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A Machine Learning Approach for Fire-Fighting Detection in the Power Industry

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Abstract

Coal kept in the coal storage yard spontaneously catches on fire, which results in wastage and can even cause a massive fire to break out. This phenomenon is known as the spontaneous combustion of coal. It is a complex process that has non-linear relationships between its causing variables. Preventive measures to prevent the fire from spreading to other coal piles in the vicinity have already been implemented. However, the predictive aspect before the fire occurs is of great necessity for the power generation sector. This research investigates various prediction models for spontaneous coal combustion, explicitly selecting input and output parameters to identify a proper clinker formation prediction model. Feed-Forward Neural Network (FFNN) is proposed as a proper prediction model. Two Hidden Layers (2HL) network is found to be the best with 5 minutes prediction capability. A sensitivity analysis study is also conducted to determine the influence of random input variables on their respective response variables.

Keywords: Spontaneous combustion of coal, Artificial Neural Network, Clinker Formation Prediction Models, Coal-fired power plant;

1. Introduction

Fire hazard is a real problem in the power industry. Countless lives have been lost in generating electricity and providing energy for everyone. Almost every aspect of the power industry has a fire involved in its processes. Fire cannot be escaped as it is essential for a fully functioning plant that deals with energy daily. The danger is present if steps are not taken and procedures are not followed. It has been a common occurrence for spontaneous combustions of coal in coal mines which is also detrimental to the environment [1-4]. The oil and gas industry has also been plagued with catastrophic events like the Deep water horizon and Piper Alpha. However, it is always important to have counter measures ready in emergencies.

Traditional systems are already in place and have been modernized to the extent that detection systems have been invented to detect minor changes in the parameters created to sense. Countless regulations have been passed, including OSHA to increase safety measures and hold companies accountable for events such as this. However, detection systems are only there for real-time data processing. So, in a fire, the response time for safety teams to react is limited. Sufficient preparation is not present in combating fires occurrences. Depending solely on the second line of defence will not prevent such events from reoccurring. A system needs to be in place at the first line of defence to collect data and analyze it using the detection system.

There is a solution; however, Information Technology has come a long way in overcoming this. Therefore, this study aims to develop a fire predictive intelligent model that uses Artificial Neural Networks to forecast and predict fire occurrences. This model can self-learn and find relationships between different variables.

2. REVIEW ON FIRE PREDICTION MODELING

The spontaneous combustion of coal and gas has been a serious issue that has plagued the industry. This issue needed a way to predict the outcome if such an incident was bound to happen. To achieve a high accuracy prediction, gas samples were studied using statistical analysis, such as rescales range analysis and The Hurst index. The COSMOL Multiphysics software was chosen to simulate the gas concentrations in a 3D model. The numerical software and the 3D image display on MATLABould predict the zone at which spontaneous combustion of coal can occur, the oxidation zone in the mine [1]. Fire destruction in Lebanon's forests has damaged the forests over a very long period. Weather data from the year 2012 was used from a weather station on the northern side of Lebanon. The artificial neural network was used to predict possible fire occurrences [5]. For fire detection in the household, a fuzzy system was employed to predict fire occurrences using smoke, gas, temperature and humidity [6].

Similarly, for fire occurrence in the wildlife of South Africa, a new model was created according to previous

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models already established, like the McArthur model. Fire rating was chosen based on specific vegetation present in South Africa. Compared to the current Lowveld fire danger rating, it was found that this fire rating model was more accurate in its prediction at 97%, while the Lowveld model was at 93% [7]. For Portugal, periodic data spanning 3 years was chosen to be fed into the neural network. Five neurons were present in the hidden layers, and this particular model obtains a prediction rating of 88.12% [8]. ANN was deployed to forecast the level of methane in the mining industry [9]. Sensors of coal mines were studied to determine the best location for installation and detection. It was concluded that flame and smoke sensors were necessary for greater detection purposes [10]. Fire detection efficiency was studied for subway trains in China. Levels of CO and CO2 needed to be significantly reduced to suppress the fire while measuring the drop in O2 levels [11]. A random forest approach was deployed to study the oxidation of coal and other methods such as the backpropagation method and multiple linear regression. The random forest method was the most accurate, followed by the backpropagation method in predicting the spontaneous combustion of coal [12]. In the pursuit of studying the phenomenon of spontaneous combustion of coal, a new variable was introduced to increase the prediction's reliability further. HLC indicator was used along with new algorithms such as metabolic and artificial bee colony[13]. An intelligent monitoring system to predict boiler tube leak trips at their early stage was developed by authors in [14]. This system was compared with a pure artificial neural network system and hybrid intelligent system for best lead prediction.[15] proposed two Intelligent Early Warning Systems (IEWSs) to detect early warning for steam turbine trips.[16] investigated implementation of ANN for a predictive fault tool for a CFB to facilitate plant operators. The purpose was to identify and narrow down the operational boiler parameters that cause the fault quickly.[17] developed an ANN model with an Adaptive Backpropagation Algorithm (ABPA) for best practice in forecasting long-term load demand of electricity.

The ABPA includes proposing new forecasting formulations that adjust/adapt forecast values, considering the deviation between different behaviours of trained and future input datasets.[18] presented an overview of recent development and research in the power plant sector using intelligent computational tools, including its applications.

However, the above studies did not consider variables, such as the absorbance of carbon dioxide, carbon monoxide and water in the coal and the exact time the spontaneous combustion of coal occurs. Various configurations of the networks, such as different training functions, number of hidden layers, number of neurons in the hidden layer, and different activation functions, were not explored.

This study focuses on the phenomenon occurring in the coal storage yards. Artificial Neural Networks is used to develop a fire predictive intelligent model to forecast and predict fire occurrences. The best configuration of the network is then identified.

3. METHODOLOGY

To develop an intelligent system to predict the spontaneous combustion of coal in the coal storage yard. Three phases are needed to be done step by step. The first phase is to present the design of the coal storage yard, and the second phase includes collecting the relevant data for developing the appropriate ANN. In the last phase, the ANN model will be developed along with the best parameters for the ANN modelling.

3.1. Design Overview of System

The research target of this study is to solve an important issue that plagues the power industry in particular. This issue is to mitigate fire occurrences in the power industry by predicting it accurately using artificial neural networks. The main target of the power industry that this study focuses on is the coal storage yard situated in the heart of the coal-fired power plant. See Figure 1 for the processes involved in a coal-fired power plant.

Figure 2 shows the coal storage yard of a coal power plant. The coal placed here are segregated based on coal type; among the coal types are Pipit, Jambayan, Envirocoal, Melawan and Malinau.

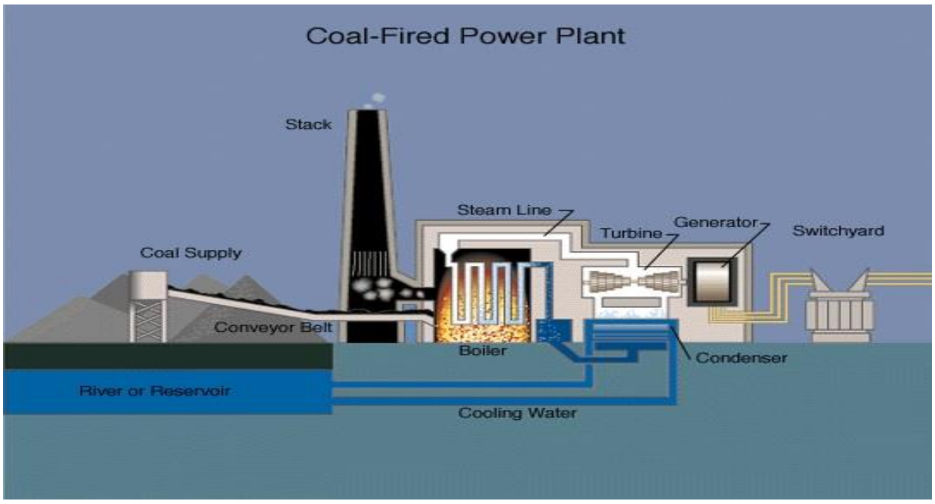

Figure 1. The processes involved in a coal-fired power plant with the input as coal and the output as electricity

They are also separated according to vessel numbers. The total stock accumulated is around 524,555 metric tons of coal. The coal types are separated into three zones: pile E, pile F, and pile G. rejected coins are kept in pile E and pile G, respectively. This specific coal yard resorts to hoses as deterrents to the fire in spontaneous combustion. The hoses are placed every 50 meters as marked by the ruler at the top and bottom of the image. There are no sensors of any type to record fluctuations of either temperature or gas that could cause the coal to comb spontaneously. Therefore, this particular coal power plant will benefit from the prediction tool of the artificial neural network once sensors have been placed at each zones E(top row), F(middle row) and G(bottom row). It is recommended to use gas concentration sensors to record the fluctuations of gasses such as carbon dioxide, carbon monoxide, nitrogen, oxygen, and methane. Temperature and humidity sensors are also required, with the gas sensors placed in each zone of the coal yard storage. This sensor placement helps monitor and feed the data to the network for prediction.

3.2. Data Preparation

Data collection of the gas concentrations is conducted to develop the prediction model for spontaneous combustion of coal formation conditions. All the necessary data obtained is from two separate studies on the spontaneous combustion of coal. The majority of the data is obtained from a study based on the temperature inversion during spontaneous combustion of coal [19].

This study focused on the phenomenon occurring in the coal mines where methane is present. Therefore, those three gasses, mainly ethane, methane, and ethylene, are removed. The second data setconsisting of absorption data of carbon dioxide, carbon monoxide and water were from an article about the characteristics of mass, heat and gaseous products during spontaneous combustion of coal using TG/DSC-FTIR technology [20]. These 3 datasets were chosen to replace the coal content during storage and diversify the input data as an increased amount of data would prevent redundancy for the ANN. See Table 1 for the types and units of the collected data variables.

No	Description	Units
1	Carbon Dioxide	PPM
2	Carbon Monoxide	PPM
3	Nitrogen	%
4	Oxygen	%
5	Absorbance of CO	-
6	Absorbance of CO2	-
7	Absorbance of H2O	-
8	Methane	PPM
9	Temperature	ºC
10	Ethane	PPM
11	Ethylene	PPM

Table 1. Data variables collected from previous studies

Data for the artificial neural network was collected from [19,20]. The data collected were then combined to form the inputs of the artificial neural networks. Experimental data to monitor gas concentrations were collected from [19]. A temperature programmed test system for spontaneous combustion of coal in an air bath is used in the experiment. The structure of the system is shown in Figure 3.

The coal samples are loaded into a special cylindrical steel coal sample tank with a bottom diameter of 10 cm and a height of 25 cm using an experimental device. As shown in Figure 3, the experiment begins after sealing. The air is supplied to a coal sample tank at 120 ml/min airflow using an air pump or gas cylinder as a gas source.

The air supplied flows after being preheated by the heating box through a glass rotor flowmeter and gas conveying copper pipe. It then flows to the coal sample via the bottom of the coal sample tank. The gas samples are then retrieved and analyzed by a gas chromatograph, SP-2120, after ½ an hour at a rate of 0.3°C/min. The gas products are finally obtained at different temperature points.

The second tests were carried out using a TG/DSC–FTIR experimental system [20] illustrated in Figure 4.

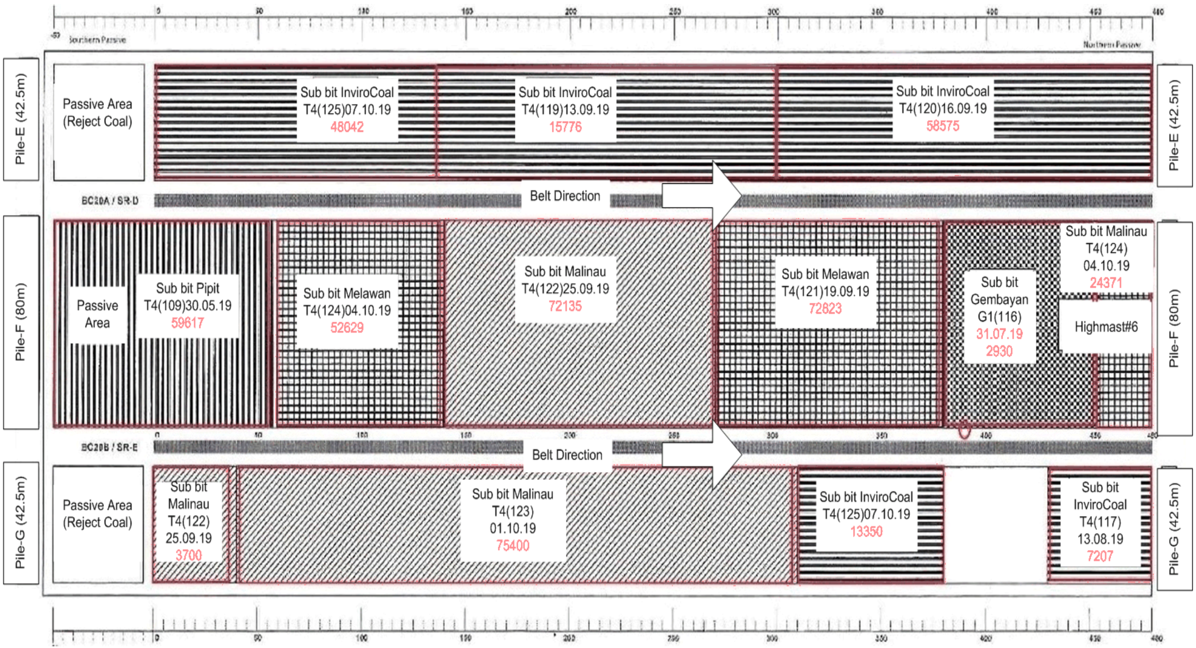

Figure 2. Coal storage yard

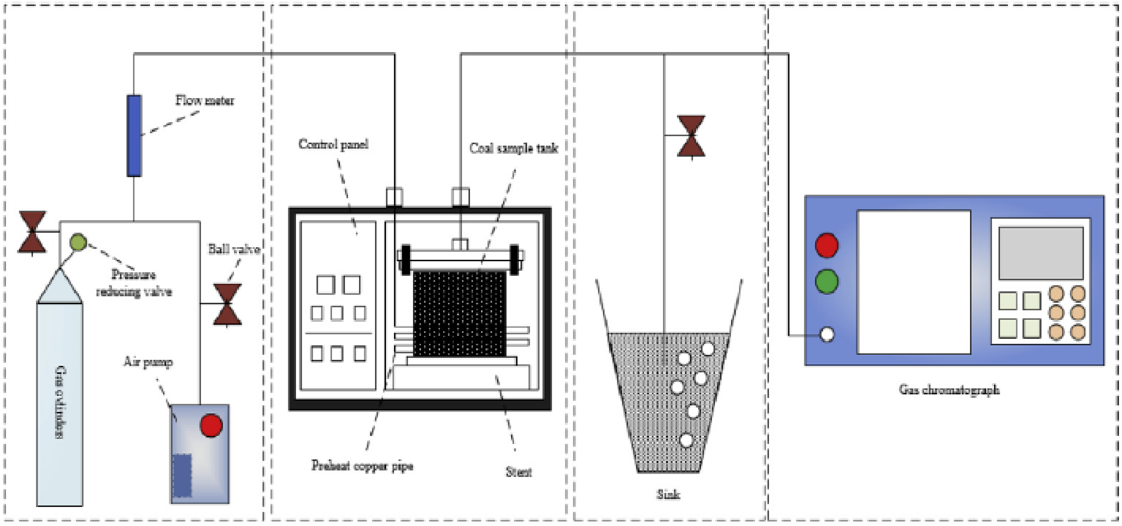

Figure 3. Experiment apparatus used to collect gas concentrations and temperature data [19]

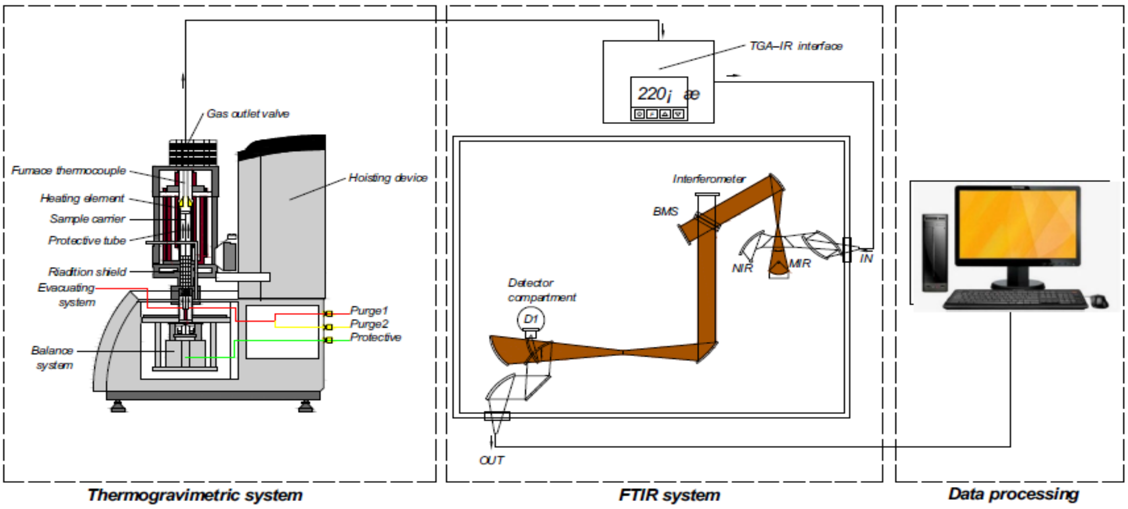

Figure 4. Apparatus used to obtain absorbance data during heating of coal [20, 21]

This experimental system comprises an STA 449 F3 series simultaneous TG/DSC thermal analyzer manufactured by Netzsch Incorporation and a VERTEX70v series Fourier-transform infrared spectrometer (FTIR) manufactured by Brucker Incorporation. A specially designed interface connected these two instruments. The temperature of the interface and the temperature of the transmission lines were kept to be around 220℃ to prevent condensation and structural transformation of oxidation products.

A coal sample of 15-mg was used for each experimental run in the thermal analyzer. The functional groups were measured by delivering the gaseous oxidation in real-time to FTIR during spontaneous combustion. Two factors were changed during the experiments: oxygen concentration and heating rate. The Protection gas used in this experiment was nitrogen, while the carrier gas was a mixture of oxygen and nitrogen with different mixing ratios. The protection and carrier gases' overall flow rate was continuously at 100 mL/min. The parameters set constant for the FTIR were the wavenumber between 400 and 4000cm-1 with a resolution of 4 cm-1.

The data for absorbance was obtained only at 170 ℃ [20]. Various input data like this is much needed for the neural network to learn the non-linear relationships between these variables that contribute to the spontaneous combustion of gas.

3.3. Artificial Neural Network Parameters

The ANN model was developed using MATLAB coding. There are 360 network combinations for the One Hidden Layer (1HL) network and 10,800 network combinations for Two Hidden Layers (2 HL). This combination includes varying the number of neurons, different combinations of activation function and types of the training algorithm. Root Mean Square Error (RMSE) values are compared, and the lowest values are obtained from 1HL and 2HL, respectively.

3.4. Root-Mean Square Error (RMSE)

Root mean square error was used to calculate the difference in the predicted data from the neural network and the actual data from the study itself. This form of error calculation is readily available in MATLAB software and can be easily integrated into the networks coding. The error calculated will be used to determine the reliability of the training system used. This error calculation will be used to identify the accuracy of the network, which can later be rectified by tweaking specific parameters such as hidden layers or even changing the training algorithm. The smaller the error found, the higher the prediction capability of the ANN.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - y_i)^2}{n}} \quad (1)$$

4. RESULT ANDANALYSIS

In this section, the ANN results will be analyzed and explained further to shed light on this work in particular. The data that has been simulated and the RMSE values using Equation (1)and performance graphs of the best performing networks will be present. The simulated data will be shown in predicted values versus the actual values in a graph. After proceeding with the simulations for the ANN models, the results were tabulated, and a table summary of the best performing combination for each training algorithm in each ANN architecture was made for easier comparison. The best performing ANN prediction model for the 1HL feedforward network is summarized in Table 2 below for the 4 different training algorithms used. The best performing combination of four different training algorithms is highlighted.

4.1. Performance indicators for 1HL Feed-Forward

The best performing ANN prediction model for the 1HL feedforward network is summarized in Table 2 below for the 4 different training algorithms used. The best performing combination among four different training algorithms is highlighted in Table 2.

Table 2. Result summary for 1HL Feed-Forward Neural Network

Training algorithm	1HL Neurons	Activation function	RMSE value
Trainlm	8	T+P	0.1009
Trainbfg	8	P+T	0.1021
Trainscg	9	L+T	0.1053
Trainrp	8	P+T	0.1080

Based on Table 2, the best performing prediction model for the 1HL feedforward network has the training algorithm trainlm at 8 Neurons using the activation function of T+P and producing a value of 0.1009 RMSE. Figure 5 shows the best performance graph for the 1HL feedforward network.

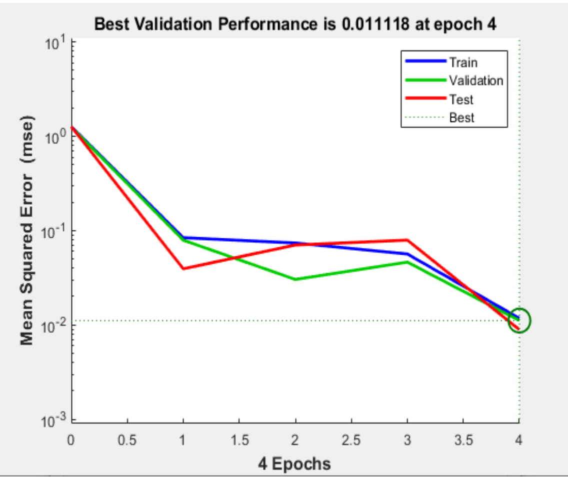

Figure 5. Performance diagram for the best network with 1HL

4.2. Performance indicators for 2HL Feed-Forward

Similarly to 1HL, the results were tabulated, and a table summary of the best performing combination for each training algorithm in each ANN architecture was made for easier comparison. The best performing ANN prediction model for the 2HL feedforward network is summarized in Table 3 below for the 4 different training algorithms used. The best performing combination of four different training algorithms is highlighted.

Table 3. Result summary for 2HL Feed-Forward Neural Network

Training algorithm	1HL neurons	2HL Neurons	Activation function	RMSE value
Trainlm	4	1	L+P+T	0.10000
Trainbfg	10	7	L+P+T	0.10010
Trainrp	7	6	T+P+T	0.10019
Trainscg	4	6	T+P+T	0.10064

Based on Table 3, the best performing prediction model for the 2HL feedforward network has the training algorithm trainlm at four 1st Hidden Layer Neurons, one 2nd Hidden Layer Neurons using the activation function T+T+T and producing a value of 0.1000 RMSE. Figure 6 shows the best performance graph for the 2HL feedforward network.

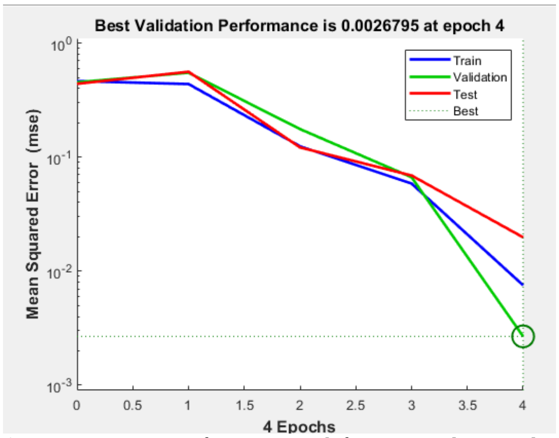

Figure 6. Best MSE performance graph for 2HL Feed-Forward

4.3. Summary of Best ANN Models

This section aims to summarize and analyze the performance of ANN models based on RMSE values. Table 4 below shows the summary for the best RMSE ANN models.

Table Error! No text of specified style in document.**.** Best RMSE ANN models

Type of ANN	Transfer function	1HL neurons	2HL neurons	Activation function	RMSE value
1HL Feed-Forward	Trainlm	8	-	T+P	0.1009
2HL Feed-Forward	Trainlm	4	1	L+P+T	0.1000

Based on Table 4, the 2HL ANN has the lowest RMSE value among 6 different types on the ANN model, although there are minor differences in RMSE value between each model from the 2HL ANN.

4.4. Outcome Analysis

The best performing ANN model has been identified in section 4.3. However, determining the RMSE value for ANN models is only one aspect for determining the performance of an ANN model; it is not sufficient to justify it as the absolute best ANN model for this work. Detailed outcome analysis of the actual and predicted output is essential to justify and supplement the best ANN model for fire prediction.

The graph of actual output versus predicted output is plotted using MATLAB R2019aB version software for the graph of fire occurrence

4.4.1. The First Fire Occurrence Analysis

In this section, the occurrence of fire is investigated. The graphs are highlighted to show the behaviour of the ANN model to produce the required prediction and are provided in Figures 7-8.

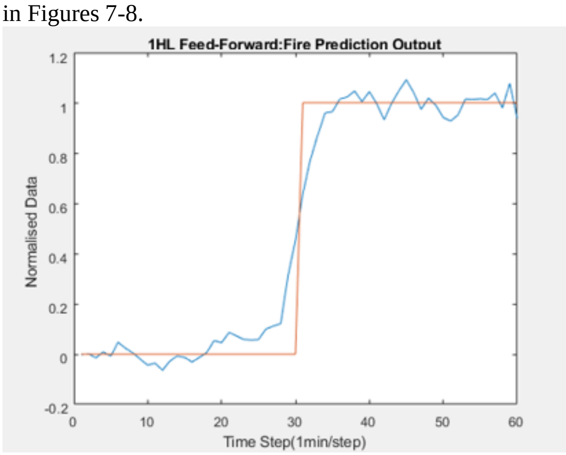

Figure 7. The predicted output of 1HL feedforward net

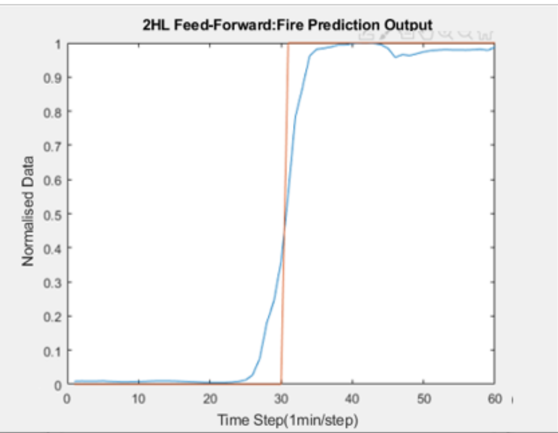

Figure 8. The predicted output of 2HL feedforward net

The points on the graph have been identified by analyzing the actual and predicted output graphs. For easier comparison, each critical point's time step and normalized valuearetabulated in Table 5 below.

Table 5. Comparison of critical points for fire occurrence

Architecture	Normalized Value
1HL feedforward	-0.2 to 1.2
2HL feedforward	0 to 1

Based on Table 5, the normalized value for both models is slightly different. The actual output of the model is either 1 or 0. The model with the closest output to the actual output is the 2 hidden layer feedforward network. The red line represents the actual output when the fire occurs. The time interval is per minute; therefore,a fire occurs at the 30th minute. Although the fire in real life occurs gradually, given the experimental data obtained from the study of the heating coal sample, the fire occurs at the 30th minute when the oxygen levels drop.

When observing the predicted output of the 1 HL feedforward network shown in Figure 7, it can be observed that the overall trend of the output is similar to the actual output. However, slight spikes and dips in the data lead up to the fire when the output becomes 1. This trend is still acceptable; however, the range of normalized values is still far from the actual output of the fire. Ranging from -0.1 to 1.2, this is far from the actual range, either 0 or 1. This network predicts that fire is about to occur at the 28th minute. This prediction shows that this network is not ideal in predicting fire occurrences during the spontaneous combustion of coal.

Figure 8, the 2 hidden layer feedforward network output, is much smoother because it closely follows the actual output value. Although there are dips when the normalized data reaches 1, the changes in the data are minute and will not interfere with the predicted output of the fire. The steady rising of the blue line (predicted output) can also indicate when the fire slowly starts to occur beforehand. The fire can be predicted at the 25th minute from this network, which is very useful for the coal yard personnel to hose down the coal to cool it down before it abruptly catches on fire.

Hence the 2 hidden layer feedforward net is the best network in predicting the outcome of a fire that occurs due to the spontaneous combustion of coal. The value of RMSE alone cannot show whether the network is suitable for a specific problem. The network output should also be analyzed carefully to see how closely it relates to the actual output of the data present.

4.4.2. The Second Fire Occurrence Analysis

A new dataset is sent to the best ANN model for the last test to check its performance. This new data is obtained from the first study as well. Figure 9 shows the predictive output for the second set of data. The type of coal is different, as well as fire occurrence. The fire occurs at the 45th minute based on the sudden spike in carbon dioxide conditions and a sudden decrease in oxygen gas concentrations.

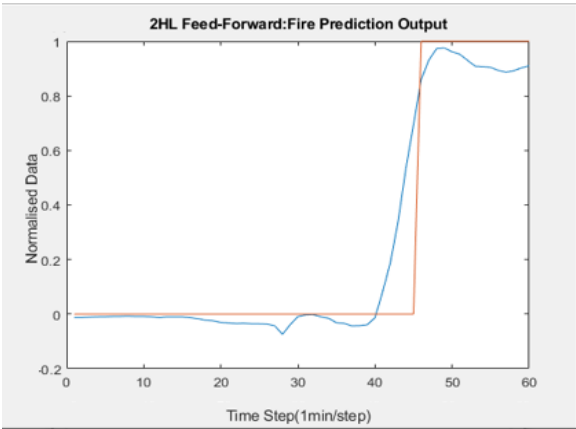

Figure 9. Predictive output for the second set of data

For this second set of data,the fire occurs at the 45th minute, as shown by the sudden increase and decrease of the target concentration of gases, carbon dioxide and oxygen gasses. This network could predict the fire will occur at the 40th minute, again 5 minutes before the actual occurrence. The RMSE value of this data is 0.133, which is very accurate. The acceptable range of RMSE values varies from 0.1 to 0.5. This neural network is suitable for this prediction problem. The blue line may not be smooth; however, the trend line is still present and can still be analyzed.

5. CONCLUSION

Careful research led to the intelligent prediction of spontaneous combustion of coal, and it was evident that ANN plays an essential role in guaranteeing that the objectives are achieved. The objectives of this study were accomplished by determining the best ANN models to predict fire occurrence due to the spontaneous combustion of coal. Also, the input-output relationship of the ANN model has to be identified.

This work focused on examining the output patterns of the model and coming up with the best ANN model to benefit the power plant station. Firstly, the primary input and output parameters were identified, and this parameter identification allowed trial and error progress to determine the best RMSE ANN model. After conducting the simulations, the 2HL feedforward network has the lowest RMSE value out of all the other 4 types of Neural Networks.

Proceeding onward to the outcome analysis, it appeared that the 2HL feedforward network could be used to represent the forecast model for fire best. It is imperative to comprehend the relationship between them so that the input parameters can be modified accordingly to forecast the phenomena of coal spontaneously combusting in the stockpiling yard.

Thus, in utilizing the 2HL feedforward network model, an intelligent prediction system has been built to monitor the coal yard storage and forecast fire occurrences. This model will help the power generation sector achieve a more sustainable and practical business solution, creating a safer working environment.

6. FUTURE WORK

Further study can be carried out to improve the current results using different prediction tools such as Machine Learning or Fuzzy Logic. Other types of artificial intelligence modeling could lead to better performance in prediction than the current ANN models utilized in this study. There are also newer activation functions that can be used instead of the traditional logsin, purelin and tansig functions, and these newer functions may be able to predict at a higher accuracy.

Precise data acquisition on the input and output parameters with a larger variable pool can also be implemented to create a better and accurate model. Increased input that corresponds to the combustion process of the coal should also be included in future work, such as smoke and humidity in the air.

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REFERENCE

[1] Y. S. H. X. S. W. S. N. C. J. X. Q. Song Y, "Prediction of gas and coal spontaneous combustion coexisting disaster through the chaotic characteristic analysis of gas indexes in goaf gas extraction" *Process Safety and Enviromental Protection* (2019), p. 29, 12 June 2019.

[2] T. P. T. Glenn B Stracher, "Coal fires burning out of control around the world: thermodynamic recipe for environmental catastrophe," *International Journal of Coal Geology,* vol. 59, pp. 7-17, 2004.

[3] S. J. D. A. S. D. J. W. John N Carras, "Greenhouse gas emissions from low-temperature oxidation at open-cut coal mines in Australia," *International journal of coal geology,* vol. 78, no. 2, pp. 161-168, 2009.

[4] F. O. J. S. Taku Ide, "Comparison of methods to estimate the rate of CO2 emissions and coal consumption from a coal fire near Durango, CO," *International journal of coal geology,* vol. 86, no. 1, pp. 95-107, 2011.

[5] A. H. B. D. a. P. C. N. Hamadeh, "Studying the factors affecting the risk of forest fire occurrence and applying neural networks for prediction," *2015 SAI Intelligent Systems Conference (IntelliSys),* pp. pp. 522-526, 2015.

[6] O. G. a. R. Sarno, "Prototype of fire symptom detection system," *2018 International Conference on Information and Communications Technology (ICOIACT),* pp. pp. 489-494, 2018.

[7] S. L. a. B. Mathibela, "The application of artificial neural networks for wildfire risk prediction," *2016 International Conference on Robotics and Automation for Humanitarian Applications (RAHA),* pp. 1-6, 2016.

[8] M. Sahu, "Integrating Artificial Neural Network," *al. International Journal of Recent Research Aspects,* vol. 2, no. 2, pp. pp. 8-11, June 2015.

[9] T. a. Brodny, "Predicting Methane Concentration in Longwall Regions Using Artificial Neural Networks," *International Journal of Environmental Research and Public Health,* vol. 16, no. 8, p. 1406, April 2019.

[10] R. A. T. J. H. R. a. L. Z. L. Yuan, "Early fire detection for underground diesel fuel storage areas," *Process Safety and Environmental Protection,* vol. 119, p. pp. 69–74, 2018.

[11] X. Z. a. Z.-F. W. W. Zhang, "Experiment Study of Performances of Fire Detection and Fire Extinguishing Systems in a Subway Train," *Procedia Engineering,* vol. 135, p. pp. 393–402, 2016.

[12] J. D. K. C. L. M. Y. X. L. R. Changkui Leia, "A random forest approach for predicting coal spontaneous combustion," *Fuel,* pp. 63-73, 2018.

[13] X. M. C. Y. Shoujun Lia, "Prediction of spontaneous combustion in the coal stockpile based on an improved metabolic grey model," *Process Safety and Environmental Protection,* 2018.

[14] FB Ismail, D Singh, MS Nasif, “Adoption of Intelligent Computational Techniques for SteamBoilers Tube Leak Trip”, *Malaysian Journal of Computer Science* 33 (2), 133-151, 2020.

[15] FB Ismail, RIB Ismail, PJ Ker, and SKB Wahidin, "Development of Intelligent Early Warning System for Steam Turbine, *Journal of Engineering Science and Technology (JESTEC)* 14(2), 844 – 858, 2019.

[16] NNM Nistah, KH Lim, L Gopal, FBI Alnaimi, "Coal-Fired Boiler Fault Prediction Using Artificial Neural Networks", *International Journal of Electrical and Computer Engineering (IJECE)* 8 (4), 2018.

[17] NA Mohammed, A Al-Bazi A. "An adaptive backpropagation algorithm for long-term electricity load forecasting". *Neural Computng and Applications* (2021).

[18] FB Ismail, A Al-Bazi, RAL Hadeethi, D Singh, "Application of Intelligent Computational Techniques in Power Plants: A Review", *Advances In Industrial Engineering And Management (AIEM),* 10 (1) (2021), 10-21.

[19] H. W. Y. f. J. Jun Guo, "Data on analysis of temperature inversion during spontaneous combustion of coal," *Data, in brief,* vol. 25, 2019.

[20] H. W. Z. L. C. Jun Guo, "A method for evaluating the spontaneous combustion of coal by monitoring various gases," *Process Safety and environmental protection,* vol. 126, pp. 223-231, 2019.

[21] J. Z. Z. H. L. Z. W. Jun Deng, "Thermal analysis of spontaneous combustion behaviour of partially oxidized coal," *Process Safety and environmental protection,* Vols. 104, Part A, pp. 218-224, 2016.