Pertanika J. Sci. & Technol. 32 (6): 2655 - 2678 (2024)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Improved Early Detection of Tube Leaks Faults in Pulverised Coal-fired Boiler Using Deep Feed Forward Neural Network

Abdul Munir Abdul Karim[1]*, Yasir Mohd Mustafah[1] and Zainol Arifin Zainal Abidin[2]

[1]*Kulliyyah of Engineering, International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia*
[2]*Faculty of Computing, Engineering & Technology, Asia Pacific University of Technology & Innovation, Jalan Teknologi 5, Taman Teknologi Malaysia, 57000 Kuala Lumpur, Malaysia*

ABSTRACT

Boiler tube leaks significantly reduce the operational availability of power units, yet their early detection and prediction have not been fully realised in the industry. This paper introduces a novel approach employing deep feedforward neural networks for early detection of boiler tube leaks in pulverised coal-fired boilers. Early detection enhances repair planning, minimising downtime and production losses. It also improves monitoring and control of boiler tube failures, thereby optimising power plant operations and revenue. Diverse deep neural network models were developed and rigorously tested by leveraging 9 years of operational data (2012–2020). Exhaustive hyper-parameter optimisation, involving seven parameters, substantially improved predictive accuracy. By achieving training and testing accuracies of 82.8% to 99.3%, the study assessed their ability to detect boiler tube leaks over the same 9-year span, providing insights into leak detection capabilities. The models notably predicted all 12 identified tube leak events, averaging a 14-day lead time before boiler shutdown. In addition to leak prediction, a leak detection matrix was devised to analyse residual behaviour and reduce the likelihood of false alarms. However, the models' predictive performance was observed to be limited to the following year, with satisfactory results for 2021 only. Incorporating the 2021 data into retraining significantly improved the predictions for 2022. The study concludes that while the models demonstrate robust short-term prediction capabilities, they require continuous retraining to maintain accuracy and relevance. This ongoing refinement is essential for keeping the models up-to-date and reliable in predicting future boiler tube leaks.

Keywords: Boiler, detection, hyper-parameter, neural network, prediction, tube leak, tuning

ARTICLE INFO

Article history:
Received: 15 December 2023
Accepted: 12 April 2024
Published: 25 October 2024

DOI: https://doi.org/10.47836/pjst.32.6.13

E-mail addresses:
abdul.munir@gmail.com (Abdul Munir Abdul Karim)
yasir@iium.edu.my (Yasir Mohd Mustafah)
zainol@gmail.com (Zainol Arifin Zainal Abidin)
* Corresponding author

ISSN: 0128-7680
e-ISSN: 2231-8526

INTRODUCTION

Coal-fired units grapple with persistent forced outages primarily attributed to boiler tube failures. The cyclic duty of the boiler results in fatigue, affecting both the boiler and associated heat exchanger tubes. In a benchmarking survey by the Electric Utility Cost Group (EUCG), covering 167 units of various sizes (from 8 MW to 1264 MW) across seventeen utilities, it was highlighted that despite the units maintaining high capacities relative to their size and age, boiler tube failures remained the predominant cause of downtime for these steam power plants (Pfeuffer, 2009). A more recent study by Kokkinos (2019) in the U.S. revealed that between 2013 and 2017, tube leaks persisted in water walls, followed by the second superheater, primary reheater, and primary superheater. Boiler leaks accounted for 54% of total outages, with the remainder caused by balance of plant (BOP), steam turbine, and generator issues. Coal-fired units struggle with forced outages due to cyclic-induced fatigue, with boiler tube failures being the primary culprit. Surveys and recent studies emphasise the persistence of these issues across various-sized units, leading to substantial downtime and high repair costs.

In the power generation industry, outage costs due to production loss, whether planned or forced, are substantial (Tam et al., 2007). One of the main reasons for the increased rate of failures of boiler pressure parts is the requirement of power units to work at greater load variability, resulting in frequent changes in operating pressure and temperature of the working fluid, i.e., feedwater and/or steam. Consequently, those units are subjected to increased sediment precipitation from the working fluid. While being transported by the working fluid, these sediments may easily be deposited on rough regions of the inner surfaces of boiler tubes. It causes further flow disorder and can result in overheating of tubes. Thus, there is interest in developing early detection methods to predict these types of faults earlier. It has been reported in a few case studies that boiler tube failures escalate slowly, sometimes up to ten days or so, before they may be detected by the staff of the power plant through conventional means (Alouani & Chang, 2003; Barszcz & Czop, 2011; Lang et al., 2004; Sun et al., 2002).

These tube leaks constitute a potential for severe physical harm to boiler pressure parts owing to pipe whip and/or steam cutting of the impacted and adjacent pipes. The ultimate harm caused by severe tube failures can range from $2 to $10 million per leak for a commercial steam generator. These high costs result from forced boiler shutdowns for repairs, which could last up to a week if the leak is not detected for an extended period (Lang et al., 2004). Tube failures can be repaired before disastrous damage if detected early, with such repairs only lasting several days and costing a fraction of the price of late detection.

The power industry does not put considerable effort into early boiler tube leak detection amid the high-cost implications of late detection. The AI approach to boiler tube leak detection is also not well established. Several studies have been conducted using AI-based methods on pulverised coal-fired boiler tube leak detection. Nistah et al. (2018) proposed a boiler fault prediction model using artificial neural networks (ANN) with multi-layered perceptrons (MLP), which achieved a 92% prediction rate of accuracy. Singh et al. (2017) developed an Intelligent Warning System (IWS) that combines ANN and Genetic Algorithms (GA) in their prediction model. The prediction model was trained and tested based on three real cases of boiler tube leak trips at a power plant with six operational units totalling a generation capacity of 2420 MW in Malaysia. Ismail et al. (2016) also employed ANN in their prediction model for one boiler unit of a power plant with a total generation capacity of 2400 MW in Malaysia. The sample data was based on a boiler tube leak incident in 2013. Rostek et al. (2015) focused their research on a boiler tube leak prediction model for a fluidised-bed coal-fired boiler in Poland. They employed a 2-stage structure of ANN in their study. The model could predict boiler tube leaks at least 2 days before the boiler shutdown.

Despite extensive prior research on the early prediction of boiler tube leaks in coal-fired power plants, several issues remain to be addressed to enhance prediction accuracy. Rostek et al. (2015) utilised a basic multilayer perceptron neural network with 19 input variables, a single hidden layer containing 16 neurons, and an output layer with one neuron. However, the training accuracy was suboptimal, with the highest-quality model needing an 80% correlation coefficient (R^2) between actual and predicted data. While some models successfully identified boiler tube leaks 2 to 9 days in advance, certain leak incidents were not detected by the selected signal sensitive to tube leaks. Furthermore, this prediction method was only validated in fluidised-bed coal-fired boilers and has not yet proven effective for pulverised coal-fired boilers.

In Malaysia, attempts to accurately predict boiler tube leaks in pulverised coal-fired boilers faced challenges due to limited available data. Ismail et al. (2016) utilised only one week of data collected at one-minute intervals, comprising approximately 11,000 data sets, selected based on a single boiler tube leak incident. The neural network algorithm was trained using 26 sensors, employing a simple feedforward neural network structure with a maximum of two hidden layers and no more than ten neurons per layer. However, this model could only detect boiler tube leaks with a 10-minute advance notice, which is inconsequential for power plant operators. Similarly, Singh et al. (2017) examined only 12 days of data collected at one-minute intervals from three boiler tube leak incidents to train their network. Their neural network, employing feedforward and backpropagation with two hidden layers, utilised only 17 sensors as input. However, the model achieved only a 20-minute advance prediction, which was also deemed insignificant.

In essence, two primary concerns need to be addressed. Firstly, previous studies have suffered from the simplicity of their neural network structures, leading to a notable difference between the actual and predicted data during training. Additionally, this simplicity has led to the failure to detect several tube leak incidents throughout the studies. Secondly, there is a limitation of available operational data from the boilers, with a relatively small number of sensors being considered during the training of the neural network algorithm. Consequently, this has resulted in insignificant early detection (within 10 to 20 minutes) before the plant operator identifies the leak.

MATERIALS AND METHODS

Deep Feed Forward Neural Network as Learning Architecture for Time-series Prediction

The power plant's data structure necessitates applying multivariate time series analysis to predict boiler tube leak occurrences. A time series is a sequence of values arranged chronologically and observed over time. While time is measured as a continuous variable, the values in a time series are sampled at constant intervals (fixed sampling frequency) (Torres et al., 2021).

The Deep Feedforward Neural Networks (DFFNN) algorithm was carefully considered for this study over alternative architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) based on several key factors. Firstly, the sensor data collected from the power plant environment comprises multivariate time series data, where each data point is influenced by multiple input variables recorded over time. In this context, DFFNN is well-suited for handling the complex interdependencies and nonlinear relationships in such data, as it can effectively model the interactions between input variables without relying on sequential processing. Furthermore, DFFNN offers scalability and computational efficiency advantages, which are crucial considerations for large-scale time series prediction tasks involving millions of data points, as in the researchers' study.

While CNN excels in capturing spatial dependencies within data, particularly in image processing tasks, and RNNs are effective for sequential data modelling due to their ability to retain information over time, DFFNN was opted for due to the unique characteristics of their dataset and the specific requirements of their prediction task. Additionally, while RNNs are capable of capturing temporal dependencies within sequential data, they may encounter challenges with long-range dependencies and vanishing/exploding gradient problems, particularly in deep architectures. In contrast, DFFNN does not suffer from these limitations and can effectively model long-range dependencies by incorporating multiple hidden layers.

The DFFNN was developed in response to the limitations of single-layer neural networks in learning certain functions. The structure of a DFFNN comprises an input layer, an output layer, and multiple hidden layers, each housing a specific number of neurons. The connections between neurons in two adjacent layers are modelled using weights determined during the network's training phase. These weights are computed by minimising a cost function through gradient descent optimisation methods, with the backpropagation algorithm used to calculate the gradient of the cost function. Once the weights are determined, the values of the output neurons are obtained using a feedforward process.

In time series forecasting, the rectified linear unit function is commonly employed as the activation function for all layers except the output layer, which uses the hyperbolic tangent function to derive predicted values. Various hyperparameters, such as the number of layers, neurons, learning rate, momentum, and mini-batch size, need to be pre-selected. The choice of these hyperparameters significantly influences the network's predictive outcomes.

Research Objective

The study was conducted on a single unit of a pulverised coal-fired boiler at a power plant in Malaysia. This study utilised data collected from the plant's process control system from 2012 to 2020.

Figure 1 illustrates the breakdown of faults that contributed to the decreased available capacity for power generation at the plant. This figure provides an overview of the key plant systems responsible for these faults across two power units during the 2012 to 2020 period. Notably, the boiler system was identified as the primary source of faults, accounting for 73.6% of all recorded incidents. Following the boiler system, the auxiliary, electrical, coal pulverising, and turbine systems contributed to these faults, with the coal supply and handling system being the least affected. Within the 73.6% of faults attributed to the boiler system, 50.3% were due to boiler tube leaks. In comparison, the remaining 23.3% were related to other issues within the boiler system, such as the air and flue gas system and operational management of the boiler.

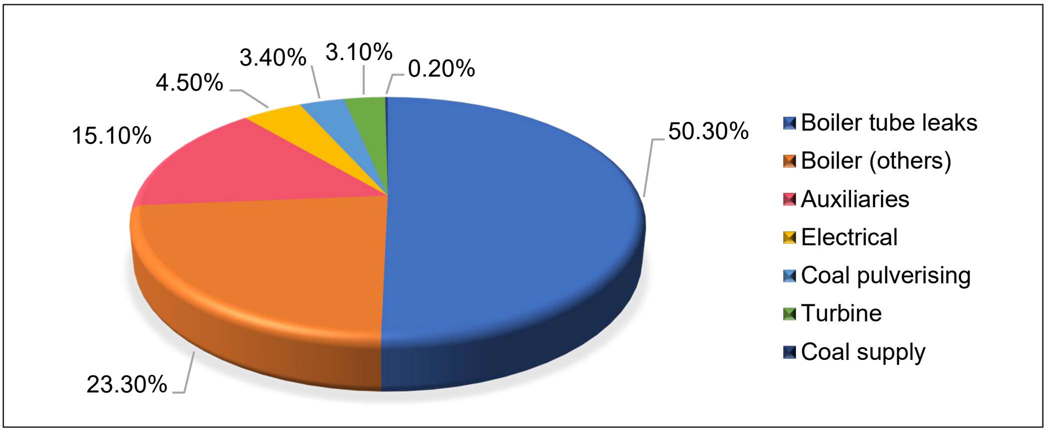


Figure 1. Main plant system contributor to power unit fault (2012 to 2020)

Data Collection

The selected algorithm for early detection of tube leaks in this study was the DFFNN. This network's structure includes an input layer, several hidden layers, and a single output layer. For DFFNN training, the input variables are boiler operation parameters not influenced by tube leaks, while the output variables are those impacted by such leaks (Karim & Mustafah, 2022). The power plant employs 120 sensors to measure the input variables, which are integrated into the input layer for training and testing the DFFNN configurations. Selected sensors for input variables include main feedwater pressure and temperature, as well as pressures and temperatures for hot and cold reheat steam and superheaters inlet and outlet steam.

Conversely, 10 sensors are dedicated to measuring output variables, creating 10 distinct DFFNN models. Each model is named according to the sensitive output variable it tracks, as listed in Table 1.

Table 1 presents the output variables sensitive to tube leaks and their corresponding model names, such as "COND WTR FLOW" for condensate water flow rate and "DEA WTR FLOW" for deaerator and feedwater tank water flow rate.

Table 1
Output variables sensitive (affected) to tube leak occurrence and the corresponding model name

No.	Output variables	Model name
1	Condensate water flow rate	COND WTR FLOW
2	Deaerator and feedwater tank water flow rate	DEA WTR FLOW
3	Main feedwater flow rate	MAIN FW FLOW
4	Economiser outlet flue gas O_2 concentration (sensor A)	ECO A OTL O2
5	Economiser outlet flue gas O_2 concentration (sensor B)	ECO B OTL O2
6	Primary air flow rate	TOTAL PA FLOW
7	Secondary air flow rate (sensor A)	HOT SA A FLOW
8	Secondary air flow rate (sensor B)	HOT SA B FLOW
9	Induced draught fan suction pressure (sensor A)	IDF A FG PRESS
10	Induced draught fan suction pressure (sensor B)	IDF B FG PRESS

This study stands out by utilising a more extensive array of sensors over a longer period compared to previous studies. Sensor data spanning 9 years, from 2012 to 2020, were collected at 10-minute intervals for neural network model training and testing and at 5-minute intervals for leak prediction. The study used 120 sensors for network inputs and 10 for outputs per data set, a significant increase from previous research, which typically used fewer than 30 sensors for inputs and a maximum of 4 for outputs. Approximately 473,000 data sets containing around 130 sensor data points were utilised, resulting in over 61 million data points collected and employed for model learning. Table 2 compares the data structures employed in earlier research for the early prediction of boiler tube leaks.

Table 2
Comparison of data structures with previous research

	This research	Rostek et al. (2015)	Ismail et al. (2016)	Singh et al. (2017)
No. of boiler units studied	1	1	1	1
No. of boiler tube leak incident	12	12	1	3
Data period	9 years (2012–2020)	8 years (2005–2012)	7 days	36 days
Sampling interval				
- Network training and testing	10 minutes	20 minutes	1 minute	1 minute
- Leak prediction	5 minutes	1 minute	1 minute	1 minute
No. of sensors for input variables	120	19	26	17
No. of sensors for output variables	10	4	1	1

DFFNN Training and Testing

The model's training data excluded periods when the boiler experienced tube leaks, starting 30 days before the leak event and ending on the event day. It ensured that all training data came from when the plant operated normally, with stable parameters. The data was divided, with 80% used for training and the remaining 20% for validation during testing.

Input variables for training were those not influenced by tube leaks, while output variables were leak-sensitive. The input data passes through the network's layers, producing output data. In this forward pass, the network's weights were initially set. The outputs were then compared to the desired values. In the backward pass, the difference (error) between the desired and calculated outputs was used to adjust the network's weights to reduce error. The supervised learning process continued iteratively until the error reached an acceptable level. Each complete cycle of processing the data set, forward and backwards, was termed an epoch. The network training aimed to reduce the error with each epoch.

Various well-known loss functions, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Square Logarithmic Error (MSLE), and Mean Absolute Percentage Error (MAPE), were used to minimise the difference between the desired and calculated outputs.

The effectiveness of network training and testing was assessed using the square of the correlation coefficient (R^2), per Behera et al. (2014). R^2 values close to 1 indicate a strong relationship. After training the network to satisfactory performance, it was validated or tested with the remaining 20% of the data. Through hyper-parameter tuning, various network configurations were explored to identify the best model for representing leak-sensitive variables. Figure 2 depicts finding the most efficient DFFNN structures for fault detection.

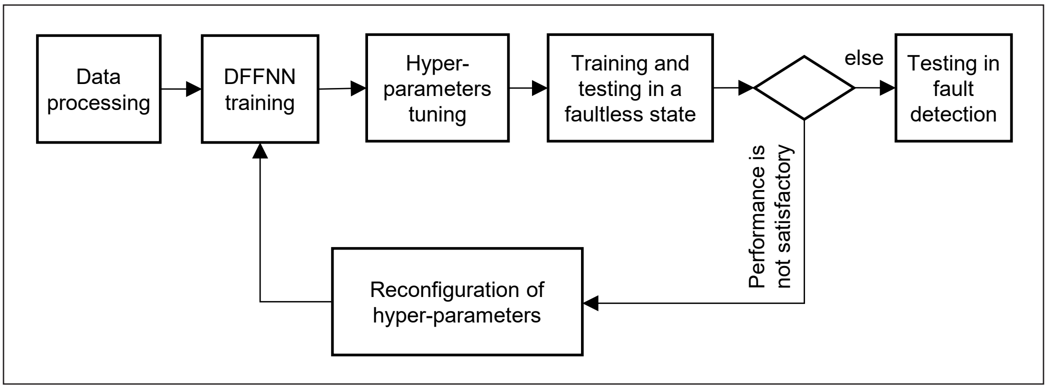


Figure 2. The algorithm for finding the best structures of DFFNN for fault detection

The models were developed, trained, and tested using Keras, an advanced programming interface for neural networks that emphasises rapid experimentation. Keras is Python-based and operates on the TensorFlow backend.

Hyper-parameter Tuning

Most hyperparameters used in this research's DFFNN were tuned to achieve optimum accuracy and minimum loss. A DFFNN network structure from Mishra et al. (2020) was selected as the base model to start the hyperparameter tuning. The model was used to analyse deep learning performance for multivariate prediction of time series wind power generation and temperature. The initial network configuration for this study can be summarised in Table 3.

ADAM was selected as an optimiser, with a default learning rate of 0.001. The 120 input data were fed to the network in mini-batches size 512 throughout 10 epochs. Once the performance of the network was obtained, the hyper-parameters were tuned in the following order:

(i) Layer activation function
(ii) Number of hidden layers
(iii) Number of neurons in each hidden layer
(iv) Optimisers
(v) Losses
(vi) Mini-batch size
(vii) Learning rate and number of epochs

Each hyper-parameter tuning step was considered one set of experiments. Therefore, seven experiments were conducted to determine the best network structure for the

Table 3
Initial DFFNN network structure

	Hidden Layer		Output Layer
	1	2	
No of neurons	512	128	2
Activation	ReLU	ReLU	NA
Dropout	0.5	0.5	NA

10 parameters affected by tube leak prediction models. The best hyper-parameter setting for the 10 models in each experiment was carried over to the next experiment, where a different hyper-parameter was tuned in the order above.

Once the models' network structure was finalised, it was revalidated by changing to different layer activation functions to confirm the initial assumption that the activation function was the most hyperparameter affecting model performance.

Detection of Leaks Using Method of Residue

In a similar approach to Rostek et al. (2015), this study also implemented a residue method for leak detection. After the models were thoroughly trained and tested under normal, fault-free conditions, they were then applied to data from periods of tube leak faults. This fault data, encompassing 30 days leading up to the boiler shutdown, was sampled at 5-minute intervals. It was then input into the models to predict the leak-sensitive variables under normal conditions. Figure 3 illustrates this data division process.

The model's predicted output was compared against the actual process signals measured. When a leak occurred, the measured signal deviated from the predicted output, creating a residual value indicative of a boiler tube leak fault. This residual value was then evaluated against a predetermined threshold, established from the network's training and testing results, to confirm the presence of a leak.

Determining the leak detection threshold involved analysing histograms from averaged time series in the fault-free state and comparing them to a normal distribution. In the residue method, the acceptable probability for false alarms was less than 0.5%. Figure 4 shows an example of leak detection using the residue method for the ECO A OTL O2 model. This model compares the residual value r against the leak detection threshold. If r exceeds this threshold, it signals a potential boiler tube leak.

Evaluation of Model Ability for Early Tube Leak Detection

The last phase of the research was to evaluate the trained models with the next 2 years of plant data in 2021 and 2022. The sensor data from 120 variables not affected by tube

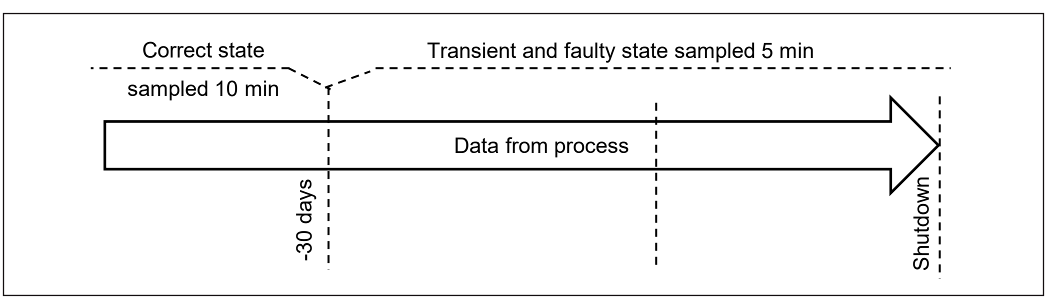


Figure 3. Data division before boiler emergency shutdown

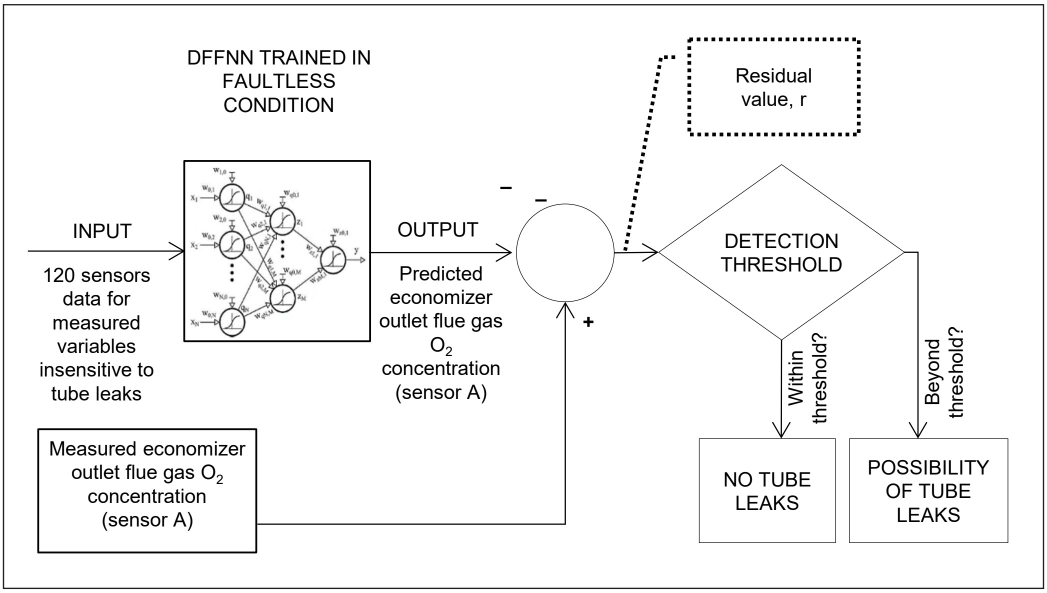


Figure 4. Example of economiser outlet flue gas O_2 concentration model for fault detection by residue method

leaks for 2021 and 2022 were input to the 10 trained models, and the predicted output by each model was recorded. The data structure was the same as in training the model, with the sensor data sampled every 10 minutes and undergoing data cleansing, treatment, and normalisation before inputting the models.

The predicted sensor data from the models' output for the 2 years was then compared with the actual data, and the residuals were subjected to a threshold for boiler tube leak detection. The performance of each model prediction was evaluated by the ability to detect tube leak events during those 2 years.

RESULTS AND DISCUSSION

Model Training and Testing with Hyper-parameters Tuning

The overall model training and testing with hyper-parameters tuning results showed that all the models' performance increased throughout the series of hyper-parameters tuning experiments. Changing the layer activation function significantly impacted the model training and testing accuracy from the initial model. The following tuning experiments on the number of hidden layers, number of neurons in the hidden layer, optimiser, and loss function did improve the accuracy slightly. Finally, increasing the number of training epochs to 50 increased the accuracy significantly, especially for the ECO A OTL O2 and ECO B OTL O2 models, which showed increments of 12.51% and 13.54%, respectively, in training accuracy. Examples of the progress on two model training and testing accuracy and losses after each hyper-parameter tuning experiment are shown in Table 4.

Table 4
Example of results of hyper-parameters tuning for COND WTR FLOW and ECO B OTL O2 model

Exp.	Hyper-parameter	COND WTR FLOW				ECO B OTL O2			
		Accuracy (R^2)		Losses		Accuracy (R^2)		Losses	
		Train	Test	Train	Test	Train	Test	Train	Test
1	Initial model	0.988	-8E+04	0.0001	5E+02	0.773	-1E+06	0.0002	3E+02
2	Layer activation function	0.970	0.759	0.0003	0.0013	0.677	-0.157	0.0003	0.0002
3	No. of hidden layer	0.989	0.938	0.0001	0.0003	0.773	-0.263	0.0002	0.0002
4	No. of neurons in the hidden layer	0.990	0.938	0.0001	0.0003	0.773	-0.263	0.0002	0.0002
5	Optimizer	0.991	0.952	0.0001	0.0003	0.788	0.544	0.0002	0.0004
6	Losses function	0.991	0.952	0.0001	0.0003	0.796	0.612	0.0002	0.0004
7	Learning rate and no. of epochs	0.996	0.964	0.0000	0.0002	0.932	0.828	0.0002	0.0003

The finalised models' training and testing accuracy and losses after completion of hyper-parameters tuning are shown together with their corresponding network structures in Table 5. All models can be considered high quality since they achieved considerably high training accuracy of more than 93%, the lowest being ECO B OTL O2 with 93.16% and the highest, IDF A FG PRESS, at 99.63%. ECO A OTL O2 had the lowest testing accuracy at 75.65%, while the highest was DEA WTR FLOW at 98.88%. The summary of this research's optimised DFFNN network structure has the characteristics in Table 6.

Table 5
Overall results of hyper-parameters tuning

	COND WTR FLOW	**DEA WTR FLOW**	**ECO A OTL O2**	**ECO B OTL O2**	**HOT SA A FLOW**
Layer Activation Function	Tanh	Tanh	Tanh	Tanh	Tanh
No Hidden Layer	9	7	9	9	8
No neurons in the hidden layer	512-256-128-64-32-16-8-4-2	512-256-128-64-32-16-8	512-256-128-64-32-16-8-4-2	512-256-128-64-32-16-8-4-2	512-256-128-64-32-16-8-4
Optimizer	Adam	Adam	Adam	Nadam	Adam
Learning Rate	0.001	0.001	0.001	0.001	0.001
Losses function	msle	mse	mse	mae	mae
No of Epoch	50	50	50	50	50
Mini Batch size	512	512	512	512	512
Accuracy (R^2)					
Train	0.9922	0.9925	0.9472	0.9316	0.9752
Test	0.9838	0.9888	0.7565	0.8275	0.8789
Losses					
Train	0.0000	0.0001	0.0000	0.0031	0.0108
Test	0.0002	0.0024	0.0006	0.0048	0.0214

Table 5 *(continue)*

	HOT SA B FLOW	IDF A FG PRESS	IDF B FG PRESS	MAIN FW FLOW	TOTAL PA FLOW
Layer Activation Function	Tanh	Tanh	Tanh	Tanh	Tanh
No of Hidden Layer	9	6	9	8	7
No of neurons in the hidden layer	256-128-64-32-16-8-4-2-2	128-64-32-16-8-4	512-256-128-64-32-16-8-4-2	512-256-128-64-32-16-8-4	512-256-128-64-32-16-8
Optimizer	Adam	Adamax	Adam	AMSGrad	Adam
Learning Rate	0.001	0.001	0.001	0.001	0.001
Losses function	mse	mse	rmse	mse	mse
No of Epoch	50	50	50	50	50
Mini Batch size	512	512	512	512	512
Accuracy (R^2)					
Train	0.9724	0.9963	0.9948	0.9889	0.9921
Test	0.8562	0.9639	0.8946	0.9658	0.8473
Losses					
Train	0.0002	0.0000	0.0070	0.0001	0.0002
Test	0.0254	0.0002	0.0215	0.0004	0.0206

Table 6
Summary of the optimised network structure

Hyper-parameter	Properties	Applicable model
Layer activation function	tanh	All models
No of hidden layer	9	5 out of 10 models
No of neurons in the first hidden layer	512	8 out of 10 models
Optimizer	Adam	7 out of 10 models
Losses function	mse	5 out of 10 models
Learning rate & no of epochs	0.001 & 50	All models
Mini batch size	512	All models

Assessment of Fault Detection by Models of the Variables Sensitive to Leaks

The validated models were subsequently applied to data from periods when tube leaks occurred. This fault data, encompassing 30 days leading up to the boiler shutdown, was sampled at 5-minute intervals and used as input to forecast variables influenced by tube leaks under normal conditions. Table 7 displays the fault detection outcomes for the top 10 models across 12 boiler tube leak events, considering leaks in the boiler pressure parts system (including the furnace water wall, radiant superheater, and reheater and heat recovery area). The final row sums up the number of faults each model detected, as shown in Table 7.

The residuals generated by the DFFNN models enabled the detection of all 12 faults, with a minimum of 3 residual variables per fault. At least 5 variables identified

Table 7
Detection of tube leak faults by means of the residue of ten variables (sensors) affected by tube leaks

No	Year	Tube Leaks Location	COND WTR FLOW	DEA WTR FLOW	ECO A OTL O2	ECO B OTL O2	HOT SA A FLOW	HOT SA B FLOW	IDF A FG PRESS	IDF B FG PRESS	MAIN FW FLOW	TOTAL PA FLOW
1	2012	Heat Recovery Area	17 days		13 days			13 days	3 days			17 days
2	2013	Heat Recovery Area	11 days				28 days	7 days	26 days	18 days		
3	2014	Heat Recovery Area	18 days	22 days	18 days			30 days	21 days	28 days		
4	2014	Heat Recovery Area	6 days	6 days				8 days			3 days	14 days
5	2016	Furnace Waterwall					29 days	22 days				21 days
6	2017	Radiant Superheater					6 days		1 day	2 days	26 days	4 days
7	2017	Radiant Superheater	7 days		9 days		18 days	18 days		3 days	3 days	
8	2018	Heat Recovery Area				15 days	9 days				6 days	
9	2019	Economiser		28 days	4 days	14 days	23 days				5 days	
10	2019	Economiser		4 days		11 days	12 days		18 days	14 days	4 days	
11	2020	Heat Recovery Area			11 days	17 days	3 days			28 days		18 days
12	2020	Radiant Superheater	9 days	9 days	5 days			21 days			9 days	6 days
Detected tube leaks			6 of 12	5 of 12	6 of 12	4 of 12	8 of 12	7 of 12	5 of 12	6 of 12	7 of 12	6 of 12

the most faults. Exceptions were Fault #5 and Fault #8, where only 3 variables' residues detected the fault. The average lead time between fault detection and boiler shutdown was approximately 14 days. The most effective variable for fault detection was HOT SA A FLOW, followed by HOT SA B FLOW and MAIN FW FLOW. These variable models could detect over half of the fault cases at least 3 days in advance. On the other hand, the ECO B OTL O2 model was the least efficient, detecting only 4 out of 12 faults at least 11 days in advance.

Example - Fault Detection by HOT SA A FLOW Model

The forced draught fan supplies hot secondary airflow in the boiler for coal combustion in the furnace. If boiler tube leaks, the main steam pressure will decrease due to the loss of steam. More steam needs to be produced; thus, more fuel needs to be burned to supply the additional heat to compensate for this loss. Additional fuel burning would require additional air to support combustion, increasing the hot secondary air. Therefore, during a tube leak event, the actual sensor reading will be more than the prediction, and the residual will increase as the tube leaks are prolonged.

The threshold for leak detection was found by analysing histograms of the difference between actual and predicted sensor readings, which were used for training the model. Compared with a normal distribution, the threshold was set at 99.5% of the distribution, yielding 1.165%, as shown in Figure 5. Tube leaks are indicated whenever the residual plot goes above the threshold.

In Figure 6, the model output for hot secondary air A flow is plotted against the measured value 30 days before boiler shutdown due to Fault #10 in 2019. The difference between the model output and the measured value is increasing around 12 days prior to the boiler shutdown, which is a symptom of a fault. Figure 7 illustrates the residual value and its 24-hour moving average from Figure 6. The moving average is considered

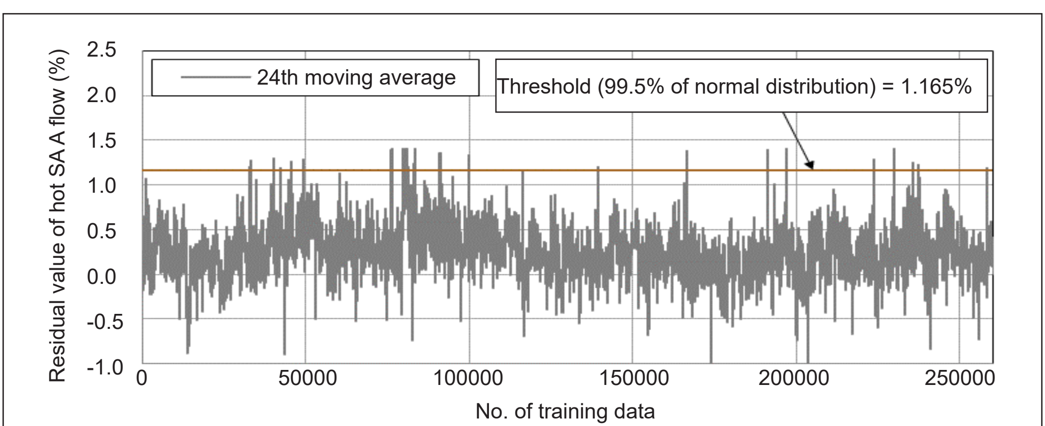


Figure 5. Determination of threshold of the detection limit for the residual value of hot secondary air A flow

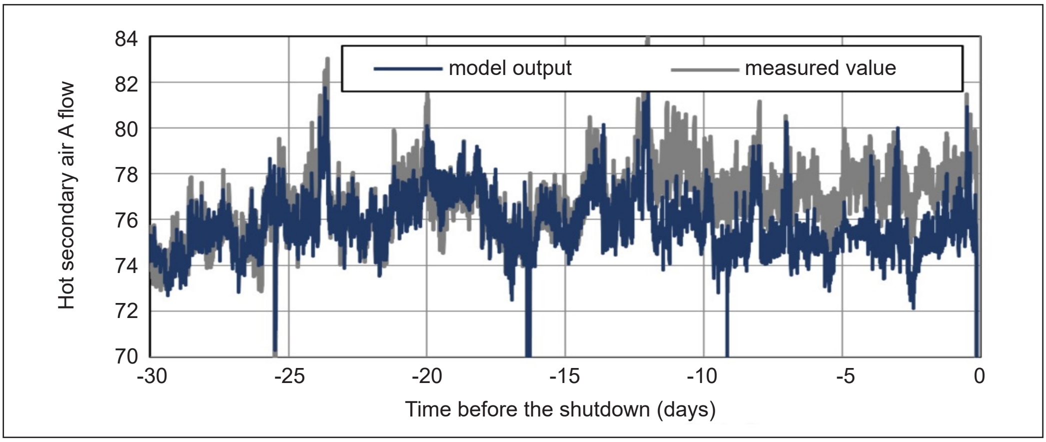


Figure 6. Exemplary courses of hot secondary air A flow, measured value and output from DFFNN model prior to shutdown of a boiler for tube leak Fault #10

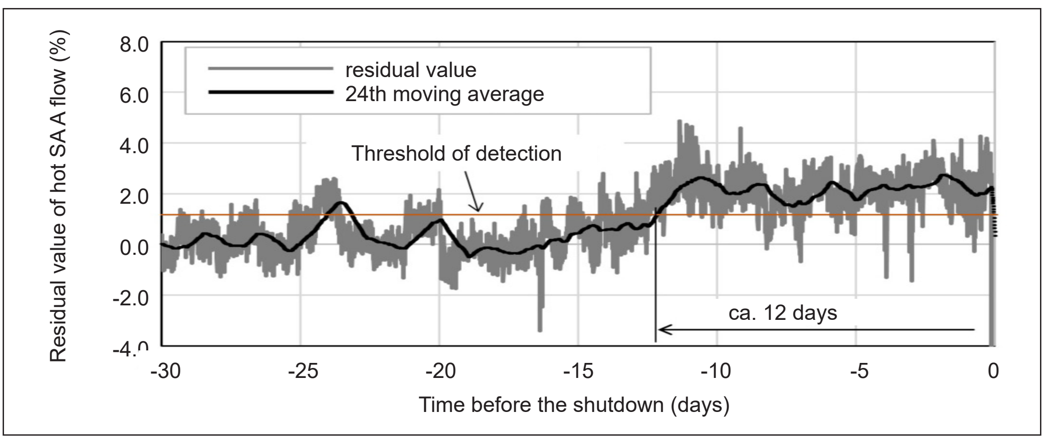


Figure 7. The residual value of hot secondary air A flow and its 24-hour moving average for tube leak Fault #10

in the detection process to smooth out transient fluctuations of process data and reduce the possibility of false alarms in leak detection. The predetermined threshold allows fault detection approximately 12 days before the boiler shutdown.

Leak Detection Matrix

Based on the leak detection analysis of all 10 models, it can be concluded that a particular boiler tube leak occurrence is confirmed if it is detected concurrently by at least three models' residuals. Referring to the leak detection time by the respective model for each Fault #1 to Fault #12 from Table 7, the following observation on the number of days that the boiler tube leaks were confirmed prior to the boiler shutdown was made and shown in Table 8.

The maximum number of days that the boiler tube leak was confirmed was for Fault #3 (circa 22 days), while the least was for Fault #6 (circa 4 days). On average, the boiler tube leak detection could be confirmed 12 days prior to boiler shutdown. As an example, referring to Fault #10 in Figure 8, the first boiler tube leak detection was by the IDF A FG PRESS model 18 days before boiler shutdown, followed by the second detection by the IDF B FG PRESS model on the 14th day. The tube leak was confirmed by the third detection from HOT SA A FLOW on the 18th day prior to boiler shutdown. Another 3 models detected the tube leaks after that, with ECO B OTL O2 on the 11th day and DEA WTR FLOW and MAIN FW FLOW on the fourth day.

Table 8
Fault detection time by at least 3 models' residuals

Fault no.	No of days that boiler tube leak was confirmed prior to boiler shutdown (detected by at least 3 model's residual)
1	13
2	18
3	22
4	6
5	21
6	4
7	9
8	6
9	14
10	12
11	17
12	9

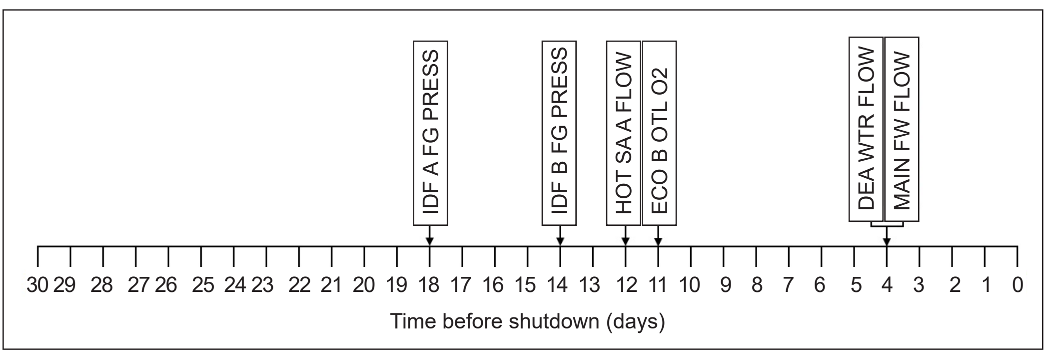


Figure 8. Sequence of boiler tube leak detection time by the corresponding models' residuals for Fault #10

Evaluation of Fault Detection Models

The 10 models, which were trained using boiler process data from 2012 to 2020, were then inputted with data from January 2021 to November 2022 to evaluate their ability to detect two tube leak faults, named Fault #13 and Fault #14, in May 2021 and September 2022, respectively.

Fault Detection in Year 2021

The results for predictions in 2021 were decent, as 5 models produced residuals beyond the threshold limit in May. It confirmed the authenticity of the detection since Fault #13 happened in the same month. There were several false alarms during other months: 2

models gave false alarms in February, and 1 model gave false alarms in April, September, and December, respectively. Detailed analysis of Fault #13 detection is shown in Figure 9. The first detection was made 28 days before boiler shutdown by the TOTAL PA FLOW model, followed by the ECO B OTL O2 model on day 17 prior to boiler shutdown. The boiler tube leak, Fault #13, was confirmed with the third detection by the HOT SA B FLOW model 14 days prior to boiler shutdown. The next detection was made by another 2 models, IDF A FG PRESS and ECO A OTL O2, on day 7 prior to boiler shutdown.

As an example, in the case of detection by the HOT SA B FLOW model, the predicted outputs of the HOT SA B FLOW model were plotted against the actual sensor readings for the 23-month period (January 2021–November 2022), as shown in Figure 10. The corresponding residuals were plotted in Figure 11. It was observed that the residual plot went above the threshold in May, at the same time when boiler tube leak Fault #13 happened. A more detailed residual trend with a 30-day period prior to boiler shutdown was plotted, as shown in Figure 12. It showed an early detection approximately 14 days

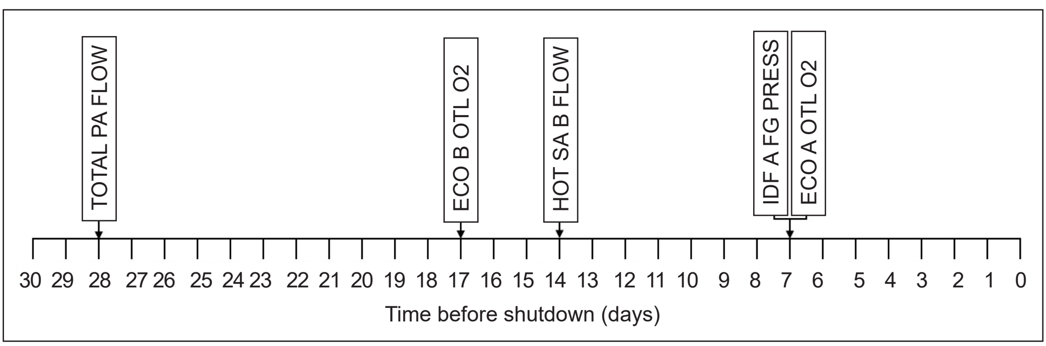


Figure 9. Sequence of boiler tube leak detection time by the corresponding models' residuals for Fault #13

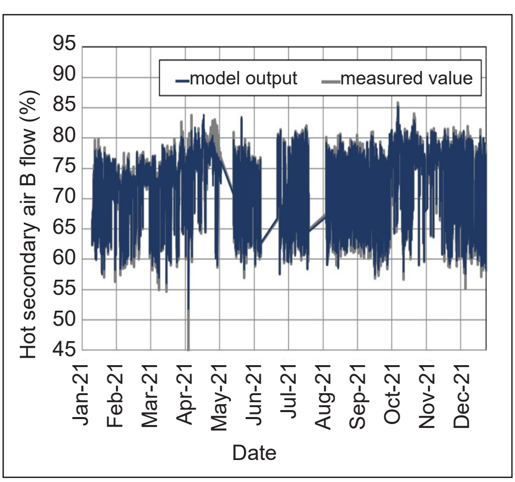


Figure 10. Measured value and output from the HOT SA B FLOW model for the year 2021

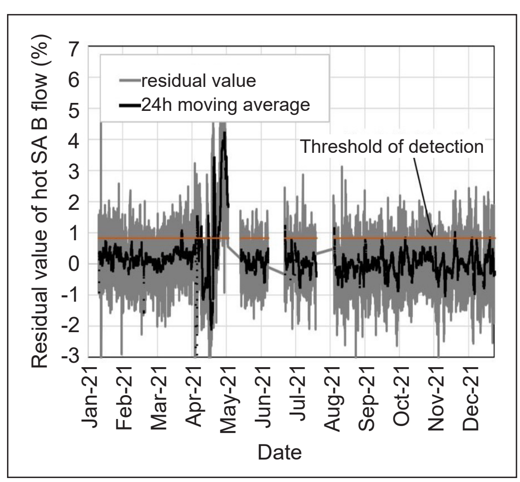


Figure 11. The residual value of hot secondary air B flow and its 24-hour moving average for the year 2021

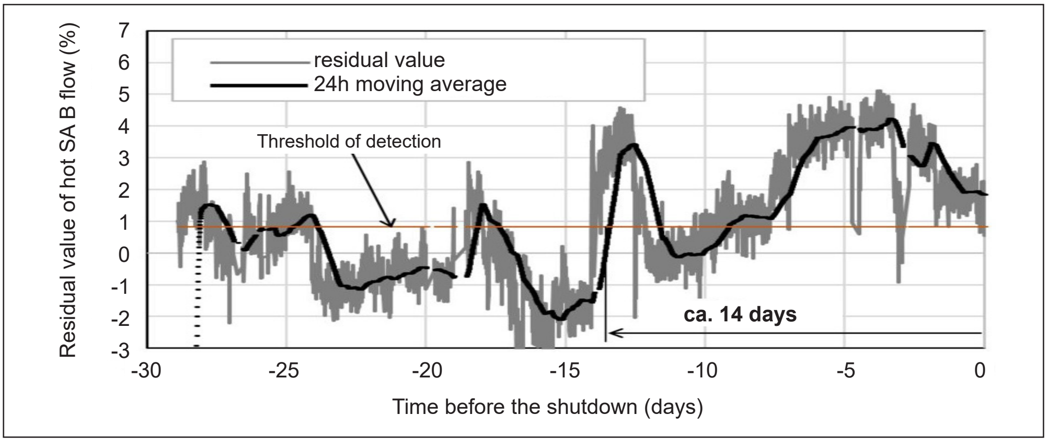


Figure 12. The residual value of hot secondary air B flow and its 24-hour moving average for tube leak Fault #13

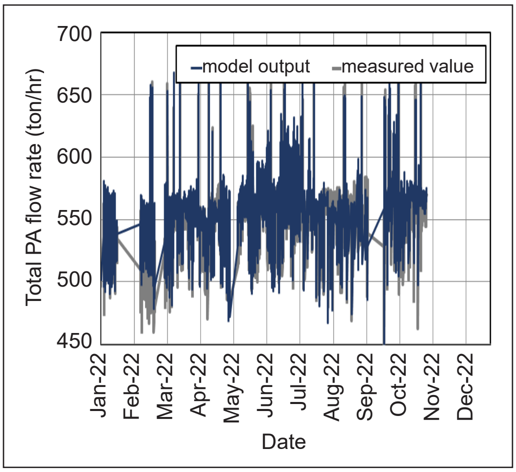
earlier before the tube leak was detected by power plant personnel, which was followed by boiler shutdown.

Fault Detection in Year 2022

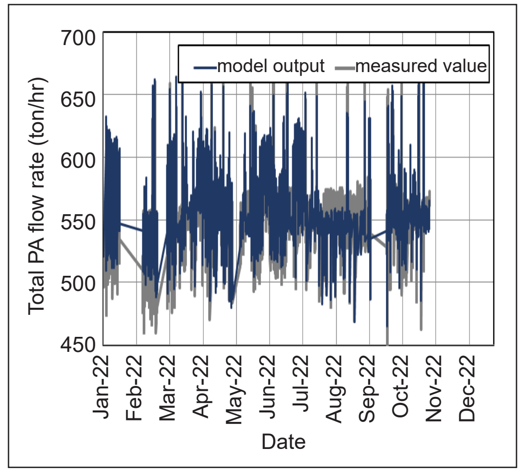
The prediction for the year 2022 was observed to be inaccurate for all 10 models. All residual plots showed values significantly beyond the threshold for most of the months in 2022, which was unusual. For example, the predicted output against actual sensor readings for total primary airflow and its residuals were plotted in Figures 13(a) and 14(a), respectively. The residual plot shows it went above the threshold many times throughout the year, from March to June and August to November. It was concluded that the trained models could not predict future sensor data accurately beyond one year from the data used in training the model.

In an attempt to improve the prediction for the year 2022, all 10 models were retrained by adding boiler operational data from the year 2021 to the process. As a result, the predictions improved significantly, with 5 models having residuals going beyond the threshold limit in September. The authenticity of this detection was confirmed with the record that Fault #14 happened in September. There were also false alarms detected, with 2 models giving false alarms in February, June, and August, respectively. On the other hand, 1 model gave false alarms in March, April, May, and October, respectively.

Illustrations of these improvements were indicated in a similar plot of predicted against actual sensor data for total primary airflow and its residuals for 2022, as shown in Figures 13(b) and 14(b), respectively. The residual plot was observed to go above the threshold in September when boiler tube leaks Fault #14 happened. A more detailed residual trend with 60 days prior to boiler shutdown was plotted in Figure 15. It showed an early detection of circa 37 days before the tube leak was detected by power plant personnel, which was

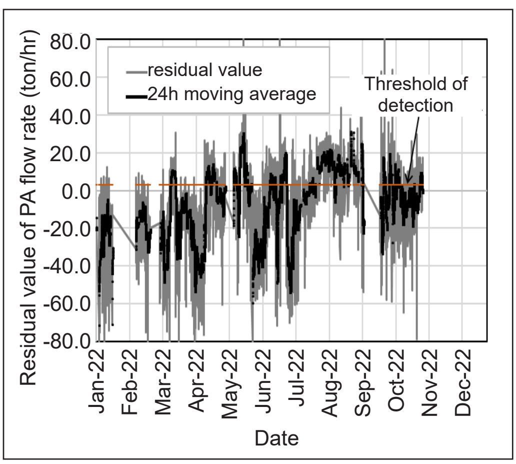


(a)

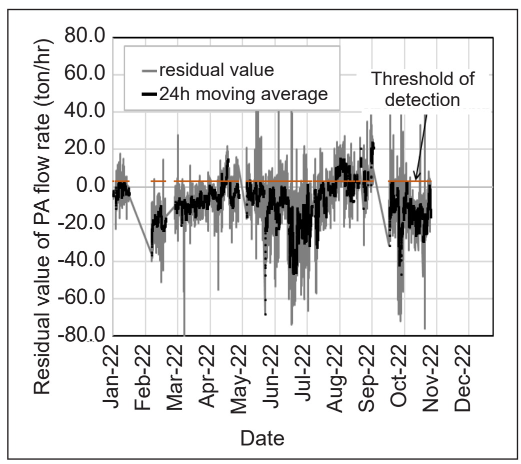


(b)

Figure 13. Measured value and output from TOTAL PA FLOW model in the year 2022 for: (a) model trained with 2012 to 2020 data; and (b) model retrained with 2012 to 2021 data



(a)



(b)

Figure 14. The residual value of total primary airflow and its 24-hour moving average in the year 2021 for: (a) model trained with 2012 to 2020 data; (b) model retrained with 2012 to 2021 data

followed by boiler shutdown. There was also a short period in April 2022 when the residual plot went above the threshold. However, other models did not detect this and considered it a false alarm.

Detailed analysis of Fault #14 detection is shown in Figure 16. The first detection occurred 37 days before boiler shutdown by the TOTAL PA FLOW model, followed by the HOT SA B FLOW model 37 days prior to boiler shutdown. The boiler tube leak, Fault #14, was confirmed with the third detection by the COND WTR FLOW model 24 days prior to boiler shutdown. Subsequent detections were made by two other models, DEA WTR

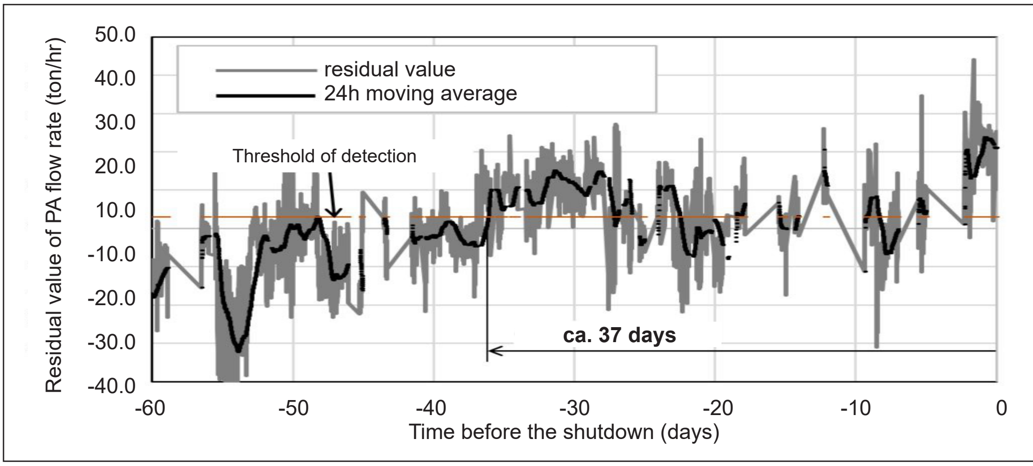


Figure 15. The residual value of total primary airflow and its 24-hour moving average for tube leak Fault #14

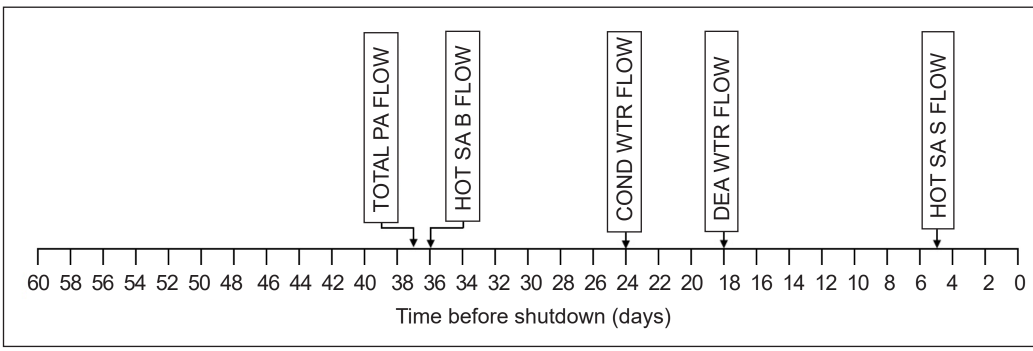


Figure 16. Sequence of boiler tube leak detection time by the corresponding models' residuals for Fault #14

FLOW and HOT SA A FLOW, on days 18 and 5 prior to boiler shutdown, respectively.

Comparison of Results with Other Studies

In benchmarking results from this study, comparisons were made with several other studies, notably Rostek et al. (2015), Kim, Lee and Park (2019), Kim, Lee, Kim et al. (2019), Khalid et al. (2020), Ramezani et al. (2020), and Ismail et al. (2020).

Rostek et al. (2015) initiated research into fault detection in fluidised bed coal-fired boilers, utilising eight years of data from 19 input and 4 output sensors. Their study, employing a simple multilayer perceptron, achieved a training R^2 exceeding 80% and demonstrated a notable improvement in leak detection time, ranging from 2 to 9 days earlier than traditional methods. However, details on model quality and validation were not provided, limiting comprehensive assessment.

Kim, Lee, and Park (2019) extended their research to thermal power plants, employing an auto-associative neural network based on 18 days of data from 13 sensors. Despite lacking detailed network structure information, their study reported a significant advancement in leak detection time, 30 minutes earlier than traditional methods. However, the absence of comprehensive performance metrics and validation results impedes thorough evaluation.

Similarly, Kim, Lee, Kim, et al. (2019) investigated fault detection in fluidised bed coal-fired boilers using a multilayer neural network. Although their study showcased a 35-minute improvement in leak detection time compared to traditional methods, the lack of detailed model quality assessment and validation data limits comprehensive comparison with other studies.

Khalid et al. (2020) explored fault detection in fluidised bed coal-fired boilers using various classifiers, including SVM, k-NN, NB, and LDA. While their study demonstrated promising accuracy results, the absence of information on leak detection time and validation with data outside the learning period limits comprehensive comparison with other studies.

Ramezani et al. (2020) focused on fault detection in pulverised coal-fired boilers, employing a deep bidirectional LSTM network. Although they demonstrate the potential of recurrent neural networks for fault detection, the lack of detailed information on network structure and performance metrics hinders thorough evaluation.

Ismail et al. (2020) addressed boiler shutdown scenarios using a backpropagation neural network. Their study reported a leak detection time of 5 minutes earlier than traditional methods. However, the absence of detailed accuracy metrics and validation results limits the comprehensive assessment of their methodology.

In contrast, the current study significantly advances fault detection methodologies for pulverised coal-fired boilers. Leveraging nine years of data from 120 input and 10 output sensors, it employed a deep feedforward neural network with optimisation of seven hyper-parameters. The network architecture included up to nine hidden layers with varying numbers of neurons and optimisation algorithms such as Adam, Adamax, Nadam, Nesterov, and AMSGrad. Notably, the study achieved impressive training and testing accuracies, with R^2 ranging from 82.8% to 99.3%. Furthermore, the leak detection time ranged from 3 to 30 days earlier than traditional methods, showcasing significant improvement in predictive maintenance capabilities. Importantly, validation with external data sets demonstrated reliable predictions for up to one-year post-learning. These findings underscore the robustness and efficacy of the methodology in enhancing fault detection capabilities in boiler and thermal power plant operations.

In summary, while previous studies have significantly contributed to fault detection in boiler and thermal power plants, the current study represents a notable advancement in data comprehensiveness, algorithm sophistication, performance metrics, and validation results. By benchmarking against this study and considering the insights from other research works, it is evident that there is immense potential for further advancements in machine learning-based fault detection methodologies in the energy sector.

CONCLUSION

The studies highlighted here achieved notable success in early leak detection and prediction through deep-feedforward neural network models. The fine-tuning of hyper-parameters notably enhanced the accuracy of predictions for parameters impacted by boiler tube leaks. The most effective model demonstrated a 99.63% correlation in training and 96.39% in testing with actual process data. During the network's learning phase, it successfully detected all 12 tube leak faults, identifying them 3 to 30 days before the necessary boiler shutdown. A leak was confirmed when at least three models consistently predicted its occurrence. However, assessments of the model using data from two years post-learning period indicated that its predictions were reliable only for the first year. To maintain accuracy, continual updating and learning of the model are essential. The recommendation is to deploy these models in real-time operations at the studied plant, which would allow for evaluating their effectiveness in identifying real-time boiler tube leak faults.

For future research, it is recommended that researchers prioritise the real-time implementation and deployment of predictive models. Integrating these models into operational workflows will enable proactive maintenance strategies and minimise downtime due to tube leaks. Collaboration with industry partners to streamline deployment protocols and optimise computational efficiency is essential for ensuring seamless integration into operational workflows.

After deploying predictive models, conducting extensive field validation and case studies emerges as a critical next step. Real-world validation across diverse operational conditions and geographical locations provides empirical evidence of the model's effectiveness and reliability. Leveraging insights gained from field validation studies, researchers can refine and optimise predictive models to address specific challenges encountered in operational environments.

ACKNOWLEDGEMENT

The authors thank the Kulliyyah of Engineering, International Islamic University Malaysia, for supporting this research work.

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