Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 12, Issue. 1 : 2021
ISSN : **1906-9685**

ASSESSMENT OF PARAMETERS OF COAL SAMPLES THROUGH PROXIMATE ANALYSIS AND PREDICTION OF GROSS CALORIFIC VALUE OF COAL SAMPLES BY REGRESSION ANALYSIS AND ARTIFICIAL NEURAL NETWORKS

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Abstract *The quality control plays a very important role in the balancing the profits and output of coal. For the processing cost of the determination of calorific value of the fossil fuels is extensively high, as it required plenty of instrumentation and skilled analyst to perform the experiment, proximate analysis information will be obtained simply victimization a standard muffle chamber compared to calorific value. Multivariate analysis and artificial neural network analysis strategies are introduced to change the task and conjointly scale back the price of research. A trial had created during this gift study to access the relevancy of that correlation and artificial neural network with an abstraction emphasize on study area. Artificial neural network model helps in designed to predict the gross calorific value of coals belonging to different mines in the study area. The 40 samples were collected from different coal samples in the study area. The intrinsic properties were determined by carrying out proximate analysis and calorific value by using bomb calorimeter. Correlation analysis was carried out to on the individually of moisture, volatile matter, ash, fixed carbon on the gross calorific value (GCV). It is observed that moisture, ash have unfavourable impact and down steps the gross calorific value (GCV). Fixed carbon and volatile matter as positive impact and increase the gross calorific value (GCV). Present study also compares the experimental results to formal given by CIMFR and create by model created by using multivariable linear regression and artificial neural network. The formulae developed by multivariable linear regression is*

GCV = 7787.75-197.44M-77.986A+12.45FC

Where GCV in Kcal/kg and moisture, ash, volatile matter, fixed carbon in air-dried percentage basis.

The study from the comparison between CIMFR GCV, Multivariable regression model and ANN model with Experimental GCV observed that all three models predict the calorific value accurately. However, the ANN model gives better prediction than the other models. Therefore, prediction of gross calorific value by ANN model could be a better option than experimentation in the laboratory. The ANN model consider the intrinsic properties determine by proximate analysis as input parameters, which is regular task in the field as these are required to determine the grade of coals and hardly demand any costly experimental setup.

1. INTRODUCTION

Coal is the world's most abundant and widely distributed fossil fuel. It is a global industry that makes a significant economic contribution to the global economy. Coal is mined commercially in more than 50 countries and used in more than 70. Annual world coal consumption is about 5,800 million tons, of which about 75% is used for electricity production. This consumption is projected to nearly double by the year 2030 to meet the challenge of sustainable development and a growing demand for energy.

India is the third-largest producer and shopper of coal within the world. Coal finds wide usage in several industries. Thermal plants are the foremost users of coal. Coal is a very advanced material and exhibits a large variety of physical properties and chemical 2 properties. The quickly increasing use of kind of coal at this time created it necessary to plan an acceptable technique for coal analysis. Hence, the empirical formulae primarily based on incorrect estimations cause variation within the combustion behavior and thereby resulting in the performance of the boilers. To realize higher maintenance on the boilers and thereby to achieve better performance, the correct computation of elemental composition is needed. During this research, a technique devises to calculate ultimate analysis supported the proximate analysis information using an Artificial Neural Network model (ANN).

Around 40 lab analysis data-points on coal for which proximate information is available had been used to Multivariable regression model and ANN model. The composition of proximate analysis is represented by Ash (per cent), Fixed Carbon (per cent), Moisture (per cent) and Volatile Matter (per cent). Based on the collected data set in the following sections, the model architecture of the developed ANN model and the results obtained are discussed briefly. The basic need of the proposed model is to predict the elemental composition of overall composition information of the proximate analysis.

In the present study, a model is developed by multivariable simple regression. 40 samples of the study area are used for model development and validation or checking purpose information samples. Straight forward simple regression conjointly won't to analyze the individual result of wetness, ash, volatile matter and stuck carbon on the Calorific value of coal. The neural network may be a new mathematical technique introduced and wide employed in analysis areas of business processes.

Importance and objectives of the study

The present study provides a brief introduction to the forecasting of coal analysis series using previous methods. Besides, the role of neural networks in the coal analysis is discussed along with their advantages over previous methods. It explains various designs and preparing the experiment to be conducted. Output on empirical analysis and correlation between every event is examined by the Regression. Designing the experiments and performing statistical analysis for finding significant factors and the results in a graphical way of exhibits the correlation exactly. Upgradation of the analysis, methods take place smoothly and accurately.

1. Assessment of different parameters that affect the calorific value of coal.
2. Determination of intrinsic properties of the coal samples using proximate analysis and bomb calorimetry.
3. Prediction of gross calorific value of coal by proximate analysis data using multivariable linear regression.
4. Develop the artificial neural network model for prediction of gross calorific value and comparison of multivariable regression and artificial neural network models.

2. LITERATURE STUDIES

Yerel et al. (2013) studied the coal quality parameters such as ash content, calorific value and moisture content, 79 borehole samples were collected from western turkey. In their study, they predicted calorific values using linear regression analysis using both simple linear regression and multiple linear regression analysis and models developed for predictions. Linear regression was applied to determine the relationship between dependent variable calorific value and ash content, moisture as independent variables. The aim of regression analysis was to determine the values of parameters for a function that causes the function to best fit a set of data observations provided and it was conclude that calorific values can estimate using a multiple linear regression model.

Swarupa (2013) has identified certain management activities and provided stakeholders with information regarding the practices that will result in their plant performance enhancement using regression analysis technique. In this they specified that the objectives of the organization can be measured as effectiveness, so it becomes important to identify factors that influences in getting the desired income and their influence on the economic performance of the organization.

Upadhyay (2014) investigated the physical and chemical properties of coal in Korba district for assessment of coal quality, in order to check it's suitability for thermal power station, by collecting samples from Gerva coal mines. Three different coal samples were collected from different areas of Gerva coal mines and analyzed for ultimate, proximate and calorific value as per standard methods and From overall analysis and according to useful heat value (UHV) of coal samples, they were concluded that the grade of Gerva coal was "F" and very useful for coal based thermal power station.

3. METHODOLOGY AND ANALYSIS

3.1 Artificial Neural Network (ANN)

ANN empirical modeling tool, Galvanized by the behavior of biological neural structures. ANN builds the process of the behavior changes of different objective goods and components. The occurrence of the substance means while done by the selection of outputs and inputs. Neural networks are powerful tools that have skills to spot underlying extremely advanced relationships and connections from input-output information. The artificial neural network model developed using mistreatment 50 samples and 15 samples used for validation.

Artificial Intelligence tools have been in use for years in a good deal of mining-related applications. Expert and knowledge-based nature of systems, probably the most popular AI tools, have found their way into several computer-based sources of applications supporting everyday mining operations as well as the production scale of mining equipment. In recent years, AI has provided tools for optimizing operations and equipment selection, problems involving large amounts of information that humans cannot easily cope with the process of decision-making. These AI systems together with an ever-increasing number of sophisticated purpose-built computer software packages have created a very favorable environment for the introduction of yet another powerful AI tool, Artificial Neural Networks.

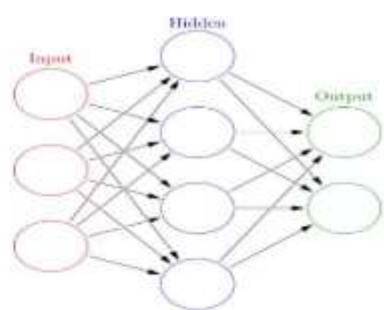

Fig 1: Schematic diagram of Artificial Neural Network

3.2 Multivariable Regression Analysis

Multivariable regression is an extension of simple linear regression. It is used to predict the value of a variable based on the value of two or more other variables. The predict variable is called the dependent variable

The linear regression (Y') is Y' = a + b X

Where,

Y' = A predicted value of Y (which is a dependent variable)

a = the value of Y when X is equal to zero. This is also called the "Y Intercept".

b = the change in Y for each 1 increment change in X

X = an X score (X is Independent Variable) for which you are trying to predict a value of Y.

The Multiple Regression (Y') is

Y' = a +b1X1 + b2X2

Y' = A predicted value of Y (which is your dependent variable)

a = "Y Intercept".

b1 = Change in Y for each 1 increment change in X1

b2 = Change in Y for each increment change in X2

X1 = an X score on your first independent variable for which you are trying to predict the value of Y

X2 = an X score on your second independent variable for which you are trying to predict a value of Y

In order to find the correlation between multiple linear regression value for the different variables the Independent and dependent variables. The nature of the equation shows the behavior of the variables either positive or negative action.

$$GCV=7787.75 - 197.44M - 77.986A + 12.45FC$$

Here these equations of the multivariable regression or multiple linear regression obtain by the 40 Samples are acts different way. This equation uses to predict the values form random 10 samples selected from the 40 samples the coordinate plot is laid.

4. RESULTS AND ANALYSIS

4.1 Relationship between Moisture, Ash Content, Volatile Matter and Fixed Carbon and Experimental GCV

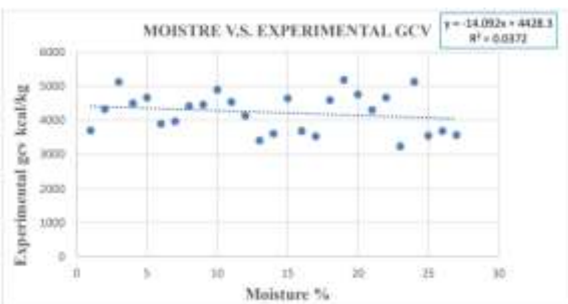

Fig 2: Relationship between Moisture and GCV by Experiment

R^2 value of 0.0372 in Fig 4.1 impels the effect of moisture on the GCV of study area. The regression value of the plot explains that the moisture has negative effects on the GCV. It shows the influence of moisture is more in the coal sample collected. Hence the moisture content should be managed for the further process.

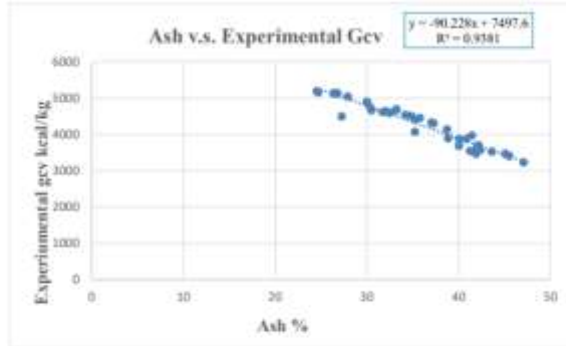

Fig 3: Relationship between Ash and GCV by Experiment

R^2 value of 0.9381 in Fig 4.2 impels the effect of ash content on GCV. The regression value of the plot explains that the ash has negative effects on the GCV. It shows the influence of is more in the coal sample collected. Hence the moisture content should be managed for the further process.

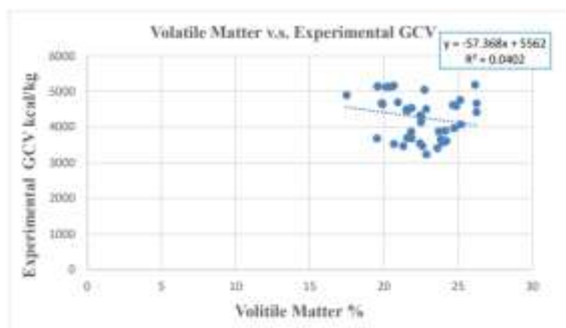

Fig 4: Relationship between Volatile matter and GCV by Experiment

R^2 value of 0.0402 in Fig 4.3 impels the effect of volatile matter on GCV. The regression value of the plot explains that the volatile matter has positive effects on the GCV. It shows the influence of is more in the coal sample collected. Hence the volatile matter should be managed for the further process.

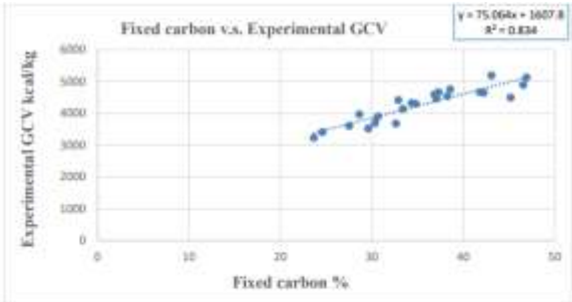

Fig 5: Relationship between Fixed carbon and GCV by Experiment

R^2 value of 0.834 in Fig 4.4 impels the effect of Fixed carbon on GCV. The regression value of the plot explains that the fixed carbon has positive effects on the GCV. It shows the influence of is more in the coal sample collected. Hence the Fixed carbon should be managed for the further process.

4.2 Relationship between Experimental GCV and Predicted CIMFR GCV

Central Institute of Mining and Fuel Research (CIMFR) developed following formulae to determine GCV based on moisture %. The equilibrium moisture and equilibrium ash is considered for the predicting CIMFR GCV

- For low moisture coals, M<=2% CGV =91.71F+75.6(V-0.2A) - 60 M
- For high moisture coals, M>=2% CGV = 85.6(100– (1.1 A+M)) –60M

Where: M, V, A, F denote Moisture %, Volatile Matter %, Ash % and Fixed Carbon%, on present air-dried basis,

Values comparison between Experimental GCV and Predicted GCV by Formula proposed by CIMFR Formula

Sample no	Experimental GCV in Kcal/kg	CIMFR GCV(Kcal/Kg)	Difference
1	4669	4660	69
2	4900	5002	-102
3	4645	4576	69
4	4760	4555	205
5	3550	3486	64
6	4074	4026	48
7	3650	3777	-127
8	5145	5292	-147
9	3700	3733	-33
10	5136	5178	-42

4.3 Relationship between Multi variable Regressions with the parameter of GCV Experimental GCV

From the study of the correlation between M, A, VM, FC and GCV, where the extraction of values be -197.44, -77.986, 0, 12.45, 7787.75 respectively makes the regression value as

GCV=7787.75-197.44M-77.986A+12.45FC

From the following above formation of the different variable equation, the valuable information obtains that the volatile matter, fixed carbon are the high digit value and moisture and ash are the low digit value, which explains the phenomenon that they are the rank parameters

4.4 Values comparison between Experimental GCV and Predicted GCV by multiple regression method

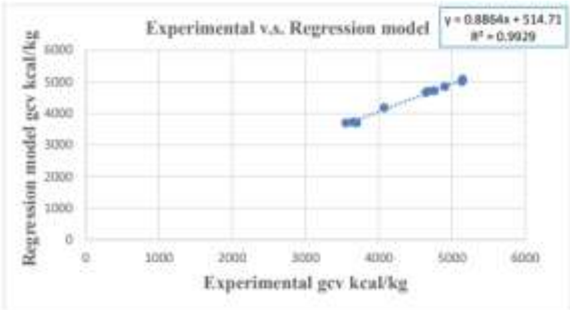

Fig 6: Coordinate points between GCV by Experiment and GCV by Regression

From the figure, R^2 value of 0.9929 impels the comparison study between Experimental GCV and GCV of Regression. The regression value of the particular plot explains the calorific value of the experimental and calorific value of the multivariable regression. Hence the regression value is more the coordination between the above two events is close to each other

4.6 Comparison relationship between Experimental GCV and Predicted GCV of Artificial Neural Network Analysis

The relation between Experimental GCV and Predicted GCV of Artificial Neural Network

Fig 7: Coordinate points between GCV by Experiment and GCV by ANN Model

From the figure, R^2 value of 0.9936 impels the comparison study between Experimental GCV and GCV of ANN Analysis. The regression value of the particular plot explains the calorific value of the experimental and calorific value of the Artificial Neural Network GCV. Hence the regression value is more the coordination between the above two events is close to each other.

4.7 Relationship between predicted GCV with multivariable regression analysis and Predicted GCV with Artificial Neural Network Analysis

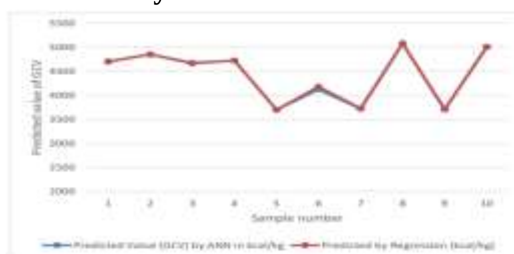

Fig 8: Relationship between predicted GCV with Multivariable regression analysis and Neural Network Analysis

4.8 Relationship between GCV of Experimental, GCV of CIMFR, GCV with multivariable regression analysis and Predicted GCV with Artificial Neural Network Analysis

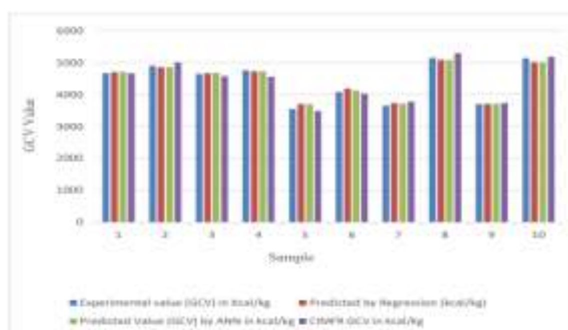

Fig 9: Comparison of GCV determined by different methods

5. CONCLUSIONS

Results from the Regression and ANN analysis is shows that difference between experimental and predicted is less and those models can use for prediction of GCV. Any industry where coal is utilized for heating applications, determinations of calorific value, proximate analysis and ultimate analysis are common practice to assess the quality of coals In India, due to non-availability of consistent power supply and higher industrial tariffs many industries are opting for coal-fired captive power plants. The multiple regression model is seen as the best model. The determination R2 of the multiple regression model is 97.71%. This value is good and identifies the valid model.

This result reveals the usefulness of a multiple linear regression model in the prediction of calorific value. These models are decision makers that examine coal deposit parameters, such as calorific value, ash content, and moisture content, in order to manage the coal deposit. By this study it was conclude that predicted GCV by Artificial Neural Network had very less difference with GCV determined by experiment. GCV predicted by ANN model also have less difference with experimental determined GCV compare to GCV predicted by other methods include regression model and CIMFR formulae. It was also found that GCV predicted by regression model have less difference with experimental determined GCV compare to GCV predicted by CIMFR formulae.

This research study has been conducted and following conclusions are drawn:

i. The moisture (%), ash (%), volatile matter (%) and fixed carbon (%) parameters affect the Gross Calorific Value (GCV). Fixed carbon and Ash have more content in coal sample of the study area than the moisture and volatile matter.
ii. Analysis of regression coefficient reveals that ash% and fixed carbon % have strong correlation with GCV.
iii. The equilibrium GCV calculated from the Bomb calorimeter i.e. experimental GCV have strong correlation with calculated CIMFR formulae.
iv. Predicted GCV from the multiple regression method and Artificial Neural Network (ANN) have sound correlation with the experimental GCV.

Hence, the both models are useful for analysis the quality of coal and helps in assessment of coal quality to run the boilers with efficiency.

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