desired model characteristics is obtained.

This reduces the risk of failure or underperformance of the model. Simulation also provides an effective utilisation of resources during design phase that eventually produces cost effective systems without under or over utilisation of resources. In general, modelling and simulation answers critical questions about system design specification, performance behaviour, failure modes and its impact during operations and its entire life cycles. Therefore, analysts, practitioners and researchers use mathematical principles to perform modelling and simulationof a system to have the general understanding of the system. Moreover, testing system hypothesis and feasibility enables both researchers and operators to observe certain phenomenaof the system over a given time range by approximating real time with via simulation process.Thus, modelling and simulation give account to the detailed performance metrics, evaluates various configurations and characteristics (Maria, 1997).

Modelling and simulation have significant importance in yielding robust and reliable gas turbine engine during its design process. It’s also an essential component during turbine entirelife cycle. Modelling and simulation enable performance evaluation, sensor validation, fault detection and troubleshooting to be carried out on the machine whist in operation. Thus, modelling and simulation of gas turbine tend to be an essential tool to OEMs, operators and researchers (Asgari, 2011). Given the profound importance of gas turbine in the industrial applications, considerable research effort has been made by both researchers and manufacturerson modelling and simulating the behaviour and design characteristics of gas turbine engine. Thus, complexity and sensitivity nature of gas turbines operations, coupled with transitional thermodynamic changes of the operational parameters from cold flow to hot flow, a considerable research effort is required in building accurate and reliable model (Asgari 2013).However, to obtain accurate and reliable gas turbine model, some important factors shall be kept in mind. These factors include objective/purpose of the modelling, design type ofthe gas turbine, its configuration, the modelling approaches as well as type and structure of thecontrol system (Asgari and Chen, 2016).

3.5.3 Factors Affecting Gas Turbine Modelling

Some important factors must be considered whilst developing gas turbine model. As discussed, gas turbine design type, gas turbine configurations, modelling objectives and modelling approaches shall be carefully considered, to obtain reliable and accurate gas turbine model.

3.5.3.1 Gas turbine design type

Obtaining adequate information regarding various gas turbine designs is necessary and serves as the initial steps of gas turbine modelling. Various gas turbines exist according to their distinct application in the industry. Boyce (2006) described various gas turbine design types as;

- Micro turbines that are suitable in premium and remote power applications, as well as grid support.
- Aeroderivative with 35-45% efficiency and net power output of 2.5-50MW usually used in rigorous applications.
- Frame type heavy duty gas turbines with 30-46% efficiency and corresponding net power output of 3-480MW.
- Industrial type for low power output of 2.5-15MW and 30-39% efficiency. This turbine has wide applications in both power generations and petrochemical plants.

- Small gas turbine for simple cycle applications with very low output (0.5-15MW) and efficiency of 15-25%.

Although, the five categories described above shared common component as illustrated in Figure 3.1, yet modelling each gas turbine type has some distinct characteristics. For instance, the modelling variations between frame industrial gas turbine type and aeroderivativegas turbine type can be seen in Yee et al. (2011) work.

3.5.3.2 Gas Turbine Configurations

Another important factor that requires careful consideration in modelling gas turbine is the engine configurations. Although all gas turbines almost share common structure and thermodynamic cycle, yet some significant differences exist among the engines, especially when detailed investigation is carried out. For instance, to optimise gas turbine efficiency, various methods such as re-heating, inter-cooling, or heat exchange, a specific gas turbine configuration are used (Asgari, 2014). The physical and model construction of gas turbine alsodepends on shaft configuration type, as either single shaft heavy duty or twin shaft aeroderivative gas turbines (Yee et al., 2011). Gas turbines can be single shaft or split shaft (twin or triple) (Asgari, 2014). The major difference between the configurations is theconnection of the compressor turbine to the power turbine (Yee et al., 2011). In a single shaftgas turbine engine, the compressor and power turbine are localised on the same shaft (Asgari,2014). Perhaps there is only single shaft linking the turbine blades with the compressor and combustion chamber as shown in Figure (3.5a) (Yee et al., 2011). Conversely, in a multi-shaftor split shaft gas turbine, the compressor turbine (CT) and power turbine (PT) are physically (mechanical) separated and does not have a shaft that link them as shown in Figure 3.5b. Theseparation of CT and PT enable them to operate at different speeds. Single shaft type has lower maintenance cost but constrained with lower efficiency and very limited speed ranges, while multi-shaft is characterised with higher efficiency, wide speed range but require higher maintenance due to its complex control system (Boyce, 2006).

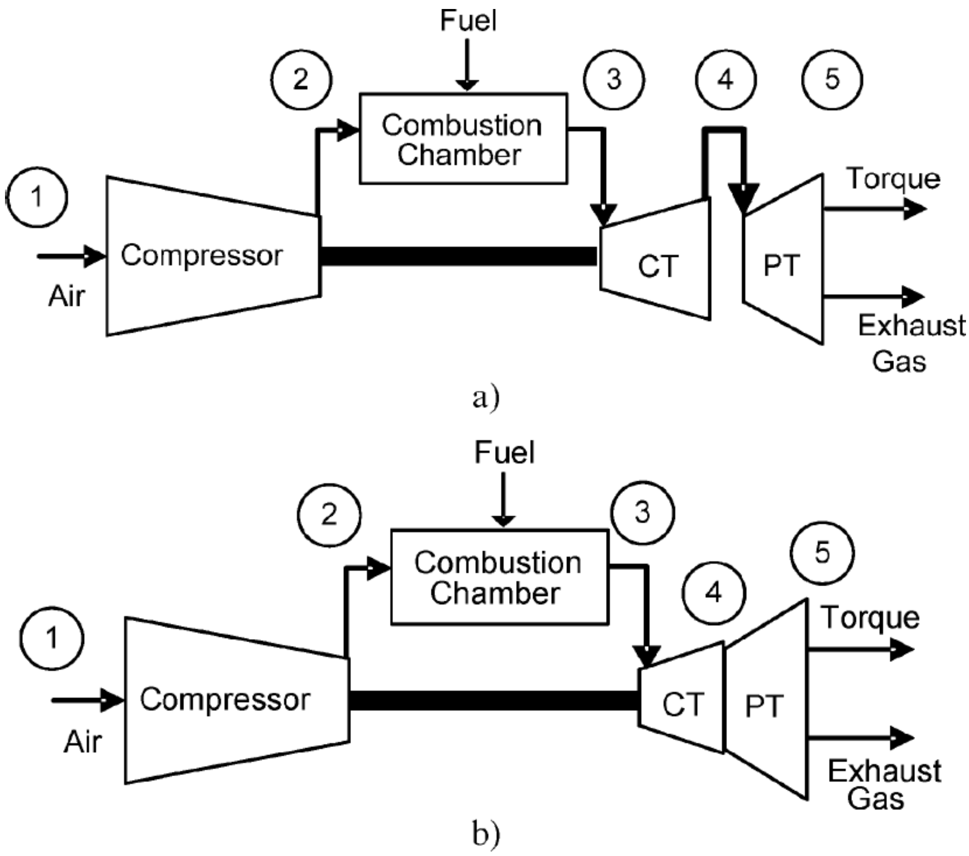


Figure 3. 5: (a-b) Schematics of gas turbines: (a) Multi-shaft aeroderivative GT (b) Single- shaft heavy duty GT (Yee et al., 2011)

3.5.4 Approaches for Gas Turbine Model Construction

Gas turbine models are designed and constructed according to the need and purpose as discussed earlier. Considerable research effort has been put in designing various models to suitsome specific purposes. Perhaps, various modelling approaches have been adopted by researchers on specific tasks. Thus, modelling approaches can be broadly classified into two distinct categories, i.e., Blackbox and Whitebox models, although in between them forms another category known as Grey box.

3.5.4.1 White-box Model

White-box model play a vital role in system modelling especially when all the necessary information is completely known. This type of model uses first principles. Thus, the mathematical equations governing the system dynamics and other relevant first principles laws (physical, chemical and mechanical, etc) are used to build the model (Asgari, 2013). Hence, as basic requirement, knowledge on rules and theories are the fundamental components and forms the bases of white-box model. As such, a comprehensive knowledge of the target modelling system is essential whilst implement white-box model (Yang, et al., 2017). It's worth noting that most white-box models involve non-linear dynamic equations. Hence, linearization of non-linear dynamic equations contributes significantly on obtainingsatisfactory model. Given this requirement, various programs and applications such as MATLAB, Simulink and MATHEMATICA prompt very useful tools to handle linearization constraints. (Asgari et al., 2014).

White-box models has been useful tool for many decades for researchers. Perhaps, much effort has been placed by gas turbine research community to model GT engine using white box modelling technique. Several models with different level of simplification for therepresentation of gas turbines for dynamic studies were proposed in the research community. An excellent review on these models can be found in Yee et al. (2008). Among the earliest white box-based gas turbine model was introduced by Rowen (1983). The work involves developing a novel model of heavy-duty single shaft gas turbine, with the quest to investigatethe power stability, developing dispatch strategy as well as proving a contingency plan for thesystem upsets. To achieve these objectives, the author developed a simplified model that has the capacity to cover full spectrum of gas turbine generator drive as well as capturing the appropriate generator characteristics. The author also discussed relevant issues affecting the modelling such as parallel and isolating operations, gas and liquid fuel systems, isochronous as well as droop governors.

Rowen's model is very useful and laid a foundation for many researchers to develop variety of gas turbine models using different approaches. Although theactual Rowen model is limited to simple cycle and single-shaft gas turbines with generator drive, yet it serves as reference base for many gas turbines models. In an effort to investigate a simplified mathematical model of gas turbine for mechanical driveservices with variable speed, Rowen (1992) work improved some limitations of Rowen (1983)model by adding some new features. Some of the new features include exhaust flow calculation, variable ambient temperature and modulating inlet guide valves (IGVs) which were not incorporated in the previous model. Hence, the improved Rowen model was simple, flexible, and fairly accurate, features that make the model robust for simulating any heavy dutysingle-shaft gas turbine.

Based on Rowen's model, Shalan et al. (2010) proposed a simple methodology to estimate parameters of single-shaft gas turbines model. These parameters were derived from both performance and operational data of the engine, which were further used for various simulation tests in Simulink/MATLAB environment. The results obtained in the study were compared with the existing relevant results in scientific literatures. Thus, verified the robustness of the proposed methodology and perhaps enables wider application of the method to any gas turbine size. Similarly, another parameter estimation was carried out by Tavakoli et al. (2009), in an attempt to modelled single-shaft heavy duty gas turbine based on Rowen's model. Both operational and performance gas turbine data were used to develop the model which subsequently derived the model parameters. Simple physical laws and thermodynamic assumptions were also applied to approximate gas turbine parameters. Thus, by comparison, the result obtained in the estimation corresponds with the typical operational values. This study is useful for educational guide purposes, especially for trainers and students who are interestedin gas turbine dynamic studies. In short, this serves as a motive to conduct a case study in section (3.5) of the report based on Tavakoli et al. (2009) work.

In a related research work, (Asgari, 2014) used white box model to simulate the transient behaviour of industrial gas turbine. The modelling was implemented in Simulink/MATLAB environment, and consequently the Simulink based-result obtained was compared with artificial neural network-based model (Black box).

Many researchers also used white box to model low power gas turbines. Abdollahi and Vahedi (2005) studied low power single-shaft micro turbine. The researchers developed a generic model for the turbine that fits different flexible operational ranges. Simulink/MATLABwas used in modelling the system and the study yield suitable result what demonstrates suitability of dynamic analysis of microturbines to model the system given variable operating conditions.

3.5.4.2 Blackbox Model

In the circumstance where the information about the physics of the plant or system iscompletely unavailable or insufficient, a Blackbox modelling approach is used instead. The Blackbox model is used to discover the relationship between the system variables using the measured operational input data or data obtained from the system performance characteristicssimulations (Asgari et al., 2014). Artificial neural network (ANN), as subset of the artificial intelligence, is one of the most important methods of modelling a system as black box (Asgariand Chen, 2016).

Considerable effort has been put by many researchers to develop ANN-based models for various types of gas turbines. Some excellent research works has been carried out by Lazzaretto and Toffolo (2001); Ogaji et al. (2002); Bettocchi et al. (2004) and Spina and Venturini (2007). In addition, Asgari (2014) recently conducted one of the most comprehensive work regarding ANN-based gas turbine modelling. The author investigated novel methodologies for modelling, simulating as well as controlling gas turbines using ANN.Different types of gas turbine engine models have been constructed for start-up and steady state operation. Both physics-based

Simulink and ANN-based models were compared to predict dynamic behaviour of gas turbines. The study found that ANN has more potential to simulate start-up operations as well as dynamic behaviour prediction of the gas turbine compared to white-based Simulink model. More literature on ANN as well as its applications has been discussed in Chapter 4.

3.5.4.3 Grey Box Modelling

The grey box modelling is a hybrid model that incorporates white-box (stochastic model) and black-box (deterministic model). Thus, this model approach incorporates elements fromresidual-based methods and parametric estimation methods (Park and Zak, 2003). In anotherwords, that practical model of a system is optimised by deploying some specific knowledge about the system parameters, which integrates both the mathematical relations that describes the system and practical knowledge to enhances the modelling accuracy (Asgari and Chen, 2016).

Some considerable gas turbine models were developed based on grey box modelling concept. Among these models include (Mohammadi and Montazeri-Gh, 2014) novel work, where a grey-box identification model based on Weiner model was proposed by the authors to modelledand estimate the dynamic behaviour of a two-shaft gas turbine. The model was developed on assumption that the static non-linear part of Weiner model is known, then an innovative approach was introduced to improve the dynamic model flexibility. This strategy provides more accurate prediction of non-linear dynamic behaviour of complicated systems such as gasturbines. In another study, a gas turbine dynamic modelling was proposed Mehrpanahi et al.(2017). The authors modelled and analysed the behaviour of industrial gas turbine (MGT-30) in both loading and unloading conditions using grey box modelling concept. The modelling was achieved by combining the thermodynamic equations (White box) and the equations derived from the values of some key parameters of the system's operation information, i.e., performance and off-design conditions (Black box). The dynamic model obtained is useful in fault diagnosis. It also serves as simulator and testing platform for various controllers.

3.5.5 Gas Turbine Model for Predictive Maintenance

Gas turbines failure is often characterized with performance deterioration due to the health state degradation, and it does not recover without intervention. Two types of gradual degradations affecting the health state of gas turbine are structural degradation and recoverable degradation. Structural degradations is associated with wear and tear mechanisms in the parts exposed to high temperature, high stress, and surface contact. It usually occurs with a slow pace for many parts of the GT in different fault modes and it is nonrecoverable, i.e., the degraded parts should be replaced or repaired to retrieve the GT performance. The recoverable degradation emerges due to fouling, i.e., adherence and congestion of aerosol particles on the air foils and the surfaces at the frontmost parts of the gas path. The entire performance-based gas turbine's diagnostics and prognostics process have been illustrated in Figure 3.6. More information about recoverable and nonrecoverable faults on the gas turbine performance deterioration can be found in (Kurz and Brun, 2000).

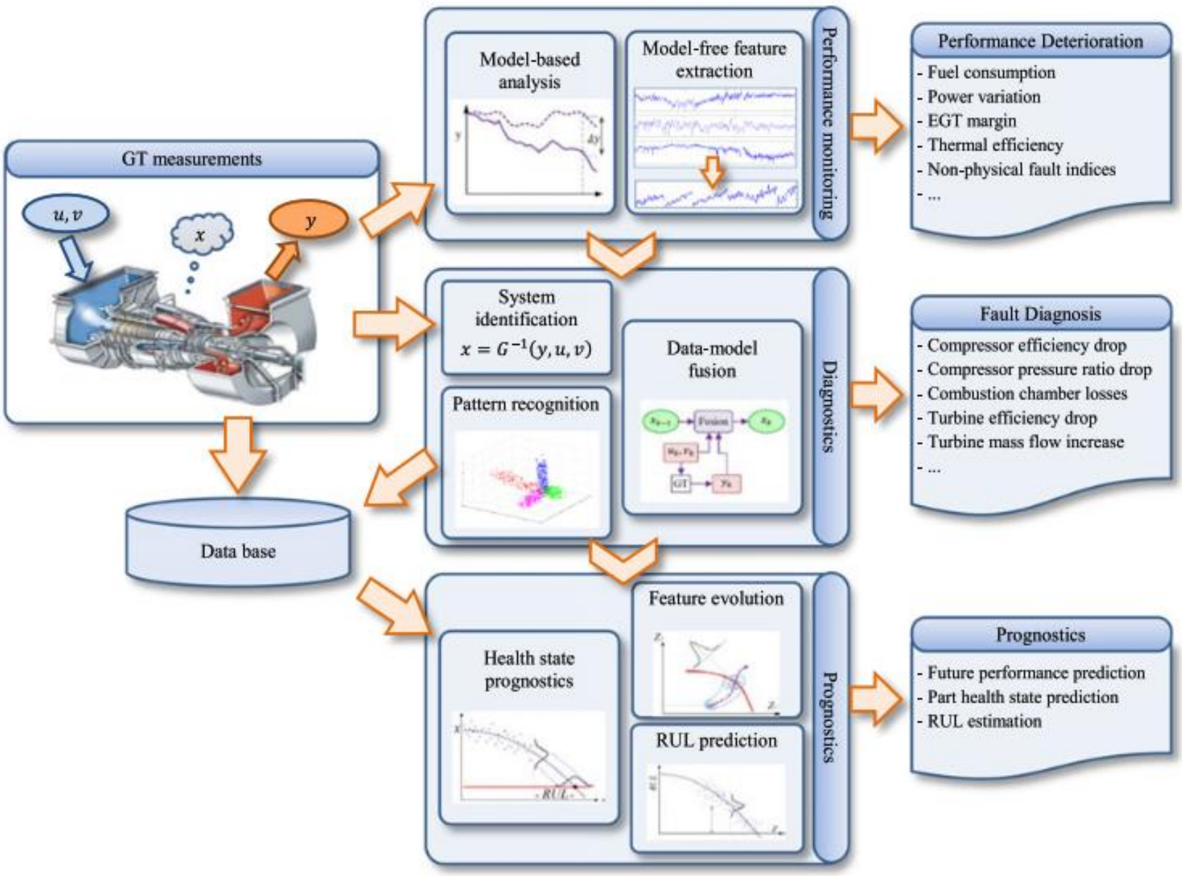


Figure 3.6: Gas Turbine CBM process-Diagnostics & Prognostics (Hanachi et al., 2018)

To predict and diagnose failure on gas turbines (GTs), a performance-based degradation diagnostic modelling can be implemented using first principles. The Diagnostics modelling is the process of mapping and classification from the gas turbine performance parameter space to the fault space. In this instance, the conditional failure refers to circumstances when performance of the GT becomes unacceptable but can be operational. The implementation of the modelling can be achieved via three distinct steps:

- **System identification**
- **Pattern recognition**
- **Data model fusion.**

The system Identification is the first step to implement on GT PdM/diagnostics modelling. its role regarding GT diagnostics is to discover the health state parameters that minimize the difference of the measured variables and those predicted by the model. This approach is applicable when a reliable GT model with sufficient information about the internal parameters is available. Basically, the models that utilizes system identification are mainly physics-based models. The approach finds the health parameters of the system by solving the mathematical inverse equation of the system model (Equation 3.7).

$$x = G^{-1}\ (y, u, v) \tag{3.7}$$

Where:

x = components of a fault vector

y = includes performance parameters

u = control input

v = ambient condition

To represent the health state of the parts, faults are introduced as a vector of numerical variables Δx into the sets of model equations. The Δx represents values of the component level fault symptoms e.g., loss of isentropic efficiency in the compressor. The fault severity could be identified through modelling Equation 3.7. The components of a fault vector (Δx) may take different values within a defined numerical domain. The idea is to find the set of component level fault symptoms, i.e., changes in the health state Δx, that minimizes the modelling error regarding the actual measurements on GT performance. The fault severity is evaluated through this process, even for small values of faults, i.e., less than 1% deviation from healthy condition. The common practice often involves estimating the relationship between the fault magnitude and performance deviation with linearization of the gas turbine. The entire fault severity iteration process is illustrated in Figure 3.7.

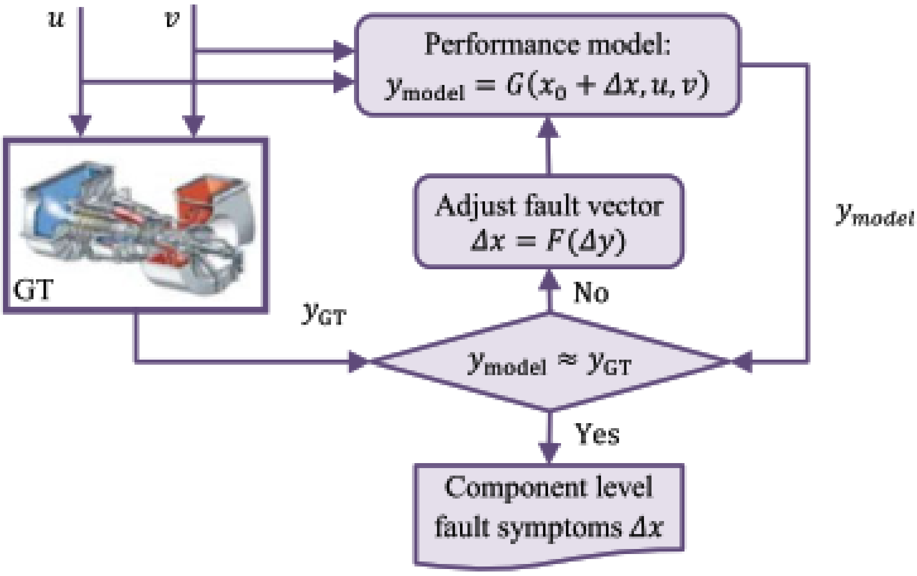


Figure 3. 7: Fault diagnostics through the iterative process (Hanachi et al., 2018)

Patten recognition is another important model approach, essentially utilized for gas turbines diagnostics when accurate physics-based models are not available for gas turbines. This approach mimics the natural learning process of humans to classify input data into classes as output, based on the information and relevant data features. Since this section dealt with physics-based models, more detailed on both pattern recognition and data fusion can be found in (Hanachi et al., 2018)

3.5.6 Case Study (Gas Turbine Simulink Model)

The objective here is to produce a model of a gas turbine. This model would take the form of a set of equations that govern the dynamic behaviour of the gas turbine. The model would involve all those variables derived from dynamic equations. While it is conceivable to construct such a model from first principles, it is not economical to do so, given that a typical turbine might have several hundred of such variables to dealt with. However, despite these constraints, some research works implemented a scalable model for gas turbines. Hence, this case study is built based on Tavakoli et al. (2009) model's procedures. This model is aimed at implementing a simplified and comprehensive gas turbine model using estimated and operational data. In this study, a 172 MW simple cycle single-shaft Heavy Duty Gas Turbine (HDGT) and its available operational and performance data were introduced and studied for deriving the parameters of the model. The model is successfully implemented and simulated by splitting the major GTs components into four categories, i.e.

- Gas turbine
- Valves and fuels systems
- Turbine dynamics and delays
- Temperature measurements

Table 3.2: Nominal Data of HDGT Selected for Modelling

Parameter	**Symbol**	**Unit**
		MW
Nominal frequency	P_{Gin}	Hz
Turbine speed	RPM	RPM
Exhaust mass flow	$\dot{m}$	Kg/s
Exhaust temperature	T_R	^oC
Pressure ratio	P_R	-

3..5.6.1 Model Equations and Data

Based on distinct categories of the modelling, these equations form the bases in which model parameters were estimated.

- Turbine Parameters

Two quantities represent the behaviour of gas turbine section, i.e.

- ➢ Exhaust temperature
- ➢ Output torque

As presented in Tavakoli et al. (2009), a compressor and turbine efficiencies can be represented based on Brayton cycle;

Exhaust gas temperature

$$\frac{T_{2s}}{T_1} = \left(\frac{P_2}{P_1}\right)^{\frac{\gamma_c - 1}{\gamma_c}} = (PR)^{\frac{\gamma_c - 1}{\gamma_c}} = x_c \tag{3.8}$$

$$\frac{T_{3s}}{T_{4s}} = (\frac{P_3}{P_4})^{\frac{\gamma_h - 1}{\gamma_h}} = (PR)^{\frac{\gamma_h - 1}{\gamma_h}} = x_h \quad (3.9)$$

Where:

$\gamma_c =$ compressor specific heat

$\gamma_h =$ Combustor, turbine ratio of specific heats

Therefore;

$$T_2 = T_1(\frac{x_c - 1}{\eta_c} + 1) \quad (3.10)$$

$$T_4 = T_3[1 - (1 - \frac{1}{x_h})\eta_t] \quad (3.11)$$

At nominal speed, the exhaust temperature can be represented as;

$$T_4 = T_R - D * (1 - \dot{m}_{fpu}) \quad (3.12)$$

$$E = 0.6T_R$$

Where:

D is the coefficient of the exhaust temperature block

E is the coefficient of the exhaust temperature block

T_R is the nominal temperature of the HDGT

3.5.6.2 Output Torque

Given Rowen's linear response as well as nominal speed assumption, the output torque and mechanical power can be represented as;

$$P_{Gpu} = \dot{m}[C_{ph}(T_3 - T_4) - C_{pc}(T_2 - T_1)] \text{ or} \quad (3.13)$$

$$P_{Gpu} = A + B * \dot{m}_{fpu} \quad \text{at nominal speed} \tag{3.14}$$

Where:

A and B are coefficients of the output torque

P_{Gpu} is the per unit output power and equivalent to p.u. torque.

Table 3. 3: Typical Operating Data for Computing Turbine and Compressor Efficiencies

Parameter	**Unit**	**Value**
Output power	MW	146.4
Turbine inlet temperature	^{o}C	1100
Exhaust gas temperature	^{o}C	532
Ambient temperature	^{o}C	27.3
Exhaust mass flow	Kg/s	438.1
Fuel	-	Gas
Fuel flow	Kg/s	8.34
Lower heating value of fuel	KJ/kg	43094

3.5.6.3 Fuel system Lag and Valve Positioner

The valve positioner moves actuator to a valve position corresponding to a set point, while fuel system of a gas turbine is designed to injects energy into the gas turbine. The valve positioner block has one parameter "b" which is usually given by the manufacturer. However, the fuel system is proportional to the product of the command signal (V_{CE}) and unit speed (N). With the assumptions of linear response actuators and valves, the fuel flow changes directly with the output signal of the valve positioner. Although, a lag associated with the gas/oil flow in the pipe and fuel system manifold (T_{FS}) affects the fuel flows. Thus, according to Tavakoli et al. (2009), this lag can be approximated using;

$$T_V = \frac{P_o}{Q_o} V \frac{\partial}{\partial P}(\frac{1}{v})\mathrm{I}_{T_o} \qquad (3.15)$$

Where:

T_v is the time constant of the lag associated with the container of the volume v .

Table 3.4: Estimated Minimum Fuel Flow and No-Load Consumption

No load fuel flow (Kg/s)	~2.56
Min fuel flow to maintain combustor flame (kg/s)	~1.5

Table 3.5: Operational Data for Fuel System Lag Time Estimation

Fuel	**Gas**
Fuel pressure (atm)	21
Average temperature (K)	320
Fuel piping approximate volume (m^3)	0.17 ~ (15mx6cm Radius Equiv. Cylinder)

3.5.6.4 Time Lag and Compressor Discharge

The behaviour of gas turbine forces its dynamic model to have small delays and lag time constants. As reported by Tavakoli et al. (2009), these time delays involve;

Small time delay between fuel injection and heat release in the combustor, which is referred to as combustor reaction delay (E_{CR}). This delay is implemented in Rowen's model after the valve system and it's in order of some milliseconds.

A delay between fuel combustion and measuring system (E_{TD}). This delay is generated by exhaust system and turbine to transport the fuel to the measuring point, which is in order of milliseconds. Although it depends mainly on the size of HDGT engine and average speed of the fluid.

Table 3. 6: Operational Data for Compressor Discharge Lag Time Estimation

Fuel	**Gas**
Average temperature (K)	~1050
Discharge volume (m^3)	~ 16

3.5.6.4 Temperature Measurement

Controlling temperature in HDGT needs measurement of the exhaust temperature, which composes of;

- Thermocouple
- Radiation shield

The excessive heat in HDGT is controlled by exhaust gas temperature out of the turbine via convection. Although, the radiation source in gas turbine itself causes error in the temperature measurement. To overcome this effect, radiation shield is used which reflects most of radiation away from the thermocouple and itself. The thermocouple is the temperature measuring device and has a lag time constant (T_{TR}) based on its type and design. This time constant can be easily extracted from thermocouple time response documents. Also, the radiation shield equipment imposes a lag according to its heat transfer that has been presented to the model. An approximated temperature at the tip of thermocouple represented by equation 3.16 will be used to estimate the radiation shield parameters (G_{SH} & T_{SH}) (Tavakoli et al., 2009).

$$\frac{T_{measure}}{T_{exhaust}} \approx \frac{A_2}{A} + \frac{1-\dfrac{A_2}{A_1}}{\dfrac{C}{h.A_1}s+1} \tag{3.16}$$

Where;

$A_1 =$ Total active area for convection heat transfer to the shield head.

$A_2 =$ Area effective for convection heat transfer to the thermocouple tip.

$C =$ Heat capacity of shield head

$h =$ convection heat transfer coefficient

Table 3. 7: Data of Radiation Shield

Parameter	Symbol	Value
Shield Alloy	-	Stainless Steel
Shield Head Diameter (cm)	D_{SH}	3
Shield Head Length (cm)	L_{SH}	7.5
Shield Head Thickness (mm)	H_{SH}	0.08
Thermocouple Tip Length inside Shield (mm)	L_{tip}	16
Convection Heat Transfer Coefficient (W/m^2K)	h	250
Specific Heat Capacity per unit Volume (J/cm^3K)	C_{sp}	3.83

3.5.6.5 Simulation

The derived and assumed parameters generated **in section 3.5.2 are summarised in Table 3.7).** This data is used to simulate the behaviour of 172 MW HDGT. The model of HDGT is simulated against two distinct scenarios, i.e. (0.1% and 0.3%) speed step when operating in nominal conditions. Also, governor-speed droop of 4% is assumed for the simulation as indicated in table 3.7. The simulation is conducted in Simulink/MATLAB environment and is illustrated in Figure 3.8.

Table 3.8: Parameters of HDGT Model

Parameters	Symbol	Value
Speed Governor Gain	W	25
Speed Governor Time Constant (s)	T_G	0.05
Fuel Demand Signal Max Limit	$\max F$	1.5
Fuel Demand Signal Min Limit	$\min F$	-0.3
No Load Fuel Consumption	K_{NL}	0.24
Value Positioner Time Constant (s)	b	0.04
Fuel System Time Constant (s)	T_{FS}	0.26
Fuel System External Feedback Loop Gain	K_F	0
Delay of Combustion System (s)	T_{CR}	0.005
Transport Delay of Turbine and Exhaust System (s)	T_{TD}	0.04
Compressor Discharge Lag Time Constant (s)	T_{CD}	0.16
Gas Turbine Torque Block Parameters	A	-0.158
Gas Turbine Torque Block Parameters	B	1.158
Gas Turbine Torque Block Parameters	C	0.5
Gas Turbine Exhaust Temperature Parameters ^oC	D	413
Gas Turbine Exhaust Temperature Parameters ^oC	E	313
Radiation Shield Parameter	G_{SH}	0.85
Radiation Shield Time Constant (s)	T_{SH}	12.2
Thermocouple Time Constant (s)	T_{TR}	1.7
Temperature Controller Parameter	G_{TC}	3.3

Temperature Controller Integration Constant (^{o}C)	T_{TC}	250
Rated Exhaust Temperature (^{o}C)	T_R	522

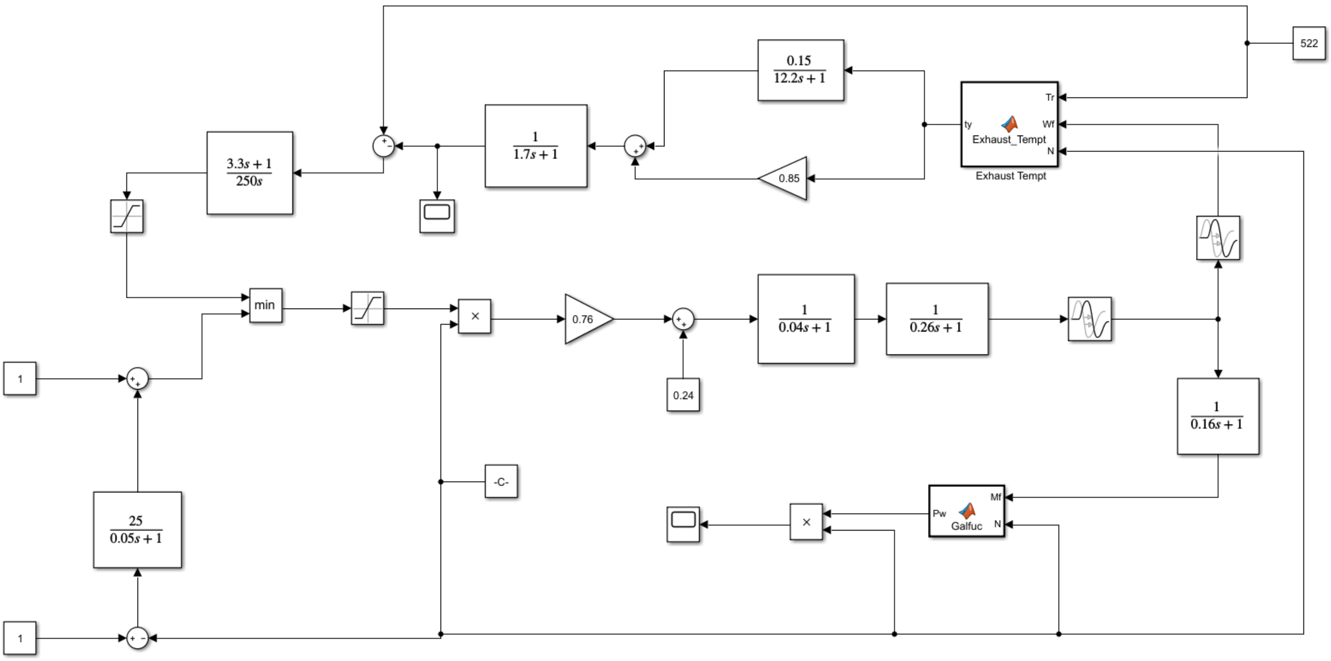


Figure 3.8: Simulink-based 172 MW HDGT model simulation

Scenario 1

In this case, the speed deviation of 0.1% is simulated and Figure 3.10 shows the mechanical output power of the model against the speed deviations. Thus, in a steady state operation with 4% droop, a final value of 1.021 p.u is obtained as indicated in Figure 3.10. Also, the exhaust temperature of gas turbine measure by the thermocouple is observed. It is a steady state temperature prior to the activation of temperature control, which is near 530 ^{0}C and indicated in Figure 3.9.

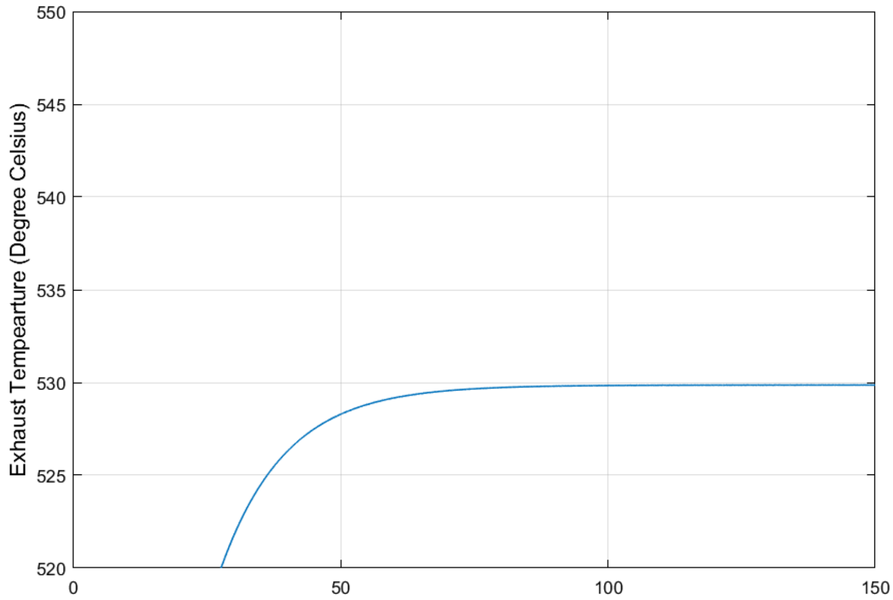


Figure 3.9: Exhaust temperature of HDGT after speed step of -0.1%

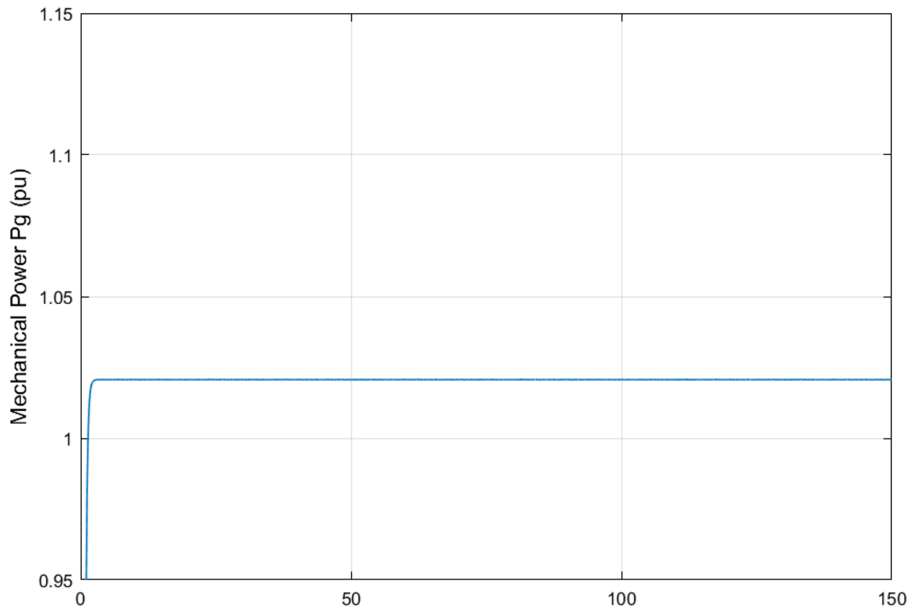


Figure 3.10**:** Mechanical output power of HDGT after speed step of 0.1

Scenario 2

In this case, the speed deviation of 0.3% is simulated, which suddenly leads to the activation of the temperature control. As indicated in Figure 3.11, The exhaust temperature increases for 70s until it reaches the value of almost 545 ^{o}C, then the temperature control activated which forces the exhaust temperature to decline to its rated value of 522 ^{o}C. Also, the final value of 1.061 p.u. of mechanical power is observed as illustrated in Figure 3.12, which remains constant after the activation of temperature control. In short, the temperature control decreases temperature at the expense of output power which helps in keeping is steady and constant.

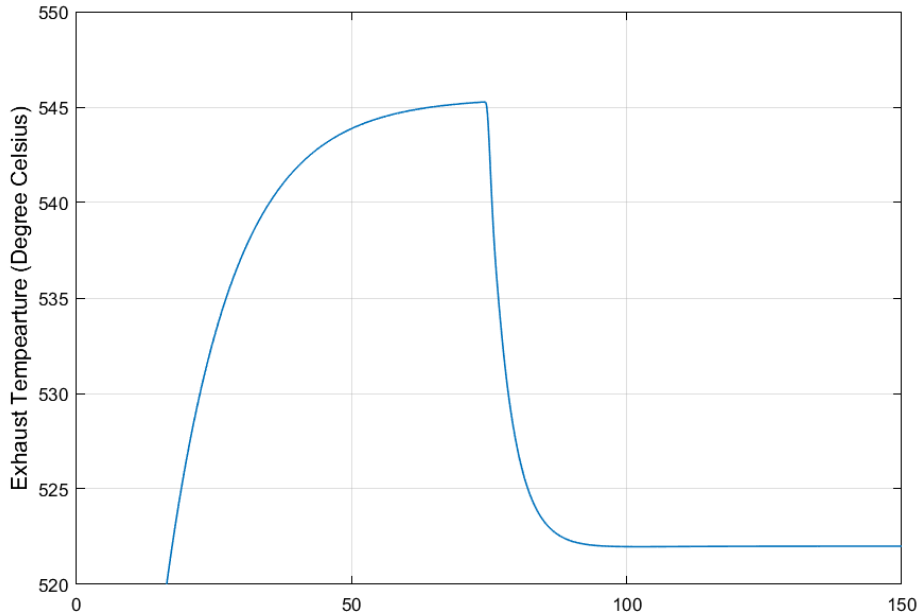


Figure 3. 11**:** Exhaust Temperature of HDGT after speed step of -0.3%

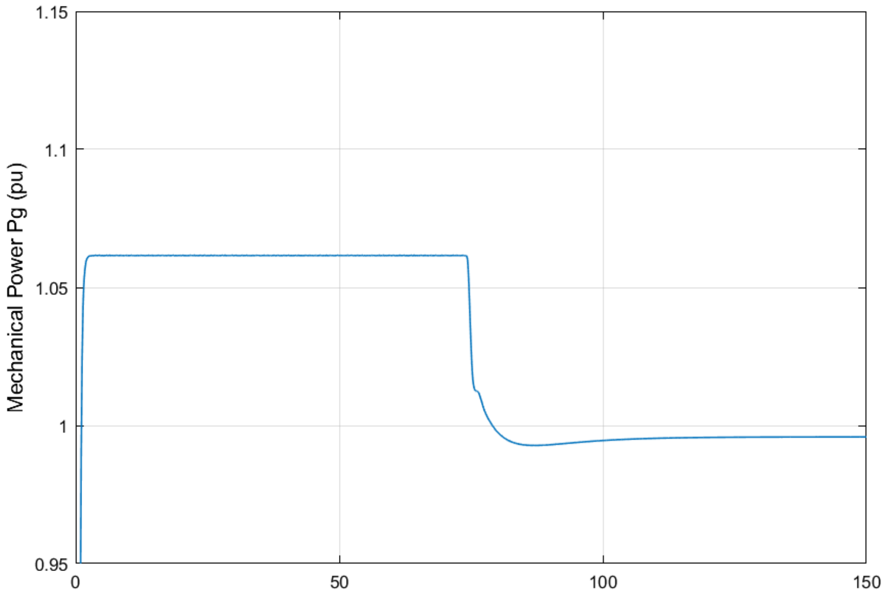


Figure 3. 12: Mechanical output power of HDGT after speed of -0.3%

Although the focus of this study is on Aeroderivative gas turbines not HDGT as discussed in the case study, the simulations of ADGT is more complicated and complex. Therefore, given the classification diversity of gas turbine, some researchers attempted to simulate a generic model for gas turbines. However, simulating a generic model for gas turbines would be very difficult. Thus, variety of gas turbine models were built by researchers from different methodological perspectives to achieve specific research objective(s). However, to underpin the generic model of gas turbine for various modelling purposes, number of commercial and institutional patent computer simulation models softwares have been developed by researchers and OEMs. Amongst institutional gas turbine modelling softwares include TURBOMATCH, PYTHIA and DETEM that has been developed by Cranfield University (Ogaji, 2003). Commercially, PROOSIS is one of the most powerful industrial software for gas turbine performance modelling. It was the first industrial modelling software for gas turbine which was released in 2005 and commercialised in 2008 after European FP6 project VIVACE (Value Improvement Through a Virtual Aeronautical Collaborative Enterprise) (PROOSIS, 2018). Industrially PROOSIS has wide range of capabilities and applications. It's used in product design, condition monitoring, optimisation, digital twin for process plants, aircraft engine and rockets as well as virtual commissioning applications (PROOSIS, 2018). Details on gas turbine modelling with PROOSIS has been explained by (Alexious, 2014).

3.6 Summary

Understanding the characteristics behaviour of gas turbine system is easily achieved by analysing operational data. The operational data is usually obtained using various sensors attached to the physical gas turbine system. However, obtaining industrial data is often expensive and difficult due to data censorship and security. Conversely, gas turbine behaviour analysis could be achieved through laboratory experiments. However, performing experiments on real system by stripping its components could be challenging and associated with rigorous fatigue, reliability challenges, error and damages. These constraints make it difficult and too dangerous and expensive to perform experiment on real systems. Alternatively, simulations can be done on model system to understand the effect of design characteristics and performance behaviour of simulated real system.

This chapter briefly discussed gas turbine modelling. Some gas turbine thermodynamics were briefly introduced, including some important factors affecting turbine modelling. The chapter briefly explained some important considerations whist modelling gas turbine system such as modelling objectives, modelling methods, gas turbine types and configurations as well as approaches in modelling gas turbines. A case study is on modelling and simulation of HDGT is implemented based on Rowen model. The behaviour of simple cycle HDGT was simulated using thermodynamic laws and operational data and the result obtained could be useful in many turbine studies. Although these results would not be sufficient for the predictive maintenance modelling task of this thesis, due to lack of relevant feature information required by the model. Hence the next chapter which seek the deployment of alternative source of dataset to develop the models (Experimental dataset).

Chapter 4

Gas Turbine Fault Classification/Diagnosis (Data-Based Model)

4.1 Introduction

Condition monitoring gains much attention in various industries due to quest for the increased reliability as well as the need to decrease the possible production loss associated with breakdown. Condition monitoring and fault diagnosis provides useful information regarding nature and localisation of failure thereby reducing the potential catastrophic failure andenhances adequate maintenance process planning (Moosavian et al., 2012). Condition monitoring improves rotating equipment reliability and availability through early fault detection and diagnosis. In recent years, various methods have been proposed to implement robust condition monitoring to industrial machineries. Modern industrial applications operate with the aid of rotary components. Thus, rotating machineries becomes one of the most critical equipment to modern industrial applications. However, these rotary components are prone to potential fault due to continuous operation. Hence, robust condition monitoring of the machinery equipment provides promising improvement on system reliability, availability as well as overall safety. Therefore, considering the importance of rotating machineries to modern industrial applications, significant research effort has been made to understand the failures of critical rotating machinery components. In short, various condition monitoring models has been studied towards implementation of robust models to detect and classify common failures modes of rotating machinery (Kaveh et al., 2008).

Fault diagnosis can be associated with pattern scenario of machinery condition. Therefore, a powerful pattern recognition tool, i.e., Artificial Intelligence (AI) has been identified and widely used by researchers in solving fault detection and diagnosis problems. Artificial Intelligence based fault diagnostics involve data processing, feature extraction and fault recognition. Given failure complexity of certain industrial machineries, diagnostics and isolation of machinery faults require more sophisticated fault diagnostic tool. Unlike model-based/signal processing-based diagnosis tool, data driven-based fault diagnosis does not require robust expertise to make judgements on machines fault diagnosis/prognostics (Wang et al., 2011). Conversely, AI- based fault diagnosis models robustly detect and classify machine failures without dependency on human experience expertise (Caesarendra et al., 2011).

Thus, AI-based fault diagnostic tools receive growing interest in the machinery research community (Gangsar and Tiwari 2017). A lot of AI tools and techniques have been widely used by researchers for fault detection and diagnostics programs. Some of these techniques are associated with convex optimisation, mathematical optimisation, and classification as well as statistical learning and probability-based methods. Given the powerful capabilities of AI and constraints and complexity of physical models of many machineries, AI-based machinery fault diagnostics attract the attention of researchers recently. Thus, vast research on AI-based fault diagnostics models appears in the literature every year.

Fault diagnosis essentially uses information about machinery operational condition to detect, identify and isolate potential faults. The condition of the machine is monitored from the trendof historical operational data obtained from robust data acquisition process. The condition monitoring data can be of various features. Thus, it can be acoustic data, vibration data, oil analysis data, temperature and pressure among others (Jardine et al., 2006). The signal variability of the condition monitoring data prompts a serious challenge to directly obtain faultpattern. Hence, an effective signal pre-processing (feature extraction) prepares an essential useful feature data for robust fault classification model (Jardine et al, 2006 & Yang et al., 2005). Then, pre-processed data serves to be the input to fault recognition/ classification model. Various techniques have been applied to fault diagnosis problem. Perhaps AI-based algorithms have shown more promising result and improved performance over conventional (statistical/model) approaches (Jardine et al, 2006). These AI-based techniques generally involve mathematical optimisation, convex optimisation, classification, statistical learning as well as probability-based methods. Although both classification and statistical learning prompts the most widely used methods among these techniques. Thus, most widely AI-based algorithms applied to rotating machinery fault diagnosis involves K-nearest neighbours (Wang,2016), support vector machines (Vapnik, 2013), Naïve Bayesian classifier (Baraldi, L. et al, 2015) and Artificial neural networks (Haykin, S., 2004). Similarly, Abed et al. (2016) identified feedforward neural network (NN), support vector machine (SVM) and adaptive neural fuzzy inference system (ANFIS) as commonly used AI based techniques in fault classification of rotating machines. Although, among the various pattern recognition methods employed for fault detection and condition monitoring of rotating machinery, NNs have been the most commonly used algorithm to classify training patterns from data sample (Yang et al.,2013; Abed et al. (2016). Figure 4.1 give an overview on the simple flow chart of AI basedalgorithms for fault diagnosis of rotating machines using both ANN and SVM models.

With recent advances of AI-based algorithms applied on rotating machinery diagnosis, Deep learning approaches also began to attract much attention among CBM researchers. Deep learning most recent machine learning method offers greater capacity to overcome some flaws and inherent disadvantages of other conventional intelligent methods. It distinguishes itself byits robust learning capabilities. Thus, it learns valuable features from raw data withoutinvolvement of feature extraction methods. Perhaps, this enhances its less dependence on various feature engineering, signal processing and domain expert. The most prominent deep learning methods applied to machinery fault diagnosis recently involves both Deep Believe network (DBN) and convolutional neural network (CNN) (Shao et al., 2018).

This chapter give an account of most popular Artificial Intelligence-based fault diagnosis applied to rotating machinery, with the specific reflection on how the algorithms were applied to rotating machinery and their basic background theories. A case study is conducted to understand how good feature extraction techniques enhances the prediction performances of the models.Various feature extraction techniques will be employed to pre-process the data before fitting them into models for classification. Models are validated after the training and ranked according to their performances.

4.2 Modelling

4.2.1 Data

The dataset used in this study has been collected by me and my DoS from Sheffield Low Carbon Combustion Centre Sheffield carbon (leading European facility for novel combustion and low carbon technology). The data used was taken from an experiment associated with a larger project, that aimed to characterize the behaviours and of gas turbine when exposed to different alternative fuels. ***fuel consumption and exhaust emissions***. These alternative fuels that are comprises of conventional kerosene-based fuel Jet-A1 and bio jet fuels. Introduction of these fuels to operate gas turbine engines, subjects the engine into different level of performance severity. While certain fuel is safe to operate the engine optimally, another different fuel would severely damage the engine components over certain period of operation.

In this study, condition monitoring strategies were explored for gas turbine engines using condition monitoring data (vibration and others). The aim here is to implement data-driven approaches and develop a reliable data-driven models that can describe the underlying relationships of the processes taking place during an engine's operation. The condition monitoring strategy developed can serve as a diagnostic solution in detecting excessive vibration levels that can lead to engine component failure. Hence, we demonstrate its performance on vibration data from an experimental gas turbine engine operating on different conditions. The data used were obtained by conducting various experiments by the centre on different Jet and gas turbine fuels with the aim to understand the underlining patterns that helps to intelligently classify various characteristics associated with engine exposure to different fuels. The facility used in testing different alternative fuels under different engine air-to-fuel ratios, is an auxiliary power unit of turboshaft gas turbine (Honeywell GTCP85-129), with its this operating principles follows a typical Brayton cycle, as described in Chapter 3.

The process involves drawing of ambient air by the engine from the inlet (1 atm) through the centrifugal compressor, where it raises its pressure by accelerating the fluid and passing it through a divergent section. This leads to the further decrease of the fluid across the centrifugal compressor. The pressure would be increased across a second centrifugal compressor, just before being mixed with fuel into the combustion chamber, and subsequently ignited to add energy into the system (in the form of heat) at constant pressure. Then a high pressure and temperature gasses emerges and expanded across the turbine. These expanded gasses further drive two compressors, as well as 32 kW generator that provides aircraft electrical power and the engine accessories, e.g., fuel pumps, through a speed reduction gearbox. There is a presence of bleed valve (BV) in the engine, which enable the extraction of high temperature, compressed air (~232°C at 338 kPa of absolute pressure) to be passed to the aircraft cabin and to provide pneumatic power to start the main engines. This mechanism allows the engine to be tested on different operating modes as the air-to-fuel mass flow that goes into the Combustion Chamber can be changed with the Bleed Valve position. When the BV opens, a decrease in turbine speed will take place if there is no addition of fuel to compensate for the lost work.

A Sensor (piezoelectric accelerometer) was connected to the engine using probes attached to the engine support structure. The sensor is characterised with sensitivity of 10 mV/g, and sampling frequency at 2 kHz (f_s = 2 kHz). Series of test were conducted with each test last for 110s duration. The fuels considered for the experiments were blends of Jet-A1 (TP10_Diesel and TP11_RedDiesel) and a bio jet fuel [hydro processed esters and fatty acids (HEFA)].

The engine was set to operate on different modes of operations using various blends of fuels, to understand some performance behaviours of the engine. For instance, the engine experiences the highest overall amplitude level across the whole spectrum when operating under condition 50% Jet-A1 + 50% HEFA. Likewise, it exhibits the highest vibration levels throughout the whole frequency spectrum. Thus, explained how changes in air-to-fuel ratio affects the statistical properties of the datasets and consequently the frequency-domain response of the engine for the different fuel blends. Various experiments were conducted on different fuel blends and datasets obtained can be categorised into two main groups, i.e., those with some strong periodic patterns and those that do not share this characteristic (non-stationary). This can be distinguished clearly with case study on Jet-A1 fuel blends (TP10 and TP11).
From the experiment above, a case study is established on two Jet-A1 fuel blends, namely TP10 Diesel and TP11_RedDiesel respectively. Both fuels were tested on the gas turbine engine test facility and its underlining operational behaviours (features) on each fuel blend ware captured by the sensor and recorded under the conditions specified above.

Some observable characteristics were emerged from the experiment in which both fuel blends (TP10 & TP11) exhibit different vibration characteristics under the same operation conditions. These observable changes could be attributed to the engine’s operational response on each fuel blend. Hence, guide our intuition to categorise the vibration responses under TP10_Diesel as steady-state operation and vice-versa for the TP11_RedDiesel. This can be clearer with exhibition of strong non-stationary trends on some time domain feature plots, and variations of periodic feature characteristics on frequency-domain features plots.

Engine's feature responses data can be categorised as belonging to the engine's "normal" condition correspond to fuels and air-to-fuel ratio combinations under steady-state, in which the engine experienced low levels of vibration, and "Abnormal" condition corresponding to air-to-fuel-ration combination under transient state. This data can be used to implement and validate the accuracy of condition monitoring-based diagnostics model. Thus, the model can be able to determine whether new unseen data points are classed as "Normal" or "Abnormal, by comparing them with the distribution learned. As such, the model should be sensitive enough to identify potential precursors of localized component malfunctioning at a very early stage that can lead to total engine failure. Perhaps, going by the analogy of establishing fault diagnosis, its known in practice that some contaminated fuels cause serious vibration to the gas turbine engines, which consequently damages some components in the gas turbine. Thus, the two classes of fuels are analogous to a faulty and non-faulty labelled dataset, which is used to develop a model that distinguishes faulty and non-faulty fuel. Table 4.1 depicts the dataset obtained from the experiment and labelled as (TP10_Diesel & TP11_RedDiesel). Both TP10_Diesel and TP11_RedDiesel represents two different types of fuels that are passed into the gas turbine engine to understand some underlining operational behaviours of the engine when either of the fuels is used as a combustion fuel to drive the engine. Some of these behaviours (features) of the engine were recorded by the sensors and identified in the Table 4.2.

The complexity of the processes taking place in a gas turbine engine from the context of dynamics, complex thermochemical, and other physical processes, and difficulty in obtaining system's failures in practice, prompts it hard to provide a theoretical explanation of the physical context behind the engine's responses acquired. This challenge is overcome with implementation of valid physics-based model that can predict the engine's vibration response as an output of a system. Although the nature of the modelling/monitoring problem, when approached from a physics-based perspective, suggests that model validation would be a significant challenge. Hence paved the way to a data-driven strategy, since the system examined (engine in operation) is treated as a black box. Therefore, the model established here follows a machine-learning framework for the condition monitoring of engines using the experimental data obtained. The framework can be used to detect patterns generated due to engine's response to various fuels exposed. These could be achieved through keys steps; the data acquisition, data pre-processing, feature extraction, and development of a learning model and model's validation.

Table 4. 1: Raw Data Groups and Dimensions

Groups	Sub-groups	Dimension
Gas TurbineLBO	TP10_Diesel	1048575 X 18
	TP11_RedDiesel	1048575 X 18

Table 4.2: Sensors and features used in the experiment

S/N	Feature	Sensor Data
1	Feature_1	Accelerometer_x1
2	Feature_2	Accelerometery_y1
3	Feature_3	Accelerometer_Z1
4	Feature_4	Accelerometer_x2
5	Feature_5	Accelerometer_y2
6	Feature_6	Pressure_1
7	Feature_7	Pressure_2
8	Feature_8	Pressure_3
9	Feature_9	Pressure_4
10	Feature_10	Pressure_5
11	Feature_11	Microphone_1
12	Feature_12	Microphone_2
13	Feature_13	Volumetric air flow
14	Feature_14	Volumetric volume flow
15	Feature_15	Air inlet temperature
16	Feature_16	Upstream air temperature
17	Feature_17	Annular air temperature
18	Feature_18	Exhaust air temperature

4.2.2.1 Sensor Types and Applications in Predictive Maintenance:

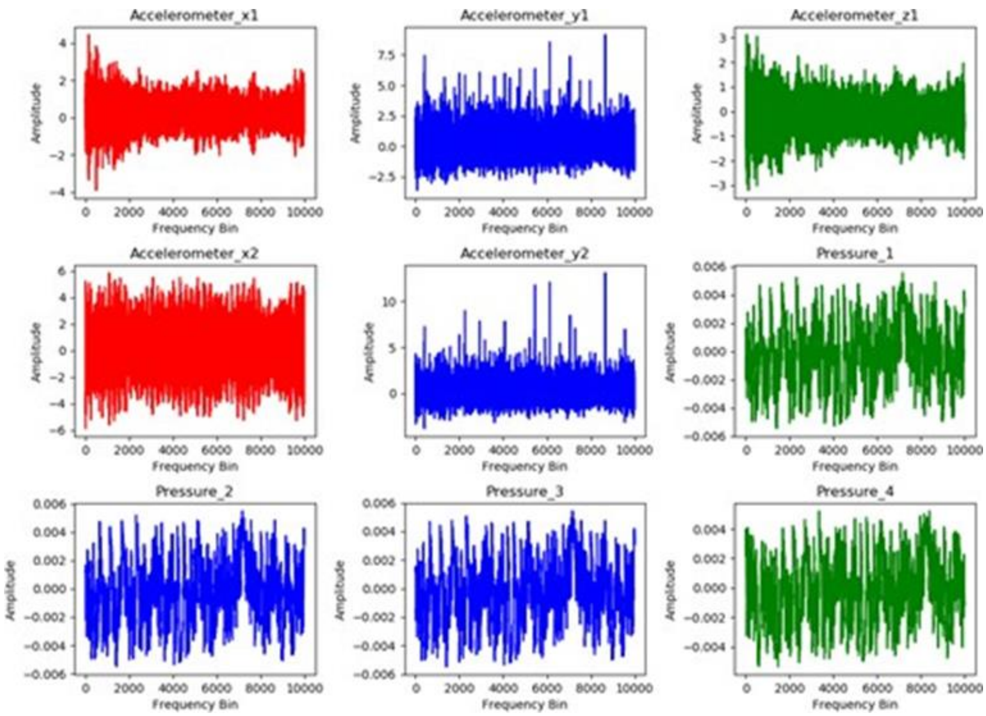
Sensors plays an important role in predicting failures in gas turbines. Some sensors can detect certain fault than others. Sensors can detect gas turbine faults, such as bearing damage, much earlier than others. Table (4.3) summarised types of sensors used in this research and their applications on gas turbines PdM.

4.3 Sensor Types and Application in Predictive Maintenance

Sensor Type	Measurement/Uses	Key Information	Target Faults
Accelerometer	Vibration	Low noise, frequencies up to 30 kHz, well established in CbM applications	Bearing condition, gear meshing, pump cavitation, misalignment, imbalance, load condition
Microphone	Sound Pressure	Low cost/power/size, frequencies up to 100 kHz	Pressure leaks, bearing condition, gear meshing, pump cavitation, misalignment, imbalance
Infrared thermography	Temperature	Expensive, accurate, multiple assets/sources of heat at one time	Change in temperature due to friction, load changes, excessive start/stop, insufficient power supply
Turbine flow meter	Volume (liquids & gases)	Expensive and accurate.	Essential in gas path analysis of gas turbine PdM.

4.2.2.2 Dataset Preparations

The dataset was prepared through normalization, by dividing each time-domain and frequency-domain acceleration amplitude by its corresponding maximum value, i.e., unit normalized, so that all amplitudes, corresponding to the different datasets, vary within the same range [0, 1]. This is preceded by removing some features that are irrelevant or carry very negligible information,essential in obtaining good robust model. Hence, all the features were plottedin their raw form to understand some underline characteristics of the signals. As depicted in **Figure 4.1**, It can be observed that some features do not change over their entire length. Therefore, by inspection, removing them is necessary. The Features that have been removed includeVolumetric Fuel Flow, Volumetric Air Flow, Air Inlet Temperature, Annular Air Temperature, and Exhaust Air Temperature.



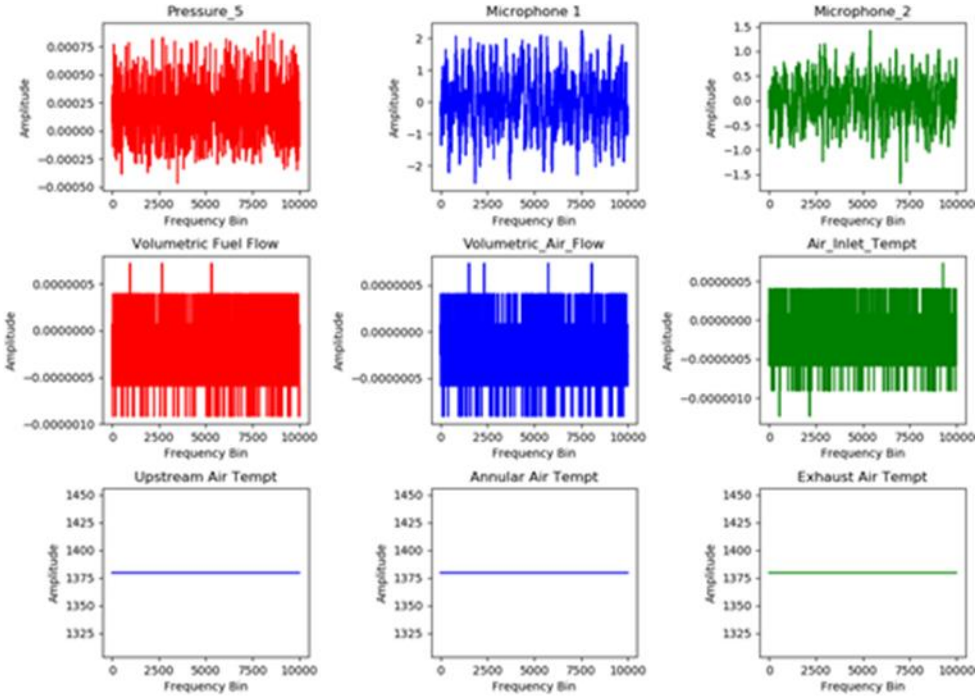
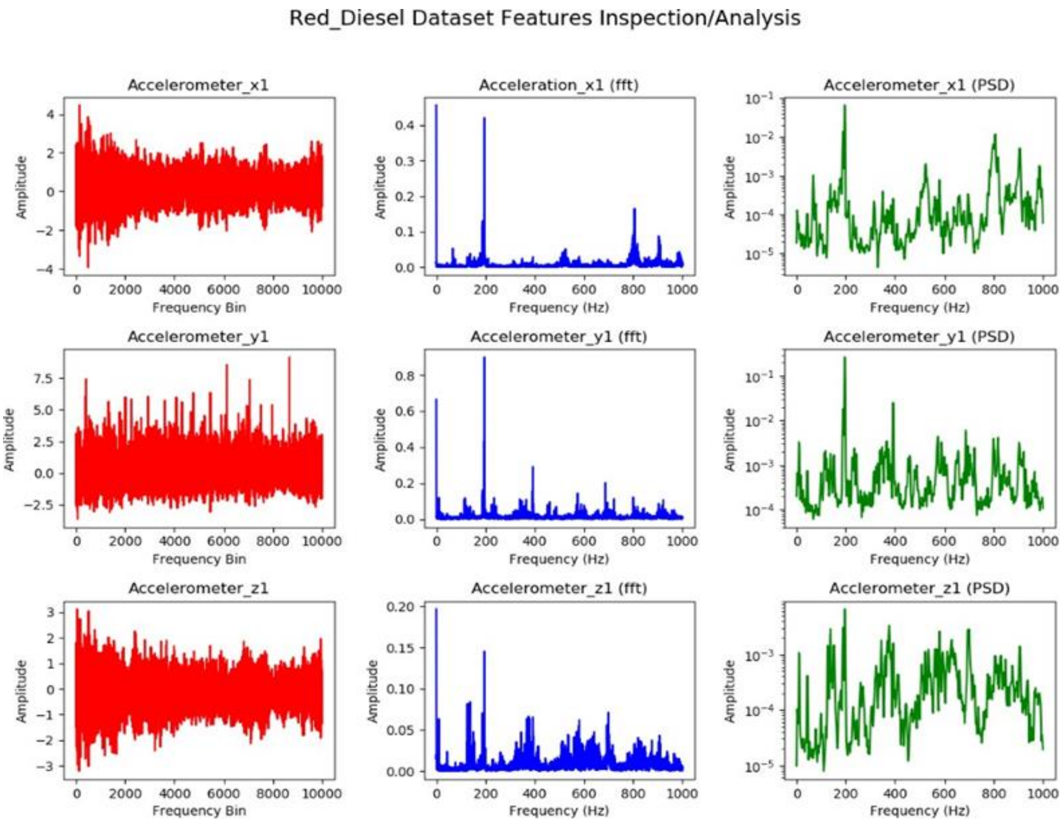
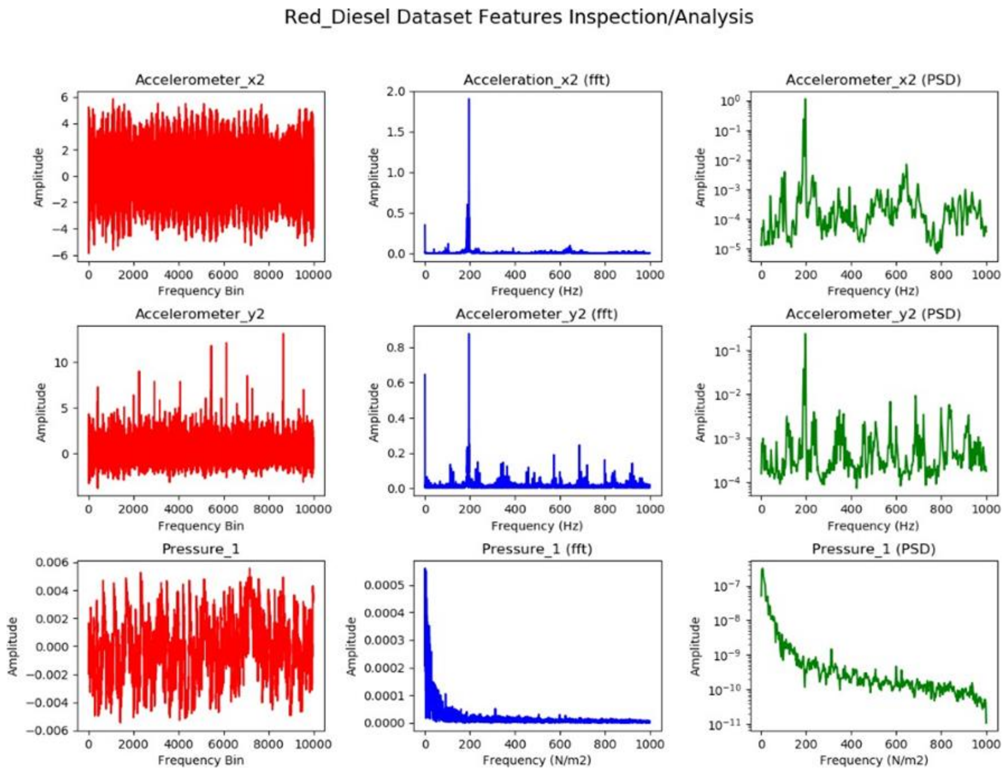


Figure 4.1: Plots of useful features of TP11-Fuel to selected for the model

The remaining sensor data retained has been further investigated using Fast Fourier Transform (FFT) and Power Spectral Density (PSD), with motivation to discriminate features with low information content as well as discarding features with similar characteristics. The FFT of 16 remaining sensor signals has been depicted in Fig 4.2.


Red_Diesel Dataset Features Inspection/Analysis
Accelerometer_x1
Acceleration_x1 (fft)
Accelerometer_x1 (PSD)
Accelerometer_y1
Accelerometer_y1 (fft)
Accelerometer_y1 (PSD)
Accelerometer_z1
Accelerometer_z1 (fft)
Acclerometer_z1 (PSD)
Amplitude
Frequency Bin
Frequency (Hz)


Red_Diesel Dataset Features Inspection/Analysis
Accelerometer_x2
Acceleration_x2 (fft)
Accelerometer_x2 (PSD)
Accelerometer_y2
Accelerometer_y2 (fft)
Accelerometer_y2 (PSD)
Pressure_1
Pressure_1 (fft)
Pressure_1 (PSD)
Amplitude
Frequency Bin
Frequency (Hz)
Frequency (N/m2)

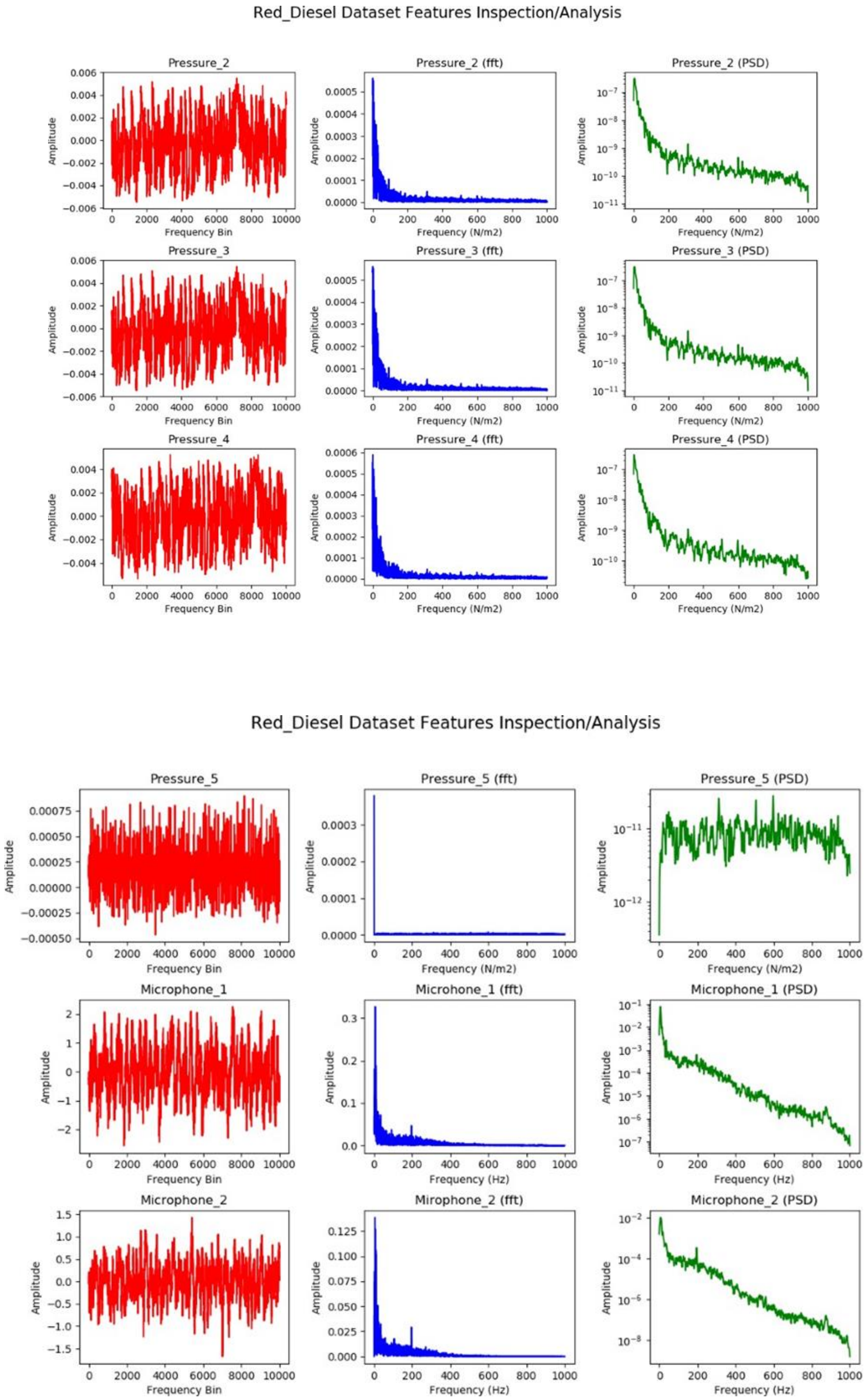


Figure 4. 2: FFT and PSD of remaining 9 TP11 features

Although FFT spectra of some signals appeared to have similar frequency patterns localisation, however the PSD give more clear frequency patterns, which significantly helps in selecting the appropriate features for the models. Both FFT and PSD helps in revealing more signal patterns, that are not clearly visible in time domain. Hence guide the selection of the features with significant information content. The features selected for the modelling include;

- Accelerometer_x1
- Accelerometer_y1
- Accelerometer_z1
- Accelerometer_y2
- Microphone_1
- Microphone_2

Visualising Figures 4.1-4.2, Pressure_1 to Pressure_5 signals have negligible fundamental frequency harmonics as revealed by FFT and decaying patterns as demonstrated by PSD. This indicate that the signals do not carry much significant information for the models, hence discarded. Both Microphone_1 and Microphone_2 contained a decaying signal, but have some frequency fundamentals as depicted by their FFTs. This prompted their usefulness and therefore selected for the model.

4.3 Models Implementations for fault diagnosis

The data obtained and selected above is used in developing machine learning (Data-Driven) models that are capable in classifying two distinct types of fuels (TP10 and TP11). The six features obtained could not be feed into the model directly due to inherent noise contained in the dataset. Therefore, data pre-processing is essential in yield high performing model. Further,when the right features have been extracted, various supervised machine learning models would be developed to handle the problem at stake. These models are developed according to the techniques employed in restructuring the raw dataset to increase nonlinear relationship between the feature vectors in the dataset. In addition, some data pre-processing/feature extraction techniques are employed, such as Principal Component Analysis and Signal Processing to extract the features that are more relevant to the models. Hence, this work has been carried out according to the feature extraction technique involves. First, the dataset is restructured to obtain more X features with many dimensions. This will increase the correlations among the feature vectors. The high dimension feature vectors are reduced to some more relevant components that contained useful information using PCA. In short, the overall models are categorized as;

- PCA-based
- Signal Processing Based
    - Time Domain Based
    - Frequency Domain Based
    - Time Frequency Domain Based
- Deep Learning Based

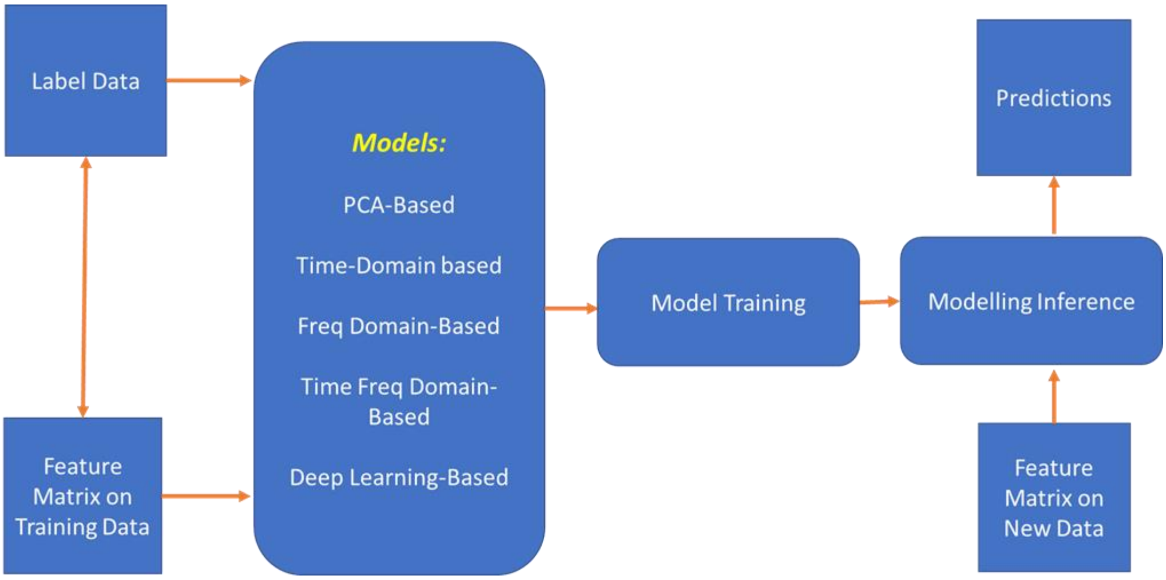


Figure 4. 3: Flow diagram of Modelling Processes

The Figure 4.3 illustrated the entire modelling process and the relationships between the models. Obviously selecting a single model for the training and validation could not justify the suitability of that model to the specific problem in context. In short machine learning algorithm works best for every problem, and this is more relevant for supervised learning Predictions. Therefore, various models were introduced to verify the best model with highest prediction accuracies. However, when variety of machine learning algorithms involved, searching on the most suitable algorithm prompts often challenging. Hence, this paved the way in trying different algorithms whilst taking into considerations some factors, such as;

- the size, quality, and nature of data.
- The available computational time
- The urgency of the task; and
- Purpose and objectives of the modelling.

4.3.1 Model-1 (Principal Component Analysis Based)

The PCA based model developed involves the process of data restructuring, normalisation, dimension reduction and as well as Artificial Neural Network model architecture. The modelling results obtained are summarised in Table 4.10. The brief overview on the models are;

4.3.1.1 Modelling Objectives

Principal Component Analysis (PCA) is one of the most used algorithms in supervised and unsupervised machine learning developments, depending on the problem in context. It's essential across a variety of applications, such as exploratory data analysis, dimensionality reduction, information compression, data de-noising, and much more. It apparent that while working on various machine learning techniques for Data Analysis, we deal with tremendous number of variables, depending on the problem at hand. Often most of the variables are correlated with each other, and in such cases, fitting the model to the dataset significantly results in poor accuracy of the Model. Therefore, Principal Component Analysis technique is used here;

1. To helps in reducing the dimensionality of the dataset and converts set of correlated variables to non-correlated variables.

2. To finds a sequence of linear combinations of variables.

3. As a tool for better data visualization of the dataset used data, to reveal the correlations between each component.

4. Used as important tool for data interpretation and variable selection for the overall model development.

4.3.1.2 Data Restructuring

Originally each dataset has dimension (1048575 X 18) before discarding the non-useful features, as explained in Section 4.2.1. Since only 5 features were selected from each dataset,then new dimension of each dataset will become (1048575X6). However, each dataset needs further restructuring to increase the correlation between the feature vectors in each dataset. On that basis, the summary of TP10 dataset restructuring as well as changes in dimension for X features has been illustrated in Table 4.4.

As indicated in Table 4.3, steps have been used in restructuring the dataset. The steps refer tothe alignment of each feature vector in horizontal orientation end to end to represent and observation of a class labels. For instance, 10 steps have been used in Table 4.4, which indicated lining 10 datapoints of each 6 features in horizontal orientation end to end to form 60datapoint. Hence represent the class in which the fuel belongs to (Y). The loop continues withthe next 10 steps of datapoints along the entire length of the dataset. The overall process changes the dimension of X_dataset from (1048575 X 6) to (174763 X 60). Same process

continues by changing the datapoint steps between (20, 30, 40, 50 and 60) as indicated in Tables (4.4-4.9).

4.3.1.3 Normalization

Normalisation is an important technique in data pre-processing stage, it’s apparent that the datato be modelled constitutes of different ranges of scales. Perhaps, within the predictor features,there is often differences between the maximum and minimum values. Normalisation scale down variation in features in such away when it’s performed the value magnitudes are scaled to appreciable values. This practice is very important especially considering that the restructured data has high dimensions which must be reduced to discard the irrelevant features.Thus, PCA requires the features to be normalised, likewise the subsequent neural networks algorithms need normalization which optimises and enhances quick convergence of the algorithm. Thus, minimising the effect of large magnitude of one predictor dimension inrespect to others, a scenario that leads to slow convergence (Kotsiantis et al., 2007). Among the most common techniques for normalisation (Min-Max and Standard-Scaler), Min-Mix is used for this work. The Min-Max technique rescale every feature to a scale between [0,1]. The Min-Max normalisation of dataset is computed using the following formula:

$$Z = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{4.20}$$

4.3.1.4 Dimension Reduction

Analysing complex and multi-dimensional dataset would be to a difficult task. Likewise, visualising complex or multi-dimensional dataset. Perhaps, the difficulty in visualisation and computation increases with increase in dimensions. However, viable solution that overcome dimension complexity of data is achieved by removing the redundant dimensions (features) and keeping the most valuable dimensions (features). Feature selection techniques and algorithms were extensively discussed in **Chapter two**, however, iterating its profound importance here is imperative as its essential in transforming patterns from the data and extracts valuable information from the data table. Further, the data is subsequently express useful information to a new set of orthogonal variables known as **principal components**. Thus, reducing the dimensionality the dataset.

The structured dataset obtained from Section 4.3.1.1, has been transformed further by reducing its dimensions into various principal components as indicated in tables 4.3, which are further fed into machine learning classifier for subsequent classifications and predictions. Various PCA components were selected (5, 10, 15, 25 and 30) for each datapoint steps (10, 20, 30, 40, 50 and 60) with each PCA component is used for classification task, hence the corresponding result for each modelling is indicated in Tables 4.3.

4.3.1.5 Classification Model

The Principal Components obtained in Section 4.3.1.3 are fed into Artificial Intelligence classifier. Various AI classifiers exist for supervise learning tasks. However, by convention Artificial Neural Network (ANN) and Ensemble learning based Extreme Gradient Boosting classifier (XGB) have proven performance, compared to other classifiers. Hence both ANN and XGB are used in this work.

ANN is based on Perceptron and Feed Forward Neural Networks (FFNN) with back propagation gradient descent learning algorithm, which is used for updating the weightsvectors. Various ANN and XGBoost Architectures were used as illustrated in Tables 4.4-4.9,depending on the datapoint steps as well as the numbers of PCA components used. For instance,when 10 datapoints steps and 5 components were used, an architecture with 3 fully connectedlayers (1 input, 1 hidden and 1 output) is used. The Input layer consists of 5 neurons, hidden layer consists of 3 neuron, and 1 neuron has been assigned to output layer. Weights and biasesin each layer have been randomly initialised and used to compute the target output values. Thelearning rate is also initiated with a minimal fixed value and kept constant until the convergenceof the training model. Two activations functions were used with ReLU formed both input andhidden layer. The output layer has Sigmoid as its activation function. The dataset for the modelhas been split into both training and test sets. Training/learning takes 80% of the dataset whilethe remaining 20% of the dataset is assigned for testing. The training rans through 300 epoch (iteration) and converges afterwards.

The capabilities of ANN in classifying various non-linearscenarios in the data is harnessed in this model to perform binary classification of two differenttypes of fuels used by gas turbine. The results of the modelling are presented in Table 4.4-4.9.

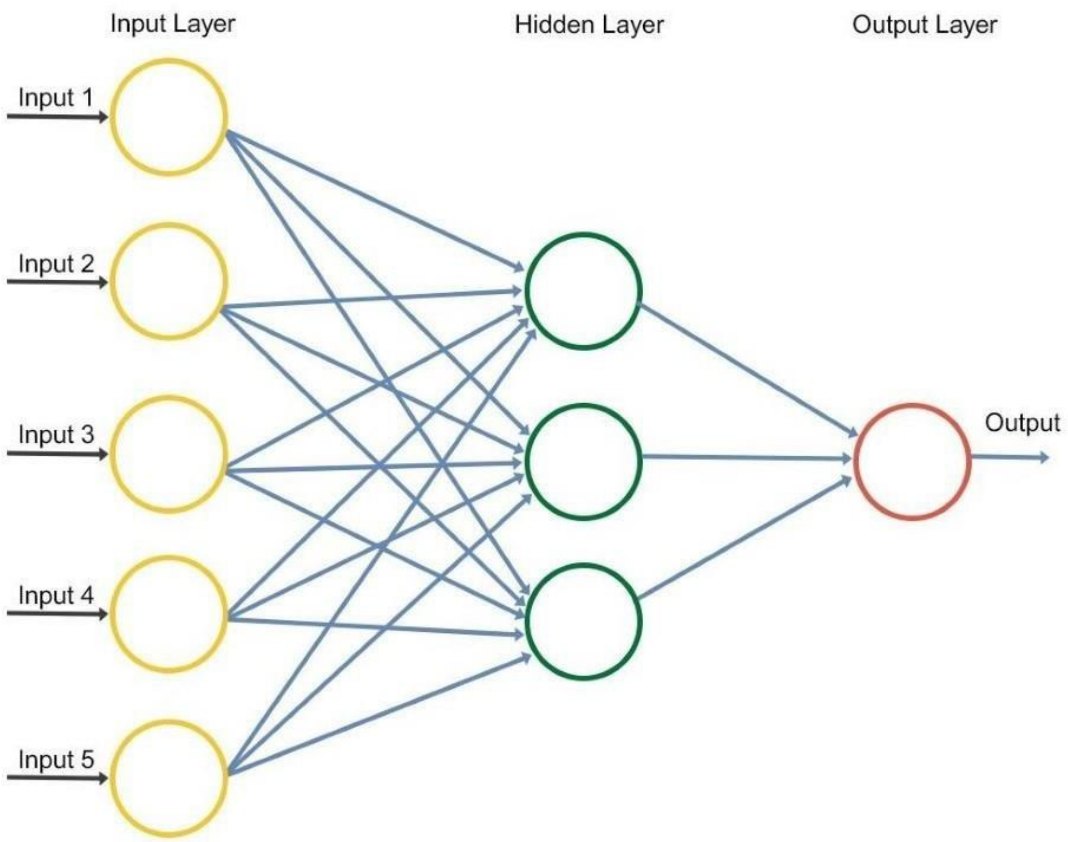


Figure 4. 4: ANN Model Architecture

Training/learning takes 80% of the dataset while the remaining 20% of the dataset is assignedfor testing. The training rans through 300 epoch (iteration) and converges afterwards. The capabilities of ANN in classifying various non-linear scenarios in the data is harnessed in this model to perform binary classification of two different types of fuels used by gas turbine. The result of the modelling has been presented in Table 4.4. stands for eXtreme Gradient Boosting.

Another classifier used in this work is XGBoost (eXtreme Gradient Boosting). The name xg XGBoost refers to the engineering goal to push the limit of computations resources for boosted tree algorithms., hence a reason why many people use XGBoost. The key motivation behind deploying this algorithm in this study is to herness the capabilities of algorithm's robust Execution Speed and enhanced Model Performance. This is essential due to some feature that ranges from Sparsity towards automatic handling of missing data values, parallel computations and Block Structure capabilities to support the parallelization of tree construction. This ensured continued Training, such that one can further boost an already fittedmodel on new data. Various PCA component are fed into this classifier, depending on the datapoints steps and number of PCA components. Although the results obtained in this study with XGB classifier is not as robust as ANN, yet the algorithm proven its capabilities when inachieving good results as illustrated in Table 4.4.

Table 4. 4: PCA-based Models (10 datapoint arrangement with PCA Components)

Steps	**Dimension_X**	**PCA Features**	**% PCA**	**Model**	**Training**	**Test/Validation**
				ANN	0.7359	0.7365
				XGB	0.744	0.741
		5	0.729			
10	209716 X 60			ANN	0.8237	0.8212
		10	0.810			
				XGB	0.808	0.805
				ANN	0.8348	0.8335
		15	0.865			
				XGB	0.807	0.805
				ANN	0.8859	0.8863
		20	0.898			
				XGB	0.816	0.812
				ANN	0.9069	0.9071
		25	0.925			
				XGB	0.835	0.832
				ANN	0.9197	0.9191
		30	0.947			
				XGB	0.840	0.836

Table 4.5: PCA based Models (20 datapoint arrangement with PCA Components

Steps	Dimension_X	PCA Features	% PCA	Model	Training	Test/Validation
		5	0.699	ANN	0.7364	0.7404
				XGB	0.738	0.742
20	104858 X 120					
		10	0.766	ANN	0.8357	0.8355
				XGB	0.829	0.822
		15	0.813	ANN	0.8570	0.8525
				XGB	0.827	0.822
		20	0.846	ANN	0.8910	0.8888
				XGB	0.816	0.812
		25	0.872	ANN	0.9232	0.9185
				XGB	0.856	0.852
		30	0.891	ANN	0.9258	0.9217
				XGB	0.860	0.854

Table 4. 6: PCA based Models (30 datapoint arrangement with PCA Components)

Steps	Dimension_X	PCA Features	% PCA	Model	Training	Test/Validation
30	69906 X 180	5	0.685	ANN	0.7287	0.7346
				XGB	0.754	0.738
		10	0.745	ANN	0.8661	0.8666
				XGB	0.855	0.840
		15	0.795	ANN	0.8755	0.8758
				XGB	0.858	0.839
		20	0.819	ANN	0.9024	0..8979
				XGB	0.862	0.845
		25	0.843	ANN	0.9283	0.9238
				XGB	0.864	0.844
		30	0.862	ANN	0.9354	0.9308
				XGB	0.863	0.845

Table 4.7: PCA based Models (40 datapoint arrangement with PCA Components)

Steps	Dimension_X	PCA Features	% PCA	Model	Training	Test/Validation
		5	0.6689	ANN	0.7377	0.7358
				XGB	0.754	0.742
40	52430 X 240					
		10	0.734	ANN	0.8574	0.8589
				XGB	0.856	0.848
		15	0.774	ANN	0.8829	0.8831
				XGB	0.858	0.851
		20	0.799	ANN	0.9259	0.9240
				XGB	0.861	0.855
		25	0.822	ANN	0.9320	0.9271
				XGB	0.862	0.858
		30	0.841	ANN	0.9425	0.9386
				XGB	0.871	0.862

Table 4.8: PCA based Models (50 datapoint arrangement with PCA Components)

Steps	Dimension_X	PCA Features	% PCA	Model	Training	Test/Validation
50	41944 X 300	5	0.6568	ANN	0.7388	0.7410
				XGB	0.755	0.751
		10	0.725	ANN	0.8515	0.8574
				XGB	0.848	0.83
		15	0.761	ANN	0.9027	0.8984
				XGB	0.858	0.849
		20	0.786	ANN	0.9348	0.9278
				XGB	0.860	0.847
		25	0.807	ANN	0.9481	0.9387
				XGB	0.879	0.866
		30	0.826	ANN	0.9535	0.9417
				XGB	0.880	0.867

Table 4.9: PCA based Models (60 datapoint arrangement with PCA Components)

Steps	Dimension_X	PCA Features	% PCA	Model	Training	Test/Validation
60	34954 X 360	5	0.642	ANN	0.7986	0.7927
				XGB	0.809	0.799
		10	0.715	ANN	0.8554	0.8484
				XGB	0.856	0.848
		15	0.751	ANN	0.9049	0.8986
				XGB	0.856	0.839
		20	0.776	ANN	0.9438	0.9386
				XGB	0.872	0.860
		25	0.797	ANN	0.9505	0.9429
				XGB	0.875	0.864
		30	0.815	ANN	0.9564	0.9436
				XGB	0.875	0.861

4.3.1.6 Analysis and Evaluation for the Models

Successful implementation of model with different datapoints steps and PCA components, it's clear that some good results have been obtained from the models as depicted in Table 4.4- 4.9. Thus, it can be observed that;

- The increase in datapoint steps leads to the increase in model performances. For instance, the performance of ANN model increases from 91.97% to 94.38% when datapoint steps has been changed from 10 to 60 (Table 4.4 & 4.9) with 20 PCA components each.
- Dimensionality reduction in the raw dataset increases the model performances. For instance, reduction of 60 features to 5 PCA components as presented in Table (4.4), prompt ANN model to achieve 73.59% when 10 datapoints steps has beenused. Although, the model performance increases when more percentage of the data information has been captured from the features as indicated in Table (4.4) where 30 components (representing 94.7% of the data) achieve 91.97% accuracy using 10 datapoints steps.
- The ANN models achieved higher performances compared to XGB. Hence, prompts us to focus more on the former as summarised in Table (4.10).

Table 4.10: Summary of ANN_PCA based Models (10 datapoint arrangement with PCAComponents)

Steps	PCA Components	PCA %	Training	Test/Validation	Accuracy (20-Comp)
	5	0.729	0.7359	**0.7365**	
	10	0.810	0.8237	**0.8212**	
10					**0.8859**
	15	0.865	0.8348	**0.8335**	
	20	0.898	0.8859	**0.8863**	
	25	0.925	0.9069	**0.9071**	
	30	0.947	0.9197	**0.9191**	
	5	0.699	0.7364	**0.7404**	
	10	0.766	0.8357	**0.8357**	
20					**0.8910**
	15	0.814	0.8570	**0.8525**	
	20	0.846	0.8910	**0.8888**	
	25	**0.872**	**0.9232**	**0.9185**	

	30	**0.891**	**0.9258**	**0.9217**
	5	0.685	0.7287	**0.7346**
	10	0.745	0.8661	**0.8666**
30				**0.9024**
	15	0.791	0.8755	**0.8758**
	20	0.818	0.9024	**0.8979**
	25	0.843	0.9283	**0.9238**
	30	0.862	0.9354	**0.9308**
	5	0.669	0.7377	**0.7358**
	10	0.734	0.8574	**0.8589**
40				**0.9259**
	15	0.774	0.8829	**0.8831**
	20	0.799	0.9259	**0.9240**
	25	0.822	0.9320	**0.9271**
	30	**0.841**	**0.9425**	**0.9386**

5	**0.656**	**0.7388**	**0.7410**
10	0.721	0.8515	**0.8574**
50			**0.9348**
15	0.761	0.9027	**0.8984**
20	0.786	0.9348	**0.9278**
25	0807	0.9481	**0.9387**
30	0.826	0.9535	**0.9417**
10	0.715	0.8554	**0.8484**
15	0751	0.9049	**0.8986**
20	0.776	0.9438	**0.9386**
25	0.797	0.9505	**0.9429**
30	**0.815**	**0.9564**	**0.9436**

The models' accuracy assessment is critical to the model performance. Although accuracy alone is not sufficient. Hence, further metrics can be used to evaluate models' performances. This is because the performance parameters usually give a good picture on model's prediction performance. Hence, another criterion to evaluate model performance isby employing either statistical or machine learning methods. Suresh et al 2014 highlighted the definitions of some statistical performance parameters that are derived from model's confusion matrix. These parameters as defined by the authors involves;

1. **Precision:** This refers to the extent to which the repeated measurement under unchanged conditions demonstrates same result. This is represented as;

$$\text{Precision} = \frac{TP}{FP + TP} \tag{4.21}$$

2. **Completeness:** On the bases of fault diagnosis, completeness refers to the ratio of the number of faults in classes classified as fault prone to the total number of faults in the system. This parameter is also regarded as **Recall** and expressed mathematically as;

$$\text{Completeness/Recall} = \frac{TP}{TP + FN} \tag{4.22}$$

3. **Accuracy:** This is defined as ratio predicted fault prone being inspected out of all modules. It's expressed mathematically as;

$$\text{Accuracy} = \frac{TN + TP}{TN + FP + FN + TP} \tag{4.23}$$

Where; TN is True Negative

TP is True Positive

FN is False Negative

FP is False Positive

Various models have been produced above, depending on the datapoint step number of PCA components. Each model has corresponding performance accuracy. However, to access other performance indicator, datapoint step (60) with 20 components has been chosen toverify ANN model performance using confusing matrix. The result of confusion matrix is illustrated in Figure 4.5.

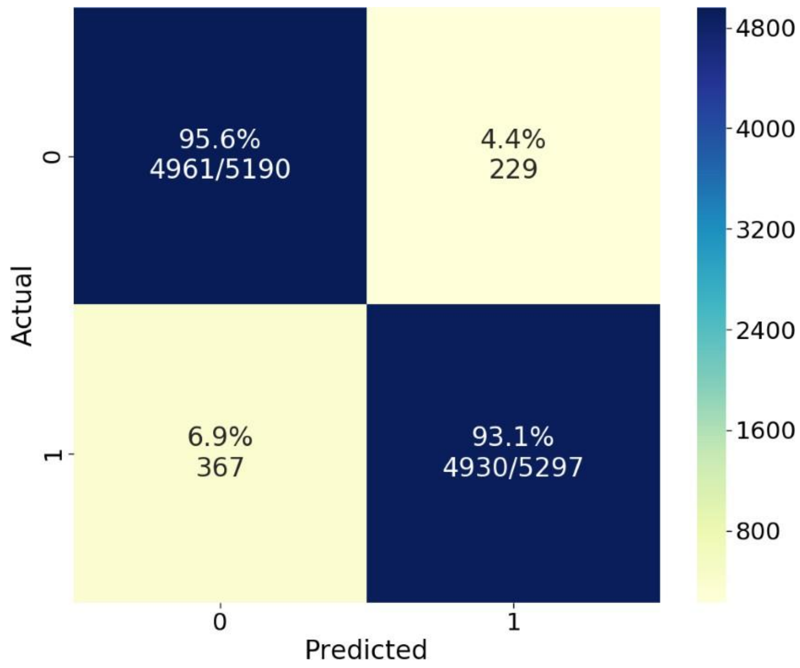


Figure 4. 5: ANN-PCA Based Confusion Matrix

It can be observed that the model achieved significant accuracy in predicting the two different classes of fuels. Hence, when new data is passed through the model;

- The model successfully classifies Red Diesel Fuel (TP11) accurately by up to 95.6%, with misclassification error of just 4.4%.
- The model also predicts and classifies Normal Diesel (TP10) accurately by 93.1% and misclassified the fuel class with the error of 6.9%.

4.3.2 Model-2 (Signal Processing Based-models)

4.3.2.1 Introduction

Signal Processing essentially helps in analysing, visualising and comparing multiple signals. In addition, it helps in detecting and extracting features or underline information/event contained in a signal. Feature detection and extraction significantly add value to the dataset meant to be used for further machine learning (ML) modelling. Figure 4.6 illustrates the procedures in preparing signals before feeding into the ML models.

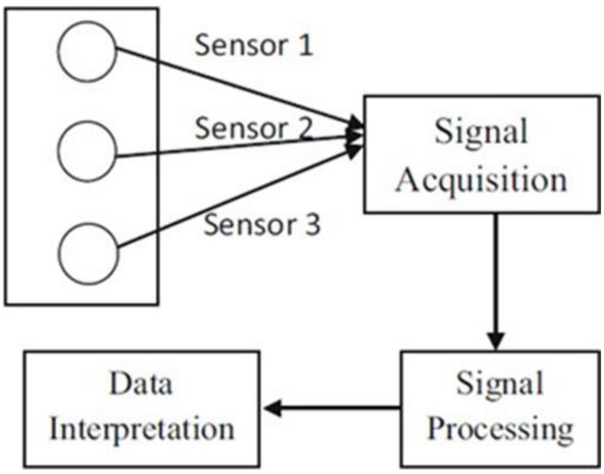


Figure 4.6: Feature Engineering Process

Various signal processing tools and techniques are used in extracting useful features from signals. However, depending on the task and requirements, these techniques are distinctly categorised into 3 groups (Time Domain, Frequency Domain and Time Frequency Domain). Therefore, we'll employ all the three signal processing categories to extract features from the fuels datasets to in developing various supervised classification models. Finally, both categories will be evaluated regarding their significance in increasing models' performances.

4.3.2.2 Objectives

The main purpose of implementing signal processing here as it's applied to the failure diagnosis is to extract an important feature information (feature extraction) to distinguish signals with different variational failure patterns in the fuel dataset. This made signal processing tool as one of the key procedures of rolling gas turbine fault diagnosis modelling. Thus, feature extraction especially signal processing-based would directly affects the diagnosis results. Therefore, to acquiring rich fault information, the traits in time-domain, frequency-domain, and time-frequency domain are extracted.

Traditionally, constructing a feature set containing all the fault information to identify and distinguish different types of faults could be done manually or through PCA-based. However, in general, the whole feature set of all the fault information are considered, redundant features, mutually exclusive features, and superior features could be mixed off together. Hence, feeding all features in the feature directly into a classifier, would significantly affects the classification process by slowing down the modelling speed and generate poor classification accuracy. Therefore, selecting the relevant features through one of the signal processing-based techniques would guarantee an improved calculation speed of the classifier and the classification accuracy of the model.

In the system of condition monitoring and fault diagnosis, the signals that are collected from the testing equipment are usually generated as time-domain signals. While these test signals are random and cannot directly reflect the state change of the system, it's necessary to analyse the test signals to find the inherent characteristics patterns useful to the model. Hence, the signal processing techniques (Time-domain, frequency-domain, and time-frequency domain) are often used as important tools for signal feature extraction. When dimensional parameters were extracted from the TP10 and TP11 dataset, and feature vectors were generated. Finally, each norm of the fault feature vector is input into model classifiers and the fault modes predictions and validations.

Time domain analysis is often used to estimate and calculate various time domain-based signal parameters. However, the variables obtained cannot be sufficient to reveal relevant underlining pattern required for the diagnostics model. Hence paved the way for frequency domain-based analysis. Analysis in frequency domain helps to describe and reveal more signals patterns and information that and can be disclosed or found in time domain. Although the time-domain feature variables can effectively be applied to distinguish between the normal and the fault case, yet frequency domain-based feature analysis reveals more inherent patterns in signals. Usually, frequency-domain feature extraction can reflect the periodic components in the signal, that cannot be found in time domain-based analysis. However, despite the capabilities of frequency domain-based analysis, yet its assumption is based on stationary theory, and not applicable to nonstationary and nonlinear signals. Hence paved the way for more improved analysis tool. Therefore, combination of both time domain and frequency domain tools, the fault features can be more accurately extracted. Below are the detailed signal processing-based feature analysis.

4.3.2.3 Time Domain Model:

Time domain features are usually extracted from raw signal. Statistical time-domain features such as root means square (RMS), mean, standard deviation and variance have been extensively used in identifying and extracting useful pattern in signals. Further, more advanced statistical-based features such as skewness, kurtosis is also applied to raw time domain signal to extract useful features for ML models (Caesarendra and Tjahjowidodo, 2017).

4.3.2.3.1 Dataset

Time domain-based model is developed by extracting statistical features from restructured and transformed dataset. The restructured dataset is produced from transformed 10 datapoints and 10 PCA components. Hence yield X_dataset with dimension (209716 X 10) for both TP10 and TP11 each as seen in Table 4.4. The corresponding targetslabels also have dimension (209716 X 1). It can be observed from Table 4.4, that the combination of 10 datapoints and 10 PCA components produced a model with 82.37%. Therefore, the objective here is to extract time-domain statistical features (TDSF) from the same 10 reduced features to and use for subsequent ML modelling. Hence, investigate the possibility of increased prediction performance accuracy from (82.37%).

4.3.2.3.2 Extracting Time Domain Statistical Features

The time domain statistical features extracted from 10 transformed components include skewness, mean, kurtosis and standard deviation. Each original feature component produces 4 from these time domain features. Hence yield overall dataset with X_dimension (209716 X 40) belonging to each fuel class (TP10 and TP11) respectively. The datasets are the concatenated to form one single dataset, which will be further used in supervised ML model.

4.3.2.3.3 Normalisation:

Features normalisation is not required here since the features were already scaled prior to PCA dimension reduction process.

4.3.2.3.4 Modelling

Considering the overwhelming performance of ANN as seen in this study, ANN based on back propagation gradient descent learning algorithm is used in training the model. The architecture consists of 3 layers, i.e., input layer (40 neurons), hidden layer (20 neurons) and output layer (1 neuron). which is used for updating the weights vectors. Weights and biases in each layer have been randomly initialised and used to compute the target output values. The learning rate is also initiated via Sklearn with a minimal fixed value and kept constant until the convergence of the training model. Two activations functions were used with ReLU formed both input andhidden layer. The output layer has Sigmoid as its activation function. The dataset for the modelhas been split into both training and test sets. Training/learning takes 80% of the dataset while the remaining 20% of the dataset is assigned for testing. The training rans through 100 epoch (iteration) and converges afterwards. The capabilities of ANN in classifying various non-linear scenarios in the data is harnessed in this model to perform binary classification of two different types of fuels used by gas turbine. The model is achieved 98.64% and 97.51% for training and testing respectively.

4.3.2.3.5 Model Analysis and Performance Evaluation

It can be observed that the statistical time domain feature extraction increases the model classification performance by 16.27% when compared with PCA based ANN model asindicated in Table 4.11. This can be attributed to the increase in correlations and nonlinear relationship in the dataset by time domain statistical features. Further performance investigation using confusing matrix also indicate an increase in model’s prediction performance as depicted in Figure 4.7.

Table 4.11: ANN-Time-Domain Based Model Result Vs PCA_ANN Model

Model	Training	Test/Validation
ANN_PCA	**0.8237**	**0.8212**
ANN_TDSF	**0.9864**	**0.9751**

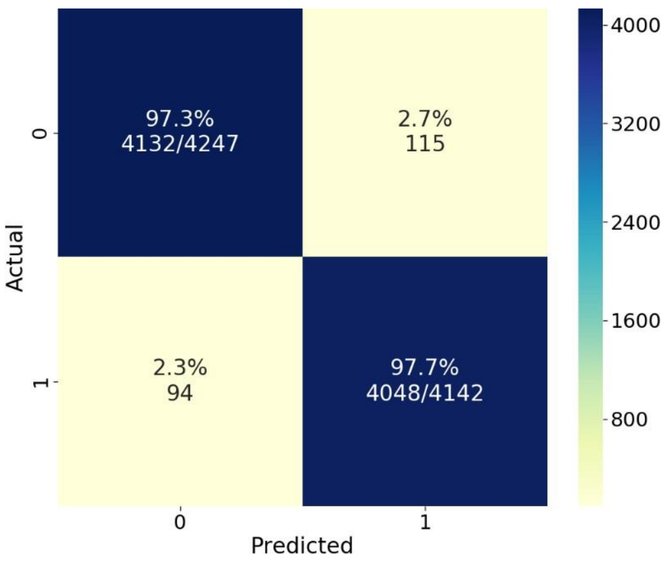


Figure 4. 7: Time Domain Based Confusion Matrix

It can be observed from Figure 4.6 that;

- The model successfully classifies Red Diesel Fuel (TP11) accurately by up to 97.3%, with misclassification error of only 2.7%.

- The model also predicts and classifies Normal Diesel (TP10) accurately by 97.7%, and misclassified error of 2.3% only.

4.3.2.4 Model-B Frequency Domain Model

Frequency domain feature extraction involves transforming and decomposing periodic time-series signal into various frequency components contained in the raw signal. Majority of real-life signals are non-stationary in nature, which comprises of events at differentfrequencies. To measure the occurrence of these events in specified time, signal must be decomposed into its underline frequency bands/components. Hence, the representation of signal by its frequency components as well as estimating all related features in frequency is usually known frequency domain analysis. Among frequency-based feature extraction, themost commonly used frequency domain feature is Fast Fourier Transform (FFT) especially invibration analysis of bearing faults. However, the most effective frequency-based methodis Power Spectral Density (PSD). Which is used to extract frequency characteristics of a signal,as well as estimating the amount of power and energy contained in a spectrum (Şengür, Guo and Akbulut, 2016). Hence, PSD is used in extracting useful features for the supervised MLmodel.

4.3.2.4.1 Dataset

The time series signals used in this case study consists of restructured 10 datapoint steps and 10 PCA components, similar to the dataset used in Section (4.3.2.1). Hence yield X_dataset with dimension (209716 X 10) for both TP10 and TP11 each as seen in Table (4.3). Thecorresponding targets labels also have dimension (209716 X 1). It can be observed from Table 4.3, that the combination of 10 datapoints and 10 PCA components produced a model with 82.37%. Therefore, the aim of this case study is to extract frequency-domain features, which would be subsequently feed into ANN classifier. The result obtained from this model will be compared with PCA-based, and Time-domain based models predictionperformances.

4.3.2.4.2 Extracting Frequency Domain Features

To effectively work with time series signals, transforming the long time series signals into small windowed datapoints chunks is imperative as discussed by (Lara and Labrador, 2013).Therefore, the fuel datasets used in this case study is split into short sub-sequences. To a achieve the dataset transformations, a window of 180 datapoints has been rolled on each 10 signal components of the dataset. Hence, both TP10 and TP11 datasets transformed from (209716 X 10) to (582 X 180 X 10).

Further pre-processing has been carried out to extract features from the transformed datasets. Power Spectrum Density (PSD) has been applied to transform the time-domain based signal to frequency-domain signal. The datapoints of 180 has been sampled at 3 seconds using 60 Hz frequency on each signal component from both datasets. Some of the sampled transformed dataset has been depicted in Figure 4.7. Further a PDS-based Welch algorithm has been usedto Compute Power Spectrum Density of each signal and transform the signal into frequency- based spectrum. Some samples of the PSD spectrum have been illustrated in Figure 4.

Although Power spectral density function (PSD) has been used to transform the signal components, which shows the strength of the variations(energy) as a function of frequency, yet some frequencies does not represent the actual useful information contained in the signal. In other words, PSD decomposes various frequencies into weak and strong frequencies. Some of the weak frequencies contained in a signal are mere microphonics, which need to be isolated and filtered. Presence of microphonics in a signal prompt the need to select prominent fundamental frequency and other relevant harmonics. Consequently, there is need to transform PSD-based data into a useful representation to extract the features that are suitableenough to train the model for effective classification. Finding peaks in a signal is an effective way to select fundamental frequencies in a spectrum, which distinguishes legitimate peaks andother feature like noise. Hence selects suitable features and ignore all other irrelevant features.

As (Fahad et al., 2018) implemented, similar approach has been adopted. Hence, some useful peaks have been detected and extracted from transform fuels spectrum signal, which subsequently been fed into ML classier of training and prediction. Two maximum peaks are identified and selected from each spectrum using thresholding technique, which select two frequencies with highest intensity. Sample of the peak representation has been illustratedin Figure 4.7. This procedure has been repeated along the entire length of both fuels'datasets. Thus, X_dataset with (582 X 20) dimensions has been generated from each dataset (TP10 & TP11).

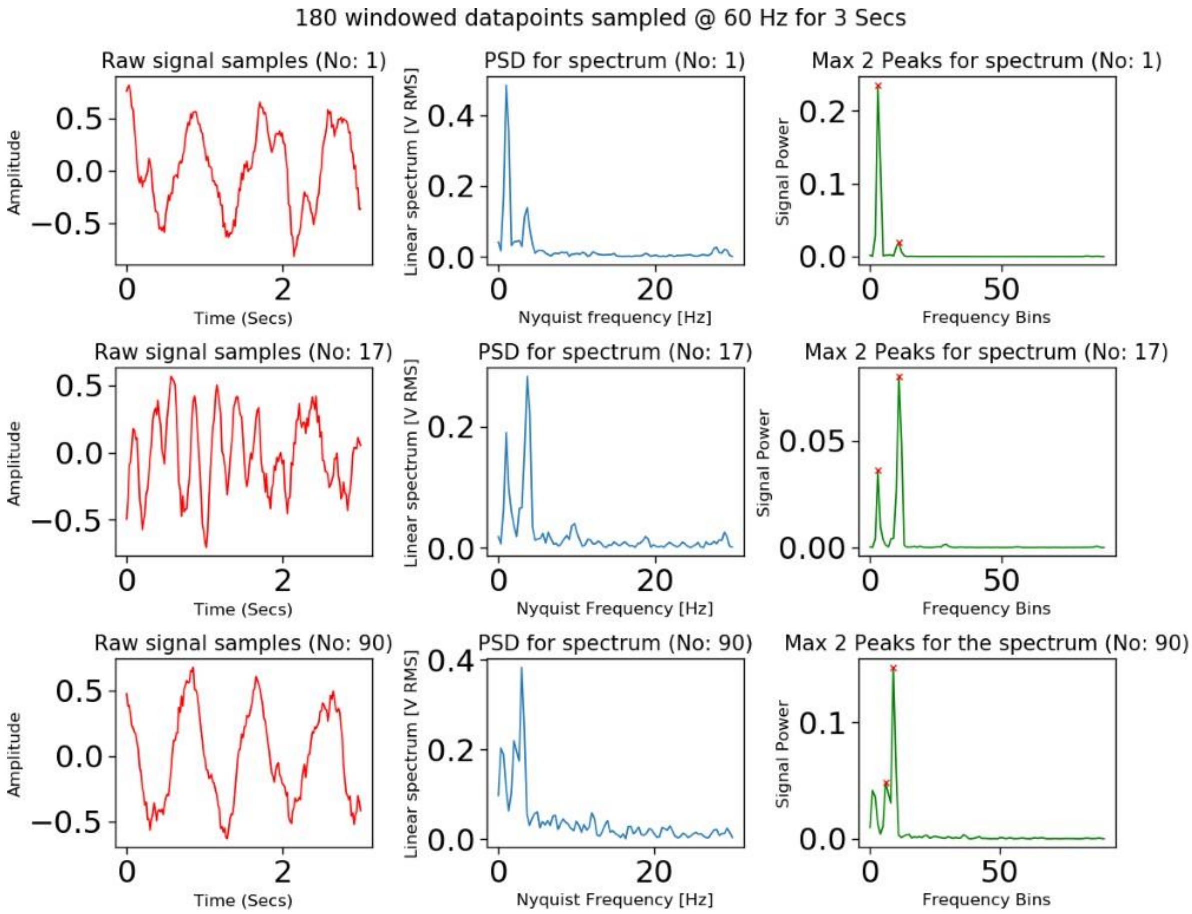


Figure 4.8: Sample Spectrum of 180 datapoint signals showing PSD and 2 Max Peaks

4.3.2.4.3 Normalisation

Features normalisation is not required here since the features were already scaled prior to PCA dimension reduction process. Although the data has been shuffled to create more correlation with the independent feature vectors.

4.3.2.4.4 Model Training

Like other case studies (PCA-based & Time-domain-based), ANN architecture based on back propagation gradient descent learning algorithm is also adopted in training the model. The architecture consists of 3 layers, i.e., input layer (20 neurons), hidden layer (10 neurons) and output layer (1 neuron). which is used for updating the weights vectors. Weights and biases in each layer have been randomly initialised and used to compute the target output values. The learning rate is also initiated via Sklearn with a minimal fixed value and kept constant until the convergence of the training model. Two activations functions were used with ReLU formed both input and hidden layer. The output layer has Sigmoid as its activation function. The datasetfor the model has been split into both training and test sets. Training/learning takes 80% of thedataset while the remaining 20% of the dataset is assigned for testing. The training has been initiated and converged after 700 epoch (iteration) cycles. The model achieved an impressive result (98.87% & 98.07%) is obtained for training and validation respectively.

4.3.2.4.5 Model Analysis and Performance Evaluation

It can be observed from both training and validation results obtained; the frequency- domain based feature extraction increases the model classification performance. As indicated

in Table 4.12, the Frequency Domain Based ANN Model (ANN_FDM) outperformed the previous PCA and Statistical Time-domain based ANN models. The by 16.27% when compared with PCA based ANN model as indicated in Table 4.1. This can be attributed tothe increase in correlations and nonlinear relationship in the dataset by time domain statisticalfeatures. Further performance investigation using confusing matrix also indicate an increase inmodel's prediction performance as depicted in Figure 4.9.

Table 4.12: ANN-Time Frequency Domain compared with Time Domain & PCA Models

Model	Training	Test/Validation
ANN_PCA	0.8237	0.8212
ANN_TDSF	0.9864	0.9751
ANN_FDM	0.9871	0.9807

Further, the model's prediction accuracy has been improved when compared with other previous models. It can be observed from Figure 4.9;

- The ANN_FDM model impressively classifies Red Diesel Fuel(TP11) with 98.3% prediction accuracy, and low misclassification error of only 1.7%.
- The model also achieved higher prediction accuracy (99.1%) when classifying Normal Diesel (TP10), with little misclassified error of 0.9% only.

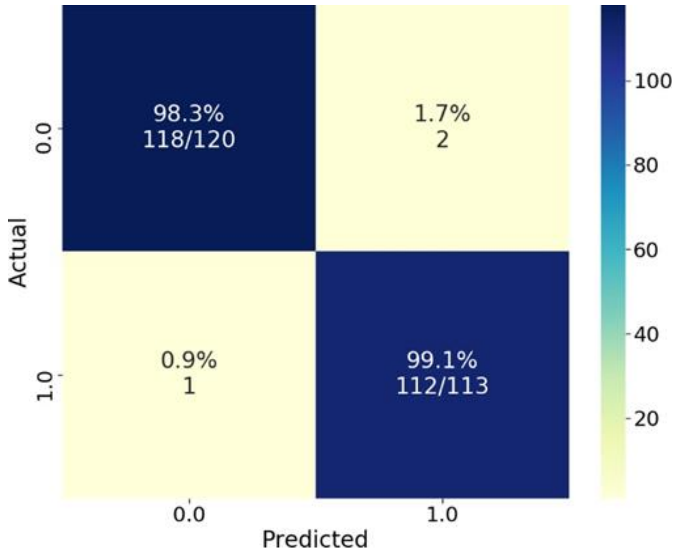


Figure 4.9: Confusion Matrix for Frequency-Domain ANN Model

4.3.2.5 Time-Frequency Domain Model

The idea behind time frequency domain is to provide true time-frequency representation of the signal. Time frequency analysis identifies the signal frequency components and reveals their time variant features. Perhaps effective feature extraction tool for machinery diagnosticsinformation (Feng et al., 2013).

Time frequency analysis is suitably used technique to extract features from non-stationary or transient signals in addition to static non-stationary signals. The process involves mapping out one-dimensional function of time domain signal to a two-dimensional function of both time and frequency. This enables good representation of signal in both time and frequency. Hence provides more information on how signal is localised in both time and frequencies, which provide more greater insight into the nature of information carried by the signal.

The techniques used in time frequency analysis involves Short-Time Fourier Transform (STFT), Wavelet Transform (WT), Wigner-Ville Distribution among other. Among them, WT is the most common and effective technique used for extracting useful features from signals.

Wavelet Transform algorithms such as continues wavelet transform (Scalogram) are effective in feature detection and pattern matching. They are normally designed as gaussian (Kernel) that convolve along time series signal to search for specific features embedded in a time series signal and extract them. Various decomposed signal coefficients are be obtained, which resulted from scaling and translating the signal into various scales depending on the requirements of the decomposition level. Thus, wavelet transform is used as feature extraction tool in this case study.

4.3.2.5.1 Dataset:

Similar 10 components PCA dataset (209716 X 10) used in previous case studies has been applied here. Likewise, a three seconds window with 60Hz frequency is used to split both dataset components into small sequences of 180 sampled datapoints signal. Hence transforming each fuel dataset to (582 X180 X 10), with corresponding class labels (522 X1) from each dataset where 0 representing Red_Diesel_TP11 and 1 representing Normal_Diesel_TP10 fuels respectively.

4.3.2.5.2 Feature Extraction

Wavelet transform feature extraction procedure differs with FFT. Perhaps, while the latter presents extracted features in 1-dimension, the former transforms 1-dimension raw signals into2-dimension scalogram. The scalogram offers more detailed information about the state spaceof the system dynamic behaviour. Morlet Continues Wavelet Transform is used in this case study to generate scalogram from both dataset signalcomponents. The scalogram is viable feature extraction tool, effectively givesdynamic behaviour of the system. In addition, it distinguishes different types of signals produced by the system. Hence makes it perfect feature extraction tool for supervised learningclassification problems.

Looking at the scalograms, two classes of fuels can be distinguishable, due to the nature and different pattern orientations present in the signals as depicted in Figure 4.10-4.13. It can be observed that the dynamic pattern in two different scalogram samples belonging to both TP11 and TP10 fuels differs. Hence, with such variation in patterns, both classes can be classified accordingly. However, the classification cannot be undertaken manually. Perhapsone way to automate this classification process that involves that resemble images is to build aConvolutional Neural Networks (CNN). The algorithm is capable in detecting the classes of each scalograms (fuels) through robust patterns detection and classify them accordingly.

Since each dataset consists of 10 components, the CWT is applied 10 times on each signal (180 datapoint short sequence windowed signal). Therefore, the CWT generate 582 scalograms from 10 components belonging to each dataset class, with the dimension (582X 10) belonging to both (TP10 and TP11) and resolution of (180X180) for each scalogram. Hence the overall dimension of (582 X 180 X 180 X 10) belonging to each class of fuel respectively. The scalogram from each signal are stalked on top of each other to form a single image with 10 channels. Perhaps, ideal image has either 1-channel (grey image) or 3-channels(RGB image). However, since CNN is used in the modelling, it can handle multichannel images (10 in this case). It shall be noted that the working principle is thesame with conventional CNN with (1 or 3) channels. The only difference is the requirements ofaddition more filters when compared to the conventional CNN. The two-fuel dataset are concatenated and split into both training and test sets.

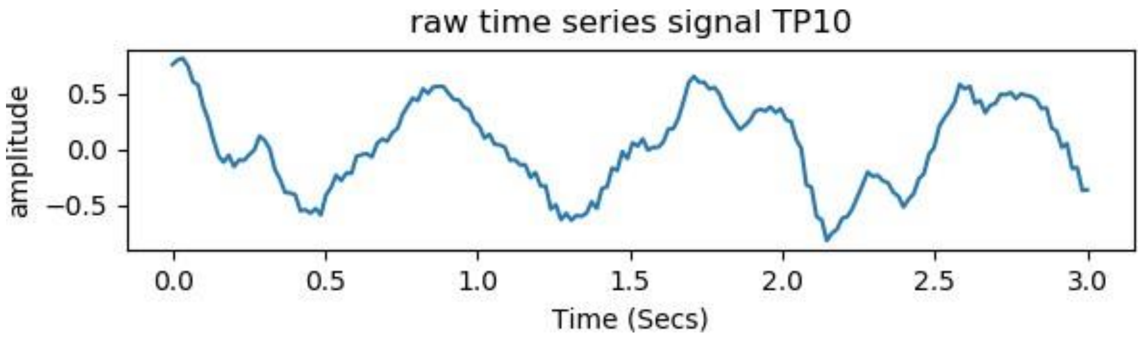


Figure 4. 10: Sample of Raw TP10 180 Datapoint signal

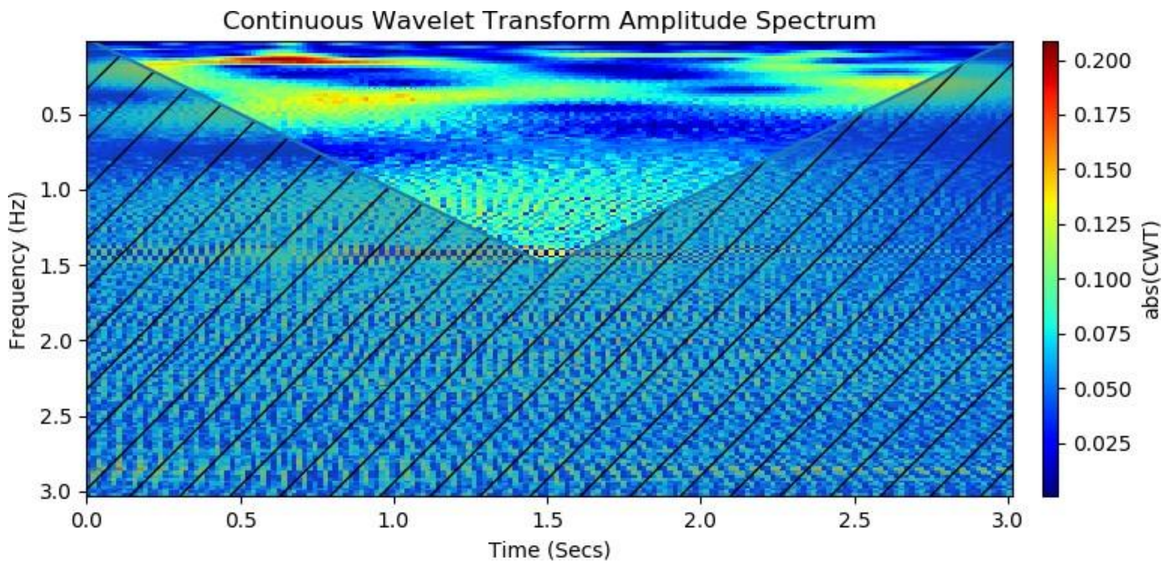


Figure 4.11: Scalogram of TP10 sampled signal

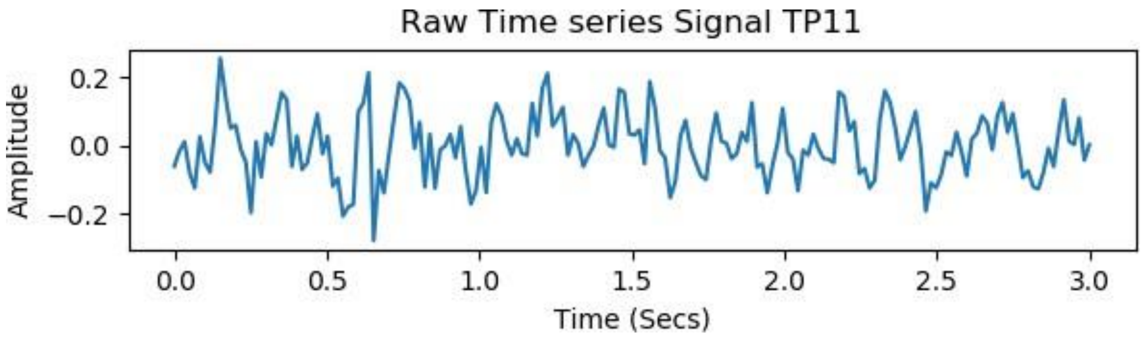


Figure 4. 12: Sampled TP11 for 180 Datapoints Signal sample @ 60Hz for 3 Secs

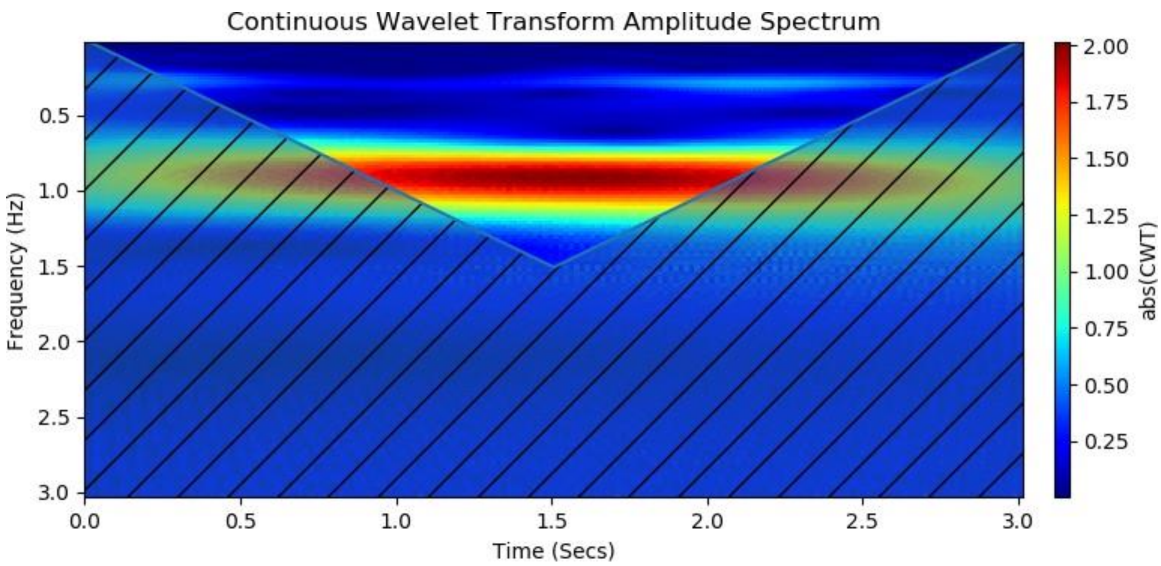


Figure 4. 13: Scalogram for TP11 sampled 180 Datapoints signal

4.2.3.5.3 Modelling & Training

Keras based CNN architecture has been developed to train the model. The model consists of3 distinct layers (Convolution, pooling and flatten). The convolutional layer extract features from the input image, by preserving the spatial relationship between pixels (information) by learning the image features. 3X3 convolutional kernel is chosen with single stride to detect features from the input images (stalked scalograms). Hence, produces feature maps. The subsampling or down sampling of the feature maps reduces the dimensionality of each feature map. This process is achieved by pooling layer. Max pooling is the most effective and is usedin this case study. A 2X2 kernel with double stride is employed to take the maximum numberin each window kernel when convolved with convoluted feature maps, hence reduces the sizeof feature maps. The pooled layer is then flattened, i.e. converted into a linear array to make the layer suitable to be fed into Neural Networks. Hence, 128 neurons are chosen for flattening, which are stretched linearly and flattened, ready to be fit into Neural Networks (NN). This is proceeded with fully connection with NN, which are subsequent complied into the network for training. Relu activation functions has been chosen in the hiddenlayer to enhance correlation and linear relationship between neurons, while the Sigmoidactivation function is used for the final binary classification process. Batch training is conducted and after 25 epochs, the training converges.

4.3.2.5.4 Model Analysis and Performance Evaluation.

The model achieved 61% training accuracy and 58% validation accuracy. Although this is lower performance when compared with previous models. However, the reduced performance can be attributed to the requirements of CNN to have as many data as possible, in order to learnmore pattern relationship from pixels. Recently, Deep learning Scientists identified mechanisms to enhances training performance of deep learning models that suffers from scantly training data. Most prominent among them is Data Augmentation.

4.3.2.5.5 Data Augmentation

To obtain robust and effective CNN model, Data Augmentation is employed to enhances models' performances in a circumstance when the training images are scantly. Hence, some new novel images can be added to the dataset. Augmentation process makes some minor changes to the existing datasets. The alterations involve flipping, rotating, or translating the existing images. Hence, increases the amount of the training dataset and improves the model's performance. Although the process of Data Augmentation is new concept in the deep learning field, but it has a lot of promising outcomes in improving the model performances. Thus, Data Augmentation is considered as further work to be carried out in the subsequent PhD research work to improve the performanceof novel proposed Hybrid Autoencoder-CNN-RNN based model.

4.3.3 Deep Learning Model

4.3.3.1 Introduction

Basically, Deep learning is a subset of both Artificial intelligence and machine learning. It involves introduction of more additional multiple layers to the models to process features. In deep learning networks, each layer extract valuable information, and each node is trained on distinct set of features based on previous layers output. In short, the further advances are made into the network, then more complex the nature of feature or nodes can be recognised, with the continuous aggregation and recombination of features from the previous layer. This is a special type of feature extraction which is known as ***Feature Hierarchy***. As the hierarchy increases, the complexity and abstraction increase, and more information couldbe extracted.

Various algorithms for deep learning such as Deep Neural Networks, Restricted Boltzmann Machine, CNN, Recurrent Neural Networks (RNN) and Auto Encoders amongothers are available in the literature and have been used on different purposes. However, sincethis case study dealt with time series data, the most suitable algorithm to dealt with time seriesdata is RNN. Although RNN algorithm works effectively with time series data, yet its prone tosome limitations which constrained its viability to datasets with short term dependencies. It's also prone to Exploding gradient and vanishing gradient problems. Therefore, more improvedalgorithm is introduced to handle time series data more robustly. Thus, RNN-based Long-ShortTime Memory (LSTM) algorithm is developed to and has been producing good result from many time series based deep learning case studies. On that basis, LSTM is employed in this case study to classify two classes of fuels based on their measured time series features obtained.

4.3.3.2 Objectives

Essentially, implementing deep learning model lies on harnessing its capabilities on both, ***Correlations*** and ***Reduction***. Deep learning extracts information that is similar to one another, while getting rid of irrelevant information. The relevant information is retained across the layers while discarding the irrelevant one. Thus, increases correlation in a data whilst reduces the data dimensionality. These functionalities make deep learning a robust tool for extracting useful information even from both structured and unstructured dataset. Further, its capabilities involve extracting features automatically without human intervention. This is achieved by combining lower-level features to form more abstract, higher level representing property classifications or feature representation of data. When compared with the previous models studied, the major difference between deep learning and traditional pattern recognition methods is that deep learning automatically learns features from big data, instead of adopting handcrafted features. Further implementation of deep learning model when benchmarked with the previous models implemented, could leads to;

- More accuracy improvements.
- Reduction of Overfitting risk.
- Speeding up in training.
- Improved Data Visualization.
- Increase in model's functionality.

4.3.3.3 Dataset

Similar 10 components PCA dataset (209716 X 10) used in previous case studies has been applied here. Likewise, a three second window with 60Hz frequency is used to split both dataset components into small sequences of 180 sampled datapoints signal. Hence transformingeach fuel dataset to (582 X180 X 10), with corresponding class labels (522 X1) from each dataset where 0 representing Red_Diesel_TP11 and 1 representing Normal_Diesel_TP10 fuelsrespectively.

4.3.3.4 Feature Extraction

As explained, deep learning algorithms are good feature extraction tools. Perhaps, robustly extract features automatically from the data, unlike conventional signal processing techniques considered earlier. Therefore, no further feature extraction would be considered in this case study. The algorithm will automatically learn from relevant features and discard the irrelevant features. Another factor to be considered here is the requirement of LSTM architectureregarding the input data structure. Since LSTM dealt with sequences of event that varied withtime steps sequences per samples, the algorithm required breaking of each long time series signals into sequence of events (windowed samples in a specific time steps). Interestingly, thedata prepared is already in the required format (Observation signal, time steps, signal component). Hence the dimension (582 X 180 X 10) from each dataset (TP10 & TP11) that fitthe LSTM input data requirement. Further, both datasets are concatenated to form (1164 X 180X 10) as X-input data, with (1164 X 1) as labels representing both fuel classes (0 for TP11 and1 for TP10).

4.3.3.5 Normalisation

LSTM algorithms are sensitive to the scale of the input data, especially when the sigmoid (default) or tanh activation functions are used. Therefore, it's a good practice to rescale the datato the range of 0-to-1. However, the data has already bee normalised whilst reducing the dimensionality of the original dataset earlier. Hence, normalisation is not requiredhere. Yet both datasets are shuffled and split into training and test/validation datasets. 70% of the data is dedicated for training and 30% are reserved for testing.

4.3.3.6 Model Architecture and Training

LSTM usually learns by making certain modification to the information that has been passed into it, through simple addition and multiplication. The information flows across LSTM architecture through a mechanism known as ***cell states*** (X_{t-1}, X_t, and X_{t+1}) as illustrated in Figure (4.14). Thus, at any instance, the LSTM can select what to remember and what to forget. These three states dependencies can be described as;

- The previous state ((X_{t-1}): refers to information being present in the memory after the previous time steps.
- The previous hidden state ((X_{t+1}): refers to output of the previous cell.
- The input at the current time step (X_t): refers to the new information being fed into that instance of time.

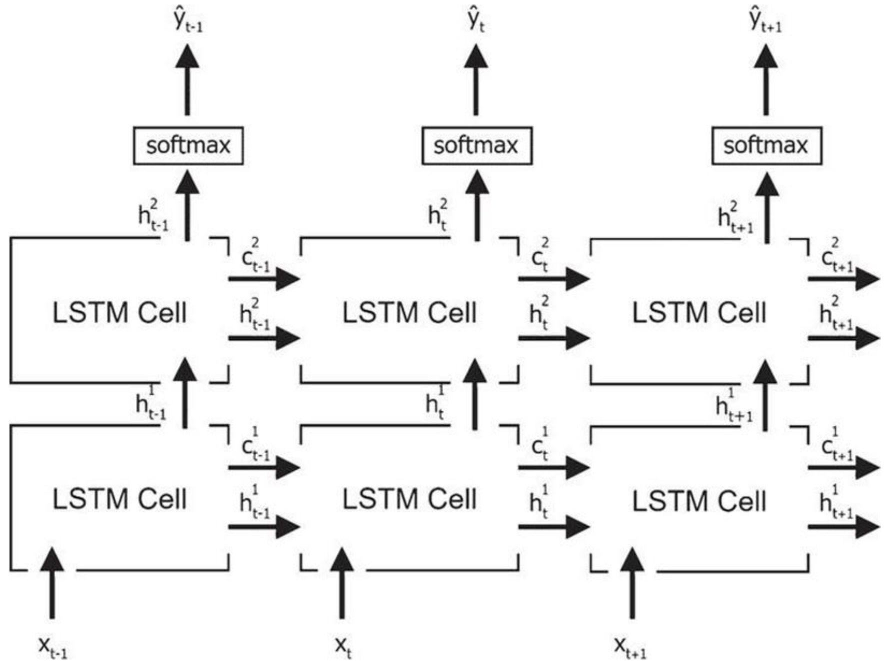


Figure 4. 14: LSTM Network Architecture (Nicholas et al., 2018)

The LSTM model developed in this case study is based on Keras architecture, consisting of 4 layers (input, 2 hidden and output). The input layer receives the input data, while the 2 hidden layers extracts feature from the data. Finally, the dense fully connected layer is used to make prediction. Stochastic gradient descent optimiser (Adam version) is used to optimise the network. A dropout regularisation is also used in both hidden layers to reduce over fitting the model to training. The binary cross-entropy function is used as loss function. The training commences and converges after 500 epoch (iteration) cycles. The model achieved good, impressive result (99.89% & 99.21%) for training and validation respectively.

4.3.3.7 Model Analysis and Performance Evaluation

LSTM algorithm has proven its capabilities as good feature extraction tool and high performing supervised learning model, considering the result obtained here. As indicatedin Table 4.13, the Frequency Domain Based ANN Model (ANN_FDM) outperformed the previous PCA and Statistical Time-domain based ANN models. However, LSTM almost achieve 100% prediction accuracy as indicated in Figure 4.15.

Table 4.13: Deep Learning LSTM Model compared with PCA & Signal Processing Models

Model	**Training**	**Test/Validation**
ANN_PCA	0.8237	0.8212
ANN TDSP	0.9864	0.9751
ANN_FDM	0.9871	0.9807
LSTM	0.9989	0.9921
CNN	0.6100	0.5800

Further, the model's prediction accuracy has been improved when compared with other previous models. It can be observed from Figure 14.5;

- The LSTM model impressively classifies Red Diesel Fuel(TP11) with 100% prediction accuracy, and no misclassification error.
- The model also achieved higher prediction accuracy (99.2%) when classifying Normal Diesel (TP10), with little misclassified error of 2% only.

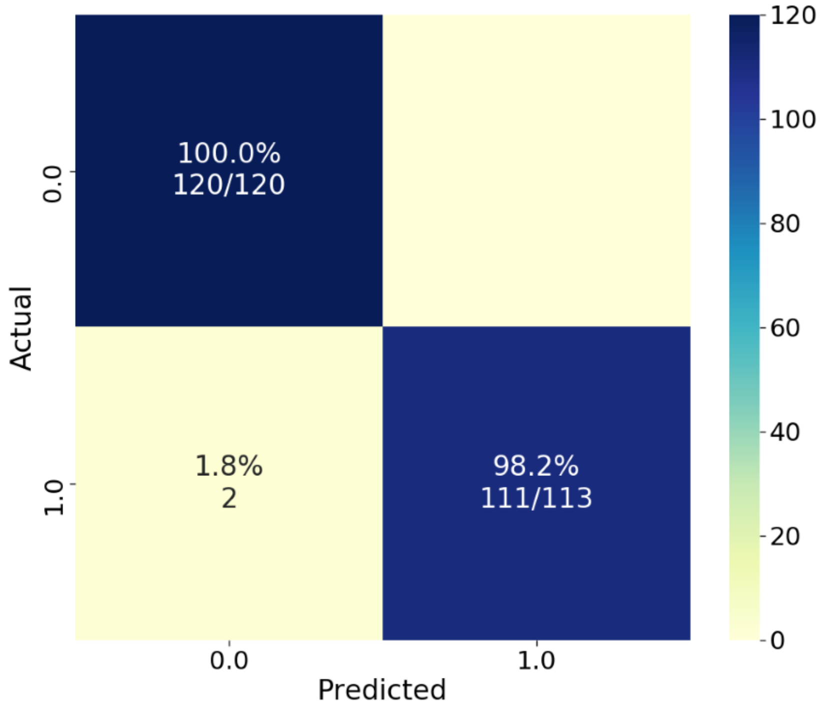


Figure 4. 15: Confusing Matrix for LSTM Model

4.4 Discussion

From Figure 4.15, it can be observed that all the models except for time-frequency based model achieved more than 90% training and validation accuracies. This can be associated withthe enhanced procedures applied to extract good features for the classification modelling. By virtue of ranking, LSTM scored the highest performance with 99.89% and 99.21% training and validation accuracies. Likewise, signal processing played a vital role in extracting good features for the model especially when comparing PCA and both time domain and frequency domain models performances. Dimensionality reduction is also an essential process in feature engineering and PCA play a vital role in reducing the redundant information from the dataset. Another important technique employed is the early restructuring the entire dataset some datapoints were lined in horizontal manner end to end as explained earlier. This procedure increases some correlation among the feature vector and as such give a better presentation of target dataset labels.

With the good performances obtained it can conclude that the models successfully classify two classes of fuels and predict fuels categories from unlabelled dataset, with high accuracy as indicated in the confusion matrixes obtained. Although the Time domain-based model has some lower performance accuracy when compared with other models. solution has been proposed (Data Augmentation) to enhances training data quality.

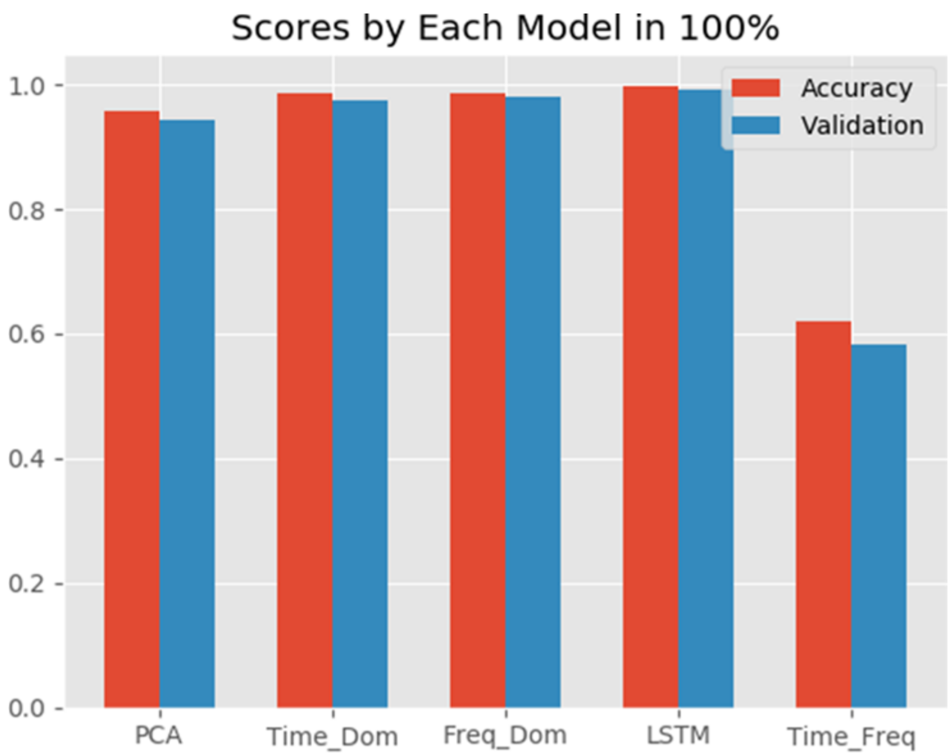


Figure 4. 16: Models Performance comparison

4.5 Summary and Conclusion

Identifying constraint in using physics-based simulated data to build model for gas turbine diagnostics condition monitoring, prompted the need to utilise the experimental data to build suitable gas turbine diagnostics model. The Dataset generated by gas turbine testing facility at Sheffield Low Carbon Energy Centre, UK, proved useful in building various gas turbine CBM models. Different machine learning models where developed and benchmarked against their performances and prediction accuracies.

The capabilities of feature extraction tools were tested and proved helpful in adding more prediction accuracies. In short, PCA and signal processing-based techniques have significantly added more correlations to the dataset and influences the prediction results obtained. Signal processing played a vital role in extracting good features for the model especially when comparing PCA. Further, quest for more prediction accuracies leads to the implementation of deep learning-based technique. As such by virtue of ranking, deep learning-based LSTM model achieved the highest performance with 99.89% and 99.21% training andvalidation accuracies.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis investigated novel methodologies for modelling aeroderivative gas turbine fault diagnosis using artificial intelligence techniques. Findings obtained from this study could help in designing new approaches towards operating gas turbines especially in offshore liquefied Natural Gas (LNG) facilities. Further it will pave the new way to design gas turbine that are more suitable to offshore environment. Likewise, the design of the engine could be improved to develop more efficient, reliable, and durable gas turbines to adopt harsh offshore environments.

In the field of modelling and simulation, two different types of gas turbines were modelled and simulated using both Simulink and neural network-based models. Simulated and operational data sets were employed to demonstrate the capability of neural networks in capturing complex nonlinear dynamics of gas turbines, especially when enough information about physics of the system is not available.

This thesis identified Aeroderivative Gas Turbine as the most critical asset in floating LNG applications. Failure investigation of such critical equipment requires more research attention. Various maintenance approaches were studied to dealt with failure of rotation machineries. However, condition-based maintenance is considered as the most effective maintenance strategy to maintain critical process equipment. Hence, CBM will be considered in detecting and predicting faults in Aeroderivative gas turbines.

Generally, it was concluded from this thesis that despite of some constraints regarding utilisation of physics-based model to implement gas turbine's CBM, data-based driven AI models developed demonstrated a strong potential in predicting gas turbines failures.

This thesis has made the following contributions the area of predictive maintenance modelling of aeroderivative gas turbines:

This thesis presented a comprehensive literature review in the field of predictive maintenance of aeroderivative gas turbines [Chapter 2]. It covers the general concepts and design of an aeroderivative gas turbines, gas turbine maintenance in LNG process. The chapter explored the limitations of conventional-based maintenance practice in the oil and gas industry and recommends condition-based maintenance as the most suitable for aeroderivative gas turbine used for FLNG process. The chapter concluded with brief structural modelling architecture of aeroderivative gas turbine's Condition Based-Maintenance.

The thesis discussed modelling and simulations of gas turbines briefly discuses modelling and simulations of gas turbines [Chapter 3]. Various challenges and significance of gas turbine model in LNG process were covered. Both white-box and black-box gas turbine models were treated, with brief introduction of grey-box gas turbines models. The theories and fundamentals for gas turbines modelling based on white-box model have been covered. The chapter concluded by establishing a case study for modelling and simulation of gas turbines. A Simulink gas turbine model was constructed based on the thermodynamic and energy balance equations in MATLAB environment, and the output responses were recorded for further PdM studies. Although the dataset obtained have not been utilised in the diagnostics modelling, yet the promising potentials of utilising physics-based modelling in gas turbine diagnostics studies was demonstrated.

This thesis developed a data driven-based model for gas turbine diagnostics [Chapter 4]. An experimental time series dataset is used to classify anomalies associated with gas turbine's exposure to different fuels. Feature extraction tools such as PCA-based and signal processing-based were used to prepare the dataset, which reduced its dimensionality and extracted good features for gas turbine diagnostics modelling. A model based on neural network was developed further to classify the gas turbine engine anomalies. Signal processing techniques has been very useful tools in extracting good featuresfor classification modelling. Although, several research works highlighted some setback of signal processing-based feature extraction techniques, such as human errors, noise and limitation in dealing with big data. To address these setbacks, researchers propose deep learning models as viable feature extraction tools, especially give its capabilities in learning features automatically from data patterns. To find the best model for gas turbine diagnostics with high performance and prediction accuracy, Deep learning-based LSTM model was developed. The overall models were tested and validated against unseen dataset, and performances of the models are compared.

5.2 Future Work

The importance of PdM on critical asset of FLNG process (aeroderivative gas turbine) have been extensively explored by this thesis. Modelling PdM for aeroderivative gas turbine can be achieved through a wide range of research activities. Both white box and black box approaches shows promising potentials in failure prediction and remaining useful life investigation.

Given the scope, results obtained by this thesis, and the limitations; the future efforts and upcoming research outputs in this area can be highlighted as follow:

- White box physics-based gas turbine model was constrained to be deployed for PdM studies in this thesis, due to lack of essential information. However, various methodologies could be employed to simulate transient behaviours and incipient faults characteristics in gas aeroderivative gas turbine engine. The simulated dataset obtained can be used for an optimum PdM studies.

- The thesis clearly identified fault, as purely classification task, and can be effectively solved using Artificial Intelligence-based data-driven techniques. This thesis used stand-alone AI based models to predict gas turbines failures. However, whilst the models developed achieved very impressive prediction performances, many researchers are still searching for solutions that provides better results. This prompt the proposal of integrated AI models, that combine the capabilities of each stand-alone model, especially with the limitations of stand-alone models in detecting fault with non-linear characteristics in gas turbines. Therefore, more robust modelling algorithms are required that integrate good feature extraction and enhanced pattern recognition capabilities. This prompt the need for further improvement towards developing good models with satisfactory prediction accuracies and good classification results. Thus, a novel hybrid model could be developed with the specific target to solve various limitations of stand- alone models and improve the accuracy of gas turbine fault detections.

- More value could be added in this area through upcoming research outputs. Therefore, future efforts could be tailored towards obtaining the dataset with desired fault characteristics and employing algorithms with good predictions capabilities.

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