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Comparative performance evaluation of blast furnace flame temperature prediction using artificial intelligence and statistical methods

Yasin TUNÇKAYA[1,*], **Etem KÖKLÜKAYA**[2]
[1]Çalık Enerji, Ankara, Turkey
[2]Department of Electrical and Electronics Engineering, Faculty of Engineering, Sakarya University, Sakarya, Turkey

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Abstract: The blast furnace (BF) is the heart of the integrated iron and steel industry and used to produce melted iron as raw material for steel. The BF has very complicated process to be modeled as it depends on multivariable process inputs and disturbances. It is very important to minimize operational costs and reduce material and fuel consumption in order to optimize overall furnace efficiency and stability, and also to improve the lifetime of the furnace within this task. Therefore, if the actual flame temperature value is predicted and controlled properly, then the operators can maintain fuel distribution such as oxygen enrichment, blast moisture, cold blast temperature, cold blast flow, coke to ore ratio, and pulverized coal injection parameters in advance considering the thermal state changes accordingly. In this paper, artificial neural network (ANN), multiple linear regression (MLR), and autoregressive integrated moving average (ARIMA) models are employed to forecast and track furnace flame temperature selecting the most appropriate inputs that affect this process parameter. All data were collected from Erdemir Blast Furnace No. 2, located in Ereğli, Turkey, during 3 months of operation and the computational results are satisfactory in terms of the selected performance criteria: regression coefficient and root mean squared error. When the proposed model outputs are considered for the comparison, it is seen that the ANN models show better performance than the MLR and ARIMA models.

Key words: Blast furnace, prediction, flame temperature, artificial neural networks, multiple linear regression, autoregressive integrated moving average

1. Introduction

Blast furnaces (BFs) are a critical part of the manufacturing procedure for the large-scale integrated iron and steel industry and have working principles totally different from those of electrical arc furnaces, the other common way of producing steel via melting scrap metal. BFs are built with welded steel plates, platforms, and piping and are surrounded by refractory bricks on an internal surface basically to resist reactions at higher temperatures to protect the furnace body and improve internal temperature stability. BFs are relatively large volume structures and they look like steel chimneys, as shown in Figure 1.

The intention of the present study is to propose novel data classification and mining approaches to analyze the BF system by dynamic modeling and generate a set of understandable symbolic rules for prediction of flame temperature, an important control and process parameter to determine the thermal state of the BF. The model results will act as a guide to help furnace operators in judging temperature change in BFs over time and provide further indication to determine the direction of controlling the operation in advance.

*Correspondence: yasin.tunckaya@calikenerji.com

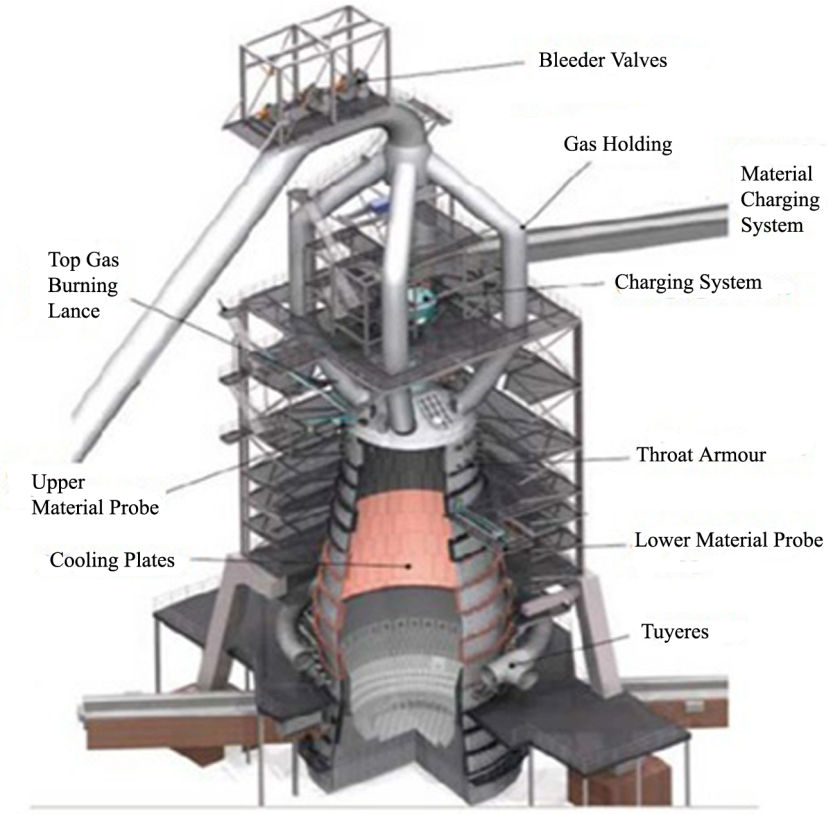

Figure 1. Physical view of a blast furnace.

Recently, several types of research papers with mathematical modeling and software simulations focusing on flame temperature prediction and control have been published. The effects of coke charging ratio, performance of a coke oven gas against blast furnace gas flow under different fuel lance angles, optimization and design of a burner for oxygen and blast furnace gas injection, linear regression applications considering enthalpy and heat capacity parameters, and investigations of different gas combinations were studied to model, predict, and control the flame temperatures in furnaces previously [1–4].

Artificial neural network (ANN), multiple linear regression (MLR), and autoregressive integrated moving average (ARIMA) models are employed for forecasting in the present paper. The ANN approach is applied because of its high potential for complex, nonlinear, and time-varying input–output mapping and generally it is thought to be more powerful than other regression-based techniques [5]. On the other hand, in most of the studies the results obtained from complex ANN models are compared with those from more standard linear techniques such as regression and time series analysis for benchmarking [5]. The model results are compared with each other in terms of the performance criteria regression coefficient (R^2) and root mean squared error (RMSE). The output of the proposed models provided close and satisfactory results for estimation of the flame temperature in order to provide a best-fit prediction with the observed data.

2. Blast furnace process and flame temperature

The main purpose of chemical reactions during the BF process is to remove oxygen from iron oxides in ore, creating pig iron as the final product of a BF [6]. This process involves massive combustion and heat transfers

inside the furnace and an internal temperature over 2000 °C. Mainly three raw materials (iron, metallurgical coke, and limestone) are used in furnaces [7].

Coke is used to raise the furnace's internal temperature to allow iron ore to be purified. In addition, coke acts as a reducing agent during that process. Limestone is mainly used as a slag-maker to remove the impurities of iron ore. Pellet is the main iron ore source in BFs where deposits of ore consist of highly concentrated iron composition inside as it is found as oxide. In some integrated iron and steel factories, sinter is used as a secondary iron resource produced in plants using re-cyclic mixing and burning and that material usage plays a key role in enhancing BF efficiency.

According to the charging principle of BFs, pellet, sinter, coke, and limestone are first arranged in the material handling and forwarding area of the plant and the materials are charged into the furnace in order using a high level control of process control systems. Continuously, oxygen is injected inside the pressurized hot blast composition through tuyere nozzles where a hot blast is supplied using huge air compressors at a power station and heated up 1100–1200 °C by the help of hot stoves. A highly pressurized blast creates a combustion reaction with coke and internal temperature rises to 2000–2500 °C in the furnace.

Meanwhile, carbon monoxide appears due to the combustion of coke and oxygen elements. This gas rises up through the furnace and removes oxygen from the iron ore. This reaction converts the iron ore to liquid molten iron and this product falls from the furnace walls to the bottom level as illustrated in Figure 2.

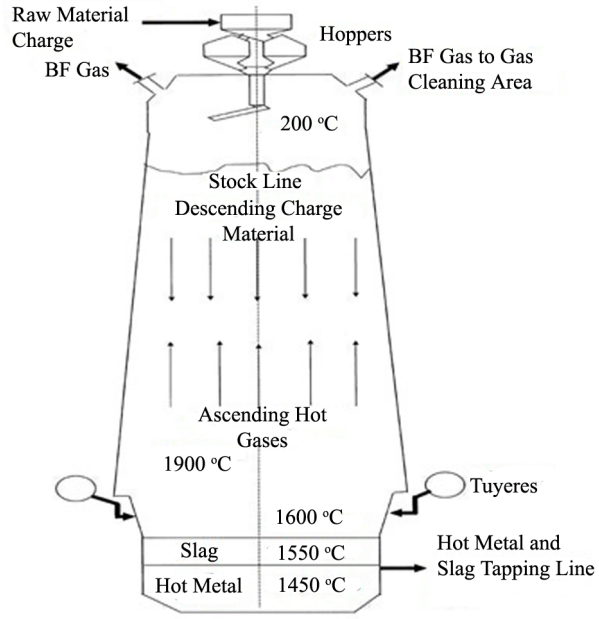

Figure 2. Reactions and temperature regions in a BF.

There are several reactions leading to the furnace process in which pellet, sinter, and limestone materials are used to reduce oxide and the main chemical reactions are formulated as follows:

$$3Fe_2O_3 + \longrightarrow CO_2 + 2Fe_3O_4 \tag{1}$$

$$Fe_3O_4 + CO \longrightarrow CO_2 + 3FeO \tag{2}$$

$$FeO + CO \longrightarrow CO_2 + Fe \tag{3}$$

$$FeO + C \longrightarrow CO + Fe \tag{4}$$

Reactions between impurities in the iron ore and residual limestone create a product, called slag, that floats on top of the hot metal as it has lower density than pig iron. Therefore, slag is separated from the hot metal due to that density difference and removed to the slag line to be cooled down. Charged materials reach the pig iron discharge line in around 5–8 h according to furnace operating conditions. The temperature of hot metal discharged from the furnace is expected to be between 1400 and 1550 °C in normal operation conditions. These materials are separated as hot metal and slag on the bottom discharge level, commonly a few meters below tuyere lines. The discharge operation is executed with a tapping procedure, which is performed from furnace body to furnace heart level [8]. The molten iron is tapped at regular intervals by opening a tap-hole with a tapping machine.

Hot metal is transferred to the torpedo ladle line to be picked up for chemical enrichment and basic oxygen furnace process plants. These ladles are surrounded by refractory bricks and capable of storing liquid hot metal inside without any major heat loss. After chemical material charge into the pig iron to balance chemical composition in the hot metal according to laboratory results of the samples of pig iron, ladles are sent through the basic oxygen furnace. The remaining impurities of the molten iron are oxidized by oxygen blasts injection during this process. This operation results in the production of carbon steel compatible with a range of international quality standards.

Silicon content in the pig iron and hot metal temperature are major quality indicators for pig iron where silicon begins entering the furnace through coke ash and iron ore. In high temperature regions, silicon becomes dissolved in melted iron and relatively high silicon content in pig iron is a sign of ineffective operation of the furnace. Silicon content in pig iron and hot metal temperature value react in similar ways in the same operation conditions. This means that if the operators control the hot metal temperature, silicon content is limited to reasonable values.

The other efficiency criterion, flame temperature, controls the rate of chemical reactions in the combustion process and has a specific effect in the design of combustion equipment [4]. The main goal is to keep flame temperature relatively in an operating range to control remaining parameters in any furnace operation. Flame temperature value is commonly used to control optimum exchange ratios between pulverized coal injection, steam enrichment, O_2 enrichment, and also coke oven gas and blast furnace gas contents in order to heat stoves up during the process. This parameter has a significant effect on the phase stability as well as final product characteristics [9].

The actual temperature in a BF body is usually lower than flame temperature as it is calculated neglecting heat losses in furnaces. Therefore, some of the parameters to calculate flame temperature sometimes do not reflect realistic values as they rely on assumptions. However, optimum flame temperature is a key reference point during the continuous process [10]. If the flame temperature begins dropping, then melting capacity and reduction process will decrease, and thermal heat balance of the furnace will fall. When there is a sudden surge in flame temperature, the melting zone becomes unstable. If flame temperature rises more than expected values, the melting zone on tuyere levels will begin increasing.

Pulverized coal injection reduces the flame temperature value. If operators want to prevent flame temperature drop, hot blast volume or oxygen enrichment value will be increased and blast moisture decreased. These actions increase the coke burning rate and oxygen concentration in front of the tuyeres. A higher oxygen concentration causes more chemical reactions and the presence of more CO content. Eventually more CO increases Fe_2O_3 reduction in parallel, which means required coke content is reduced and furnace efficiency increases. The rule based system can help the operators improve the BF's efficiency by making timely control adjustments with the goal of minimizing the variation of flame temperature over time.

3. Proposed models

3.1. Artificial neural networks model

ANNs are inspired by and defined as a functional demonstration of the biological structures of the human central nervous system. ANNs are commonly used for prediction, matching, identification, pattern recognition, classification, and optimization of problems [11]. They proved of great use to solve a significant quantity of complex mathematical problems where complex parameters and lots of variables are involved. They have multiple advantages: easy to program, present a good adaptation to nonlinear systems, and robust against noise to adapt to changes in the system conditions [6].

However, modernization of industrial factories using a high level of automation has yielded a huge volume of data that has to be analyzed and processed [7]. It is reasonable to implement a neural-based model when there are adequate data on hand to develop new or existing systems accordingly. Prediction success of ANN models depends on selected input variables [12]. When more input parameters are considered than required, there will be calculation problems in terms of memory capacity and calculation speed. If fewer input parameters are considered, model outputs will not be accurate enough to identify the system properly. Therefore, input parameters should be selected to optimize the system in an appropriate way and reduce the calculation complexity in parallel [8].

ANNs include a set of simple processing units that communicate by transmitting signals to each other over a large number of weighted connections. The inputs are multiplied by a weight factor, summed up, computed, moved, and distributed to the transfer function [13]. The threshold is the magnitude offset that affects the activation of the node output. Input, hidden, and output layers may have several different variations depending on model configuration [14]. A neural network structure with input parameters, weights, transfer and activation functions, and output is shown in Figure 3.

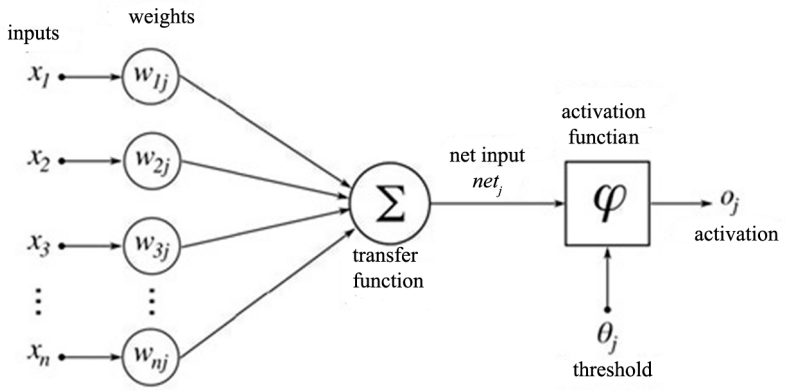

Figure 3. Artificial neural network model.

A neural network model is commonly described with following equation:

$$o_j = \varphi(\sum_{i}^{n} x_i w_{nj} + b), \tag{5}$$

where φ represents activation function; x_i is input where $i = 0, 1, 2, \ldots, n$; w_{nj} is weight; $b$is bias value; and finally o is output of the neuron. Activation functions can be selected linear or nonlinear type and sigmoid and

hyperbolic-tangent functions are used in common applications [15]. These functions are used for normalization and the values are limited between –1 and 1 or 0 and 1. Total error is shown in the following formula at the output layer:

$$Total\,Error = \frac{1}{2}\sum\nolimits_{m} E_m^2 \tag{6}$$

$$Error = E_m = Y_m - Ex_m, \tag{7}$$

where Ex_m is expected output value and Y_m is obtained output value. The designer should reconsider the model and change weight factors between interconnections when the total error is bigger than the defined threshold value. This procedure is used to reduce errors and train the neurons for new calculations, called the error back propagation process. Back propagation involves two phases: a feed-forward phase in which the external input information at the input nodes is propagated forward to compute the output information signal at the output unit, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and actual information signals at the output units [5]. The main rule is to minimize the mean squared differences and error using an iterative procedure between outputs and the forecasted values [16].

Eventually the weights are updated until the error is limited within acceptable levels. This rule is called the generalized delta learning rule and is commonly used to supervise the learning algorithm of feed-forward multilayer neural networks [17]. The most popular learning procedure, called the Levenberg–Marquardt algorithm, is created by combining the Gauss–Newton and steepest-descent algorithms. The Levenberg–Marquardt algorithm is capable of minimizing a linear or nonlinear function providing a numerical solution over a set of parameters, and this optimization algorithm is more powerful than the conventionally used gradient descent technique [5].

The gradient descent algorithm changes weights and biases proportional to derivatives of the network in order to minimize the error. The gradient descent algorithm is relatively slow as it requires a smaller training rate for more stable learning and this is a clear drawback due to its time consuming process. Both the Levenberg–Marquardt and gradient descent algorithms are used in this study to evaluate possible effects and performance of the training algorithms of neural networks models. ANNs also can be integrated with many other approaches including connectionist expert systems to improve the prediction quality further [18].

3.2. Multiple linear regression model

MLR is a statistical model and determines a mathematical relationship between a given set of several independent or predictor variables and a dependent variable. MLR is a computationally demanding downscaling technique and has been widely used in time series analyses and statistics. It is usually less complicated than its nonlinear counterparts with lower demands regarding computational power, and, unlike nonlinear methods, without many parameters to be determined prior to application [19]. The model works to create a relationship between a few or more explanatory variables and a response variable by fitting a linear mathematical equation to observed data [19]. Each value of the independent variable x is associated with a value of the dependent variable y[5]. If y is a dependent variable and $x_1, x_2, ..., x_i$ are independent variables, then the basic model will be given in Eq. (8) below.

$$y = a + b_1 + x_1 + b_2x_2 + \cdots + b_ix_i + e, \tag{8}$$

where a and b_i are constants and e error random variable. The MLR models are an extension of a simple linear regression model to incorporate two or more explanatory variable in a prediction equation for a response variable. The constants $a, b_1, b_2, ..., b_i$ are the regression parameters computed by the method of least squares [5]. Multiple regression modeling is very popular method of statistical analysis in most fields because of its power and flexibility.

The model requires relatively little effort to compute and estimate complicated models with huge numbers of variables considering a group of random variables that is trying to find a mathematical relationship between them. Regression models attempt to make the developed relationship as predictive of the data as possible by selecting the best weights with which to combine variables, in order to minimize the variance or the mean square error between the predicted value and the actual value for each observation in the series [20]. That means the model will forecast exact actual values with some error. More precisely, the goal of regression is to minimize the sum of the squares of the vertical distances of the points from the line [20].

3.3. Autoregressive integrated moving average model

ARIMA methodology was first developed by Box and Jenkins for forecasting of time series events in 1976 [21]. This model is stated as *ARIMA(p, d, q)* with the integers where *p*refers to the autoregressive (AR), d refers to integrated (I), and q refers to moving average (MA) sections of the data structure. ARIMA models are used to analyze the historical data in order to provide estimates for the future, and the idea is to separate a nonstationary series one or more times until the time series becomes stationary, and then find the fit model [22].

Depending on the nature of this process, past observations contain information about future development and the task is to identify a statistical model that explains the current value of the process as a weighted sum of past values as autoregressive part, AR, and past error terms as moving average part, MA, where the stochastic process is assumed to be stationary taking the first difference as integration part, I [23]. The model consists of four steps of algorithms: identification, estimation, diagnostic checking, and forecasting.

ARIMA is a popular prediction method where each variable is described by its past values and stochastic error terms. However, when it is applied to nonstationary and huge nonlinear process data, sometimes forecasting errors may increase when the forecasting horizon is longer. The pure ARIMA model is described by the below equation:

$$Z_t = \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \ldots + \varphi_p Z_{t-p} + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \ldots + \theta_q a_{t-q}, \tag{9}$$

where p, d, and q describe the integer parameters of the ARIMA model; φ_p describes the parameters for autoregressive operator; a_t describes the parameters of error term; θ_q describes the parameters of moving average operator; and Z_t describes the time series of d order difference term of original series.

4. Materials and methods

The BF process consists of hundreds of variables stored, monitored, or controlled using high level automation systems while some of the variables directly affect flame temperature, some of them with minimum or no influence.

The parameters shown in Table 1 are selected for this paper as the most effective in order to predict flame temperature due to previous experience and recommendation by furnace operation engineers. The input parameters are described with engineering units, and minimum, maximum, and average operation values according to the sample data set.

Table 1. Selected input parameters.

Selected input parameters	Min. value	Max. value	Average value	Eng. units
Cold blast flow	2561.90	3612.25	3379.18	Nm^3/min
Cold blast temperature	984.05	1113.62	1071.59	°C
Additional O_2 flow	106.90	178.05	163.86	Nm^3/min
Additional steam injection	18.61	28.33	21.93	g/Nm^3
Pulverized coal injection rate	13.84	35.45	27.63	T/h
Blast pressure	1.94	3.17	2.93	Bar

Graphical trends of the cold blast temperature, oxygen enrichment, additional steam injection, cold blast temperature, blast pressure, and pulverized coal injection rate are shown in Figure 4 during 24 h of operation as a reference since it can be seen that the rates are changing very fast due to instantaneous operating conditions and operator interventions. Various kinds of abnormalities sometimes occur during furnace operation and the estimation of the cause of the abnormalities and the performance of necessary actions are compulsory for the long-term control of furnace operation [24].

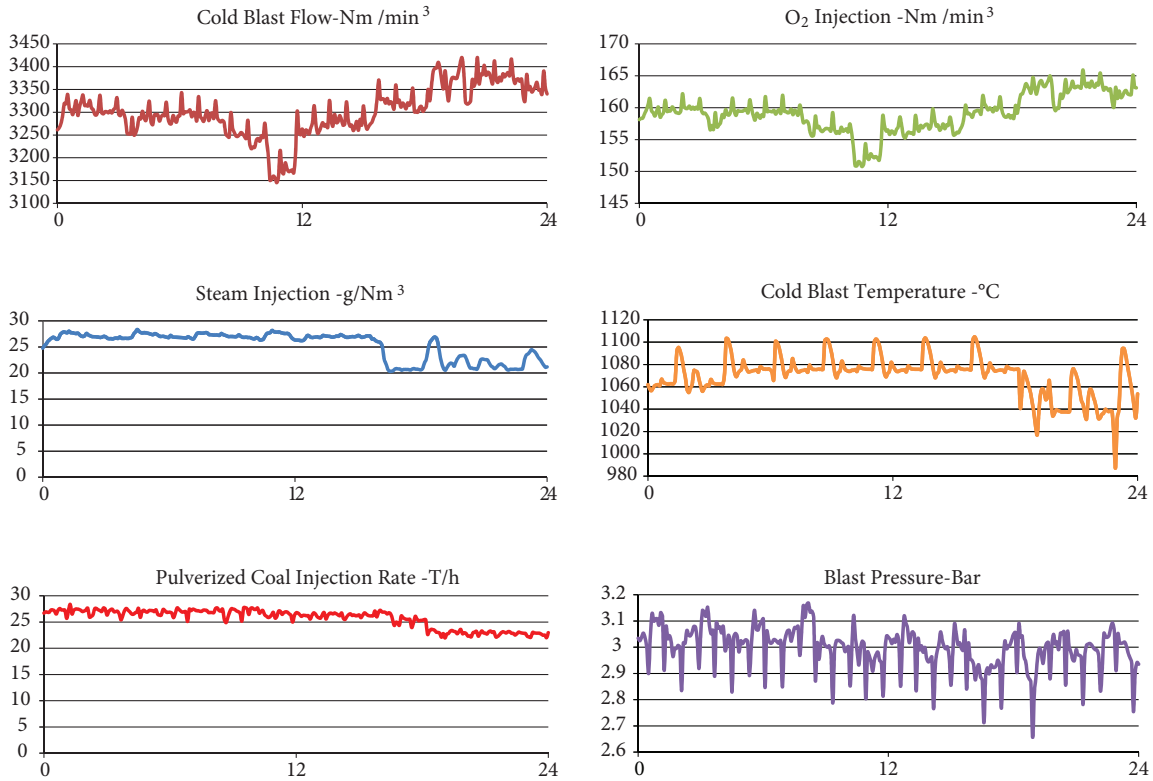

Figure 4. Values of the variables used in the model during a period of 24 h.

The process control system records the data when the new measurement is carried out, and repeats this value until the next measurement [25]. In order to define sampling rates of the variables before usage in the model, interpolation is used to obtain regularly distributed values in the same period of time. Several models can be used for nonlinear systems such as NFIR, NARX, NOE, NARMAX, and NBJ. NARX (Nonlinear AutoRegresive models with eXogenous input) is chosen for the ANN model structure that is described with the

below equation:

$$y\hat{}(k) = F(y(k-1), y(k-2), ..., y(k-p), ..., u(k), u(k-1), ..., u(k-q)) \tag{10}$$

The forecasted value of variable y for sampling time k is considered as a function of the values taken by this variable at the p previous sampling times and of the values of the input variables, generically represented by u at the previous sampling times q [25].

After definition of the NARX model for the ANN approach, the next step will be the selection of a neural network as a feed forward model is considered for the study. Some of the variables executed directly in the model and remaining parameters were preprocessed before the execution to reduce the total quantity of past data and prevent use of new model inputs.

Hidden layer neuron quantity is a critical parameter that depends on the researcher's experimental decision. The design should be identified according to the complexity of the problem in order to achieve successful results. Before training and testing, all the data are scaled using the extremes between 0 and 1 for each neural network model as given in Eq. (11).

$$x_i^{scaled} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \tag{11}$$

where x_i, $x_{\max}$, and $x_{\min}$ are the original, the maximum, and the minimum values, respectively. MATLAB R2009b was used for the training of neural networks since it is possible to change transfer functions, training algorithm, % of trained neurons, etc. using this toolbox. Total data were divided into the three following groups: training, verification, and testing.

In total 1728 collected data items for 6 input and 1 output parameters during 5 s of operating time were used in the ANN model during 3 working months of the Erdemir No. 2 BF. While 60% of the data were used for training, 15% were used for validation and the remaining 25% for testing purposes. The Levenberg–Marquardt algorithm was employed to train the neurons. The method of trial and error was employed to select suitable quantities of hidden neurons and hidden layers. Four neurons in one hidden layer were considered after experimental studies.

Model outputs and the comparison of actual and predicted flame temperature for 432 tested values are shown in Figure 5 below. Blue color shows the predicted values and red color refers to actual values of flame temperature. It is seen that both actual and forecasted values almost overlap and track each other, which meant that the proposed model works quite successfully.

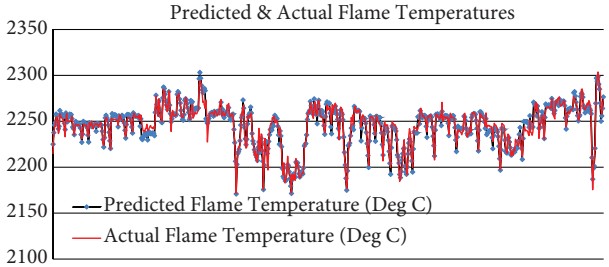

Figure 5. ANN model results for actual and predicted flame temperatures.

According to ANN prediction results, it is apparent that the model can recognize positive and negative movements of the temperature values on time and successfully. The maximum prediction error is 23.14 °C

and it is seen that the average errors are distributed between 0 and 10 °C. Figure 6 shows the error rates between the actual and predicted temperatures of the first ANN model with the Levenberg–Marquardt training algorithm.

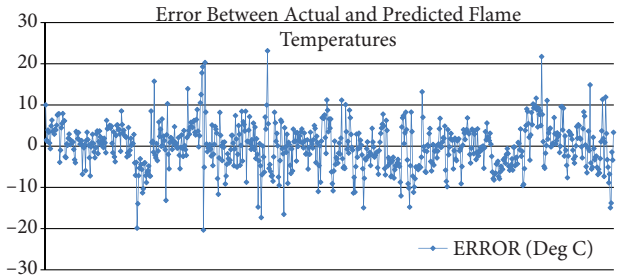

Figure 6. ANN model error rates between actual and predicted flame temperatures.

There are very limited peak errors above 20 °C, which means 0.008% difference from the actual temperature value, as unstable operations and extreme interventions may sometimes affect the overall operation. Average absolute error between the actual and predicted set of values is 4.45 °C. Moreover, 99.93% of predicted flame temperature values do not differ more than 10 °C from the actual temperature values and this performance shows the accuracy of the model better.

In the second phase of this study, the training algorithm of the neural network is changed to gradient descent instead of Levenberg–Marquart to evaluate the effects of the training algorithm selection on error rates and overall performance. The same input, hidden, and output layers and flame temperature data were used and all settings were kept in order to have an exact comparison. The outputs of the second ANN model show that the gradient descent algorithm is time consuming and shows worse performance than the other ANN model.

Finally the proposed statistical models, MLR and ARIMA, were executed using the same parameters and data. The independent variables of the MLR and ARIMA models are the input nodes of the ANN model and the calibration period is selected along with the ANN training duration. Again, in total 1728 data items collected during 5 s of operating time were considered as 6 independent parameters against the dependent parameter, the flame temperature. IBM SPSS Version 17.0 was used for the MLR and ARIMA modeling as this software has intensive and flexible parameter settings and used as a reference statistical tool in the present studies. All p, d, and q parameters are selected 1 for each ARIMA(1, 1, 1) model.

The ANN, MLR, and ARIMA models are compared using the following performance criteria: regression coefficient and root mean squared error. Regression coefficient describes a degree of collinearity between simulated and measured data; the regression coefficient, ranging from –1 to 1, is an index of the degree of linear relationship between actual and simulated data [26]. When the regression coefficient is 0, no linear relationship exists. However, if it is 1 or –1, a perfect positive or negative linear relationship between these two types of data exists. Similarly, coefficient of determination describes the proportion of the variance in measured data explained by the model and R^2 ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable [26]. R^2 value is used as a comparison factor and correlation criterion in the present paper.

RMSE is a widely used parameter of the differences between values forecasted by a model or an estimator and the observed values actually. It is a measure of reliability and efficiency for actual and predicted data sets

and defined below [26]:

$$RMSE = \sqrt{\frac{1}{\mathrm{n}} \sum_{i=1}^{n} \left(Y_i^{\mathrm{obs}} - Y_i^{\mathrm{sim}}\right)^2}, \tag{12}$$

where Y_i^{obs} is observed value, Y_i^{sim} is predicted value, and n is number of samples. When the RMSE value is reduced, it means that the error is minimized and the system gives a more efficient performance. The comparison between the proposed models after several simulations is shown in Table 2 as a summary of this research.

Table 2. Comparison of the model outputs.

Comparison parameters	ANN model - 1	ANN model - 2	ARIMA model	MLR model
RMSE	7.203	7.405	8.274	8.789
R^2	0.964	0.945	0.907	0.892
Min. flame temp. (°C)	2171.501	2169.035	2164.284	2156.103
Max. flame temp. (°C)	2345.394	2340.578	2347.968	2343.809
Mean flame temp. (°C)	2303,556	2240.893	2243.271	2240.364

According to MLR and model outputs, the regression between dependent variable flame temperature and remaining independent variables is 0.892 and 0.907, respectively, which shows that there is a strong correlation with selected parameters affecting the flame temperature values. When the ANN approach using the Levenberg–Marquardt and gradient descent training algorithms are considered, the regression coefficients are 0.964 and 0.945, respectively, as per model outputs. Consequently, the neural network models show better performance than the MLR and ARIMA models in terms of correlation criteria. MLR model outputs show that the minimum flame temperature is 2156.103 °C, maximum flame temperature is 2343.809 °C, and mean is 2240.364 °C, while ARIMA model outputs show a minimum flame temperature of 2164.284 °C, maximum flame temperature of 2347.968 °C, and mean of 2243.271 °C.

RMSE is calculated as 7.203 and 7.405 for the Levenberg–Marquardt and gradient descent algorithms in the ANN models, and 8.789 and 8.274 for MLR and ARIMA models, respectively. As the ANN model has a lower RMSE value than MLR and ARIMA, it is seen that both ANN models have better performance than the MLR and ARIMA models in terms of RMSE and R^2 criteria. It is also concluded that the ARIMA model shows a slightly better performance than MLR.

5. Conclusions

In this paper, the flame temperature of the Blast Furnace No. 2 in Ereğli, Turkey, is modeled using ANN, MLR, and ARIMA models considering 6 process parameters that directly affect that temperature. These models are set up, computed, and executed using Mathworks MATLAB and IBM SPSS, as these tools are easy to configure and change model settings during execution of the calculations. The flame temperature movement is crucial information to instruct the furnace operation team for necessary interventions and corrective actions playing with furnace parameters immediately in order to control the overall furnace operation. The proposed prediction system proves its accuracy and reliability to track the temperature movements and fluctuations properly as per the experimental studies.

Model results verified that the error rate and temperature drift between predicted and actual flame temperatures are quite limited and the model tracks temperature regime very well. Compared with the previous research on BF process parameter predictions [17,25], it is shown that the prediction success for

flame temperature has been improved up to 99.93% against maximum 10 °C error with the first ANN model where the Levenberg–Marquardt training algorithm is used and the error rate is minimized relatively within this paper.

Based on this study, the following specific conclusions can be summarized as follows:

- Artificial neural network models have better performance than multiple linear regression and autoregressive integrated moving average models as per the performance criteria: R^2 and RMSE,
- The Levenberg–Marquardt training algorithm has shown better performance than the gradient descent algorithm in terms of ANN forecasting success,
- Flame temperature can be tracked using the ANN scheme accurately where the proposed model can predict smooth and extreme temperature movements perfectly,
- Selected prediction parameters have very high regression with the flame temperature parameter and it is shown that these parameters affect the temperature changes directly,
- Tracking of the flame temperature value increases operator awareness, and also furnace efficiency and stability in parallel,

Further to this study, a Level 2 suggestion system can be developed to lead operators for further actions using the proposed model and set points of the mentioned parameters can be automatically adjusted via DCS control system integration in future.

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