Prediction of Iron Ore Pellet Strength Using Artificial Neural Network Model

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(Received on August 21, 2006; accepted on October 13, 2006)

Cold Compression Strength (CCS) is an important property of iron ore pellets that are used for the production of DRI from shaft furnace or for use in blast furnace. CCS is one of the control parameters during the pellet production and it is supposed to be closely monitored to control the process. In order to develop control-strategy, an Artificial Neural Network model has been developed to predict CCS of pellets in straight grate indurating machine from 12 input variables viz. feed rate of green pellets, bed height, burn through temperature, firing temperature, specific fuel gas consumption; bentonite, moisture and carbon content in green pellets; Al₂O₃, MgO, basicity and FeO in fired pellets. CCS was found to be more sensitive to variation in Bentonite, basicity, FeO and Green pellet moisture. Generalized Feed Forward neural network with back propagation error correction technique was successfully used to predict the CCS. The predicted results were in good agreement with the actual data with less than 3% error.

KEY WORDS: neural network; CCS; pelletization; induration; green pellet; burn through temperature; basicity; bentonite; pellet quality.

1. Introduction

Blast furnace or shaft furnace needs burden that form a permeable bed of material, permitting gas to flow through it uniformly at a high rate. Powdered iron ore concentrates are not suitable in their as-produced form because they tend to pack into voids, permeable areas and responsible to make bed non-permeable. These fine particles are also likely to be carried away as dust by the high gas flow rates. The powdered ore must therefore be agglomerated into larger particles that will improve permeability of the furnace burden, increase the rate of reduction, and reduce the amount of material blown out of the furnace as dust. The most common agglomeration technique is pelletization, which requires preparation of green balls from powders and heat hardening them at higher temperatures to get the required properties. Compressive strength is regarded as one of the principal criteria parameter of suitability to assess the pellet for metallurgical processing in blast furnaces. Pellets with low strength can not withstand load of the burden in the blast furnace. As a result, generation of fines increases, which lowers the permeability of the burden. The higher the CCS the better is the pellet behavior in the furnace. Improving the CCS of pellets decreases the fines and dust generation during their reduction, this in turn helps in increasing the productivity of the iron-making unit.

There have been many attempts made to model the pelletization process to predict the quality parameters. The complexity of heat and mass transfer processes coupled with large number of gas–solid, solid–solid reactions and the combustion processes makes the modeling an extremely difficult task. Batterham (1986) explained certain formalisms to predict the strength using shrinking models and thereby deriving shrinkage to strength relationship. Given the range and complexity of mechanisms of the strength development, no single cogent theory is available to numerically describe the development of strength. The available models could not directly bring out the effect of many critical operational parameters on the quality of pellets. For modeling such complex systems, neural network is an attractive technique. Neural networks have the ability to capture non-linear and highly complex relationships between the inputs and outputs of the process. They are computationally efficient and no prior domain knowledge required for the process to be modeled. There have been several successful attempts at modeling metallurgical systems using neural networks. In the present work a prediction model based on artificial neural network has been developed and trained relating CCS with a set of twelve process variables to predict the CCS of pellets. Large amount of data for training and testing the network was collected from a 4.2 Mtpa capacity Pellet Plant running at JSW Steel. Sensitivity analysis was also carried out to identify the critical input parameters that affect the CCS to a large extent.

2. Pelletization Process

Production of iron oxide pellets from iron ore fines involves different operations like drying of ore fines to remove the moisture and grinding to get the required fine-
ness. After mixing these ground ore fines along with other additives like bentonite, limestone, Corex sludge and iron ore slurry, green pellets are prepared using pelletizing disc. These green pellets are fired in an indurating machine to get the required physical, mechanical and metallurgical properties making them suitable feed for iron making units.

The operation and control of pellet indurating machine poses a great challenge because of the difficult measurement and control problems associated with the unit. The induration process consists of three main steps; 1) Drying for green pellets 2) Firing of pellets at 1250–1300°C to sinter the iron oxide particles 3) Cooling of hot pellets before discharging them on to the conveyors leading to the stockpiles. Pellets are transported through the furnace by a traveling grate, which retains the pellets while allowing the air to flow through it. The traveling grate is loaded with approximately 0.05 m height of fired pellets as hearth layer to protect the grate and then 0.50 m of green pellets.

Figure 1 shows a simplified flow sheet of indurating machine. The indurating machine consists of seven different zones, viz., up-draft drying (UDD), down-draft drying (DDD), preheating (PH), firing (FZ), after-firing (AFZ), primary cooling (CZ1) and secondary cooling zone (CZ2). Five interconnected process fans are provided to circulate air throughout the different zones of indurating machine.

Fired pellets show an FeO content of less than 1%, cold compressive strength (CCS) of around 200–250 kg/pellet, tumbler index (TI) 90–95%, abrasion index (AI) ~5%, reduction degradation index, RDI (~6.3 mm) less than 15% and RDI (~0.5 mm) less than 5%. Among these quality properties, CCS plays an important role during the iron making process. Quality of pellets depends on many input parameters like chemistry and granulometry of ore fines (Al₂O₃, SiO₂), amount of flux and binder additions (CaO, MgO and Bentonite), green pellet carbon and moisture contents, firing conditions (firing and burn-through temperatures) and other process parameters (feed rate, bed height and specific fuel gas consumption).

3. Network Architecture and Learning Mechanism

3.1. Neural Network Architecture

Neuron model has been developed for understanding the governing parameters, which mainly affect the strength of pellets. A generalized feed forward back propagation technique has been adopted to train the network. Efforts have been made to improve the training by adjusting variables like number of neurons in hidden layer, transfer function or activation function; number of epoch, learning rate and momentum factor. The three layers structure, 12-12-1 used in the present modeling has shown in Fig. 2. The number of input neurons is taken to be same as the number of input variables and the neuron in output layer represents CCS. The hidden layer consists of twelve neurons for input-output mapping.

3.2. Learning Mechanism

Initially training is done with two-third of the total input-output data. While training, weight of the interconnection between neurons keep on adjusting till mean square error of training minimizes. Once network is trained properly then the best weight generated is used for testing purpose. The mechanism of the network is explained below:

Input to the neurons in hidden layer and output layer is the sum of product of all input neurons and the weight of the interconnecting neurons:

$$I_i = \sum_j I_j W_{ji} + b_i$$

Where,

- $i$: ith neuron in k layer ($k=2, 3$), $i=12, 1$ for $k=2, 3$
- $j$: jth neuron in k-1 layer, $j=12$ for input and hidden layer
- $W_{ji}$: weight of interconnects between jth neuron in k-1 layer and ith neuron in k layer
- $I_j$: input of jth neuron in k-1 layer
- $I_i$: input sum of the jth neuron in the layer $k$ ($k=2, 3$)
- $b_i$: bias term of ith neuron in k layer

In the present work hyperbolic tangent function has been used.
used for transferring the signals from the neighboring neuron to the succeeding neurons. Hyperbolic tangent function used is:

\[ O_i = \frac{e^l - e^{-l}}{e^l + e^{-l}} \quad \text{..........................(2)} \]

\( O_i \): output of \( i \)th neuron in layer \( k \) (\( k=2,3 \))

Initially, input to the system is \( I \), i.e., \( I_1, I_2, I_3, \ldots, I_{12} \) is known

Therefore, using the weights and bias of the neurons in hidden and output layer, signals transferred by each neuron to the proceeding neuron can be estimated by:

\[ I_{13} = I_1W_{1-13} + I_2W_{2-13} + \ldots + I_{12}W_{12-13} + b_1 \quad \text{...............(3)} \]

Thus using transfer function output of the hidden layer \( O_{13}, O_{15}, O_{16}, \ldots, O_{24} \) can act as an input to the output layer \( I_{13}, I_{15}, I_{16}, \ldots, I_{24} \).

Total input to the neuron in output layer can be given by:

\[ I_{25} = I_{13}W_{13-25} + I_{14}W_{14-25} + \ldots + I_{24}W_{24-25} + b_2 \quad \text{...............(4)} \]

Again using transfer function, \( I_{25} \) can be converted to \( O_{25} \).

In the back propagation method, least square error \( (E_k) \) is given by [6]:

\[ E_k = \frac{1}{2} \sum (t_i - O_{ik})^2 \quad \text{...............(5)} \]

\( k \): \( k \)th layer
\( O_{ik} \): estimated output of the \( k \)th layer
\( t_i \): targetted output of the \( i \)th layer

Before training starts, all the weights are randomized. In the learning mode, the network generates weights while training and generates output. Then, its output is compared with the target output of all the neurons of the output layer, and if there is any discrepancy, the error is back propagated by changing the interconnect weights after \((n+1)\)th iteration.6,7

4. Training and Evaluation of Network

Based on the preliminary regression analysis and on the operational experience, the variables chosen for the analysis are given in Table 1. For modeling purpose, 370 d operational data were collected from the pellet plant. After preprocessing the data to eliminate the noise and considering stable plant operating data, 200 data sets were finalized for training and testing the neural network. The data were split into 70\% for training and 30\% for testing.

4.1. Network Results for CCS, kg/Pellet

The network was trained till the minimum Mean Square Error (MSE) is achieved. Training the network for 1 000 iterations resulted in the regression coefficient \( (R^2) \) of 0.85 and Normalized Mean Square Error (NMSE) of 0.19. During testing, \( R^2 \) and NMSE obtained were 0.75 and 0.28 respectively. Actual and predicted network outputs during training and testing are shown in Fig. 3. The initial training set is used for learning the initial weights of the model. The test set is used to validate the performance of the model. Mean Absolute Error (MAE) during training is 3.57 that
gives an error of 1.69% in predicting the CCS. During testing MAE is 5.37 resulting in 2.51% error in prediction.

4.2 Effect of Input Variables on CCS

Sensitivity analysis of all inputs was carried out to understand their effect on CCS. For performing the sensitivity analysis one variable at a time was held constant at its mean value. Effect of input variables, as observed from the sensitivity analysis trends, on CCS of the pellets is one of the most vital information obtained from this neural network analysis. Results of sensitivity analysis are shown in Fig. 4.

Pellet strength found to be increasing with increasing bentonite dosage. This can be attributed to the formation of low melting alkali silicate melt at high temperature. The melt phase between the particles exerts pressure to pull them together due to interfacial forces there by increasing bonding strength.8) Increase in pellet basicity also shows major impact on CCS. This could be attributed to the fact that higher CaO results in the formation of stronger calcium ferrite phase through the reaction between calcium oxide and iron oxide.9) High FeO in fired pellets adversely affects pellet CCS. Higher amounts of FeO (or Fe3O4) are the indication of poor oxidation during induration of pellets. This leads to the duplex structure in pellet with unoxidised core surrounded with hematite shell. Micrograph of poorly oxidized pellet with duplex structure is shown in Fig. 5. Core and inner mantle shows high amounts of magnetite whereas shell and outer mantle shows high hematite content and traces of magnetite. Load bearing capacity of this duplex structure is low, resulting in low pellet strength.10) Increased green pellet moisture also found to be reducing the pellet strength. Higher moisture creates cracks and discontinuities during the drying of green pellets. With increasing moisture, pellet is supposed to be less compact and more porous resulting in low strength.11) High firing temperature improved the pellet strength. It is because of the surface fusion that creates solid bonds between the particles. The cross section of these bonds (neck between two adjacent particles) increases with increase in temperature, which in turn improves the strength.12)

Higher feed rates found to decrease the pellet strength. At high feed rate pelletizing grate moves at faster speed re-
ducing the residence time of pellets in high temperature sintering region resulting in low strength. Low strength at higher bed height can be attributed to the fact that a temperature gradient exists across the height of pellet bed. More the bed height, lower the temperature in the bottom layers of the bed leading to poor strength. High specific gas consumption is a result of low burn-through temperature, which in turn is an indication of low firing in the pellet bed. Low burn-through temperature can be attributed to poor bed permeability resulting in low strength. Increasing green pellet carbon content found to be reducing the pellet strength. It could be attributed to increased FeO content, especially in the inner layers of fired pellet resulting in duplex structure leading to lower strength. High alumina found to be decreasing the pellet strength. It was reported by Loo (2003) that increasing the alumina decreases the melt fluidity, which reduces the ability of bubbles to coalesce and reshape. Increased alumina resulted in branch-like irregular

5. Conclusions

In order to predict the cold compression strength of pellets, neural network model can be used as an effective tool with wide range of industrial data available for training. A generalized-feed-forward neural network with back propagation error correction technique made up of one hidden layer with 12 processing elements was successfully used to predict the CCS of pellets from 12 input variables. There is a good agreement between the predicted and experimental CCS values with less than 3% standard error. The following conclusions were drawn from the sensitivity analysis of the input variables;
High bentonite dosage, high basicity and high firing temperature increases the cold compression strength of pellets.

Higher FeO content in fired pellets drastically reduces the pellet strength.

Green pellet moisture should be closely controlled as excess moisture results in low CCS.

Higher bed height, high feed rate, excess green pellet carbon content, high specific gas consumption and higher alumina levels reduces the pellet strength.

Acknowledgement
Authors wish to thank the management of JSW Steel for permitting to use necessary data in this publication. Their thanks are due to, Mr. D. L. Saralaya, Mr. M. Prabhu, Dr. Madhu Ranjan and Dr. U S Yadav for sharing the necessary technical information. Authors are thankful to Dr. Dewashish Bhattacharjee (Chief R&D and SS, Tata Steel) for his encouragement, support and permission to publish this paper.

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