Simulation of non-linear dynamic objects of mineral processing production

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Abstract
The approach to space-time modeling of mineral processing non-linear dynamic objects, which presented in the form of an unknown nonlinear system with distributed parameters, based on nuclear conversion of Volterra is proposed.
Key words: MINERAL PROCESSING, DECISION-MAKING, OPERATIONAL MANAGEMENT, MODELING OF DYNAMIC OBJECTS, VOLTERRA MODEL

Modern mineral processing factory is a set of complex, multiply, spatially distributed hierarchical objects, which operates in terms of their structure, parameters and operation modes variability with numerous external and internal perturbations both of systematic and random nature. This determines the complexity of the task of operational control in different modes of operation.

In industrial conditions the phenomenological approach, based on the analysis of data from both active and passive experiments is often applied [1-5]. This allows to determine the dependencies between the quality characteristics of the modeled process and conditions in which it takes place. This heuristic approach based on fundamental laws of simulated phenomena allows to define a justified model form too. The final results of the processing plant operation depend on the complex of interrelated processes. This fact requires the application of appropriate approach to modeling of technological processes, which takes into account their combinations and which guarantees optimization of the entire structure.

The technological units as control objects of mineral processing production can be represented as some operators that convert the vectors of input variables in the output parameter vectors [2-5].

Thus, for example, the output parameters of the complete grinding process should be considered as input for subsequent stages of the technological process of mineral processing. The elements of output parameters vectors of shredding aggregates are their qualitative and quantitative indicators. The main quantitative indicators are load and fit class size performances. The quality of the ground product is characterized by a density or solids content in the pulp, the solid phase particle-size composition as well as indicators of the original ore quality (content of useful components, mineral composition, etc.) beyond the grinding circuit technological regime operation. Thus, the elements of the output parameters vector generated by the crushing division (load performance and its particle size distribution), can be taken as control actions in solving problems of beneficiation optimization [3,4, 6-11].

A promising direction in the simulation of beneficiation technological processes is the use of fuzzy logic methods, neural network technology, genetic algorithms and hybrid structures based on these approaches.

The difficulties of dynamic objects modeling of mineral processing production especially clearly manifested in the project management tasks, which is associated with limited or no data at the time of data designing for its space-time description, the need to consider multi-parameter nonlinear relationships "input-output", the presence of the elements with different dynamic characteristics in the structure of the modeling object, etc.

The approach of space-time modeling of unknown nonlinear systems with distributed parameters based on Volterra nuclear conversion is proposed. The spatio-temporal Volterra model can be constructed by adding variables space in the Volterra traditional model. Thus, this type of spatial-temporal Volterra model must be able to simulate a wide range of non-linear systems with distributed parameters with a stable dynamics and memory characteristic fading. Since there is no feedback, the Volterra model is guaranteed to be stable. The spatio-temporal Volterra approach to modeling is as follows. First, an unknown nonlinear system with distributed parameters should be approximately expressed by spatio-temporal Volterra model with a set of spatio-temporal kernels. In order to assess the spatio-temporal kernels in the input-output, each kernel has to be decomposed into spatial and temporal basis functions with unknown coefficients. To reduce the parametric complexity, the method of Karhunen-Loeve (KL) is used [12]. Secondly, the spatio-temporal modeling problems become problems of temporary modeling by Galerkin method. Thirdly, the unknown parameters can be easily evaluated in time domain using the least squares method. After the spatial and temporal kernels synthesis the spatio-temporal Volterra model can be built. The convergence of models guaranteed under certain conditions. Modeling and experiments confirm the efficiency of the proposed method.

It is well known that the linear system with distributed parameters can be represented as a linear mapping of input $u(\mathrm{x},t)$ on the output $y(\mathrm{x},t)$ where $x \in \Omega$ denotes the spatial variable. This mapping can be converted to a Fredholm integral equation of the first kind, which integrates the kernel (i.e. the impulse response function or Green's function) [13].

$$y(x,t)=\int_{\Omega}\int_{0}^{t} g\left(x,\zeta,t,\tau\right)u\left(\zeta,\tau\right)d\tau d\zeta. \quad (1)$$

On the other hand, systems with lumped parameters $y(t)=N\ (\{u\ (\tau)\})+d\ (t)$, where $\{u(\tau)\}=\{u(\tau)\,|\,\tau=1,...,t\}$ - is the input, t - is the discretized time, y and d - are the output and stochastic perturbations respectively, N - is the operator with the memory function fading can be approximated by using a discrete Volterra model [14].

$$y(t)=\sum_{r=1}^{\infty}\sum_{\tau_{1=0}}^{t}\cdots\sum_{\tau_{\gamma=0}}^{t} g_r(t,\tau_1,\ldots,\tau_r)\prod_{v=1}^{r}(\tau_v) \quad (2)$$

Let's transform (1) and (2), for systems with distributed parameters

$$y(x,t)=N(\{u(\zeta,t)\})+d\ (x,t), \quad (3)$$

where $\{u(\zeta,t)\}=\{u(\zeta,t)\,|\,\zeta\in\Omega,\tau=1,...,t\ \}$ - is the entrance, spatio-temporal Volterra model is constructed by adding variables space in the traditional Volterra model

$$y(x,t)=\sum_{r=1}^{\infty}\int_{\Omega}\cdots\int_{\Omega}\sum_{\tau_{1=0}}^{t}\cdots\sum_{\tau_{r=0}}^{t} g_r\ \zeta_1\ \zeta_r\ \tau_1$$

$$\tau_r)\prod_{v=1}^{r}u(\zeta_{v,}\tau_v)d\,\zeta_{v,}\,(\mathrm{x},,\ldots,,\mathrm{t},,\ldots \quad (4)$$

where $g_r\ r^{th}$ - is a function-order of space-time Volterra kernel, which indicates a change in space $\zeta_1\ \zeta_r$ and time $\tau_1\ \tau_r$. As in (1), the spatial and temporal variables in (4) are symmetrical. Obviously, that the Green's function of the first kind of spatio-temporal Volterra model, and kernel of spatio-temporal Volterra model can be seen as a multidimensional generalization of the Green's function.

The model (4) can work both for changing in time and fixed systems. For the invariant at this point system, the kernel is invariant and can be represented as follows:

$$g_r(\mathrm{x},\zeta_1,...,\zeta_r,\mathrm{t},\tau_1,...,\tau_r) = g_r(\mathrm{x},\zeta_1,...,\zeta_r,\mathrm{t}-\tau_1,...,\mathrm{t}-\tau_r)$$
(5)

Similar models (4) can also work in the changing or spatially-invariant systems. When the model is homogeneous in the spatial domain, there is a

$$g_r(\mathrm{x},\zeta_1,...,\zeta_r,\mathrm{t},\tau_1,...,\tau_r) = g_r(x-\zeta_1,...,x-\zeta_r,\mathrm{t},\tau_1,...,\tau_r)$$
(6)

Substituting (5) into (4) we get the following expression

$$y(x,t) = \sum_{r=1}^{\infty}\int_{\Omega}\cdots\int_{\Omega}\sum_{\tau_1=0}^{t}\cdots\sum_{\tau_r=0}^{t} g_r(\mathrm{x},\zeta_1,...,\zeta_r,\mathrm{t},\tau_1,...,\tau_r)\prod_{v=1}^{r}u(\zeta_v,t-\tau_v)d\zeta_v. \quad (7)$$

Model (7) is not applied because of its infinite order. In practice, members of the higher order can be ignored, and only the first kernel (R) must be taken into account, as it is shown below

$$y(x,t) = \sum_{r=1}^{R}\int_{\Omega}\cdots\int_{\Omega}\sum_{\tau_1=0}^{t}\cdots\sum_{\tau_r=0}^{t} g_r(\mathrm{x},\zeta_1,...,\zeta_r,\mathrm{t},\tau_1,...,\tau_r)\prod_{v=1}^{r}u(\zeta_v,t-\tau_v)d\zeta_v + \upsilon(x,t) \quad (8)$$

where $\upsilon(x,t)$- is the last term with unmodelled dynamics and external noise. The accuracy of modelling and model complexity can be controlled using the order *R*.

Simple spatio-temporal discretization for kernels $q_r(\mathrm{x}\,\zeta_1,...,\zeta_r,\mathrm{t},\tau_1,...,\tau_r),\ (r=1,..,R)$ will lead to a large number of estimated parameters. Therefore, in order to improve the state and numerical dispersion reduction of estimated parameters, it is important to reduce the complexity of the product. This can be accomplished by using spatio-temporal method, that is, by the kernel extension under conditions of relatively small number of orthonormal basis functions, such as spatial databases of Karhunen-Loeve and Laguerre temporary bases. After a spatial and temporal separation, the original space-time problems are transformed into the problem of the traditional temporal modeling. Thus, you can easily evaluate unknown parameters in a temporary area. And then using the spatio-temporal synthesis the spatio-temporal Volterra model can be restored. The spatio-temporal separation and synthesis are very important for identification of this approach and are key differences from traditional Volterra model.

Conclusions

The proposed simulation algorithm ensures convergence and satisfactory evaluation. Modeling and experimental studies have demonstrated the effectiveness of the proposed modeling method and it substantiated the possibility of their use for a wide range of non-linear dynamic objects and mineral processing production. The results of the research show that the modeling approach of control formation for complex organizational and technical systems based on projection methods can significantly improve the quality of decision making under fuzzy and incomplete information

References

1. Tikhonov O.N. Zakonomernosti effektivnogo razdeleniya mineralov v protsessakh obogashcheniya poleznykh iskopayemykh [Laws of effective separation of minerals in mineral processing], Moscow: Nedra, 1984.
1. Linch. A. J. Tsikly drobleniya i izmelcheniya [Cycles of crushing and grinding], Moscow: Nedra, 1981.
2. Protsuto V.S. Avtomatizirovannyye sistemy upravleniya tekhno-logicheskimi protsessami obogatitelnykh fabric [Automated process control systems for concentrating plants], Moscow: Nedra, 1987.
3. 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., Kryvyi Rih, 1999.
4. Podgorodetsky M.S. Power effective adaptive control of the closed disintegration cycle of ore on the basis of hybrid fuzzy model, PhD diss., Kryvyi Rih, 2011.
5. Porkuyan O.V. Control of nonlinear dynamic objects of concentrating productions on the basis of Hammerstein

hybrid models, ScD diss., Kryvyi Rih, 2009.

6. Morkun V., Morkun N., Tron V. (2015). Identification of control systems for ore-processing industry aggregates based on nonparametric kernel estimators, Metallurgical and Mining Industry, No1, pp. 14-17.
7. 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.
8. Morkun V., Morkun N., Pikilnyak A. (2014). Modeling of ultrasonic waves propagation in inhomogeneous medium using fibered spaces method (k-space), Metallurgical and Mining Industry, No2, p.p. 43-48.
9. 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.
10. Morkun V., Morkun N., Pikilnyak A. (2014). Ultrasonic facilities for the ground materials characteristics control, Metallurgical and Mining Industry, No2, pp. 31-35.
11. Qi C. K., Li H.X. (2008a). Hybrid Karhunen-Loève neural modeling for a class of distributed parameter systems. International Journal of Intelligent Systems Technologies and Applications, No4(1-2), pp.141-160.
12. Butkovskiy A. G. Green's functions and transfer functions handbook (1st ed.). Chichester, NY: Ellis Horwood, 1982.
13. Boyd S., Chua L. O. (1985). Fading memory and the problem of approximating nonlinear operators with Volterra series. IEEE Transactions on Circuits and Systems, No 32(11), pp.1150-1161.