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Comparative Analysis of Coal Properties And Flue Gas Temperature of Thermal Power Station Using Machine Learning

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***Abstract*— In this work the model has been designed to estimate the Flue Gas Temperature and Power Generation of Sagardighi Thermal Power Plant using Artificial Neural Network. The model will be able to identify the efficient coal received in thermal power station. In power station the high temperature measurement of Flue Gas is done by a temperature probe. Using the model derived from the proposed work the temperature can be estimated by just correlating between coal parameters and Flue Gas Temperature & Power generation of the said plant. It means we will able to estimate the power generation without burning the coal in advance. So, the load forecasting will be done very efficiently. The Python software was used to implement the ANN simulation.**

***Keywords*— FC, Ash, VM, Moisture, Temperature, Generation, ANN, Python**

I. Introduction

The basic properties [1] of coal [11] are Gross Calorific Value (GCV) [12, 13], Fixed Carbon (FC), Coal Ash, Volatile Matter (VM), Inherent Moisture (IM) and Total Moisture (TM).

Fig. 1. Coal Handling Process

Different fuels, including coal, natural gas, diesel, etc., are used in thermal power plants to turn liquid into steam, which produces electricity. The energy derived from the heated substance's temperature [10] is known as thermal energy. Additionally, the majority of thermal plants use steam as a source of energy to run their turbines. Electric power generation is the primary usage of thermal plants in the industrial sector.

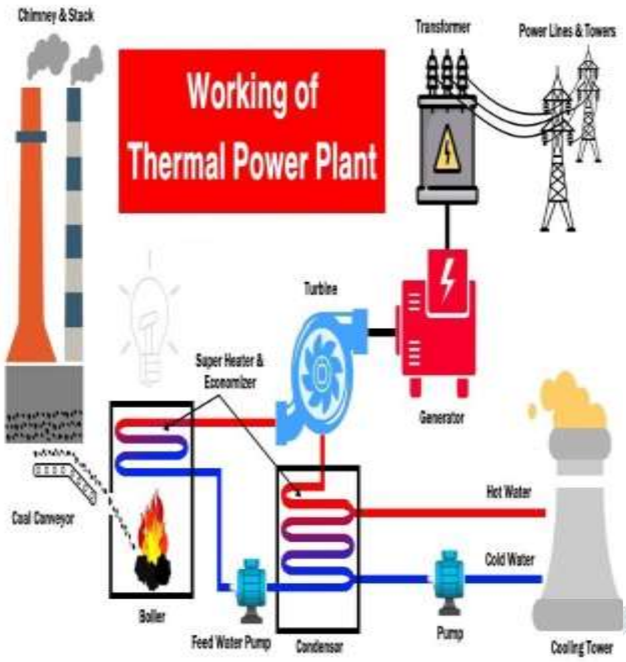


Fig. 2. Working Of Thermal Power Plant

India's population growth is causing an increase in energy consumption, accounting for around 6% of global primary energy consumption. Over the last 70 years following India's independence, the country's power capacity has increased from 1300MW to 267,000MW. However, even with this surge in electricity generation, demand still exceeds supply. The three main categories of thermal power plants that India focuses on are indicated here, along with their installed capacities as of May 31, 2023 [22].

Coal: 205235 MW

Gas: 24824 MW

Liquid Fuel (Diesel): 589 MW

The majority of fossil fuels, especially coal, which produces over 75% of the electricity produced in our nation, are used in thermal power plants to generate electricity. The Ministry of India's data indicates that the production of coal increased by 6% in 2023 over 2022. Furthermore, as of May 31, 2023, India's installed generation capacity stood at 4,17,668 MW.

II. LITERATURE REVIEW

The various journals, thesis papers research papers were gone through for references. Rajeev Ramanath et al. [2] studied on the image processing. Y Yan et al. [3] suggested a system that measured the majority of the flame's physical characteristics by combining optical sensing, digital image processing, and computational approaches. Recently, the system was put through experimental trials on a 1 MWth coal-fired combustion test facility. Gang Lu et al. [4] described the use of spectral analysis and image processing techniques to monitor the oscillatory properties of flames made on pulverized coal. Huajian et al. [5] using the same flame image processing method, a carefully calibrated portable flame temperature measuring device was created because it was more practical for industrial flame measurements. Huang et al. [6] outlined the development and assessment of a unique optical instrumentation system intended for the continuous on-line measurement of a furnace's temperature distribution. Manoj Khandelwal and T.N. Singh [7] by combining the proximal and ultimate studies of coal, an artificial neural network (ANN) was used in an attempt to forecast the concentration of macerals in Indian coals. Kaymakci and Didari [8] presented the relationship between coal parameters—obtained from proximate, ultimate, and petrographic analyses—and spontaneous combustion parameters—derived from time-temperature curves obtained from laboratory tests—has been described. Peng LIU and ShuranLV [9] measured and calculated of calorific value of raw coal based on artificial neural network analysis method. Raluca Nelegai et al. [20] utilized a long short-term memory recurrent neural network (LSTM-RNN) model, evaluated the prediction accuracy of two forecasting strategies: the recursive strategy and the non-recursive Multiple-Input and Multiple-Output strategy. Bowoo Kim and Dongjun Suh [21] studied in order to minimize computational load, the model defines and synthesizes regions of interest (ROI) and surrounding areas of ROI (ROI_{surr}) within satellite images.

III. BLOCK DIAGRAM OF THE WORK

The coal properties e.g. GCV, FC, ASH, IM and TM of Sagardighi Thermal Power Station from February 2022 to March 2024 have been taken and temperature [17] of Flue Gas & power generation of the same plant were also taken for the same period of time. After processing the collected data70% was used to train the ANN [15, 16] and rest 20% was used to test the model.

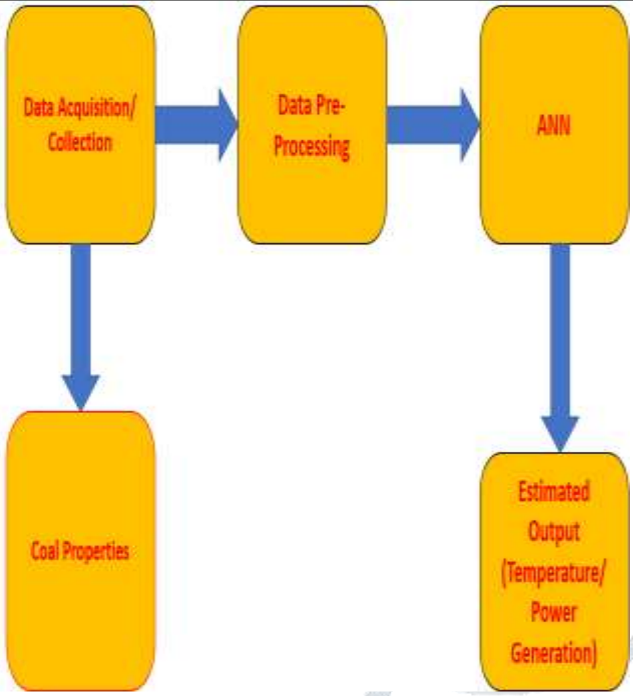


Fig. 3. Work flow diagram of Temperature /Generated power estimation

A. Artificial Neural Network (ANN)

The Artificial Neural Network model will be used for prediction of outputs in the present work. The prediction using Artificial Neural Network [14] will be a kind of regression model for accurate generation of the results. In this work, ANN [18, 19] is taken into consideration because

(i) a neural network can perform tasks that a linear program cannot.

(ii) Due to its parallel features, a neural network item that is declining can continue without any problems.

(iii) Neural networks are self-determining and do not require reprogramming.

(iv) It is compatible with all applications.

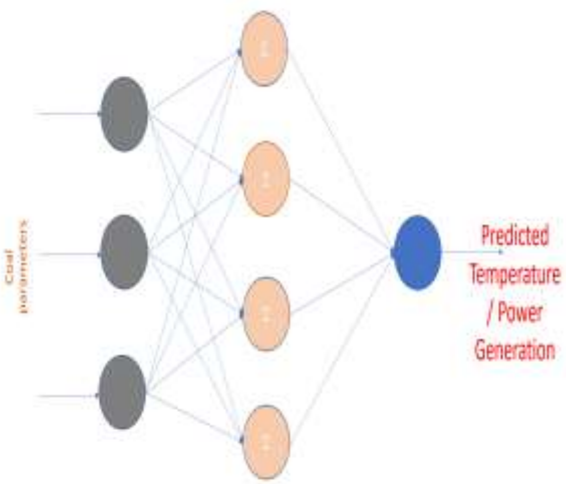


Fig. 4. ANN model for the proposed system

B. ANN Implementation

The Artificial Neural Network algorithm is used to find the regression model for the prediction of Flue gas temperature against six different parameters for coal quality, namely, (i) Gross Calorific Value (GCV), (ii) Fixed Carbon, (iii) Ash Content , (iv) Volatile Matter, (v) Inherent Moisture (IM), and (vi) Total Moisture (TM). The input dataset contains seven hundred sixty data for each of these properties. The output variables are two: the Accuracy and mean absolute error (MAE). The ANN algorithm is implemented using python programming language.

The 'KERAS' sequential model for ANN as implemented in numpy library is utilized. The input layer sir five variables as mentioned above. A systematic study is carried out to optimize the number of neurons/nodes used for the input layer. The dense class of neurons that are fully connected is used in the input layer. The rectified linear unit activation, referred as ReLU, is used for the activation of neurons in the input layer.

In addition to the input layer, two hidden layers with dense class of neurons are used for the model. The neuron numbers for each of the hidden layer is again optimized from a systematic analysis of variation of output against the neuron numbers in each of the input and hidden layers. In this study, we use n-2n-n number of neurons for the input layer, first and second hidden layers respectively. All the hidden layers are also activated using ReLU activation function. The ANN algorithm often encounters overfitting due to excessive number of neurons in both input layer and hidden layers. To circumvent the issue of overfitting the dropout layers were added both after the input layer and hidden layers. The dropout layer randomly deactivates a fraction of neurons while training iterations. We used an arbitrary dropout rate 0.2 for each of input and hidden layers.

C. Python

The Python software was used for this work.

Python code that is well-organized and efficient is built around functions. It is explored functional programming using lambda, filter, and map functions.

Python's greatest asset is its vast array of standard libraries, which can be applied to the following tasks:

Python's Built-in Modules and Python DSA Libraries

Robotic Learning

GUI Libraries for Python

Packages for Web Scraping

Packages for Game Development.

Python is a high-level, versatile programming language that is renowned for being easy to understand and use. It is appropriate for a range of applications, including artificial intelligence and web development, as it supports multiple paradigms. Rapid development is made possible by Python's large standard library. Productivity is increased by its automatic memory management and dynamic typing. Python's community-driven development encourages a vast ecosystem of libraries and frameworks, and it is widely used in data science, machine learning, and automation. Both novice and experienced developers will find it to be the perfect option due to its cross-platform compatibility and simplicity of integration. Python's growing popularity highlights its significance as a top language for contemporary software development.

IV. MAJOR CONTRIBUTION OF THE WORK

The model will be able to identify the efficient coal received in thermal power station. Using the model derived from the proposed work the temperature can be estimated by just correlating between coal properties and Flue Gas Temperature (FGT) & power generation of the plant. It means we are able to estimate the power generation without burning the coal in advance. So, the load forecasting will be done very efficiently. The model suggests that the power plat efficiency can be enhanced by controlling the coal quality.

V. RESULT

There are two output variables in our implementation: mean absolute error (MAE) and accuracy. The MAE is defined as the average of absolute difference between the predicted results and actual value (in the dataset)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \overline{y_i}| \qquad (1)$$

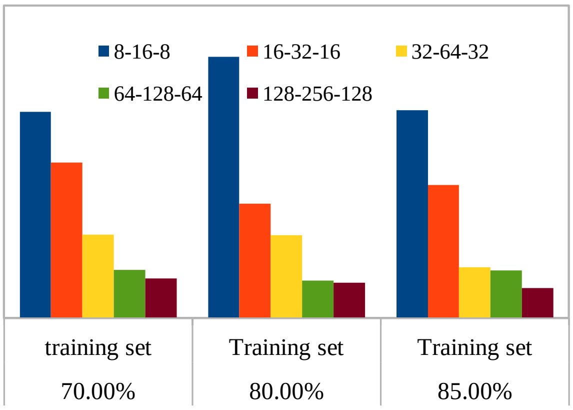
Since the output layer contains only two variables, we used two neurons for this layer. The ANN minimizes a loss function iteratively. The loss function is the quantitative measurement of the difference between the predicted outcome and real outcome. We use mean square error (MSE), defined as the average squared difference between the predicted value and real value as the loss function:

$$Loss = \frac{1}{N}\sum_{i=1}^{N}(y_i - \overline{y_i})^2 \qquad (2)$$

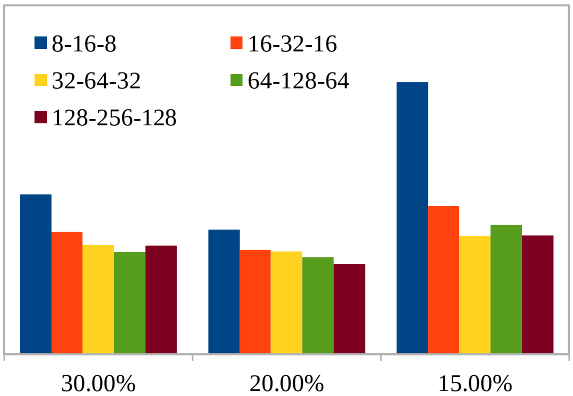
The keras model is compiled using 'adam' optimization routing in numpy library, which is an extension of stochastic gradient descent algorithm for fitting data. The 'linear activation' function is used for the output layer.

For execution of the model, the dataset is divided into training set and test set. The data in the training set are chosen

Loss for Traning set

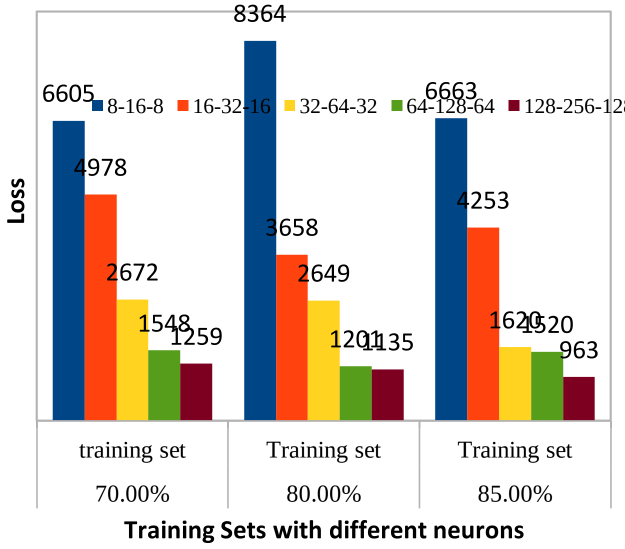


Loss for Test set

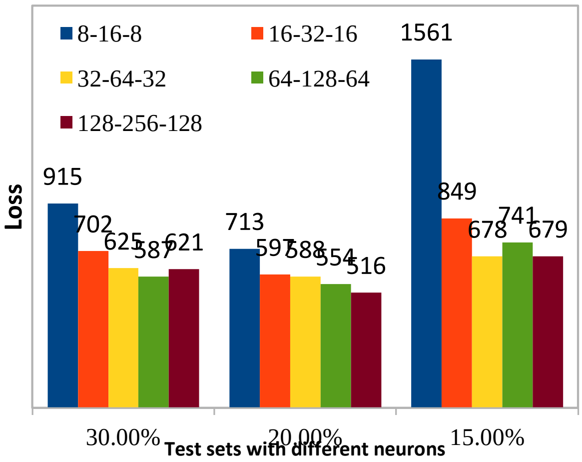


randomly. There are two factors that control the quality of the training in ANN algorithm: number of epoch and batch size. The number of epoch represents the number of times the entire dataset used for training. On the other hand, the batch size which is defined as the subset of dataset that is used for training in iteration. The data in the 'training set' were train iteratively using various 'epoch' and 'batch size' values and a systematic study is carried out on the number of epoch and batch size against the loss and MAE value.

We first carried out a systematic study on the variation of loss function and MAE with respect to the neuron numbers in input layer and hidden layers. For this, three different training and test sets were defined. In the first set, 70% of data are included in the training set and 30% in the test set; in the second set, 80% of data are put in the train set and thus 20% are put in the test set. The third set contains 85% in the training set and 15% in the test set. The epoch value and batch size are fixed at 300 and 32, respectively.



(a)



(b)

Fig. 5. (a) The loss value for train set (b) The Loss for test set

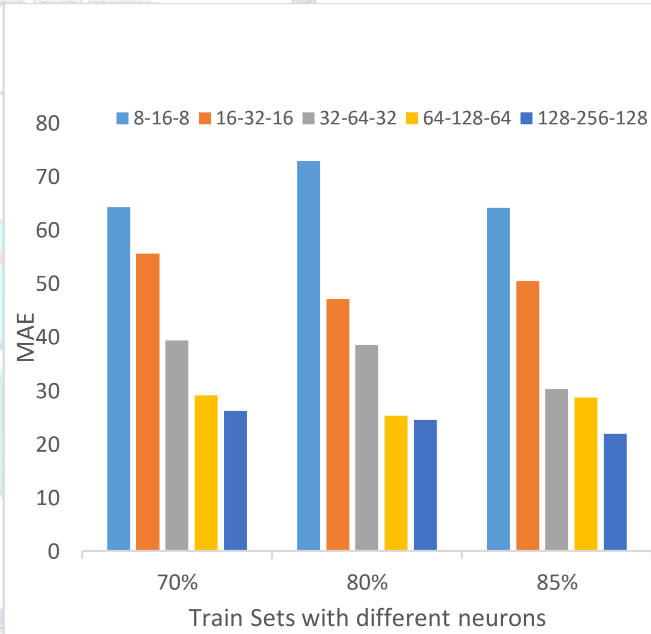
In Fig 5, the variation of loss function, i.e., MSE is plotted against the neuron numbers in input layer, first and second hidden layers, respectively for all the three sets. For all three sets, as expected, the loss function value decreases with increasing the number of neurons in the layers for the training sets.

Moreover, the loss also decreases with increasing the size of the training set.

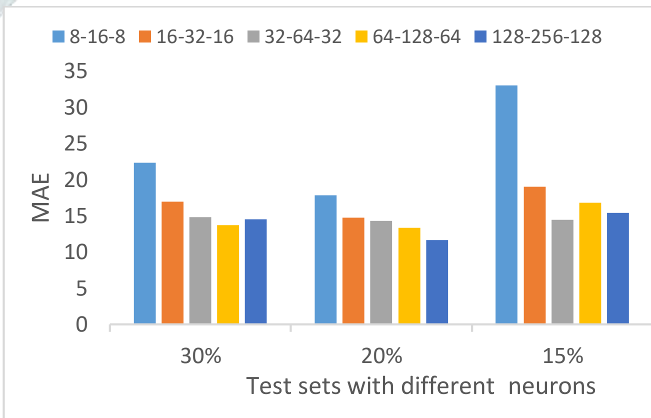
On the other hand, for the test sets having 30% and 20% of the total data, the loss is found to decrease from 30% test set to 20% test set. Such a trend is expected since the model for the later one is a better trained with 80% in the training set compared to 70% in case of the former one.

Such a deviation is probably due to overfitting of the data in train set having 85% of data. All five sets of neurons show much higher value of loss for this test set. The loss value is significantly higher for the train set compared to the test sets, implying high accuracy of the fitted model. Indeed, the accuracy of the model lies above 99% for all the sets studied here.

With an increase in the size of the train set leads to marginal improvement of the fitting by reducing the MAE value only marginally in the train set. However, the corresponding test set does not follow a pattern. Though the MAE decrease from 30% test set to 20% test, it is again increased for the 15% test sets for all five sets of neurons used in the calculations. From both Figures it is evident that the loss and MAE values are saturated with the neuron set 64-128-64, i.e., 64 neurons for the input layer, 128 neurons for the first hidden layer and 64 neurons for the second hidden layer, respectively. A further increase in the neuron numbers does not improve the fitting much, though increases the chance of overfitting.



(a)



(b)

Fig. 6. (a) MAE for the train (b) MAE for the test set

Finally, variations of loss, MAE and accuracy with respect to the number of epoch are plotted in Fig. 7. For this set of calculations, the train set with 80% of data and the corresponding test set with 20% of data is used.

The batch size of each iteration is fixed at 32. The results show that the results are converged with about 100 epoch value. Initially, the loss and MAE values are extremely large which decrease sharply with epoch number about 10. With epoch number about 50, both loss and MAE curve are flattened. The loss value gets converged by about 150 epoch value for both train and test (validation) sets. However, the MAE decrease with epoch value more than 150. We noticed a slight oscillation on the MAE curve for the test set.

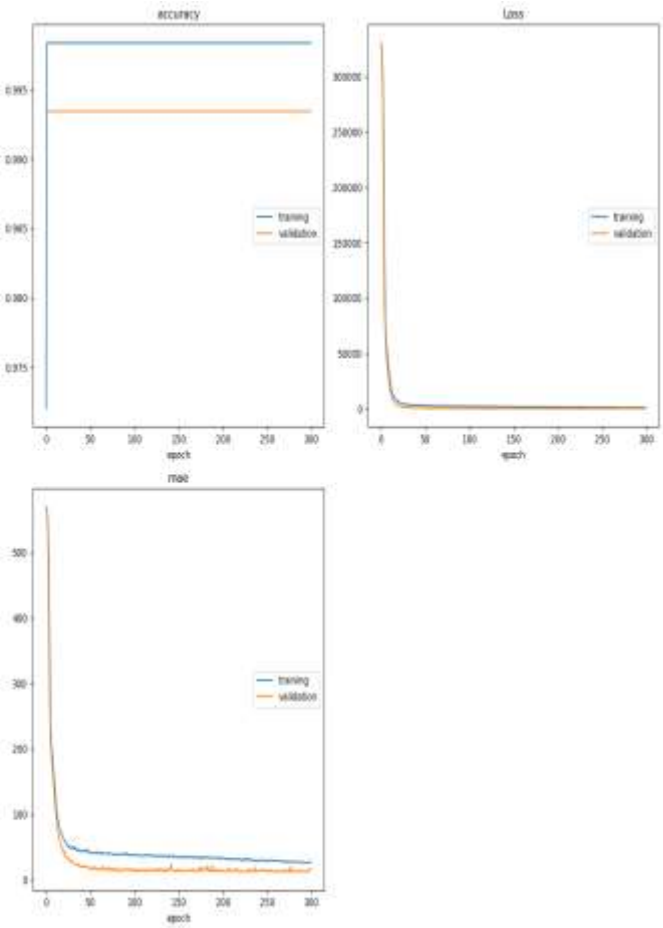


Fig. 7. Accuracy, Loss & MAE

V. CONCLUSION

In this work we employed machine learning (ML) technique with the artificial neural network algorithm for the prediction of Flue temperature based on six different parameters for coal quality, namely, (i) Gross Calorific Value (GCV), (ii) Fixed Carbon, (iii) Ash Content, (iv) Volatile Matter (VM), (v) Inherent Moisture (IM), and (vi) Total Moisture (TM). The algorithm was implemented using python programing language and its in-built libraries for Machine Learning. The dataset was obtained from Sagardighi Thermal Power Station, West Bengal, on daily basis from the period February 2022 to March 2024. The entire dataset comprises 760 sample collections.

The KERAS sequential model is used for the fitting. On taking 80% of the data for the training of ANN, and employing the resultant model to a test set comprising of 20% of total data, we got about 99.4% accuracy for the validation set and about 99.8% for the training set. The mean absolute error for such a test set was only about 14. The study highlights the effectiveness of Machine Learning and ANN algorithms to predict the flue gas temperature and power generation of the Thermal Power Plant based on coal quality and thereby enable to optimize the coal quality to be used to get desirable flue temperature.

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