Predicting Foaming Slag Quality in Electric Arc Furnace Using Power Quality Indices and ANFIS

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Abstract— Foaming slag quality is an important parameter that can be used to improve the efficiency and quality of electric arc furnace process. However due to its fast and unpredictable changes, its quality is difficult to control. In this paper, an Adaptive Neuro Fuzzy Inference System (ANFIS) is used to determine slag quality based on power quality indices in electric arc furnaces. In order to train the intelligent system, a power quality analyzer is installed on an electric arc furnace feeder to record its power quality parameters. All electrical power quality parameters have been measured for 13 melting. Twelve groups of power quality parameters are examined for prediction slag quality and finally one group including total harmonic distortion, seventh current harmonic, and three phase current unbalance are selected which shows the best prediction accuracy. The intelligent system trained by six melting data and tested experimentally by connecting power quality analyzer to furnace feeder to predict the slag quality every minute. Experimental results show the accuracy of prediction is about 95%. The designed intelligent system can also be used in slag control process.

Keywords- Adaptive neuro fuzzy inference system (ANFIS), Electric arc furnace (EAF), Foaming slag

I. INTRODUCTION

Foaming slag quality is known as an important parameter in steel making process. Reduction in energy costs due to increasing the retention of heat, improving the efficiency and decreasing the electric arc furnaces (EAFs) sound and electrode consumption during melting process are some advantages of good foaming slag. Despite of these desirable attributes, there is not a reliable method for predicting slag quality. It is usually evaluated by an expert person during steel making process. The main difficulty is fast changes and nonlinearity of slag quality that depends on a lot of factors. There are many researches on modeling the EAF [1,2], reactive power compensation of EAF [3-5] and electrode control to improve efficiency and unbalance of EAF current[6-9]. Intelligent systems are used recently for modeling, compensation, and electrode regulation of EAFs [10-12]. In [13] slag is predicted by an intelligent program using 30 parameters including electrical, physical and chemical parameters. The Industrial Solutions and Services (I&S) Group and the Corporate Technology (CT) department of Siemens AG have developed a new method of measuring the changes in the level of foaming slag in arc furnaces over time and in the various parts of the furnace. The method is based on the measurement of structure-borne noise at the furnace shell [14]. Slag quality detection using oxygen lance vibration is another method presented in [15].

In this paper, an intelligent system is developed which is used to detect the slag quality using only 3 electrical parameters. A power quality analyzer is connected to EAFs transformer secondary. Different power quality parameters such as total current and voltage harmonic distortion, current and voltage harmonics up to 23th harmonics, current and voltage phase unbalances, and other power quality parameters are measured and stored using power quality analyzer. Electrical parameters related to 13 melting process for a furnace are recorded and an expert person reported the slag quality during each melting process. Expert persons usually determine the slag quality using EAFs sound, slag height, color and the velocity of slag from EAF. Recorded data by power quality analyzer and the expert person quality prediction are divided into two groups to train and test the intelligent system. Six melting data are selected for train process and three melting data are selected for test. In order to find best parameters, 12 groups of variables containing three or four parameters are tested. The group with best prediction of slag quality is selected to determine the slag quality on line. Furthermore the power quality analyzer was connected to EAFs transformer secondary again and measured data were transferred to computer connected to it via RS232 port almost every one second. In fact the sampling time in power quality analyzer is set to one second. But the intelligent system determines the slag quality every minute which compared to experimental results and show good accuracy in predicting the slag quality. In section II, the intelligent system based on ANFIS is described briefly. Measurement process to obtain training data is explained in section III. The method of selecting best parameters to perform the prediction is discussed in section IV. Finally, the experimental results are shown in section V.

II. ANFIS STRUCTURE

Since the Adaptive Neuro Fuzzy Inference System (ANFIS) has an excellent estimation of a function and doesn’t need the knowledge about output and input relationship, it is selected to predict slag quality. It is mainly a first order Takagi and Sugeno fuzzy system. Fig. 1 shows the ANFIS structure with two inputs (x and y) and one output (f).
Assume that the rule base contains two fuzzy if-then rules:

Rule 1: if x is $A_1$ and y is $B_1$, then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: if x is $A_2$ and y is $B_2$, then $f_2 = p_2 x + q_2 y + r_2$

Fuzzification is accomplished at first layer. Thus the first layer outputs are membership values. The membership functions can be different. The calculated membership values are multiplied in layer two. Therefore the output of the layer two can be obtained as follow:

$$w_1 = \mu_{A_1} * \mu_{B_1}$$

$$w_2 = \mu_{A_2} * \mu_{B_2}$$

(1)

Inputs of layer three are normalized. Then the output of this layer can be calculated as:

$$w_3 = \frac{w_1}{w_1 + w_2}$$

$$w_4 = \frac{w_2}{w_1 + w_2}$$

(2)

It is clear that $w_3$ and $w_4$ are the inputs of layer four. In this layer, the output is the linear combination of main inputs (x and y) multiplied by the previous layer output.

$$o_1 = w_3 f_1 = w_3 (p_1 x + q_1 y + r_1)$$

$$o_2 = w_4 f_2 = w_4 (p_2 x + q_2 y + r_2)$$

(3)

Finally, the fifth layer is simple summation of its inputs. At first it is necessary to determine the number and type of membership functions. After that, training data should be used to train system. In training process, input training data is given to system and the output training data are compared with system output. The error is calculated by least squares method and the parameters in layer two are modified using gradient descent. This process will be executed M times that M is number of epochs. In this paper, five membership functions are selected for each inputs and output. The type of membership functions is Gaussian. Also the number of inputs is three and there is only one output. 124 training data are used to train system. The number of epoch is 50.

III. MEASURING ELECTRICAL PARAMETERS

At first stage, a database is needed to train the intelligent system and test various parameters. For this purpose, power quality analyzer (ION7600 from PML) is connected to EAFs transformer secondary and various electrical parameters recorded for 13 melting during 4 days. Slag quality is reported by an expert person during each melting process. Expert person determines the slag quality by hearing the EAFs sound and observing the operation condition of EAF. In fact, they report the slag quality using their experience.

Reported slag quality by the expert person is synchronized with recorded data by measurement device. Subsequently, a slag quality reported by expert person in a specific time is assigned to electrical parameters recorded in that time. Also, slag quality is numerical coded, for this purpose, 1 and 0.2 are assigned to best and worst quality respectively. Table 1 shows the coded values of slag quality.

<table>
<thead>
<tr>
<th>Slag quality</th>
<th>Assigned code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>1.0</td>
</tr>
<tr>
<td>Good</td>
<td>0.8</td>
</tr>
<tr>
<td>Normal</td>
<td>0.6</td>
</tr>
<tr>
<td>Bad</td>
<td>0.4</td>
</tr>
<tr>
<td>Very bad</td>
<td>0.2</td>
</tr>
</tbody>
</table>

IV. PARAMETER GROUP TEST

To select best parameters for best prediction of slag quality, it is needed to test various parameters. 12 groups of variables, including three or four parameters in each group are tested. In order to test parameters, six melting data are selected to train and three melting data are selected for testing. Electrical parameters and related slag quality in each group are used to train the intelligent system. Electrical parameters of one melting are used as intelligent system input to estimate the slag quality and output is compared with slag quality reported by expert person and the accuracy is evaluated.

Smoothing is a technique to improve the intelligent system output accuracy. Output and also input data should be smoothed for acceptable results. Input smoothing is performed by averaging sixty successive sampled electrical parameters in one minute. The first group of parameters is tested with and without input smoothing to show the improvement gained by input smoothing.

A. Testing The First Group of Parameters With and Without Input smoothing

At first step, one group of parameters is tested with and without smoothing to show the importance of input smoothing. This group is include of average, seventh harmonic and total harmonic distortion of current ($I_{ave}$, $I_{H7}$, $THD_I$). Without input and output smoothing, parameters are tested with one melting data. The result is shown in Fig.2. In this figure slag quality reported by expert person is shown by circle (●) and slag quality estimated by intelligent system is shown by rectangular (□). Also, there are two lines in Fig.2 which shows the slag quality level. When the slag quality is divided to two levels, quality values less than 0.5 show the bad and more than 0.5 show the good quality. When the slag quality is divided to three levels, quality values less than 0.5 show the bad, more than 0.5 and less than 0.7 show the normal and more than 0.7 show the good quality. For example, if the expert has reported the normal slag quality in specific time and intelligent system
output is between 0.5 and 0.7, it means that the prediction is correct. In Fig.2, when the slag quality is divided to two levels, the intelligent system output accuracy is 44.4%. This value is the same for triple level. Fig.3 shows the result when the input is smoothed. Although electrical parameters are same with previous state, the intelligent system output accuracy has been improved.

![Figure 2](image-url)  
**Figure 2.** Prediction result with Iave, IHD7,THDI, (without smoothing)

![Figure 3](image-url)  
**Figure 3.** Prediction result with Iave, IHD7,THDI, (with input smoothing)

In this case, when the slag quality is divided to two levels, accuracy is 77.7 percent. However for triple level, it is decreased to 66.6 percent.

Since the input smoothing improves the prediction result, the others group of the parameters are tested with input smoothing. Test results with other 9 groups of parameters are given in table 2.

### B. Output smoothing method

As mentioned before, output smoothing will done by averaging the intelligent system output, if the difference between present output and previous output is more than 0.2. In the other hand, if the difference between Nth and (N-1)th output value of intelligent system is more than 0.2, the average of Nth and (N-1)th value is introduced as the Nth output of system. The output smoothing is necessary, because the slag quality doesn’t change much during one minute. But the intelligent system output may have abrupt changes. In order to find best value for output smoothing threshold, one group of parameters including THDI, IHD7, THDV, is selected and output is smoothed with three different smoothing threshold values. According to table 3, the best value for output smoothing threshold is 0.2. Although the accuracy is same for double level, but for triple level the accuracy is increased when the output is smoothed and this increment is most when the output smoothing threshold is 0.2.

### C. Testing the selected group of parameters with output smoothing

According to table 2, with THDI, IHD7, Iun as input, the prediction accuracy is 100 percent for double level and 77.7 percent for triple level. With THDI, IHD7, Vun as input, the prediction accuracy is 100 percent for double level and 88.8 percent for triple level. In order to selected the best group of parameters, two selected groups are tested using new measured data obtained from another two melting. Of course, input and output smoothing method are applied. Obviously, these data are not used in training process.

For Iun, IHD7, THDI, accuracy for the first set of new melting data is 71.5 percent in double and triple level quality and it is 100 and 75 percent in double and triple level quality for second set of new melting data.

For Vun, IHD7, THDI, accuracy for the first set of new melting data is 71.5 percent in double and triple level quality and it is 75 and 50 percent in double and triple level quality for second set of new melting data. The results are shown in table 4.

### D. Testing two new groups of parameter with input and output smoothing

Since the current has a great rule in determination of slag quality, two groups of parameters including current unbalance are tested. These groups are containing the following parameters:

For Iun, IHD7, THDI, THDV, prediction accuracy is 55.5 and 11.1 percent when the slag quality is divided to two and three levels respectively.

For Iun, THDI, THDV, prediction accuracy is 88.8 and 44.4 percent when the slag quality is divided to two and three levels respectively. According to mentioned results, the best accuracy can be achieved with the following group of parameters:

1. Total current harmonic distortion.
2. Seventh current harmonic.
3. Current unbalance.

### V. EXPERIMENTAL RESULTS

The intelligent system using the best group of parameters is tested experimentally and on line. Power quality analyzer is connected to electrical arc furnaces transformer secondary again and measured electrical parameters are transferred to Computer. Sampling time is set 1 second. Intelligent system, determines the slag quality every one minutes. Also one expert person reported the slag quality at the same time and intelligent system output is compared with expert’s report.

Expanding the range of output seems to improve the prediction accuracy. For this purpose, table 1 should be changed according to table 5 and the intelligent system should be trained again. Therefore the range of output is from -1 to 4. The output range was from 0.2 to 1 before
expansion. In this way, 4 and -1 are assigned to best and worst quality respectively.

At first state, slag quality is divided to two levels. More than 1.5 shows the good and less than 1.5 shows the bad quality. The accuracy is 95.87 percent. Fig. 4 shows the result.

When the quality is divided to three levels, more than 1.5 is good, less than 1.5 and more than 0 is normal and less than 0 shows the bad quality. The prediction accuracy is 94.21 percent. It is noticeable that the prediction accuracy of triple level quality with previous range is 82 percent.

Fig. 5 shows the result when the quality is divided to four levels. In this figure, more than 1.5 is good, less than 1.5 and more than 0.5 is normal, less than 0.5 and more than -0.5 is bad and less than -0.5 shows the very bad slag quality. Very bad slag quality state occurs at beginning of the melting process that scraps are not melted and there is not enough slag in EAF. In fact, when the quality is divided to four levels this state is separated from bad quality.

A special melting with heavy scraps is tested on line. Prediction accuracy is 78.08 percent for double level and 74.6 percent for triple and quadruple level. Fig. 6 and Fig. 7 show the results for double and quadruple level respectively. Table 6 shows the prediction results.

**VI. CONCLUSION**

Since the slag quality is important in steel production process, prediction and control of its quality is necessary during the process. Determination and control of slag are accomplished by an expert person in most of steel factories rightness. In this paper, an adaptive neuro fuzzy inference system is introduced to determine the slag quality by electrical parameter measurement. Total current harmonic distortion, seventh harmonic and three phase current unbalance are selected to estimate the slag quality after various group of parameters are tested and evaluated. The obtained accuracy is up to 95 percent. The additives for better foaming slag quality in EAF can be controlled automatically or manually using this intelligent slag quality predicting system.
### TABLE II. PREDICTION RESULTS WITH 10 GROUPS OF PARAMETERS WITHOUT OUTPUT SMOOTHING

<table>
<thead>
<tr>
<th>Selected parameters</th>
<th>input smoothing</th>
<th>output smoothing</th>
<th>Accuracy in double level</th>
<th>Accuracy in triple level</th>
</tr>
</thead>
<tbody>
<tr>
<td>seventh current harmonic</td>
<td>no</td>
<td>no</td>
<td>44.4 %</td>
<td>44.4 %</td>
</tr>
<tr>
<td>average of current</td>
<td>no</td>
<td>no</td>
<td>44.4 %</td>
<td>44.4 %</td>
</tr>
<tr>
<td>total current harmonic distortion</td>
<td>yes</td>
<td>no</td>
<td>77.7 %</td>
<td>66.6 %</td>
</tr>
<tr>
<td>seventh current harmonic</td>
<td>yes</td>
<td>no</td>
<td>55.5 %</td>
<td>22.2 %</td>
</tr>
<tr>
<td>average of current</td>
<td>yes</td>
<td>no</td>
<td>55.5 %</td>
<td>22.2 %</td>
</tr>
<tr>
<td>total current harmonic distortion</td>
<td>yes</td>
<td>no</td>
<td>100.0 %</td>
<td>77.7 %</td>
</tr>
<tr>
<td>seventh current harmonic</td>
<td>yes</td>
<td>no</td>
<td>66.6 %</td>
<td>55.5 %</td>
</tr>
<tr>
<td>fifth current harmonic</td>
<td>yes</td>
<td>no</td>
<td>44.4 %</td>
<td>33.3 %</td>
</tr>
<tr>
<td>total current harmonic distortion</td>
<td>yes</td>
<td>no</td>
<td>77.7 %</td>
<td>66.6 %</td>
</tr>
<tr>
<td>seventh current harmonic</td>
<td>yes</td>
<td>no</td>
<td>88.8 %</td>
<td>44.4 %</td>
</tr>
<tr>
<td>total voltage harmonic distortion</td>
<td>yes</td>
<td>no</td>
<td>100.0 %</td>
<td>77.7 %</td>
</tr>
<tr>
<td>voltage unbalance</td>
<td>yes</td>
<td>no</td>
<td>88.8 %</td>
<td>55.5 %</td>
</tr>
</tbody>
</table>

### TABLE III. PREDICTION RESULTS WITH THREE OUTPUT SMOOTHING THRESHOLD

<table>
<thead>
<tr>
<th>Selected parameters</th>
<th>Input smoothing</th>
<th>Output smoothing</th>
<th>Accuracy in double level</th>
<th>Accuracy in triple level</th>
</tr>
</thead>
<tbody>
<tr>
<td>I HD 7, THDI, THDV</td>
<td>yes</td>
<td>changes more than 0.1</td>
<td>88.8 %</td>
<td>66.6 %</td>
</tr>
<tr>
<td>I HD 7, THDI, THDV</td>
<td>yes</td>
<td>changes more than 0.2</td>
<td>88.8 %</td>
<td>77.7 %</td>
</tr>
<tr>
<td>I HD 7, THDI, THDV</td>
<td>yes</td>
<td>changes more than 0.3</td>
<td>88.8 %</td>
<td>66.6 %</td>
</tr>
</tbody>
</table>

### TABLE IV. PREDICTION RESULTS WITH TWO NEW MELTING PARAMETERS

<table>
<thead>
<tr>
<th>SELECTED PARAMETERS</th>
<th>MELTING NO.</th>
<th>DOUBLE LEVEL</th>
<th>TRIPLE LEVEL</th>
</tr>
</thead>
<tbody>
<tr>
<td>THDI, IHD7, IUN</td>
<td>1</td>
<td>71.5</td>
<td>71.5</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>100</td>
<td>75</td>
</tr>
<tr>
<td>THDI, IHD7, VUN</td>
<td>1</td>
<td>71.5</td>
<td>71.5</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>75</td>
<td>50</td>
</tr>
</tbody>
</table>
TABLE V. NEW ASSIGNED CODES TO SLAG QUALITY

<table>
<thead>
<tr>
<th>Slag quality</th>
<th>Assigned code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>4</td>
</tr>
<tr>
<td>Good</td>
<td>3</td>
</tr>
<tr>
<td>Normal</td>
<td>2</td>
</tr>
<tr>
<td>Bad</td>
<td>1</td>
</tr>
<tr>
<td>Very bad</td>
<td>-1</td>
</tr>
</tbody>
</table>

TABLE VI. EXPERIMENTAL RESULTS

<table>
<thead>
<tr>
<th>Melting no. division</th>
<th>Output range</th>
<th>accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>.8</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

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