Hardgrove Grindability Index Estimation Using Neural Networks

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ABSTRACT

In a previous study, different techniques for the estimation of coal HGI values were investigated (Özbayoğlu et.al, 2008). As continuation of that research, in this study a revised neural network methodology is used for estimating the HGI values using the same data from 163 sub-bituminous coals from Turkey. The parameter set used for estimating HGI consisted of moisture, ash, volatile matter and Rmax ratios. These 4 coal parameters were fed into different neural network topologies. The network parameters were optimized by genetic algorithms. The test results indicate that estimation rate was improved %10-15 over the previous results (Özbayoğlu et.al, 2008) by using this new parameter set and optimized neural network configurations.

1. INTRODUCTION

Coal is geologically metamorphosed sedimentary rock containing a mixture of constituents which can be classified as mineral matter and carbonaceous material. Coal contains a wide range of minerals in which quartz and pyrite are harder and other mineral matters such as clays, carbonates, sulphates, phosphates are much softer. Carbonaceous constituents of coal are the coalified remains of plant tissues which can be characterized by petrographic analysis. The proportion of these petrographic constituents correlate some of the properties of coal that are of major industrial significance. Coal is composed of chemically C,H,O,N and S . Proximate and ultimate analyses determine the chemical properties of coals.

The heterogenous nature of coal which is dependent upon the source of the original material, the geological history and the contiguous materials affects the comminution behaviour. In order to characterize this behaviour, the amount of breakage under standardized conditions is measured which is expressed as a "grindability". Grindability is a loose term meaning the ease with which the coal can be comminuted by mechanical action. Hardgrove test is the most widely used standard grindability tests for coal. A high value of Hardgrove Grindability Index (HGI) indicates a coal which will grind easily. The reproducibility of the standard grindability test is considered by ASTM as being 2 and 3 HGI units. It has been reported that for certain coals, the reproducibility has exceeded 5 units (Sengupta, 2002).

The grindability of coal is an important practical and economic property to coal handling and utilization aspects, particularly for pulverized coal fired utilities. Enormous quantities of coal are presently ground to produce power plant feed.The energy required to grind a standard bituminous steam coal to pulverized fuel burner in a 15 tph high speed(suction) mill is 19.5 kW/ton of coal milled (Anon, 2008). In general, coal grindability characteristics reflect the coal hardness, tenacity, and fracture which are influenced by coal rank, chemical and petrographic composition and the distribution and the types of minerals (EUB-AGS, 2005)(Mitchell, 2005).

The use of low-rank coals as pulverized fuel has increased rapidly, however low rank coals are difficult to grind than high rank coals (Encyclopedia Britannica, 2005). Changes in inherent moisture content cause the most variation in the HGI, particularly for lower rank coals (Conroy and Sligar, 1991). In general, lignite and anthracite are more resistant to grinding than are bituminous coals (Hower and Wild, 1988). Coals that are easiest to grind are found in the medium-volatile and low volatile groups (Leonard and Mitchell, 1968). This moisture range coincides with the lowest HGI value.

Although the Hardgrove machine is not costly, it is not a routine testing item in coal fired power plants. So, a mathematical method to predict the HGI can be helpful for coal-fired power plants where facility of HGI determination is not available. According to the China National Standard for testing of HGI, a maximum error less than 5 is acceptable for the testing of HGI in different laboratories (Li et.al, 2005).

Many different methodologies were implemented to predict HGI. Neural network has been used in the present study to predict the HGI of Turkish coals by considering not only the proximate analysis, but also group maceral analysis, mineral matter content and the rank of the coal (R_{max}). As suggested by Hower (Hower, 2006), a narrow rank and age of coals have been chosen for a correlation between grindability and these parameters. A new method using neural networks for predicting the HGI for Tersier age Turkish sub-bituminous coals is proposed in this study.

2. NEURAL NETWORKS

Neural Networks can create input-output relationships that can successfully predict the output from the given input. Neural networks are particularly useful in cases where mathematical or statistical methods, such as linear, nonlinear regression, curve fitting, etc. can not provide a satisfactory solution. In some cases, the solution might be too general; in other cases it might be too specific such that the model can not react well to new data points. A successful model must have good generalization capabilities and at the same time be able to successfully react to new unknown data points. In other words, it should not memorize the training set, just understand it, so that it can apply the corresponding relationship to the test or production data.

Neural networks are consisted of interconnected neurons that might have several input, hidden, output layers working sequentially and parallel (Haykin, 1999). When an input pattern is introduced to the neural network, the synaptic weights between the neurons are stimulated and these signals propagate through layers and an output pattern is formed. Depending on how close the formed output pattern is to the expected output pattern, the weights between the layers and the neurons are modified in such a way that next time the same input pattern is introduced, the neural network will provide an output pattern that will be closer to the expected response.

Even though the basic underlying structure is similar, there are several different types of neural networks using different topologies such as Backpropagation (Rumelhart et.al, 1986) neural networks (sometimes referred as Multilayer perceptron), Self Organizing Maps (SOM) (Kohonen et.al., 1990), Radial Basis Function (RBF) networks (Poggio and Girosi, 1990), etc. However there are no specific guiding rules to indicate when one network would perform better than the others.

3. MATERIALS AND METHODS

The data set for the estimation of the HGI consisted of 163 Tersier age Turkish sub-bituminous coals obtained from various districts in Turkey (Tuncalı, et.al., 2002). The input parameters used for the system are Moisture, Ash, Volatile Matter and R_{max} respectively. The only output parameter is the estimated HGI. The characteristics of the coal samples are summarized in Table 1.

ANALYSIS	MIN (%)	MAX (%)
Moisture	0.66	15.37
Ash	5.88	58.38
Volatile Matter	21.65	46.66
R_{max}	0.312	0.782
HGI	21.0	88.0

Table 1 Chemical and petrographic analyses of Turkish Tersier age sub-bituminous coals

The data set was divided into 3 sections. 99 data points were used for training the neural network, 32 data points was used for cross validating the network and 32 data points were used for testing, each picked randomly by the neural network software. Five different neural networks types (Backpropagation, Jordan/Elman (JE) (Jordan, 1986)(Elman, 1990), SOM, RBF and a hybrid network that consisted of the average of outputs from BP, JE and SOM) were trained and tested using the same data sets in each of them. The activation function used in the neurons were chosen as hyperbolic tangent, also momentum term is used in the learning algorithm.

During training, the network parameters such as number of hidden neurons, momentum rate, etc. were optimized using a genetic algorithm. Optimization were based on choosing the best parameter values providing the lowest MSE in the cross validation set. After the network was optimized, the test set was introduced to the network and the results were analyzed.

4. RESULTS AND DISCUSSIONS

The HGI estimation results obtained in the previous study (Özbayoğlu et.al, 2008) and current study using the test data points were tabulated in Table 2. Even though the number of inputs were reduced from 11 to 4, the results obtained during the tests were slightly better than the previous study. In the previous experiments the lowest average error for HGI prediction was 4.74 and it was obtained from a hybrid network configuration. In this study the SOM network was able to map the input output relation better than any previous or current model such that the average error was 4.50, so a 5% improvement over the previous study was achieved in average HGI prediction error. At the same time all networks tested in this study were able have average HGI estimation within the ±5 HGI range.

Model	**Previous Study Avg Error**	**Current Study Avg Error**	**Previous Study Std Dev Error**	**Current Study Std Dev Error**
BP	5.04	4.98	4.02	3.26
JE	4.94	4.65	3.78	3.26
RBF	4.96	4.87	3.61	3.52
SOM	5.30	4.50	3.92	3.01
Hybrid	4.74	4.61	3.50	2.91

Table 2 HGI Estimation comparison of results in the previous study and current study

The improvement compared to previous study was not only on the average HGI estimation error, but also in the percentages of deviation from target values for HGI predictions. In the previous study, the best results were obtained from the Backpropagation network where %60.12 of the HGI predictions were within the ±5 range, whereas in the current study the hybrid network had %68.75 of the HGI predictions within the ±5 range. This resulted in a %14 improvement over the previous study. The HGI estimation deviations for different range values were shown in Table 3.

HGI deviation from target	BP Network (%)	RBF Network (%)	Jordan Elman Net (%)	SOM Network (%)	Hybrid Network (%)
Less than 1	9.38	12.50	9.38	12.50	9.38
Less than 2	18.75	21.88	21.88	25.00	18.75
Less than 3	28.13	43.75	34.38	37.50	34.38
Less than 4	40.63	46.88	50.00	50.00	34.38
Less than 5	59.38	56.25	65.63	53.13	68.75
Less than 6	71.88	65.63	71.88	68.75	78.13
Less than 7	71.88	71.88	84.38	81.25	78.13
Less than 8	84.38	75.00	87.50	84.38	87.50
Less than 9	87.50	84.38	90.63	90.63	87.50
Less than 10	90.63	84.38	90.63	96.88	90.63
More than 10	9.38	15.63	9.38	3.13	9.38

Table 3 HGI estimation deviation from target for various models

From the results, it was observed that using only 4 input parameters (moisture, ash, volatile matter and Rmax ratios) instead of the 11 input parameters used in the previous study, the model was able to perform a slightly better prediction.

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