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# Construction of a Dynamic Neural Network Model as a Stage of Grate Cooler Automation

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**Abstract:** The analysis of clinker grate cooler "Volga-75" in terms of systems theory. Proposed to use for the construction of a mathematical model of the grate cooler the Elman neural network. In a comparative analysis of the main types of dynamic neural networks for modeling was chosen Elman network. Decomposition is performed on the grate cooler units, reflecting the characteristic processes: the movement of clinker on the grate, heat exchange between the air and clinker, the movement of air. For each of the systems were allocated control and output variables and were trained a network of statistical data obtained during the operation of the cooler. Based on the test results of each of the models and the comparative evaluation of the experimental data is shown the value of a neural model of the real object.

**Key words:** Cement · Grate cooler · The mathematical model · Neural networks · NARX network · Elman network

## INTRODUCTION

In the CIS countries, more than 80% of the cement clinker produced in rotary kilns. The share of the cost of Portland cement clinker is 70 - 80%. Therefore, studies on intensification and optimization of clinker were and remain relevant.

The central problem is the intensification and optimization of processes of clinker in cement kilns.

To ensure the effective operation of kiln plant (cement kiln + cooler) clinker cooler shall ensure supply of the cement kiln sufficient amount of secondary air at the highest possible temperature, the maximum possible cooling of the clinker, the minimum excess air consumption and minimal heat losses to the environment through the body.

Clinker cooling in the refrigerator has two main objectives: the maximum temperature reduction of clinker and maximum return (recuperation) of heat in the kiln. Therefore it is so important to consider the possibility of automation of such a complex process as the cooling clinker grate cooler. The most widespread in CIS countries has received shearing grate clinker coolers of the "Volga". They are most rational when solving problems of heat recovery and cooling clinker and more flexibility in the control [1,2].

To solve the problem of automatic control grate cooler is necessary to synthesize control methods that would allow the most rational modes of operation of the facility. The synthesis of the control methods is not possible without the adequate mathematical model of the control object. Currently, however, has not been developed a dynamic model of a closed heat transfer processes in the grate cooler that relies on interrelated processes of filtration, heat transfer and aerodynamics and adequately describes the real processes [3-5].

**Main:** Analytical description of the dynamics of processes in grate cooler, in the form of differential equations, does not allow full consideration of various communications and disturbances which have a significant impact on the whole cooling process and, consequently, the quality of the final product. The multiplicity of relations generates models of high complexity, often unsuitable for solving existing problems. The most efficient way seems the approximation of the

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grate cooler heat exchange processes dynamics by the mathematical model constructed using the statistical data obtained during the start-up of the unit and it's working in operation in the form of dynamic neural networks.

Decomposition of the control object into separate components, with loosely coupled processes can greatly simplify the process of obtaining a mathematical model. There are three main components which are characteristic for the grate cooler in terms of managing them:

- Movement of clinker on the grate,
- Heat exchange between the air and the clinker,
- Air movement in grate cooler.

We point out the control variables, occurs most significant effect on the quality of the clinker cooling and reflective process:

- Loading of the aspiration smoke pump motor нагрузка($M_{asp}$),
- Loading of the overfire air fan electric motor ($M_{ostr}$),
- Loading of the hot chamber grate electric motor ($M_{gor}$),
- Loading of the cold chamber grate electric motor ($M_{hol}$),
- Loading of the common blowing electric motor ($M_{obsh}$),
- The position of aspiration smoke pump ($H_{asp}$),
- The position of overfire air ($H_{ostr}$),
- The position of common blowing ($H_{obsh}$),
- The position second chamber common blowing ($H_{obsh2}$).

**By Controlled Variables Include:**

- Cooler performance ($Q_{klink}$),
- Clinker layer thickness($H_{kl}$),
- Pressure in the first chamber ($P_{1c}$),
- Vacuum hot furnace of cement kiln ($P_{gor}$),
- Aspiration air temperature ($T_{asp}$),
- Secondary air temperature($T_{vtor}$),
- First line fixed grate temperature ($T_{kol}$),
- Clinker temperature at the end of cooler ($T_{kl}$),
- Double stroke time of the hot grid grates ($t_{hgor}$),
- Double stroke time of the cold grid grates ($t_{hhol}$).

Then grate cooler as the control object can be represented as a black box:

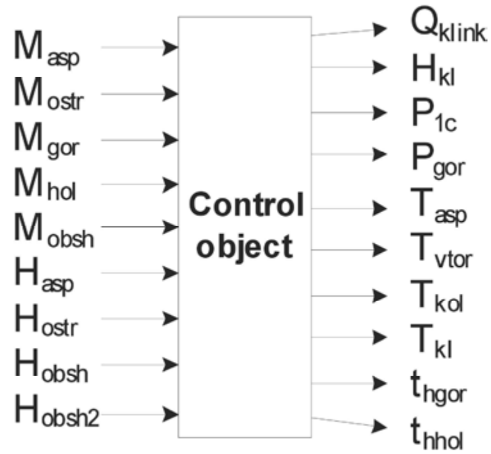



Fig. 1: Control object as a black box

Currently, for the identification of dynamic objects are most applicable dynamic recurrent neural networks [6,7]. Consider the following types of neural networks:

- Nonlinear Autoregressive Network (NARX),
- Elman network - special case of the multi-layer recurrent network (LRN).

NARX-network belongs to the class of recurrent neural networks. The presence of feedback allows NARX-networks to make decisions based not only on the input data, but also taking into account the history of the dynamic state of the object.

In general, the non-linear autoregressive model with external inputs is described by the recurrence equation:

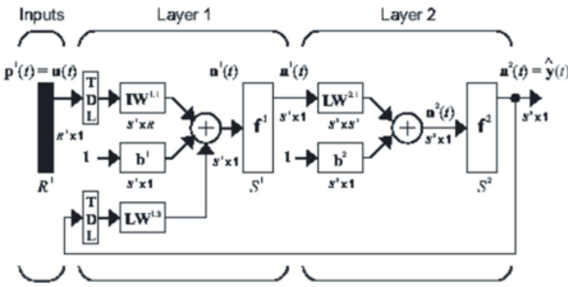
$$y[n+1] = \psi\ (x[n] \ldots x[n-n_x], y[n] \ldots y[n-n_y]),$$

where

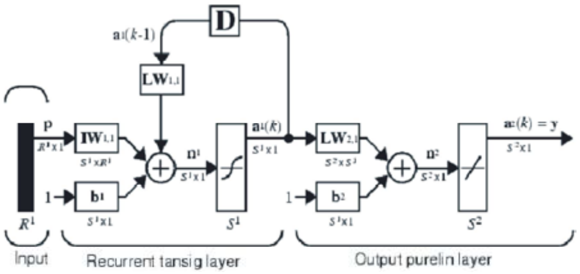
$x[n]$ - input signal; $y[n]$ - output signal; $\psi$ - some non-linear transformation; $n_x$ and $n_y$ - maximum number of delays in the input and output signals, accordingly. The architecture used in the NARX-network shown in Fig. 2.

where

IW - weight matrix of input; LW - weight matrix of neurons of the intermediate layer; p - input vector; y - output; TDL - tapped delay line. The delay lines are defined by vector $L=(l^{in}; l^{out})$, where $l^{in}$, $l^{out}$ - length of the input and output lines, accordingly.




Pic. 2: NARX-network structure




Pic. 3: Elman network structure

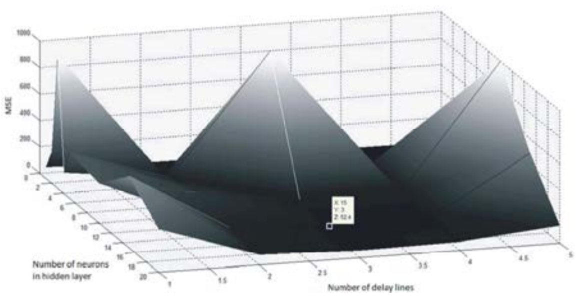



Fig. 4: Results of NARX network testing

Elman network is a type of recurrent network, which is obtained from the Multilayer Perceptron through the introduction of feedback from the output neurons of the internal.

To implement the neural networks will use Matlab Neural Network Toolbox.

Now consider each of the components of the control object obtained as a result of decomposition.

Movement of clinker on the grate. As input variables, we can specify:

- Cooler performance ($Q_{klink}$),
- Double stroke time of the hot grid grates ($t_{hgor}$),
- Double stroke time of the cold grid grates ($t_{hhol}$).

The output variable in this case would be the thickness of the layer of clinker on the grate ($H_{kl}$).

Conduct research to select the specific structure of the neural network modeling the movement of clinker in the refrigerator. We'll set NARX network and Elman to evaluate the simulation accuracy for each structure individually and quantitative impact of network parameters on the accuracy of the simulation. For the NARX network will vary the number of delay lines (1 to 5) and the number of neurons in the hidden layer (1 to 20). As a learning algorithm choose Levenberg-Marquardt algorithm (trainlm). For Elman network will only vary by neurons in the hidden layer (1 to 20). As a learning algorithm to select the Elman network gradient descent algorithm with indignation and adaptation speed parameter settings (traingdx).

NARX network smallest standard deviation (52.4) was obtained for a network with 15 neurons in the hidden layer and 3 delay lines. It should be noted that when feeding the input of the trained network in such a way, different from the learning sample data, the output signal does not meet the required performance in terms of quality stability. The resulting network was poorly applied for modeling.

Elman network smallest standard deviation (41.83) was obtained for a single-layer network with 15 neurons in the hidden layer and a single delay feedback. Increasing the number of hidden layers and the number of delays resulting in loss of sensitivity to the variation of the input pattern signal thus best results were obtained for the single-layer network unit delay feedback signal in the hidden layer. Model based on Elman network showed better stability compared with NARX network and, in general, reflect the characteristics of the object model. Therefore, as the structure of the neural network for each of the components of the model was selected Elman network with the number of neurons 15 and the unit delay feedback hidden layer.

MSE training set and trained network was 82.5. The structure of the resulting network is shown in Fig. 7.

Model of heat exchange between the air and the clinker. As input variables, we can specify:

- Cooler performance ($Q_{klink}$),
- Clinker layer thickness($H_{kl}$),
- Pressure in the first chamber ($P_{1c}$),
- Vacuum hot furnace of cement kiln ($P_{gor}$),
- First line fixed grate temperature ($T_{kol}$).

**Output Variables in this Case Would Be:**

- Clinker temperature at the end of cooler ($T_{kl}$),
- Secondary air temperature($T_{vtor}$),
- Aspiration air temperature ($T_{asp}$).

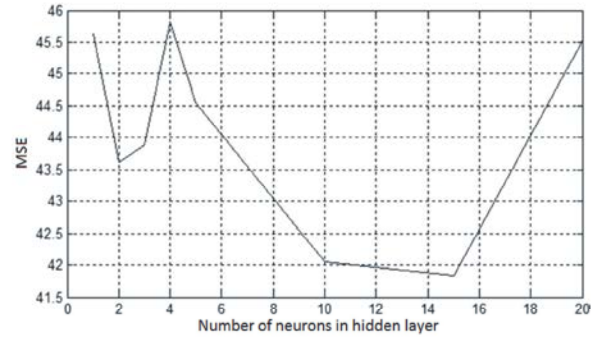



Fig. 5: Results of Elman network testing

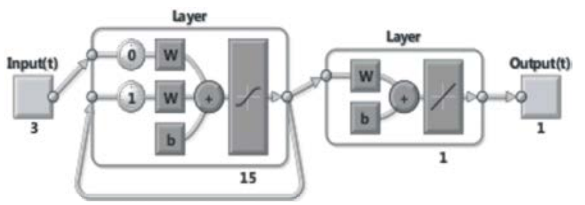



Fig. 6: The structure of the network for model the movement of clinker in the cooler

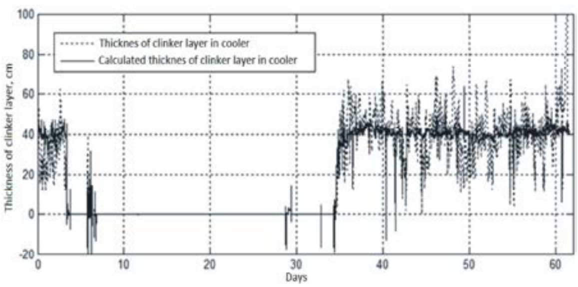



Fig. 7: Results of testing the network with the training set

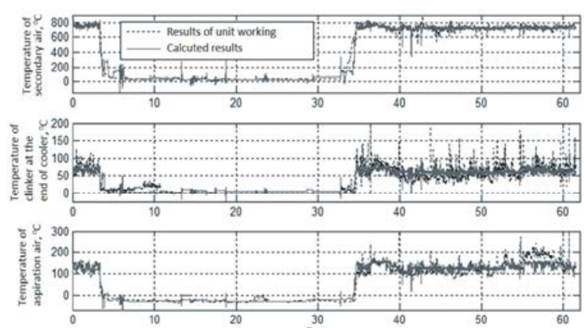



Fig. 8: Results of testing the network with the training set

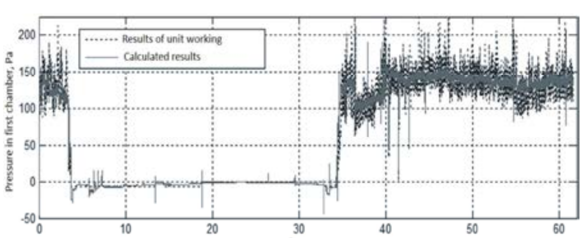



Fig. 9. Results of testing the network with the training set

As the structure of the neural network has been selected Elman network with the number of neurons 15. MSE training set and the network was trained in 1590. The structure of the resulting network is shown in Fig. 8.

Air movement in grate cooler. As input variables, we can specify:

- Loading of the aspiration smoke pump motor нагрузка($M_{asp}$),
- Loading of the overfire air fan electric motor ($M_{ostr}$),
- Loading of the common blowing electric motor ($M_{obsh}$),
- The position of aspiration smoke pump ($H_{asp}$),
- The position of overfire air ($H_{ostr}$),
- The position of common blowing ($H_{obsh}$),
- The position second chamber common blowing ($H_{obsh2}$),
- Clinker layer thickness($H_{kl}$),
- Vacuum hot furnace of cement kiln ($P_{gor}$).

**Output Variable:**

- Pressure in the first chamber ($P_{1c}$).

As the structure of the neural network has been selected Elman network with the number of neurons 15. MSE training set and the network was trained in 123. The structure of the resulting network is shown in Fig. 9.

The built-in neural networks Neural Network Toolbox package can transmit the acquired network in the program package Simulink (Fig. 10). major physical processes that affect the quality of the final product. In a comparative analysis of the main types of dynamic neural networks for modeling of the systems obtained was

## CONCLUSION

During research was analyzed clinker grate cooler in terms of systems theory and performed decomposition to the chosen Elman network. For each of the systems were allocated control and output variables and trained a network of statistical data obtained during the operation of the cooler "Volga-75" at CJSC "Oskolcement." For estimate the adequacy of the model have been tested on the training set and shown satisfactory results. The results of the studies showed that using dynamic recurrent neural networks in the process of developing a mathematical model of the control object allows significantly speed up the process and the obtained models are suitable for solving the synthesis of control methods according the concept described in [8-10].

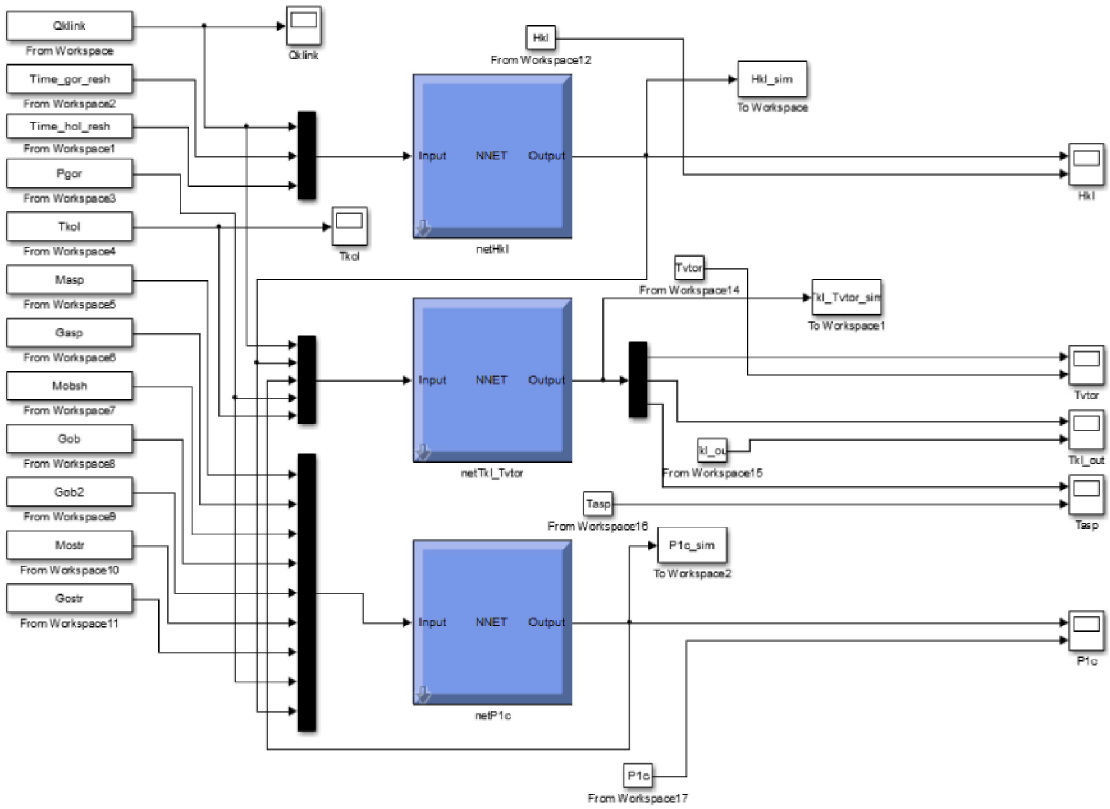



Fig. 10: Grate cooler model in Simulink

## ACKNOWLEDGMENTS

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