MODERN METHODS FOR IDENTIFICATION OF THE DYNAMICS OF TECHNOLOGICAL THERMAL UNITS

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Abstract

The optimization of technological aggregates is important from several aspects. These aspects include high requirements according to the technology of heating, shorter retention times, a rapid heating, and improving of products quality a friendly handling of technologies and a reducing of an ecological footprint. To optimize the operation it is necessary to solve problems of the optimal control, whether by classical methods or by simulation. For both methods of the solution, it is necessary to know the dynamic characteristics of the system where the control is trying to optimize. In this article we will focus on the analysis of some methods of identifying dynamics of such systems.

Keywords: artificial neural networks, identification, dynamic system, control

1. INTRODUCTION

Especially in the field of metallurgy reheating and cooling processes are very often and important parts of manufacturing metals. So the fuel and energy consumption by reheating furnaces is very high. High energy-intensive working of metallurgical aggregates in not one isolate problem. So the optimization of technological aggregates is important from several aspects. These aspects include high requirements according to the technology of heating, shorter retention times, a rapid heating, and improving of products quality a friendly handling of technologies and a reducing of an ecological footprint. To optimize the operation it is necessary to solve problems of the optimal control, whether by classical methods or by simulation. For both methods of the solution, it is necessary to know the dynamic characteristics of the system where the control is trying to optimize. In this article we will focus on the analysis of some methods of identifying dynamics of such systems.

2. 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. The optimum of functional for the fuel consumption, material losses, technology amortization and so on must be found. For the reason of optimize the process of re-tempering material a we must know the surface temperature of material. This temperature in some cases we may measure directly using some kind of an temperature sensor placed in the material but with the process of getting the surface temperature of the material passed into the continuous reheating furnaces we cannot measure the temperature using direct both contact or non-contact. So we can try to use the dynamic model of calculation of this temperature. 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 and
- the dependence of temperature of some internal points on the surface temperature of the heating body of material [1, 2, 3].

2.1 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. For the identification analyze data of more than eight hours of reheating walking beam furnace. We try to use two basically different methods. The first method is commonly used method of identification of processes and the identification toolbox from MATLAB is used. The second method is based on the principle of the time series prediction using neural nets.

3. DISCUSSION

In the **Fig. 1** the chart of the flow of heating gas and the temperature in fifth zone of the furnace we can see.

From this chart we can see, that the transients don´t and there are no steady states. From this system behavior we can try to determine the dynamic characteristics of the system power - the furnace temperature. For system identification we used the System Identification Toolbox of Matlab.

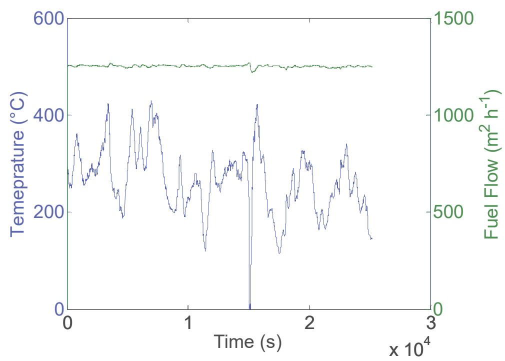

Fig. 1 Input and output of system to be identification

3.1 Classical system identification

This toolbox gets various methods for determination of systems parameters. System Identification Toolbox lets us create models from measured input-output data. We can:

- Analyze and process data
- Determine suitable model structure and order, and estimate model parameters
- Validate model accuracy

These routines include autoregressive models (ARX, ARMAX), Box-Jenkins models, Output-Error models, and state-space parameterizations. Estimation techniques include maximum likelihood, prediction-error minimization schemes, and subspace methods based on N4SID, CVA, and MOESP algorithms [4]. From the point of physical view of this system we used linear model identification methods and we try to determine the parameters of the first, second and third order model.

The first order model has the form

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

The second order model has the form

$$G(s)\ \frac{Kp}{(1+Tp1*s)*(1+Tp2*s)} \tag{2}$$

The third order model has form

$$G(s)\ \frac{Kp}{(1+Tp1*s)\,(1+Tp2*s)\,(1+Tp3*s)} \tag{3}$$

where *Kp* is the gain, *Tp*1, *Tp*2 and *Tp*3 are time constants of the system. In the case of the whole data are using we cannot obtain suitable results. The **Fig. 2** shows the results of identification. It can be said that the error in the range of +20 -30 °C is a good result. But if we compare the behavior of the real system and the behavior of the model, we can see, that the model doesn't respond on its input. Fit to estimation data is 1.424% (the prediction focus), FPE is 1.539e+06 and MSE is 97.4.

Probably the best known technique of estimating the model accuracy is Akaike's Final Prediction Error (FPE) [5].

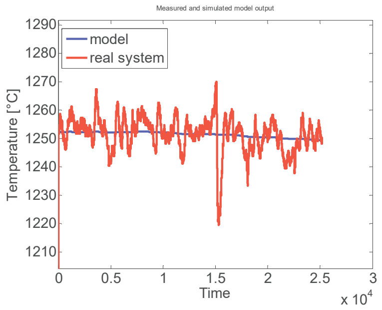

Fig. 2 Identification from the whole interval

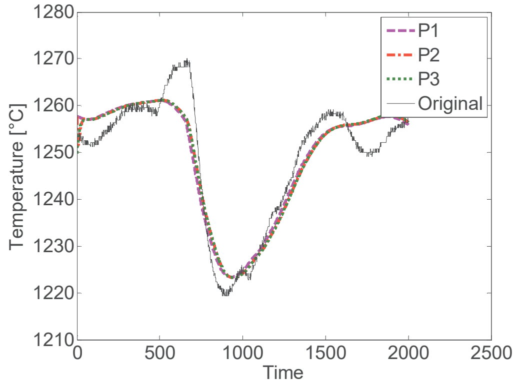

Fig. 3 Real system output and response of model

The FPE is formed as

$$FPE = \frac{1+\frac{d}{N}}{1-\frac{d}{N}} V \qquad (4)$$

where *d* is the total number of estimated parameters and *N* is the length of the data record. *V* is the loss function (quadratic fit) for the structure in question. MSE is the acronym of Mean Square Error. The time constant *Tp*1 was estimated as 1.3228e+06 +/- 5.9611e+0 s and the gain *Kp* is set to 4.1166 +/- 1836.6. 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. 3**. In the **Table 1** the results of three identifications of the first, the second and the third order systems are collected.

Table 1 Estimated parameters

Parameter/ Order	Kp	$Tp1$	$Tp2$	$Tp3$	MSE	FPE
$P1$	4.2137 $\pm$ 0.00084889	6420.6 $\pm$ 11.461	-	-	22.37	22.43
$P2$	4.2175 $\pm$ 0.0039973	6354.3 $\pm$ 52.089	0.24555 $\pm$ 0.16768	-	41.93	1096
$P3$	4.2168 $\pm$ 0.0039912	6364.8 $\pm$ 51.925	6.696 $\pm$ 8944.6	6.6979 $\pm$ 8945	1657	41.93

3.2 Neural networks

Artificial neural networks are a good tool for prediction time series and its evaluations [6]. 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, or NARX and can be written as follows:

$$y(t) = f\big(y(t-1), \dots, y(t-d), x(t-1), \dots, (t-d)\big) \qquad (5)$$

It could also be used for system identification, in which models are developed to represent dynamic systems. In the second type of time series problem, there is only one series involved. The future values of a time series *y*(*t*) are predicted only from past values of that series. This form of prediction is called nonlinear autoregressive, or NAR, and can be written as follows:

$$y(t) = f(y(t-1),...,y(t-d)) \quad (6)$$

The third time series problem is similar to the first type, in that two series are involved, an input series *x*(*t*) and an output/target series *y*(*t*). Here you want to predict values of *y*(*t*) from previous values of *x*(*t*), but without knowledge of previous values of *y*(*t*). This input/output model can be written as follows:

$$y(t) = f(x(t-1),...,x(t-d)) \quad (7)$$

From our needs the NARX model seems to be best choice.

3.2 Simulation results

We selected the ANN with 100 delays and ten hidden neurons and one output neuron. The whole interval of input values (fuel flow) and output values (temperature) was used. Data was divided into two sets: training, validation and test sets. 70% will be used for training. 15% will be used to validate that the network is generalizing and to stop training before over fitting. The last 15% will be used as a completely independent test of network generalization. Results are presented in follows figures. Correlation between Input 1 and Error 1 = Target 1 - Output (see **Fig. 4**), autocorrelation of error (see **Fig. 5**) are within confidence limits.

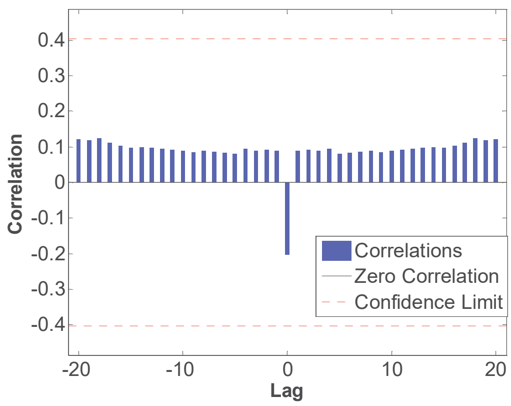

Fig. 4 Correlation between input and error

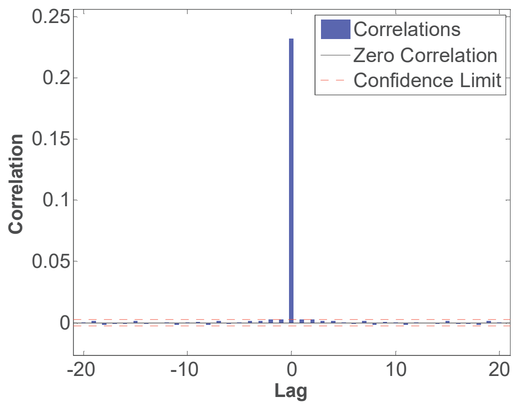

Fig. 5 Autocorrelation of error

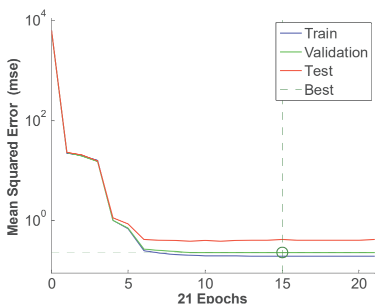

Fig. 6 Performance of the ANN

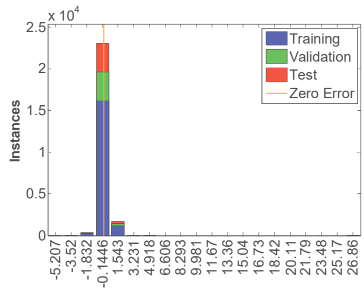

Fig. 7 The histogram of errors

In **Fig. 6** we can see, that the best performance of the ANN we obtain after 15 epochs (iterations). In **Fig. 7** the chart of histogram of errors is shown. It can be seen, that most error instances is in the range around -0.14 °C of difference between output of real system and model output. In the figure we can see correlations between training, validation, test and all data. The correlation coefficients are for all sets very closed to one, the responds of learned ANN very good correspond to the output of modelled system.

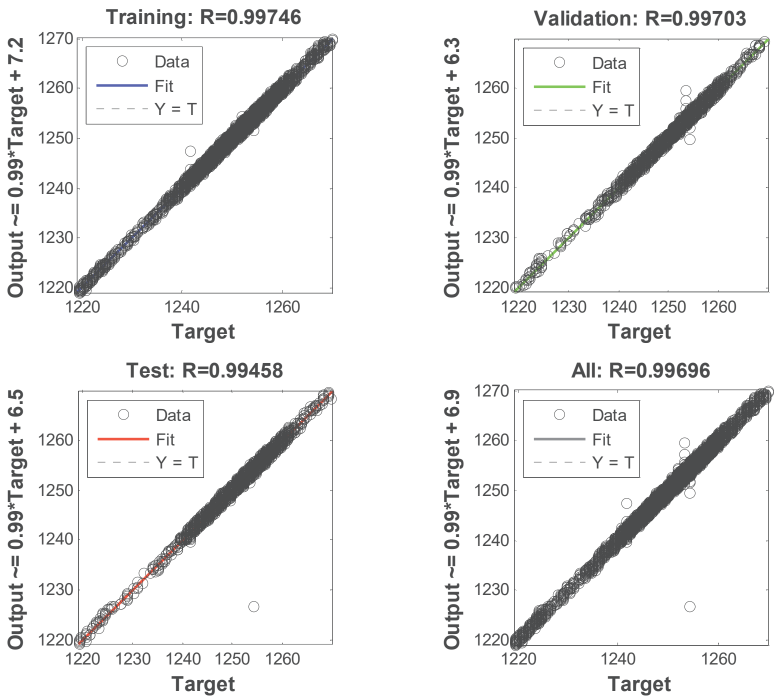

Fig. 8 The correlations between training, validation, test and all data

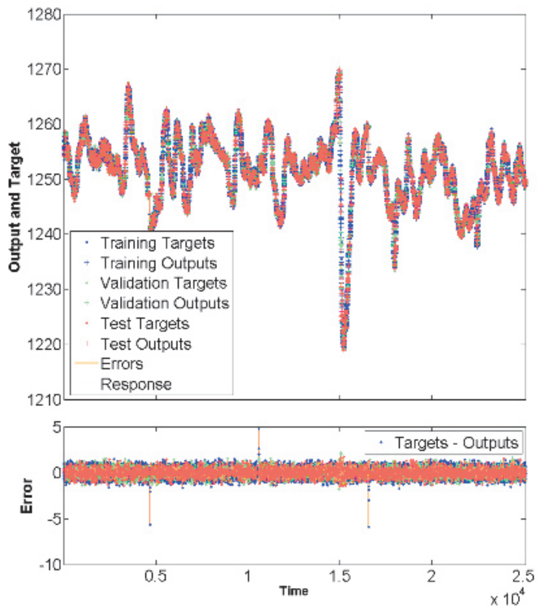

Fig. 9 The time response for all data

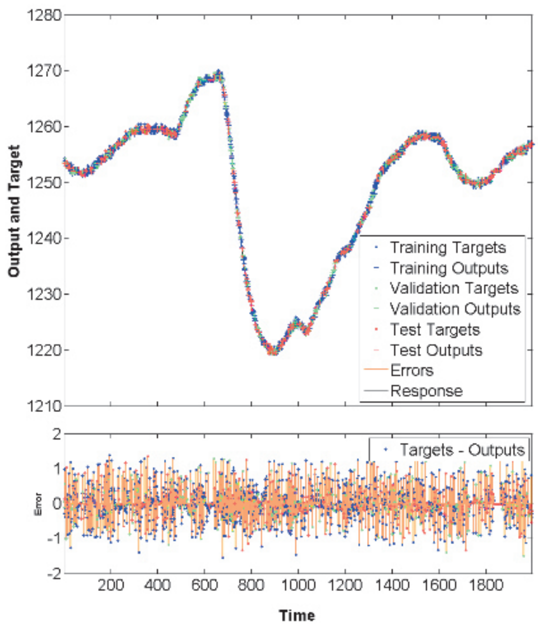

Fig. 10 The time response for selected interval

In **Fig. 9** the time response for all data and in the **Fig. 10** the time response for selected interval (the same in the case of system identification) is shown.

The MSE for all data is 0.2037 and for selected interval is 0.2463. The results are better than MSE in the case of classical system identification (22.37, 41.93 and 1657). Similar methods can be used in the wide range of applications

CONCLUSION

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 behavior of identify system [7, 8, 9]. 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 behavior for the whole interval of system inputs and outputs.

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