# HEATING MODELS USING ARTIFICIAL INTELLIGENCE)

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**Abstract**

The aim of the article is to show the use of artificial intelligence in improving the heating process in continuous industrial furnaces. To improve the heating in continuous furnaces, heating control based on models that consider the dimensions, material, and heating method can be used. These models can be built based on the classical description by differential or differential equations. The difficulties in solving them, especially considering the variable parameters of these equations, seem to be a reasonable possibility of using artificial intelligence tools, namely, genetic algorithms for parameter estimation and artificial neural networks, to create your own heating model.

**Keywords:** Metallurgy, furnaces, model, simulation, artificial intelligence

## 1. INTRODUCTION

This paper discusses the use of artificial intelligence in industrial metallurgical manufacturing technologies. In particular, it analyses the possibility of using artificial intelligence in the heating furnaces of rolling mills. We are concerned with selecting suitable technological nodes where positive results can be expected when introducing artificial intelligence elements and summarising the risks and benefits.

### 1.1. Heating furnaces

A key element of hot rolling mills is the heating furnaces. Increased attention will be paid to the step heating furnace:

a) classical control,

b) control using a neuro-fuzzy system,

c) design methodology for designing fuzzy systems,

d) methodology for model creation and system simulation,

e) design of an industrial application.

The problem of describing the behaviour and control of complex natural systems, characterised in particular by the difficulty of their formal mathematical description, which are difficult to know and operationally problematic to measure, stems from classical approaches. Classical approaches based on numerical mathematical analysis and the apparatus of mathematical statistics encounter limits in these applications. These arise from the use of general, objective laws of nature, which are interpreted by the relations of classical mathematics. These practically always lead to several necessary simplifications that cause the inadequacy of the mathematical description. Thus, as the complexity of real systems increases, the practical applicability of the mathematical description decreases very rapidly.

If the cause of the failure of a mathematical model is the lack of information or its extreme complexity, artificial intelligence methods can be used to advantage. The principles of artificial intelligence are based on the use of human experience, i.e. subjective knowledge. It is also advantageous to use simple but powerful non-numerical algorithms that allow the integration of objective knowledge with subjective knowledge, resulting in higher quality conclusions. With the development of artificial intelligence methods, there is a trend to move from data processing to knowledge processing. These approaches allow the creation of non-conventional non-numerical language models. These models can go well beyond conventional, mathematical-analytical ones in their applicability.

### 1.2. Artificial Intelligence Tools

The discipline of artificial intelligence seeks to create algorithms and systems that exhibit intelligent behaviour and capabilities and is concerned with methods for decision making and solving complex problems. This field encompasses many developments. Among the most important are:

a) qualitative modelling

b) fuzzy models

c) genetic algorithms

d) neural networks.

Qualitative modelling uses so-called naive physics to construct models based on the integration of deep and shallow knowledge. Qualitative description is approached when we do not want or cannot describe analytically precisely the relationships between the variables of the processes being described.

The principles of fuzzy set mathematics and multivalued linguistic (fuzzy) logic are used. Fuzzy models are often conceived as sets of conditional production rules. The most widely used fuzzy systems are expert systems, aimed at solving specific complex problems.

The natural mechanism of natural selection and the laws of genetics have inspired the development of genetic algorithms, which are a versatile and robust means of solving optimisation problems. The primary objects in GA are string, gene and population. The basic operations that work with these objects are crossover, mutation and selection.

Methods inspired by the processes in biological entities have achieved a considerable spread. Neural networks have been developed to partially mimic the processes occurring in the human brain and nervous system. They are particularly suitable for modelling the behaviour of complex systems because their typical characteristic is the ability to learn by themselves

## 2. RECENT DEVELOPMENTS WITH SIMILAR ISSUES AND THE METHODS USED TO SOLVING

The step heating furnace is characterised by high nonlinearity, time delay, significant time constant and change of parameters and structure over time. From another perspective, the furnace is a distributed-parametric process in which the temperature distribution is not uniform. Therefore, this process unit has complicated nonlinear dynamic equations that do not work entirely accurately. This paper proposes a one-stage nonlinear predictive model for a real step-heating furnace using nonlinear black-box subsystem identification based on a locally linear neuro-fuzzy model [1].

Another effort was to develop a two-dimensional mathematical heat transfer model for predicting the temperature history of steel plates to achieve optimal heating of these plates with minimum energy consumption in the step heating furnace. The algorithm developed by the simplified conjugate-gradient method (SCGM) combined with the shooting method was used as an optimiser to design the temperature distribution of the furnace, including the temperature of the preheating zone and the heating zone. Comparison with experimental data showed that the current heat transfer model works well to predict the plate's thermal behaviour in the heating furnace [2].

The optimal setpoints for the simulation of zones of a step heating furnace in steady-state operation are presented in the study [3]. Here, the authors try a new approach to achieve optimal setpoints for zone temperatures in a heating furnace in steady-state operation. This new methodology was developed to simulate a heating furnace and compared with the old traditional method (FDM). This model is implemented in the commercial software Matlab. The main advantage of this new methodology is that it allows the calculation to be solved quickly and accurately, thus achieving a significant reduction in calculation time compared to the old traditional method.

The adaptive neural network model for predicting the temperature of steel plates after passing through the rolling mill while the plates are still in the heating furnace uses measured data collected from the production line. The model uses adaptive neural networks to predict the temperature after the steel plates have been rolled while the plates are still in the heating furnace. This prediction can be used as a feedback value to adjust the furnace parameters to heat the steel plates more accurately to predetermined temperatures [4].

Similarly, the GA-BP neural network model for predicting the plate temperature in the heating furnace is composed of 48 BP neural networks in series are designed to predict the plate temperature, taking complete account of the continuous process of heating the plate from inlet to outlet. Simulation results show that almost all the errors of the test plates are within +/- 5 degrees C, which means that the GA-BP model is verified as valid and efficient, thus useful for online prediction and optimal control [5].

In [6], the authors compared models for optimal control of selected metallurgical units. The optimal heating under different given temperature conditions of the zones in the furnace was modelled, and the heating method was optimised both in terms of minimising the heating time and achieving minimum heating cost. Cost minimisation can minimise the consumption of heating media or reduce the loss of material during combustion. For this task, a solution based on the use of a genetic algorithm is advantageous. Simulations of the heat used in all dimensions and the quality of the material could be performed to solve the optimisation procedures. Based on these simulations, it would be possible to find a suitable strategy to develop an algorithm for optimal control of the furnace. This model can be used to find the optimal control trajectory using a genetic algorithm, where the fast ANN response significantly improves the performance of the optimal search.

## 3. FURNACE ZONE TEMPERATURE BEHAVIOUR MODEL

From the previous research, the world is looking for ways to develop furnace models to predict furnace behaviour. For this paper, we have selected a single zone model of a pass-through heating furnace. The model developed is intended to replace the standard first or second-order heat system model.

**Figure 1** shows the structure of the neural network. The input is a variable x, which contains data about combustion gas flow rate, combustion airflow rate and combustion ratio. The output variable y contains data on the furnace atmosphere temperature in the modelled furnace zone.

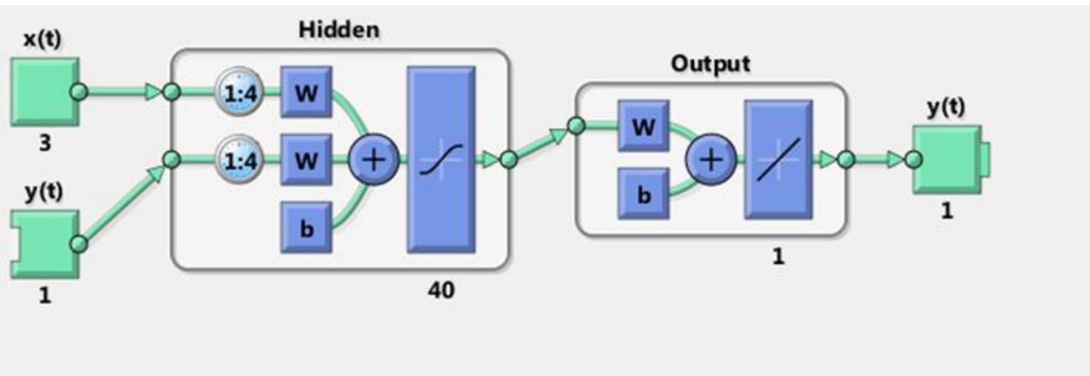


**Figure 1** Structure of ANN

**Figure 2** contains a diagram of the simulation model for three different neural networks in blue. They all have the same data but use different time series terms, namely two, three and four. The number of neurons in the hidden layer is also different, with the number of neurons successively 20, 30 and 40.

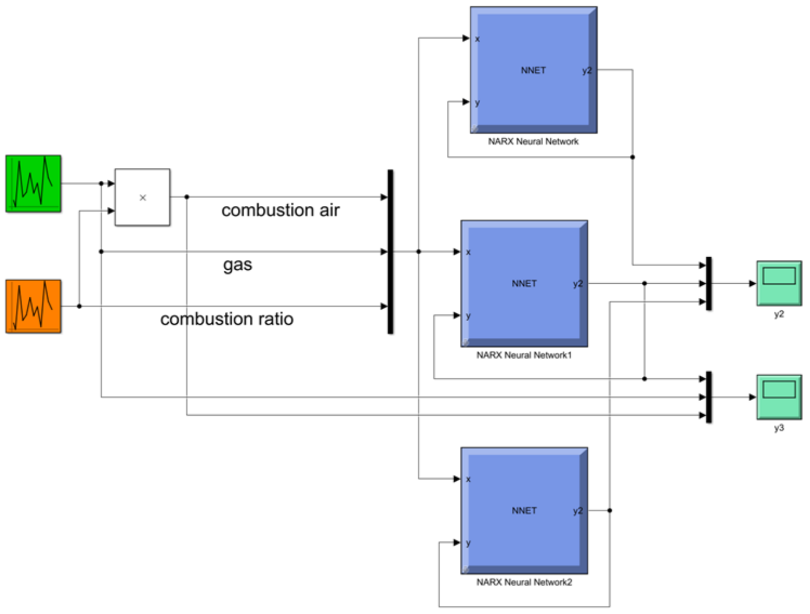


**Figure 2** Simuling model with ANN

The following figures refer to learning the largest neural network with four-time series members and 40 neurons in the hidden layer. The response error of the network is captured by the histogram not shown in **Figure 3**. For the 20-column histogram, the dominant errors are -0.69 °C and +0.96 °C with a median and a range of one column of 1.64 °C. The best performance value is achieved by the network at epoch 319 and reaches a value of 0.18157, captured in **Figure 4**. The response of the network to the training data and the prediction error is presented in **Figure 5**, Except isolated locations, the prediction error is in units of °C.

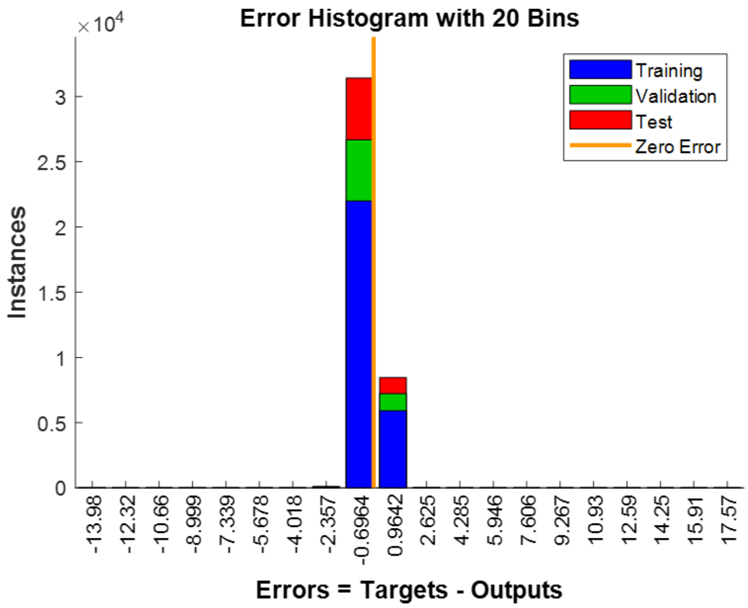


**Figure 3** The error histogram

To test the behaviour of the learned network on data other than the original data, we used the capabilities of SIMULIK to build a simulation circuit where, within the limits of the range of data on which the neural network was learning, we generated random signals representing gas flow rate, combustion ratio, and used these two values to feed the third signal, combustion air flow rate, to the network input.

The simulation result is shown in **Figure 6**, where the red line is the neural network's output - the simulated furnace environment temperature. The green line on the graph shows the simulated gas flow rate. The combustion ratio is not shown in the graph, it is given by the ratio of the airflow value to the gas flow value at the corresponding time instant. To assess the effect of non-compliance with the combustion ratio value, we chose to change the gas flow value at an interval of 1000 s and to change the combustion ratio every 200 s. The network responds well to non-compliance with the combustion ratio by reducing the simulated furnace environment temperature.

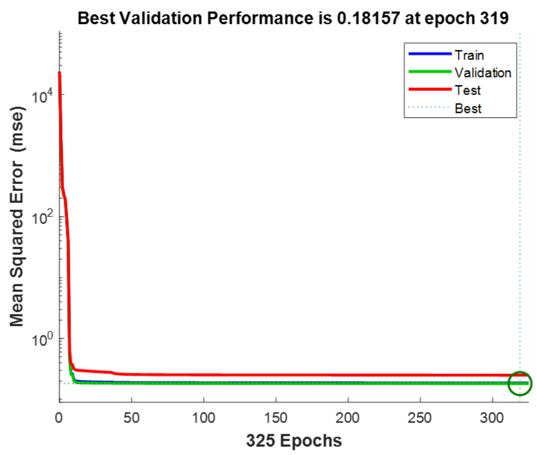


**Figure 4** Performance chart

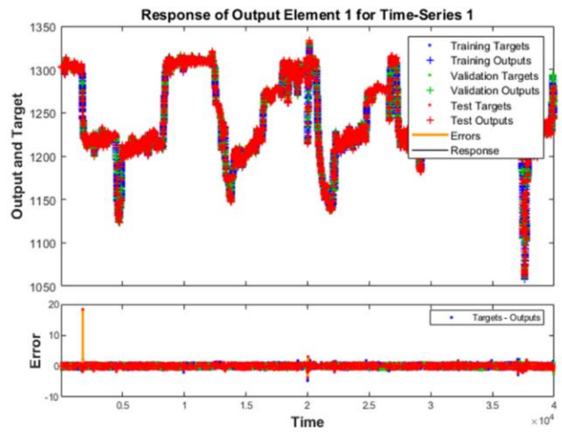


**Figure 5** Responce of ANN

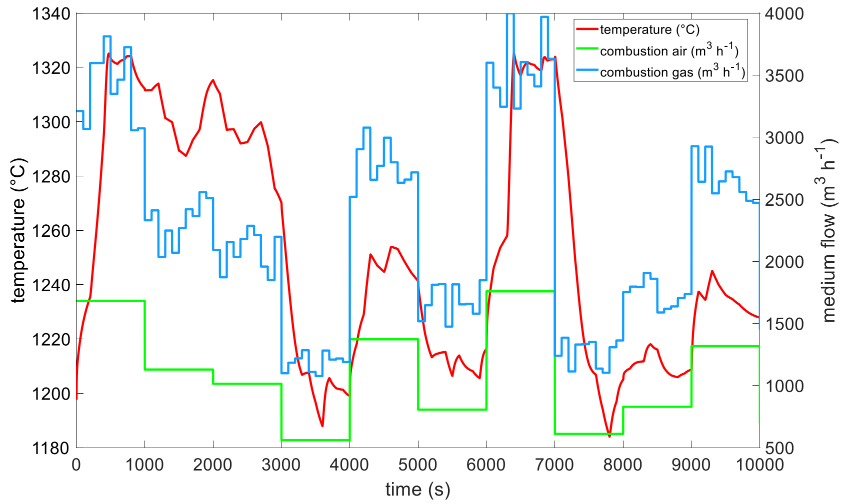


**Figure 6** Results of simulation

## CONCLUSION

This paper set out to reimagine the possibilities of using artificial intelligence tools. In the research part, we have tried to capture the breadth of issues and difficulties in using AI tools in a thermal process environment in metallurgy. The scope of the article does not allow us to cover in detail all the possibilities that these tools suggest. We have selected only one tool, namely neural networks, capable of time series prediction. Even in this reduced scope, we were able to show only a part of the simulations performed.

In any case, it appears that the use of learned neural networks to model, predict and control thermal systems is realistic. The research will continue by studying the robustness of these models, creating complex and complex models of furnace aggregates so that they can be used to study the behaviour of these technologies, finding new technological approaches, finding weak points and ways to remove them.

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