COMPARISON OF MODELS FOR OPTIMAL CONTROL OF SELECTED METALLURGICAL AGGREGATES

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Abstract

Optimal control systems is still relevant topic. In industries (especially in the range of metallurgy) that are primarily dependent on energy there are desirable either changes in technology and changes in existing technologies or changes of traditional materials for substituting ones or to explore possibilities for energy savings. Optimal control, as the term itself suggests, leads to savings on principle, even energies that are required to ensure these processes. The core is the optimal control model. That describes the behaviour of the controlled system. We try to summarize modern methods, for example using the principles of artificial intelligence and genetic algorithms, to balance the core of modules, which are used to optimize process control. The main focus will be concentrate on selected aggregates in rolling mill plants especially on continuous reheating furnaces.

Keywords: Heating, furnace, model, optimal control, simulation

1. INTRODUCTION

A heating of materials is a common technological process. In the process of metallurgical production this operation is particularly common in hot rolling mills. The whole area of metallurgy is characterized by a high energy consumption. Therefore, even in heating furnace segment it is true, that even a little reduction of an energy consumption can lead to interesting economic benefits. As a mathematical-physical model of an optimization of heating can be used the model built upon the idea of the Pontragin's principle of maxima using various models of heating process the genetic algorithm can be used. In the following text we can show, how various types of model of the heating process we may use for building the core model for finding the optimal control strategy.

2. MATHEMATICAL- PHYSICAL MODEL AND DESCRIPTION OF THE PROCESS OF HEATING AS A DYNAMIC SYSTEM.

For mathematical and physical description is based on the common theoretical combustion gas temperature, theoretical calorific value of gas, the amount of heat contained in preheated air. For models of two factors are important:

- a relationship between the power the furnace and slab surface temperature;
- a relationship between the temperature of furnace environment and surface temperature of the slab.

The relationship between the system and heating efficiency can be determined only with difficulty. In [1] and [2] is described the relationship between the specific consumption and the temperature of the surface of the material in the form of a transfer function of the first order. Relationships using the variable *p* are images in the Laplace transform.

$$\frac{T(S,p)}{K_y Q_{cp}(p)} = \frac{A}{p\tau_r + 1} \tag{1}$$

where $T(S, p)$ is the image of the material surface temperature [K], K_y is the coefficient indicating how much of the total amount of heat is distributed to a place in the oven measuring coordinate y. A is the amplification of this system [kg K W^{-1}], τ_r is the transfer time constant [s], $Q_{cp}(p)$ is the image of the specific power consumption [W kg^{-1}].

3. THE POSSIBILITIES OF MODELLING OF HEATING

For a description of the dynamics behaviour of system power of the furnace - the furnace environment temperature changes and the surface slabs temperature changes amplification A ,factor K_y , time constant τ_r and specific power Q_{cp} were calculated. To calculate the relation for specific surface burn the dependence on the surface temperature of the material can be used in the form

$$a_t = \sqrt{\frac{2K}{T_{pov}} e^{-\frac{B}{T_{pov}}}} \tag{2}$$

The values of coefficients are $K = 76233[\mathrm{kg^2Km^{-4}s^{-1}}]$ and $B = 17057[\mathrm{K^{-1}}]$ [1], [2]. An oxidation process may be solved using artificial intelligence, too. [3], [4].

3.1. The accurate models of heating

The transfer function of the system the temperature of environment - the temperature of the point within the prism [5, 6], we describe as the transfer function in the next formula

$$F(x,y,s) = 1 - \sum_{i=1}^{\infty}\sum_{j=1}^{\infty} \frac{D_i^X D_j^Y \frac{s}{b_i^X + b_j^Y}}{\frac{s}{b_i^X + b_j^Y} + 1}, \tag{3}$$

D_j^Y where D_i^X is the gain relevant to x-coordinate, is the gain corresponding to the y-coordinate. The reciprocal of the time constant is equal to the reciprocal value of the contributions from of x-axis and of the y axis. The resulting time constant determines the relationship

$$\tau_{i,j} = \frac{1}{b_i^X + b_j^Y} = \frac{\tau_i^X \tau_j^Y}{\tau_i^X + \tau_j^Y}. \tag{4}$$

3.2. Simplified models of heating

The aim is to create a sufficiently accurate simplified model of heating, the implementation of which can carry a large amount of computation in real time. Models can be based on many principles. One solution mentioned in the article [7].

These may be formulated by the following mathematic formulae:

$$\tau_1(t)\frac{dT_s(t)}{dt} + T_s(t) = T_f(t) \tag{5}$$

and

$$\tau_2(t)\frac{dT_c(t)}{dt} + T_c(t) = T_s(t) \tag{6}$$

Where $\tau_1(t)$ is outside heat transfer time-variable time constant [min], $\tau_2(t)$ is inside heat transfer time-variable time constant [min], Ts(t) is temperature of the heated material surface [°C], $T_f(t)$ is furnace temperature [°C], Tc(t) is material heated material core temperature [°C].

3.3. Differential model of an ingot

The literature [8, 9] describes the basic procedures used for the numerical calculation of temperature fields for both one-dimensional, and two-and three-dimensional temperature field, steady state and transient state. The increase in the x-direction

$$\Delta T_x|_{x\neq\pm\frac{m}{2}} = Fo\left(T^p_{x+1,y,z} + T^p_{x-1,y,z} - 2T^p_{x,y,z}\right) \quad (7)$$

$$\Delta T^p_{\left(x\middle|x=\frac{m}{2}\right)} = 2Fo\left[Bi\left(T^p_\infty - T^p_{x,y,z}\right) + T^p_{x-1,y,z} - T^p_{x,y,z}\right] \quad (8)$$

$$\Delta T^p_{\left(x\middle|x=-\frac{m}{2}\right)} = 2Fo\left[Bi\left(T^p_\infty - T^p_{x,y,z}\right) + T^p_{x+1,y,z} - T^p_{x,y,z}\right] \quad (9)$$

similarly the increase in the y-direction and the increase in the z-direction. Here *x, y* and z represent a discrete position for which cpalculation is done. *T* is the temperature and p denotes the index of the time step. *Fo* is a Fourier number, *Bi* is a Biot number both quantities are dimensionless.

4. GENETIC ALGORITHMS

Genetic algorithms GAs [10, 11] is a powerful search algorithm that performs an exploration of the search space that evolves in analogy to the evolution in nature. The power of GAs consists in only needing objective function evaluations. So derivatives or other auxiliary knowledge are not used. Instead probabilistic transition rules of deterministic rules, and handle a population of candidate solutions (called individuals or chromosomes) that evolves iteratively are used [21, 22, 23]. Each iteration of the algorithm is called generation. The evolution of the species is simulated through a fitness function and some genetic operators such as reproduction, crossover and mutation [24, 25].

5. OPTIMIZATION METHODS

For example in the process of optimization of reheating furnaces it is necessary to use not only static optimization process but it must be solved integrating optimize criteria. Using this way we must set the condition for dynamics of dependences:

- the dependence of furnace temperature on heating power in particular positions in the furnace;
- the dependence of the surface temperature on the temperature in the particular point in the furnace;
- the dependence of temperature of some internal points on the surface temperature of the heating body of material [12,13].

5.1. Dynamic characteristic of system: power of one zone - the temperature of the zone of the furnace

For the identification of the behavior of the system the power of one zone - the temperature of the zone of the furnace we use technological data producing directly by the control system of the furnace.

5.2. Classical system identification

From the point of physical view of this system we used linear model identification methods .The first order model has the form

$$G(s)\ \frac{Kp}{1+Tp1*s} \quad (10)$$

where *Kp* is the gain, *Tp*1 is the time constant of the system

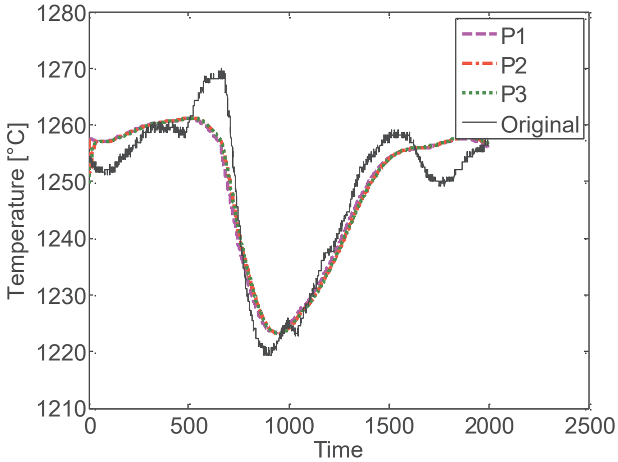

Fig. 1 Real system output and response of model

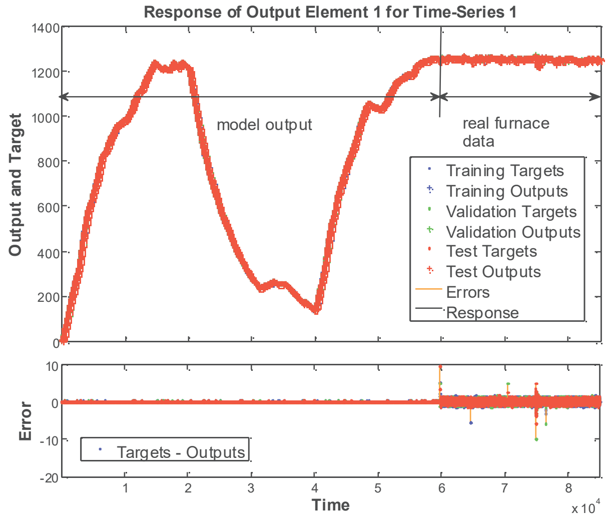

Fig. 2 ANN learning, response and error

The time constant Tp1 was estimated as 6420 +/- 11 s and the gain Kp is set to 4.2137 +/- 0.00008. For useful results we restricted all data to the range where the input of identified system rapidly change its value. The selected interval is shown in the **Fig. 1**.

5.3. Neural networks

Artificial neural networks (ANN) are a good tool for prediction time series and its evaluations [14]. In the first type of time series problem, you would like to predict future values of a time series $y(t)$ from past values of that time series and past values of a second time series $x(t)$. This form of prediction is called nonlinear autoregressive with external input. From our needs the NARX model seems to be best choice.

6. THE COMBINATION OF CLASSICAL IDENTIFICATION AND ARTIFICIAL NEURNAL NETWORK

To be able to use an artificial neural network model even the situation for which we have not measured data, we can use the description of the behaviour of the furnace by the transfer of the first order. On the basis of this transfer we are able to combine the measured data from the furnace and modelled behaviour using a simplified model nicely captures the dynamic behaviour of the furnace's system.

The combined data is shown in **Fig. 2** together with error of prediction using training, validation and test data. The simulation model build in SIMULINK is shown in **Fig. 3**.

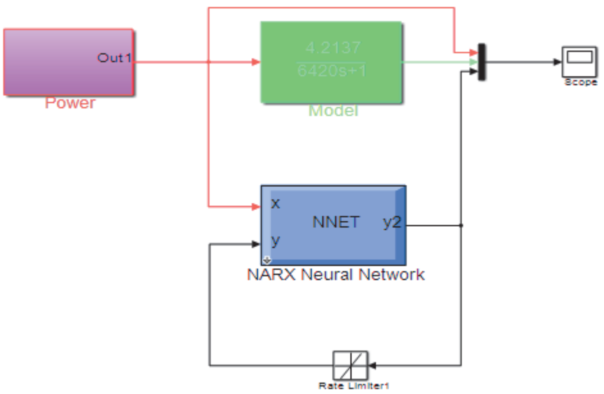

Fig. 3 Test of ANN using model of plant

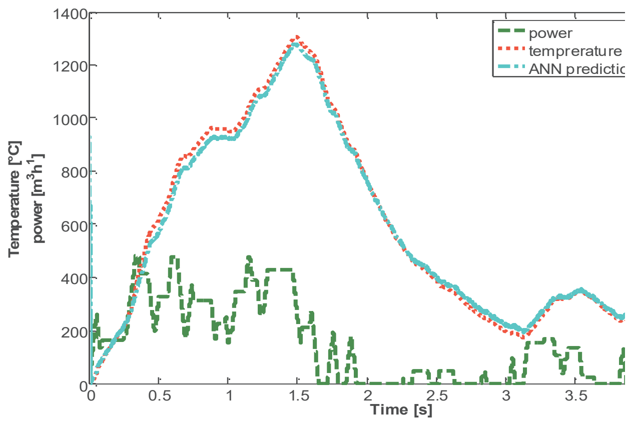

Fig. 4 Result of test ANN

7. USING NEURAL NETWORKS AS A MODEL OF THE BEHAVIOR OF THE FURNACE

From results in the previous chapter it is clear that the network is able to learn with acceptable errors the dynamics of the furnace. To be useful as a core model for the optimization algorithm i tis necessary to verify its behaviour in other general data and compare the by the behaviour of the model. In the **Fig. 4** we see the original system reaction modelled as a system of first order and the reaction of the neural networks as the result of action the same input stimulus to both systems

8. CONCLUSION

Optimum heating at different given conditions, especially temperature zones in the oven, the optimization of heating both in terms of minimizing the heating time, together with the achievement of the minimum cost of heating was done. Minimizing costs can either be afraid focused on minimizing the consumption of heating media or I to reduce the material loss at burn. [15,16]. Very useful for this task is solution based on using of genetic algorithm. For solving optimization procedure care could be carried out simulations of heat used for all dimensions and material quality. Based on these simulations, it would be possible to find a suitable strategy for heating the algorithm of optimal control furnace. However optimization algorithms must be able to choose as a strategy for various heating rate of the material, as well as irregular operation of the furnace, where the passage of material through the furnace stops for a shorter or longer time [17]. Here it is necessary to look for a strategy responding to the power the furnace, to a furnace environment temperature, so that at the end of downtime and subsequent smoothly furnace work to reach required parameters of the heated material on the one hand, and to minimize losses and fuel consumption during downtime on the other hand. For system identification especially for nonlinear systems and system with influence of various errors the ANN, especially NARX model are very suitable. The learned ANN can very good predict the behaviour of identify system [18, 19, 20]. But we must take into account ability of ANN predict the system manner outside the interval of training, validation and test data. The results of these predictions are in mostly cases unpredictable. The classical system identification has higher error, but it can predict the system behaviour for the whole interval of system inputs and outputs. We can combine all previous mentioned methods to generate ANN model, which can be learned for prediction the behaviour of the furnace even if nonstandard situations. This model can be used for searching the optimum trajectory of control using genetic algorithm, when quick response of ANN significantly increase performance of optimum searching.

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