Design of a neural network controller for the electrode control system in the electric arc furnace

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ABSTRACT. *The significance of steel making in the modern world has made the development of electric arc furnaces one of the top priorities in researches. The goal of this thesis is to design an artificial neural network in order to optimize the function of electric arc furnaces. At first the current loop of electrode control system has been simulated in MATLAB Simulink for Cassie-Mayr mathematical model of electric arc furnace. In this case, the input of the system is constant impedance set-points which are implemented by operators. So, change of conditions and output of the furnace do not affect the system input. Then, by using the output data from two different steel complexes of Iran, an artificial neural network has been designed for simulating a compensator system. Considering the RMS data achieved by the transformers, the RMS of input current is used as input current of EAF. By implementing this system on the current loop as the external loop, which includes furnace related inputs, a coefficient factor is created. By this factor, the constant impedances are corrected and optimized. In addition, it is observed that the impedance error of the new system significantly decreased compared to the impedance error of the simulation of the current system.*

RÉSUMÉ. *L'importance de la fabrication de l'acier dans le monde moderne a fait le développement des fours à arc électrique (FAE) l'une des principales priorités de la recherche. L'objectif de cette thèse est de concevoir un réseau de neurones artificiels afin d'optimiser la fonction de fours à arc électrique. Au début, la boucle de courant du système de contrôle des électrodes a été simulée dans MATLAB Simulink, en utilisant le modèle mathématique Cassie-Mayr du FAE. Dans ce cas, les données saisies du système ont été des points fixes à impédance constante sélectionnés par l'utilisateur. Ainsi, les changements de conditions et de sortie du fourneau n'ont pas affecté l'entrée du système. Ensuite, en utilisant les données expérimentales de deux complexes d'acier Iraniens différents, un réseau de neurones artificiels a été formé pour simuler un système compensateur. Les données moyenne quadratique émises par les transformateurs ont été utilisées comme entrée du FAE. En mettant en œuvre ce système sur la boucle de courant, qui comprend les entrées reliées au four, un facteur de coefficient a été créé. Par ce facteur, les impédances constantes ont été corrigées et optimisées. De plus, on observe que l'impédance du nouveau système est considérablement réduite par rapport à l'erreur de la simulation du système.*

KEYWORDS: *electric arc furnace (EAF), electrode control system, neural energy control (NEC).*

MOTS-CLÉS: four à arc électrique (FAE), système de contrôle des électrodes, contrôle de l'énergie neurale (CEN).

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1. Introduction

Steel making industry is one of the most important industries in the world. This industry has undergone many changes in recent decades, and Electric Arc Furnaces (EAFs) have been introduced to control and save energy in the steel making industry. The electrode regulator system is one of the most important subsystems in the Arc Furnaces and its task is to regulate the arc length. This system is a complex, multivariate and high nonlinearity system, and conventional control methods such as PID (Proportional-Integral-Differential) and feedback linearization methods cannot meet the stability and increases energy consumption (Ping *et al*., 2009 ; Li *et al*., 2012).

In the recent years, different methods have been used for modeling electrode control system of the electric arc furnaces.

Janabi-Sharif *et al.* (2009) conducted a study on modeling and simulating the EAF electrode regulator system using adaptive neuro-fuzzy inference systems (ANFIS). In this article, the results show the feasibility of using ANFIS for modelling an EAF.

Chang *et al.* (2010) have presented neural-network-based method for modeling the non-linear voltage-current characteristic of the EAF.

Moghadasian *et al.* (2011) introduced a new application of a genetic-fuzzy control system to control the input energy to three-phase EAF. In order for that, the coefficients of the fuzzy PI controller are regulated by the genetic algorithm. In the same years, in order to control the electrode of the EAF, a PID controller was designed by Hong-Jun *et al.* (2011). In this paper, by using the traditional back propagation (BP) algorithm jumped out of the local minimum and achieved a good result and control ability.

Li *et al.* (2012) used an adaptive neural network controller (ANNC) for the electrode regulator system. Pre-training is not required for the neural net adaptive control and the weights of the neural networks are directly updated online based on the input–output measurement.

Ismail *et al.* (2011) studied the prediction of energy consumption, and specifically gas, by using the neural networks. In this paper, by evaluating some type of artificial neural network, the best one in order to optimize performance has been chosen.

Currently, in Iran steel complexes, there is a device called TDR for controlling the arc furnace electrodes. This equipment is PC based. Another type of control system is the SIMELT control system, which is PLC based. In general, the control method of both control systems is the same; so the arc flow and arc voltage enter the system, and after processing, the suitable signal for controlling the hydraulic valves is produced. These valves are connected to the electrodes. So according to this signal, the electrodes are raised or lowered, and their distance with scrap and also electric arc length is controlled. In addition there is a compensation part in these systems. By activating this part, another control loop is created. By creating a coefficient factor for current or impedance, this loop causes more accurate control of the electrodes. The main purpose of this research is to simulate and design an optimal neural network system for compensation part. In this paper, according to the SIMELT documents and using ANN in modeling, the compensating part is called NEC (Neural Energy Control). The purpose of adding this system is to improve the performance of the electrode control system and to optimize the energy consumption (SIMELT, 2006). In future development, new features can also be added to this set and improve its performance without the need to add new hardware and just with change in the software. It should be noted that existing systems, as well as articles on control of the electrode regulation systems of the electric arc furnaces, that have been presented so far, are more based on current control. According to the initial definition of this project, with the aim of controlling the arc furnace electrodes based on impedance, this research is based on impedance control. In addition, it has been shown in previous studies that control based on impedance makes independence in control of the phases (Kiyoumarsi *et al.*, 2011).

The structure of this paper is organized as follows. Section 2, describes the mathematical modeling of EAF and simulates it. Section 3 deals with the design and simulation of the NEC. In section 4, the current control loop and the control loop after implementing the compensator have been simulated.

2. Electric arc furnace, mathematical model and simulation

Electric arc furnaces used in the steel making industry are generally divided into two types, Alternating Current or AC furnaces and Direct Current or DC furnaces.

Electric arc furnaces studied in this paper are AC electric arc furnaces. There are three types of AC furnaces; one-phase, two-phase or three-phase. Three-phase with three electrodes are common in industry.

2.1. Mathematical model of electric arc furnace

In different articles, various methods of modeling electric arc furnaces have been used such as Cassie-Mayr model, Acha model and the hyperbolic-exponential model. In this paper, the Cassie-Mayr model is considered.

2.1.1. Cassie Mayr Model (Awagan *et al.*, 2016)

The characteristics of the arc are affected by electrode material, position of the electrodes and some other factor. The Cassie model yields good performance for arcs with high current while the Mayr model shows good behavior and results for arcs with low current.

The following equations show mathematical relations of Cassie-Mayer EAF model.

$$g = g_{\min} + \left[1 - \exp\left(-\frac{i^2}{I_0^2}\right)\right] \cdot \frac{vi}{E_0^2} + \exp\left(-\frac{i^2}{I_0^2}\right) \cdot \frac{i^2}{P_0} - \theta \frac{dg}{dt} \tag{1}$$

$$i = gv \tag{2}$$

$$\theta = \theta_0 + \theta_1 . \exp\left(-\alpha |i|\right) \tag{3}$$

where v is the arc voltage, i is the arc current and g is the arc conductance.

Other parameters and their values are shown in Table 1.

Table 1. Parameters for Cassie-Mayr EAF model

Parameter	Description	Value
g_{min}	Minimum arc conductance	0.008
I_0	Transition current	10A
E_0	Constant steady-state arc voltage	250V
P_0	constant power loss	110W
θ_0	Arc time constant	110µs
θ_1	Arc time constant	100µs
A	Constant	0.0005

In this paper, the simulation of the Cassie-Mayr model was performed precisely according to the relevant reference paper in this section (Awagan *et al.*, 2016) as well as the extraction of some constants and values of elements from Mokhtari *et al.* (2002).

The voltage-current characteristics of the simulation of this model is shown in Fig. 1.

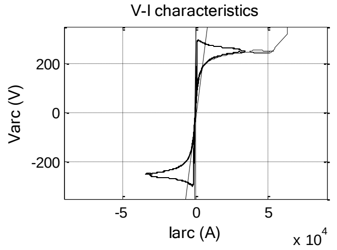


Figure 1. Voltage-current characteristics of arc

3. Artificial neural network, design and simulation of NEC

One of the main goals of any scientific-practical project is to optimize energy consumption. In this paper, this goal is achieved by calculating the optimal impedance via the neural network.

Energy consumption prediction has always been one of the main research fields. ANN recently is one of the computational methods in research and used in prediction application. ANN can model any nonlinear relationship with good accuracy by adjusting the network parameters (Ismail *et al.,* 2011).

In this article, the goal is to simulate and design an optimal neural network system using the same algorithm as Ismail *et al.* (2011) for the NEC. In this regard, it is necessary to test the network with implementing input data and choosing different structures and different number of layers and the neurons in each network layer. So, according to the training error, the best structure is used as an artificial neural network in energy consumption prediction.

In this article, data of two Iran steel complexes have been used for simulations. The ANN training is done using input and output data of various elements. In simulation the voltage and current of the electrodes are used as input data and the impedance of the electrodes is used as output data of ANN. It should be noted that the number of samples of each data set equal to 1,000; which randomly 70% of this amount is used for training, 15% is allocated for validation and the remaining 15% is used for testing.

3.1. Using the MATLAB ANN tools in simulation

As previously mentioned, the purpose is to simulate and design an optimal neural network using the same algorithm as Ismail *et al.* (2011) for the NEC. In this paper, the nntool toolbox is used to design and simulate the network. This toolbox has the ability to change most of the elements that affect the network structure.

In all tests of this paper, feed-forward back-propagation has been used as network type, TRAINLM as training function and TANSIG as transfer function of the output layer of the two-layer network (Ismail *et al.,* 2011). Other elements have also been changed step by step. Due to the importance of time in practical implementations and decreasing error as much as possible, we have tried to choose ANN structure in order to maintain acceptable training time and minimum performance. Therefore the neural network structure with 27 neurons, the TANSIG transfer function and the MSEREG performance function are selected as the optimum structure. Fig. 2 shows the obtained curve of this structure. As can be seen, best validation performance is achieved at epoch 135. It should be noted that in these tests, the validation checks are set to 100. This will prevent the local minimum; on the other hand it will cause increasing the training time, which is also the reason for the reduction of training error. As can be seen, generalization of analysis of the graphs behavior is not possible. So the network and its structure should be selected according to the priorities of each project.

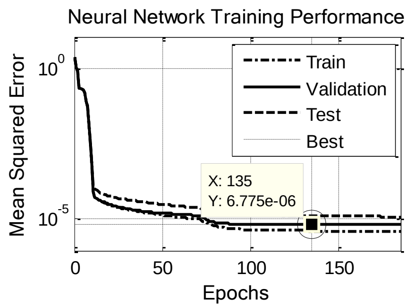


Figure 2. Performance of ANN structure

4. Simulation of the control loop

In this section, in addition to simulation of the NEC, which was simulated in the previous section using the neural network toolbox, the control loop is also simulated. Also the results of the previous section are used to select the appropriate neural network structure.

The EAF line diagram is shown in Fig. 3. As previously mentioned, this research is based on impedance control. The equations that have the significant role in shaping the control loop and its behavior are defined as follows (SIMELT, 2006; Samet *et al*., 2015; Eduardo *et al*., 2015):

The impedance is given by

$$Z = \sqrt{X_L^2 + \left(R_V + R_B\right)^2} \tag{4}$$

where z is total impedance, X_L+R_V is line impedance and R_B is arc impedance. Their values are as follows:

$$R_{V1} = R_{V2} = R_{V3} = 0.4\, m\Omega$$

$$X_{L1} = X_{L2} = 15.97\, \mu H \text{ , } X_{L3} = 15.33\, \mu H$$

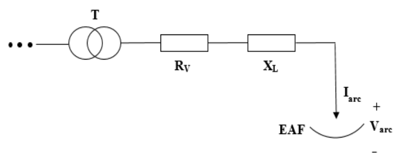


Figure 3. EAF line diagram

4.1. Controller loop with constant set point (without NEC)

In this section, as shown in Fig. 4. the constant impedance is applied to the system. This value and PID controller coefficients are selected in accordance with the values applied to the actual system. For current input of Cassie-Mayr EAF, according to $i=v/z$ equation, the output voltage of transformer is divided by the controller output which is the impedance. This voltage is determined according to the table for arc furnace transformers by the steel complexes (Table 2).

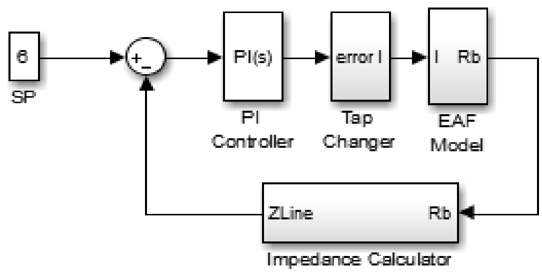
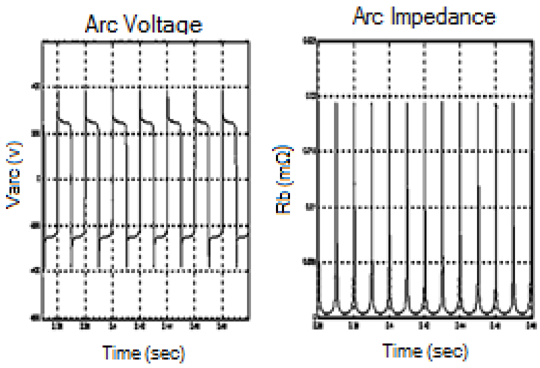


Figure 4. Controller loop with constant set-point

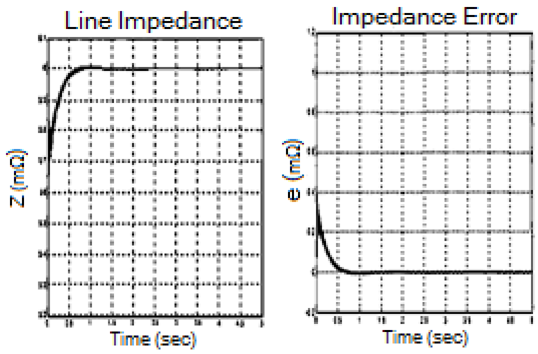
Table 2. Information of the EAF transformer

<table>
<tr><th colspan="2"></th><th colspan="2">NORMAL</th><th colspan="2">OVERLOAD</th></tr>
<tr><th>O.L.T.C Pos.</th><th>Secondary Voltage (V)</th><th>Secondary Current (A)</th><th>Primary Current (A)</th><th>Secondary Current (A)</th><th>Primary Current (A)</th></tr>
<tr><td>1</td><td>430</td><td rowspan="8">38100</td><td>816</td><td rowspan="8">47625</td><td>1019</td></tr>
<tr><td>2</td><td>455</td><td>863</td><td>1079</td></tr>
<tr><td>3</td><td>480</td><td>911</td><td>1139</td></tr>
<tr><td>4</td><td>505</td><td>959</td><td>1198</td></tr>
<tr><td>5</td><td>530</td><td>1006</td><td>1258</td></tr>
<tr><td>6</td><td>555</td><td>1054</td><td>1318</td></tr>
<tr><td>7</td><td>580</td><td>1102</td><td>1377</td></tr>
<tr><td>8</td><td>605</td><td>1149</td><td>1436</td></tr>
<tr><td>9</td><td>630</td><td>36750</td><td rowspan="9">1155</td><td>45940</td><td rowspan="9">1445</td></tr>
<tr><td>10</td><td>655</td><td>35340</td><td>44180</td></tr>
<tr><td>11</td><td>680</td><td>34040</td><td>42550</td></tr>
<tr><td>12</td><td>705</td><td>32830</td><td>41030</td></tr>
<tr><td>13</td><td>730</td><td>31700</td><td>39620</td></tr>
<tr><td>14</td><td>755</td><td>30650</td><td>38310</td></tr>
<tr><td>15</td><td>780</td><td>29660</td><td>37080</td></tr>
<tr><td>16</td><td>805</td><td>28740</td><td>35920</td></tr>
<tr><td>17</td><td>830</td><td>27870</td><td>34840</td></tr>
</table>



(a) *(b)*

Figure 5. (a) Arc Voltage, (b) Arc Impedance of current control loop with sinusoidal current



(a) *(b)*

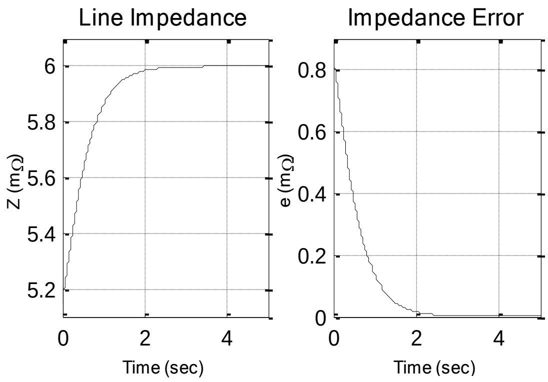
Figure 6. (a) Line impedance (b) Impedance Error of current control loop with sinusoidal current

It should be noted that in the actual system, the applied current to the EAF is sinusoidal. The following figures show arc voltage with flicker (Fig. 5(a)) and oscillating arc impedance (Fig. 5(b)). These curves have been obtained by implementing sinusoidal current. Also as can be seen in Fig. 6(a) the line impedance has reached to 6 mΩ set point value, so the impedance error is limited to zero (Fig. 6(b)).

The result of this simulation is completely similar to the results of previous researches (Awagan *et al*., 2016; Samet *et al*., 2015; Seker *et al*., 2014; Zhao *et al*., 2010; Zheng *et al*., 2000). The goal of this research is simulating and adding the NEC system to the loop. The achieved data by PT (Potential Transformer) and CT (Current Transformer), which are used in the training of the NEC system, are RMS. So from this point on the RMS of input current is considered as input current of EAF.

To ensure the same result in line impedance and impedance error, previous simulation is repeated by applying the RMS current.

The result is shown in Fig. 7. As can be seen, the line impedance curve follows the set point value applied to the system and converges to that value after a short period of time.



(a) *(b)*

Figure 7. (a) Line Impedance (b) Impedance Error of current control loop with RMS current

4.2. Controller loop with correct set point (with NEC)

The standard electrode controller based on constant impedance set points does not react to changing furnace conditions. The setup of the impedance tables is fixed, long-term experience is necessary to find suitable settings (SIMELT, 2006).

The NEC system is developed as an additional package unit to the **A**rc **C**ontrol (AC) to optimize the electrical operating points dynamically to fulfill basic aspects of melting strategy (SIMELT, 2006). A block diagram of this optimizer system as part of the research and development project of SIEMENS can be seen in the following figure (Fig. 8).

In fact, NEC system acts like a compensator loop, which by being activated creates another control loop. This loop generates optimized set points by generating a suitable coefficient for impedance.

Access to NEC and its internal structure and program is not possible in the steel complexes of Iran. Some Iranian scientists have been designing an external loop including a PID controller to simulate this system. In this paper, the design of this compensator is based on neural network and SIEMENS methods.

4.2.1. Types of NEC structure

In this paper, NEC is designed in two ways. The first method was investigated in the previous section. For the purpose of communication between the NEC and SIMELT, which is PLC-based, to applied the programs and setting and control the electrodes, it is necessary that MATLAB and PLC communicate with each other. Therefore, using the programming in the m-file environment, the corresponding neural network block is designed and produced. It should be noted that in this programming, it has been tried to use the results of the first method as much as possible.

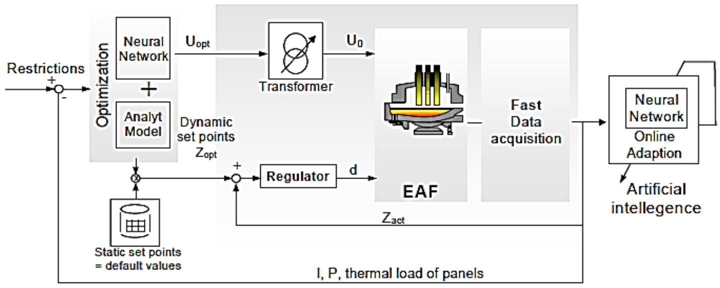


Figure 8. General overview of EAF

The block diagram of implementation of the NEC system to the previous system is shown in Fig. 9. In this case the output of the NEC system is multiplied by the previous impedance constant value and corrects this value.

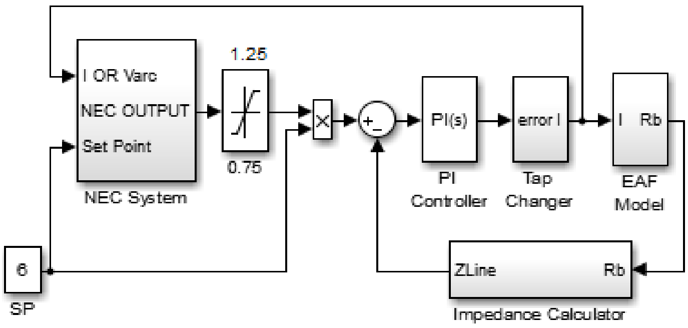


Figure 9. Controller loop with NEC implementation

The corrected set point value and the line impedance are illustrated in Fig. 10.

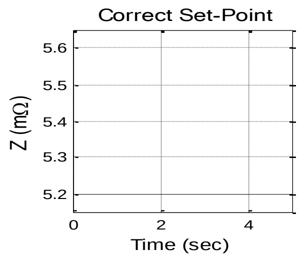


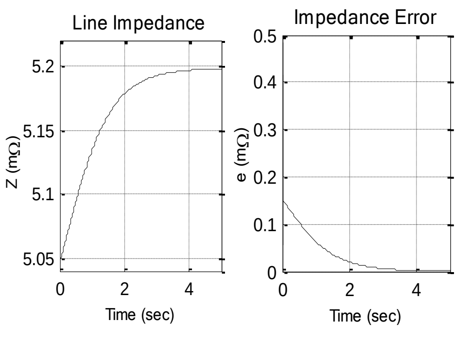
Figure 10. Corrected set-point

As can be seen, the corrected line impedance obtained from this simulation is equal to 5.19 mΩ. The output line impedance also converges to the same value and then the steady state error reached to 763.76 nΩ (Fig. 11). So the system output is tracking the set point value without error.

In order to simplify simulations comparison, the results are summarized in Table 3. As can be seen, adding NEC system to the loop has reduced the impedance error of the system.

As can be seen, the NEC system corrects and optimizes the current impedance which is applied to the system by the operator. In addition, according to the SIEMENS results of "reducing the value of the set point for some point" due to applying the NEC system, in this research reducing this value is obtained for a range of set points. According to questions from steel experts, the typical set point used by operators is 6 to 6.5.

To ensure system performance in other situations, the simulation results for the other set point values are summarized in the Table 4. It should be noted that these values are selected according to the range of impedance values in the measured data.



(a) *(b)*

Figure 11. (a) Line Impedance (b) Impedance Error of control loop with NEC implementation

Table 3. Compare error for current control loop and control loop with NEC implementation

	Without NEC	With NEC
Error	4.279 μΩ	763.761 nΩ
Fall Time	1.016 secs	1.802 secs

Table 4. Simulation results for the other set point values

SP	Correct Value	Correct Set-Point (Ω)	Line Impedance (Ω)	Error (nΩ)
4.5	1.156	5.198	5.197	763.761
5	1.04	5.198	5.197	763.761
5.5	0.945	5.198	5.197	763.761
6	0.866	5.198	5.197	763.761
6.5	0.8	5.198	5.197	763.761

5. Conclusion

In this paper, by using the output data from two different steel complexes of Iran, an artificial neural network for simulating a compensator system has been designed.

This system is implemented on the current loop as the external loop and is affected by furnace related inputs. By creating a coefficient factor, the constant impedances are corrected and optimized. In addition, it is observed that the impedance error of the new system significantly decreased compared to the impedance error of the simulation of the current system.

In addition, this system causes reducing set point value for a range of set points which includes the typical range used by operator. So, by this reduction in the set point, the energy consumption is reduced.

In the future, we will try to design a neural network with online training. This will improve the performance of the NEC system and accepts more changes from the furnace output.

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