Electric Arc Coverage Indicator for AC Furnaces Using a Laser Vibrometer and Neural Networks

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A common operational practice in the electric arc furnace (EAF) consist in keeping the electric arc covered with metallic scrap or foaming slag, this is to prevent that the refractory and water cooled panels absorb part of the radiation that should heat the steel. The radiation not absorbed by the steel is not only a waste of energy and money, it is also a latent danger because it damages the walls of the furnace. Today furnace operators use their experience and common sense to predict the degree of coverage of the arc and decide the electrical power the EAF can safely absorb along the process, without damaging the walls and increase the risk of an internal explosion. However, this method is subjective and might leads to human errors. This research was aimed to find robust indicators of arc coverage that could assist the furnace operator in deciding the amount of electrical power the furnace can safely absorb. During this research, it was found a strong relation between the vibrations of the furnace's shell and the level of coverage of the electric arc. The vibration measurements were done with a laser and the vibration signal was processed using an Artificial Neural Network (ANN) implemented in LabVIEW™. The ANN was trained to emulate the intelligence and knowledge of a very productive and safe furnace operator. Excellent field results were obtained with this implementation and are reported in this paper.

KEY WORDS: electric arc furnace; EAF; arc coverage indicator; EAF vibration; neural networks; laser vibrometer.

1. Introduction

Today the Electric Arc Furnace (EAF) is one of the most used technologies worldwide for steelmaking, it contributes approximately to one third of the world production, but it does so in a very inefficient way. This high production volume implies that small improvements in the EAF energy consumption could lead to substantial economic savings.¹⁾ Currently there are several areas of opportunity that can be exploited to make more efficient the use of energy in the melting process and reduce losses; one of these opportunities is to estimate arc coverage to control electric power injected to the process.

The electric arc produces a huge amount of radiation, this makes possible the melting of metallic scrap. The amount of radiation emitted by the arc is intrinsically related to its length and voltage; an increase in arc length leads to an increment in the radiation emitted.^{2,3)} Because of this huge radiation it is common to operate the furnace with long electric arcs when a good arc coverage, by scrap or foamy slag, can be ensured. The arc coverage is one of the most important process parameters, but it is very difficult to measure due to the lack of visual information and the

impossibility to install sensors inside the EAF.⁴⁾ To overcome this drawback, shell furnace's vibrations, has become an important source of information about the arc coverage level. For example in⁵⁾ vibrations were used to determine the foamy slag height in an AC furnace, similar results were reported in a DC furnace in.⁶⁾ Nevertheless, the use of contact sensors in the shell is very problematic due to the hostile environment near the furnace. Other approach was proposed in⁷⁾ where the sound of a DC furnace was used to estimate the arc coverage level. It is expected that the sound emitted by the electric arc and the shell's vibrations present similar behaviors, however the use of sound can lead to measurement errors when two or more furnaces are working in the same steel shop. In the present study the use of laser technology to measure vibrations, provide a good solution to overcome the problems encountered with sound and accelerometers attached to the shell. In addition, in this work a mapping Artificial Neural Network (ANN) was used to correlate the furnace's shell vibrations with the best and most experienced furnace operator criterion, regarding the arc coverage level.

ANNs have found success application in steel industry, in⁸⁾ an ANN was used to model the effects of process parameters and chemical composition on the tensile strength of hot strip mill products. In⁹⁾ flow stress variations during the hot rolling process are modeled using an ANN. In¹⁰⁾ a control

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system using an ANN was developed to keep the mold steel level steady in continuous billet casting process. Despite the succeed application of ANNs in steel industry and also the good results reported with furnace's shell vibrations measurement, there are not studies applying laser vibration technology in conjunction with ANNs to estimate the arc coverage level as it is proposed in this work. The objective is to develop reliable arc coverage indication that will help the operator's practices, like the injection of foaming agents or changing the height positioning of the electrodes. Those practices rely on the expertise of each operator and this inevitably leads to human error.

2. Vibration Measurement

When foamy slag or scrap surrounds the arc and cover it, the radiation energy goes primarily to the metallic charge or slag. However, should this not happens, radiation, power, water-cooled panels and refractory losses occur decreasing significantly the efficiency and life of the EAF. It is also important to consider the compromise between arc length and arc stability, in other words, to ensure energy efficiency is important to control the arc's length to be sure that it is always covered by scrap or foamy slag.^{1,11)} A first approach, regarding furnace's shell vibrations, indicates that when the electric arc is well covered by metallic scrap or foamy slag, the furnace's vibrations are less intense in comparison with the operation with poorly covered electric arcs.^{3,5,12)} The electric arc produces acoustic pressure that hits the walls of the EAF producing vibrations, the scrap and the slag attenuate the arc's acoustic pressure before it reaches the walls, thus reducing the vibrations induced in the furnace's shell. **Figure 1** schematized the attenuation in two different scenarios.

Nevertheless, vibration of the shell is an indirect variable with not sufficient information to fully determine whether radiation is impinging the walls. It is also necessary monitoring electrical variables.⁵⁾ The electric arc can be viewed as a variable ohmic resistance working in a constant power system, the resistance increases its value with an increase in arc's length. Certain arc power level can be achieved with both, a long arc or a short arc. Working with a short arc implies a lower resistance and in consequent a higher electric current in the system. In contrast, when working with a long electric arc, the high resistance reduces the current in the system, it is clear that in this case the voltage must be higher than in the case of the short arc. In other words, the phase current can be monitoring during the melting process to obtain important information regarding the arc's length.

Fig. 1. Damping of vibrations in the furnace's shell (a) uncovered arc, (b) covered arc with foamy slag.

Vibrations measurement in the EAF using contact sensors is a complicate task, because the environment surrounding the furnace is very harsh for electronic devices, also the constant movements of the EAF may damage the sensor's cables. To overcome this issues a non-contact scheme using a laser vibrometer was chosen. The AC EAF studied in this work was the one in Ternium, Apodaca México, Largos Norte Plant.

The vibrometer retained features a low power helium-neon laser, which must strike a reflective surface solid mounted on the vibrating object, the measurement is made by a heterodyne interferometer. Depending on the speed of the vibrating object and the amplitude of its movement, a frequency modulation is generated over the laser due to Doppler Effect. The modulated signal enters to a demodulator whose output is feed to a filter, the filter provides a voltage output proportional to the instantaneous velocity of the vibrating object.¹³⁾ The signal path is shown in **Fig. 2**.

The voltage output is positive when the object moves towards the sensor head and negative when it moves in the opposite direction. For the acquisition and processing of the vibration signal LabVIEW™ platform was chosen. The first part of the application developed consisted on the acquisition and pre-processing stage, here the Root Mean Square (RMS) value of the vibration signal is obtained to give equal treatment to shell's movements independently of their direction. In the second stage, this RMS value is fed to an ANN where the final processing is made to estimate the arc coverage level at its output. The ANN must be subjected to a training process prior its implementation, the learning approach used in this work was supervised learning, in this scheme a master (furnace operator) bring to the ANN a set of training patterns. Each pattern consist in a RMS value of the vibration signal along with the corresponding desired output which is, as said before, the operator's criterion regarding the arc coverage level.¹⁴⁾ **Figure 3** shows the supervised learning scheme applied in the EAF.

The calculation of the RMS value of the vibration signal was done in real time during the field measurements. The vibrometer signal was sampled at 10 kHz, therefore every 0.0001 seconds a raw sample was recorded. The RMS calculation was done every 0.1 seconds using 1 000 samples

Fig. 2. Signal path of the laser vibrometer.

Fig. 3. Supervised learning diagram.

of raw data to perform each calculation.

3. Neural Networks

The steelmaking process is very complex, it is not easy to establish a set of differential equations to describe the dynamic behavior of the process. This imply that finding a precise mathematical model for an EAF is a difficult task.¹⁵⁾ However, ANNs provides a practical way to find solid relations in complex processes. An ANN can learn with the vibration patterns in the furnace as the steel melts, it can adapt to unusual scrap conditions,¹⁶⁾ therefore ANNs are an attractive tool for arc coverage level estimation. The input-output relations in an ANN are constructed based on the activation functions, weights and bias parameters of each neuron.⁹⁾ A Typically ANN present two layers in contact with the environment, the input and output layers, the layers in between are called hidden layers. The number of hidden layers and the number of neurons in each hidden layer depends on the complexity of the problem to solve.¹⁷⁾

The ANN implemented in this work consists of one input identified by subscript i , eight neurons in the hidden layer each identified by subscript j , all of them with sigmoid¹⁸⁾ activation functions. Finally, in the output layer there is one neuron identified with the subscript k , which present a linear activation function. The neural network described is shown in Fig. 4.

The input to the ANN defined by a_i is the RMS value of the vibration signal, this input travels to each hidden neuron being affected by the weights w_{ji} . Let us define θ_j as the product of the bias input and the bias weight of each hidden neuron. The weighted inputs of the hidden neurons are combined using a summation and the result of this operation enters to the activation functions f_1 to f_8 , the value that takes each activation function correspond to the outputs s_j of the hidden neurons. Later the outputs of the hidden neurons are affected by the weights w_{kj} , these ponderations are summed in the output neuron along with θ_k , which is defined as the product of the bias input and the bias weight of the output neuron. Finally the summation in the output neuron activate its linear function giving the arc coverage indication defined by o_k .

In order to work properly the ANN must be trained; to achieve this, an input-output training set must be presented to the ANN in an iterative fashion. The objective consist in finding the combination of weights that minimize the error function, which is a measure of the difference between the actual output o_k and the desired output d_k (operator's crite-

Fig. 4. Representation of the implemented neural network.

rion). The mean square error for each pattern presentation of the training set is given by:

$$E_{(n)} = \frac{1}{2} (d_{k(n)} - o_{k(n)})^2 \dots\dots\dots (1)$$

Where the subscript n indicate the number of iteration.

The algorithm used to perform the minimization process was Back Propagation, which is one of the most popular algorithms for training mapping ANNs.^{9,19)} The basic concept was initially presented by D.E. Rumelhart and it is also well explained by Paul Werbos.^{20,21)} The idea consist on making the partial derivatives of the error function respect the elements of the weight vectors, this in order to obtain the gradient and find the minimum of the error function. This procedure is repeated for each network entry.^{14,17,21,22)} To determine the weights update between the output and the hidden layer the error function is derived respect each w_{kj} value, in addition o_k can be expressed as function of the inputs of the neuron k . This is formally expressed as follows:

$$\frac{\partial E_{(n)}}{\partial w_{kj}} = \frac{1}{2} \frac{\partial}{\partial w_{kj}} \left(d_k - f_k \left(\sum_{j=1}^8 w_{kj} s_j + \theta_k \right) \right)^2 \dots\dots\dots (2)$$

Solving the partial derivatives and grouping terms, the gradient of the error is expressed as follows:

$$\frac{\partial E_{(n)}}{\partial w_{kj}} = (o_k - d_k) \dot{f}_k \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_8 \end{bmatrix} \dots\dots\dots (3)$$

where $\dot{f}_k$ is the derivative of the activation function of the output neuron.

Using the gradient to update the weight vector, the values for iteration $n+1$ are given by:

$$w_{kj(n+1)} = w_{kj(n)} - \eta (o_k - d_k) \dot{f}_k \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_8 \end{bmatrix} \dots\dots\dots (4)$$

where η is a learning factor that may accelerate the iterative process.

To carry out the adjustment of the weights between the hidden and input layer, the error function is derived respect each w_{ji} value. In addition o_k can be expressed as function of the inputs of the hidden neurons. This is formally expressed as follows:

$$\frac{\partial E_{(n)}}{\partial w_{ji}} = \frac{1}{2} \frac{\partial}{\partial w_{ji}} \left(d_k - f_k \left(\sum_{j=1}^8 w_{kj} f_j (w_{ji} a_i + \theta_j) + \theta_k \right) \right)^2 \dots (5)$$

Solving the partial derivatives and grouping terms, the gradient of the error is expressed as follows:

$$\frac{\partial E_{(n)}}{\partial w_{ji}} = (o_k - d_k) \dot{f}_k a_i \begin{bmatrix} \dot{f}_{1l} w_{k1} \\ \dot{f}_{2l} w_{k2} \\ \vdots \\ \dot{f}_{8l} w_{k8} \end{bmatrix} \dots (6)$$

where $\dot{f}_{1l}$ to $\dot{f}_{8l}$ correspond to the derivative of the activation function of each hidden neuron, w_{k1} to w_{k8} correspond to the weights between the output and hidden layer and a_i corresponds to the input of the neural network.

Using the gradient to update the weight vector, the values for iteration $n+1$ are given by:

$$w_{kj(n+1)} = w_{kj(n)} - \eta (o_k - d_k) \dot{f}_k a_i \begin{bmatrix} \dot{f}_{1l} w_{k1} \\ \dot{f}_{2l} w_{k2} \\ \vdots \\ \dot{f}_{8l} w_{k8} \end{bmatrix} \dots (7)$$

where η is the learning factor that accelerates the iterative process.

The process described in this section will be applied to the data acquired in field measurements to train our ANN.

4. Measurements in the EAF

In this section some experimental tests carried out at Ternium Largos Norte, Apodaca, México, are described. The laser vibrometer was placed at a safe distance of the furnace, to avoid damages to a high cost piece of equipment. Qualified personnel installed a reflective surface near top of the furnace's shell, such surface consisted in a powerful magnet with reflective fabric glued to it. The laser beam was aimed to the magnet and the acquisition system connected to the vibrometer's voltage output. In Fig. 5 can be seen a top view of the EAF in order to show the location of the measurement point. For further analysis of the arc coverage level, the electric current set point of the phase identified as B, and the cooling water temperature of the nearest panel to the reflective surface were monitored during the vibration measurement.

The criterion of the furnace operator was recorded at regular time intervals during many heats, this allowed the construction of the training set for the ANN. For the construction of the training set, the application developed in LabVIEW™ allows matching the RMS value of the vibrometer's output signal with the operator's criterion in real time, which is a numeric value entered manually that goes from one to five, where one represents a good arc coverage and five a bad arc coverage. The construction of the training set is shown in Table 1, this table do not represent the total

Fig. 5. Selected measurement point.

Table 1. Construction of the training set.

Network Input (vibration RMS)	Desired Output
0.419805	5.000000
0.330619	5.000000
0.212414	4.000000
0.189028	4.000000
0.195957	3.000000
0.209034	3.000000
0.171033	2.000000
0.165043	2.000000
0.117625	1.000000
0.124761	1.000000

training set and it is merely demonstrative.

With the training set ready, the neural network was trained using Back Propagation algorithm as described in the previous section. The groups of blue xxx... in Fig. 6, corresponds to each training pattern of the training set, the x axis corresponds to the RMS value of the vibration signal (ANN input) and the y axis to the operator's criterion (desired output). The red circles seen almost as a line, corresponds to the input-output behavior of the ANN once the training process concludes.

It is important to note the presence of points in the training set that are far away from the expected value, as seen in Fig. 6. These points are generated by sudden drops of scrap attached to the walls, or for the shell tilting originated by the operator to remove scrap attached to the walls. Another issue is the presence of corrupted data, because the laser reflection was lost during shell's tilting movements in our experiments. Despite the issues mentioned in the training set, the neural network found a clear relation between increased vibration and the operator's criterion regarding the arc coverage level.

Fig. 6. Raw training set and neural network response.

Fig. 7. Neural network response and filtered training set.

The Pearson correlation coefficient was used for validation, R represents the strength of linear relation between the RMS value of the vibration signal and the operator's criterion.¹⁹⁾ The Pearson correlation coefficient is calculated as follows:

$$R = \frac{\sum_{i=1}^n X_{1i} X_{2i} - n \bar{X}_1 \bar{X}_2}{\sqrt{\sum_{i=1}^n X_{1i}^2 - n \bar{X}_1^2} \sqrt{\sum_{i=1}^n X_{2i}^2 - n \bar{X}_2^2}} \quad \text{..... (8)}$$

where,

X_{1i} is each data item from the list created with the operator's criterion

X_{2i} is each data item from the list created with the RMS values of the vibration signal

n is the number of data in the lists

$\bar{X}_1$ is the average value of the list created with the operator's criterion

$\bar{X}_2$ is the average value of the list created with the RMS values of the vibration signal

Finally, the R value obtained with Eq. (8) was 0.7039, this value indicates that there is indeed a strong relation

between the increased vibration in the furnace and the electric arc coverage according to the operator's criterion. When working with ANNs, is recommended pre-processing the training data, this includes wrong data elimination.⁹⁾ In order to improve the correlation obtained prior the implementation of the ANN, the training data gathered during our field experiments were filtered and reordered, this in order to re-train the ANN. **Figure 7** shows the new training set and the ANN response.

A new value of R was calculated using the training set shown in Fig. 7, the result obtained was 0.9525, which shows that the correlation between the operator's criterion and the RMS value of the vibration signal, improved once the training set was filtered. With the training process completed the performance of the ANN was validated.

5. Results and Discussion

Several weeks of field work were needed to get sufficient information to train the ANN and obtain a robust arc coverage estimation, simultaneously the behavior of the panel's cooling water temperature and the electric current set point of the phase nearest to the measurement point were observed.

In **Fig. 8(a)** a considerable temperature increment, due to a bad coverage of the electric arc, is shown. Here the cooling water reached approximately 65°C at 220 seconds. It is observed, in **Fig. 8(c)**, that for the temperature increment shown, the arc coverage indicator started to oscillate near the top of the scale (near 5) at the beginning of the graph, and subsequently reaches the maximum value (5) during a few minutes. In addition, **Fig. 8(d)** show the raw vibration signal in order to appreciate the mapping capability of the ANN. Panel temperatures do not react immediately to suddenly uncovered arcs, an average delay time is in the range of 30 seconds.³⁾ The sudden loss of the measuring point due to tilting movements of the furnace was inevitable with the arrangement done in the field, because of this the arc coverage indicator presents unwanted increases. The shell's movements always follow the same geometrical pattern, so it is possible to design a larger reflective surface that will assure that not losses of the laser beam measuring signal will take place.

In **Fig. 8(b)** it can be observed at 290 seconds an increment of the current set point, this implies a reduction in the electric arc length that caused a better arc coverage. Under this scenario the arc coverage indicator dropped to safe levels (near 2) as shown in **Fig. 8(c)** at 300 seconds. In these almost soundless conditions (due to excellent arc coverage in short arc), the cooling water gradually reduces its temperature from near 65°C to 56°C.

More results were obtained in the same line in many other heats. **Figure 9** presents another interesting working condition presented during the field observations done in this research. The variables of interest are here shown; panel temperature, phase current set point, arc coverage indicator and raw vibration. In this case under analysis, a good coverage of the electric arc was achieved allowing to work with a long arc. A longer arc emits more radiation, and therefore under normal working conditions of the EAF, it is expected to observe an increment in panel's temperature.

Fig. 8. Charts during bad arc coverage of (a) water cooling temperature, (b) phase current set point, (c) arc coverage indicator and (d) raw vibration.

When working with long electric arcs, the temperature can increase in a fast and dangerous way if the arc coverage is poor or in a slow and safe way if the arc coverage is good, like in this case. At 140 seconds in Fig. 9(c) it can be seen that the coverage level improve, this allowed the operator to enlarge the arc without risk of damage to the EAF, this length increment (drop in electric current) is observed later at 160 seconds in Fig. 9(b). The steel primarily absorbed the radiation of this long arc, but inevitably, the shielding of the arc by foamy slag never is perfect so part of this increase in radiation heated the panel, as can be seen in Fig. 9(a). However, due to the good coverage experimented at that point, the slow increase in panel temperature (two to three degrees) did not represent a concern for the operation at that particular stage. Despite long arc operation the temperature of the cooling water did not exceed 55°C.

The collected experimental data shows that vibrations provide very useful information about the conditions of the electric arc. A good indicator of arc coverage level can contribute to adjust the electrical operating point to the actual process conditions, this intended to achieve maximum melting power with acceptable thermal losses and acceptable flicker level.^{3,23)}

Fig. 9. Charts during good arc coverage of (a) water cooling temperature, (b) phase current set point, (c) arc coverage indicator and (d) raw vibration.

6. Conclusions

In this work it was demonstrated that furnace's shell vibration is correlated to arc coverage and, in addition, it is possible to safe measure arc furnace's vibrations using laser technology, keeping sensitive electronic equipment far away from surrounding areas of the furnace, where most electronic devices attached or near to the furnace's walls fails. The hypothesis regarding the relation between vibrations and the level of coverage of the arc was validated by field measurements. The field data obtained shows that at certain times of the melting process a poor coverage of the electric arc was present and the radiation emitted was not properly absorbed by the slag, then overheating in cooled panel was registered. Poor electric arc coverage can be attributed to scrap falling from the furnace walls which produces waves motion in the slag. As well as certain common tilting practices of the furnace done by the operator to drop attached scrap from the furnace's walls.

Electrical variables of the process, like the phase current, provides important information related to the length of the electric arc. This information in conjunction with the coverage indicator based on vibrations, makes possible to predict whether a temperature increment in the cooled panels will or will not occur. This is the starting point for the design of a more robust ANN for multivariable processing. The inputs for the multivariable ANN can be any which provide relevant information about the conditions of the electric arc,

the combination of electrical variables and vibration can be a good initial configuration. It should be noted that the number of inputs of the ANN can be increased, thus other variables such as the sound produced during the process⁷⁾ can be included in the processing to obtain a better arc coverage indication. These integration of variables is presently under research of other team working on the same project. It is important to mention that at this stage, the EAF is not yet controlled using the developed arc coverage indicator. A future work, will carry out statistical tests once the EAF is controlled using our arc coverage indicator. This in order to show how, in general, the radiation emitted to the panels is reduced when the electrical set point of the EAF is adjusted depending of the level of coverage of the electric arc.

In summary, excellent field results were obtained with this implementation that proved the hypothesis that EAF shell's vibration, measured with a laser beam and processed by an Artificial Neural Network, it is by itself a very robust arc coverage indicator.

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