ADAPTIVE NEURO FUZZY MODEL FOR PREDICTING THE COLD COMPRESSIVE STRENGTH OF IRON ORE PELLET

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ABSTRACT

Cold Compressive strength is considered as one of the important parameter of fitness to assess the pellet for metallurgical processing in blast furnace or DRI. During the pellet production Cold Compressive strength should be monitored to control the process. For this an adaptive neural fuzzy inference system (ANFIS) was modelled in this paper using MATLAB® toolbox to predict the cold compressive strength of the iron ore pellet. Pellet size, Bentonite and green pellet moisture was taken as input variables and cold compressive strength as output variable. Various architectures of ANFIS were tested to obtain a model having lowest Mean Relative Percentage error (MRPE). It was found that MRPE of 1.1802% was obtained with 3 membership function for each input and the type of membership function used was triangular with output to be constant. The training was done using hybrid algorithm (mixed least squares and back propagation). The simulated values obtained from the ANFIS model was found close to the actual values, thus the model can act as a guide for the operator and thereby helps to attain the desired objective in iron ore pellet process.

KEYWORDS: *Adaptive neural fuzzy inference system, pelletization, Cold compressive strength*

I. INTRODUCTION

It was found that pellets having low compressive strength cannot sustain the load of burden in blast furnace. Due to which, the fine generation increases and reducing the permeability of the burden. Pellets with higher CCS are desirable for blast furnace in order to reduce dust (fine) generation and increase the productivity of steel unit. Thus during the pellet production Cold Compressive Strength is supposed to be closely monitored, to control the process. Simulation of a system, modelling and prediction of the output can be done with the help of ANFIS in which neural network and fuzzy logic has an important place. Thus ANFIS can be implemented to make models used for the prediction of cold compressive strength of iron ore pellet. ANFIS provides a methodology to imitate human expert and allow the use of information and data from expert knowledge. ANFIS also provides a simpler mechanism in developing the model which allows decision making process easier. It has been used in various applications like prediction of material property [11], predicting water level in reservoir [12], demand forecasting [13] etc. It can also be used for control process like controlling the robot manipulator [14], in trajectory estimation and control of vehicle [15] etc. Pelletizing is a process used for agglomeration of the raw iron-ore fines, which consist of two steps: balling of powdered fine using rotating disk/drum and induration (thermal hardening) of green pellet on a moving straight grate .Input parameters like percentage bentonite by weight, Blaine number and green pellet moisture content directly affect the CCS of iron ore pellet. Attempts have been made by the researchers to make models to predict the quality parameters of iron ore pellet. Sushanta Majumdera et al [1] made a Virtual indurator which acted as a tool for simulation of induration of wet iron ore pellets on a moving grate. Srinivas Dwarapudi et al [2] has presented the artificial neural network model for predicting the

Strength of iron ore pellet in straight grate indurating machine from 12 input variables. The model was compared with the regression model and it was found that feed Forward back propagation error correction technique predicted the CCS of iron ore with a result less than 3% error. Jun-xiao Feng et al [3] has made a mathematical model of drying and preheating processes and also studied the effects of pellet diameter, moisture, grate velocity, and inlet gas temperature on the pellet bed temperature. S.K. Sadrnezhaad et al [4] have made a mathematical model for the induration process of the iron-ore pellet based on the laws of heat, mass and momentum transfer. In the present work computerised Adaptive neural fuzzy inference system models have been created so as to predict the CCS of pellet. Kishalay Mitra[16] has done multi objective optimization of an industrial straight grate iron ore induration process using an evolutionary algorithm. Maximization of pellet quality indices like cold compression strength (CCS) and Tumbler index (TI) is adopted for this purpose, which leads to an improved optimal control of the induration process as compared to the conventional practice of controlling the process based on burn-through point (BTP) temperature.

This paper is organized into five sections. The next section describes the pelletization process in brief and formulates the problem related to it. The section also deals with the selection of process parameter. Basics of ANFIS and prediction of Cold compressive Strength using the ANFIS model is explained in section 3. Results obtained from the ANFIS model is shown and discussed in the 4th section. Section 5 gives the concluding remark.

II. PELLETIZATION PROCESS

Production of pellets from iron ore fines involves various operations like drying and grinding of iron ore to required fineness. Green pellets are prepared in pelletizing disc by mixing the ore fines with additives like bentonite, limestone, corex sludge and iron ore slurry. These green pellets containing moisture content are fired in the indurating machine to acquire the required physical and metallurgical properties making them suitable feed for blast furnace. The green pellets are discharged onto the travelling grate induration machine where it is subjected to the sequential zones of preheating updraft drying, downdraft drying, after firing and cooling. The pellets are heated to about 500 to 1000°C in the preheated zone. In the firing zone the temperature is increased to 1300°C. At this stage only the strength of the pellet increases. After the firing zone, the fired pellets undergo cooling process where ambient air is drawn upward through the bed.

2.1 Problem Formulation

Iron ore pelletizing is a complex process which includes several fields like metallurgy, chemistry, estimation and control theory. The pelletising process has a continuous character which means that the output of one stage is the immediate input for the next. Because of this, the total production as well as the quality of the final product of the process is directly affected by the performance of each individual stage. In the pelletization process decision makers frequently face the problem of deciding the right quantity of input parameters to obtain the desired output quality. For this a computerised model was created in this paper to facilitate the decision maker to take correct decision.

2.2 Selection of Process Parameters

The selection of process parameters that affect the cold compressive strength is an important step in carrying out the analysis. A survey was conducted in the iron ore plant and based on the heuristic knowledge provided by the plant expert and literature review, a total of 3 input process parameters were taken. Quality control data from plant were used in the modelling studies. The data were randomly separated into two parts of which the first one contained 120 data's for training and the second part had 30 data's used for testing the models created using ANFIS. CCS was found to be more sensitive to variation in Bentonite, Blaine Number and Green pellet moisture, thus these attributes were used as input variable to control the CCS. Srinivas Dwarapudi [5] has shown the influence of Pellet Size on Quality of Iron Ore Pellets. S.P.E. Forsmo [6] attempted to revaluate the relationship behaviour of wet iron ore pellet with variation in bentonite binder. Table 1 Show the Quality Variables chosen for the analysis of iron ore Pellet. The standard deviation measures the spread of data set.

Table 1 Statistical value of training and testing quality variables

Statistics	Bentonite (% weight)		Pellet Size (mm)		Green Pellet Moisture		Compressive Strength	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Maximum	0.93	0.93	11	11	9.83	9.58	231.8	226.2
Minimum	0.66	0.66	8	8	8.17	8.58	210.2	214.6
Mode	0.84	0.75	10	9	9	9.2	220.6	220
Standard Deviation	0.0605	0.0758	0.9167	0.8469	0.3049	0.2871	4.2669	3.6079

III. ANFIS MODELLING

Both fuzzy logic and neural network has proved to be an excellent tool for modelling process parameters and output when there is no mathematical relation or models available. During the fuzzy modelling, the membership functions and rule base can be determined by experts only, thus the modelling of best fitting boundaries of membership functions and number of rules is very difficult. Also neural network cannot be used for processing fuzzy information. Thus to overcome these demerits, a hybrid adaptive neuro fuzzy interface system was developed by researchers. The Adaptive neuro Fuzzy Inference System was developed by professor Jang in 1992 and is used in the GUI of Matlab software [7]. The properties of neuro-fuzzy systems are the accurate learning and adaptive capabilities of the neural networks, together with the generalization and fast-learning capabilities of fuzzy logic systems. To explain the ANFIS architecture, the first order Sugeno model should be understood first [8-9].

$$\textit{Rule } 1\text{: } \textit{If } \left(x \textit{ is } A_1\right) \textit{ and } \left(y \textit{ is } B_1\right) \textit{ then } \left(f_1 = p_1 x + q_1 y + r_1\right)$$

$$\textit{Rule } 2\text{: } \textit{If } \left(x \textit{ is } A_2\right) \textit{ and } \left(y \textit{ is } B_2\right) \textit{ then } \left(f_2 = p_2 x + q_2 y + r_2\right)$$

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i , q_i and r_i are the design variables that are ascertained during training process. The ANFIS architecture to implement these two rules is shown in Figure 1 in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

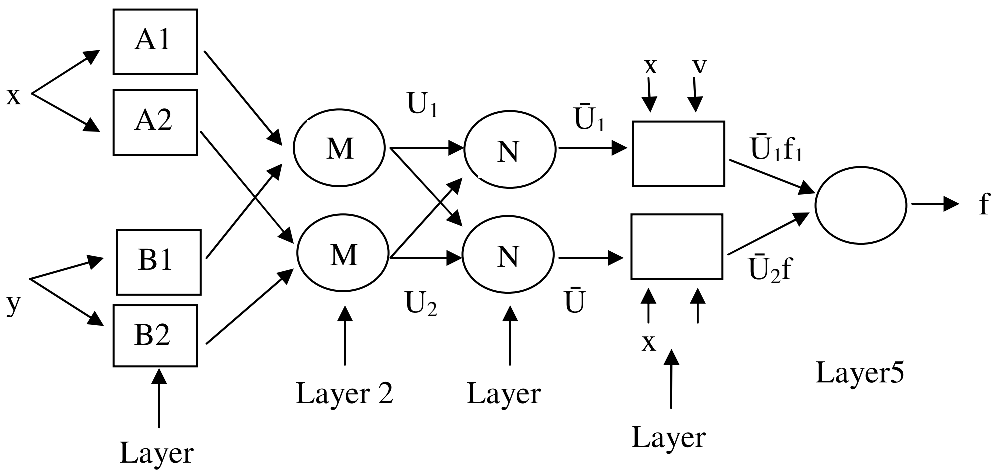

Figure 1 ANFIS architecture

Layer1: Each node in this layer is adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by equation 1 and 2

$$O_i^1 = \mu_{A_i}(x) \qquad i = 1,2 \tag{1}$$

$$O_i^1 = \mu_{B_{i-2}}(y) \qquad i = 3,4 \tag{2}$$

where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any membership function. Variables in this layer are referred to as premise variables.

Layer 2: The nodes in this layer are fixed nodes. They are labelled with M, which multiplies the incoming signals and sends the product out. The outputs of this layer can be represented by equation 3

$$O_i^2 = U_i = \mu_{A_i}(x)\mu_{B_i}(y) \qquad i = 1,2 \tag{3}$$

which are the firing strengths of a rule.

Layer 3: In this layer nodes are fixed nodes. They are labelled with N, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented by equation 4

$$O_i^3 = \bar{U}_i = \frac{U_i}{U_1 + U_2} \qquad i = 1,2 \tag{4}$$

which are the so-called normalized firing strengths.

Layer 4: The nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by equation 5

$$O_i^4 = \bar{U}_i f_i = \bar{U}_i (p_i x + q_i y + r_i) \tag{5}$$

Layer 5: Only one single fixed node is present in this layer. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by equation 6

$$O_i^5 = \frac{\sum_i \bar{U}_i f_i}{\sum_i U_i} \tag{6}$$

In order to tune premise design variables (pi, qi, ri) the hybrid learning algorithm was proposed by Jang in 1997[8-9]. The hybrid learning algorithm combines gradient descent and least square methods and it is faster than a back propagation algorithm. The least squares method (forward pass) is used to optimize the consequent variables with the premise variables fixed. Once the optimal consequent variables are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise variables corresponding to the fuzzy sets in the input domain. By this passing process, optimum variables are determined.

3.1 Prediction using ANFIS

The Training data which consisted of three input and one output parameter was loaded in the ANFIS editor. The Training data's were preloaded in the workspace. The FIS structure was generated using grid partitioning method. There are two partition methods i.e. grid partitioning and subtractive clustering but due to increase in error subtractive partition method was not considered for the analysis, figure 2 show the structure of the FIS which can be viewed by clicking the structure button. Various models with different architecture (number of membership function, type of membership function) were created and training was performed. These models were compared on the basis of mean relative percentage error (MRPE) which is given by equation 7.

$$Mean\,Relative\,Percentage\,Error\,(MRPE) = \left(\frac{1}{n} \sum \frac{|Actual\,CCS - Predicted\,CCS|}{Actual\,CCS} \right) * 100 \tag{7}$$

Where n = number of observation

Table 2 shows the models with different architecture and MRPE. Where MFs represent Membership function.

Table 2 Models with different architecture and MRPE

Model	Number of MFs	Type of MFs	MRPE
ANFIS 1	[2 3 3]	trimf	1.2213%
ANFIS 2	[2 3 3]	trapmf	1.2926%
ANFIS 3	[3 3 3]	trimf	1.1802%
ANFIS 4	[3 3 3]	trapmf	1.1818%

IV. Results and Discussions

In this study, prediction of cold compressive strength has been done using ANFIS model. Three parameters, i.e. pellet size, percentage weight of bentonite and green pellet moisture percentage weight obtained from literature have been considered for prediction of CCS. As shown in table 2 ANFIS model number 3 gave least mean relative percentage error, thus it was used for predicting the cold compressive strength of iron ore pellet. The 30 data's kept for testing the network was used and comparisons of the measured and predicted CCS values by ANFIS model with correlation coefficient are shown in Figure 3. If all the predicted value and actual value are same then all the points will lie in the same straight line and correlation coefficient will be 1 thus we can see that the correlation coefficient "R" was 0.536 which is good. It can be seen in the table 2 that ANFIS model with an architecture [3 3 3] membership function for input and the type of membership function used was triangular with output to be constant gave least MRPE of 1.1802% providing better prediction results. [3 3 3] shows that 3 membership function was used in pellet size, bentonite and green pellet moisture respectively. The response plots for CCS with different input parameters (Bentonite, pellet size and green pellet moisture) for ANFIS model have been presented in Figures 4-6. From the Figure 7 which is plotted between CCS and Data Order we can see that Predicted value and actual values are almost same except for some points. Residual graph was plotted for the predicted value which is shown in the Figure 8. The residual $\in$ is obtained by the formula

$$\in = V - \hat{V} \tag{8}$$

Where V is the actual value and $\hat{V}$ is the predicted value. It can be seen that about 83.3% points lie within the range $\pm$ 4. Only 5 point lie beyond $\pm$ 4 rest all the points are are scattered around the value 0. It is also noticed that negative prediction is obtained for CCS value less than 223. Negative prediction means the predicted value will be less than that of actual value and after 223 positive predictions is obtained i.e. the predicted value will be greater than the actual value.

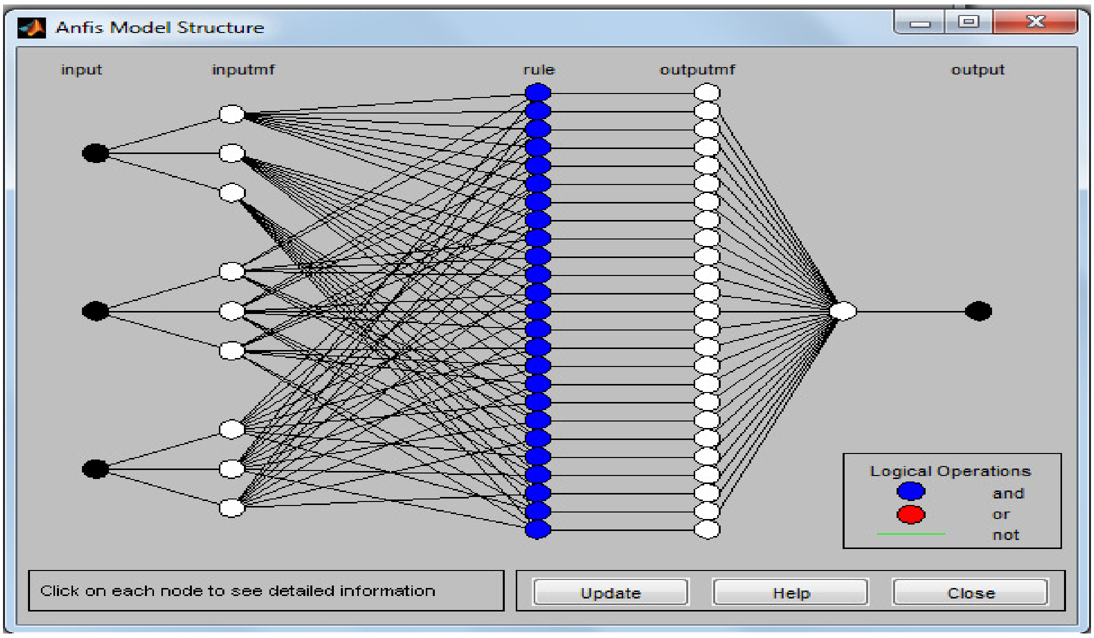

Figure 2 FIS model structure

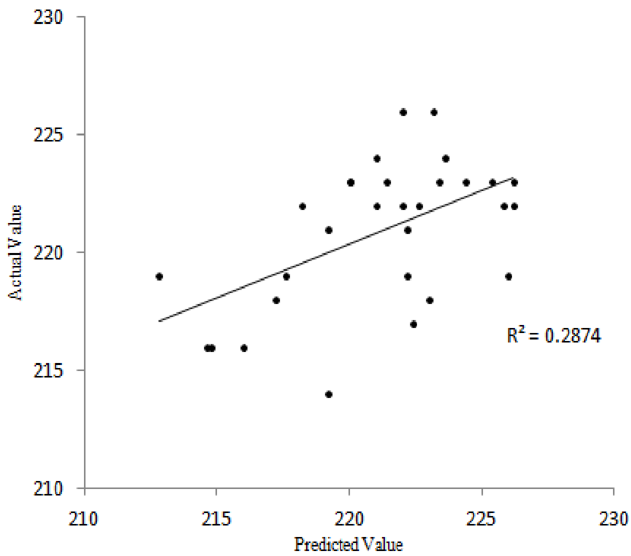

Figure 3 Actual and predicted CCS from ANFIS (correlation Coefficient 0.536)

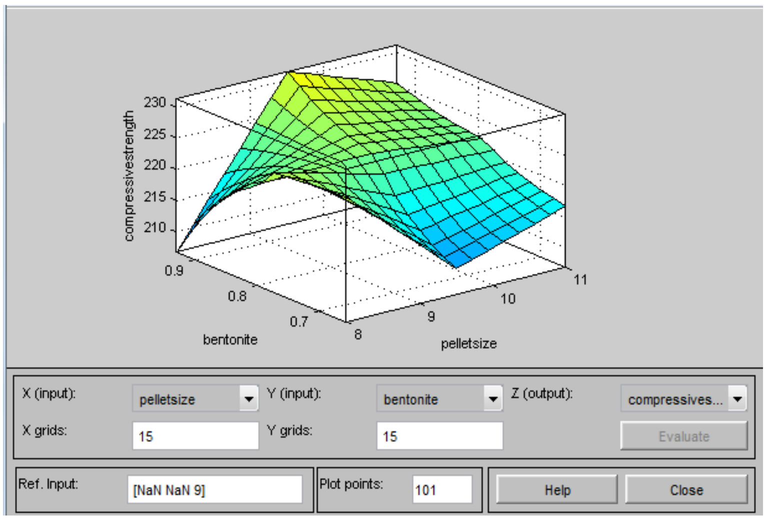

Figure 4 Surface plot of CCS with Pellet Size and Bentonite

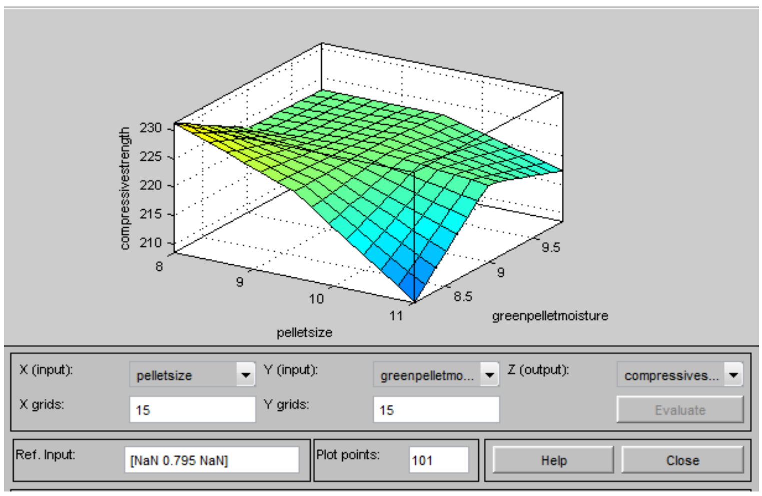

Figure 5 Surface plot of CCS with Pellet Size and Green Pellet Moisture

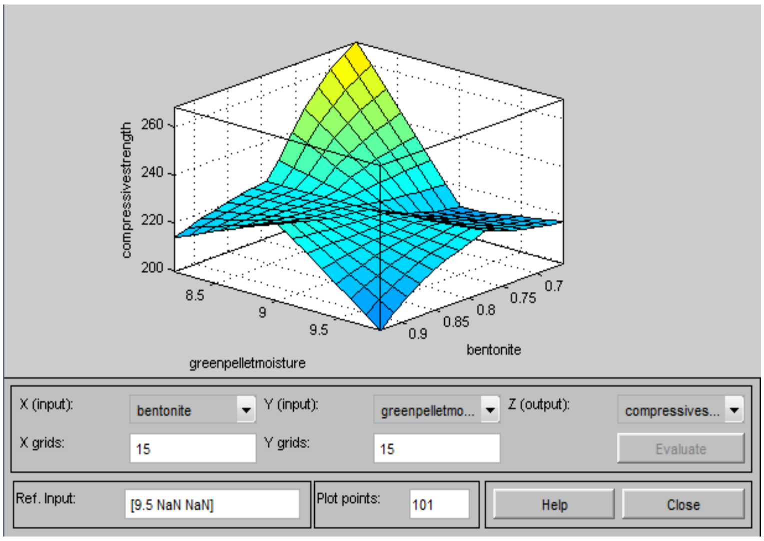

Figure 6 Surface plot of CCS with Bentonite and Green Pellet Moisture

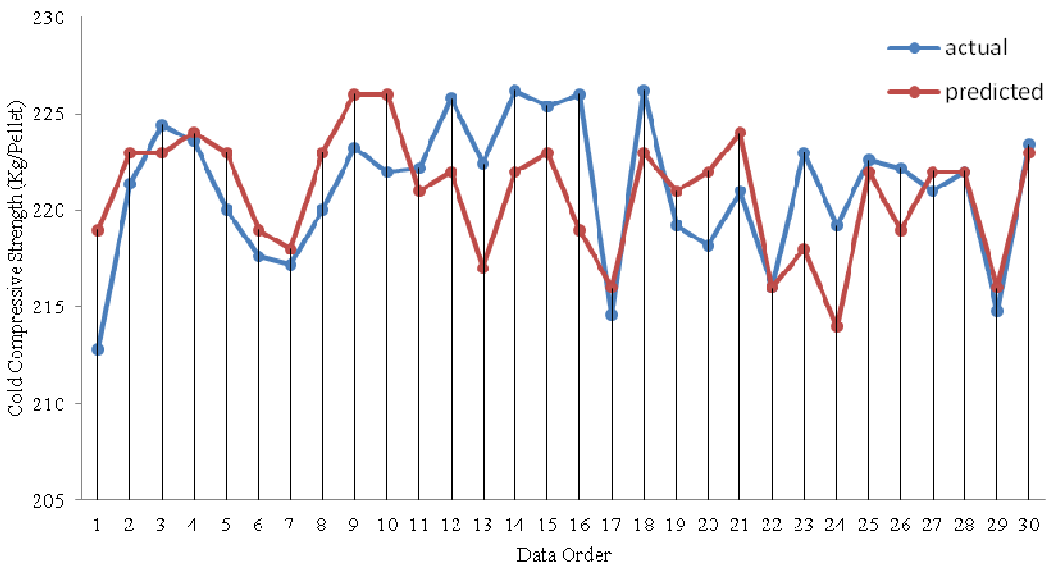

Figure 7 Actual Vs Predicted Cold Compressive Strength from ANFIS-3

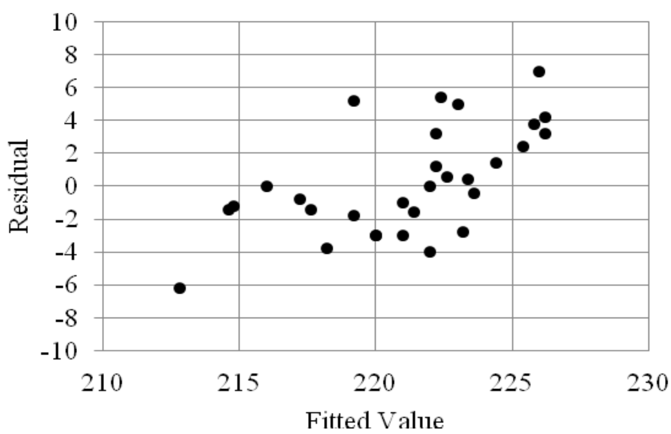

Figure 8 Residual graph of prediction from ANFIS

V. CONCLUSION

For predicting the cold compression strength of iron ore pellets, Adaptive neural fuzzy inference system model can be used as an effective tool if we have wide range of industrial data available for training. Pellet size, bentonite and green pellet moisture affect the CCS of iron ore pellet thus these were taken as input parameter. The predicted value obtained from the ANFIS model was analysed and following conclusion were made.

1) There is a good similarity between the predicted and actual Cold Compressive Strength values with around 1.1802% mean relative percentage error.
2) If a larger database is available for creating the rule-base then prediction accuracy can be improved.
3) Fine tuning of the ANFIS model can be done by changing the architecture.

It is expected that the results of this study will benefit the engineers and researchers in predicting the cold compressive strength of iron ore pellet and accordingly plan and control the pelletization process.

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