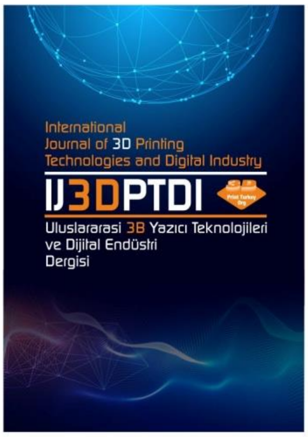

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THE USE OF ARTIFICIAL NEURAL NETWORKS IN THE CONTROL OF ELECTRIC ARC FURNACES

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ABSTRACT

Today, control systems have become an important branch of science in parallel with the increase of production and quality needs. There are purpose-specific automatic control systems and algorithms controlling them for production in industrial facilities. In this study, modeling electric arc furnace scrap melting plant, which has an essential place in the iron-steel industry has been made using artificial neural networks. The facility where the study is carried out is in active production and controlled by classical algorithms. Artificial neural networks were trained using the data taken over the current control system and pressure sensors attached to the electrodes and the modeling and control of the arc furnace with the trained network was carried out. The software developed with an artificial neural network to control the electrodes used in electric arc furnaces provided 98% success in monitoring the system including the operator's intervention out of the algorithm. All input and output data of an active production facility were copied to the network with the developed software. Since this software does not require various calculations, calibrations and parameter changes, it responds faster than the classical control algorithm used in the factory.

Keywords: Electric Arc Furnace, Artificial Neural Networks, Steel Production.

1.INTRODUCTION

The iron and steel industry is a sector that is generally integrated and complements each other. The iron and steel factories are in the first place in the supply of raw materials for many production and manufacturing sectors. It is the engine of industrialization and development.
Today, liquid steel production is made under two main topics. These are blast furnaces and electric arc furnaces. Due to the flexibility of their processes and their low investment and operating costs, electric arc furnaces are preferred more in liquid steel production than blast furnaces.

Approximately 12% of the energy used in the world is consumed in the Iron-Steel Industry. This reveals the importance of the energy used in this sector. Steel production with electric arc furnaces is the most energy-consuming production method per unit production in the industry [1].

The increase in energy costs has caused an increase in the number of studies about reducing the energy amount consumed per unit of production.

Computer technology is developing very rapidly. This development gives acceleration to all engineering fields. Artificial Intelligence (AI) is an important field in this development. Different methods are used for different problems under the title of AI. For example, Genetic Algorithms for issues including optimization, Fuzzy Logic for issues containing control and Artificial Neural Networks for issues about Pattern Recognition come to the fore.

In this study, Artificial Neural Networks were used in the modeling and control of the electric arc furnace.

Artificial Neural Networks (ANN) is a calculation method that is adaptive, can work with incomplete information, provide results under uncertainties and is tolerant of errors [2]. In general, ANN is used because of its ability to determine the relationship between non-linear, complex input-output data in a system. The solution of problems that cannot be modeled with classical control algorithms makes this method more advantageous. For this reason, ANNs with various applications in many different engineering branches. There are many studies on electricity and control using this method. Some studies using ANN; [3, 4] was used in the electrical energy consumption estimation analysis. Successful results have been reported in fault detection in industrial processes [5]. An optimum Ad Hoc Network has been established between land vehicles [6]. It has been used for minimizing harmonics, condition monitoring and diagnostics in electric motor drives [7, 8]. It has given good results in system identification in three-phase ferrosilicon coated arc furnaces [9]. Heat losses and energy needs have been estimated [10, 11]. Force Control of Hydraulic Actuator is provided[12]. Estimation of arc voltage was made in EAF [13]. It has been used in modeling and control of arc welding [14].In this study, input-output data of an electrode regulation system of the Electric Arc Furnace (EAF) of a factory producing iron and steel using an EAF unit were collected. These collected data were used in the training of ANN we developed to control the EAF unit in real-time.

The current and voltage balance of EAF is irregular which makes its modeling to be hard with classical algorithms. For this reason, it was aimed in this study to model EAF current and electrode characteristics with ANN for the efficient and stable use of power by performing more effective regulation of electrodes.

In the study, a database was created with the data of current, voltage, impedance, reactance, active power, reactive power, apparent power, power factor, arc powers, arc resistances, electrode pressure during the steel production of different quality. These data were used in the training and test of ANN with various combinations. The network learned the normal course of the system without any problems. However, it did not learn that the operator controls the system manually. For the solution to this problem, the data taken from the pressure sensors added to the rive arms of the electrodes of the EAF and the manual intervention data of the operator apart from the algorithm were added and all behaviors of the system were learned by ANN. Real values of EAF and the results given by ANN overlap at a rate of 98%. ANN produces the same result approximately 100 ms faster. This is due to the time classical algorithms spend for processes. Thus, a by-pass software has been developed that works in parallel with an existing control system and does the same task faster.

2. RELATED WORKS

EAF contribute to almost a third of EAF global steel production. Arc furnaces use significant amounts of electrical energy to process iron. For this reason, small developments in their efficiencies correspond to the significant amount of energy. In order to increase both process performance and energy savings, studies on various control techniques are carried out.

In this section, studies conducted on our subject are examined from less relevant to more relevant.

Hong, Sheng and Li developed a control system for AC current EAF based on a fuzzy neural network [15]. As a result of their practical work, they showed that the system has high control sensitivity and reliability, it provides a smooth regulation of the electrodes by increasing the up and down movement of electrodes and their position sensitivity, it provides the three-phase current balance and showed the stability of the EAF temperature.

Sadeghian and Lavers to find a solution with a feedforward adaptive neuro-fuzzy network for the estimation of non-linear V-I characteristics of EAF [16].

EAF is one of the unbalanced loads causing fluctuations in the electrical power transmission and distribution system. Wang, Jinn and Zhu provided a solution to describe the unbalanced behavior of the power system of the EAF using the combination of chaos theory and ANN. With this study, it was shown that EAF can be used to predict the arc voltage [17].

British Gas plc and SD-Scicon UK Limited companies introduced an ANN model providing an experimental EAF control and performance evaluation and showed that ANN exhibited perfect performance in temperature prediction [18].

Hui and Wang tested the current estimation model of EAF in Matlab using ANN and showed that electrodes were effectively controlled [19].

Paranchuk proved an increase in sensitivity in voltage measurement with ANN-based on continuous voltage monitoring [20].

Staib W. and Staib R., in their study, controlled the position of the electrode in an 80-tonne EAF using ANN. As a result of the control made with ANN, it was confirmed with the tests and trials that millions of dollars can be saved because of the decreased wear in the furnace and the electrodes [21].

King and Nyman stated that the working dynamics of the EAF are irregular and previous experiences and intuitive control of the operator working in EAF control is used in every casting. For these reasons, they claimed that standard control techniques are not sufficient. They also stated that ANN can learn the system dynamics of the electric arc furnace and showed that the introduced model with ANN can be used for the control of the arc furnace later on [22].

Garcia-Segura et al. proposed in their study a method using real-time current and voltage values of EAFs along with arc length as parameters suitable for the ANN model. They showed that the arc length can be estimated with this method. The obtained results showed that the model estimates not only stable arc conditions but also unstable arc conditions which are difficult to define in a real melting process [23].

In this study, by using real data taken from an actively operating EAF, the arc furnace was controlled with ANN that we developed to adapt to the existing system. Unlike other studies, the intervention of the operator was also taught to the network. The results are presented in detail in the relevant sections.

3. MATERYAL AND METOD

In this study, a scrap melting plant with EAF, which is active in production in Turkey, is modeled with ANN. The modeled EAF is driven by a transformer with a capacity of 160 tons and has the property of a short circuit of 156 MVA. The electrodes of the furnace are controlled by proportional valves and a separate design has been made for each electrode.

EAF electrode control system is controlled by Siemens brand S7 – 400 Programmable Logic Controller (PLC). Current, voltage, active power, and reactive power data of each electrode are read by PLC from Siemens energy analyzer using Profibus (Siemens Serial Communication) protocol. Other auxiliary units (hydraulic motors, system protections, etc.) are controlled over Profibus.

In order to read and graph the phase currents, phase voltages, voltages of electrode drive cylinders, PLC outputs, impedance data, and related files in different formats of EAF, IbaPDA client-server software along with an interface prepared in Borland Delphi 7.0 were used. These data taken from the system were used in the training of the ANN developed in Borland Delphi 7.0 environment.

IbaPDA software was installed on a computer having Intel® Core™2 Quad CPU Q950 @ 3.00 GHz processor and 2.99GHz, 8GB RAM, 300GB HDD and Microsoft Windows XP Pro. SP3 operating system.

3.1 Electric Arc Furnace and General Structure

The general structure of the EAF is given in Figure 1. The system is composed of electrodes (E0, E1, E2), a transformer (T), and a portable cable (C) joining the copper busbar holding the electrodes and hydraulic actuator (H).Materials entering and leaving the EAF (in Figure 1) are scrap, pig iron, slag-making agents, deoxidizing agents, carbon electrodes, natural gas, oxygen and cooling water. The substances coming out of the furnace are liquid steel, slag, dust, flue gases and cooling water. The total amount of materials charged into the furnace is approximately 65 tons.

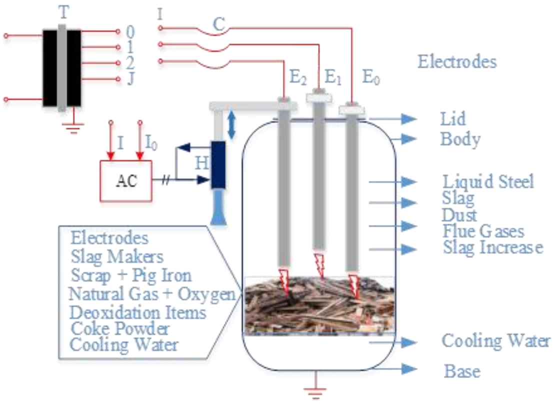

Figure 1. Schematic representation of electric arc furnace and material entering and leaving the furnace.

During regulation, hydraulic actuators (H) adjust the arc length by providing vertical movement of the electrodes. By changing the position in line with the data coming from the control system, (J) secondary voltage is adjusted.

EAF transformer used in the factory is a 3-phase, 16-stage special type transformer with Dd0 connection group. Set values and the feedback values received from the system are calculated in PLC. The regulation process is performed in line with the values obtained when the system is on load and the voltage is adjusted by selecting the transformer step according to the process.

Apparent power, primary current, secondary current, primary voltage, turn ratio, voltage drop and reactance of each step in transformer are different. These values are important to calculate regulation. In order to transfer appropriate power to the scrap material, it is necessary to select suitable step, to calculate impedance value and to select appropriate step in the reactor as in the transformer. In addition to these parameters, it is also important for regulation speed to be at appropriate values in order to draw balanced power in terms of equipment life and energy efficiency, which is an important cost in EAF.

The reactor used in the system has 12 stages. By changing the steps, the inductive reactance is adjusted. In the first step, primary and secondary of the reactor are short-circuited. In other words, it disables the reactor. Since the steel in the furnace has become liquid in the step after melting at this stage, the regulation will move the electrodes in a stable manner. Therefore, the unstable electrode movement during melting will cause the need for more power. This need is met by short-circuiting the reactor. In addition, the rate of the harmonics that will affect the transformer is lower in the smelting stage compared to the melting stage.

EAF is composed of 5 main parts including bowl, body, cover and mechanism, gantry, electrode and movement group. The electrode group consists of a copper carrier placed horizontally on the group and pliers gripping the electrode at its tip. The electrodes are connected to horizontal copper columns by pliers and from there to the connection groups through high current cables and to the secondary windings of the transformer with flexible busbars.

In the calculation of EAF reactance, the transformer output, high current cables, electrode arms and the geometric averages of the distances from the center to center between the phases of electrodes used, pitch circle conductor diameters, conductor diameter and lengths, networks frequency, material properties are important parameters.

For the short circuit calculation, reactance starting from the high voltage transformers of the switchgear and up to the electrode tip are first determined and the short circuit powers are found accordingly. The equivalent electrical circuit of the system is shown in Figure 2.

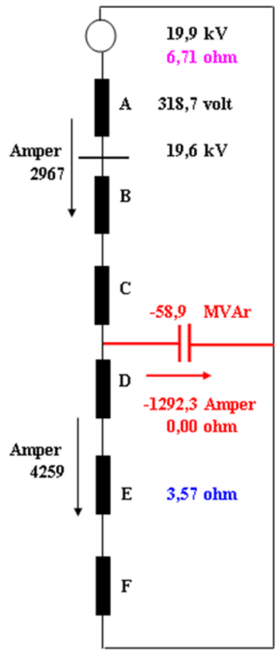

Figure 2. Electrical equivalent circuit of EAF.

Short circuit reactance (A) of the primary of high voltage transformer, the reactance of the secondary (B), the reactance of the line between secondary and EAF reactor (C), reactor reactance (D), the reactance of the primary part of EAF transformer (E), EAF reactance (F), the red line is specified as Static VAr Compensation (SVC).

Reactance and compensation power are calculated in the calculation made by referencing primary voltages, short circuit powers and voltages, secondary voltages, powers, voltage drops, line length, number of parallel lines, reactor reactance, maximum voltage drop values of the common connection point of the network and EAF.

3.2. Data Collection, Network Training and Testing

Hydraulic cylinders are used in speed and direction controls of electrodes in EAF. The proportional valves of the hydraulic cylinders are controlled with voltage values between -10V and +10V. The control information is sent to the proportional valve by Siemens brand S7-400. CPU 417 – 2DP PLC from 8x13bit analog output (AO) port. In the same way, the secondary currents of the electrodes are read from an 8x14 bit analog input (AI) channel.

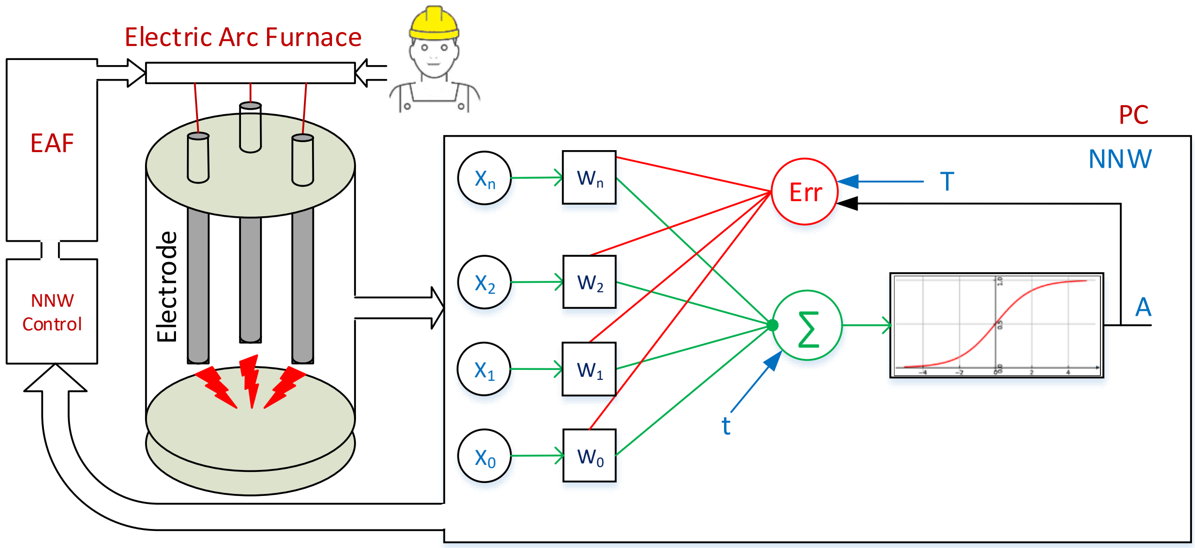

Figure 3. Principle scheme of control of EAF with ANN.

Analog information received from the current transformers (T1, T2, and T3) with a 1000/100V conversion ratio in EAF busbars is converted into digital information on the communication card and transferred to the regulation computer using the Profibus protocol. The communication between the regulation computer with the PLC controlling the proportional valves of the electrode drive systems is provided by using the TCP/IP (Ethernet) protocol. Hydraulic equipment and field processes are transferred to the CPU and controlled via Profibus with distributed remote inputs and outputs.

3.3. Reading the Data of EAF

In order to get the data from EAF, its PLC is connected to the Ethernet network with the iba server. There is a software called ibaPDA Analyzer installed on another computer. This software makes it possible to analyze PLC data (with 10 ms sampling time) with high accuracy. For the furnace tilting process, data like proportional output, furnace angle information, hydraulic pressure and level, electrode positions, active power, reactive power, apparent power, primary currents, secondary currents, Phase-Phase, Phase-Neutral voltages, main line hydraulic pressures, power factor, transformer stages, reactor stages, electrode pressures, casting numbers, carbon, oxygen, natural gas amounts, number of insulating material coming under the electrodes, casting start and end time, position of the electrodes are recorded.

3.4. Artificial Neural Networks (ANN)

Artificial neural networks give successful results with the ability to learn and generalize what they have learned in problems that do not have a mathematical model or algorithm.

The output of each neuron is a function of its inputs. The output and weights of a neuron in any layer are defined by the equations given below, and the neuron is shown in figure 4.

$$N_{Outj} = \sum (X_i . w_{ij}) \quad (1)$$

N_{Outj}: the output of the neuron, X_i: input value, w_{ij}: weight,

$$A_J = F(N_{Outj} + t_j) \quad (2)$$

A_j: The actual output, F: the activation function, t_j: threshold value,

$$w_{ij} = w'_{ij} + LR.e_j.X_i \quad (3)$$

w: the new weight value, w': the previous weight value, LR: learning rate, e_j: error

$$e_j = A_j.(1 - A_j).(D_j - A_j) \quad (4)$$

e_j: error, A_j:actual output, D_j: desire output

$$w_{ij} = w'_{ij} + (1-M).LR.e_j.X_j + M.(w'_{ij} - w''_{ij}) \quad (5)$$

M: momentum, w'': the weight value of the step before w'

X1	X2	X2 - X1	Y1	Y2	Y2 - Y1
02:32:15	03:14:00	41:44	0.00	0.00	0.00
02:32:15	03:14:00	41:44	0.00	0.00	0.00
02:32:15	03:14:00	41:44	0.00	0.00	0.00
02:32:15	03:14:00	41:44	3361.00	3361.00	0.00

Figure 4. Current trends of casting no 3361 in the Iba editor.

The ANN developed for the control of the EAF was trained using the input/output data obtained from an active EAF controlled by traditional control software, parameter tables, and expert technician experience. And the control of the EAF with the trained network is provided in parallel with the existing control system. In Figure 3, the simple flow diagram of the ANN system developed for the control of the EAF is shown. The network is trained with the data collected from the EAF and the EAF is controlled by the trained network.

3.5. Generating Datasets for ANN

For the ANN training, it is necessary to create data sets and make these sets suitable for ANN. All data used in the training of ANN are normalized within the range of [0–1]. For this calculation, max(x) and min(x) are found in the data set and the new value (z_i)is calculated with the following formula

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (6)$$

The casting records of EAF are filed starting from '1' by associating with the number of last casting reached as of the end of the year. An average of 30 castings can be made per day. Our study was conducted with different casting numbers and therefore with different steel qualities. In this way, the performance of the developed software was tested for different castings.

For example, in order to use the I1, I2, and I3 current values of the secondary of the transformer taken from the casting no 3361 in the training of the ANN, the operations performed using the Iba Analyzer editor are explained step by step below. The first three graphs belong to the current values according to time. The final graph gives the casting number. First of all, the data in the process were saved

on the computer including IbaPDA, and the data set was opened in the Iba editor (Figure 4).
Settings for the cast selection, time range of the data and time resolution are made from the program editor. In this casting, the time resolution was set as 10 milliseconds. The obtained data are shown in Table 1. In the production, the change rate in the electrodes during the melting phase is much higher compared to the change rate at the smelting time. Therefore, the test was carried out with samples taken from the melting stage. When the data taken from Iba Analyzer are examined, it is seen that the same values are obtained from the process repeatedly. The reason is that the rate of change in the process is approximately 30-120 milliseconds.

Table 1. Sample data set taken from the casting no 3361. The unit of I is Ampere.

Sampling Time (msec)	I1(A)	I2(A)	I3(A)	The casting no
10	0	76,8956	77,4906	3361
20	0	76,8956	77,4906	3361
30	0	76,8956	77,4906	3361
40	0	76,8956	77,4906	3361
50	0	76,8956	77,4906	3361
60	0	78,0006	79,0772	3361
70	0	78,0006	79,0772	3361
80	0	78,0006	79,0772	3361
90	0	78,5106	79,9272	3361
100	0	78,5106	79,9272	3361

3.6 Use of the Collected Datasets

The data prepared with IbaPDA are transferred to ANN with the developed interface program. The interface and ANN have developed in Borland Delphi 7.0 environment.

Data of casting no 3361 was selected as the sample data set and the ANN was trained with it. The selection of ANN architecture varies depending on the problem size. The number of layers, number of neurons in the layers, the learning rate, and the momentum coefficient are entered into the interface of the program. The training of the network is made by using I1, I2, and I3 secondary current data of casting no 3361 and the control data of the valves.

The data set obtained from the related casting also contains the manual interventions made by the operators to the electrodes during the melting and smelting phase. The training of the ANN was performed using the data sets taken from the "melting" phase of the arc furnace. The sample data set taken from the melting stage is seen in Table 2.

In the data set used in the training of ANN, the highest value of the current data of the secondary is 112,295 and the lowest value is 0. For the position data of the electrode, the highest value is 19.906 and the lowest is -9953. The position data of the electrode in the EAF System was set as -10 V (-27648) minimum value and +10 V (27648) maximum value with Simatic manager while programming PLC. 19.906 corresponds to +7.2 Volt voltage and the value of -9953 corresponds to -3.6 Volt voltage. The network was trained with %80 of these values and the performance of ANN was tested when the training was completed. The graphs of the training data set of the ANN are shown in Figure 5 below. The graph shown in blue at the top gives I1, the red one in the second row gives I2, the green color in the third row gives I3, and the graph shown again in red gives the data of electrode_1. The final blue-colored and solid line gives the casting number (3361). The data set consisting of three inputs including I1, I2, and I3 secondary currents of the casting no 3361 and one output data sent to the valves was uploaded to the ANN. Sigmoid function was used in the ANN program. In the experiments, the learning rate was set to 0.6 and the Momentum to 0.4, and learning took place with an error rate of 1.2% in about 7000 iterations. The response of the ANN trained with the real data from the EAF unit to the same data set is given in the graph in Figure 6. In Figure 6, the response of ANN could not follow the real data set at 55-67 (marked with the number 1) and 205-217 time intervals (marked with the number 2) Figure 7 below shows the range that ANN cannot learn. This range corresponds to a voltage level of 0.5 Volts. In the regulation software, electrodes were wanted to maintain their position if the value sent to the electrodes is 0.5 Volts or less ("Death Band" interval). To solve this problem, pressure sensors are installed in the electrode drive system. Details will be explained in the next section.

Table 2. Sample data set of the melting phase and the smelting. The unit of I1, I2 and I3 in the table is ampere.

	The melting phase				The smelting phase			
	I1	I2	I3	E_1	I1	I2	I3	E_1
1	56,4652	56,6136	57,9908	-2367	55,138	59,3429	40,1745	-1550
2	56,5807	56,6301	57,496	-2412,3	54,7009	59,464	39,7638	-1924
3	56,6796	56,358	57,026	-2435	54,4981	59,1902	40,2851	-2149,7
4	56,2508	56,1271	56,6466	-2435	55,1064	59,3482	42,0677	-2178,3
5	56,0364	56,0116	56,457	-2435	56,3992	60,2197	42,6233	-1920
6	55,4426	55,8879	56,2838	-2472,3	57,1259	60,0591	41,9861	-1678,9
7	55,022	57,026	56,5064	-2491	55,97	58,8268	41,025	-1505,4
8	54,8241	58,0156	56,6879	-2491	55,346	58,1264	41,0698	-1657,8
9	54,8159	58,898	56,8528	-2491	55,5092	58,3029	40,5537	-1785
10	55,22	59,8546	56,9105	-2640	55,3749	59,1744	40,1482	-1862
11	55,7312	59,9371	56,5312	-2640	56,1938	60,612	43,2973	-1851,2
12	55,8632	59,3763	56,1353	-2640	57,3207	60,9411	43,8634	-1779,3
13	55,9292	58,766	55,7395	-2640	58,7057	61,3019	45,014	-1775
14	55,9622	58,4609	55,5416	-2767,3	59,7642	62,018	48,0578	-1529
15	54,6014	57,2981	54,8241	-2831	60,9332	61,0833	46,9546	-1445
16	53,785	56,8775	54,4777	-3001	62,2392	60,3698	49,7271	-1157,3
17	53,5376	56,8116	54,387	-3086	62,4735	60,9359	50,783	-1000,1
18	53,0098	56,6714	54,1974	-3086	62,1286	62,8395	50,4064	-938
19	52,8449	56,6466	54,1644	-3140	61,5836	64,5431	51,7256	-880
20	52,647	56,6301	54,1314	-3167	61,0201	64,9881	51,1542	-851,2
21	52,3748	56,2838	54,552	-3167	60,4066	63,9454	48,9478	-761
22	52,3254	56,1601	54,6757	-3198,3	59,959	63,0028	47,5365	-733
23	53,0181	55,9869	54,8736	-3214	59,1507	61,997	45,4169	-808,6
24	54,4448	55,624	55,2035	-3214	57,8316	62,234	45,0746	-937
25	54,8241	55,2447	55,4674	-3214	57,2865	65,6648	46,6017	-1153,9
26	55,1705	54,7251	55,789	-3195,3	58,2449	69,4194	48,0446	-1293,7
27	55,2694	54,1809	56,1023	-3186	59,2481	71,023	48,982	-1282
28	55,0963	53,5624	56,457	-3186	59,1033	71,4258	48,9293	-1129,3
29	54,7911	53,1335	56,4817	-3167,3	59,2139	71,6601	47,9788	-1168
30	54,6757	52,8202	56,3827	-3158	60,0117	72,0946	50,9357	-1248,6
31	54,3046	52,1522	56,1271	-3158	60,0696	71,9761	51,2859	-1272
32	53,7355	51,9295	56,0281	-3158	61,6415	70,9334	50,3459	-1313
33	53,1913	51,7811	55,9622	-3169,3	64,5168	72,2605	55,583	-1036,3
34	52,5068	51,4759	55,4261	-3175	64,5984	72,8898	56,4071	-751
35	51,1378	50,8657	54,354	-3259,7	65,9491	71,6338	57,3708	-397

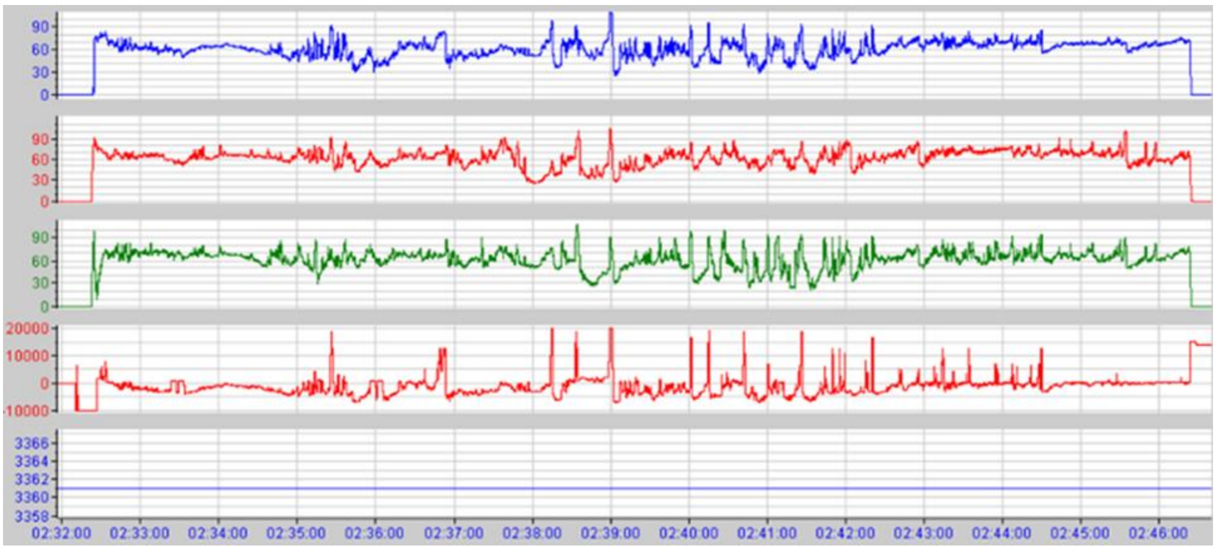

Figure 5. Graphs of the melting data set of the casting no 3361.

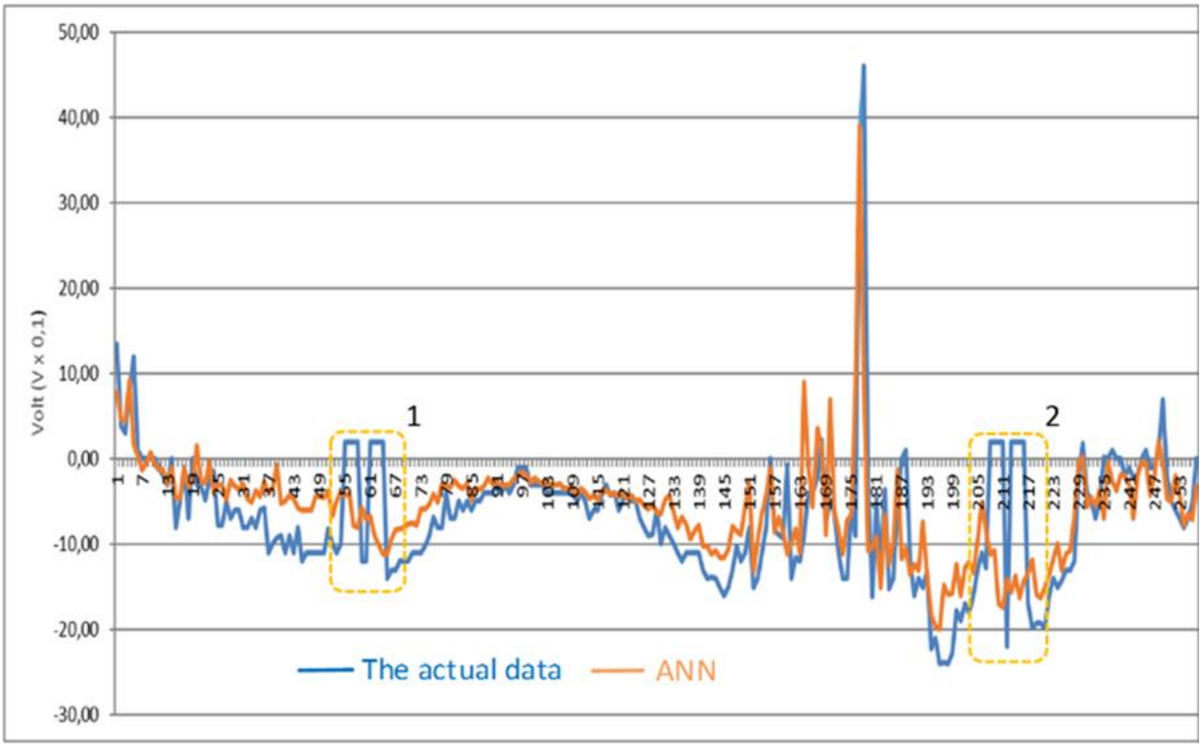

Figure 6. Comparison of the values produced by the ANN trained with the real data set of EAF.

Figure 7. Data range that ANN cannot learn. (Enlarged view of the region marked with 1 in Figure 6).

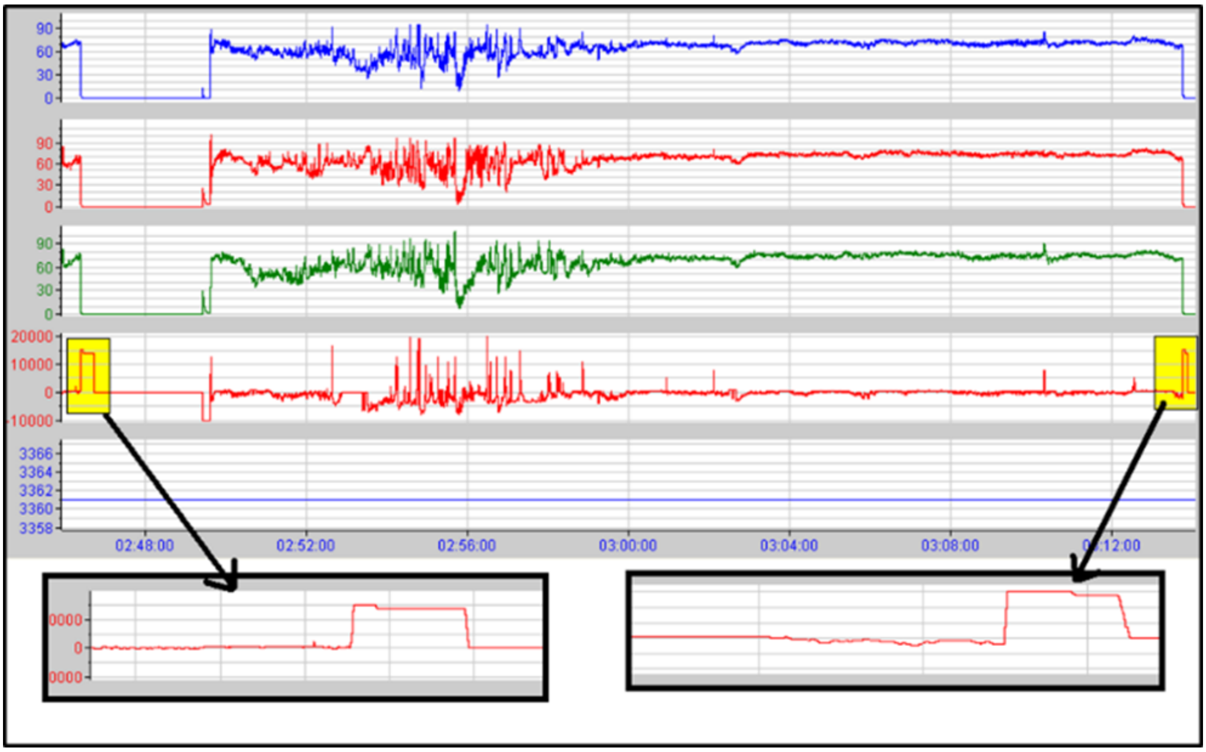

Figure 8. Smelting casting number, current, and electrode signal graphs.

The illustration of IbaPDA for the smelting phase is shown in Figure 8 and the sample data set for the smelting phase is given in Table 2

Operations marked in yellow in Figure 8 above were formed by manual control of the electrodes by the operator. Enlarged images of the sections marked in yellow are shown with arrows. It is seen in the graph given in Figure 9 that the ANN trained with these data cannot see the manual intervention. The response of ANN under normal conditions and when there is no non-algorithm intervention to the system is given in figure 10.

The system is modeled with the data applied to the ANN inputs. ANN showed a response 100 milliseconds earlier than the current regulation algorithm (Figure 10). This is because of the high processing load of the regulation algorithm.

ANN could not learn the interventions made by the operators and the external operations that are not included in the classical regulation algorithm. It was understood that data of the manual operations should also be entered into the network in order for ANN to solve this problem.

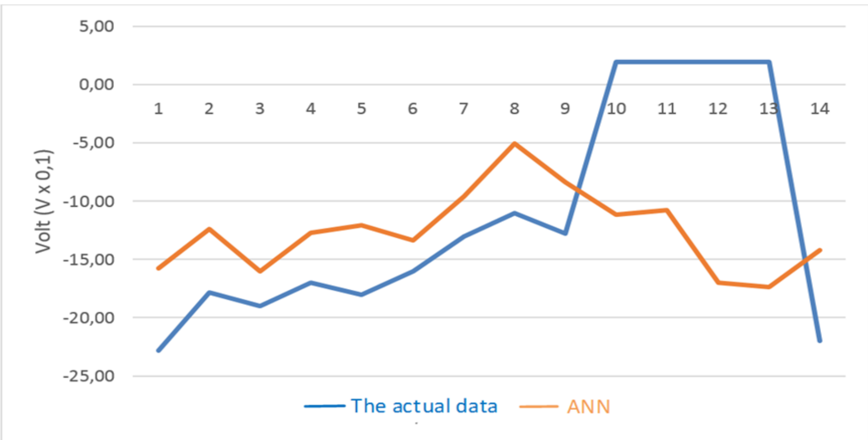

Figure 9. Response of ANN to manual operations.

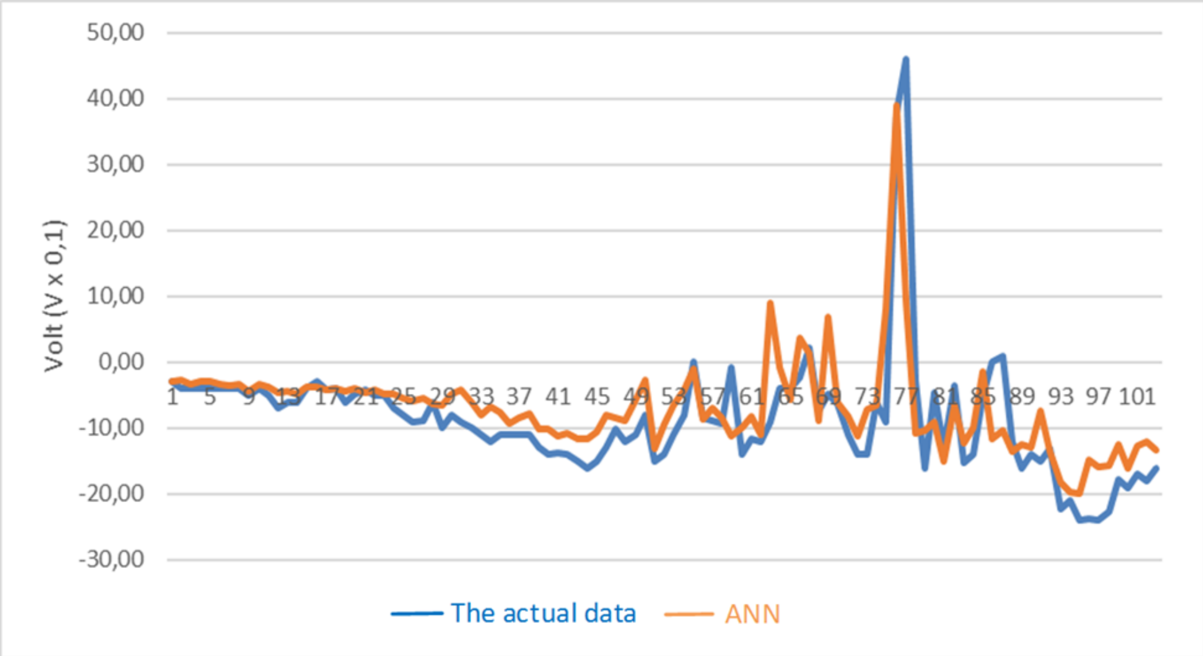

Figure 10. Comparison of the output of the regulation algorithm used in EAF and the ANN result.

With the current data and network structure, this problem could not be solved. In order to teach the problem caused by the manual operation, a pressure sensor (separate for each electrode) was installed on the hydraulic unit providing driving power to the electrodes. The pressure measurement range of the pressure sensors used is 0-250 bar. For this range, 4 mA corresponds to (0) bar and 20 mA corresponds to 250 bar. Pressure information was connected to the analog input of PLC of EAF as a physical signal of 4-20 mA. The sizing process of the signal was regulated with a short code in the Simatic editor and the analog signal was made ready for use by converting it into a digital signal.

A new ANN network structure and data set were created for the input of the pressure data of the electrodes. The network architecture consists of 6 inputs, a hidden layer with 6 neurons, and an output. In this data set, I1, I2, and I3 current values and p1, p2, and p3 pressure values are entered into the network as input, and electrode reference was used as the output.

The response to manual operations and performance of the ANN trained with the new data set, including electrode pressure information is shown in Figure 11. Here, ANN has successfully learned manual operations with newly added inputs.

Considering that the results of the network were sufficient after the training, the network parameters were not studied.

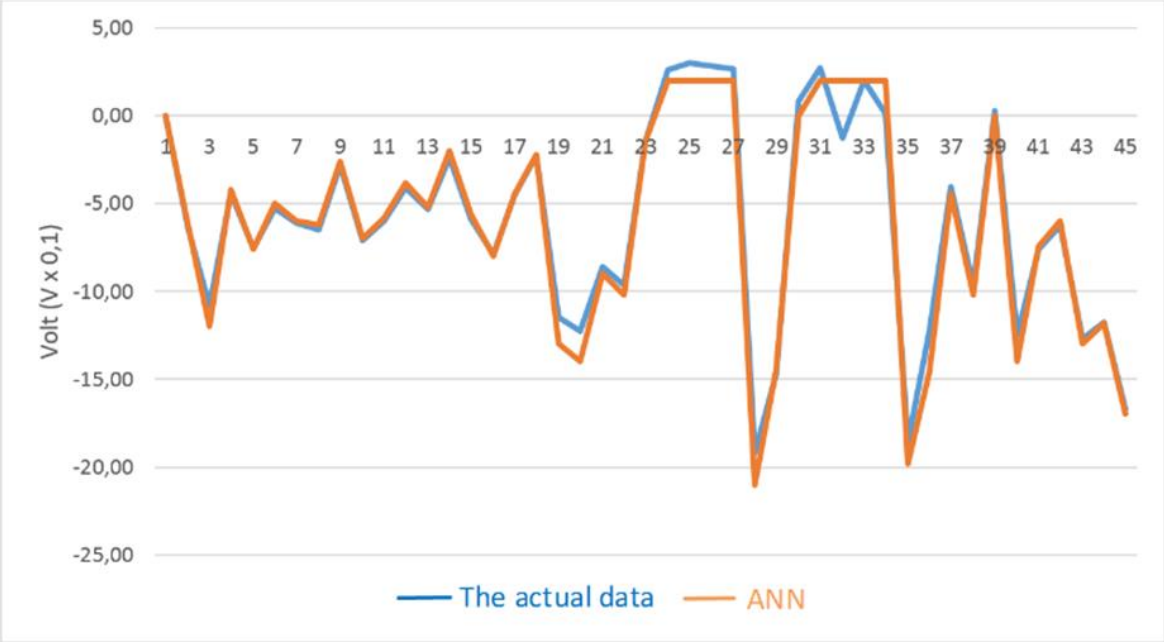

Figure 11. Comparison graph of the real data of EAF and the results produced by ANN

4. CONCLUSION AND RECOMMENDATIONS

In this study, ANN training was carried out by using real data sets obtained during production in an iron and steel factory with an electric arc furnace operating in our country. It was seen that the network learned the system and the electrodes could be controlled by the ANN.

In our study, the ANN software we developed was used in order to be compatible with other software used in the facility. For training and performance tests, the production function of EAF was copied into the ANN by preparing the data set appropriate for the problem, selecting the network architecture, momentum, and learning coefficients according to the experimental results and it was seen that the network responded to new situations that it did not encounter before.

Our study on the control of EAF with ANN progressed in 3 main stages. In the first stage, the network was trained with the data taken when the EAF was operating continuously and the system tracking of the network reached 98,5%. In the second study, it was seen that the network could not learn the manual intervention to the system, pressure sensors were installed on the arms to which the electrodes were attached to solve this problem. Manual intervention data obtained from these sensors were used. Manual intervention data were taught to the network. When the real data of EAF and the results of the new network were examined in the manual intervention, the network was seen to follow the system at a rate of 98%.

With these obtained results, it can be said that the knowledge and skill of an expert operator working in a steel production facility is copied to the network and a control network that will be an alternative to the classical algorithms controlling the system is designed.

The smallest increase in efficiency is important for an arc furnace which has high energy costs. More data is needed on arc furnaces. These are data such as the time and amount of additive materials to be added into the furnace, the generated heat, and the gases released during the processes. With these data, studies can be expanded on temperature prediction of liquid steel and casting termination.

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