MODELLING OF TEMPERATURE FIELD OF WARMED INGOT

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Abstract

To verify the operation of heating furnaces is very suitable to measure directly on the heated material that is placed in a heating furnace. In the case of the furnace, where the material is shifted on the growth of the furnace, the situation is complicated and measuring is arduous. Therefore, it is usually necessary to think over the location of sensors in the material carefully. The disadvantage is generally spot measurements of the temperature field and it should be counted as a direct and an inverse method for unsteady conduction of heat. Article will be shown one of the methods, how to solve this task by means of artificial intelligence tools.

Keywords: Artificial intelligence, furnace, heat conduction, temperature field

1. INTRODUCTION

1.1. The use of dynamic models in the control algorithm

Conventional control circuits utilize proven PID controllers connected in the feedback when their input is the deviation between the inquired value and the actual value of the output of the regulated system.

The control performance improving, especially its acceleration, requires the connection of the forward couplings. These links cannot be realized without the knowledge of the controlled system dynamics [1, 2]. If it is possible to describe the dynamics, e.g. by transmission, then it is possible to implement these algorithms. As an example the well-known example of control levels in tanks can be used [3]. Another suitable example can be a vacuum regulation in the furnace by using the knowledge of the instantaneous input values of the furnace burners.

In many cases such models cannot be made on the basis of mathematical description in the form of differential equations with constant parameters or clearer transmissions of the given systems. Especially in the field of industrial furnaces the system parameters depend on many factors, whether it is the position of the material in the furnace or its instantaneous temperature [4, 5].

Anyhow, we are trying to improve the management processes by using of the predictive control forms. Then the continuous identification of heating systems and dynamic models of the systems how we have described them above will find their use.

1.2. The verification of differential model

To verify the differential model itself the direct measurement on a heated ingot in a continuous furnace was performed. The measurement results showed some anomalies that could not be explained by a simple model of type Furnace surroundings temperature - Stated place in the heated material temperature, where at the moment of decreased furnace input, despite the temperature measured by the furnace thermocouples was higher than the temperature of the measured material, the material in the stated place started to cool (see **Figure 1**). Therefore, the reasons of this phenomenon were searched. In another article (also presented at this conference), we show that it is necessary to correct the furnace surroundings temperature depending on the heating medium inputs for the given furnace zone.

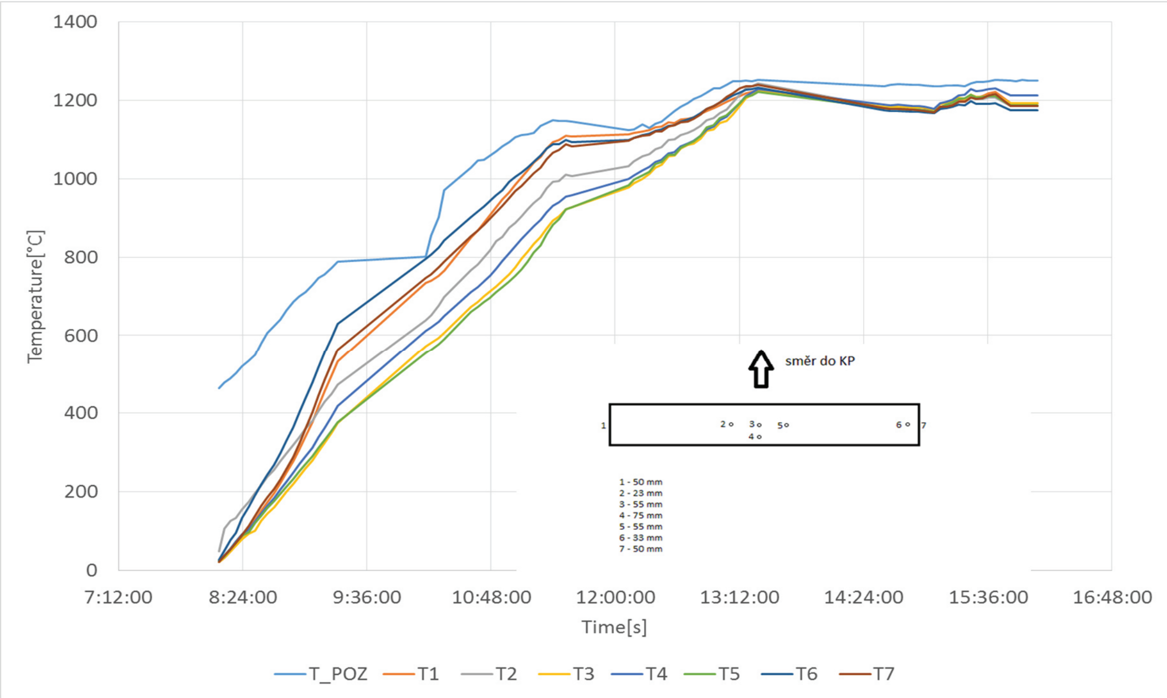

Figure 1 The course of temperature in the furnace and the course of the measured temperature by seven thermocouples

2. METHODOLOGY OF SIMULATION AND SEARCH MODEL PARAMETERS

The solution is based on three consecutive steps:

1. Formulation of the dynamic model:
   a. model, which includes only the impact of the furnace temperature,
   b. model that reflects the influence of temperature and of also of heating system of the furnace,
   c. model, which in addition also considers the influence of the correction on the speed of movement of the material in the furnace.
2. Use of genetic algorithms to search for parameters of the model 1a - 1c [6, 7].
3. Iterative calculations of the temperature field of the heated ingot by using the corrected temperature of the furnace atmosphere using a dynamic model with preset parameters.

3. THE USE OF GENETIC ALGORITHMS TO FIND SIMULATION MODEL PARAMETERS

For the separate dynamic models described above, the parameters were searched by the genetic algorithm. The summary **Table 1** gives us the overall table about number of parameters, population size, number of generations, the conditions for termination and the number of function calls that counted functional.

Table 1 Number of parameters, population size, number of generations, the conditions for termination and the number of function calls that counted functional

Model	No. of parameters	No. of individuals	No. of generations	Function count	Termination condition
1a	12	400	600	240 000	average chance less then option
1b	27	400	92	36 800	average chance less then option
1c	28	200	2 800	560 000	exceed max number of generation

The number of parameters, whose value is optimized to rank functional, i.e. the integral of the square deviations of model output and the actual course of the temperature locally ingot was minimal. Criteria function in this case was modeled by a dynamic model in Matlab Simulink surroundings. The simulated time corresponded to the length of heating of the material in the furnace and was set to 27 800 seconds. The simulation pitch was determined in accordance with the real values' sampling period, it means to one second. One course of simulation computation lasted approximately 0.5 seconds. From the number of calls of this simulation (in case of ad 1c) it is visible that the total time of searching for an optimal parameters' set was time-consuming.

The model including all aspects which we considered as affecting the material heating running, i.e. input in the furnace zones, furnace surroundings temperature and the speed of the movement of the material in the furnace, proved as the most appropriate one by comparing of the models' results 1a, 1b and 1c. The speed of the movement of the material in the furnace had the lowest impact on the heating course.

Histogram of the distribution of the individuals' number for single functional values can be seen in **Figure 2**.

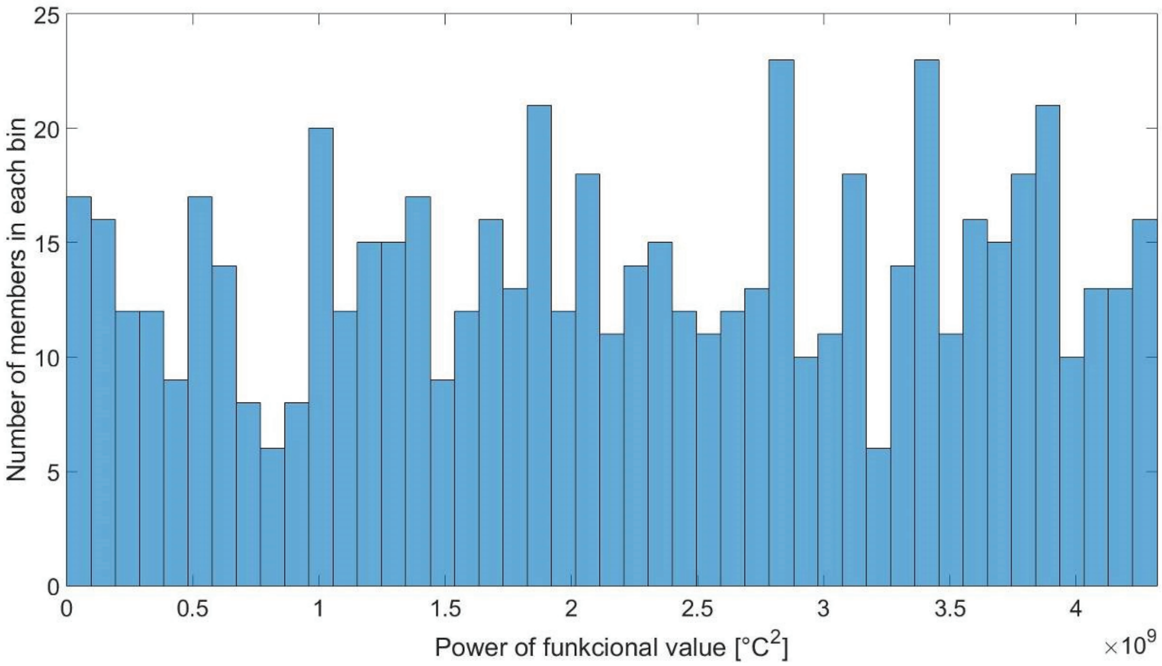

Figure 2 Histogram of the distribution of the individuals' number for single functional values

4. ITERATIVE CALCULATIONS AND TEMPERATURE FIELD IN INGOT

The course of the temperature field of the heated material is determined by the Fourier's partial differential equation of heat convection. Generally the problem of a heat conduction can be divided into two groups. The first group, so called direct tasks are tasks in which on the basis of initial conditions and boundary conditions we can determine the temperature field described by partial differential equation. The boundary condition solution is given as a function of temperature in time $T = f(t)$, or is determined by the value of heat flux on the edge of solved systems $q_s = f(t)$ or is determined by the surroundings temperature $T_\infty = f(t)$ and the overall heat transfer coefficient α_Σ. These problems are generally called direct heat conduction tasks.

Tasks of the second group are complement of the direct tasks of heat conduction. Here we know the distribution of thermal field in the body and determine the parameters of the relevant boundary conditions. This group of tasks is called the inverse heat conduction problem.

In our case, we know the temperature of the body surface, but only at selected points, and the ambient temperature as a time function. Neither is it purely direct one nor purely inverse heat conduction problem. It would be a direct role with appropriate initial conditions in case the temperature field $T = f(t, \vec{x})$ on the body surface was described as a function of time and spatial data $\vec{x}$ f points on the body surface. If we determine the missing parameter of the boundary task, it means an overall heat transfer coefficient, then it is certainly an inverse role. So, if we determine the temperature field in the body on the basis of surface temperature we will deal with the direct task of heat conduction.

To summarize the previous thoughts then, provided we know the initial conditions of the solution, we are able to deal with both a heat conduction problem and an estimation of the global coefficient of the heat transfer from the body to the surroundings by iterative methods, a combination of direct and inverse task of heat convection.

To have the task solvable we will assume that the general heat transfer coefficient is a function of the surroundings temperature and the body surface temperature.

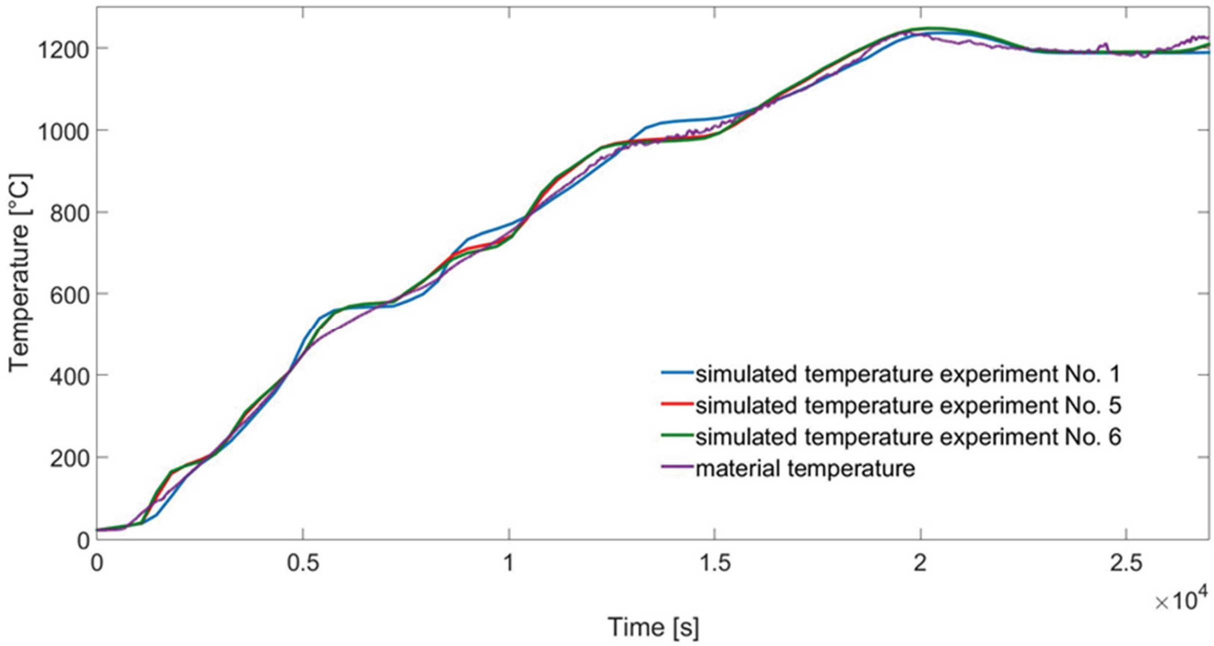

Figure 3 Comparison between output temperature of selected experiments and measured temperature

The following calculations will be carried out until the results of two following steps will differ more than a predetermined error value. The courses of actual measured temperature at a specified point of the ingot and of the simulated temperatures at the same point are shown at the **Figure 3**. Here the experiment No. 1 shows a temperature course at the given point after the first iteration, experiment No. 5 the temperature curve after the fifth iteration and experiment No. 6 last performed sixth iteration. It is visible from the routing of resultant curves that the conformity between the measured and simulated temperature from time 10 000 seconds since the beginning of the heating in case of experiments Nos. 5 and 6 has a minimal deviation from the measured curve.

For illustration we show the course of the thermal field in the ingot at time of 265 000 seconds, when the surface of the ingot began to warm again. The figure shows how the thermal wave is moving from the surface to the center of the ingot (see **Figure 4**).

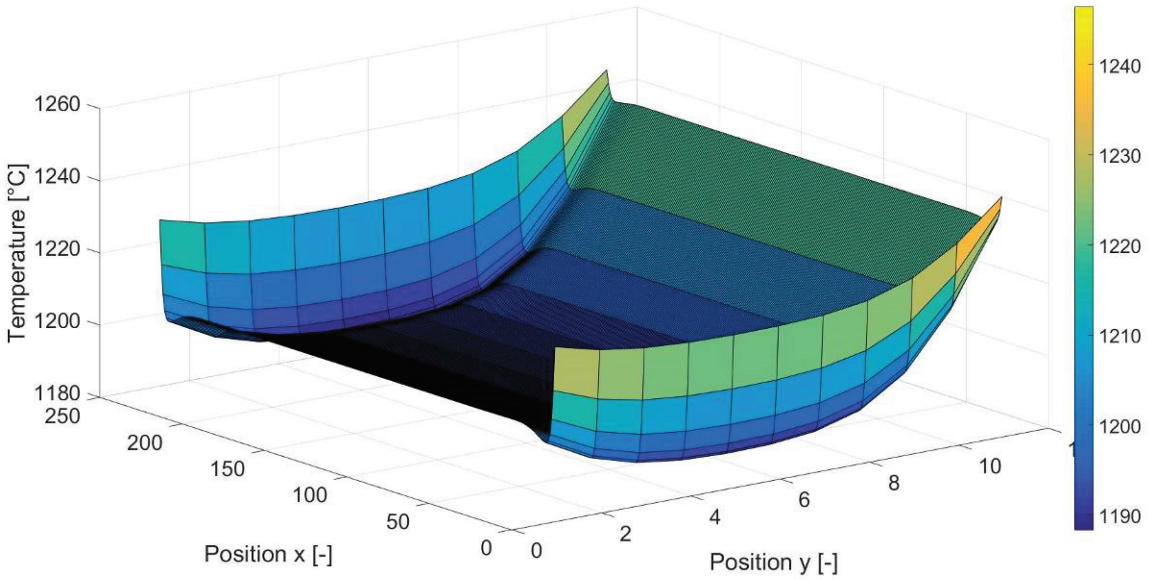

Figure 4 The courses of actual measured temperature at a specified point of the ingot and of the simulated temperatures at the same point

5. CONCLUSION

The previous text tried to show a complex approach to the solving of modeling heating of steel continuously cast in a continuous walking beam furnace. Similar result were presented in wide range of papers [8-11]. If we just went from ambient temperature furnace environment, it would be impossible to explain the decline in the temperature of the strand at the end of cooking [12-14]. Without the use of genetic algorithms it would be impossible to find the value of a total of 28 parameters that affect the behavior of the model, as it was created in Matlab Simulink. The output of this model was then noticeable temperature, which can be defined as the sum of the temperatures measured by thermocouples and temperature kiln converted from power, the quantity of gas for each zone [15, 16]. This noticeable temperature then allow the iterative procedure to find the value of the overall heat transfer coefficient for each position of the material in the furnace.

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