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A new approach for modeling energy information and investigation of the energy consumption of furnaces with various steel grades

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Original Research

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Abstract:

Accurate prediction of furnace energy consumption in the steel industry by considering different grades has received less attention, despite its importance in energy optimization. In this study, the modeling of steel furnace energy consumption information flow using an artificial neural network (ANN) was investigated for four steel-grade furnaces (A283, KA37, S235, S355). Experimental data, including furnace volume, heating time, average slab temperature, average furnace temperature, and fuel energy consumption, were collected from an industrial unit. Independent variables (furnace volume, heating time, slab and furnace temperatures) and dependent variable (fuel energy consumption) were modeled using a feedforward multilayer neural network (MLP) and presented as a function. The results showed that the performance of the ANN was poor for regression coefficients (R) less than 0.5, acceptable in the range of 0.5 to 0.7, and very accurate for R > 0.8. The agreement between the numerical and experimental results confirms the validity of this method and demonstrates its application in optimizing fuel consumption and reducing waste.

Keywords: Energy consumption information; Artificial neural network; Steel-grade furnace; prediction of furnace energy

Article highlights

- This research can play a significant role in predicting fuel consumption under various conditions and for different alloys, with acceptable accuracy, to help the steel industry optimize energy use and reduce production waste.
- The influence of various factors on energy consumption in steel furnaces has been identified and analyzed. Using a neural network, the impact of these relevant variables has also been quantified.
- Based on recorded data, the energy information flow model has been developed to predict furnace fuel consumption across different steel grades.

1. Introduction

Throughout history, access to energy has been recognized as one of the fundamental pillars of national development, as it plays a pivotal role in economic, industrial, and social success.

However, the world's widespread dependence on fossil and nuclear fuels for energy production has had significant negative impacts on both the environment and human health. As a result, sustainable development in energy production and distribution has become a critical and widely debated issue worldwide [1]. Since the steel industry play a decisive role in the economy, energy management within this sector has attracted considerable attention.

For example, Yuan et al. [2] conducted a comprehensive review that examined methods for improving energy efficiency in steel production from various perspectives-assessment, optimization, and energy recovery-and emphasized the need for intelligent, multi-level approaches. Moreover, studies have shown that optimizing iron and steel production processes can increase energy efficiency and simultaneously reduce both fuel consumption and CO_2 emissions, particularly when variables such as the ratio of injected coal and the structure of the furnace charge are considered [3]. Furthermore, theoretical analyses have shown that energy consumption in various steelmaking processes (such as ironmaking with 8.81 GJ and hot rolling with 0.76

GJ) can be reduced under the influence of factors such as raw material moisture [4].

In another study [5] used machine learning models, including Naive Bayes, combined with Weighted SHAP and PFI methodologies, to analyze energy consumption patterns in a steel company, which identifies the importance of various key variables for energy management in advance. However, the importance of energy consumption management in this industry has not been thoroughly explored. In particular, accurate prediction of furnace energy consumption considering different steel grades has received less attention. Several studies have addressed the modeling of energy consumption in steel furnaces, Zhao et al. [1], in a review of industrial reheating furnaces, examined the characteristics of the heating process and the potential for waste heat recovery and emphasized the need for advanced modeling to reduce energy consumption. Karem et al. [6] proposed an effective method for saving energy in industrial natural draft furnaces and analyzed a furnace associated with liquefied petroleum gas (LPG) production in Libya with model-based simulation. Similarly, Okosun et al. [7] investigated the effects of hydrogen and natural gas injection in a blast furnace using computational fluid dynamics modeling and showed that hydrogen injection of up to 15 kg/t hot material (thm) in combination with natural gas provides stable performance. These studies highlight the importance of accurate modeling for energy optimization.

Artificial intelligence has emerged as a powerful tool for optimizing furnace energy consumption. Niekurzak and Mikulik [8], using expert systems based on the ID3 algorithm and simulation, presented a model for predicting energy consumption in walk-in furnaces that not only optimizes electricity and gas consumption but also reduces pollutant emissions.

Khalid et al. [9] also predicted the energy efficiency of energy-intensive processes in the steel industry using a regression tool in MATLAB and emphasized the importance of process data and energy performance indicators (EnPIs) in line with Industry 4.0. Manojlović et al. used machine learning to evaluate the energy efficiency factors of an electric arc furnace by analyzing five years of data from a steelmaking plant and demonstrated the superiority of neural networks due to their high flexibility [10]. Similarly, a data-driven approach using neural networks has examined the energy consumption of kilns by considering the impact of variables such as input materials and has shown that combining these variables can help to more accurately predict and optimize energy efficiency [11].

Temperature, as a key factor in energy consumption, has been of interest in recent studies. Yang et al. [12] proposed a method for real-time prediction of the temperature field in reheating furnaces using neural networks, which can be a basis for modeling energy consumption, especially for different steel grades with different thermal properties. Lima et al. [13] also predicted reheating furnace temperatures with a mean absolute error (MAE) of less than 7 °C for short-term horizons using recurrent neural networks (RNN, LSTM, GRU, and TCN), although their study focused on temperature control and did not consider energy consumption or steel grades.

In the field of electric arc furnaces, Saidmurodov et al. [14] reviewed the application of machine learning methods such as linear regression, genetic programming, and LSTM to predict energy consumption with limited knowledge of process parameters and showed the diversity of approaches and challenges. Khan et al. [15] presented an integrated framework of artificial intelligence and genetic algorithms and developed a furnace model in Aspen EDR with industrial data. Liang et al. [16] also predicted the energy consumption of ventilation systems using a neural network optimized with the Hunger Games search algorithm, which shows the adaptability of these methods. Also, Khallaghi et al. [17] evaluated the feasibility of pre-combustion carbon capture for decarbonization of the steel industry. These studies confirm the capabilities of artificial intelligence in modeling complex processes.

Despite these advances, the prediction of furnace energy consumption considering different steel grades has received less attention. The present study, using multilayer feed-forward (MLP) neural networks, models the relationship between fuel consumption and variables such as furnace volume, heating time, average slab temperature, and average furnace temperature for grades A283, KA37, S235, and S355. With a maximum error of 0.97%, this study presents a practical approach to energy optimization that is more innovative than studies focused on temperature (such as [13]) or without considering grades. In this regard, first, the neural network is introduced, then the independent and dependent variables are identified and their relationship is explained. Finally, numerical and experimental results are compared to verify the accuracy of the proposed method.

2. Methodology

This section provides necessary information regarding the proposed technique. ANN used for predicting energy consumption is outlined in the beginning, then the proposed method is explained, and finally, the furnace analysis is illustrated.

2.1 Dataset

Data collection for this study was carried out using industry-standard tools and a supervisory control and data acquisition (SCADA) system at a production unit of the Khuzestan Steel Company. The data, collected in 2023 by the energy management unit, the data was continuously recorded from sensors installed on the furnace equipment. This automated and accurate method enabled the recording of the furnace operating conditions throughout daily work shifts.

The collected data includes performance data from an industrial furnace in the steel production process, which was prepared with the aim of providing an energy consumption baseline and analyzing the relationship between operational variables and energy consumption. This dataset has a total of 18,000 records, the key variables of which include furnace volume, heating time, average slab temperature, average furnace temperature, and fuel energy consumption. To improve data quality, preprocessing was performed by removing outliers caused by abnormal deviations or recording errors. Finally, the data was categorized for four different steel grades (A283, KA37, S235, S355) and their exact numbers are presented in Table 1.

To ensure accuracy and consistency with actual production conditions, the dataset was verified by both the production planning and operational units at Khuzestan Steel Company. This level of accuracy in data collection, refinement, and verification has ensured a high-quality dataset for the development and validation of the proposed model.

2.2 Artificial neural network

Artificial neural network (ANN) techniques are used to establish mathematical relationships between process inputs and outputs [10]. In this study, a specific architecture of artificial neural networks, known as a multilayer perceptron (MLP), was adopted due to its robustness in modeling complex nonlinear relationships. An MLP consists of an input layer, one or more hidden layers, and an output layer, with neurons fully connected between adjacent layers (as shown in Fig. 1). The presence of multiple hidden layers increases the network's ability to capture complex patterns in the data.

In this study, a multilayer neural network (MLP) was designed with two hidden layers, each containing 10 neurons. This configuration was selected based on a grid search process to strike a balance between model complexity and computational efficiency and to prevent overfitting. The selection of two hidden layers was based on the complexity of the nonlinear relationships between the input variables (kiln volume, heating time, average slab temperature, and average kiln temperature) and the output (fuel energy consumption). The number of neurons was also evaluated through repeated experiments with different configurations (5, 10, and 20 neurons per layer), and 10 neurons were selected because it provided the best balance between prediction accuracy and convergence speed.

Neurons are connected through weighted links, which are adjusted during the training of the artificial neural network. The main function of an artificial neuron is to compute the weighted sum of inputs from the previous layer, add a bias term, and apply an activation function to the result. This relationship between input and output data is expressed by the following equation:

$$y = f[\sum_{i=1}^{n} x_i w_i + b] \tag{1}$$

In Eq. (1), b, x_i, w_i, and f is the bias, the inputs, the weight from the ith neuron in the preceding layer, and the activation function, respectively. The activation function is generally divided into three categories: Linear, threshold, and sigmoid equations.

It is crucial to choose the activation function, adjust all the weights, and reduce the error between the simulated output data and the data produced when training a neural network. Calculating the weight derivative is also necessary for the training process. The level of inaccuracy changes when each weight is significantly increased or decreased. One of the most popular techniques for optimizing weights is the backpropagation algorithm, which updates weights layer by layer in the opposite direction of the forward data propagation.

First-order methods, such as gradient descent, are used to iteratively optimize the weights. The optimal solution can be found using the quasi-Newton approach, which converges significantly more quickly. The inverse Hessian matrix and the direction of the steepest descent are combined to create the weight update, which is used to calculate the second-order derivative on the Hessian matrix **H**. The Hessian ma-

Table 1. The total number of experimental, training, validation, and test data for each grade.

Steel grade	Experimental data	Training data	Validation data	Test data
A283	163	113	25	25
KA37	122	86	18	18
S235	15342	10740	2301	2301
S335	545	381	82	82

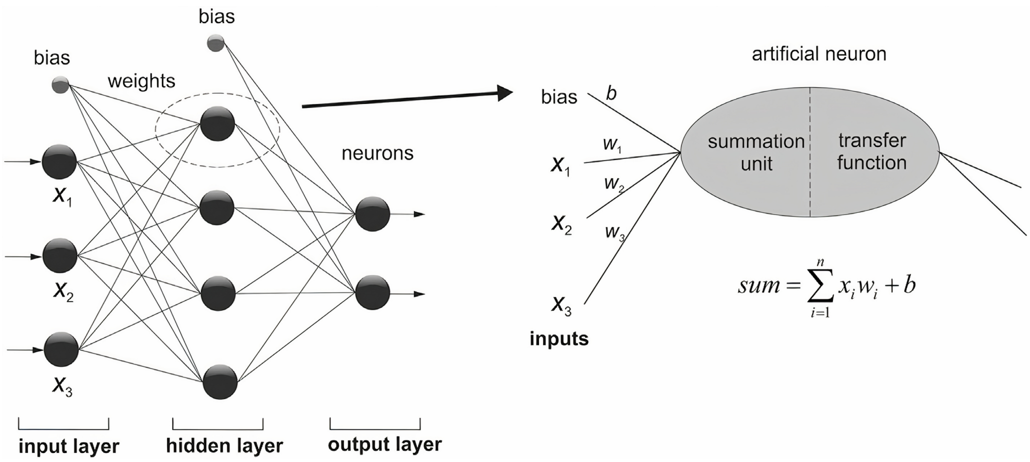

Figure 1. The schematic representation of MLP (ANN) and an artificial neuron.

trix must be calculated using all of the partial derivatives of the second order, which takes time. Therefore, the speed is increased by using the Hessian approximation.

The BFGS algorithm (Broyden et al.) [18] is employed in this article as the most effective method for computing weight updates. This algorithm is highly efficient for small to medium-sized datasets, such as the one in this study (18,000 records), and offers faster convergence than first-order methods such as stochastic gradient descent (SGD) or Adam due to the use of second-order derivative information (via Hessian matrix approximation).

Compared to the Adam algorithm, which is suitable for deep learning problems with large data sets, BFGS requires fewer parameter tunings and performs more stably for the dataset in this study. Initial experiments showed that BFGS achieves lower mean square error (MSE) in fewer iterations compared to SGD and Adam.

Artificial neural networks—particularly the MLP architecture—offer several important advantages, including the capacity to handle large datasets, the ability to detect complex nonlinear relationships between dependent and independent variables, and the capability to capture potential interactions among predictor variables [19]. Therefore, ANN with its MLP implementation is considered the most appropriate choice for this comparative analysis. In this study, kiln volume, heating time, average slab temperature, and average kiln temperature are considered independent variables, while fuel energy consumption serves as the dependent variable. The coefficients in the model function as the parameters of the MLP and are automatically selected and optimized by the algorithm during training. This optimization follows a predetermined strategy to minimize prediction error.

2.3 Proposed method

In this study, feed-forward multilayer perceptrons (MLPs), a specific type of artificial neural network (ANN) introduced in section 2.2, are trained to develop an optimal model for evaluating the impact on electric arc furnace (EAF) fuel consumption based on key variables: Furnace material type, furnace volume, heat time, average slab temperature, and average minimum furnace temperature. The MLP is implemented and trained using MATLAB software, which also facilitates the simulation of the observed process. The network training process was controlled using a combination of early stopping and a maximum epoch limit. In the early stopping method, the validation error (MSE) was monitored, and training was stopped if the error did not improve after 10 consecutive epochs. In addition, a maximum of 200 epochs was set as the computational time limit to avoid overtraining. These dual criteria ensured that the model achieved optimal performance without overfitting, as can be seen in the mean square error plots (Figs. 2, 6, 10, and 14). Model evaluation metrics such as MSE (Mean Squared

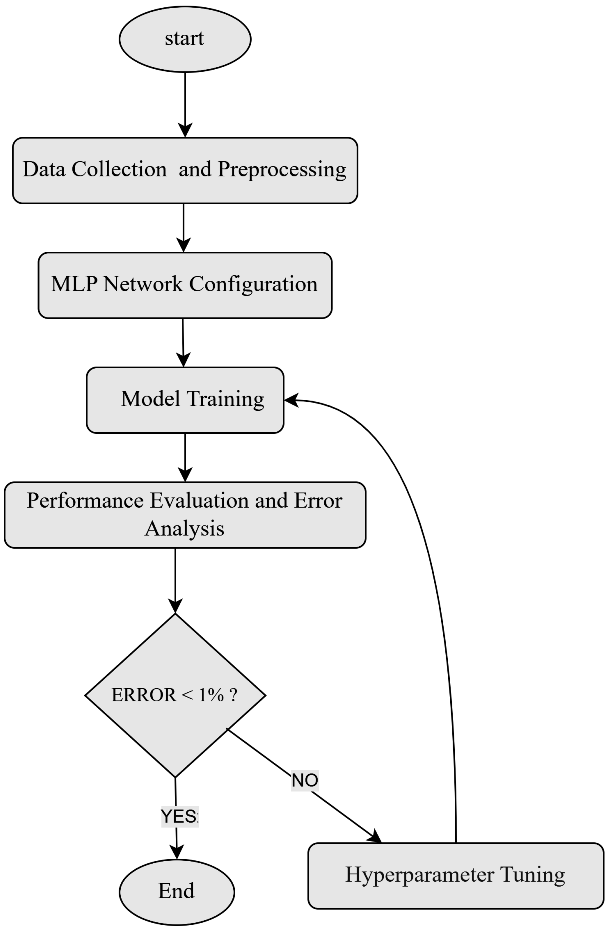

Figure 2. Flowchart of simulation and error detection in furnace energy consumption modeling with an MLP neural network.

Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and R^2 (Coefficient of Determination) are used to assess the model's goodness of fit. The values of the error metrics and the coefficient of determination are calculated using the equations (Eqs. (2)-(5)) provided below.
Fig. 2 shows the flowchart of the simulation and error detection process for modeling furnace energy consumption using MLP neural networks. The flowchart shows the steps of data acquisition, preprocessing, model training, and evaluation with an iterative error correction process based on a maximum error threshold of 1%. This process ensures accurate fuel consumption prediction for steel grades A283, KA37, S235, and S355. The following equations (Eqs. (2)-(5)) are used to determine the values of the error parameters and the coefficient of determination [20]:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(y_i^e - y_i^p)^2}{n} \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i^e - y_i^p)^2}{n}} \tag{3}$$

$$\mathrm{MAE} = \frac{|y_i^e - y_i^p|}{n} \tag{4}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(y_i^e - y_i^p)^2}{(y_i^e - \bar{y}_i^e)^2}\right) \tag{5}$$

where y_i^p is the predicted value, y_i^e is the experimental value, $\bar{y}_i^e$ is the average experimental value, and n is the number of experiments.
In this study, we introduced a multilayer perceptron (MLP) neural network architecture to predict the energy consumption of the fuel used. This architecture consists of three layers: an input layer with four neurons for independent variables, a hidden layer with 10 neurons for modeling nonlinear relationships, and an output layer with one neuron for predicting the energy consumption of the fuel. The hyperbolic tangent activation function (Tanh) was used for the hidden layer, and the linear activation function was used for the output layer. The network training process was performed using the pseudo-Newton BFGS algorithm, and the initial learning rate was set to 0.01. The number of training cycles varied based on the type of steel and continued until convergence (reaching the minimum error). Finally, the simulation and error correction process is shown in the graphs.

2.4 Furnaces analysis

In this section, an industrial furnace operating with four distinct steel grades is analyzed. The experimental measurement variables for each grade-A283, KA37, S235, and S335-include furnace volume, heating time, average slab temperature, average furnace temperature, and fuel energy consumption. The total experimental, training, validation, and test data for each grade are shown in Table 1. As described in section 2, the multilayer perceptron (MLP) architecture was trained using a data split of 70% for training, 15% for validation, and 15% for testing from the total dataset. This data allocation was chosen to achieve reliable results.
Typically, allocating approximately three-quarters of the data for training and the remaining portion for validation and testing yields optimal performance in ANN modeling. This data split aligns with established best practices for ANN model development, particularly for MLP-based approaches. Typically, a split of 70% for training data, 15% for validation data, and 15% for testing data is recommended to ensure that the model is trained on enough data to learn the patterns in the data but also to avoid overfitting the training data. Kiln volume (m^3), heating time (min), average slab temperature (°C), and average kiln temperature (°C) were taken as inputs, and fuel energy consumption was selected as output in kWh/t.
The BFGS technique was used to model the experimental data using a 3-layer MLP model. As learning occurs, the weights and activation functions are adjusted and changed to increase the predictive ability of the proposed network. Various activation functions, including hyperbolic tangent, linear, and logistic sigmoid, were tested for both the hidden and output layers. The input of the output layer is the output of the hidden layer.

3. Results and discussion

The energy consumption of the furnaces is examined in this part using the available data and an artificial neural network, and the simulation results are then shown. Tables 2-5 compare fuel energy consumption for some MLP model data for the furnace grades A283, KA37, S235, and S335 using experimental and forecasted data.

Table 2. Comparison of some data between exact and predicted data for A283 furnace grades.

EXP	Volume (m^3)	Heat time (min)	Slab. Ave.Temp	Slab Furn.Temp	Fuel energy consumption	Predicted data	ERROR%
1	2.600796	306	1239.48	1207.5	72649	72370	0.38
2	2.58213	316	1243.90	1215.5	93470	92600	0.93
3	2.600796	317	1243.72	1226	92678	91970	0.76
4	2.600796	225	1263.01	1230.5	125093	126000	0.73
5	2.600796	225	1263.29	1230.5	125093	125880	0.63
6	2.596648	218	1263.67	1232.5	130231	131270	0.8
7	2.586278	219	1262.11	1222.5	128784	129710	0.72
8	2.596648	289	1217.34	1220.5	138042	136910	0.82
9	2.596648	289	1214.75	1220.5	138639	138060	0.42
10	2.5925	293	1046.52	1213	114693	113690	0.87

Table 3. Comparison of some data between exact and predicted data for KA37 furnace grades.

EXP	Volume (m^3)	Heat time (min)	Slab. Ave.Temp	Slab Furn.Temp	Fuel energy consumption	Predicted data	ERROR%
1	2.600796	551	1239.24	1233.5	178785	177190	0.89
2	2.5925	551	1105.80	1230.5	178785	178480	0.17
3	2.588352	254	1100.25	1227	190535	190490	0.02
4	2.609092	261	1256.35	1229	167788	169160	0.82
5	2.580056	259	1260.17	1228	182124	181810	0.17
6	2.584204	263	1259.98	1227.5	179319	177950	0.76
7	2.5925	404	1192.53	1222	157949	159480	0.97
8	2.5925	419	1155.03	1202	137821	139240	1.03
9	2.586278	414	1141.48	1198	144045	144650	0.42
10	2.604944	416	1243.71	1224	165435	165940	0.31

3.1 Model performance analysis for different steel grades

The proposed neural network model for predicting the energy consumption of steel furnaces with grades A283, KA37, S235, and S355 obtained average regression coefficients of 0.78, 0.87, 0.55, and 0.71, respectively. This indicates acceptable model performance across most grades, but significant differences in prediction accuracy are observed between grades, especially the lower regression coefficient for grade S235 (R = 0.55). In the following, the likelihood of these differences is analyzed.

One of the key factors affecting the model's performance is the dataset for each grade. As shown in Table 2, grade S235 is the largest dataset with 15342 records compared to the other grades (A283: 163, KA37: 122, S355: 545). This excess volume may be increased by the operating conditions of the furnace (such as changes in the upper temperature or heating time), which can lead to increased noise in the data and modeling complexity. Conversely, smaller data sets may include operating conditions that make the prediction easier.

Another factor is the chemical properties and consideration of the steel grades. Grade S235, as a lower carbon steel construction than grades such as S355, may exhibit different thermal behavior during the furnace heating process. To investigate this, a regression analysis was performed, which showed that the average slab size affected the prediction accuracy, which may vary due to the grade being considered. Furthermore, Fig. 13 shows significant fluctuations in the training process variation for grade S235. This behavior could indicate convergence challenges, possibly due to the presence of local minima in the error level or to the complexity of the large data set. In contrast, grades such as KA37 (Fig. 9) and A283 (Fig. 5) showed more stable convergence, which is consistent with their higher regression coefficients (0.87 and 0.78).

To improve the accuracy of the model for grade S235 in future research, it is suggested that several additional inputs (such as slab chemical composition or furnace heating rate) be added to the model to better model the specific variations of this grade. Also, the use of regularization methods (such as Dropout) or more advanced neural network architectures (such as deeper networks) can help reduce data noise and improve convergence.

Overall, the above analysis suggests that the differences in model accuracy are related to a combination of the dataset, specific characteristics of the steel grades, and the behavior of the model during training. These observations not only contribute to a better understanding of the model but also guide future improvements.

The findings show that the maximum error for the furnace grades A283, KA37, S235, and S335 is around 0.93%,

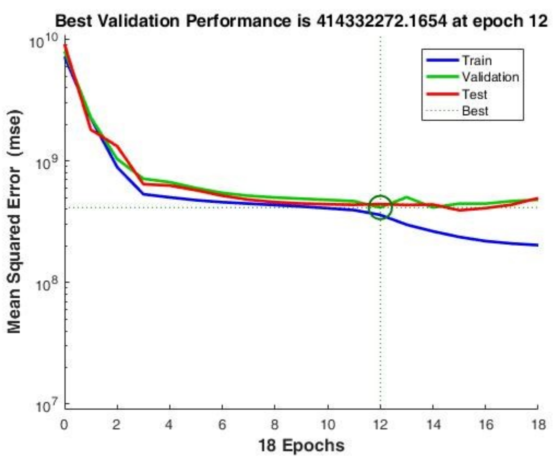

Figure 3. Mean squared error (MSE) for A283 furnace grades.

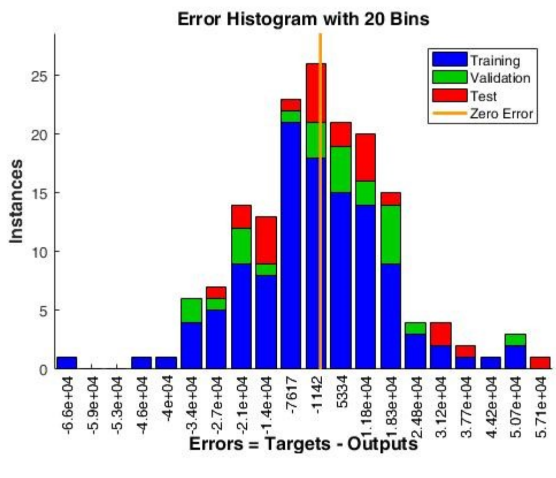

Figure 4. Error histogram for A283 furnace grades.

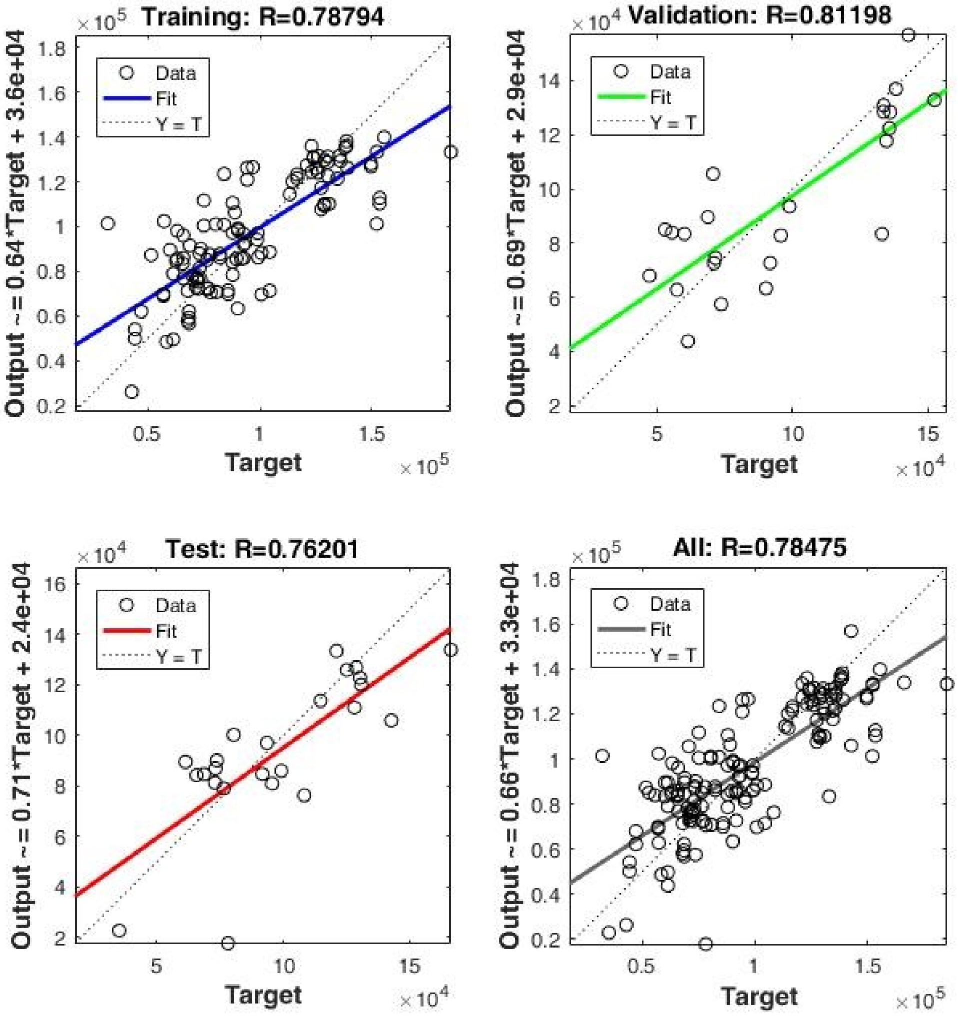

Figure 5. Regression data for A283 furnace grades.

0.97%, 0.08%, and 0.97%, respectively. Based on the results, these artificial neural networks are the most accurate function for estimating energy usage.
The outcomes of a neural network performance study for the furnace grades A283, KA37, S235, and S335 are shown in Figs. 3-17. Fig. 3 shows the mean square error (MSE) plot for the A283 furnace grade. The horizontal axis represents epochs, and the vertical axis represents MSE (on a logarithmic scale). The error for the training, validation, and test data decreases up to epoch 12 and then remains

Table 4. Comparison of some data between exact and predicted data for S235 furnace grades.

EXP	Volume (m^3)	Heat time(min)	Slab. Ave.Temp	Slab Furn.Temp	Fuel energy consumption	Predicted data	ERROR%
1	2.5925	282	1253.0936	1218	129149	129164.8082	0.01
2	2.60287	205	1234.8471	1220	170716	170810.3451	0.06
3	2.607018	271	1257.8754	1234	152305	152327.2844	0.01
4	2.5925	224	1259.9860	1235	162429	162565.4423	0.08
5	2.60287	229	1260.1530	1234.5	168131	168094.7511	0.02
6	2.588352	257	1256.5957	1244.5	140168	140161.8091	0
7	2.598722	217	1245.0051	1224	169708	169622.5389	0.05
8	2.60287	430	1266.9777	1216	93298	93278.15933	0.02
9	2.5925	297	1240.4678	1217.5	125206	125224.1425	0.01
10	2.586278	203	1258.7069	1214	129149	129164.8082	0.01

constant, indicating good convergence of the model and an optimal choice of the number of epochs. At epoch 12, where the optimal performance is marked, the MSE values are approximately as follows: 4.143×10^8 (414,332,272) for the validation and test set, 3.8×10^8 (380,000,000) for the training set.
In Fig. 4, the histogram of the error distribution for the training, validation, and testing data of the A283 grid is shown. The horizontal axis represents the error amount (kWh/t), and the vertical axis represents the number of occurrences. For the training set, the highest number of occurrences is in the error range of about -7617 to 1142, with more than 27 samples. In the validation data, the errors are also mostly in the same range, with a maximum frequency of about 6 to 8 samples reported in a similar range. For the test data, the highest number of errors occurs in the range of -7617 to 5834, with a maximum frequency of about 7 to 9 samples. The concentration of errors around zero indicates the high accuracy of the model.
In Fig. 5, the regression plot of the training, validation, and test data of grade A283. The horizontal axis is the actual values (kWh/t), and the vertical axis is the predicted values. The regression coefficients are 0.78, 0.76, and 0.81, respectively, and the average is 0.78, indicating a good accuracy of the model. The training status of the A283 furnace grid is shown in Fig. 6. The horizontal axis is the epochs, and the vertical axis is the gradient (based on the BFGS algorithm). A decrease in the gradient to negative values indicates successful model convergence. The correlation coefficients for training, validation, test, and the entire dataset are $R = 0.78794$, $R = 0.81198$, $R = 0.76201$, and $R = 0.78475$, respectively, indicating a good fit of the model output with the target values. The equations of the fitted line are specified in the figure itself.
The mean square error (MSE) plot of the KA37 grid is shown in Fig. 7. The horizontal axis is epochs, and the vertical axis is MSE (on a logarithmic scale). The errors decrease until epoch 8 and then remain constant, indicating rapid convergence of the model. At this point (epoch 8), the training error is 8.0456×10^7, the validation error is 3.0823×10^8, and the test error is 1.4004×10^8.

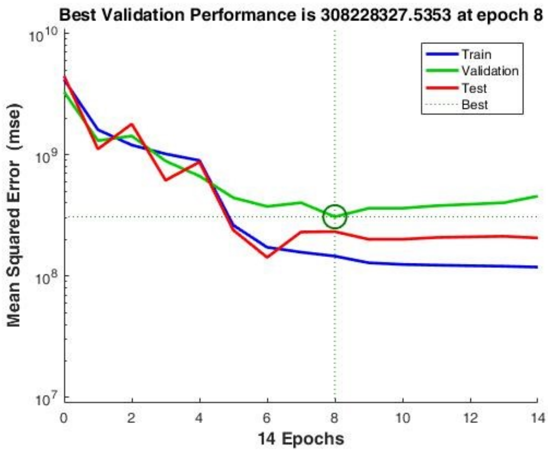

Figure 7. Mean squared error (MSE) for KA37 furnace grades.

For training, testing, and validation data, Fig. 8 displays the histogram error. The center of the graph is where the mistake is concentrated. The highest error frequency is related to the training data in the range around the value 141, with 22 samples. In the same range, there are also about 3 validation samples and 2 test samples. This concentration of errors around zero indicates the high accuracy of the model in prediction and its good convergence. The regression graph is shown in Fig. 9. Regression coefficients for training, testing, and validation data are indicated in the figures as 0.89, 0.84, and 0.82, respectively. Calculations show that the average regression coefficient is 0.87. Fig. 10 depicts the training condition for the KA37 furnace grade. A decrease in the downward gradient indicates successful convergence of the model.
Fig. 11 displays the mean square error of the S235 furnace grade. Results show that training, testing, and validation data are decreasing and halting at 141 epochs. The best validation performance is recorded in period 135 with an error value of 1884056696.9293. At this point, the MSE error value for the training set is about 1.66×10^9, for the validation set about 1.88×10^9, and for the test set about 1.89×10^9. These numbers indicate that the model converges well and its performance on the unseen (test) data is

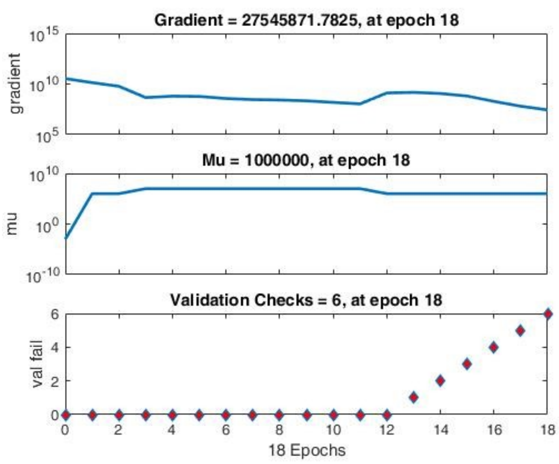

Figure 6. Training state for A283 furnace grades.

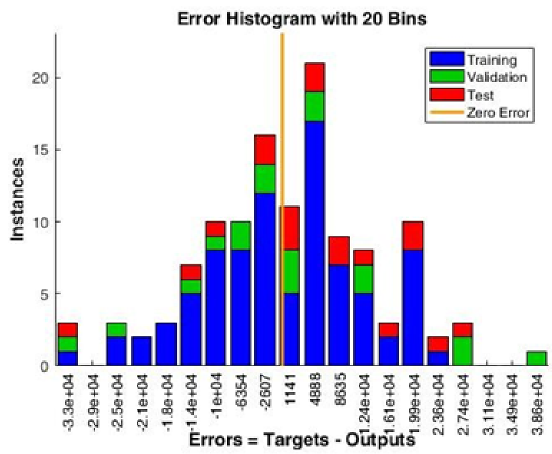

Figure 8. Error histogram for KA37 furnace grades.

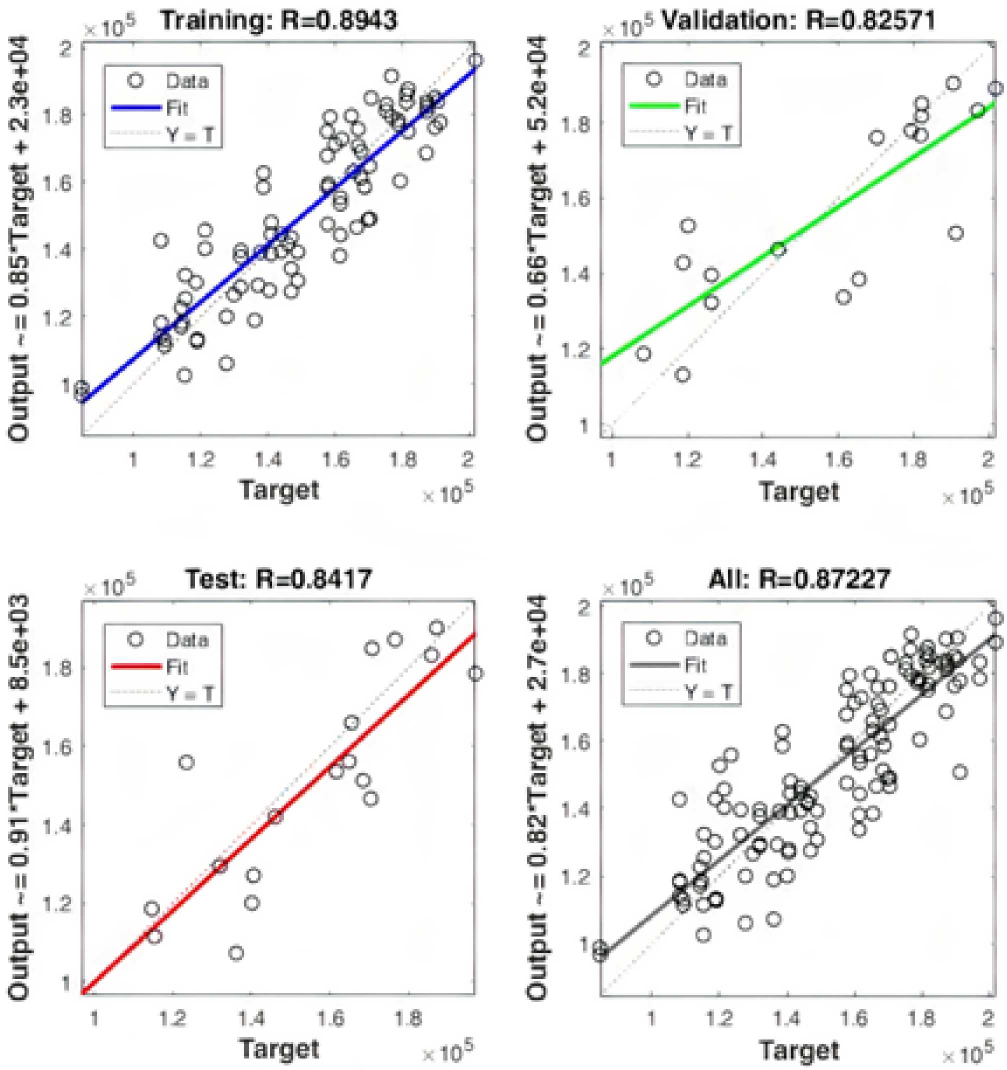

Figure 9. Regression data for KA37 furnace grades.

almost equal to the training and validation data.
The histogram of the error distribution for the training, validation, and test data of the S235 grade furnace (20 intervals) is shown in Fig. 12. The errors are mainly concentrated in the range of −0.01 to 0.01, but the peak of the distribution is slightly skewed towards negative values (around −0.01).

Table 5. Comparison of some data between exact and predicted data for S355 furnace grades.

EXP	Volume (m^3)	Heat time (min)	Slab. Ave.Temp	Slab Furn.Temp	Fuel energy consumption	Predicted data	ERROR%
1	2.588	235	1273.33	1257.50	169220.00	169328.7056	0.06
2	2.593	239	1273.57	1255.50	169220.00	168615.0739	0.36
3	2.593	585	1244.62	1205.50	96184.00	96645.10945	0.48
4	2.601	368	1238.42	1219.50	94018.00	93509.93093	0.54
5	2.593	408	1220.14	1216.50	85817.00	86124.65976	0.36
6	2.593	388	1272.03	1229.00	87737.00	87732.39834	0.01
7	2.601	432	0.00	650.00	96403.00	96893.18338	0.51
8	2.588	302	1272.77	1237.00	118422.00	117729.6273	0.58
9	2.582	202	1266.43	1232.00	185707.00	184340.8207	0.74
10	3.111	197	1259.43	1233.00	108375.00	109430.9303	0.97

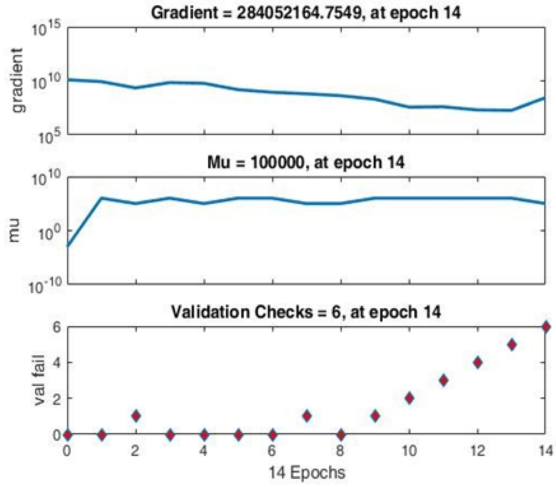

Figure 10. Training state for KA37 furnace grades.

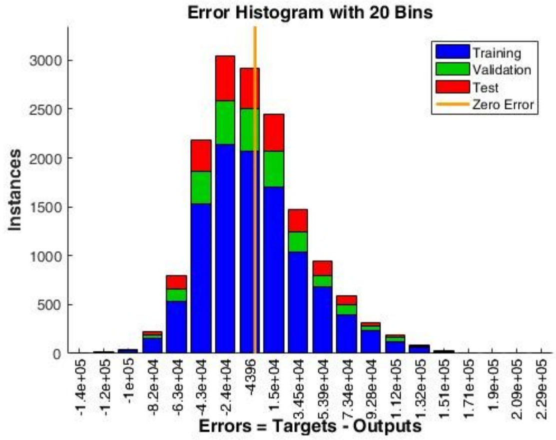

Figure 12. Error histogram for S235 furnace grades.

This pattern confirms the relative accuracy of the model. At the peak of the distribution, the number of samples for training, validation, and testing data was about 2200, 400, and 400, respectively. This pattern confirms the relative accuracy of the model. Overall, the distribution of the error and its concentration in a range close to zero, along with the relative balance in the validation and testing data, indicate the optimal performance of the model and its appropriate generalizability.

The regression plot for the training, experimental, and validation data of the S235 grade furnace is presented in Fig. 13. The regression coefficients were calculated to be 0.55, 0.56, and 0.54 for the training, experimental, and validation data, respectively. The average regression coefficient, which is 0.55, indicates an acceptable performance of the model in predicting the energy consumption of this furnace. Fig. 14 depicts the training status of the neural network for the S235 grade furnace. The results show significant fluctuations in the gradient changes, which could indicate challenges in fully converging the model for this particular grade.

The mean square error (MSE) plot for the S355 grade furnace is shown in Fig. 15. The results show that the error for the training, test, and validation data decreases up to epoch 39 and remains constant thereafter. At this point, the MSE value for the training, validation, and testing data is reported to be about 1.36×10^9, 1.368×10^9, and 1.55×10^9, respectively. This behavior indicates good convergence of the model and the optimal choice of the number of periods for this grade. Fig. 16 presents the histogram of the error distribution for the training, test, and validation data of the S355 grade furnace. The concentration of errors is observed near the center of the graph (close to zero), which indicates the high accuracy of the model in predicting the energy consumption for this grade. In the central region of the distribution, the number of samples for training, validation, and testing data was about 60, 20, and 20 samples, respectively, indicating a good alignment of model performance across data types.

The regression plot for the training, test, and validation data of the S355 grade furnace is shown in Fig. 17. The regression coefficients for the training, test, and validation data are 0.73, 0.66, and 0.72, respectively. The average regression coefficient, which is calculated to be 0.71, indicates the favorable and reliable performance of the model in predicting the energy consumption of this furnace.

Fig. 18 depicts the training status of the neural network for the S355 grade furnace. The horizontal axis shows the number of epochs, and the vertical axis shows the gradient value. The findings indicate fluctuations in gradient changes, which could indicate the complexities involved in optimizing the model for this grade; however, the overall reduction in gradient indicates relative convergence of the model.

The regression coefficient values obtained in this study are comparable and in some cases better than previous state-of-the-art techniques. For example, Manojlović et al. [10] modeled the energy efficiency of electric arc furnaces using artificial neural networks and reported an average regression coefficient of 0.75, indicating acceptable model accuracy. In another study, Niekurzak and Mikulik [18] predicted the energy consumption of walk-behind furnaces using expert systems based on the ID3 algorithm and obtained a relative error of less than 2%, which also led to the optimization of electricity and gas consumption. The advantage of the proposed MLP-based model in this study is the accurate

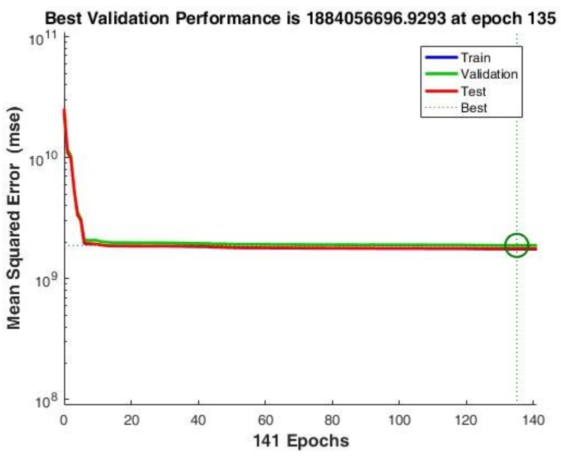

Figure 11. Mean squared error (MSE) for S235 furnace grades.

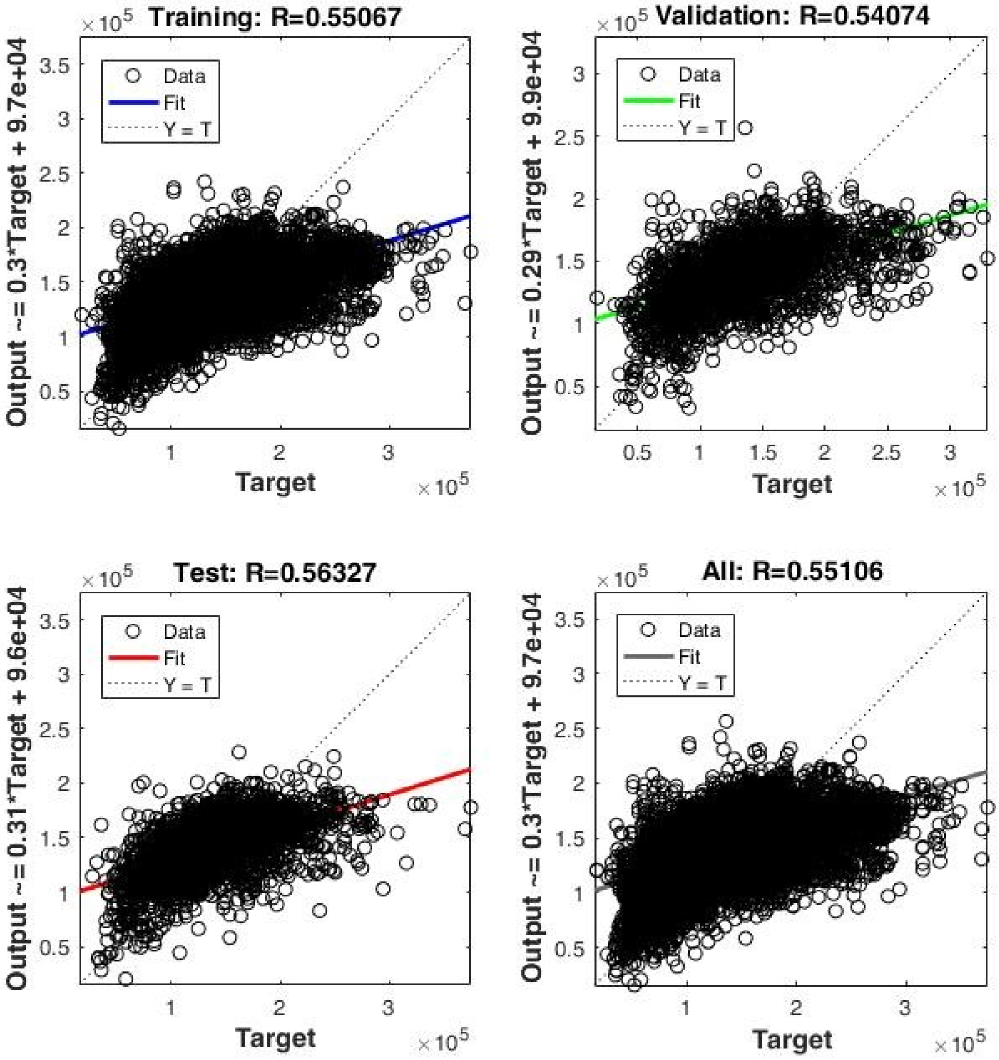

Figure 13. Regression data for S235 furnace grades.

prediction of furnace energy consumption for specific steel grades (A283, KA37, S235, S355) with a maximum error of 0.97%. This method is not only reliable in terms of originality and regression coefficient values (0.55 to 0.87) but also, according to the literature results, the error rate observed in it is completely within the acceptable range.

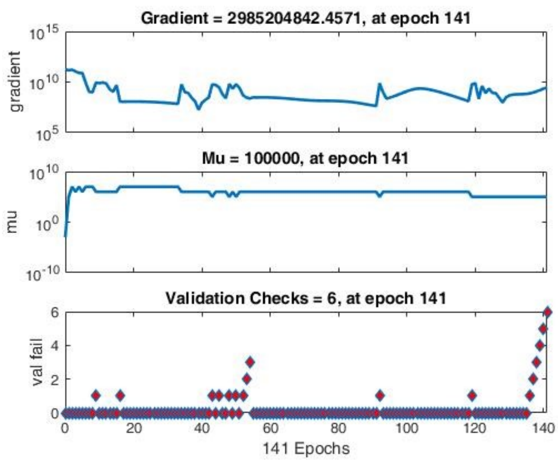

Figure 14. Training state for S235 furnace grades.

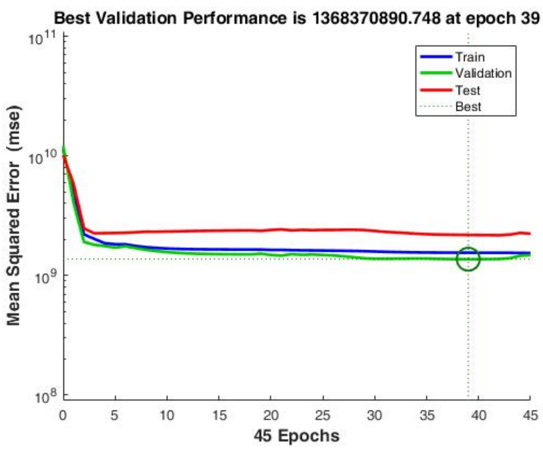

Figure 15. Mean squared error (MSE) for S355 furnace grades.

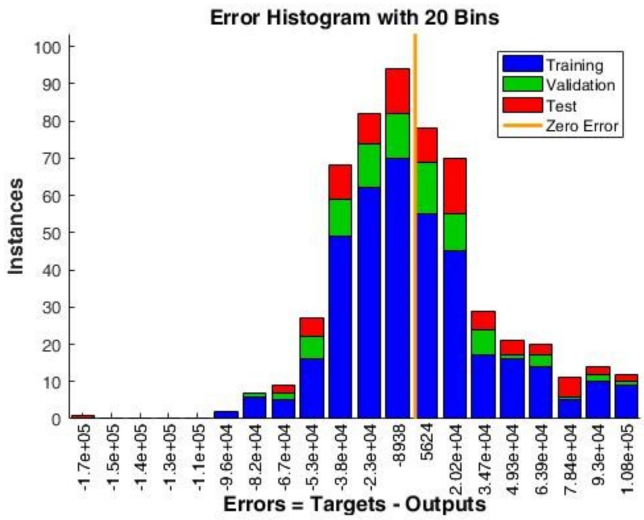

Figure 16. Error histogram for S355 furnace grades.

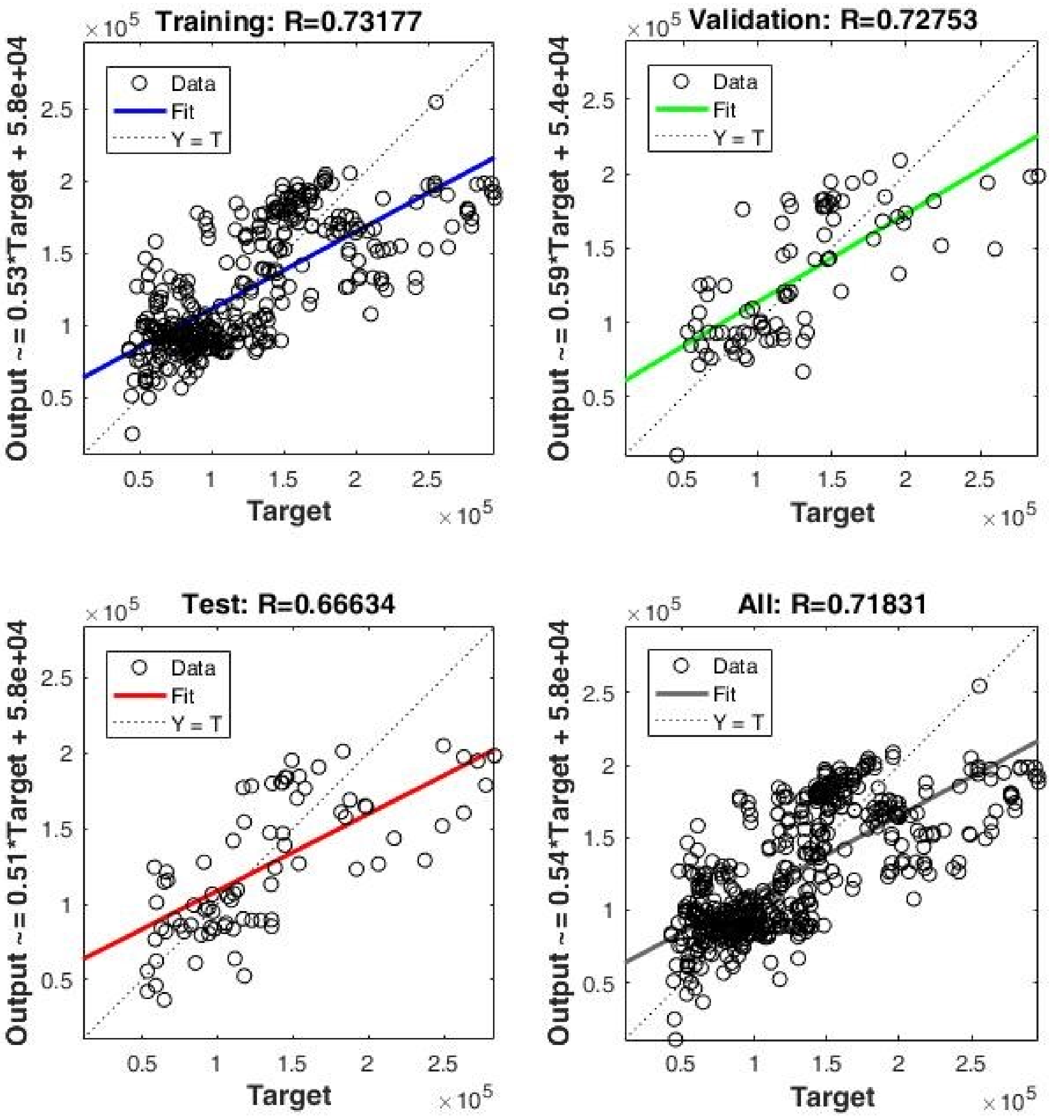

Figure 17. Regression data for S355 furnace grades.

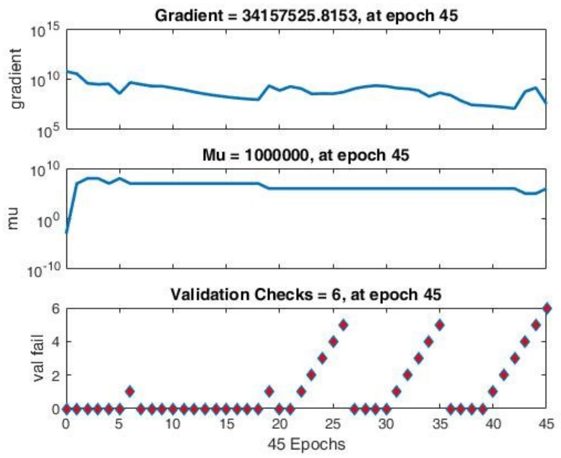

Figure 18. Training state for S355 furnace grades.

4. Conclusions

In summary, feedforward ANNs were used in this study to model the relation between fuel consumption with furnace volume, heat time, average slab temperature, average furnace temperature, and practical minimum for A283, KA37, S235, and S355 grades of furnace steel. Regarding the regression coefficient values ($R < 0.5$), ANN's performance is weak, and it must retrain the data and change the network structure. The network structure is approximately acceptable for $0.5 < R < 0.7$, and for $R > 0.8$, it is an excellent structure to predict energy consumption. The computed average regression coefficient values for A283, KA37, S235, and S355 were 0.78, 0.87, 0.55, and 0.71, respectively. Hence, the outcomes of the regression coefficient are proper for predicting the energy consumption in the furnaces. Besides, the agreement observed between the numerical and empirical outcomes emphasizes the authenticity of the adopted approach. Future investigations are necessary to validate the types of conclusions that can be drawn from this study. Other branches of artificial intelligence, namely machine learning and deep learning, can also be employed in future work.

4.1 Study limitations

The data used in this study were collected from a steel industrial unit in Khuzestan since this unit was equipped with an energy information management system and the ISO 50001 standard, which allowed for accurate and validated recording of energy consumption and furnace performance. Many of these industries do not have the necessary systems to collect data from furnaces. Therefore, this unit was selected for training the neural network model due to its accurate documentation of operating conditions and access to high-quality data. The main objective of this study is also to create and develop a Baseline Model that evaluates the performance of a specific furnace over time and does not aim to compare different furnaces in different industrial units.
However, using data from only one industrial unit may limit the generalizability of the model to other industrial units, because furnaces in the steel industry have significant differences in terms of design, operation, raw materials, and final products. For example, changes in fuel type, heating rate, or slab specifications in other units may affect the accuracy of the model predictions. This limitation was partly due to the lack of data collection systems in many other industrial units, as most of them lack energy meters or production recording systems. To overcome this limitation in future research, it is suggested that data from several industrial units with diverse characteristics and operating conditions be collected so that the model can cover a wider range of industrial scenarios. This could be done through collaboration with industrial units equipped with energy management systems or the development of common databases in the steel industry. Also, the use of simulated data that recreates different furnace conditions can help assess the generalizability of the model. These measures can ensure that the proposed model is reliable for wider applications in the steel industry.

Authors contributions
Authors have contributed equally in preparing and writing the manuscript.

Availability of data and materials
Data sharing does not apply to this article as no new data were created or analyzed in this study.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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