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An Intelligent Monitoring Interface for a Coal-Fired Power Plant Boiler Trips

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This thesis is presented for the Degree of

Master of Philosophy (Mechanical Engineering)

Of

Curtin Malaysia

October 2018

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature: ………………………………………….

Date: 31st October 2018

Acknowledgements

In the name of Allah, the Most Gracious and Most Merciful.

Alhamdulillah. All praises to Allah Almighty for His blessings in the completion of this work, and for giving me the strength, endurance and grit throughout the whole research term. Without His will, this MPhil. thesis will not be completed accordingly. For my parents and significant other, whom I will always be in debt to for the support and prayers throughout this journey; Hj. Mohd Nistah Kabul, Hjh. Subiah Laten, and my husband Zulkifli Osman.

My highest appreciation goes to my supervisors; Associate Professor Garenth Lim King Hann and Associate Professor Lenin Gopal, for their patience, constructive comments, tireless support, guidance and ideas that lead to a renewed motivation and learning curve for me to continue and complete this research work especially in the last gruelling years. As well as to my associate supervisor and former supervisor(s); Mr. Foad Motalebi, Dr. Firas Basim Ismail Alnaimi, and Professor Yudi Samyudia, who has supported and guided me in the initial stages of my research journey.

I am also grateful to the former Dean of Graduate Studies of Curtin Malaysia, Professor Marcus M.K. Lee for his kind words of wisdom and advice. Without his direction and recommendation, I don't think I will get this far. In addition, I would like to thank all the supporting administration staff of the Graduate Studies and R&D office, HR and Finance department for helping me with my postgraduate affairs and staff study support. A special thanks to the Dean, Professor Lau Hieng Ho and everyone in the Faculty of Engineering & Science; with special mentioned to my dear colleagues; Jameson Malang, Kamaroizan Mohamad, Dr. Anita Jimmie, Lai ZhenYue and Loh Wan Ning who was there to support and help me with the technicalities.

Last but not least, I would also like to thank the experts who have assisted me in the data collection and various site visits at SARAWAK Energy Sdn. Bhd., Miri and MPG (Mukah Power Generation) Plant. This includes my former student and colleague Muhammad Uwaes for helping me with the data recording and my fellow postgraduate associates, Noraini Mohd for the collaboration and discussions; it has been an eye opening experience.

Abstract

Coal-fired power plant boiler trip happens when the fuel feed to the furnace is stopped. This practice is carried out to clear any residue of combustible substances from the boiler. It is a safety procedure to prevent explosive occurrences. The combustible substances residue consists mainly of slag, ashes and flue gas desulphurization gypsum. These chemical deposits have been the major part of many literatures in assessing its impact on environment and public health. A power plant monitoring system has the potential to (1) improve plant performances, (2) reduce down time, and (3) address possible issues before it results in an unplanned downtime or costly equipment damage. An existing monitoring system embedded with artificial intelligence can enhance the effectiveness of the preventive maintenance further. It contributes in reducing the time spent in trip analysis and following up with supervisory approval. The intelligent feedback from the interface allow operators to use the information as guideline in analyzing the affected operational parameters that are causing the trips. The work involved in this research include the development of an intelligent interface that optimizes the boiler monitoring system in a coal-fired power plant. The tools used in the development include (1) an Artificial Neural Network multi-layered model, and (2) and an interface to provide the advisory feedback. These tools utilize a simulation prototype and an Integrated Development Environment executable file that can run in a portable platform. Experimental results shown that Multi-layered perceptron neural network trained with Levenberg-Marquardt algorithm achieved the least mean squared error. These predictions of possible trips were recorded to have occurred at a specific time interval and this information is important as a guideline for the effective inspection and maintenance work.

List of Publications

1. **N.N. Mohd Nistah,** K.H. Lim, L. Gopal, and F.B.I. Alnaimi, "Coal-Fired Boiler Fault Prediction Using Artificial Neural Networks," *Int. J. Electr. Comput. Eng. (IJECE),* vol 8, no. 4, 2018.

2. **N.N. Mohd Nistah,** F. Motalebi, Y. Samyudia, and F.B.I. Alnaimi, "Intelligent Monitoring Interfaces for Coal Fired Power Plant Boiler Trips: A Review," *Pertanika J.Sci. Technol.*, vol 22, no. 2, pp. 593-601, 2014.

Conference and Poster

1. **N.N. Mohd Nistah**, K.H. Lim, L.Gopal, and F.B.I. Alnaimi, "Artificial Neural Networks to Predict Coal-fired Boiler Fault Using Boiler Operational Parameters," *International Conference on Electrical, Electronic, Communication and Control Engineering (ICCEECC),* 2017 – Conference presentation
2. **N.N. Mohd Nistah**, F. Motalebi, Y. Samyudia, F.B.I. Alnaimi, "An Intelligent Monitoring Interface for a Coal-Fired Boiler Trip," *poster presented at Postgraduate Colloquium*, 2014 – Poster presentation
3. **N.N. Mohd Nistah**, F. Motalebi, Y. Samyudia, F.B.I. Alnaimi, "Intelligent Monitoring Interfaces for Coal Fired Power Plant Boiler Trips: A Review," *7th Curtin University Technology, Science and Engineering Conference (CUTSE)*, 2012 – Conference presentation

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Chapter 1. Introduction

1.1 Introduction

Frequent electrical power outages have tremendously disrupted the operational cost and production process of most industries. The accumulative effects of unscheduled power outages incur cost in power restoration, interrupted production loss, equipment maintenance and protection. These factors of unscheduled power outage are mainly due to a sudden shortfall of electrical load failure and frequency drop in the electrical power plant. To restore the operation of power plant, a series of electrical standard set by Energy Commission [1] has to be carried out. One of the standards requires a time lapse after the system inspection before start-up can be safely administered. This delay can cause cost setbacks to small businesses, office equipment's failure, and even traffic flow interruption. Hence, it becomes more apparent to consider improving the existing equipment monitoring system for a more stable contingency plan for power recovery.

The current monitoring system continuously tracks the plant's equipment's operating condition. Any identified features that affects the availability, capacity, safety and quality of the energy production will be displayed on the plant monitoring system. These displayed information helps plant operators to report the data for the scheduled maintenance as part of the action items. Generally, most of the tell-tale signs of an equipment's degradation will be overlooked until the maintenance is carried out. As a result, additional cost and time are required to carry out the necessary equipment overhaul.

In this research work, a coal-fired boiler is one of the two main components of a thermal power plant. A schematic diagram for a coal-fired boiler in a thermal power plant is shown in Fig.1.1. A boiler is a vessel used to contain the combustion process and facilitate heat transfer from flame and hot gases to water and steam tubes [2]. A boiler unit trip has a huge impact on a plant's continued operation and may lead to power production process interruption. A trip condition happens when the fuel feed to the furnace is stopped in order to clear any residues of combustible substances from the boiler and to prevent explosive occurrence [3]. Common factors for boiler unit trips are mainly related to the combustion process. Consequently, damages to the boiler tube, back end corrosion, loss of flame and interruption of fuel, air supply or ignition energy to the burners may occur. Hence, it is important for plant operators to be able to identify and narrow down the affecting operational parameters.

The energy conversion process starts from the fuel handling systems where coal supplies are pulverized and then transported to the boiler. A forced-draft (FD) fan is then used to supply combustion air to the burners where the air is preheated in an air heater to improve the cycle efficiency and to dry the pulverized coal. As the mixture of fuel-air flows through the pulverizer into the burners, a primary air fan is used to supply heated air to be burned in the furnace portion of the boiler. Heat is recovered from the combustion in the boiler to generate steam at the required pressure and temperature. Along with the steam, combustion gases, also known as flue gas leave the boiler, economizer and finally to the air heater, which will then pass through the environmental control equipment to remove the acid gases so that the cleaned flue gas can flow to the stack through an induced draft (ID) fan. The carefully controlled conditions of the steam generated in the boiler will then flow to the turbine that drives the generator for electricity production [4]. In order to provide continuous supplies of electricity, the steam is cooled and condensed back into water which is then circulated back into the boiler to repeat the whole process. Based on the conversion process

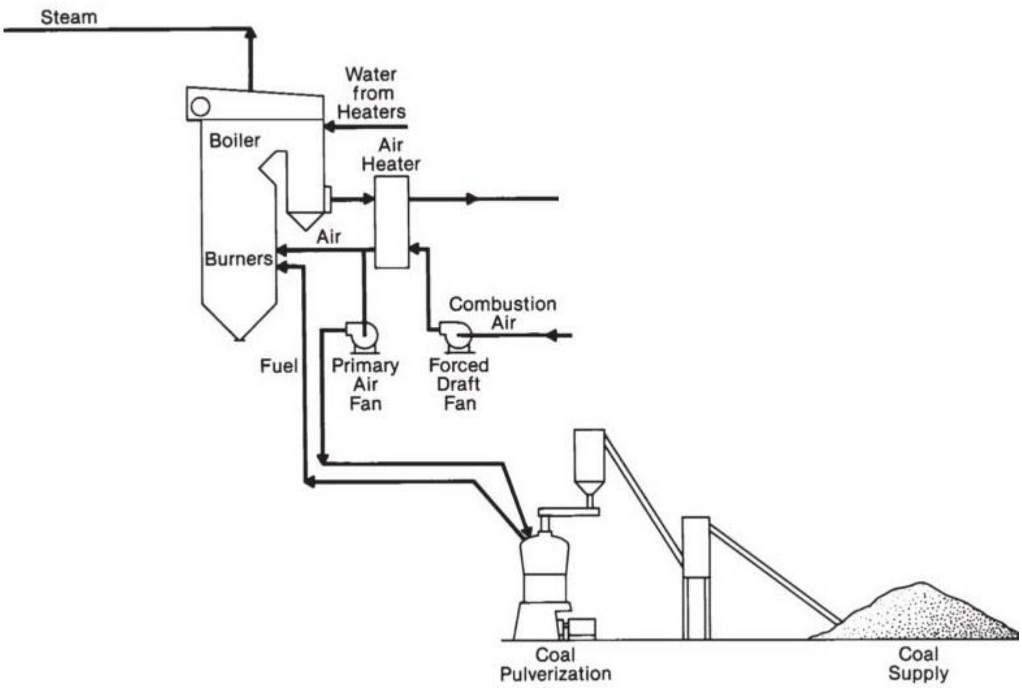


Figure 1.1 Pulverized coal processed as fossil fuel in a thermal power plant boiler.

described, 32 operational parameters have been identified. They include monitored parameters for steam production, pressure and temperature of the air supply, feedwater supply, and pulverized coal. Data for these parameters from an actual plant has been collected for the purpose of designing a simulation model for boiler trip condition monitoring. These parameters were identified as the influencing factor or critical to monitor for boiler unit trip prediction.

1.2 Problem statement

To address the issues and determining fault in the combustion process, scheduled equipment maintenance is carried out. However, it is an ineffective strategy for it either results in unnecessary inspections of a healthy equipment or the exercise is carried out after equipment has degraded. Therefore, it is crucial for plant operators to monitor the boilers to ensure that the plant is able to operate at its best condition to avoid any unnecessary interruption of service caused by faulty condition and trips. However, to properly define, access and predict a boiler trip is not easy. The complexity of the boiler mechanism makes it harder to monitor and identify any occurring trip in real time. Furthermore, whenever the trip occurs, plant operators will need time to report the incident, get approval from their immediate plant supervisors to take action and submit an incident report sheet to the maintenance team to carry out physical inspection of the equipment. While these standard procedures were carried out, businesses linked to the plant's power grid are losing required power supply due to the power outage. Consequently, this unnecessary delay can cause financial setbacks for the businesses. In existing systems, historical data are used mainly for monitoring, control and over-limit alarm; but not for trip prediction or diagnosis [5]. A quick decision making and solution is required whenever there is an interruption of power service. Hence, an intelligent interface is proposed for a coal fired boiler trip monitoring in a power plant to improve the current available boiler trip monitoring system and assist plant operator in identifying the trip more effectively.

1.3 Research questions

1. How to apply machine learning approach to utilize historical data collected in existing power plant monitoring system for an automated boiler fault detection?

2. How to effectively use the recorded plant data to improve the work flow for plant operators to carry out equipment inspection and maintenance work only when necessary?

1.4 Objectives

The overall aim of this research is to design an advisory interface system for an existing coal-fired thermal power plant boiler trip detection system using artificial neural network. It can be sub-divided into the following objectives:

1. To implement a boiler trip monitoring model using multi-layered perceptron modelling approach.
2. To design an interface for the monitoring system that provides an advisory feedback to the operator for the trip.

1.5 Research Contribution

In this research work, a multi-layered perceptron model for a coal-fired boiler trip is implemented. The simulation of the model used the data collected from an actual power plant. Various simulations have been carried out, and the performance of the proposed model is reported in this thesis. From the findings of this research work, a comparative study of the model can be derived when it is implemented on an actual power plant.

To date, many literatures have reported the different methods of improving faulty conditions identified in a power plant boiler unit. This include knowledge base system, numerical simulation model, operation optimization models, and control-oriented models [6]. However, very few of these literatures have mentioned the root cause of the trip. This research can serve as a platform to further investigate the root cause including the generated advisory guideline in the proposed interface.

In any power generation industry, continuous and timely production is considered important economically. As this research was carried out using historical data from an actual power plant, it may offer a more practical maintenance scheduling compared to existing ones in the industry. This depends on the accuracy of the prediction and the number of instances where trips have occurred.

The proposed intelligent mechanism of the system helps to provide guided actions and prediction of a possible faulty condition alert of the boiler's operational parameters. It allows the technical and maintenance team to carry out maintenance and physical inspection on the identified parameters. Following this, an advisory guide generated based on the incident will be included as part of the maintenance reports for a schedule boiler shutdown in order to clear any residual combustible substances from the boiler and to prevent any possible explosive occurrence. The known explosive conditions include interruption of fuel or air supply or ignition energy to the burners, fuel leakage into an idle furnace and the accumulation in the ignition, repeated attempts of light up without proper purging and an accumulation of explosive substances due to a complete furnace flameout [3].

1.6 Organization of this thesis

This thesis consists of six (6) chapters and they are organized as follows:

- Chapter 2 describes the importance of coal-fired boiler in a thermal power plant. Theories related to boiler performance monitoring using artificial neural network and earlier research on factors affecting the boiler performance will also be elaborated.
- Chapter 3 describes the unit operational parameters of a coal-fired power plant. The architecture and components that construct a coal fired power plant and the important parameters investigated and monitored for trips and alerts are introduced.
- Chapter 4 detail out the framework for a multi-layered perceptron network based boiler trip prediction scheme using data samples collected from an actual power plant. This chapter also report on the simulation and experimental result of the boilers' performance monitoring.
- Chapter 5 proposes an advisory guide for an intelligent interface that uses the prediction output from the proposed MLP network. The interface design and corresponding advisory guide generated from the interface are discussed.
- Chapter 6 concludes the research work with its findings and results, followed by suggestions for future work.

Chapter 2. Review of Intelligent Approach to a Coal-Fired Power Plant Boiler Trip Monitoring System

2.1 Introduction

In industries, a reliable alarm system is crucial to provide an advance warning to plant operators before abnormal reading is measured beyond the normal threshold. The existing power trip monitoring systems are limited in diagnosing and processing problems reported on screen; often display information that are not the root cause problems [2]. Instead, the alarms simply indicate that a problem exists, yet no course of action is provided as a guideline for operators to analyse before conducting a physical inspection of the equipment. When an upgrade of electrical and mechanical systems was carried out, the human factors are neglected. Plant operators need to be informed with clear and informative instructions on what actions to take in order to recognize signals exhibit by the equipment monitoring system [7]. Therefore, the current situation in fault and trip diagnosis of a boiler in a utility plant reports many improvements in its approaches to assess the health of the equipment and system involved. These include monitoring the operational readings such as temperature, pressure, vibration and noise; physical inspection of the boiler unit for leakage, cracks, stress or other defects, and most recently, observation of pre-existing condition using historical data to predict the trips and unscheduled shut down of the utility unit [8]–[16]. However, an adequate response time is identified to be another important requirement especially in a real time environment. In this chapter, the importance of integrating the existing trip monitoring system in the current power generating plant in Malaysia with an intelligent approach is discussed.

2.2 Importance of a boiler unit in a power plant

The continuous evaluation of the boiler's operating condition helps to identify any features that may affect the quality, availability, capacity, safety, risk and cost incurred relating to the boiler unit. The practice has in many cases extends the time between maintenance shutdowns, minimizes downtime and ensuring the equipment is maintain accordingly. It helps operators to be more informed of the decision for performance optimization and its maintenance needs [17]. For instance, it will notify operators when a major problem may be developing and this allows the operators to anticipate a potential failure and to take action to resolve it. Any observed abnormal deviations could therefore be investigated to avoid unscheduled shutdowns.

As the overall performance of an energy generating plant is evaluated by its efficiency, it depends on its boilers for continuous operation and maintenance. The efficiency of a boiler may be due to different reasons, such as poor combustion, heat transfer fouling, including poor operation and maintenance. In recent years, the deterioration of fuel and water quality is also considered as contributing factors to thermal inefficiencies in boilers. The normal practice to evaluate boiler efficiency is by defining its ratio of heat output to the heat input [18]. This method is proven to assist plant operators to quickly evaluate the boiler's health because it requires less operational parameter monitoring. Operational parameters monitoring can help operators identify the root cause problem more efficiently. Additionally, observation of pre-existing condition based on historical data may provide insights of the degradation of the equipment to better understand ways to carry out scheduled maintenance works.

2.3 Factors contributing to boiler trips and efforts to reduce the impact on energy production

Issues leading to tripping of boiler in a coal-fired power plant are usually related to the coal combustion. These issues include the state of the coal when transferred into the furnace, such as sticky coal blocking conveyors and chutes, fine coal causing stockpile slumps following heavy rain and also wet coal. Other condition such as contaminated coal supply with large rocks or pieces of steel that can damage the conveyors and pulverizing mills may also contribute to boiler instability due to the excessive holdup in mills [2].

There are limited literatures reporting on the exact cause of faulty condition leading to a trip and shut down in a coal-fired boiler of a power plant. Nevertheless, common factors have been noted by many industrial experts and plant operators as reported by Wilkinson [7] which may include the following operational parameters;

- Flame loss or instability
- High steam pressure
- Low or unstable fuel pressure
- Low or high boiler water level
- Low or high feed water temperature
- Unstable boiler water level (foaming)
- Low or unstable combustion airflow
- Incorrect combustion air damper position
- Incorrect combustion air fan status
- High, low, or unstable firebox pressure
- High or low stack gas temperature; and
- High or low stack gas oxygen content

Subsequently, fault diagnosis study of the health of the boiler equipment using historical data after a physical inspection and maintenance were carried out to improve the current monitoring system. The reports added tube leakage and corrosion in a boiler due to slagging or fouling as leading factors to unscheduled boiler shut downs [8]–[14]. In a more recent work, wall thinning and overheating has also been identified as a major damage mechanism leading to boiler tube failure [15]. In most of these papers, the power plant boiler's performance is measured by assessing its efficiency in some of these following parameters losses, using the American Society of Mechanical Engineers (ASME) performance test codes-4 (PTC-4), as reported by Umrao et al. [16]:

- Dry flue gas loss
- Moisture in fuel loss
- H2 in fuel loss
- Unburnt carbon loss
- Other unaccounted loss

Slagging in a boiler happened when leftover cooled molten ash and incombustible by-products from coal combustion gets hardened and sticks to the surface of the furnace walls. On the other hand, deposits build-up that occurred in the convection pass after the combustible gasses exits the furnace are known as fouling. These accumulated deposits are usually formed at the leading edges of the superheater and re-heater tubes. Although they are easily dislodged using soot blowers, the ash particles blown by the soot blowers may result into the flue gas stream and create cinders which can plug air heater baskets and block selective catalytic reduction catalyst flow paths or bridge across the boiler tube in the convection pass [19]. The most common sections of the boiler affected by slagging and fouling are from the burner belt to the furnace exit. Typically, boiler slagging and fouling are caused by low furnace excess oxygen, extreme stratifications of the Furnace Exit Gas Temperature (FEGT), high primary airflows, burner damage and deficient mechanical condition or tolerances, poor coal pulverizer performance and inconsistent fuel properties and chemistry. These slagging and fouling occurrences, when left untreated eventually result in a significant increase of the flue gas temperature that reduces the system overall efficiency and leading to an increase in corrosion problems in boilers [20].

Continuous research and efforts has been carried out to manage and reduce the impact of fouling and slagging in a coal fired power generation system. This includes the use of soot blowers as a blowing medium to blow water or compressed air directly at the deposits through a nozzle. However, the success rate of fully removing the slag on the back side of the tubes is very low. Hence, the invention of an intelligent soot blowing mechanism is introduced by incorporating intelligent system to allow the soot blowing system to 'learn' and trigger initiation for appropriate sequence of cleaning actions. Coal blending method has also been implemented to combine different types of coals that can be measured and analyse using thermos mechanical analysis technique to produce a slagging propensity index for monitoring purposes. This approach has high potential with low investments cost to minimised slagging problem. Other promising innovations also include pulse detonation wave technology to remove slag from various parts of the boiler, installation of internal cameras to monitor boiler deposition problems, and inserting stain gauges devices to measure the deformation of an object (in this instance the forming of slag within the boiler) [20].

2.4 Intelligent Monitoring System for Coal-Fired Boiler Trip Condition

A Power Plant Boiler Condition Monitoring System is an automated computer system that tracks the condition of the boiler unit continuously. The system retrieves the boiler operational parameter readings from the sensors with a one-minute time interval. The continuous data reading provided the plant operator with information on the health of the boiler unit. An addition to monitoring and retrieving data, the system can also be incorporated with an intelligent mechanism. For instance, an Intelligent Monitoring Interface (IMI). It is a human-machine interface system that tracks and improves the responses of an event associated with monitored equipment. It enables user to perform potentially complex tasks more effectively and quickly with greater accuracy. This is made possible by presenting users with information on the equipment condition, user's next actions, and warnings of undesirable consequences and suggestions of an alternative action [21].

The study of developing a computer system that is equipped with the capability of processing information intellectually like a human being has been conducted since the early 1950s, known as Artificial Intelligence (AI) [22]. One of the branches of AI is machine learning. It is a computer with learning capacity that learns through experience or prior knowledge and recognizes patterns of outcome in a huge amount of data to carry out a given task [23].

The most common techniques of an AI found in power systems applications include Expert Systems, Fuzzy Logic, Genetic Algorithm (GA) and Artificial Neural Network (ANN) [24]–[28]. Recent studies have suggested ANN as one of the most popular schemes for power systems fault diagnosis, where the sources of diagnostic information derive from the error between predicted and actual behaviour of the system. The required expectation (prediction) is based on a model of what should happen. Such techniques have been very well researched and implemented in many utility plants [29]–[31].

An ANN is a model of reasoning based on the human brain [22], and it is one of the most preferred branches of the study of AI. Due to its interconnected structure of neurons and numerical weights that mimics the biological neurons of a human brain; it learns to understand the relationship between the input parameters and variable by acquiring knowledge through pre-recorded data also known as training process. One of the key advantages of an ANN is that it is adaptable due to its non-linear characteristics [32]. Instead of being built from specific sets of parameter value, the neural and adaptive systems use external data to automatically set their parameters [33]. The group of interconnected artificial neurons in an ANN processes information in parallel. The performance of the network is continuously improved by rendering it to be “aware” of its output value through a performance feedback loop that includes a cost function. The feedback is used to adjust the network parameters through systematic procedures called learning or training rules, in order to improve the system output with respect to the desired goal [33]. This process is called ‘supervised learning’. It is an iterative process that continues to loop until an acceptable level of errors is obtained. The number of time for a whole set of data (both a forward and a backward pass) is processed is known as an epoch. This method is defined as the error back-propagation training [29].

Meanwhile, another popular intelligent system is known as an expert system (ES). It is a computer software program built to perform a narrow, specialized domain problem solving using existing expert knowledge acquired from a set of rules, decision trees, models and frames. The simplicity of each given rules and existing information allows a quick respond to the identified problem through reasoning, heuristics and judgement. This method is useful when it involves large amount of data that needs to be processed in a short period of time [22], [25]–[27]. However, it is limited to produce good feedbacks to only known situation, where ES may exhibit important gaps in knowledge when an unknown incident occurred. This is due to the fact that ES are unable to learn or adapt to new problems or situation that are not included in its knowledge database.

There is also an optimization technique, known as Genetic Algorithm (GA). It is based on biological metaphors, which is the process of natural selection and genetics [26], [27]. It is known to be highly efficient at reaching a very near optimal solution in a computationally efficient manner, where it continuously use a set of candidate description of the given system called population to gradually improve the quality of the population until sufficient level of quality is achieved or no further improvement occurs [25], [27]. Since the algorithm is simple and robust, it is a very good technique for solving complex problems and nonlinear problems that usually occurred in power generation planning, transmission and distribution system to properly adjust its parameter's excitation and control problem of reactive power compensation and voltage [28]. However, GA is widely applied for optimization, and not classification of data. It is not known if GA is able to identify and recognize a trip pattern from a normal condition.

The study of fuzzy logic involves classes of objects with uncertain boundaries, it allows uncertainties in problems formulation to be expressed and processed [25], [27]. This approach is similar to a human decision making with an ability to produce exact and accurate solutions from an approximate information and data. The fuzzification provides superior expressive power, higher generality and an improved capability that allows ambiguity throughout an analysis that specifies the available information and minimizes the problem complexity. Fuzzy logic is commonly applied in stability analysis and enhancement, power system control, fault diagnosis and security assessments [26]. Although it can be a very useful tool in a control system, implementing fuzzy logic as a predictor in a trip monitoring system may not yield efficiency required for the proposed interface in this research.

2.5 Current methods to improve the monitoring system

Table 2.1 provides a summary of work done by previous scholars to monitor, diagnose and predict plant equipment faults and trip operational condition with their proposed methods. The approach varies from mathematical to artificial intelligence model, acoustic signal analysis and hybrid intelligent modelling.

Table 2.1. A decade of methods implementing intelligent mechanism to diagnose and support plant equipment monitoring

Year	Author(s)	Objective	Method Specifications
2010	Ismail F.B and Al-Kayiem [11]	To monitor trip for a high temperature superheater in a steam boiler	Using AI technique; the multi-dimensional minimization training algorithm for the monitoring system.
2011	Pena B., E. Teruek and L.I. Diez [34]	To predict the effectiveness of soot blowing in a pulverized fuel utility boilers	The model developed is based on ANN and Adaptive Neuro-Fuzzy Inference system.
2012	Bekat T., M. Erdogan, F. Inal and A. Genc [35]	To predict the ratio of bottom ash produced to the amount of coal burned	Using 3 layered, feed forward artificial neural network model architecture.
2012	Kljajić M., D. Gvozdenac and S. Vukmirović [36]	To predict the efficiency of boilers based on measured operating performance	Utilizes neural network to analyze, predict and discover possibilities to enhance the efficiency of boiler operation.

Year	Author(s)	Objective	Method Specifications
2013	Hamid S.S. and D.N. Jamal [12]	To automatically detect and analyse a boiler tube leakage incident	Using an acoustic signal processing by sound wave using transducers. The method uses backpropagation neural network (BPNN) efficiently.
2013	Mayadevi, V. and Ushakumari [37]	To develop a simulation for an expert plant operator's action in decision making and management to various plant related activities	Using expert system with fuzzy logic, neural network, machine vision and data acquisition system
2014	Behera S.K., E. R. Rene, M. C. Kim and H. S. Park [17]	To improve the energy efficiency in the industry, by assessing and optimizing the performance of a refuse plastic fuel-fired boiler. This is done by predicting the temperature, pressure and mass flow rate of steam produced.	Using ANN with a feed forward backpropagation model that is trained with 5 months' worth of real plant data.
2015	Rostek M. et al. [13]	To detect and predict leaks in fluidized-bed boilers earlier before a boiler shutdown.	Using ANN using virtual sensors, classifiers of fault and two stage structure of ANN.
2015	Shi Y. and J. Wang [14]	To monitor ash fouling in a coal-fired power plant boiler and analyze the key variables affecting its performance	Implemented ANN to optimize the boiler soot blowing model and using mean impact values to determine the important key variables
2016	Mohan S. P., R. Kanthavel and M. Saravanan [38]	To develop a generic prediction tool of an early detection fouling/slagging in a boiler, due to excessive fireside deposits.	Using a hybrid fuzzy clustering method and an ANN
2016	Kumari A., S.K. Das and P.K. Sri Vastava [39]	To predict the fireside corrosion rate of superheater tubes in coal fired boiler assembly	Using Multi layered perceptron method from ANN with a gradient based network training algorithm.
2017	Bhavani S. et al. [40]	To continuously monitor the combustion quality and flame temperature of the boiler.	BPA (Backpropagation) and Ant colony Optimization (ACO) with Internet of Things using embedded intelligent sensors.
2017	Vakhguelt A. , S.D. Kapayeva et a.[15]	To assessed and detect damages and predict the life span of boiler tubes more efficiently.	Using Non-destructive test (NDT) by combining Electro-Magnetic Acoustic Transducer and an internal oxide layer measurement with specialized ultrasonic.

Year	Author(s)	Objective	Method Specifications
2017	Zhen T., L. Xu, J. Yuan, X. Zhang and J. Wang [6]	To developed a monitoring platform of an online estimation key state variables and performance evaluation of a thermodynamic balances in a thermal power plant unit.	Using a combination of Matlab based mathematical model, with a data management tool (MySQL) and a C++ coded OPC client server, and an Apache web server based web page as an interface.
2018	Dehghani A. S. [41]	To predict the exhaust steam vacuum of the steam turbine (ST) output and power output of the ST under two gas turbines' varying load conditions.	Two ANN network were constructed, one for the steam turbine and another for the main cooling system. These networks were modelled using Multi-layered perceptron (MLP) with backpropagation training.
2018	Chen X. and J. Wang [42]	To improve the combustion efficiency of a coal-fired power plant boiler by measuring the flue gas oxygen content.	Backpropagation neural network model with nine hidden neurons, tansig function and a purelin linear transfer function.

2.6 Summary

In summary, for thermal power plant equipment monitoring, specific techniques most favoured to accomplish the task to monitor machinery performances are expert systems and neural network. These approaches have been widely applied in a number of successful applications for classifications task, forecasting, control systems and optimization and decision making. More importantly, ANN has been reported to have successfully interpret the behaviour of machinery processes in energy conversion plants. Generally, large number of operational data is captured continuously by the on-line plant's monitoring system during operation and stored in large databases. Using these data, ANN models can be trained and used in a power plant operation simulation to predict a possible trip condition in an actual plant. Additionally, by comparing the prediction of ANN model with actual system, plant degradation or fault detection may also be assessed for both off-line and on-line applications.

Chapter 3. Coal-Fired Power Plant and Boiler Unit Operational Parameters

3.1 Introduction

A coal fired power plant is a complex facility. It consists of fuel supply system (coal is used), combustion and steam generators system, environmental safety control system, turbine and electric generator system, condenser and feed water system and heat extraction and rejection system. The focus of this research will be the combustion and steam generator system, involving the boiler unit. This chapter briefly describes the functional and operational control of the boiler and its parameters. It is divided into three sections. Section 3.2 will illustrate the six components of the entire power plant and its functionality. Section 3.3 will describe the coal-fired boiler unit and its importance. While section 3.4 presents the operational parameters selected to be used and monitored to identify the trip condition for a boiler unit.

3.2 Functional & Operational Control

Electricity is an essential utility for a household, thus the existence of power plants that could process our natural resources such as coal or gas into energy are very important. For instance, a coal-fired power plant can generate up to 700 MW of power, which can provide electricity for about 500,000 residential and business units continuously.

As illustrated in Figure 3.1, a thermal power plant consists of the following components:

C1: Coal supply and preparation system
C2: A combustion and steam generator
C3: Environmental and safety control system
C4: Turbine generator and electric production system
C5: Condenser and feed water system
C6: Heat extraction and rejection system which includes the cooling tower.

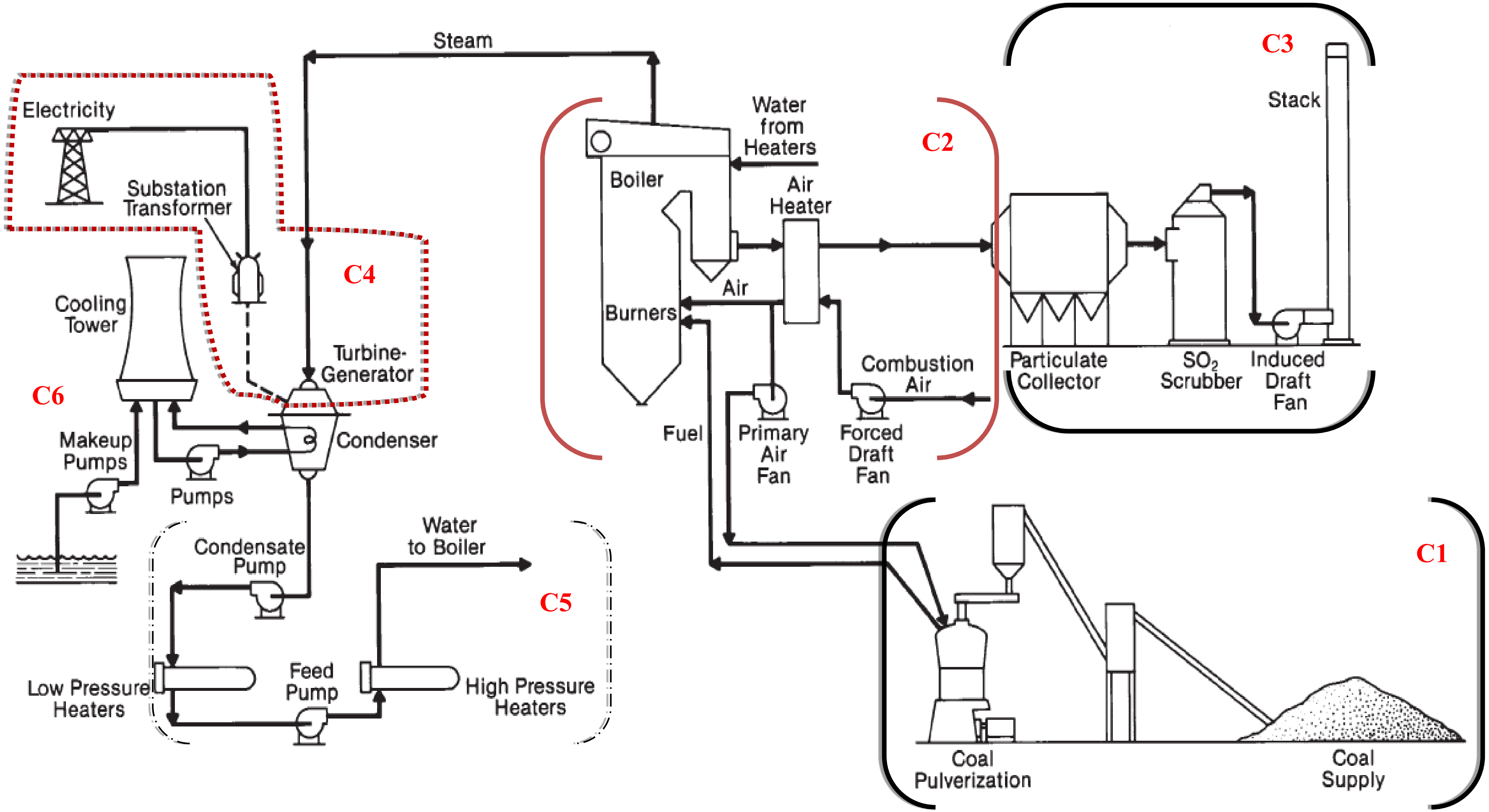


Figure 3.1 A block diagram of a thermal power plant

3.2.1. Component 1 (C1): Coal supply & Preparation system

The major component of a pulverized coal fired power plant involves the manner in which the coal is received, handled and delivered to the boiler. Hence, it is important to ensure that the fuel supply is kept well and dry for high rate combustion in the burner.

In a thermal power plant such as the one under study, coal is used as its main fuel supply for combustion. To ensure a high quality refined coal, it is important to ensure that the coals are transported in a control manner into the pulverizer. Dry and high quality coal is transferred into the pulverizer using a conveyor to be crushed and refined into coal powder for the combustion process in the burner. The refined powders are kept dry by using heated air supplied through a primary air (PA) fan. A PA fan is the source for heated air to dry the coal in the pulverizer, and to provide primary air to the burners as the fuel air mixture flows from the pulverizer into the burner.

3.2.2. Component 2 (C2): Combustion & Steam generator

In the second component of the power plant, the heated dried powdered coals are transferred into the burners through a pipe. These fuel and hot air mixture are then burned in the furnace portion of the boiler. For a complete combustion, preheated air is supplied through the forced draft (FD) fan as the combustion air. However, before it can be fed into the burner, the air is re-heated using air heaters. This process improves the air cycle efficiency in the boiler.

Meanwhile, purified water supplies are pumped using pipes into the boiler from the feed water pumps through a high pressure heater. The tremendous heat generated from the combustion turns the highly purified water into steam. The high temperature and pressure steam generated in the boiler are carefully managed to retain its specific readings in a controlled condition before being transferred into the turbine generator.

3.2.3. Component 3 (C3): Environmental & Safety Control system

As required by the Energy Commission, the plant needs to be equipped with an environmental and safety control system. This include the Flue Gas Desulfurization (FGD) system, which is used to scrub the flue gas leaving the boiler during combustion to control the Sulphur Dioxide (SO_2) emission level at the stack. Meanwhile, a tangential combustion system is used to achieve minimum discharged of Nitro Oxide

(NOx) by delivering excess air to the top of the combustion zone to reduce combustion zone stoichiometry and supress the NOx formation.

3.2.4. Component 4 (C4): Turbine Generator & Electric production

The recovered high temperature and pressure steam from the boiler provides the force to turn the turbine blades in the turbine generator to spin electromagnet within copper coils in the generator. This is the process in which electricity are generated. A substation transformer is used to distribute the electricity into its proper and safe voltage to be supplied to residential and business units accordingly.

3.2.5. Component 5 (C5): Condenser & Feed water system

To improve the overall process efficiency in preserving energy, the steam used in the turbine is converted back to water to be reuse as boiler feed water using the condenser. The condensed water is recycled back into the boiler through a series of pumps and heat exchangers called feed water heaters. These processes have indirectly increases the pressure and temperature of the water prior to its re-entering the boiler.

3.2.6. Component 6 (C6): Heat extraction & Rejection system

At the final stage of the energy conversion process, the remaining cooling water that passes through the condenser will absorb the rejected heat from condensing and releasing it to the atmosphere through the cooling tower. Any excess steam is cooled and condensed back into water which is then circulated back into the boiler to repeat the whole process. This essential cooling process requires large quantities of fresh water; thus, most thermal power plants are located on lakes or rivers.

3.3 Boiler unit in a Thermal Power Plant

A boiler is designed to optimize thermal efficiency and to economically benefit an energy conversion plant. Its main purpose is to transfer heat from flue gas to water or steam circulation. Heat transfer surfaces in a boiler play an important role. They include the furnace, evaporators, superheaters, economizers and air preheaters. These surfaces are the main interior built of the boiler from the furnace to the boiler exhaust. It is crucial to have the correct arrangement of the heat surfaces within the boiler. Because it dictates the durability and fouling of the material use, temperature of steam and final temperature of the flue gas [43]. An illustration of the arrangement of heat transfer surfaces in a boiler is presented in Figure 3.2.

Pulverized coal-fired boiler is one of the major equipment in the thermal power plant. It has a high thermal cycle efficiency with a fuel price advantage, although it comes with a costly SO_2 and NO_x control. Using coal as its fuel supply has its pros and cons. Organic particles of the coal are highly combustible, while its inorganic particles can cause a build-up of ash and slag in the furnace. Hence, pulverizing coal into finer particles allows the inorganic substances to be filtered before it reaches the furnace. Moreover, finer coal particle allows a more stable and complete combustion. This contributes to the reduction of soot and carbon monoxide in the flue gas [44].

To increase the temperature of the saturated steam leaving the furnace, superheater is required. By increasing the temperature of the saturated steam, the efficiency of the energy production is further improved. However, the tubes of the superheater used to conduct the steam from one connected header to the other are constantly exposed to the high temperature flue gas passing outside the tubes. Therefore, flue gases leaving the superheater zone are cool down using economizers. For overall performance, a suitable amount of furnace cooling is imperative within a boiler. Yet, removing too much heat will affect the combustion process, and leaving the temperature too high will cause smelting of ash. This will result in a more serious issue such as ash deposition and high temperature corrosion on the superheater tubes. In order to stabilize the boiler and prevent an explosive occurrence, a boiler trip will be executed. This procedure is implemented to check the boiler condition and clear any residue or combustible substances from the it [3].

3.4 Boiler Parameters & Performance Monitoring

Due to the extent of the boiler complexity, the number of operational parameters has been narrowed down to 32. The selection is based on the plant operator's past experience and system knowledge. Various researchers [13], [45], [46] has carried out studies on different types of boiler representing different range of industrial grade boilers to generate steam and hot waters. They suggested that although boilers of a particular type will behave differently due to its specific design or assembly tolerances, each unit does have common operational parameters which impose a significant effect on its efficiency, such as the main steam temperature, reheat temperature and reheat pressure variation.

Although the boiler operating conditions are important variables, another vital role in other faulty condition, such as the fireside corrosion rate in a boiler should also be considered. This includes the chemical reaction mechanism of the inorganic content of the coal [36]. Additionally, due to the unpredictable atmospheric conditions, power units have the high tendencies of working with greater load variability, resulting in changes in temperatures and pressures. Hence increasing the exposure of precipitation of sediment from water, this can easily deposit on rough areas of the inner pipes. Even though this condition escalates slowly and may easily be overlooked by plant operators; it will still posed a threat to a total shutdown when it causes pipe overheating and feed water flow disorder [14].

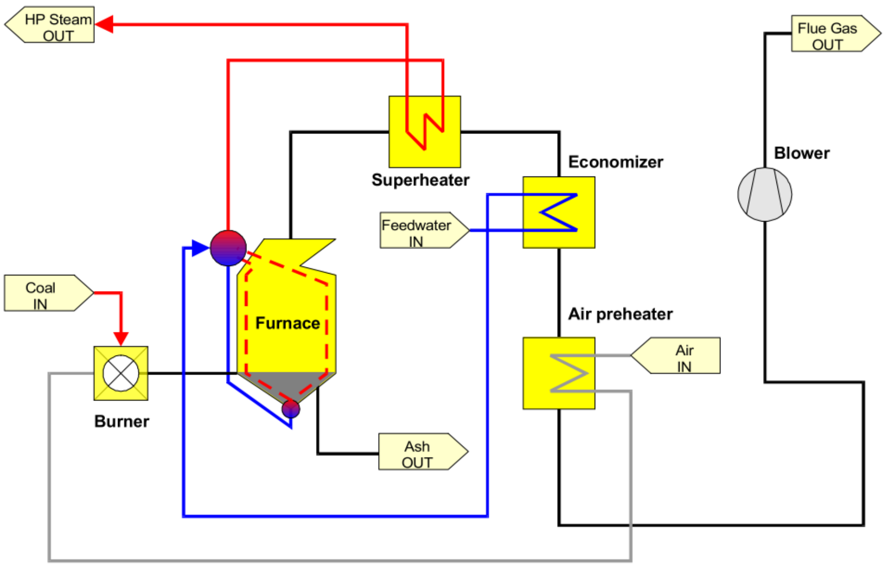


Figure 3.2. Process drawing of the arrangement of heat transfer surfaces in a furnace equipped boiler.

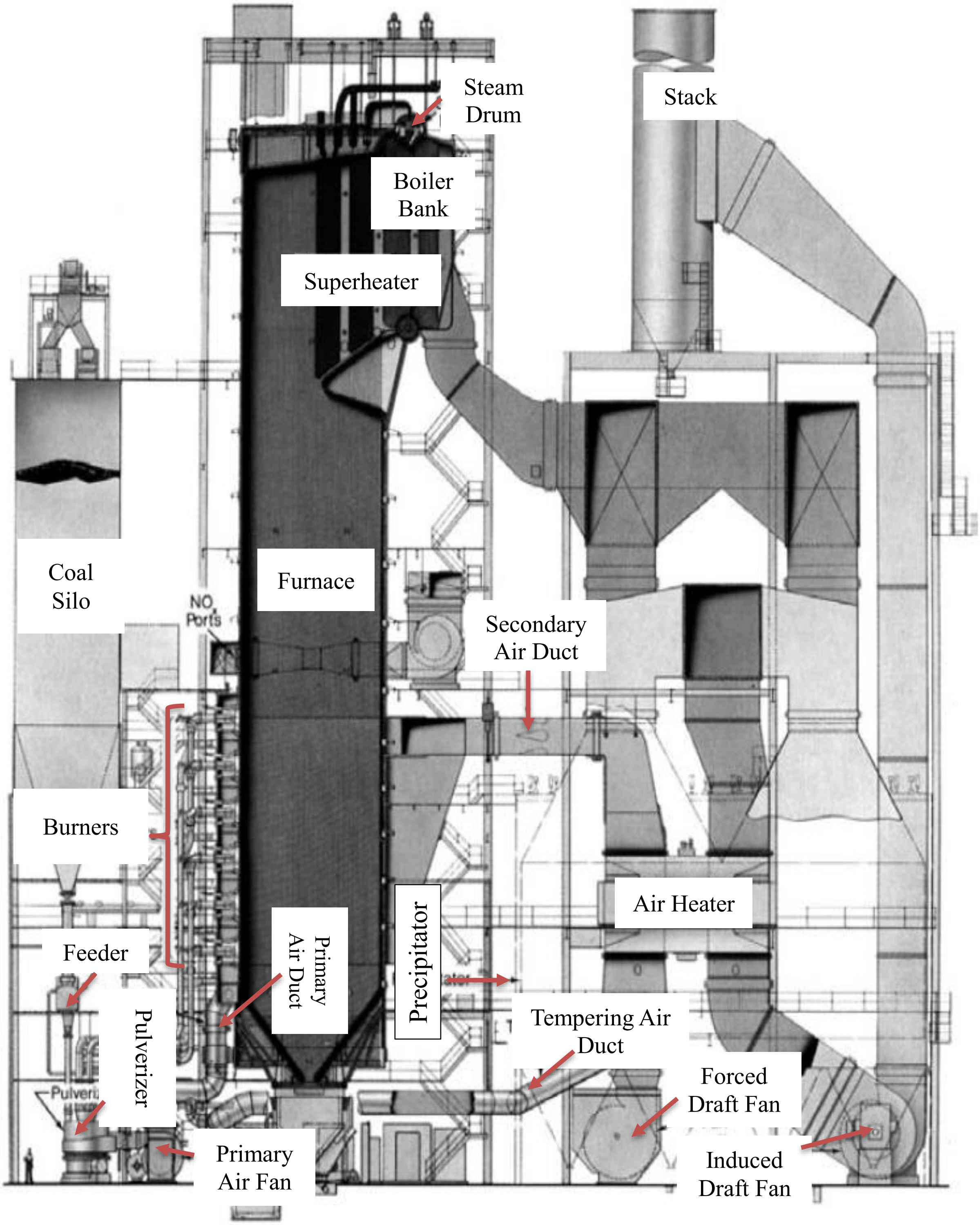


Figure 3.3 A large coal fired utility boiler unit

Table 3.1 Boiler Operational Parameter List

Parameter List	Description	Unit
V1	Total combined steam flow	**ton/hr**
V2	Feed water flow	**ton/hr**
V3	Boiler drum pressure	**bar**
V4	Super heater steam pressure	**bar**
V5	Super heater steam temperature	**°C**
V6	High temperature re-heater outlet temperature	**°C**
V7	High temperature super heater exchange metal temperature	**°C**
V8	Intermediate temperature (A) super heater exchange metal temperature	**°C**
V9	High temperature super heater inlet header metal temperature	**°C**
V10	Final super heater outlet temperature	**°C**
V11	Super heater steam pressure transmitter (control)	**bar**
V12	Feed water valve station	**ton/hr**
V13	Feed water control valve position	**%**
V14	Drum level corrected (control)	**mm**
V15	Drum level compensated (from protection)	**mm**
V16	Feed water flow transmitter	**%**
V17	Boiler circulation pump 1 pressure	**bar**
V18	Boiler circulation pump 2 pressure	**bar**
V19	Low temperature super heater left wall outlet before super heater dryer	**°C**
V20	Low temperature super heater right wall outlet before super heater dryer	**°C**
V21	Low temperature super heater left wall outlet after super heater dryer	**°C**
V22	Low temperature super heater right wall exchange metal temperature	**°C**
V23	Intermediate temperature (B) super heater exchange metal temperature	**°C**
V24	Intermediate temperature super heater outlet before super heater dryer	**°C**
V25	Intermediate temperature super heater outlet header metal temperature	**°C**
V26	High temperature super heater outlet header metal temperature	**°C**
V27	High temperature re-heater outlet steam pressure	**bar**
V28	Superheated steam form intermediate temperatures outlet pressure	**bar**
V29	Super heater water injection compensated flow	**ton/hr**
V30	Economizer inlet pressure	**bar**
V31	Economizer inlet temperature	**°C**
V32	Economizer outlet temperature	**°C**

In big utility plant such as the one illustrated in Figure 3.3, detailed observation on each of its operational parameters is crucial. According to [47], it is important to acquire real data from an actual working boiler unit in order to be able to identify possible scenario for the simulated fault detection system to be trained and provide feedback accordingly. Identifying faults and trip condition of a boiler in its most effective operating condition requires in depth understanding and knowledge of its faulty parameters and factors causing the malfunctions. Since there are a large number of data obtained from the industry, irrelevant values and outliers need to be identified and removed. The parameter selection is based on plant operator's experience on identifying the essential variables that contributed to the boiler trips of the particular unit. The boiler operational parameters identified for this study are listed in Table 3.1.

The design of the steam cycle and its operating condition involving the steam supply and discharge condition; dictates the pressure, temperature and flow rate of the steam required to generate the specified power output [48]. In order to achieve this requirement, steam is directed through a piping system to the turbine as the point of use. Throughout the steam circulating system, the steam pressure is regulated using valves and checked with steam pressure gauges [49]. Parameters monitored for ideal condition of the steam cycle are listed in Table 3.2.

Table 3.2 Steam circulation parameters

	Steam flow & Control	**Unit**
V1	Total combined steam flow	**ton/hr**
V28	Superheated steam form intermediate temperatures outlet pressure	**bar**

The water supplied to the boiler is called feed water. The two main source of feed water are condensate steam returned from the combustion process and make up treated raw water that comes from outside of the plant, such as lakes or rivers. The feed water system functions as a regulator for the boiler to continuously provide water supply to generate the steam. As the heat rate of the produced steam decreases, the requirement for heated feed water increases. Hence, for higher efficiency, the feed water is preheated by an economizer, using the waste (rejected) heat in the flue gas [49]. The list of parameter related to the feed water supply and control are shown in Table 3.3.

Table 3.3 Feed water supply and control parameters

	Feed water supply & Control	Unit
V2	Feed water flow	**ton/hr**
V12	Feed water valve station	**ton/hr**
V13	Feed water control valve position	**%**
V14	Drum level corrected (control)	**mm**
V15	Drum level compensated (from protection)	**mm**
V16	Feed water flow transmitter	**%**
V29	Super heater water injection compensated flow	**ton/hr**

For most boiler, water and steam flow through tubes, where they absorb heat resulting from the fuel combustion. To ensure continuous generation of steam, water must be circulated continuously through the tubes. The common method applied is to use a forced circulation system that involves a pumped control system (refer to Table 3.4). A pump is added to the flow loop between the boiler drum and the burner. The pressure difference created by the pump controls the water flow rate. Small diameter tubes are normally used where pumps can provide adequate head for circulation and for required velocities [4].

Table 3.4 Boiler drum & pump control system parameter

	Boiler drum & Pump control	Unit
V3	Boiler drum pressure	**bar**
V17	Boiler circulation pump 1 pressure	**bar**
V18	Boiler circulation pump 2 pressure	**bar**

Steam heated above the saturation temperature is called superheated steam. This steam contains more heat than does saturated steam at the same pressure, and the added heat provides more energy for the turbine to convert it into electric power. A super heater surface has steam on one side and hot gasses on the other. The tubes are therefore dry with steam circulating through them. In order to prevent overheating of the tubes, the unit is designed to tolerate the heat transfer required for a given steam velocity based on the desired steam temperature. Hence, it is important to ensure that the steam is distributed evenly to all the super heater tubes and at the velocity sufficient to provide a scrubbing action to avoid overheating of the tube metal surface [4]. It is therefore crucial to monitor the condition of the super heater control parameters as listed in Table 3.5.

Table 3.5 Super heater control parameter

	Super heater Control	**Unit**
V4	Super heater steam pressure	**bar**
V5	Super heater steam temperature	**°C**
V7	High temperature super heater exchange metal temperature	**°C**
V8	Intermediate temperature (A) super heater exchange metal temperature	**°C**
V9	High temperature super heater inlet header metal temperature	**°C**
V10	Final super heater outlet temperature	**°C**
V11	Super heater steam pressure transmitter (control)	**bar**
V19	Low temperature super heater left wall outlet before super heater dryer	**°C**
V20	Low temperature super heater right wall outlet before super heater dryer	**°C**
V21	Low temperature super heater left wall outlet after super heater dryer	**°C**
V22	Low temperature super heater right wall exchange metal temperature	**°C**
V23	Intermediate temperature (B) super heater exchange metal temperature	**°C**
V24	Intermediate temperature super heater outlet before super heater dryer	**°C**
V25	Intermediate temperature super heater outlet header metal temperature	**°C**
V26	High temperature super heater outlet header metal temperature	**°C**

Meanwhile, a re-heater (or reheat of super heater) is used in utility application for the re-heating of steam after it leaves the high pressure portion of a turbine. The reheated but lower pressure steam then returns to the low pressure portion of the turbine. The incorporation of both re-heater and super heater into the boiler unit improves the overall plant efficiency [4]. The following table (Table 3.6) list the temperature and steam pressure reading parameters to ensure that it is within the safe threshold for a normal boiler operation.

Table 3.6 Re heater outlet parameter

	Re-heater	**Unit**
V6	High temperature re-heater outlet temperature	**°C**
V27	High temperature re-heater outlet steam pressure	**bar**

Finally, to efficiently optimize the cost of electrical power generation in a utility boiler unit; an economizer or an air heater is use and usually located downstream of the boiler bank. An economizer is a mechanical device that preheats fluids to reduce energy consumption. Specifically, in a steam boiler, it is used to recover heat from combustion products which in turn is used to preheat boiler feed water before it is re-introduced into the boiler to be converted into super-heated steam. Correspondingly, a condensing economizer is applied to reduce the flue gas temperature leaving the boiler and to provide an efficient boiler cycle. Parameters monitored to ensure the normal reading of the economizer as the flue gas flows out of the boiler are listed in Table 3.7.

Table 3.7 Economizer parameter

	Economizer	**Unit**
V30	Economizer inlet pressure	**bar**
V31	Economizer inlet temperature	**°C**
V32	Economizer outlet temperature	**°C**

The need for boiler plant availability is becoming one of the important considerations of boiler’s efficiency rating. Therefore, it is crucial to ensure that the plant’s boiler units are able to continuously operate with regards to energy efficiency, as well as safety and reliability.

3.5 Summary

In Malaysia, a thermal power plant has been an important asset and facility to generate and supply electricity demand of the country. Hence, the continuous development and commissioning of Manjung 4 plant in 2015, followed by Tanjung Bin coal fired plant for 2016, another Manjung 5 coal-fired plant in 2017 and another 1MDB project planned for 2018 [50]. The need for proper monitoring and diagnosis system of early detection of trip and faulty condition of the boiler units in these type of utility power plants has been constantly discussed in recent studies [13], [39], [51]. Thermal power plant boiler unit trips often lead to the reduction of a boiler’s efficient rate for a high utility availability demand. To resolve this problem, an intelligent interface that uses neural network as a tool to monitor and predict boiler trip condition will be discussed in the following chapter. Due to the high cost of a new monitoring system deployment, relocation and set up, an incorporation of a neural network and an advisory guide interface is considered.

Chapter 4. Boiler Fault Detection Using Artificial Neural Networks (ANN)

4.1 Introduction

Fault conditions are common in huge machinery such as the energy generating power plant that may lead to lost, both financially and operationally. Fault is defined as an unpermitted deviation of a standard machine operation from the acceptable or usual operational condition [45]. The complexity of a boiler makes it difficult to monitor and identify any occurring fault in real time. Therefore, in the past decades there have been many research in developing a model and system to analyze, evaluate, monitor, predict, detect and diagnose faults of a boiler in a power generating system [8], [9], [11], [13], [14], [36], [46], [47]. All of these papers suggested that the implementation of ANN would improve the existing systems considerably. This chapter will describe the ANN model design and power plant boiler simulation result using a set of pre-randomized data attained from an actual power plant here in Malaysia. The outcome of the proposed network's "predicted" output will be used to compare findings and simulation results from previous work to report any variation of the pre-selected features and suggests possible modification on the network parameters for future work. This chapter is divided into two sections. The first section will be a discussion on the development and design of the ANN model. While the experimental setup and simulation result of the prediction system is reported in the second section.

The following diagram (see Figure 4.1) illustrates the framework of the proposed boiler fault detection system implementing artificial neural network.

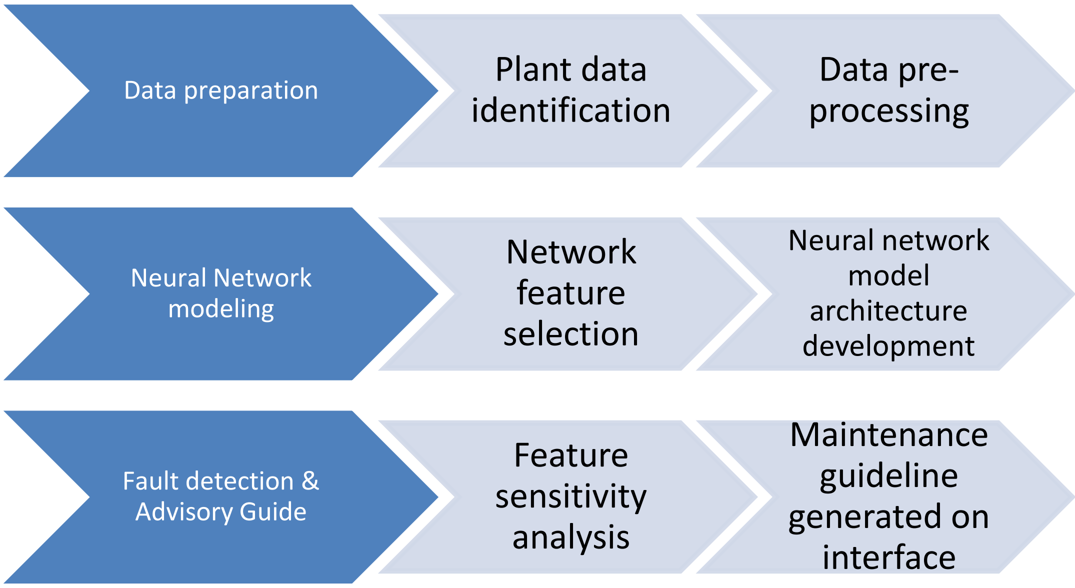


Figure 4.1. Boiler fault detection framework

4.2 Artificial Neural Network (ANN)

An ANN is a method used to replicate how interconnected neurons of a human brain communicate to learn a common pattern and experience to predict and make decisions. These neurons are linked with numerical weights which are the basic means of a long term memory of an ANN. The process of learning occurs through the repeated adjustments of these weights. Figure 4.2 represents the connections of a single building block artificial neuron. To build an artificial neural network, many of these neurons can be linked together. When more than one neurons are interconnected and arranged in different layers, it is then known as a multi layered neural network [52]. Most networks will have between zero and two hidden layers. Figure 4.2 shows how an output is produced when the sum of each input is multiplied by a weight in an artificial neuron that is later passed to an activation function.

The learning process of a network is known as training. ANN has a strong modelling environment that lets user test and explore simulated model faster and easier. The training process of the model is done with available data. An ANN program is used to introduce the input and output data. Once the training is completed, the model is ready to predict the outputs for 'unknown' data not presented to the ANN before. In order to design an ANN, the basic components need to be determined. The following steps were carried out to process the raw data and properly screened the trained dataset with validation and testing.

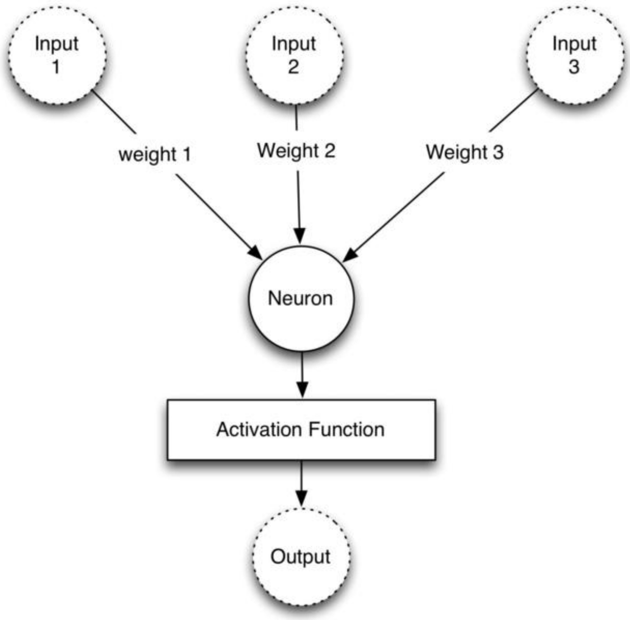


Figure 4.2 An abstract structure of a single artificial neuron.

The boiler fault detection model utilizes the output of the neural network as the boiler condition prediction. Therefore, the modeling should have a high accuracy rate for the model to be implemented in the system. Since modeling accuracy depends on how the network is trained, the selection of neural network type as well as the training algorithm is very important. There are various types of neural network, such as Radial Basis Networks (RBF), Elman network, Jordan network and Multi-layered perceptron (MLP). These networks are classified under two main categories, namely static and dynamic neural networks. For example, Elman network represents the dynamic neural network, and MLP is one of the static type networks. Once the type of network is selected, the training algorithm should be chosen to match it accordingly. Due to the nature of this research, MLP based network will be used and discussed.

4.2.1 MLP based boiler fault detection

In this study, a feed forward MLP network was used. It is one of the most well documented and frequently used types of ANN architecture [53]. An MLP is a feed forward neural network consisting of a number of neurons connected by weighted links. The neurons are organized in several layers, namely the input layer, hidden layer(s) and output layer.

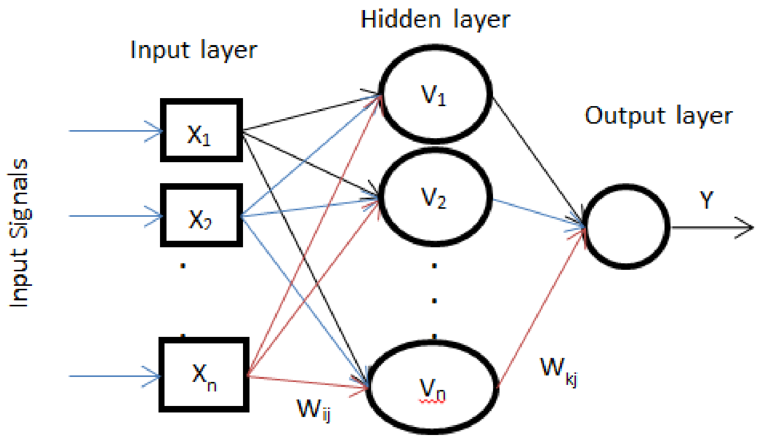


Figure 4.3 A typical multilayer perceptron structure

An example of a typical MLP is illustrated in Figure 4.3. In this network architecture, the input layer receives an external activation vector, and passes it through the weighted connections (w_{ij}) of the neurons in the hidden layer. This process computes their activations (w_{kj}) and passes them to neurons in succeeding layers until it reaches the output layer [54]. Basically, the input vector is propagated forward through the network producing an activation vector in the output layer at the end of the process. The mapping of input vector onto output vector is in fact determined by the connection weights of the net. As the weights of the neural network has an important role in determining how well the network is train and its output, it is often initialized to a random state [52], [55].

4.2.2 Data pre-processing and normalization

Data for 32 parameters from the plant under study were obtained for an interval of 1 minute for one week. Parameters selection listed in Table 4.1 for the boiler unit has been discussed in the previous chapter, which include those related to air, fuel (coal), feed water and steam. To remove any outliers and eliminate negative effect on the prediction performance; data filtering was carried out. Max, min and median value of the sample collected was calculated and data normalization was performed using the min-max method as shown in Eq. (4.1) to fit the range of 0 – 1. Any unreliable data collected during boiler shutdown period and when there was no power (electricity) generated were also removed.

$$\text{Data normalized} = \frac{(A_x - A_{x_{min}})}{(A_{x_{max}} - A_{x_{min}})} \tag{4.1}$$

where A_x represents the original value of the data before normalization.

Next step is to identify the right activation function for the selected MLP. According to [53], it was found that an MLP does not increase the computing power if the activation functions are linear for a single layer network. Hence, the unique advantage of an MLP comes from a non-linear activation functions.

4.2.3 Activation functions

An activation function or transfer function establishes the bounds for the output of neurons within a neural network. Choosing the right activation function is important because it affects the formatting method of the input data. There are six activation functions to select from, depending on the target outcome of the network [52]. However, for the purpose of this research, an MLP is used as the network for training; hence only two of the commonly used non-linear activation functions for a feedforward network are discussed. They are as follows;

4.2.3.1 Sigmoid activation function

In a feedforward neural network, the common choice is the sigmoid or logistic activation function, when the expected output is only positive numbers and to ensure values stay within relatively small range. Eq. (4.2) is an example of a sigmoid function. Due to its continuous and differentiable behaviour, sigmoid function plays an important role in weight adaptation during training when it produces a nonlinear response in the interval of 0 to 1 [35]. Though it is widely used, in many research; the hyperbolic tangent seem to produce a better outcome and becoming a more popular option [14], [30], [52], [56].

$$\emptyset(x) = \frac{1}{1 + e^{-x}} \tag{4.2}$$

4.2.3.2 Hyperbolic tangent activation function

The hyperbolic tangent (tanh) function is another popular choice for a feedforward network that has the output value range between -1 and 1. The advantage of hyperbolic tangent when compared to the sigmoid function is evident when it involves the derivatives used when training neural network. An example of a hyperbolic tangent function is given in (4.3).

$$\emptyset(x) = \tanh x \tag{4.3}$$

4.2.4 Training algorithm

The training algorithm is the procedure used to carry out the learning process in a neural network. Each type of training algorithm has its unique characteristics and performance. In this research, the common five training algorithm will be discussed to determined which one fits the network best to achieve the best outcome.

4.2.4.1 Levenberg-Marquardt (LM)

The Levenberg-Marquardt algorithm, also known as the damped least-squares method was designed specifically for loss functions that take the form of a sum of squared errors. This makes the training process very fast. LM is a hybrid algorithm that is based on Newton's method and on gradient descent (backpropagation). A neural network is trained with LM algorithm by calculating the loss, gradient and the Hessian approximation. If the stopping criteria are false, then the damping parameter is adjusted to reduce the loss in each iteration. As shown in Eq. (4.4), the LM algorithm enhances the Newton's algorithm as follows:

$$\Delta w = (H + \lambda I)^{-1} g \tag{4.4}$$

In this equation, the damping factor, represented by a lambda λ is multiplied by an identity matrix represented by I. Where I is a square matrix with all the values are at 0 except for a northwest line of values at 1. As the damping factor increases in value, the Hessian, represented by H will be factored out of the above equation. Meanwhile, as the damping factor decreases, the Hessian becomes more significant than the gradient vector (g), allowing the LM training algorithm to interpolate between gradient descent and Newton's method. The training iteration of an LM algorithm begins with a low λ and increases it until a desirable outcome is achieved [52].

4.2.4.2 Resilient Backpropagation (RProp)

The resilient backpropagation training algorithm is also known as the RProp is a local adaptive learning scheme that performs supervised batch learning in an MLP. Its main objective is to eliminate the harmful influence of the partial derivative size on the weight step. This means only the sign of the derivatives is considered to indicate the direction of the weight update. This is illustrated in Eq. (4.5), where the size of the weight change is exclusively determined by a weight specific 'update value' $\Delta w_{ij}^{(t)}$:

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)}, if \dfrac{\partial E^{(t)}}{\partial W_{ij}} > 0 \\ +\Delta_{ij}^{(t)}, if \dfrac{\partial E^{(t)}}{\partial W_{ij}} < 0 \\ 0, else \end{cases} \tag{4.5}$$

while $\frac{\partial E^{(t)}}{\partial W_{ij}}$ denotes the summed gradient information over all patterns of the batch learning. The way that RProp adapt its learning process to the error function topology, is by following the principle of 'learning by epoch'. This means that the weight update and adaptation are performed after the gradient information of the whole pattern set has been computed [54].

4.2.4.3 Scaled Conjugate Gradient (SCG)

The SCG is a training function that updates weight and bias values according to the conjugate direction method. For this method to work, the availability of a set of conjugate vectors s(0), s(1),…, s(w-1) is required. The successive direction vectors are generated based on a conjugate version of the successive gradient vectors of the quadratic function f(x) as it progresses. Therefore, the direction vectors set {s(n)}, where n = 0 is excluded is determined in a sequential manner at successive steps of the method. Eq. (4.6) illustrates how the SCG algorithm is used to adjust the step size as a reduction in the error estimation.

$$\Delta_k = \frac{2\delta_k[E(\widetilde{w}_k) - E(\widetilde{w}_k + \alpha_k \tilde{P}_k)]}{\mu_k^2} \begin{cases} if\ \Delta_k > 0.75, then\ \lambda_k = \dfrac{1}{4}\lambda_k \\ if \Delta_k < 0.25, then\ \lambda_k = \lambda_k + \dfrac{\delta_k(1-\Delta_k)}{\mu_k^2} \end{cases} \tag{4.6}$$

The SCG function is explained as follows. Here, Δ_k is a measure of the approximation of the global error function $E(\widetilde{w}_k)$, a better approximation can be determined when Δ_k is closer to 1. First, the weight vectors of $\widetilde{w}_k$ and scalars need to be set to positive values, then the second order information need to be calculated. Next, the delta δ_k value is scaled using; δ_k: $\delta_k = \delta_k + (\lambda_k - \bar{\lambda}_k)|\tilde{p}_k|^2$. If the $\delta_k$is less than zero, then the Hessian matrix needs to be made into positive definite. To calculate the step size, μ_k and α_k is used. This is followed by the calculation of the comparison parameter of Δ_k as seen in the above equation. If $\Delta_k \geq 0.75$, then the scale parameter (λ_k) is reduced. Otherwise, if $\Delta_k < 0.25$ the λ_k is increased. SCG is independent of any user parameters, which gives it an advantage over other line search based algorithms [57].

4.2.4.4 Gradient Descent with momentum and adaptive learning rate (GDX)

Steepest descent also known as the gradient descent (GD) is known to be the simplest training algorithm. Since it only requires information from the gradient vector, it is a first order method. It is normally considered in a neural network training when the size of the network is big, where big number of parameters are involved. This is possible because this method only stores the gradient vector and not the Hessian matrix which requires a small memory capacity. However, based on the way the training direction is computed, it requires more iterations resulting in a slow convergence.

The function GDX is a gradient descent method that combines adaptive learning rate with momentum training. It is invoked in the same way as a GD except that it has momentum coefficient (mc) as an additional training parameter. It is able to train any network as long as its weight, network input and transfer functions have derivative functions. As for each of the weight (w) and bias variables, it has to be adjusted according to the gradient descent with momentum as illustrated in the following Eq. (4.7).

$$\Delta w = mc * dw_{prev} - lr * mc * dperf/w \tag{4.7}$$

Where dw_{prev} is the previous change to the weight or bias, lr represents the learning rate and $dperf$ is the calculated derivatives of performance.

4.3 Experimental Results & Discussion

Based on existing literature [29]–[31], a non-linear transfer functions are better for modelling real life coal-fired thermal power plant. To validate the theory, data was pre-randomized before dividing into training, validation and testing dataset. The training of the boiler model was carried out to identify the suitable transfer function under identical conditions of 500 epochs with 32 hidden neurons, repeated for ten runs, using the same set of pre-randomized data with random initial weights in each run to avoid local minima or over training and normalization boundaries of [0 1]. The only variances in the trial runs were the activation functions and training algorithms.

Generally, a physical model requires an exact number of parameters values for calculations. Hence, the choices are dictated by the equation representing the processes involved. This limits the choice of input and output parameters by the "cause and effect" relations [30]. Unlike a physical model, the input and output parameters in ANN are selected on the basis of the objective of the equipment monitoring and the boiler's operators' experience. In fact, the input parameters are usually optimized to compromise between the number of parameters and the desired accuracy of the ANN prediction.

The final set of input parameters for this experiment was defined on the basis of observations related only to the boiler unit, advice and feedback from the plant operator, removal of parameters that has non-effective factors on the faulty scenario and any redundant readings from the same sensors [58]. The input parameters and their dataset description are listed in Table 4.1.

Table 4.1 Input Parameters Description

Input Parameters		***Unit***
Temperature	• Boiler re-heater and super heater inlet/outlet and exchange metal temperature • Economizer inlet/outlet temperature	°C
Pressure	• Boiler drum pressure • Superheated steam pressure • Circulation pump pressure • Temperature and steam outlet pressure • Economizer inlet pressure	Bar
Flow rate	• Steam flow • Feed water flow • Super heater water injection compensated flow	Ton/hr

All experiments are carried out in a simulation environment software running on a 2.20GHz Intel® Core^{TM} i5-5200U processor with 8GB RAM memory. To demonstrate the comparison result, the following criteria were set:

- All sample data used for the experiments were normalized using the Min-Max normalization method Eq. (4.1).
- The MLP network consists of 3 layers; input layer, one hidden layer and an output layer. The number of hidden neurons used in these experiments was set between 2 to 32 hidden neurons, and two target output values of 0 and 1. The number of iterations for each epoch was set to 500 and each data set was trained for 10 simulations.

- There were four selected training algorithm tested for their convergence speed, accuracy and robustness; and two types of activation functions were tested to identify which one is more likely to produce output that are on average closest to zero.
- The same proportion of data for training, validation and testing was applied for each data set, namely 70% for training, 15% for validation and 15% for testing.
- To determine the minimum difference or error between the actual output Y and the target output Z of the network during training; the minimization of error using Mean Squared Error (MSE) method is used as given in Eq. (4.8). where Z_j is the target output and Y_j represents the output of the network, while n is the number of true values, and i is the number of samples.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Z_j - Y_j)^2 \tag{4.8}$$

- To evaluate the performance of the network in achieving an acceptable accuracy rate, the misclassification rate (MCR) given in Eq. (4.9) is used. TP represents true positive, TN represents the true negative and TS is the total number of samples used.

$$MCR\ (\%) = \left(1 - \frac{\sum TP + \sum TN}{\sum TS}\right) \times\ 100\% \tag{4.9}$$

According to [59], [60], the initial values of weights in a network have a significant effect on the training process. To produce a well-trained network, coordination between the normalization training data set, selection of training function and the choice of weight initialization are important. To evaluate how much influence each assumed initial weights has on the output while identifying the best initial weight for the simulation, two sets of weight values are used; namely W1 and W2. Where W1 consist of initial weights that are set to zeros and W2 are random initial weights. In the initial stage of the experiment to compare the different initial weight application, these two sets of weights are applied to one of the 10 available sets, using RProp as the training algorithm. The comparison was carried out to observe how the initial weights influence the accuracy of the MCR achieved. With reference to Table 4.2, it is observed that the selected training algorithm (RProp) was able to compute the training in an average of 1.42 milliseconds for 500 iterations using W1. It was also able to achieve a fairly good MSE of 0.0317 and an MCR of 3.53%. When the weights were modified to be initialized at random values using W2, the outcome has improved, where a minimum error of 0.0254 was achieved and an even lower MCR of 2.71% was recorded.

Table 4.2 Initial weights identification to achieve least MCR & MSE

	Weight set	MSE	MCR (%)
Training	W1	0.0317	3.53
	W2	0.0254	2.71
Testing	W1	0.0487	5.86
	W2	0.0491	6.06

However, when the network is presented with a new set of data for testing, there was a slight increment in both the MSE and MCR for both initial weights setup. This may be due to a few contributing factors, such as the training algorithm used, generalization method, and the convergent rate [61], [62]. There has been an improvement in the result when other training algorithms were applied as seen in the following section of the experiment (see Table 4.3).

Table 4.3 Training algorithm identification using the same sets of initial weights to achieve the least MCR and MSE

	W1		W2	
Training Algorithm	MSE	MCR (%)	MSE	MCR (%)
LM	0.057018	5.8%	0.008006	1.8%
RProp	0.072464	7.2%	0.042608	4.7%
SCG	0.091411	11.2%	0.084871	11.6%
GDX	0.097826	9.8%	0.10057	11.2%

The next experiment is to determine the best activation function to train the network. In the initial stage, the sigmoid activation function was used for both layers in the network, namely hidden layer and at the output layer in the training. This decision was considered because the expected predicted output is within the range of 0 to 1. However, the training results indicate a higher rate of MCR (refer to Table 4.4). To improve the recognition rate, changes were made to use hyperbolic tangent (tanh) activation function for one of the layers.

As seen in Table 4.4, the MCR achieved is still higher than the acceptable range of below 10%. However, when the activation functions for both layers were changed to use the tanh activation function, the training result has improved noticeably. Where the MCR recorded was below 10% during training with a slight difference of 1.96% during testing. A good indicator that the network was able to learned and recognized the pattern of the boiler performance if it is faulty or normal. For this experiment, the LM training algorithm was used for the purpose of identifying the best selection of activation function for the dataset. The recorded MCR is a calculated based on an average of 10 simulations of one randomized dataset.

Table 4.4 A comparison table showing MCR with different combinations of activation functions, namely the sigmoid and hyperbolic tangent (tanh) functions.

	Activation function structure	**MCR (%)**	
		training	**testing**
1.	sigmoid (hidden layer) + sigmoid (output layer)	13.78%	13.99%
2.	tanh (hidden layer) + sigmoid (output layer)	14.19%	11.96%
3.	tanh (hidden layer) + tanh (output layer)	9.02%	10.98%

In the previous two experiments, two different types of training algorithm were used. To validate the most suitable training algorithms for the neural network; another experiment was carried out and the identified network parameters from the previous experiments' outcome were included. At the beginning, a total of 58, 784 raw data from 32 boiler variables were collected from an actual power plant here in Malaysia. These collected data units range from temperature, pressure to volumes of energy productions. The main objective of this research is to identify trip conditions classified under two values of 1 for fault and 0 for normal. Hence, these raw data have been normalized to be in the range of 0 and 1. Then, these normalized data were sub divided into 10 randomized data sets for neural network simulation purposes. From the first two experiments discussed earlier, two of these data sets have already been used for the activation function and network weight setup. Therefore, the remaining 8 data sets will be used to determine the next important neural network parameter, the training algorithm. The following network criteria were set up:

- An MLP with 3 layers; input, one hidden and an output layer.
- The number of iterations for each epoch was set to 500 and a data set was trained for 10 simulations

- The number of hidden neurons is set to 32, using random initial weights for both input and hidden layers
- The activation function, as identified in the previous experiment will implement the hyperbolic tangent (tanh) for both network layers
- The training algorithms considered for this experiment include RProp, LM, SCG and GDX.
- Performance standard used are the least MSE and MCR.

Table 4.5 Mean and standard deviation of minimum MSE obtained for each training algorithm

	Epoch (500)	
	Mean$_{mse}$	**Stdev$_{mse}$**
LM	0.0223	0.0074
RProp	0.0420	0.0058
SCG	0.0943	0.0056
GDX	0.1090	0.0029

In this work, the focus of the experiment is to identify the best optimization backpropagation technique for the prediction model. Hence value of the mean MSE and MCR of ten rounds is best achieved by LM in comparison to the rest of the training algorithm. The standard deviation of LM recorded in this experiment is seen to have a higher deviation in comparison to the other training algorithm. This may be due to the random weight initialization method implemented in this experiment. As reported by [61], [62], the standard deviation can be improved by considering a deep learning neural network technique. Since the focus of this experiments is only to identify the best optimization backpropagation technique, a deep learning method was not considered.

Table 4.6 Mean and standard deviation of MCR for 500 epochs

	Epoch (500)					
	Training		**Validation**		**Testing**	
	Mean$_{mcr}$	**Stdev$_{mcr}$**	**Mean$_{mcr}$**	**Stdev$_{mcr}$**	**Mean$_{mcr}$**	**Stdev$_{mcr}$**
LM	7.435%	3.952	8.239%	3.580	8.978%	3.697
RProp	8.380%	2.994	8.873%	2.866	9.351%	2.842
SCG	13.205%	0.938	13.207%	2.013	13.543%	2.067
GDX	13.848%	0.536	13.725%	1.791	13.971%	1.872

4.4 Summary

The boiler fault detection comprising a replicated MLP network architecture is used in this chapter. In order to train the MLP, a standard feedforward algorithm is applied and a fairly high prediction rate was obtained. The simulation result shows the Rprop algorithm was found to compute faster when the initial weights are set to zero, however a better performance and misclassified rate are evident when LM algorithm was used. The initialization of the random weights in the network results in an improved misclassified rate of the overall learning pattern. Additionally, an equal distribution of the normal and faulty reading in the training set is also important to avoid data overfitting when testing of the network is carried out. To conclude, it appears that LM was able to reach the minimum MSE in Table 4.3. The result demonstrates LM dominants in pattern recognition network against the other three training algorithm for the trip prediction of the thermal power plant boiler parameters.

Chapter 5. Intelligent Boiler Trip Monitoring Interface and Advisory Guide

5.1 Introduction

An Intelligent Monitoring Interface (IMI) is a human-machine interface system that tracks and improves the responses of an event associated with monitored equipment. It enables user to perform potentially complex tasks more effectively and quickly with greater accuracy. This is made possible by presenting users with information on the equipment condition, user's next actions, and warnings of undesirable consequences and suggestions of an alternative action. The basic idea behind the IMI for a coal fired boiler unit is due to the limited capabilities of the current monitoring system. It does not allow simultaneous collaboration between plant supervisor and boiler operator when a trip occurred.

In Chapter 4, we have discussed the computational optimization algorithm and network architecture of the boiler trip monitoring. Many researchers have been focusing on improving the monitoring system using various methods, see [5], [8]–[10], [14], [17], [46], [63], [64]. These methods include comparative analysis, hybrid fuzzy clustering, ANN, support vector machine, data mining, and a multi agent system to name a few. The next part of the intelligent monitoring is the interface development for the boiler trip advisory guide.

In 2002, an expert system to manage abnormal condition of a manufacturing system has already been proposed by [65] where their main objective was to develop a system that was able to detect unusual events early, assess the potential impacts of the identified event, diagnose the root cause and provide operators with guided advice for an appropriate immediate actions. In their paper, "smart" generic and reusable objects known as "Generic Heaters" developed using Gensym Optegrity software were used to provide proactive diagnostic to manage these identified abnormality and performance indices. Generic Heaters are software objects containing diagnostic, fault models and advisory messages for managing over 80 faults typical for boilers, furnaces, ethylene crackers and incinerators. Using their method for a 32 sensor parameter reading to identify the fault condition of a boiler will require over 2,560 fault models objects to consider. This will be time consuming and may not be practical for real time implementation. Hence, in this work the method of using ANN as the prediction tool for fault detection and forecasting of a boiler's abnormal reading is used instead. Additionally, the user interface will be developed using a simulation environment software to generate the data reading and prediction along with the advisory guide whenever a fault is forecasted. The following sections of this chapter will elaborate on the steps involved to design and develop the Graphical User Interface (GUI) of the advisory guide for the monitoring system using an Integrated Development Environment (IDE) program. The preliminary design of the user interface is based on the following flowchart (Figure 5.1).

5.2 Power plant boiler monitoring interface

An extension to the current monitoring system is the GUI development for both client side data representation and control and maintenance operations. The most common interface implementation of a monitoring system is through an on-site server where authenticated user access the data collected through their local workstation connected to a Virtual Private Network (VPN). Meanwhile, a remote server monitoring system allows data collected on site to be sent to a remote server and accessible through any standard web browsers (e.g. Mozilla, Explorer, or Google Chrome). Anyone with an authentic username and password can view the data without installing the client software. The advantage of the latter; plant staff, analyst and equipment and maintenance operators and technicians can simultaneously look at the data to collaborate on remedial actions [66]. Rather than delivering machine data in-house only (on-site control rooms), the Internet allows information to be accessible from anywhere, anytime.

Ideally, plant operators of this monitoring system are made accessible at different levels, and possibly different types of views and control, depending on their profile, conditions of the system and the current task being executed. As suggested in the illustration in Figure 5.2, the operator is responsible in monitoring and inspecting physical condition of the equipment whenever an alarm is triggered on the monitoring system.

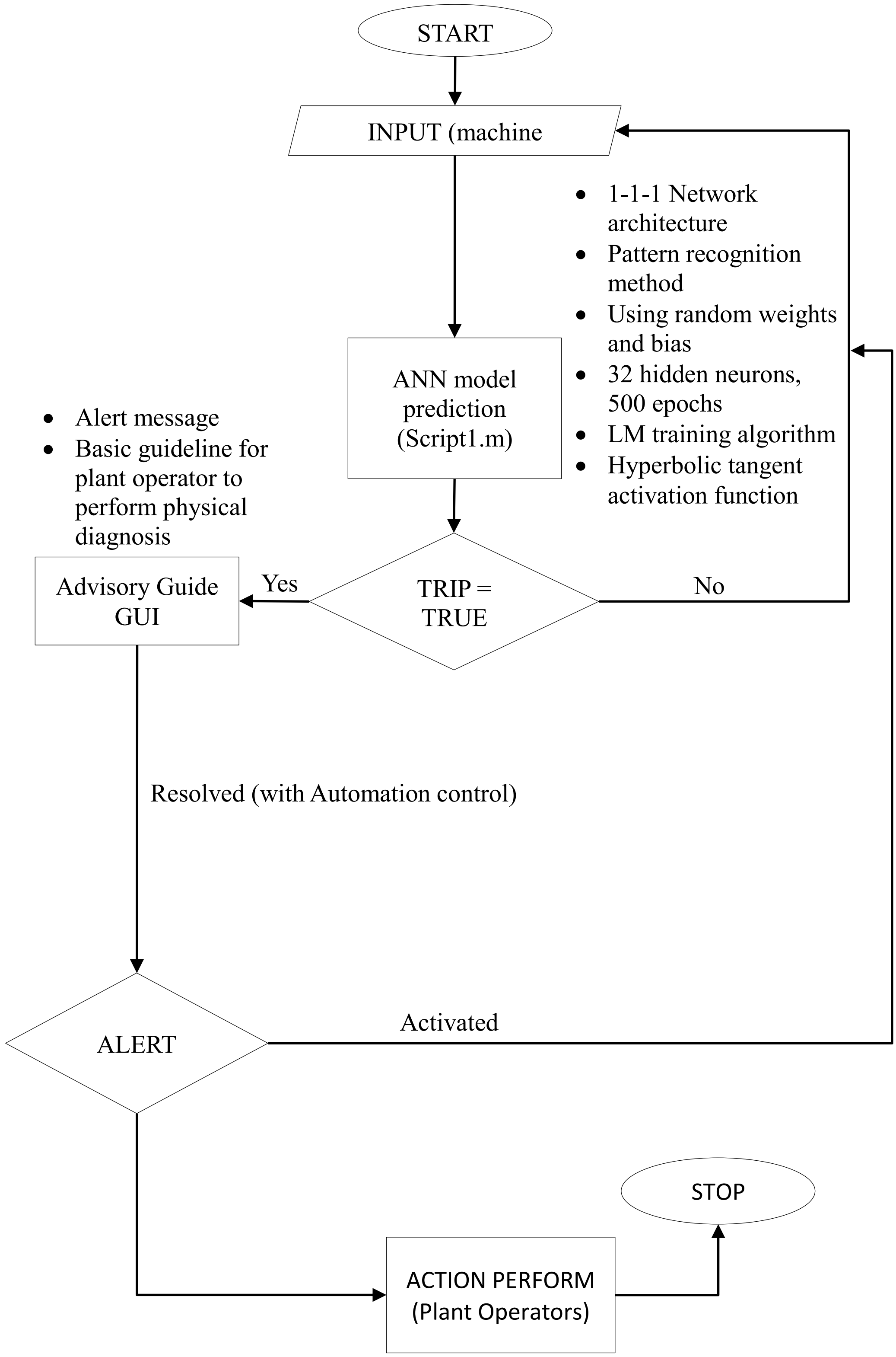


Figure 5.1 The flowchart outlining the features of the GUI

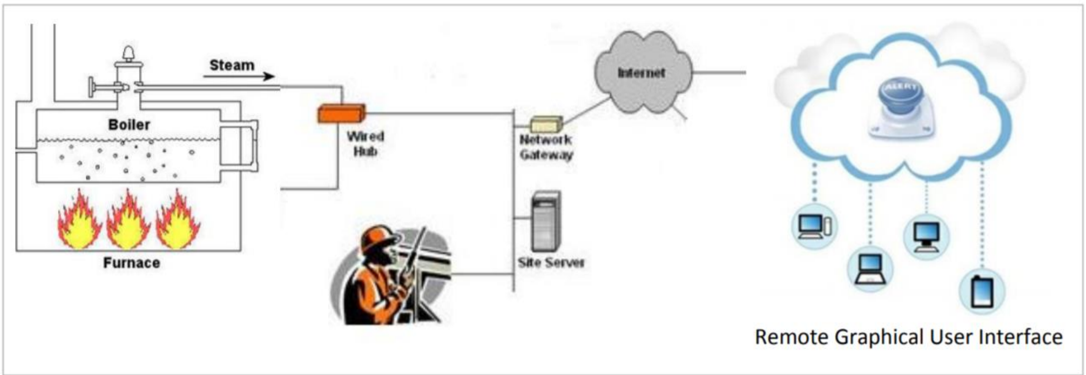


Figure 5.2 An illustration of the interaction between plant operator and the monitoring system

A user interface is used to represent the functionality of the system by categorizing user actions and their working paradigms into interactive visual objects on a user's screen or monitor. These important features of a user interface makes a system easier to use [67], [68]. Visualization and interactivity are important aspects when designing a monitoring system interface. This is because the graphical capabilities of a computer using images, buttons or animation, helps the user to easily navigate the system. Furthermore, the intractability between the system and the user allows simultaneous response to any changes or feedback of the system. This rich visual content allows user to gain useful practical insights into the monitoring systems [69]. However, to successfully put all the interactive and functionality features in a system; its development, testing and maintenance proved to be more challenging [68].

Currently, there are many tools available to build a user interface for a wide range of engineering systems; the most common ones include MATLAB, LabVIEW, and SCADA. Other open source tools for some programming languages like Netbeans for JAVA and even a few with numerical computing libraries such as NumPy/SciPy for Phyton, and Numeric.js for JavaScript are now equipped with an Integrated Development Environment (IDE) to develop graphical interfaces [69]. However, they could be challenging to use for inexperienced programmers to develop interactive tools. To define a best fitting user interface to link the ANN boiler trip mechanism, a set of basic requirements of the system needs to be considered. They are listed as follows:

- The knowledge of the system to be monitored needs to be specified
- An executable user interface must be possible and logical based on the specification provided

- It must be feasible to verify properties and to validate the specification
- It must be possible to classify users into different profiles
- It must be possible to define the tasks that may be available to only some user profile

Apart from the above listed requirements, the human factor is also an important feature; to achieve productivity gains from the monitoring system. This involved the main four personnel directly in contact with the monitoring system and its corresponding interface. They are:

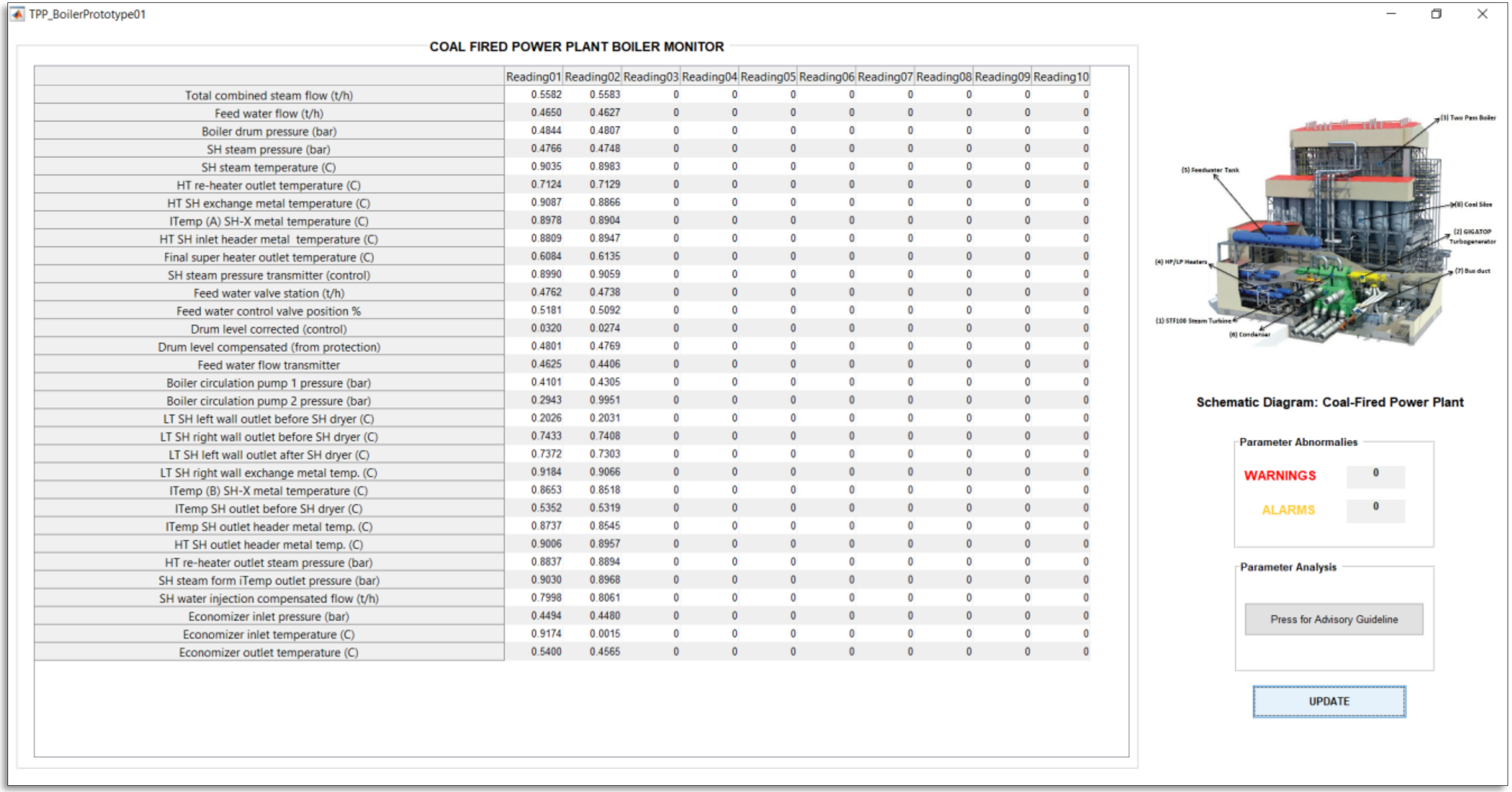
- Expert: An expert will be the direct person to contact for an alarm event involving an equipment sensor malfunctions or trips. The purpose of the user interface is to provide the expert on the equipment sensor installation, ANN design, and testing and diagnosis report.
- Maintenance: The user interface will be used to display statistics or machine reading for various parameter measurements to the maintenance team.
- Supervisor: The task of a supervisor is to manage the machinery processes and oversee the learning process of the embedded ANN into the system. Hence, the user interface will provide information regarding the movements of the plant equipment operators and the communication link and channel for information exchange between the two personnel.
- Operators: Generally, the operators are the one handling the continuous innovation and improvements of the machinery. Furthermore, should there be any need for equipment changeover and reporting anomalies during inspections; direct communication to the supervisors are critical especially for triggered alarm or trip inspections. The user interface should provide the interaction medium in real time.

The above requirements are known as the Human Machine Interaction (HMI). It provides the link between the ANN based monitoring system and the end user by providing the means for a long term analysis and aid improvements and innovation of the equipment [70], [71]. The monitoring system runs a boiler condition reading at regular intervals of one minute throughout the day. These captured data are then stored into a data management system, that manages them into a database as historical data and ease of retrieval to be analyse in the developed prediction model. To predict any possible trip occurrences, a dedicated program was coded in a simulation environment software with neural network as discussed in the previous chapter.

5.3 Power plant boiler trip advisory guide

The output of the sample user interface consists of a time stamp and normalized data reading for the 32 parameters being observed, an identified number of parameter abnormalies for both warning and alarm indicator and an advisory message box alert detailing the root cause explanations and suggested actions to be carried out. A sample of the designed GUI is shown in Figure 5.3. Using a simulation environment software, the custom interface has been developed in Microsoft Windows 10 operating system, using a 2.20 GHz Intel® Core^{TM} i5-5200U CPU with 8GB RAM. One of the features added in the GUI is an update button, where for each button press; a new set of time stamp data is retrieved from the (.mat) file and displayed in the first column for review and analysis purpose. In this prototype, data displayed have already been normalized between the values of 0 to 1. This is due to the specification requirement of the developed neural network model which identifies faults when a reading is closer to the value of 1. As for the parameter anomalies feature in the GUI, a set of condition based algorithm is added to identify the number of warnings and alarms identified (if any) whenever the data reading is updated in the table.

Meanwhile, in the parameter analysis section of the GUI, a button that generates the text file of the advisory guideline is included. The action performed when this button is pressed; it will open a text document on a separate window using the notepad program. In this text file, detailed information of the alarm/fault reading is displayed. Where the description of the parameters identified to be affected by the trip alert is listed with its suggested actions to be considered when an inspection or maintenance exercise is carried out on the parameter.



	Reading01	Reading02	Reading03	Reading04	Reading05	Reading06	Reading07	Reading08	Reading09	Reading10
Total combined steam flow (t/h)	0.5582	0.5583	0	0	0	0	0	0	0	0
Feed water flow (t/h)	0.4650	0.4627	0	0	0	0	0	0	0	0
Boiler drum pressure (bar)	0.4844	0.4807	0	0	0	0	0	0	0	0
SH steam pressure (bar)	0.4766	0.4748	0	0	0	0	0	0	0	0
SH steam temperature (C)	0.9035	0.8983	0	0	0	0	0	0	0	0
HT re-heater outlet temperature (C)	0.7124	0.7129	0	0	0	0	0	0	0	0
HT SH exchange metal temperature (C)	0.9087	0.8866	0	0	0	0	0	0	0	0
ITemp (A) SH-X metal temperature (C)	0.8978	0.8904	0	0	0	0	0	0	0	0
HT SH inlet header metal temperature (C)	0.8809	0.8947	0	0	0	0	0	0	0	0
Final super heater outlet temperature (C)	0.6084	0.6135	0	0	0	0	0	0	0	0
SH steam pressure transmitter (control)	0.8990	0.9059	0	0	0	0	0	0	0	0
Feed water valve station (t/h)	0.4762	0.4738	0	0	0	0	0	0	0	0
Feed water control valve position %	0.5181	0.5092	0	0	0	0	0	0	0	0
Drum level corrected (control)	0.0320	0.0274	0	0	0	0	0	0	0	0
Drum level compensated (from protection)	0.4801	0.4769	0	0	0	0	0	0	0	0
Feed water flow transmitter	0.4625	0.4406	0	0	0	0	0	0	0	0
Boiler circulation pump 1 pressure (bar)	0.4101	0.4305	0	0	0	0	0	0	0	0
Boiler circulation pump 2 pressure (bar)	0.2943	0.9951	0	0	0	0	0	0	0	0
LT SH left wall outlet before SH dryer (C)	0.2026	0.2031	0	0	0	0	0	0	0	0
LT SH right wall outlet before SH dryer (C)	0.7433	0.7408	0	0	0	0	0	0	0	0
LT SH left wall outlet after SH dryer (C)	0.7372	0.7303	0	0	0	0	0	0	0	0
LT SH right wall exchange metal temp. (C)	0.9184	0.9066	0	0	0	0	0	0	0	0
ITemp (B) SH-X metal temperature (C)	0.8653	0.8518	0	0	0	0	0	0	0	0
ITemp SH outlet before SH dryer (C)	0.5352	0.5319	0	0	0	0	0	0	0	0
ITemp SH outlet header metal temp. (C)	0.8737	0.8545	0	0	0	0	0	0	0	0
HT SH outlet header metal temp. (C)	0.9006	0.8957	0	0	0	0	0	0	0	0
HT re-heater outlet steam pressure (bar)	0.8837	0.8894	0	0	0	0	0	0	0	0
SH steam form iTemp outlet pressure (bar)	0.9030	0.8968	0	0	0	0	0	0	0	0
SH water injection compensated flow (t/h)	0.7998	0.8061	0	0	0	0	0	0	0	0
Economizer inlet pressure (bar)	0.4494	0.4480	0	0	0	0	0	0	0	0
Economizer inlet temperature (C)	0.9174	0.0015	0	0	0	0	0	0	0	0
Economizer outlet temperature (C)	0.5400	0.4565	0	0	0	0	0	0	0	0

Figure 5.3. A time stamp parameter data reading advisory thermal power plant boiler monitor user interface

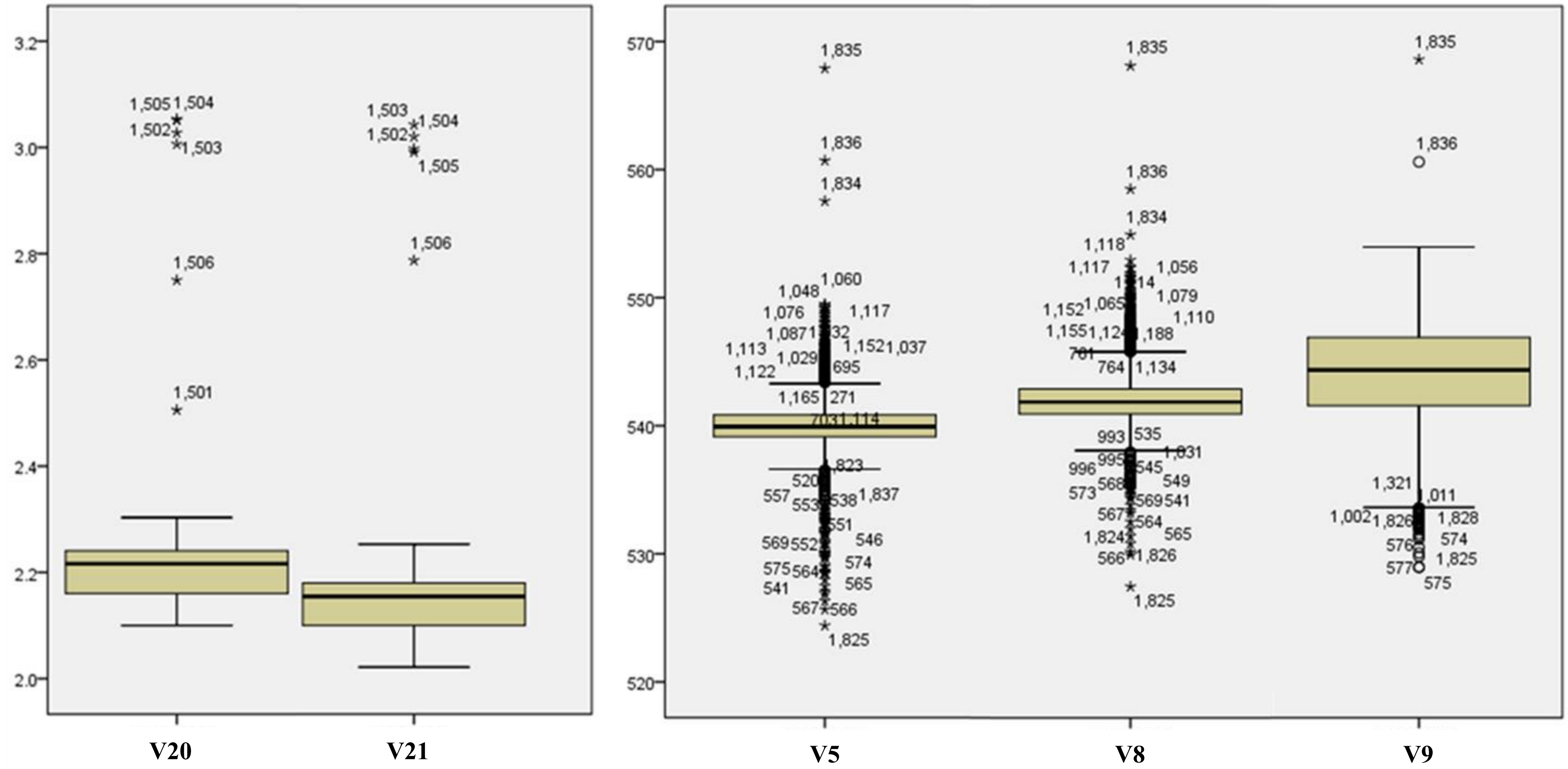


Figure 5.4. Outliers identified and labelled with an (*) for variables V5, V8 and V9 related to super heater steam, exchange metal and inlet header metal temperatures. This figure also includes outliers for low temperature readings at the super heater wall outlet before and after the super heater dryer, V20 and V21 respectively

In chapter 3, a set of observed parameters were listed in Table 3.1 and these parameters were identified as crucial data for monitoring the performance of the overall boiler unit. To validate its impact on the boiler performance, a sensitivity analysis was carried out to see which parameters may have been the cause of the boiler trip. The outcome of the analysis is illustrated in the boxplot in Fig. 5.4.

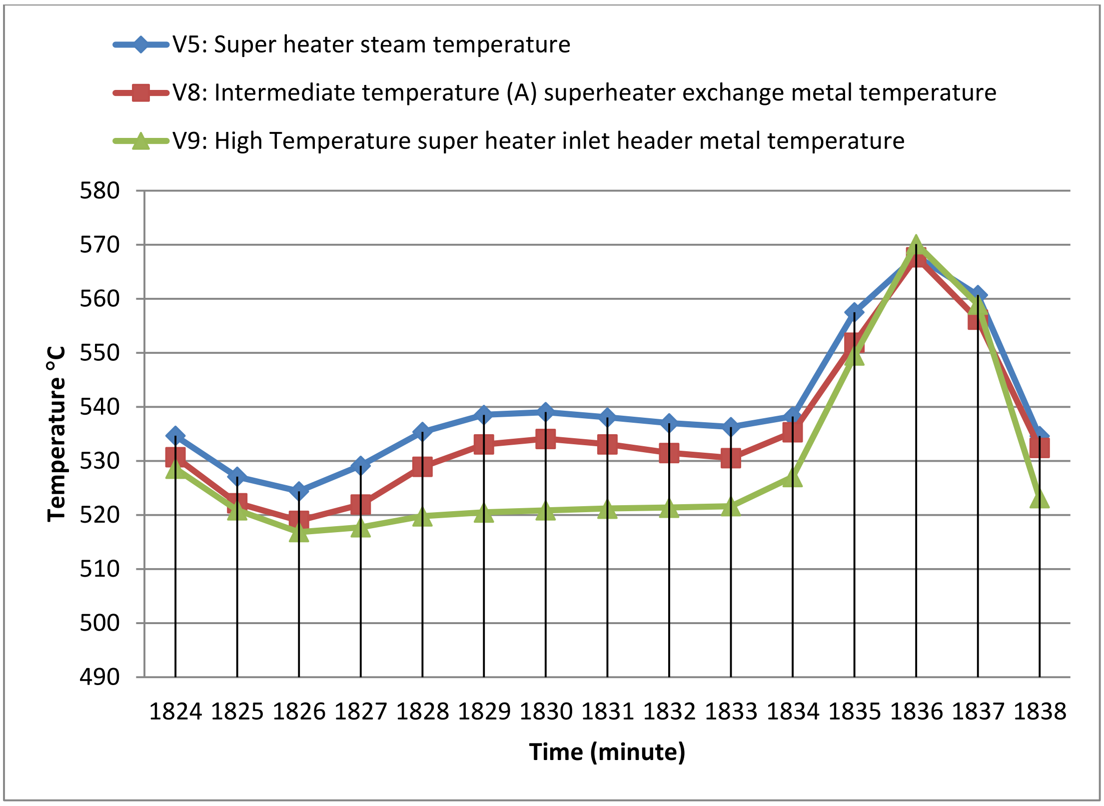


Figure 5.5. V5, V8 and V9 a sudden upsurge of temperature reading at interval 1835 to 1837

As illustrated here in the boxplots, there are a group of outliers identified between the 1501 to 1508 minute intervals for V20 and V21. This could be an indicator that the low super heater wall outlet parameters may be experiencing some disturbances causing some faulty reading which is about 12.6% exceeding the lower and upper bounds of the confidence intervals. Apart from these two parameters, three other parameters related to the super heater temperature were also showing a slight increment in its reading at intervals 1835 to 1837. They are V5, which is the super heater steam temperature, V8 the intermediate temperature (A) super heater exchange metal temperature, and V9 as the high temperature super heater inlet header metal temperature which were above the upper bounds of the confidence interval of 544.8°C, 567.7°C, and 570.2°C respectively. This can be seen in the snippet of the chart shown in Fig. 5.5. The correlation between these variables are unclear when analysed with a statistical tool, hence the importance to use neural network to make the correlation between these variable reading.

5.5 Summary

A description of the proposed intelligent monitoring user interface has been presented and discussed. The advantages of the proposed system were described along with the comparison of a traditional and existing monitoring system. Some of the feedback provided on the advisory system were also provided. As a conclusion, the boiler fault condition identification tool and advisory guide was able to save thousands in revenue as well as the lives of people involve in the work of maintaining the boiler operation in the power plant. The gains for these improvements added to the existing monitoring system not only benefit the industry economically, but it also improved the overall optimization of the boiler equipment unit in a power plant.

Chapter 6. Conclusion and Future Work

6.1 Conclusion

Thermal power plant boiler unit trips often lead to the declining rate of boiler efficiency for the high utility availability demand. Due to the alarming rate of the frequent blackouts resulting from an unscheduled power unit trips, various new methods have been proposed for the diagnosis and monitoring of the boiler unit in a power plant. In Malaysia, a thermal power plant is an important asset and facility to generate and supply electricity demand of the country. Hence, the continuous development and commissioning of Manjung 4 plant in 2015, followed by Tanjung Bin coal fired plant in 2016, Manjung 5 coal-fired plant in 2017 and another 1MDB project planned for 2018 [50]. These new projects are a necessity to meet the demand of the growing number of users. However, building more utility plants does not necessarily resolve the boiler unit trip occurrences issue. Despite new efforts to diagnose and monitor the trips, more research is needed to develop new system that is able to monitor and diagnose factors leading to the degradation of boiler unit(s) in a power plant.

In chapter 2, a comprehensive literature review on the specific techniques most favoured to accomplish the task to monitor boiler performance was presented. Based on previous work, ANN has been identified as the most appropriate candidate. It has been widely applied in a number of successful applications for classifications task, forecasting, control systems and optimization and decision making. For instance, ANN has been reported to have successfully interpret the behaviour of machinery processes in energy conversion plants [29], [31], [38], [58], [72]–[74]. Commonly, large number of operational data is captured continuously by the on-line plant's monitoring system for its proper operation. These are usually stored as parameter record and historical data in a database. By utilising these data, ANN can be used to simulate a power plant operation to recognize and identify boiler unit degradation that eventually leads to trips in an actual plant. Furthermore, a comparison study of the simulated data to an actual plant data can be used to assess the plant degradation rate. By being able to establish the timeline of a boiler unit's lifespan, better maintenance schedule and planning can be carried out.

In chapter 3, the boiler unit operational parameters were presented. In big utility plant, detailed observation on each of its operational parameters is crucial. Due to the extent of the boiler complexity, the number of operational parameters to be used as sample in this work include the 32 most influential parameters to the boiler unit. The selection is based on the plant operator's past experience and system knowledge. Identifying faults and trip condition of a boiler in its most effective operating condition requires in depth understanding and knowledge of its faulty parameters and factors causing the malfunctions. Since there are a large number of data obtained from the industry, irrelevant values and outliers need to be identified and removed accordingly.

In chapter 4, an ANN model implementing the LM algorithm was presented. As suggested in the literature [29]–[31], a non-linear activation functions are better for modelling coal-fired thermal power plant. Hence, an MLP were used and simulations were carried out under an identical condition of 500 epochs, with 32 hidden neurons, pre-randomized initial weights and a hyperbolic tangent activation function. There were four training algorithm tested for their convergence speed, accuracy and robustness. They were LM, RProp, SCG and GDX. Simulation outcome and result showed LM has proven to be consistent in achieving the least MSE and MCR in all of the simulations.

In chapter 5, major issues associated with an intelligent approach for an intelligent monitoring system was reported. Most of the issues was due to the high cost for deployment, relocation and set up [75]. Thus, the incorporation of neural network for boiler fault identification with an interactive GUI was also studied. In this chapter, an application of an intelligent monitoring GUI was presented and discussed. A simulation environment software was used to develop the GUI in a standard CPU setup of a windows based operating system. The advantages of the proposed system were described along with the comparison of a traditional and existing monitoring system.

To conclude, the problems related to thermal power plant boiler trips were identified and analyzed with existing literatures. Comparison of existing monitoring systems and the research gap using various methods and approaches have also been highlighted and acknowledged. The boiler fault condition identification tool and advisory guide was able to save thousands in revenue as well as the lives of people involve in the work of maintaining the boiler operation in the power plant. The gains for these improvements added to the existing monitoring system not only benefit the industry economically, but it also improved the overall optimization of the boiler equipment unit in a power plant.

6.2 Future Works

In developing the proposed advisory guide interface for the existing boiler power plant trip identification, some of the costing issues identified will be addressed. For instance, a portable executable file setup for the interface module should be considered. This is to avoid any additional cost on software installation and licensing to run the extended module.

Another recommendation would be to look into other machine learning approach for feature selection and analysis. By enabling the intelligent feature selection module, the parameters monitored could be simplified and reduced to improve the overall efficiency of the monitoring system. One neural network method that could be considered is the Convolutional Neural Network (CNN). In recent studies, CNN has been widely used to extract robust and informative features from a set of sequential data [76], [77]. The collected real time data usually contain noise, CNN is used to extract only the most significant features. It does this through the convolutional layers (also known as convolutional kernels) by combining multiple local filters with the raw sequential data to generate invariant local features. Then, the following pooling layers extracts the sequence of the local robust features hence reducing the data spectrum in a multiple variables sequential data [77].

Additionally, in a real-time computing process, plant controllers need to quickly make a decision based on the predicted output of the prediction model. To accelerate and simplify the overall computing process, a simpler network architecture for a faster predicted result are required. As a static feedforward ANN, an MLP may not be suitable when longer time steps are involved [78]. With the conventional Backpropagation Neural Network (BPNN), error signals flowing backwards has the tendency to either blow up or vanish. This means, more time will be needed for the model to simulate the analysis and produced a forecasted trip. To solve the issue, [79] addresses it by introducing a novel and time efficient gradient based method known as Long Short-Term Memory (LSTM). It enforces the constant error back flow of a traditional backpropagation method by applying a multiplicative gate that opens and closes the access to the constant flow creating a “constant error carousels”. Hence, to further improve the current proposed monitoring system, integrating the LSTM may be consider as the next method for quicker trip predicted result. Finally, it is hope that the improved version of the proposed intelligent monitoring system can be implemented on an actual coal-fired power plant.

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