# ASSESSMENT OF THE FURNACE STATUS FOR POSSIBLE OPTIMIZATION OF HEATING AND FITTING THE MODEL HEATING LEVEL

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**Abstract**

This article aims to survey and evaluate the current state of the heating furnace and to analyze the operational data using data mining tools and artificial intelligence in order to capture the complex weaknesses of the current system and to propose those modifications that would allow deployment model management levels in its entirety.

**Keywords:** Furnace, data mining, statistical analysis

## 1. INTRODUCTION

The heating of the material in industrial furnaces can be characterized as a very energy-intensive process. Any reduction in energy intensity or efficiency increase of the furnace aggregate results in not insignificant savings, namely both fuel and metal savings.[1]

Combination of data mining, artificial intelligence (AI) and neural networks with classic mathematical description, including regress and statistical analysis in order to correct a wrong prediction of AI tools, can be seen as beneficial. The failure of certain quantities' impact can be considered as the behaviour weakness of many models. In the range of industrial reheating furnaces, the data describing the material reheating process are stored in various kinds of industrial databases.

Monitoring and control systems collect for the purpose of monitoring a number of operational data. These systems construct their databases as easily as possible; each trend is usually stored in a separate table. Data in the tables are stored in two basic principles, either periodically after a preset time interval or after a certain event - change of a variable value. But this leads to redundancy. The solution could be to store each reference variable in a separate table. Many systems use their own mechanisms for storing data that combine both periodic data storage and storage management using a change of value. These data must be pre-processed before deploying data mining [2,3] and before using them for optimizing the heating control system due to the neural network use.

The rolling mill (continuous, carousel, stepping) furnaces have an important place in the metallurgical production. These aggregates cannot be solved as a separate technological unit but as part of a wider technological complex. Their integration into the production line significantly affects the operation of the furnace aggregate. The furnace performance is then determined by the requirements of the following technology and the furnace's own control system must respond appropriately to these requirements.

The whole furnace control problem can be divided into the following levels:

- The basic stabilization level of the furnace control, the task of which is to maintain the required parameters of the furnace aggregate; it is mainly to stabilize the furnace temperature.

- A superior level of control that is designed to respond to changed requirements and, based on these requirements, to set the selected setpoints for the lower level of control so that the heating process runs optimally according to the selected criteria. The selection of the optimum values is based on the continuously evaluated temperature field of the heated material.

## 2. METHODOLOGY FOR ASSESSING FURNACE OPTIONS

The data provided consisted of three files. The first set contained the furnace operating data as stored in the frame of historical data. This file contains the main operating parameters of the furnace and the inquired values entered by the operators.

The second set of data was stored in the second level, which collected data o the used billets and their further processing. From this file, data relating to the carousel furnace were used, in particular, the dimensions of the billets, the time of setting, of the furnace zones course and of their withdrawal.

The third set consisted of furnace rotation and positioning data. The data contained in this file generated a map of the furnace occupancy within one month.

Data stored in the second level were identified by individual heats, set billets, and finished products. For further processing the block identifiers were used, to link the second level data to the furnace rotation and setting data. The resulting map of the furnace then consists of the billets in individual rows and individual positions placed in the furnace. From the billet dimensions, their volumes were calculated. For the analysis, it was possible to ignore other thermal temperature characteristics of the materials, such as specific heat capacity, density, etc. The occupancy of the individual zones as a whole, the individual zones for each position, and the total furnace occupancy were calculated from the data of the billets dimensions occupied positions in the furnace.

The link between the traffic data and the furnace map was based on the time taken as a key in both tables. The furnace operating data were stored at ten-second intervals. The furnace setting and rotation were recorded at the time of each event, i.e. at the billet setting, at the billet withdrawal, and at the furnace rotation.

In order to link the two tables, the time data in the furnace map table were rounded to the nearest ten seconds. Then, using a time key, the two tables were joined. Changing of the values of process variables within the interval of setting, removing and furnace rotating had been neglected, having in mind the fact that their time changes were not so significant to affect the overall data analysis.

### 2.1. Data analysis

As it is required to detect the furnace weaknesses and the way of the furnace operation, we have investigated how the heating lengths differ during the researched period. Since the values of the material stays in the individual furnace zones were available, we divided all heats into ten groups. In each group, those heatings are assigned whose times of stays in the individual furnace zones were the most similar. The similarity was determined as the time interval (distance) from the center of gravity (can be understood as the median) of these intervals. As the values of five quantities are evaluated, their values can be understood as coordinates of a point in a five-dimensional space. The distance was then calculated by Euclidean distance.

### 2.2. Production organization and planning

By optimizing of the production planning process it would be possible to reduce furnace downtimes. The data show that time 5:51 hour is sufficient for billets heating in the furnace. Shorter times can lead to uneven heating of the material, longer times lead to reduced furnace production. The heating time histogram is shown in the following **Figure 1**.

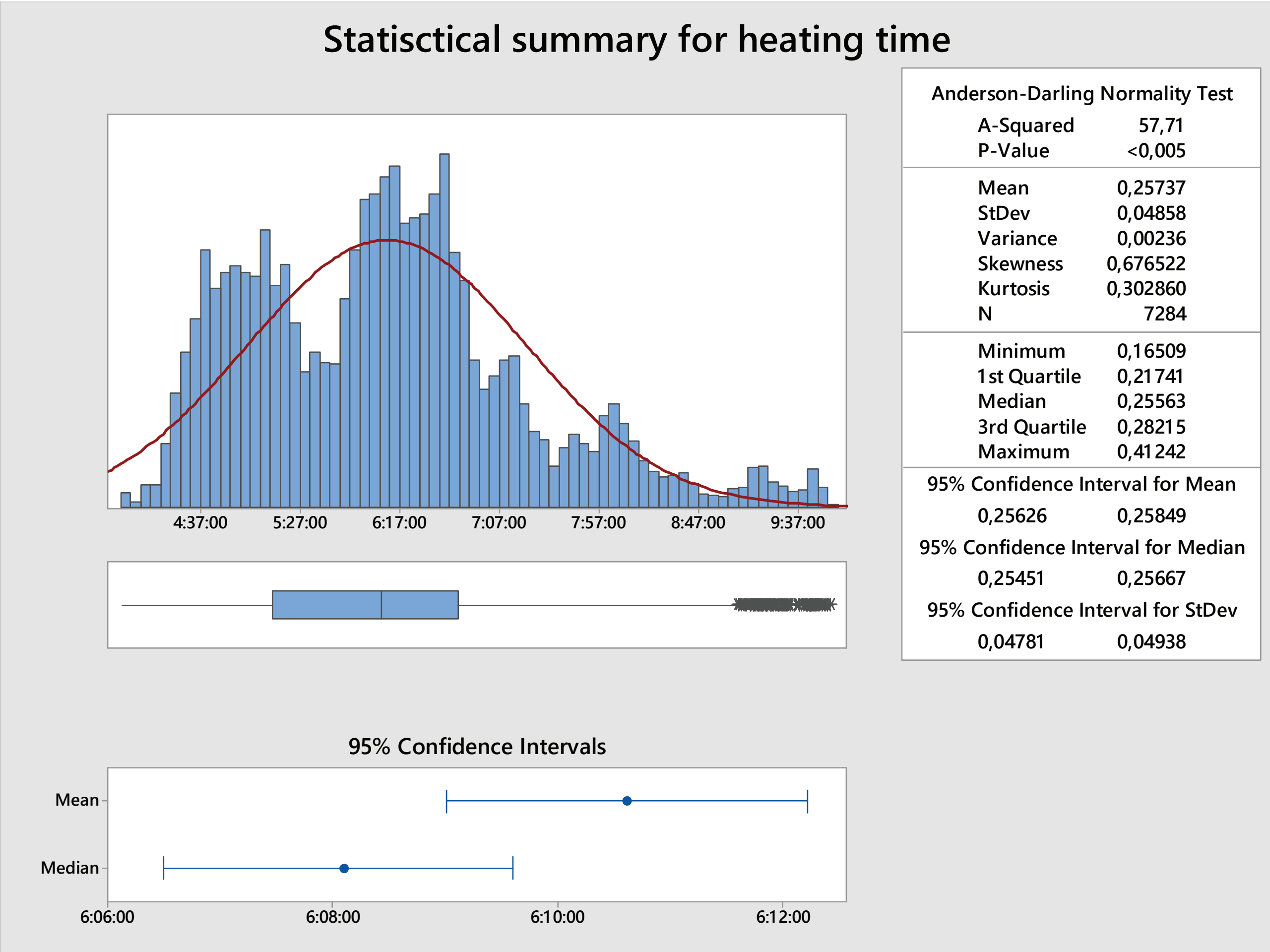


**Figure 1** Statisctical summary for heating time

Due to the fact that all furnace zones are operated at a constant temperature, it is not necessary to insert blanks between the individual range of products.

From the data, it is not clear whether the billets material composition is taken into account when selecting the heating strategy. Various types of materials need to be heated to different temperatures for subsequent processing but this is not solved by the current furnace operation mode.

## 2.3. Analysis of heating time dependence on length and diameter of heated material

The statistical analysis focuses on searching dependencies between the geometric dimensions of the heated material and the stay time in the furnace as so the material was heated during the observed period.

Although the determination coefficient is low (there are large variations between the predicted and observed values), it is possible to determine the dependence between the geometric dimensions of the heated material and the time of the material heating in carousel furnace. The dependencies between the heating time and the length, diameter and volume will be discussed in the following text.

**Dependence of heating time on billet length**

With billet lengths exceeding three times the diameter, heating times should not be significantly different.

The dependence of the heating time on the billet length. Because of statistical analyze, the heating time does not depend on the billet length (average heating time = 6:10 hours). Regression function (represented by a regression line), that has basically a horizontal course, is indicating this fact.

**Dependence of heating time on billet diameter**

The following graph shows the dependence of the heating time on the billet diameter. The dependency is here given by:

**Heating time = 1:36:27 + 0:00:45 * billet diameter**,

where time is given in hours (as opposed to the graph where time is given in the parts of the day) and the billet volume is given in $m^3$.

**Dependence of heating time on billet volume**

The following graph shows the dependence of the heating time on the billet volume which can be mathematically given by:

**Heating time = 5:02:50 + 25:52:19 * billet volume,**

where time is given in hours (as opposed to the graph where time is given in the parts of the day) and the billet volume is given in $m^3$.

The previous regression relationship gives the most accurate results but it should be noted that only 15.5 % of cases are statistically clarified.

In summary, we can say that the time of the material heating in the furnace does not depend on any dimension of the billet and seems to be completely random.

**Recommendations resulting from that finding**

Not to exceed the heating time of 5:50 hours. The time of about five hours stay in the furnace is sufficient for the heating which means the heating time reduction of about 30 minutes on average.

**Evaluation of heat transfer to material**

Higher heat exchanger inlet temperatures indicate less heat transfer to the material (excess heat contains flue gas). The heat exchanger protection flap was opened for more than one percent for the time of 7400 seconds.

Dependence of flue gas temperatures at the recuperator input on the heating time and on the volume of the charge material in the furnace is shown in the following graphs.

The following graph shows the dependence of the flue gas temperature on the charge volume.

Dependence can be expressed as:

**Flue gas temperature = 800.3 - 1,793 * volume of material.**

The constant 800 °C is related to the set maximum flue gas temperature at the recuperator input.

The regression line of the dependence of the flue gas temperature on the material stay time in the furnace has the equation

**Flue gas temperature = 798.3 - 70.85 * heating time.**

## 3. DISCUSSION

Data for the regression analysis used was obtained by data mining technique. In terms of regression relations, the determination coefficient was small. Therefore, in the following research, we will focus on the possibilities of prediction of kiln aggregate operation using artificial intelligence methods. [6-8]

**Artificial neural networks**

Based on cluster analysis, it will be possible to use a set of learned neural networks to predict individual production parameters of the kiln aggregate [3-5].

**Fuzzy logic**

The use of fuzzy logic for prediction seems to be perspective. The advantage is some blurring of input data as well as the use of appropriate defuzzification [6].

**Genetic algorithms**

For complex relationships, the use of genetic algorithms to determine both static and dynamic furnace characteristics appears to be significant.

## 4. CONCLUSION AND RECOMMENDATIONS

From all the above graphs it is visible that the regression dependencies between the heating time and the billet dimensions can be obtained. It is also possible to find the dependence between the charge volume and the flue gas temperature before the recuperator. From the graph of the heating time versus the volume (weight) of the billet too large scatter of the values even for individual billets sizes can be seen.

This implies that by reducing the heating time (keeping a maximum time of about 5 hours) the flue gas temperature at the recuperator input is reduced what may result in the recuperator life increase, resp. heat loss reduction in case the recuperator is cooled by cold air.

By reducing the temperatures in the first two zones of the carousel furnace during long heating times the reduction of the temperature of the flue gas at the heat exchanger input can be achieved.

**Maintenance and monitoring of furnace technical condition, data archiving**

On the basis of the analysis of provided data and other received information we recommend the implementation of measures in the following areas:

**Technical condition of furnace, measurement, and regulation**

To diagnose and eliminate the measurement and regulation malfunctions in time (thermocouple measurement deviations, non-functional pyrometer at the furnace output, etc.).

**Data archiving**

To complete the data archiving for flue gas exhaust, including the exhaust gas data and the related waste heat utilization technology, to connect the furnace aggregate diagnostics and control and the following technologies.

To supply the archiving of temperatures measured on the track until further heating. These temperatures, resp. data about rolling forces, etc., will enable the following analysis of the degree of warming and the uniformity of the billets heating in the furnace.

**Realization of new measurement**

To perform a new measurement of the heating using thermocouples, resp. data-pack, within the normal operation of the furnace, if possible.

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