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Neural simulation of ball mill grinding process

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Abstract. This study is aimed at getting simplified model of mill filling technological process of fine crushing in a closed-circuit grinding with screen separation. Optimal and simple model structure are supposed to be used in adaptive predictive control loop. The minor factors that directly affect the mill load indicator are not taken into account, since some of them cannot be directly measured, and other ones affect the process only in the long term. In this paper the athors considered mill filling process identification in the center-discharge ball mill by the method of neural networks (NN). The method includes the identification of the nonlinear process using nonlinear autoregressive with external input (NARX) neural network. The most accurate model was found by varying the structural parameters of the network. The best models were tested in the course of the actual grinding process. The best estimation of the NN model to the real object is obtained with 72.1% match.

1. Introduction

Optimal control remains a complex problem in the mining industry for many years due to various uncertainties in the models of control objects, nonlinearities, changes in parameters and their interdependences [1]. Figure 1 shows the parameters that directly affect to the apatite-nepheline fine crushing process in a closed-circuit grinding with a ball mill and vibrating screens separation.

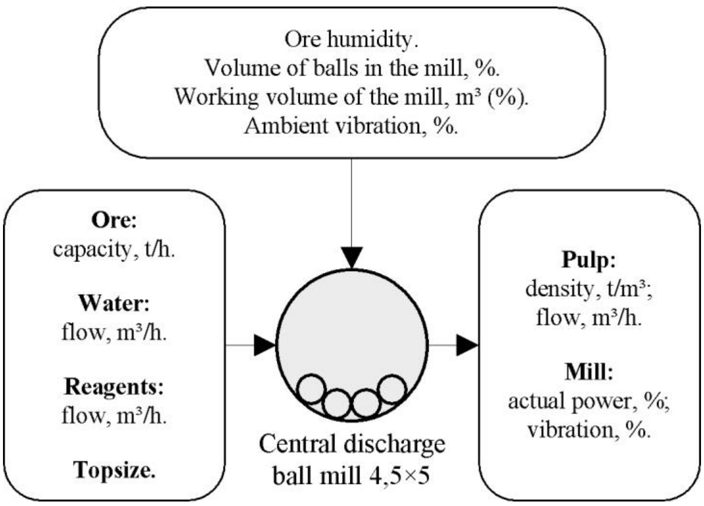

Figure 1. Simplified functional block of the mill.

The flowrates of ore and water are the main material flows entering in the closed grinding cycle. The ore is fed into the mill load by a frequency-driven belt conveyor. The water is supplied at several points of the grinding cycle in order not to clog the chutes and changing the density of the output pulp product to the flotation process. The flowrate of reagents does not affect the processes occurring in the mill. The reagents are fed in the mill to obtain the necessary properties of the output pulp product for flotation. The topsize product returning to the mill from screen separation cannot be measured either qualitatively or quantitatively. The topsize product flow is a dependent parameter on the main input material flows for a stationary process, because the constancy of the technical characteristics of vibrating screens. Other inputs are short-duration perturbations such as ore moisture, ambient vibration and long-term perturbations such as volume of balls in the mill and working volume of the mill [2, 3]. Thus, the number of input parameters indicates the complexity of the object.

The main output parameter of the control object is a load, i.e. material mill filling [4]. Practice shows that the stabilization of the load at the optimum level gives maximum quality indicators of the grinding and a possibility to avoiding the mill overload. The mill overload is achieved if the mill overflows with a material. The overload indicator is the vibration which is measured on the main bearing housing at the discharge chute. This parameter is also called as «noise». The overload adversely affects to the service life of the equipment and the implementation of the grinding plan. In addition, load stabilization is important for the energy efficiency of the entire production process due to the high energy consumption of the process [4].

Modern control systems for grinding include a load stabilization algorithm based on various control approaches [1,6,7]. Domestic algorithms are developed on a cascade PID controller, and still often operate in manual mode or to a limited extent due to the fear of overloading of the mill. PID is stable and efficient, but only around the set of nominal operating points. The permissible overshoot value, determined by the experience of operating the apatite-nepheline fine crushing process control system, is 3% for the control channel. PID approach does not allow achieving this quality of regulation in the mode of the maximum productivity of the mill. Also, advanced control algorithms are actively used and very promising. Model Predictive Control (MPC) is the most popular and successful strategy in non-stationary process control with parameter changes. A special feature of the approach is the using of the process model to calculate the predicted response of the process at future times. The optimal model is the most important part of the MPC strategy. Such a model should cover the key dynamic characteristics of the process and allow calculating predictions [8]. To apply MPC strategy for a particular industrial process, it is necessary to build a custom simulation mathematical model of the object. Thus, to simulate the process of filling the mill with the material, we choose key measuring channel characterizing mill load dynamic: flowrate of ore in the mill / «noise».

2. Description of the method of modelling

The task is to synthesize the optimal structure of the neural model of the control object, to determine the initial parameters of the neural network of the neural model at the current operating point of the control object. The method included the identification of the object with using Neural Network Toolbox 8.4 with the Time Series Tool for the synthesis of custom neural networks with delay lines for input and output signals. The presence of delay lines provides the dynamics of the model, i.e., current output $y(t+1)$ is predicted as a weighted sum of past output values and current and past input:

$$y(t+1) = f(x(t), x(t-1), ..., x(t-d_x), y(t), y(t-1), ..., y(t-d_y)). \quad (1)$$

Equation (1) is called the "regression" equation and d_x, d_y are the numbers of input and output delays required by the autoregressive model.

One important aspect of identification of nonlinear systems is choosing the right time delays for each of the input variables and choosing the number of regressors, i.e., the number of previous samples of each variable that will be considered in the system model at a given moment [9]. The choice of fixed and variable factors is based on the analysis of literary sources [10, 11]. Therefore, the following key factors have changed to build a autoregressive neural network model of the of the

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control object: d_x, d_y and the number of neurons in the hidden layer. All tested NNs models had the following fixed factors:

- type: recurrent neural network (RNN);
- layers: one input layer, one hidden layer, one output layer;
- transfer function of neurons in hidden layer: tansig;
- transfer function of neurons in output layer: purelin;
- number of neurons in output layer: 1.

The values of the limits and intervals of variation of variable factors:

- number of neurons in hidden layer ranging from 7 to 12 with an interval of 1;
- the number of feedbacks of the input of the neural network (d_x) ranging from 1 to 7 with an interval of 1;
- the number of feedbacks of the output of the neural network (d_y) ranging from 1 to 3 with an interval of 1.

The differences of the RNN model output and control object output are calculated using fit and mean squared error (MSE). Estimations are given by the following equations:

$$fit = \left(1 - \sum_{k}^{n} \frac{(y_k - \hat{y}_k)}{(y_k - \bar{y})}\right) \cdot 100\%, \tag{2}$$

$$MSE = \frac{\sum_{k}^{n} (y_k - \hat{y}_k)^2}{n}. \tag{3}$$

where n – number of training samples, k – model sample time, y_k – real plant output at sample time k, $\hat{y}_k$ – model RNN output at sample time k, $\bar{y}$ – mean real plant output.

All NNs were trained using Levenberg-Marquardtt backpropagation algorithm (trainlm) in 2000 epoch with testing and validation. The data are measured from apatite-nepheline grinding process for training networks. The measurements were provided every second for about 10 hours of mill operation. There were 33555 training input/output samples with 1 second sample time. The input data is the flowrate of ore (t/h) and the output data is the «noise» (%). Trained NNs were checked on training data, on test data and on online data during the grinding process. For online test the laptop is connected to the local computer network of the grinding section automation system. Modbus OPC server is used to establish a connection to the Simulink model and PLC-system. Access to the data "inside" the SCADA-server is carried out according to the standard Modbus rules. We focused on finding the best fitting neural network and in the end compared the best fitting neural network with others Matlab System Identification Toolbox techniques for nonlinear identification: tree partition method, wavelet method, Hammerstein-Wiener model.

3. Results and discussion

It is established that the increase in the number of delays of the output signal by 1 decrease the fit on training data by 2-3 times. That's why further networks were built with one delay of the output signal. In general, 42 neural networks were synthesized varying dx from 1 to 7 and number of neurons from 7 to 12. The learning time increased with the increase in the number of neurons of the hidden layer and dx. Training of some networks stopped on exceeding validation checks. Most of the networks were trained during all 2000 epochs. Performances of all training procedures were less than 0.0001. The graphs and results of the online simulation of some models obtained and the output of the real object are presented in figure 2 and in table 1.

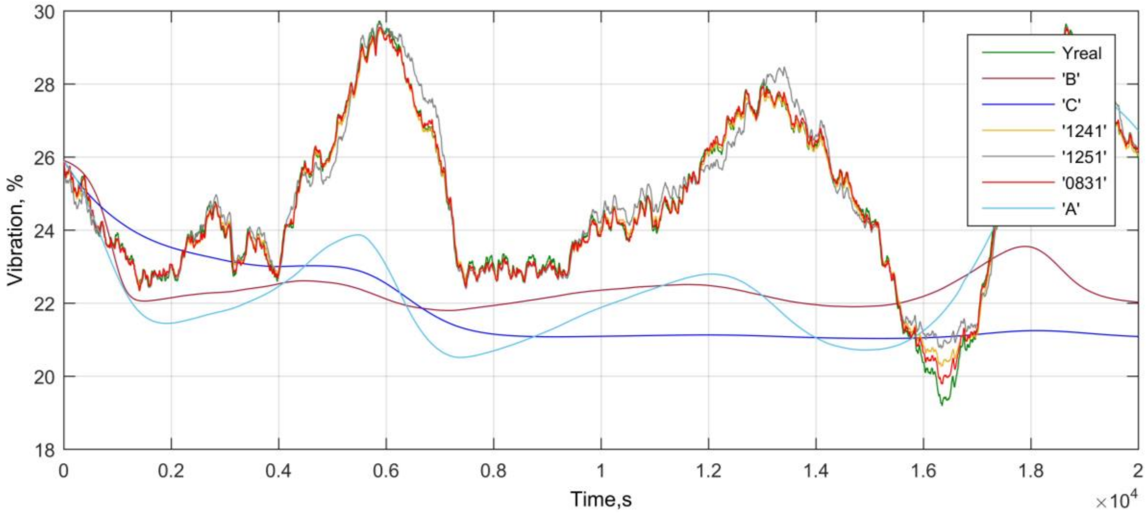

Figure 2. Results of models simulation

Table 1. Results of the simulation.

Model	Training data		Test data		Real data	
	fit, %	MSE	fit, %	MSE	fit, %	MSE
'0831'[a]	92.889	0.0104	65.863	0.2546	72.132	0.2501
'1241'	93.118	0.0098	65.217	0.2643	68.482	0.3200
'1221'	93.770	0.0080	63.107	0.2973	66.428	0.3630
'1271'	94.313	0.0067	61.666	0.3210	64.797	0.3991
'1261'	93.189	0.0096	64.025	0.2827	64.050	0.4163
'1131'	93.244	0.0094	63.856	0.2854	64.027	0.4168
'0941'	95.097	0.0050	64.773	0.2711	63.916	0.4194
'0751'	84.292	0.0508	61.409	0.3253	62.931	0.4426
'0851'	84.292	0.0508	61.407	0.3254	62.643	0.4495
'1251'	84.282	0.0509	61.405	0.3254	62.640	0.4496
'A'	95.473	0.0050	52.848	0.4857	45.429	0.9592
'B'	97.733	0.0039	70.251	0.1933	8.55	2.0971
'C'	97.544	0.0043	67.616	0.2291	5.73	3.2791

[a] Models name decoding: 0831 – 08 - number of neurons in hidden layer; 3 - dx; 1 - dy.

The results in the table 1 are sorted in descending order of fit on the real process data. Three models of other NARX techniques are shown in the end of table 2: 'A' - Hammerstein-Wiener model with 1 output and 1 input (linear transfer function nb = 2, nf = 3, nk = 1, input nonlinearity: pwlinear with 10 units, output nonlinearity: pwlinear with 10 units); 'B' - nonlinearity: wavenet with 25 units, standard regressors: na = 1, nb = 5, nk = 1; 'C' - tree partition method.

An increase in the number of neurons in the hidden layer in the general trend showed an increase in modelling accuracy. The number of input feedbacks of the neural network greater than 3 had an advantage over the others. Comparing with other methods of nonlinear identification, the result of repeating the object on the training sample (33555 samples) and on the test sample (30000 samples) in nonlinear models was higher than the neural models. But on a real process data, these models showed poor results relative to NNs. As in [12], neural networks showed the best results.

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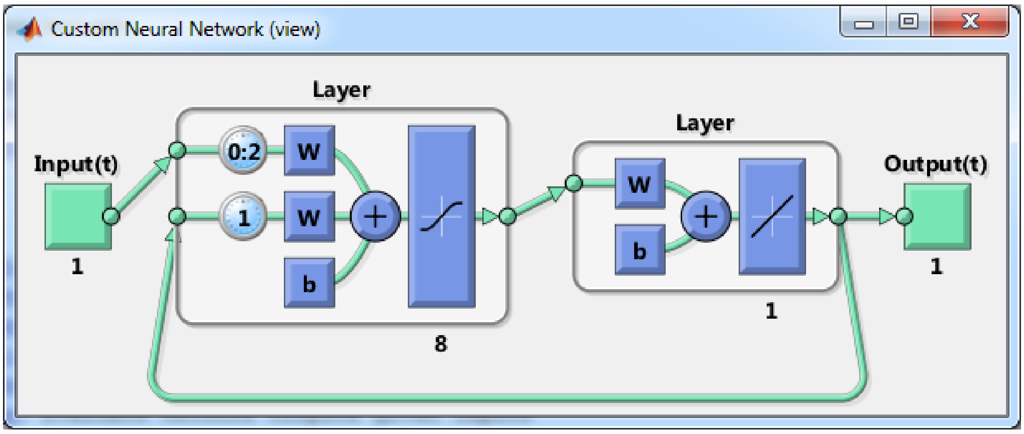

Figure 3. “0831” structure view in Matlab

The following neural network weights for layer 1 (hidden) were obtained for the best fit neural network "0831" architecture (figure 3):

$$w=\begin{bmatrix} w_{1x0} & w_{1x1} & w_{1x2} & w_{1y} & b_1 \\ w_{2x0} & w_{2x1} & w_{2x2} & w_{2y} & b_2 \\ w_{3x0} & w_{3x1} & w_{3x2} & w_{3y} & b_3 \\ w_{4x0} & w_{4x1} & w_{4x2} & w_{4y} & b_4 \\ w_{5x0} & w_{5x1} & w_{5x2} & w_{5y} & b_5 \\ w_{6x0} & w_{6x1} & w_{6x2} & w_{6y} & b_6 \\ w_{7x0} & w_{7x1} & w_{7x2} & w_{7y} & b_7 \\ w_{8x0} & w_{8x1} & w_{8x2} & w_{8y} & b_8 \end{bmatrix} = \begin{bmatrix} 0.2189 & 0.1181 & 0.1113 & 2.9277 & 22.5779 \\ -0.0122 & -0.0297 & 0.0460 & 0.4335 & 26.6599 \\ -0.2558 & 0.4663 & -0.2103 & -4.5690 & -0.9303 \\ 0.0916 & 0.0995 & 0.1035 & 3.6185 & -32.4337 \\ -0.1458 & -0.0604 & -0.0386 & -2.2258 & 32.4675 \\ 0.0398 & 0.0932 & 0.1566 & 1.9836 & -23.2386 \\ -0.1249 & -0.1389 & -0.0293 & -2.2115 & 20.6883 \\ 0.0035 & -0.0198 & 0.0163 & -62.7261 & 0.3475 \end{bmatrix} \tag{4}$$

for layer 2 (output):

$$\begin{gathered} w=\begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & w_{15} & w_{16} & w_{17} & w_{18} & b_1 \end{bmatrix} = \\ =\begin{bmatrix} -0.5739 & 0.2819 & -0.0882 & -0.5142 & 0,2982 & -0.7147 & -0.4983 & -0.0158 & 4.0286 \end{bmatrix}. \end{gathered} \tag{5}$$

The obtained neural network model is characteristic of this control object only for the considered steady-state control mode, since disturbances affecting the process are not taken into account in the model. The disturbances need to be taken into account in order to manage quality, so the initial model must be constantly refined. Refining the parameters of the object model in the process of obtaining new data from the worker consists in the repeated parametric identification of the neural network model of the object. Thus, in order to predict the behaviour of an object, it is sufficient to perform online training of a neural network with initial parameters. Re-training should be carried out to achieve the critical deviation of the output predicted by the model from the real output of the object. To do this, it is sufficient to supplement the online algorithm with a recursive parameter estimate to detect deviations of the system operation parameters for a given operating point.

4. Conclusions

Experiments were carried out to search for the optimal model of a ball mill as a control object over the channel “flowrate of ore - noise” using NARX neural networks. We succeeded 72.1% fit of the real control object behaviour with the neural network "0831" architecture. The model can be used to synthesize MPC or advanced nonlinear regulators, including the best fit NN model in the predictive control loop. Also modern methods of neural network modelling are applied in this study and the intuitive algorithm for constructing a process model based on a recurrent neural network is obtained. Undoubtedly, the model obtained by such a method is more complicated from the point of view of

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solving the MPC problem in comparison with the state-space model. The solution of the MPC problem with the neural model can be obtained by numerical methods with an approximation to the desired simulation accuracy. In addition, it will take more computing resources. However, the flexibility of the neural network approach as a universal approximation function allows us, in spite of the shortcomings, to achieve greater modelling accuracy.

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