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Thermal mode modeling using neural network technologies and the finite element method

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ABSTRACT

This study presents the analysis and modeling of the thermal regime of a furnace lining at an industrial copper smelting facility using a combined approach based on neural network (NN) technologies and the finite element method (FEM). Experimental temperature data were collected from a laboratory setup equipped with three thermocouples (TP-2488/1 and TCRosemount 0065), with a sampling frequency of 1 Hz over a total duration of 5 hours, resulting in 18,000 measurement points. The measurement uncertainty of the thermocouples did not exceed ±1.5 °C. These data were used both for model development and for validating the numerical FEM simulations. A feedforward neural network was trained using 70% of the dataset, while 15% and 15% were used for validation and testing, respectively. The prediction error of the neural network remained within 3% with a 95% confidence interval of [2.6%, 3.4%]. The results show that the proposed hybrid approach improves temperature prediction accuracy and reduces static control error by 15% when combined with a proportional–integral controller. The methodology demonstrates significant potential for improving thermal process stability and reducing energy consumption in high-temperature metallurgical systems.

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1. INTRODUCTION

Thermal processes play a key role in various industrial applications, such as metallurgy [1]-[3], mechanical engineering [4]-[6] and ceramic production [7]-[9]. In these industries, precise temperature control [10]-[13] allows to optimize production processes and improve product quality. One of the effective methods for the analysis and modeling of such processes is the finite element method (FEM) [14], [15], which provides a detailed study of the thermal regime in complex structures and materials. In recent years, more and more attention has been paid to neural network (NN) technologies, which open up new prospects for predicting temperature conditions and controlling thermal processes [16]-[18]. Modern industrial processes place high demands on the quality and stability of the thermal regime, especially in high-temperature processes such as metallurgy and ceramics production. Violation of the optimal temperature regime can lead to a decrease in product quality, an increase in energy costs and a reduction in the service life of equipment. In this context, the introduction of innovative technologies for modeling and controlling thermal processes is becoming an important condition for increasing the competitiveness and efficiency of production. The use of NN technologies in conjunction with the FEM [19]-[21] is a promising solution for achieving high accuracy in modeling and predicting temperature characteristics. In this study, the term "copper smelting complex" refers to the production line in which the Vanyukov furnace is the central unit. Therefore, the modeling and control procedures presented in this work are specifically applied to the Vanyukov furnace lining.

The study introduces an integrated approach combining FEM and NN technologies for thermal regime modeling. The implementation of a PI controller enhances temperature stabilization, ensuring higher accuracy compared to traditional methods. The methodology provides industrial applicability, improving process efficiency and reducing energy consumption. Thermal process control is associated with a number of difficulties due to the multidimensional and non-stationary nature of thermal fields. Temperature distributions change in time and space, and traditional control methods are often not accurate enough to account for all factors affecting the process. Moreover, adequate control requires the construction of models that take into account the physical properties of materials and the geometry of the system, which complicates the tasks of thermal modeling. The lack of reliable methods for predicting thermal processes and effective control negatively affects the overall efficiency of the system. To solve this problem, a combined approach is proposed that combines FEM for detailed modeling of heat transfer and NN technologies for predicting temperature characteristics. The FEM allows taking into account complex geometric and physical features of modeling objects, and neural networks provide an accurate prediction of temperature changes based on data obtained in real conditions. This approach allows not only to model thermal processes in detail, but also to promptly predict deviations from optimal conditions, which helps improve product quality and reduce production costs.

Al-Haddad *et al.* [22] discussed the development and evaluation of an innovative design of an electric vehicle battery pack that provides uniform temperature distribution and operates in an optimal temperature range. 3D modeling of the battery cell and thermal simulations were performed at different ambient temperatures (15 °C, 25 °C, and 35 °C), the results of which showed a nearly uniform temperature distribution. A heat flow analysis was also performed using the FEM, which revealed a slight increase at the edges of the cell, and a NN model was proposed to predict the heat flow. The comparison of NN and FEM demonstrated the high accuracy and efficiency of NN, with an RMSE of 0.87%, highlighting the potential of applying machine learning in thermal analysis problems. In this paper [23], the authors investigated the direct metal deposition (DMD) process used in additive manufacturing and focused on predicting the residual stresses generated during the manufacturing process. Six complex metallic structures made of AISI 304L material were considered, for which a comparative evaluation of the results of thermomechanical analysis by the FEM and the integrated approach ANN-FE (neural network+FEM) was performed. The results showed that the distribution of residual stresses in ANN-FE is comparable to FEM, while errors exceeding 15% were localized in areas with low stress levels and did not affect critical areas. In addition, the proposed method demonstrated a significant improvement in computational efficiency, increasing the analysis speed by about 6 times.

Zhou *et al.* [24] proposed a hybrid method for predicting residual stress after machining based on a combination of finite elements, analytical approach and neural network to improve the machining quality and extend the service life of dies. First, the stress, strain and temperature data on the machined surface were obtained using an orthogonal finite element cutting model (FEM), and the analytical stress relaxation algorithm was used to simulate the stress relief process, providing a faster calculation. Then, the improved neural network BP (SSA-BP) model optimized using the SSA algorithm was used to quickly predict the residual stress characteristics. In the future, further development of the proposed model is expected, including taking into account additional factors such as the influence of humidity, chemical composition of the material and external influences. The integration of additional parameters into the neural network model can improve the prediction accuracy and expand the possibilities of its application in other industries where maintaining an accurate thermal regime is required. Another promising direction is the development of adaptive control methods based on NN technologies, which will automate the process of temperature regulation and increase the system's resistance to external influences. The purpose of this work is to simulate the thermal regime in industrial installations using a combined approach based on neural networks and the FEM. The use of FEM to build heat transfer models in combination with neural network methods for predicting temperature characteristics allows improving the quality of process control and predicting possible deviations from a given mode [25]. This is especially relevant for metallurgical production, where strict control of temperature distribution is required to ensure the stability and reliability of the technological process.

Thermal processes play a crucial role in metallurgy, mechanical engineering, and ceramics production. Precise temperature control is essential for optimizing production and ensuring high product quality. The FEM provides a detailed study of thermal regimes, while neural network technologies enhance temperature prediction and control. Traditional control methods often lack precision due to the multidimensional and non-stationary nature of thermal fields. A combined approach, integrating FEM and neural networks, is proposed to address these challenges. FEM accounts for geometric and physical properties, while neural networks improve prediction accuracy.

The novelty of this study lies in the integration of an experimentally validated FEM model with a neural-network-based temperature prediction module specifically designed for the lining of a Vanyukov furnace a key unit within the copper smelting complex considered in this work. Unlike previous studies that analyze general metallurgical heating processes, this research focuses on a real industrial geometry, includes experimentally measured non-stationary temperature fields, and incorporates closed-loop control using a PI-regulator. The proposed framework enables high-accuracy temperature prediction in regions with strong thermal gradients and provides a practical tool for optimizing thermal stability in Vanyukov furnace operation.

Despite the growing body of research combining finite element modeling and neural network techniques for thermal analysis, most existing studies focus either on generic geometries, simplified boundary conditions, or purely predictive frameworks without closed-loop control integration. In particular, recent state-of-the-art works primarily address battery thermal systems, additive manufacturing processes, or residual stress prediction, while the application to real industrial metallurgical furnace linings with experimentally validated non-stationary temperature fields remains insufficiently explored. Furthermore, previous approaches rarely integrate numerical FEM modeling, data-driven temperature prediction, and controller-based stabilization into a unified framework validated under realistic operating conditions. Therefore, a methodological gap exists in developing an experimentally supported hybrid FEM–NN model specifically tailored to high-temperature metallurgical systems with integrated PI-based thermal stabilization.

2. METHOD

A combination of the FEM and neural network technologies was used to simulate the thermal regime. The FEM was used to create a two-dimensional model reflecting the heat transfer process in complex industrial installations. COMSOL Multiphysics was chosen as the modeling environment, which allows taking into account such physical processes as thermal conductivity, convection and radiation, which is critical for adequately reproducing the conditions of a real environment. Initially, a physical model was developed, which was a fragment of a furnace lining made of fireclay refractory bricks with high thermal insulation properties. Cavities were created in the studied brick sample to accommodate heating elements. To increase resistance and regulate the heating temperature, nichrome wire spirals were used, which were connected to an alternating current network with reduced voltage using a laboratory autotransformer (LATR). During the experiment, temperature surveys were carried out using thermocouples, the data from which were recorded and transmitted to a computer for further analysis (Figure 1).

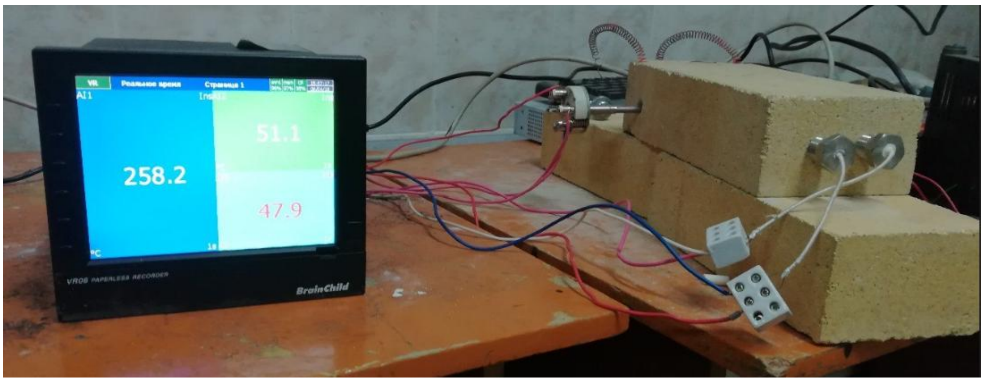


Figure 1. Physical model

Four cavities were created in the studied fireclay brick sample to accommodate the heating elements. Nichrome wire spirals were used as heating elements. By changing the geometry of the spirals (twisting), their electrical resistance was increased. This made it possible to reduce the current when connected to a 220 V AC network and thus prevent overheating and destruction of the heaters. For precise regulation of the heating power, a step-down voltage was used using a LATR. In order to ensure the estimated thermal power of 192.4 W, the voltage of the heating element was set to 46 V. To measure the temperature field in the fireclay brick, a temperature survey was performed. One of the thermocouples was placed at a distance of 20 cm from the heater to record the maximum temperature gradients. The other two thermocouples were placed on the opposite side of the brick to assess the temperature distribution over its surface. The obtained temperature data were recorded by a recorder and then transferred to a computer for analysis. To conduct the experiment, a setup was assembled, the basic diagram of which is shown in Figure 2. The key elements of the setup are: a power source, a heating element made of nichrome wire, a sample made of fireclay brick, thermocouples TP-2488/1 and a thermal resistance TCRosemount 0065.

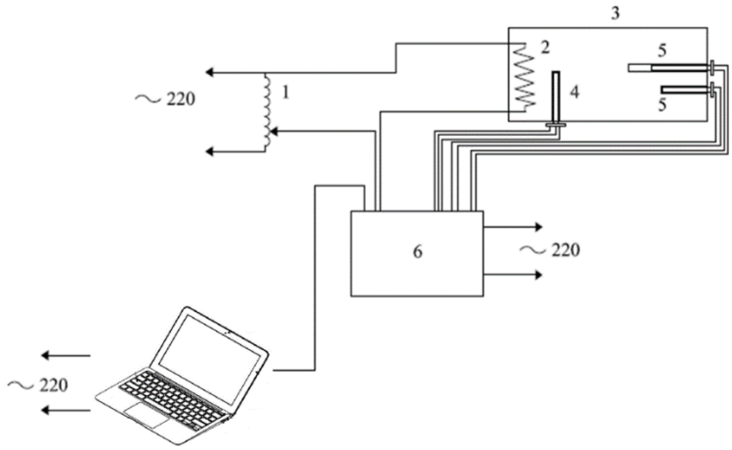


Figure 2. Schematic diagram of the experimental setup

During the experiment, it was found that the temperature field in the sample was a function of time, which indicates the non-stationary nature of thermal processes. Such non-stationarity is associated with a change in the internal energy of the body during its heating or cooling. The speed of these processes is determined by the thermal diffusivity coefficient a= $\lambda/c\rho$ of the material, which characterizes the relationship between thermal conductivity λ and heat capacity cρ. For the mathematical description of non-stationary thermal conductivity, a differential equation of thermal conductivity is used, which allows one to determine the temperature field at any point in the body depending on time. The basis for deriving this equation is the law of conservation of energy (1):

$$dQ=dU \tag{1}$$

Let us select an infinitely small volume in the medium in the form of a rectangular parallelepiped. According to Fourier's law, the heat flow is proportional to the temperature gradient. Equating the rate of change of the internal energy of this volume to the difference in the heat flows flowing into and out of it, and applying the expansion in a Taylor series, we obtain a differential equation in partial derivatives of the second order, describing the change in temperature in space and time (2):

$$\frac{\partial T}{\partial \tau} = a\frac{\partial^2 T}{\partial x^2}. \tag{2}$$

where T is the temperature, t is the time, x is the coordinate, and a is the thermal diffusivity coefficient. Figure 3 shows a three-dimensional diagram of an elementary volume in the form of a rectangular parallelepiped. The directions of heat flows (dQ) through its faces in three mutually perpendicular axes $x, y,$ and z are shown.

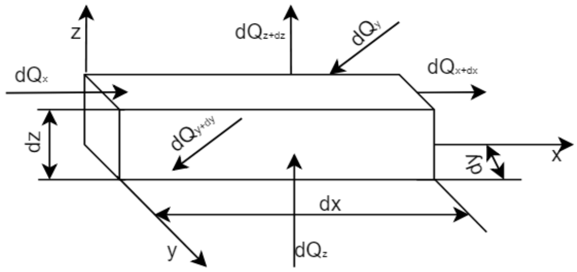


Figure 3. Designation of heat losses and heat gains

where dQ_x, dQ_y, and dQ_z are heat flows for the directions along the x, y, and z axes, respectively, dQ_{x+dx}, dQ_{y+dy}, and dQ_{z+dz} are heat flows through the opposite faces of the elementary volume. The arrows indicate the directions of each flow through the faces, which demonstrates the heat exchange between the elementary volumes in different directions. Such a scheme is usually used to analyze heat transfer in an elementary volume and is the basis for deriving the partial differential heat equation.

3. RESULTS AND DISCUSSION

For the mathematical description of thermal processes, a differential heat conduction equation was used, describing the change in temperature in time and space. Boundary and initial conditions were specified, and the computational domain was divided into finite elements, which ensured the ability to accurately reproduce the thermal regime in different zones of the model. The computational grid and solver parameters were configured for the numerical solution of the problem, which made it possible to obtain a detailed distribution of temperature fields. In order to verify the analytical solution obtained for the heat conduction equation, a numerical experiment was conducted using the COMSOL Multiphysics software package. The geometric model of the sample under study was built in a CAD system and imported into the numerical modeling environment. The corresponding boundary conditions and initial conditions were specified, and the computational grid was determined. In the process of preparing the computational model, the boundary conditions were modified. To clarify the mathematical model of the physical process, it was decided to set a non-isothermal boundary condition on the brick surface opposite to the heat source. To simulate the heat exchange process at the boundary of the computational domain, a condition of constant temperature (boundary condition of the first kind) was set, which corresponds, for example, to contact with a thermostat (Figure 4).

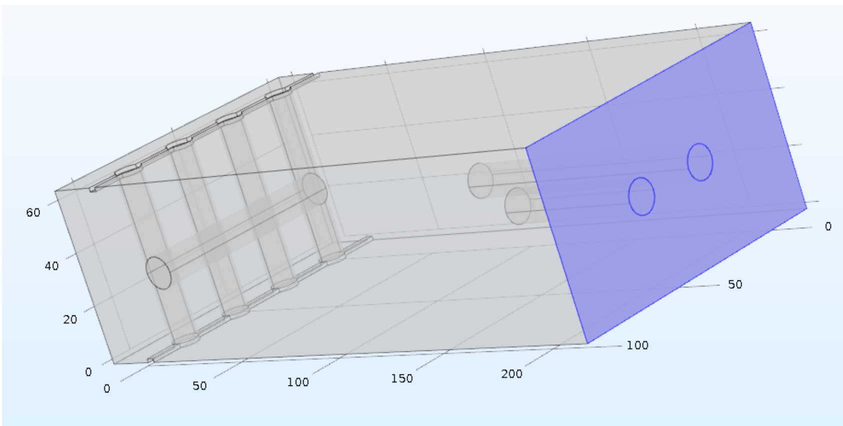


Figure 4. Simulation of thermal contact of brick with hot environment of furnace

To simulate the process of heating the brick in the kiln, boundary conditions were set that corresponded to the thermal interaction of the brick with the environment. A visual representation of these conditions is shown in Figure 4. After creating a geometric model and determining the material properties, a computational grid was built dividing the modeling area into finite elements. Solver parameters were configured for the numerical solution of the problem of non-stationary heat conduction in a solid. The duration of the numerical experiment and the time step were chosen in such a way as to adequately describe the process of heating the brick. The results of the numerical experiment, shown in Figure 5, were obtained as a result of 5-hour modeling with a time discretization of 1 hour.

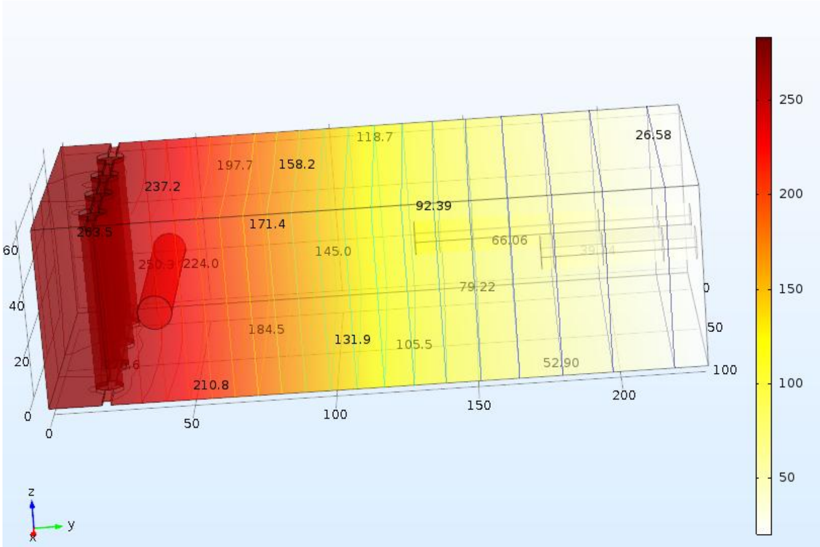


Figure 5. Heat distribution

The numerical simulation confirmed the theoretical assumptions regarding the uniform temperature distribution in the sample during heating. To analyze the temperature field dynamics in more detail, characteristic points were identified in the calculation area (Figure 6). Based on these points, change graphs were constructed.

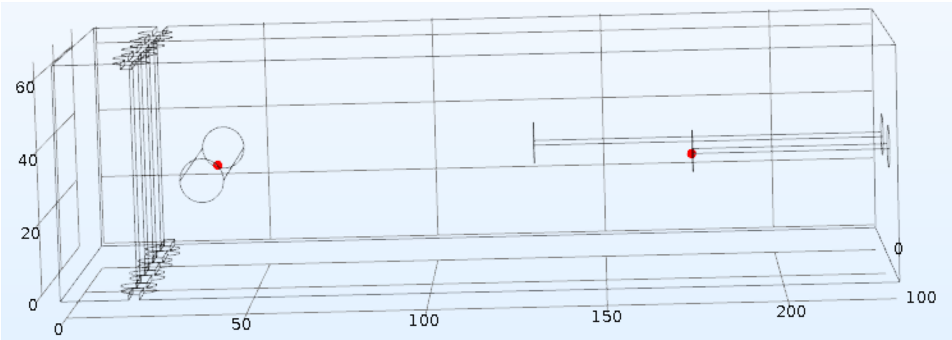


Figure 6. Selected control points of the calculation area

The dynamics of the temperature field in the model for 5 hours is presented by graphs of temperature changes at characteristic points. Figure 7 shows the change in temperature over time for two points with coordinates (57, 40, 30) and (57, 175, 30). The temperature increases with time, but at the point with coordinates (57, 40, 30) a sharper increase is observed, reaching approximately 260 °C in 5 hours, while at the point (57, 175, 30) the temperature increases more slowly and reaches approximately 40 °C by the end of the period. This difference in the temperature curves indicates non-uniformity of the temperature distribution, which may be associated with the peculiarities of heat transfer in the material or system.

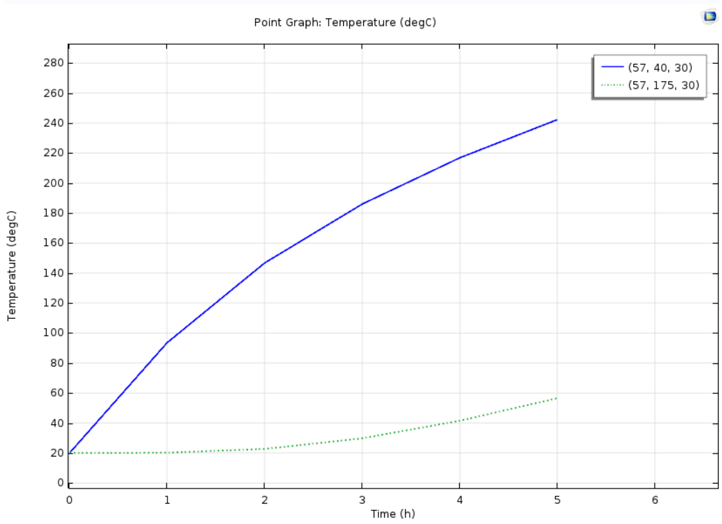


Figure 7. Temperature curves for selected points

Figure 8 shows the temperature change over time for several points, represented by different lines. The temperature increases over time, with the upper lines (blue and red) showing a sharper increase, reaching approximately 220 °C after 5 hours, while the lower lines (blue and green) show a more gradual increase in temperature, reaching approximately 40 °C by the end of the period. This difference in the curves indicates variations in the temperature distribution in the studied system, which may be due to non-uniform heat transfer in different regions. For comparison with the experimental data, the latter were imported into the COMSOL Multiphysics software package and combined with the calculated data in Figure 8.

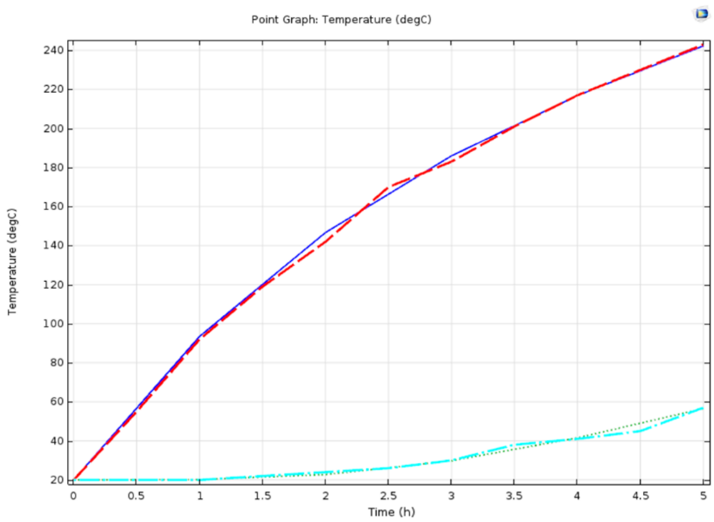


Figure 8. Fit of the model to the experimental data

The analysis of the graph of comparison of calculated and experimental data presented in Figure 8 allows us to conclude that the numerical modeling of the non-stationary heat conduction process is highly accurate. Given the complexity of the analytical solution to this problem, the FEM implemented in the COMSOL Multiphysics software package was selected for its numerical solution. The results obtained confirm the efficiency of the chosen approach. During the second experiment, it is planned to study the effect of periodic thermal effects on the temperature field of the object. To implement the experiment, a relay connected to the digital output of the VR06 recorder will be used. The relay will periodically turn the heater on and off, thereby creating conditions for obtaining a non-stationary thermal process with a variable temperature gradient. The parameters were predicted using a feedforward neural network implemented in the

MATLAB environment using the Neural Network Toolbox package. The network structure: one input layer, one hidden layer with 50 neurons using the logistic activation function, and one output layer with a linear activation function. The Levenberg-Marquardt algorithm was chosen to train the network. The input data were 220×2 and 220×1 matrices, which were pre-transposed and multiplied together to obtain the feature matrix (Figure 9).

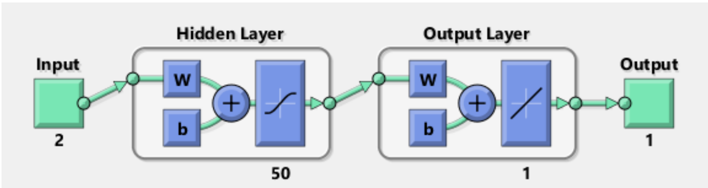


Figure 9. Neural network architecture diagram

The neural network model is a feedforward multilayer perceptron consisting of one input layer, one hidden layer, and one output layer. The input layer receives two normalized features representing spatial and thermal state variables obtained from FEM simulations and experimental measurements. The hidden layer contains 50 neurons with a logistic sigmoid activation function (logsig), enabling nonlinear mapping between input and output variables. The output layer consists of a single neuron with a linear activation function (purelin) to predict continuous temperature values. The total number of trainable parameters (weights and biases) is determined by the number of connections between layers and equals:

$$N=(n\_input\times50)+50+(50\times1)+1$$

where n_input is the number of input features. The Levenberg–Marquardt backpropagation algorithm was used for training due to its fast convergence for small and medium-sized networks. The neural network training process was completed after 30 iterations due to convergence. Figure 10, which illustrates the dependence of the mean square error on the number of iterations, shows that the error reduction slowed down towards the end of training. In particular, after the 25th iteration, the error on the validation sample stopped decreasing significantly, indicating stabilization and the optimal training completion point for this model.

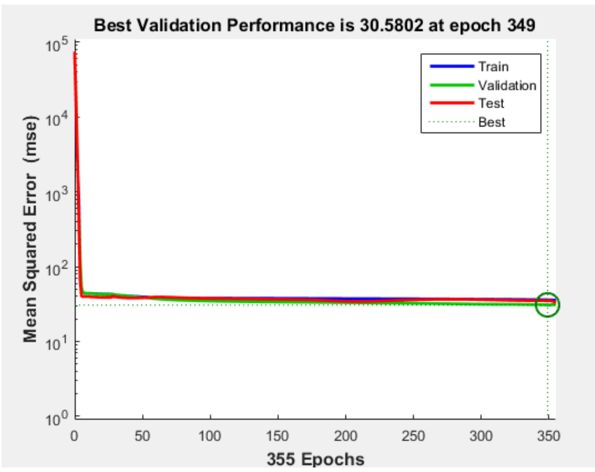


Figure 10. Graph of the change in the mean square error during the training process

After the neural network was trained, it was evaluated on a test data set to check the accuracy and reliability of the model. This step allowed us to determine how well the neural network copes with predictions on new data that it did not encounter during the training process. The evaluation results, presented in Figure 11, showed that the model demonstrated satisfactory accuracy and stability, which confirms its suitability for solving the task.

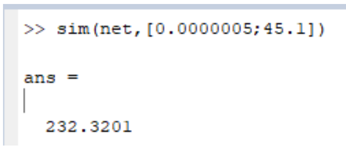
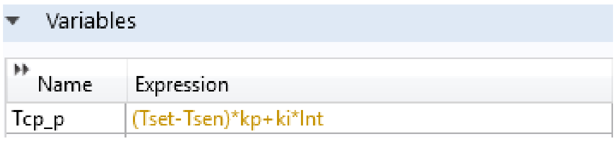


Figure 11. Evaluation of the performance of the trained network

The trained neural network successfully solves the problem of temperature forecasting, automatically identifying complex dependencies in the data. A computer model was developed to study the dynamics of a closed system with a PI controller, where the gain coefficient of the integral component ki is 0.002. The mathematical description of the controller is presented in Figure 12.


Variables

Name	Expression
Tcp_p	(Tset-Tsen)*kp+ki*Int

Figure 12. Regulator model

As a result of the simulation, the temperature distribution in the studied area was obtained at different time stages, which made it possible to trace the dynamics of thermal processes. The simulation provided a detailed idea of how the temperature changes depending on time, identifying areas with the largest and smallest temperature gradients. Figure 13 shows the temperature field at a time value of t=1500 seconds, where the characteristic heating and cooling zones are clearly visible, which makes it possible to analyze the efficiency of heat transfer in this system.

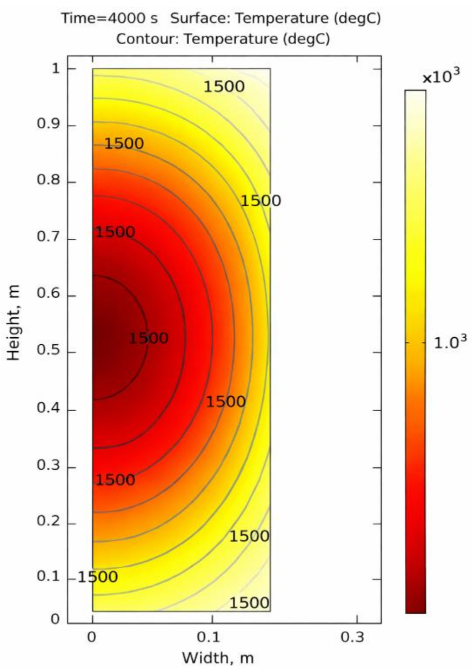


Figure 13. Temperature field at t=1500

For a more detailed analysis of the heating dynamics, key points in the study area were identified, designated as C_1, C_2, and C_3. These points allowed us to track the temperature change in different zones of the model, which helps to identify the features of the heat distribution and heating rate. Figure 14 shows the temperature curves for each of the selected points, showing the differences in heating depending on their position. These curves provide useful information for understanding the thermal characteristics of the system and allow us to evaluate the efficiency of heat transfer in different areas of the model.

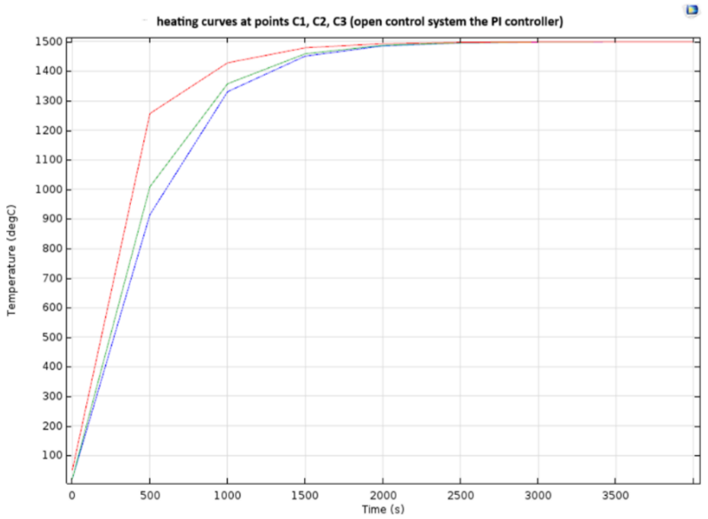


Figure 14. Heating curves at points C_1, C_2, and C_3

Figure 15 shows the control function of the proportional-integral (PI) controller used to stabilize the temperature regime. This function plays a key role in maintaining a given temperature level, compensating for deviations by regulating the heater power. The PI controller takes into account both the current error (proportional component) and the accumulated deviation over time (integral component), which ensures more accurate and smooth control of thermal processes. The control function of the controller allows you to optimize the system, minimizing temperature fluctuations and improving the stability of operation under external influences.

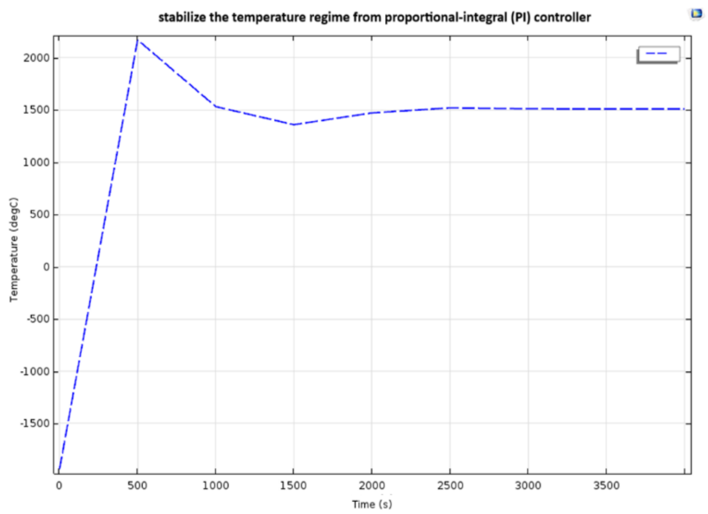


Figure 15. Control function of the proportional-integral controller

The analysis of heating curves at characteristic points shown in Figure 14, in combination with the control action data of the PI controller (Figure 15) demonstrates the high efficiency of the selected control algorithm. It is observed that the PI controller successfully maintains the temperature regime, minimizing fluctuations and providing smooth control of thermal processes. In addition, the algorithm allows eliminating the static error, which is especially important for maintaining stability in the system. The data show that when the controller is applied, the system quickly returns to the set temperature, which confirms the reliability and accuracy of the proposed control method. The results of the study showed that the developed neural network was successfully trained and is able to effectively predict the temperature regime in the furnace. Testing the performance of the trained model confirmed its reliability and high accuracy of predictions. In the course of the work, a study was also conducted on the stability of the thermal regime using various control algorithms, which made it possible to determine the optimal parameters for regulating the firing process. The data obtained indicate that the use of neural network technologies in combination with the FEM can significantly increase the efficiency of temperature control in the Vanyukov furnace. The implementation of this methodology has the potential to improve product quality and reduce energy costs. In the future, it is expected that the study will be expanded to include more complex models and additional physical factors affecting thermal processes.

All input variables were normalized to the [0,1] range using min–max normalization prior to training. This preprocessing step improves numerical stability, accelerates convergence, and prevents dominance of variables with larger magnitudes. The output temperature values were rescaled back to physical units (°C) after prediction. To ensure model generalization and prevent overfitting, early stopping was applied based on validation dataset performance. The dataset was divided into 70% training, 15% validation, and 15% testing subsets. Training was automatically terminated when the validation error failed to decrease for six consecutive epochs. This approach ensures stable convergence and prevents excessive adaptation to the training data.

Although the proposed hybrid FEM–NN approach demonstrates high prediction accuracy, several limitations should be noted. First, the experimental dataset was collected under controlled laboratory conditions and does not fully reflect the variability of industrial furnace operation, such as fluctuations in charge composition, airflow, or slag layer thickness. Second, the current model considers conduction as the dominant heat transfer mechanism, while radiation and convection are included in simplified form. Third, the neural network was trained on a single furnace geometry, which may limit the generalizability of the model to other furnace types without additional retraining. These limitations should be addressed in future work to improve the robustness and industrial applicability of the methodology.

4. CONCLUSION

This study presented a hybrid modeling framework integrating the FEM and a feedforward neural network for predicting and stabilizing the thermal regime of a Vanyukov furnace lining. The FEM model enabled accurate simulation of non-stationary heat transfer processes, while the neural network provided reliable temperature prediction based on experimentally validated data. The proposed approach demonstrated high prediction accuracy, with a relative error below 3%, and stable performance across training and test datasets. The integration of a proportional–integral controller further improved temperature stabilization and eliminated static control error. The main contribution of this work lies in the development of an experimentally validated FEM–NN–PI integrated framework tailored to real industrial furnace geometry under non-stationary conditions. The results confirm the practical applicability of the proposed methodology for improving thermal process stability and energy efficiency in high-temperature metallurgical systems. Future research will focus on incorporating additional heat-transfer mechanisms and extending the model to adaptive real-time control strategies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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