

Identification of control systems for ore-processing industry aggregates based on nonparametric kernel estimators



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Abstract

The study results of nonparametric kernel estimator methods for solving the control systems identification problems of concentrating production technological aggregates in conditions of characteristics instability of the raw material, which is fed to processing, are presented.

Key words: AUTOMATION, NONPARAMETRIC IDENTIFICATION, ORE-DRESSING.

Introduction

To improve the efficiency of the mining enterprises functioning under the market conditions, it's necessary to reduce the cost price and power consumption of technological processes of extraction and processing of raw materials. In the structure of mining enterprises energy consumption the share of the ore processing plant is about 20%, as well on the electricity consumption the concentrating transformation is the most power-consuming - it accounts for about 44% of the amount consumed on the enterprise.

In modern conditions on mining enterprises the several technological ore types are processed. Thus the mining operations conducting system does not allow to produce the same type of ore quite a long time, which causes instability of mineral raw materials coming on beneficiation. One way to reduce the negative impact of the iron ore raw materials characteristics variability on the technological equipment energy consumption is to increase the identification accuracy of the concentrating production control objects, which will improve the quality of the process control.

For today to solve the mining and processing industry technological processes identification problem the parametric functions are the most widely used [1-7]. Their characteristic feature is a strictly defined boundaries of forms varying, which may not always be adequately represented by one or another experimental dependence [8]. Therefore, it is advisable to switch from parametric functions to the non-parametric representation based on the weight functions.

The approach to the representation of the weights sequence is to describe the shape of a real symmetric weight function $W_{mi}(x)$ – kernel – by means of density function with a scalar parameter that controls the size and shape of the weights near x [9]. In the case of one-dimensional x the weights sequence for the kernel estimates is determined as follows

$$W_{mi}(x) = K_{h_m}(x - X_i) / \hat{f}_{h_m}(x), \tag{1}$$

where $\hat{f}_{h_m}(x) = 1/m \sum_{i=1}^m K_{h_m}(x - X_i)$ – is the Rosenblatt-Parzen kernel density estimator; $K_{h_m}(u) = 1/h_m K(u/h_m)$ – is the kernel with the width of h_m . The weights normalization of $\hat{f}_{h_m}(x)$ warrants that their sum is equal to one. Note that a kernel function and a smoothing window width should be chosen to satisfy the conditions of regularity [10].

There are enough large variety of kernel functions, the most common of which are the following [9, 10]: the quadratic kernel function, the Epanechnikov's kernel, the Gaussian kernel, the triangular kernel, the rectangular kernel.

Objective of the work is the study of identification methods for the iron ore raw materials beneficiation technological processes based on the nonparametric kernel estimators methods and choosing their optimal parameters in order to create automated control in the conditions of the iron ore characteristics instability.

Materials and methods

To evaluate the effectiveness of the kernel functions is advisable to use the integrated mean squared error (IMSE), which is a global measure of error and has the form [11]

$$IMSE[\hat{f}(x)] = \frac{\Phi_0}{nh} + \frac{h^4}{4} \kappa_2 \Phi_1, \tag{2}$$

where $\Phi_0 = \int K^2(z) dz$; $\Phi_1 = \int (f''(x))^2 dx$. After performing minimization IMSE by h , we get the width of the window, which globally balances bias and variance

$$h^* = \Phi_0^{1/5} \kappa_2^{-2/5} \Phi_1^{-1/5} n^{-1/5}. \tag{3}$$

The studies have shown that the optimum in terms of ensuring minimum mean square error is the Epanechnikov kernel [11, 12].

A significant impact on the identification quality renders the width of the window [8, 9, 12, 13]. Too small values of $h \rightarrow 0$ lead to a small number of observations, which catches the window. At the same time the smoothing function tends to pass through the every sample point, undergoing sharp jumps, because in this case estimation is based only on a small number of observations from the narrow neighborhood of the point x , thereby decreasing the robustness. A large windows sizes $h \rightarrow \infty$ leads to excessive smoothing. Let's consider the research results of the basic nonparametric kernel estimators efficiency. There are Nadaraya-Watson, the Gasser-Müller, Priestley-Chao. The Nadaraya-Watson estimation of the expected value of the recoverable dependence $E(y|x)$ on the basis of the kernel weights $W_{mi}(x)$ is defined by the following formula [9]

$$\hat{m}_{NW}(x) = \frac{1}{m} \sum_{i=1}^m K_{h_m}(x - X_i) Y_i / \frac{1}{m} \sum_{i=1}^m K_{h_m}(x - X_i). \tag{4}$$

The Gasser-Muller estimation has the form

$$\hat{m}_{GM}(x) = \frac{1}{h} \sum_{i=1}^m \left[\int_{s_{i-1}}^{s_i} K_{h_m}(x - u) du \right] Y_i, \tag{5}$$

Automatization

Where $s_i = 1/2(X_i + X_{i+1}), s_0 = 0, s_m = 1$. The Priestley-Chao estimation is given by

$$\hat{m}_{PC}(x) = \frac{1}{h} \sum_{i=1}^m (X_i - X_{i-1}) K_{h_m}(X_i - x) Y_i \quad (6)$$

The most common indicators of selection optimality estimation for smoothing bandwidth are as follows [14]: the mean square error (MSE), the integral square error (ISE), the mean integrated squared error (MISE), the expected value of the integral square error (ISE), the average square error (ASE).

For the Nadaraya-Watson estimation the criteria ASE, ISE and MISE asymptotically provide the same level of anti-aliasing, that allows to use the most simple of them - the average standard error (ASE) [15]

$$ASE(h) = ASE\{\hat{m}_h\} = \frac{1}{m} \sum_{i=1}^m \{\hat{m}_h(X_i) - m(X_i)\}^2 w(X_i) \quad (7)$$

where $w(\cdot)$ - is the weighting function used for points weight loss in the areas of the sparse data (at measurements interruption) as well as on the edges of the sample - to eliminate the errors due to edge effects. After substitution of the evaluation function $m(\cdot)$ on the results of observations Y , we obtain a function that can be calculated from the experimental data [14]

$$p(h) = \frac{1}{m} \sum_{i=1}^m \{Y_i - \hat{m}_h(X_i)\}^2 w(X_i). \quad (8)$$

The drawback of this approach is that Y_i is used in $\hat{m}_h(X_i)$ to predict itself.

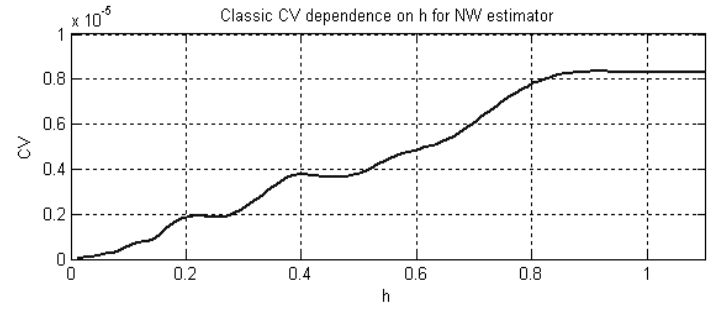
As a result the $p(h)$ can be made arbitrarily small by setting $h \rightarrow 0$. In this case $m(\cdot)$ becomes the interpolation of Y_i . To eliminate this drawback the $\Xi(u)$ function in the $p(h)$ is introduced, which fines by too small values of h with the result that $p(h)$ takes the form

$$G(h) = \frac{1}{m} \sum_{i=1}^m \{Y_i - \hat{m}_h(X_i)\}^2 w(X_i) \Xi\left(\frac{1}{m} W_{hi}(X_i)\right) \quad (9)$$

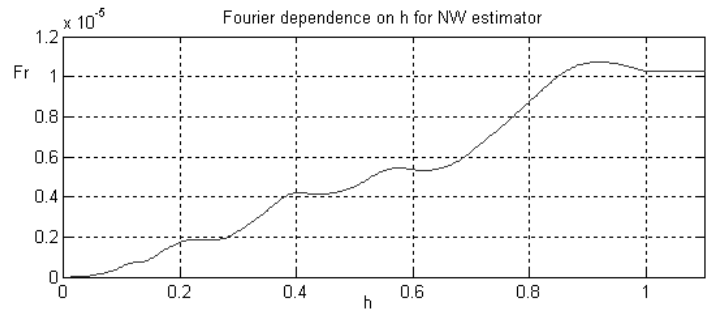
where Ξ - is the corrective function.

The following corrective functions were investigated: Shibata's model selector, generalized cross-validation, Akaike's information criterion, Finite Prediction Error, Rice criterion, Koláček bandwidth selector, Fourier, Mallows.

The examples of the corrective function dependencies on the window width, obtained by using the software package Kernel Smoothing Toolbox [16] is shown in Fig. 1.



a)



b)

Figure 1. The dependence of the correction function on the smoothing window width: a) cross-validation function; b) Fourier function

The best results were obtained using a Watson-Nadaraia estimation using the Epanechnikov core for window width $h = 0,11$ (Fig. 2).

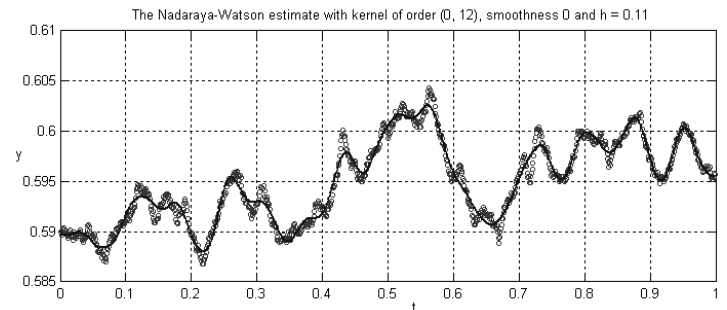


Figure 2. The results of identification using Nadaraya-Watson estimation

Conclusions

The research results analysis of the identification methods for control systems units of the concentrating production on the basis of nonparametric kernel estimates showed that the most advisable is to use the Nadaraya-Watson estimates in conjunction with the cross-validation penalty function based on the Epanechnikov kernel. Further studies are advisable to carry out in the area of the convergence accuracy and speed improvement for the considered identification methods.

References

1. Morkun V. S., Potapov V.N., Morkun N.V., Podgorodetsky N.S. *Ultrazvukovoy kontrol kharakteristik izmelchennykh materialov v ASU TP obogatitel'nogo proizvodstva* [Ultrasonic testing of crushed materials characteristics in ACS of processing industry]. Kryvyi Rih: KTU, 2007.
2. Morkun V. S. Ultrasonic control for technological characteristics of the crushed materials and adaptive regulation of the grinding and classification processes on its basis ScD diss., Krivoy Rog, 1999.
3. Tron V. Power efficient automatized control of ore-dressing process using thermographic recognition of ore's types. PhD diss., Krivoy Rog, 2003
4. Morkun V., Tron V. (2014). Ore preparation multi-criteria energy-efficient automated control with considering the ecological and economic factors, *Metallurgical and Mining Industry*, No5, p.p. 4-7: <http://www.metaljournal.com.ua/assets/Journal/1-MorkunTron.pdf>
5. Morkun V., Morkun N., Pikilnyak A. (2015). The study of volume ultrasonic waves propagation in the gas-containing iron ore pulp, *Ultrasonics*, No 56C, p.p.340-343.
6. Morkun V., Tron V. (2014). Automation of iron ore raw materials beneficiation with the operational recognition of its varieties in process streams, *Metallurgical and Mining Industry*, No6, p.p. 4-7: http://www.metaljournal.com.ua/assets/MMI_2014_6/1-MorkunTron.pdf
7. Morkun V., Morkun N., Pikilnyak A. (2014). Simulation of high-energy ultrasound propagation in heterogeneous medium using k-space method, *Metallurgical and Mining Industry*, No3, p.p. 23-27: <http://www.metaljournal.com.ua/assets/Archive/en/MMI3/4.pdf>
8. Timofeev V.S (2010). *Yadernyye otsenki funktsii plotnosti pri identifikatsii uravneniy regressii* [Kernel estimators of the density function for the identification of regression equations]. Nauchnyy vestnik NGTU, No3(40), p.p. 41-51.
9. Härdle W. K. Applied Nonparametric Regression. Moscow, *MIR*, 1993.
10. Pagan A., Ullah A. Nonparametric econometrics. N. Y., *Cambridge University Press*, 1999.
11. Racine J. S. (2008). Nonparametric Econometrics, A Primer, *Quantile*, No4, p.p. 7-56.
12. Lagutin M. B. *Naglyadnaya matematicheskaya statistika* [Visual Mathematical Statistics]. Moscow: BINOM. Laboratoriya znaniy, 2009.
13. Wand M. P., Jones M. C. Kernel smoothing. London, Chapman & Hall, 1995.
14. Härdle W. K. Müller M., Sperlich S., Werwatz A. Nonparametric and Semiparametric Models, Berlin, Springer, 2004.
15. Marron J. S., Härdle W. (1986). Random approximations to some measures of accuracy in nonparametric curve estimation. *J. Multivariate Anal.*, No20, p. 91-113.
16. Horová I., Koláček J., Zelinka J. Kernel Smoothing in MATLAB: Theory and Practice of Kernel Smoothing, Singapore, World Scientific Publishing, 2012.