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APPLICATION OF ARTIFICIAL NEURAL NETWORKS AND REGRESSION FOR ANALYSIS OF CHEMICAL STEEL REHEATING

APLIKACE UMĚLÝCH NEURONOVÝCH SÍTÍ A REGRESE PŘI ANALÝZE CHEMICKÉHO PŘÍHŘEVU OCELI

Abstract

Metallurgical processes belong to complex physical-chemical processes theoretically described by means of multidimensional generally nonlinear dynamic systems with different transfer lags in their structure. Before realization of these systems control requested by practice it is necessary to execute their structural and parametric identification. As these processes are very complex, all exact relations for their mathematical description are not known so far.

Some metallurgical systems are practically non-described so far (black box), further described only partially (grey box), while only a little of them are described almost fully (white box).

Determination of internal structure of insufficiently described systems is done by means physical modelling, by measurement if important data and subsequently by means of regression analysis or artificial neural networks applied to measured data.

There is certain chance to determine a proper system internal structure at system identification by means of statistical analysis (i.e. to come from black box to grey box or from grey box to white box), though this approach is knowledge and time-consuming.

Identification by means of artificial neural networks enables rather external system description (i.e. black box models creation), when we get an acceptable accordance between real and modelled outputs, i.e. so called output estimation (prediction). This approach is thus more suitable for control than for identification itself.

Contribution deals with a possibility of prediction of a temperature after a steel chemical heating on device of integrated system of secondary metallurgy by means of regression analysis and artificial neural networks and with a comparison of both of these approaches.

Abstrakt

Metalurgické procesy patří mezi složité fyzikálně-chemické procesy teoreticky popsatelné pomocí vícerozměrných obecně nelineárních dynamických systémů s různými dopravními zpožděními v jejich struktuře. Před realizací praxí požadované úlohy řízení těchto systémů je potřebné provést jejich strukturální a parametrickou identifikaci. Jelikož jde o procesy velmi složité a komplexní, nejsou doposud známé všechny exaktní vztahy pro jejich matematický popis.

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Některé metalurgické systémy jsou zatím prakticky nepopsané (tzv. černá skřínka), další popsané pouze částečně (tzv. šedá skřínka), zatímco jen velice málo z nich je popsaných téměř úplně (tzv. bílá skřínka).

Zjišťování vnitřní struktury nedostatečně popsaných systémů se děje prostřednictvím fyzikálního modelování, prostřednictvím měření důležitých veličin a následně pomocí regresní analýzy či umělých neuronových sítí aplikovaných na měřená data.

Při identifikaci systémů pomocí metod statistické analýzy je určitá šance dopátrat se jejich vhodné vnitřní struktury (tj. přejít od černé skřínky k šedé, či od šedé k bílé), i když tento přístup je velice náročný na znalosti a čas.

Identifikace pomocí umělých neuronových sítí umožňuje spíše vnější popis systémů (tj. vytvoření modelů černých skřínek), kdy dostáváme přijatelnou shodu mezi skutečnými a modelovanými výstupy, čili tzv. estimaci (odhad, predikci) výstupu. Tento přístup je tedy vhodnější spíše k řízení než k samotné identifikaci.

Příspěvek se zabývá možnostmi predikce teploty po chemickém příhřevu oceli na zařízení integrovaného systému sekundární metalurgie pomocí regresní analýzy i umělých neuronových sítí a porovnáním obou těchto přístupů.

1 INTRODUCTION

The objective of the contribution is a creation of a model for prediction of the temperature after steel chemical heating on device of integrated system of secondary metallurgy (ISSM) by means of neural networks and regression analysis and a comparison of the both approaches.

If the caisson device is equipped by an oxygen nozzle, there is an occasion to execute chemical heating. During chemical heating process the operator comes out from the arriving temperature of steel after homogenization on ISSM device. On the basis of this temperature computer recommends an appropriate quantity of aluminium (Al), oxygen (O2) and lime (CaO) that should be added to the ladle. These components relate to each other, given amount of aluminium, oxygen and lime is added according to arrival temperature. Together with added aluminium another elements melted in steel including iron are burned. Significant thermal contribution is represented by elements such as manganese, silicon, aluminium and carbon. Output variable (temperature) is measured at the end of chemical heating after oxygen blowing termination.

On the basis of prediction of temperature after steel chemical heating and subsequent calculation of temperature change before and after chemical heating it will be possible to plan length of subsequent operations at steel treatment on ISSM, eventually to change input parameters so that required output value is achieved before chemical treatment process itself.

2 ARTIFICIAL NEURAL NETWORKS

Neural networks use the distributed parallel processing of information during the execution of calculations, which means that information recording, processing and transferring are carried out by means of the whole neural network, and then by means of particular memory places. The basis of mathematical model of the neural network is a formal neuron which describes by a simplified way a function of a biological neuron by means of mathematic relations.

Learning is a basic and essential feature of neural networks. Knowledge is recorded especially through the strength of linkages between particular neurons.

Linkages between neurons leading to a "correct answer" are strengthened and linkages leading to a "wrong answer" are weakened by means of the repeated exposure of examples describing the problem area. These examples create a so-called training set.

Neural networks are suitable for approximating complex mutual relations among different sensor-based data, especially among non-structured data, with a high grade of non-linearity, and with inaccurate and incomplete data.

For all types of predictions neural networks are suitable to be used for their learning Backpropagation algorithms. This algorithm is convenient for multilayer feedforward network learning which is created minimally by three layers of neurons: input, output and at least one inner (hidden) layer. Between the two adjoining layers there is always a so-called total connection of neurons, thus each neuron of the lower layer is connected to all neurons of the higher layer. Learning in the neural network is realized by setting the values of synaptic weights between neurons, biases or inclines of activation functions of neurons. The adaptation at Backpropagation types of networks is also called „supervised learning", when the neural network learns by comparing the actual and the required output and by setting the values of the synaptic weights so that the difference between the actual and the required output decreases.

2.1 Prediction of temperature after steel chemical heat

Technological data which were gained from records acquired on furnace aggregates and devices of secondary metallurgy in the steelworks were used for creation of artificial neural network for prediction of temperature after steel chemical heating.

These data were subsequently adjusted to the form suitable for neural network application. The whole database contained in total 697 input-output patterns. The database was divided to data for network training and data for testing network capability of generalization.

Data about heat weight, temperature before chemical heating, vacuum treatment time, weight of aluminium, manganese, silicon, CaO and oxygen consumption were used as an input vector and output neuron represented the temperature after steel chemical heating. Generalized block structure of neural network inputs and outputs is shown on *Fig. 1*.

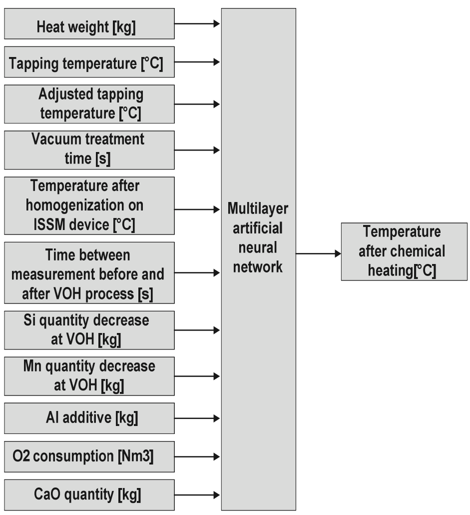

Fig. 1. Block structure of neural network

On the basis of adapted data artificial neural networks were designed and verified. Neural networks were created in software STATISTICA – Neural Networks. This system enables among others a choice of most suitable with the best performance, it contains efficient investigative and analytic techniques and enables to achieve summary descriptive statistics, to execute sensitive analysis and to create response graphs. For particular neural network models a quality of network adaptation to the submitted patterns and generalization scale were observed.

The rate of inaccuracy between the predicated and actual output represents a prediction error. In technical applications the error is mainly represented by following relation:

SSE – (Sum of squared error):

$$SSE = \sum_{i=1}^{n} (y_i - o_i)^2 \tag{1}$$

RMS error – (Root mean squared error):

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} (y_i - o_i)^2}{n-1}} \tag{2}$$

R^2 – determination index:

$$R^2 = 1 - \frac{SSE}{SST} \tag{3}$$

where:

n - number of patterns of a training or test set,

y_i - predicted outputs [°C],

o_i - measured outputs [°C],

SSE - sum of squared errors [°C^2],

SST - total sum of squared errors [°C^2].

The best results of prediction proved multilayer feedforward neural network with topology 11-5-1. Above mentioned prediction errors for this neural network are: SSE = 21 715 °C^2, R^2 = 0.876, RMS = 5,6 °C.

A histogram of number of cases in dependence of residues between predicted and measured outputs and a graph of predicted and measured temperature is shown on *Fig. 2*.

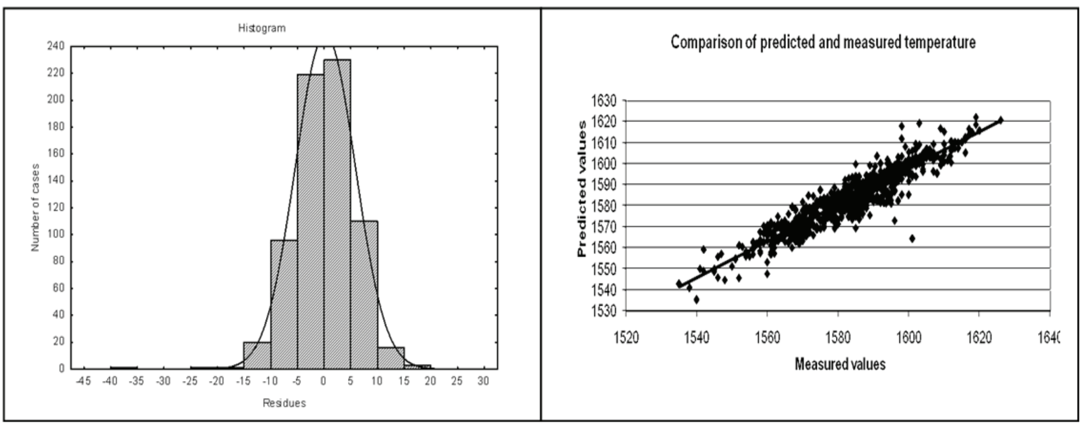

Fig. 2. Histogram of residues of neural model and comparison of predicted and measured temperature

From this graph results that a majority of predicted values differ from measured ones in temperature range up to ± 5 °C.

The parameters of selected neural network were implemented to the program independent on STATISTICA software. This program enables on the basis of input data setting to predict the temperature after steel chemical heating and subsequent calculation of temperature change before and after chemical heating. On the basis of this information it is possible to plan length of subsequent operations at steel treatment on ISSM, eventually to change input parameters so that required output value is achieved before chemical treatment process itself.

3 REGRESSION ANALYSIS

For selected set of 11 regressors (inputs on *Fig. 1*) full multiple linear regression model which has following general form, was used:

$$y \;=\; b_0 + b_1 \cdot x_1 + ... + b_{11} \cdot x_{11} + \varepsilon \;=\; b_0 + \sum_{j=1}^{m} b_j \cdot x_j + \varepsilon \qquad (4)$$

where:

y - regressand [°C],

b_0 - constant [°C],

b_j - regression coefficients,

x_j - regressors,

ε - regression error [°C],

m - number of regressors (m = 11).

Regression diagnostics of application results of this model showed that model is statistically significant, stable in time, with practically non-collinear regressors but 4 of them appeared as statistically non-significant. Model is not linear (it misses nonlinearities of regressors of power, inverse function, hyperbola or logarithms type). Model is statistically incorrect because its residues showed non normality, heteroscedasticity and autocorrelation. Practically it means that model had to be adjusted analysis of nonlinearity of regressors and their implementation to the model and removal of statistically non-significant regressors.

Regression diagnostics and component and residual graphs showed that it is convenient to add to certain regressor its square, to another its reciprocal value and interaction (product) of some regressors. After these adjustments model showed some statistically non-significant regressors which were gradually removed. Resultant reduced model with transformed 10 regressors showed statistically good properties: SSE = 19 279 °C^2, R^2 = 0.876, RMS = 5,3 °C.

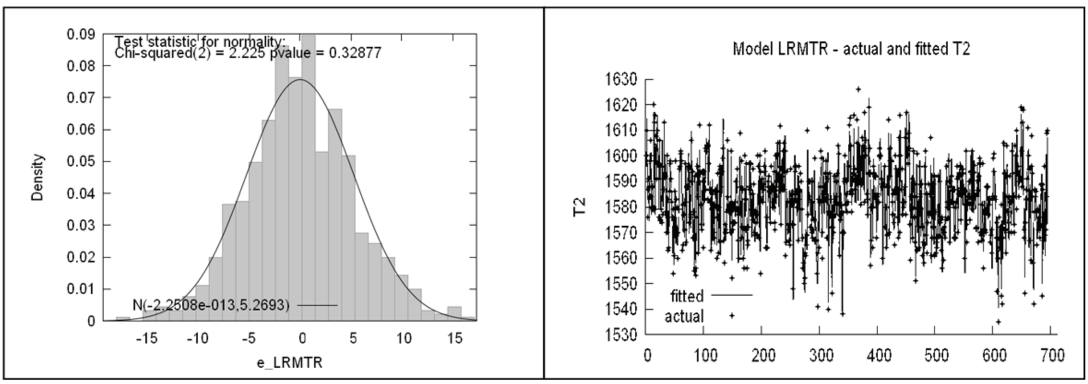

Fig. 3. Histogram of residues of regression model and comparison of predicted and measured temperature

Histogram of residues of the regression model and graph of predicted and measured temperature is shown on *Fig. 3*. From the graph results that model appropriately predicts temperature after chemical heating. Its residues showed normal distribution with mean root square error 5°C.

4 CONCLUSION

The objective of the contribution is to present possibilities of prediction of temperature after chemical heating on ISSM device by means of neural networks and regression analysis. After evaluating the achieved results, we can state that neural networks are generally applicable rather for prediction of output and for control of analyzed system and regression analysis is more suitable for system identification, i.e. for determination of adequate structure and transfer coefficients of the process. Both neural and regression model enable the prediction of temperature after chemical heating with a sufficiently small error.

However regression analysis enables the correct output estimation and the correct identification of the system providing at least partial knowledge of the internal structure of the system (system is known as a grey or white box) and sufficient knowledge of the theory and modern methods of mathematical statistics. Neural networks enable the correct output estimation for systems which can be given as a black box, i.e. without knowledge of the internal structure of the system.

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