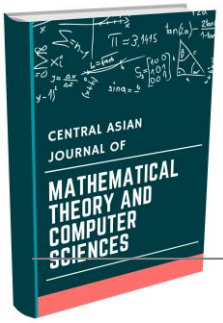

CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES

https://cajmtcs.centralasianstudies.org

Volume: 03 Issue: 07 | July 2022 ISSN: 2660-5309

HEURISTIC MODELS FOR MULTIPARAMETER IDENTIFICATION OF HYDRODYNAMIC OBJECTS OF ANALYSIS

Suvonov Olim Omonovich

Associate Professor of the Department of Informatics, Navoi State Pedagogical Institute

olimsuvonov54@umail.uz

Abstract

The article develops algorithms for constructing heuristic models of multi-parameter objects of hydrodynamics, identifying the parameters of physical processes based on the results of the experiment. A technique for constructing an optimal model for changing the filtration properties of oil field reservoirs is proposed.

ARTICLE INFO

Article history:
Received 27 may 2022
Revised form 24 june 2022
Accepted 26 july 2022

Keywords: *principle of self-organization, heuristic model, physical experiment, three-criteria selection, ranking, response function, group argument accounting method, optimal model.*

The solution of many problems of statistical data processing is associated with the generalization and identification of patterns in the processes under study based on observations of their real flows or physical experiments. These processes are always influenced by many random and discrete factors. In a physical experiment, statistical data are collected, which are usually incomplete. In such cases, the only research method is the mathematical analysis of the information received, where heuristic self-organization methods are widely used [1]. One of them is the method of group accounting for an argument (GAM), which is based on a multi-row selection of particular models with successive complications.

A.G. Ivakhnenko [1] gives a list of programs based on GAM algorithms. The logical substantiation and a fairly accurate presentation of the principle of self-organization contributed to the deepening of these studies.

This article is devoted to the development of algorithms for parametric identification of the qualitative and dynamic states of the system, respectively.

Determination of qualitative estimates of geophysical parameters under various artificial impacts on the reservoir system is one of the most important issues in the analysis of oil and gas field development processes. To identify the information content of features, a generalized parametric identification algorithm has been developed to study the dynamic states of the system based on the principle of "Heuristic self-organization".

The input data of the object of study here are the results of a physical experiment, which are accepted as training information, and the information obtained with the help of the constructed model is as a verification one.

To select the optimal object model, the algorithm provides for checking the standard deviations using the "left corner" principle.

Main part

Let us consider the construction of heuristic models of multipara meter objects based on the results of a few physical experiments. Let some information about the studied process be collected from observations with volume ω, which is the starting point for building the model. This volume of information is divided into three parts: training ω_0, verification ω_n and examining $\omega_э$. In contrast to the algorithms of the method of group accounting for an argument (GAM), this separation is not carried out in a unique way. The model built by the GMDH method is optimized by the ranking of the initial information ω. So there is a third possibility of choosing the optimal model. For this, root mean square errors are used. $\omega_э$, calculated by the optimal model of each ranking of the initial information ω.

Thus, the task of constructing a mathematical model of multi-parameter processes based on the MGAA reduces to the following: incomplete information is given ω, consisting of system parameter values $\vec{x_i} - x_{ij}, i = \overline{1,n}$, corresponding to the studied parameter y_j, $j = \overline{1,R}$ and parameters at the predictive point x_{ni}. Required to define a dependency function $y = f(x_1, x_2, \ldots, x_n)$ and its predicted value y_n (n-number of measured parameters in the system, R - number of observations).

Stages of building a three-criteria selection model.

1. Transition from dimensional to dimensionless variable formulas

$$\begin{cases} x_{ij}^* = x_{ij} \,/\, x_{i\max}, \ i = \overline{1,N}, \\ y_{ij}^* = y_{ij} \,/\, y_{\max}, \ j = \overline{1,N}, \end{cases} \qquad (1)$$

$x_{i\max}$, $y_{\max}$ - maximum values. This stage makes it possible to calculate the values necessary for constructing the model, regardless of the setting of the system of parameter dimensions, therefore, all parameters can be represented in the dimensions accepted within the studied limits. This makes it easier to prepare the initial information.

2. Pre-processing of initial information. We calculate the range of parameters in the response function, the mean value of the variance and the standard deviation using the formulas.

$$\begin{cases} P_x = x_{i\max} - x_{i\min}, \\ P_y = y_{\max} - y_{\min}, \\ \bar{x}_i = \sum_{j=1}^{R} x_{ij} / R, \\ S_i^2 = \sum_{j=1}^{R} (x_{ij} - \bar{x}_i)^2 / (R-1), S_i = \sqrt{S_i^2}, i = \overline{1,N}. \end{cases} \qquad (2)$$

3. Selection of the examining sequence from the initial information. To do this, we calculate the distance between the point and the steel points of the definition using the formula

$$\rho_i = \sqrt{\sum_{i=1}^{N} (x_{ij} - x_{ni})^2}, \ j = \overline{1,R} \qquad (3)$$

Source Information points ω sorted by increasing distance $\rho_1 < \rho_2 < \ldots < \rho_R$. Points corresponding to the first M values ρ_j, form examining sequences $\omega_э$, the rest are under study ω_u.

4. Separation ω_u on the ω_o and ω_n with volume R_1 and R_2. For this point from ω_u, located in ascending distance from the forecast point, are collected in various combinations and are formed ω_o and ω_n. For example, ω_o consists of points with even numbers, a ω_n - odd. Vice versa, ω_n consist of even, ω_o - from the odd ones. The first two in ω_o, the third is in ω_n etc. Can arrange M_1 combinations.

5. Pairing x_k and x_e parameters and construction of particular descriptions. Dependencies can be taken from support functions

$$y_s = a_0 + a_1 x_k + a_2 x_e + a_3 x_k x_l \qquad (4)$$

or

$$y_s = a_0 + a_1 x_k + a_2 x_l + a_3 x_k x_l + a_4 x_k^2 + a_5 x_l^2,$$
$$k = \overline{1, N-1}, \quad l = \overline{2, N}, \; l = \overline{2, M_2},$$

where $M_2 = l_N^2$ - number of private descriptions.

Dependencies of the form (4) are constructed by the least squares method in ω_o. The first selection criterion is used

$$\frac{1}{R_1}\sum_{j=1}^{R_1}\left(y_j - y_{sj}^*\right)^2 \to \min.$$

Here y_{sj}^* calculation according to dependence (4) of the value of the studied parameter y_j.

6. Calculation of quantities

$$\delta_s^2 = \frac{1}{R_2}\sum_{j=1}^{R_1}\left(y_j - y_{sj}^*\right)^2$$

and ordering particular models in ascending order δ_s^2

$$\delta_1^2 < \delta_2^2 < \ldots < \delta_{M_2}^2.$$

After that, from the set of particular descriptions, the first.

Let's move on to the next set of selections. The selection process continues until

$$\delta_1^2 > \xi \quad \text{or} \quad \overset{*}{\delta}{}_1^2 > \delta_1^2 \qquad \delta_1^2 \geq \overset{*}{\delta}{}_1^2 \qquad (5)$$

Here ξ required calculation accuracy; δ_1^{*2} mean square error values from the previous selection corresponding to the best of particular descriptions.

Condition (5) corresponds to the “left corner” principle. After fulfilling the condition $\delta_1^2 \geq \overset{*}{\delta}{}_1^2$. The next selection does not improve the model; in the general case, condition (5) for this statistic is also satisfied for all subsequent selections, i.e. further improvement of the model is not possible.

This is how the only optimal model is determined that satisfies the criterion of minimum mean square error and corresponding to M - th ranking of the initial information ω_{uc}.

7. Calculation of the value of the root-mean-square error for the examining sequence in the optimal model using the formula

$$\delta_m^2 = \frac{1}{M_1}\sum_{j=1}^{M_1}\left(y_j - y_i^b\right)^2,$$

where y_i^b - calculated value corresponding to the table y_j and calculated by the optimal model.

8. Repeat steps 5-7 for another ranking. This determines the set of the best models corresponding to the ranking options.
9. Model corresponding to the minimum of the set $\hat{\delta}_i^2$, is considered the best and its accuracy is determined by the formula

$$\delta_{io}^2 = min\hat{\delta}_i^2$$

Thus, the best model of multiparametric processes based on the principle of self-organization is built. It is practically impossible to get the model form, as in [1], because the addition of ranking options will again increase the number of terms in the polynomial. Apparently, this is not necessary. If you want to get the numerical value of the forecast, this can be achieved by calling the function procedures.

When using the above algorithm, its features should be taken into account. If one of the pairs of arguments x_k, x_l takes uniform values, i.e. they can be represented as

$$x_{k_j} = jh_1,\ x_{l_j} = jh_2,\ j = \overline{1, R_1},$$

then the determinant of the normal system of equations is equal to zero. In this case, it is impossible to obtain solutions to the normal system of equations and, consequently, to build a model for this pair. We exclude the model corresponding to this case from the set of models and proceed to the next pair of parameters. Therefore, the total number of models in each row of selections may be less than C_N^2.

Consider the problem of determining the parameters of the system if the value of the response function is given. Let the best model of the system be built, it is required to determine the values of the parameters $(x_1^0, x_2^0, \ldots, x_n^0)$ under which the function $f(x_1^0, x_2^0, \ldots, x_n^0) = f_0$. It is known that this problem reduces to finding the minimum of the functional

$$F(x_1, x_2, \ldots, x_n, y_0) = f(x_1, x_2, \ldots, x_n) - y_0$$

with restrictions on parameters $x_{i\min} \le x_i \le x_{i\max}$.

An algorithm and a program for determining the global minimum of the functional based on the random search method were developed [2]. The program can be successfully implemented in this case as well, for which the GAM function procedure should be used as a function.

The proposed MGAA algorithm for constructing a model of multi-parameter processes is implemented on a computer in the C++ language. We use the proposed technique to simulate the well killing process, considering it in two stages.

1. The process of filtering the washing liquid. The permeability of the reservoir depends on the physicochemical properties of the drilling fluid and the properties of the reservoir. The following dependency is used:

$$K_{нт} = K_{нт}(T_{нс}, V, \mu, \gamma, B, C_{нс}, K_н), \qquad (6)$$

where $K_н$ - initial air permeability of the core to saturation with solution; $K_{нт}$ - permeability of the core with washed crust; $T_{нс}$ - duration of core saturation with solution; V - the volume of the passed filtrate; μ - solution viscosity; γ - specific gravity of the solution; B - water yield in 30 min. solution; $C_{нс}$ - static shear stress.

The initial information is given in table.1.

Table 1

$K_н$	$T_{нс}$	V	μ	γ	B	$C_{нс}$	$K_{нт}$
761,4	18	0,1	117	1,02	7	18	168,3
698,2	16	8,6	63	1,02	38	0	150,4
1037,3	19,5	4,9	36	1,04	8	84	507,8
1025,9	20	9,4	50	1,05	8	12	428,2
593,5	14	8	28	1,062	9	0	128,2
698,2	14,5	3	28	1,07	8	0	287,0
1047,3	16	3,9	56	1,12	10	24	204,9
1044,5	17,5	11	38	1,13	18	20	448,1
698,2	17	9	28	1,14	12	9	229,0
530,1	20	4,5	28	1,13	32,5	0	198,3

Table 2

$K_{нт}$	$T_{пр}$	μ	γ	B	$C_{нс}$	$K_н$
168.3	2,5	117	1,02	7	18	725,5
150,4	3	62	1,02	38	0	553,9
507,8	1,75	36	1,04	8	84	946,01
428,2	1,66	50	1,05	8	12	814,56
128,2	3,5	28	1,062	9	0	539,5
287	2,75	28	1,07	8	0	584,4
204,9	4	56	1,12	10	24	827,37
448,1	2,33	38	1,13	18	20	857,33
229	2,66	28	1,14	12	9	609,53
198,3	2,75	28	1,13	32,5	0	416,66

2. The process of displacement of the filtrate by gas. In this case, the permeability of the reservoir can be slightly improved. The dependence is considered

$$K_n = K_n(K_{нм}, T_{пр}, \mu, \gamma, B, C_{нс}) \qquad (7)$$

where K_n - core permeability after blowing; $T_{пр}$ - air purge time.

Initial information is given in tables 1, 2.

The proposed method was used to construct dependences (6) and (7). Where $K_{нм}^b$ and $K_н^b$ - calculated values of the parameters according to the optimal model.

The change in the initial permeability of the rock is judged by the following data (Table 3):

Table 3

$K_{нм}$	$K_{нм}^b$	$(K_{нм} - K_{нм}^b) / K_{нм}^b$
168,3	176,96	-0,05140
150,4	162,48	-0,0732
507,8	502,67	0,0101
428,2	437,26	-0,0211
128,2	133,88	-0,0443
287,0	264,51	0,0783
204,9	201,31	0,0175

448,1	458,11	-0,0223
229,0	249,29	-0,0886
198,3	191,51	0,0342

The change in rock permeability after gas blowing is characterized by the following data (Table 4):

Table 4

$K_н$	$K_н^b$	$(K_н - K_н^b) / K_н^b$
725,5	703,86	0,0298
553,8	548,69	0,0092
946,01	931,18	0,01577
814,56	827,46	-0,0158
539,5	506,39	0,0614
584,4	567,23	0,0294
827,37	828,03	-0,0008
857,53	874,02	-0,0198
609,53	634,77	-0,0411
416,66	445,15	-0,0684

The optimal model was obtained for the first stage after 27, for the second after 6 rows of selections. The mean square errors are 0.0796 and 0.00034. The reason for stopping the selection of models was the "left corner" principle for both stages, i.e. improvement of the mean square error in the future is impossible. The relative error ranges from 1 to 8%. Similar results were obtained with other data of the problem.

Naturally, in the cases described, it is fundamentally impossible to bring the model into an analytical connection of the response function of the studied parameters. Such a model would include at least 28 terms of varying degrees of variables.

Thus, the proposed method can be used to build an optimal model for changing the filtration properties of reservoirs when flushing fluids with different properties move through them [4].

A good agreement between the experimental and calculated data shows the acceptability and effectiveness of the proposed parametric identification algorithm when developing a formulation of lightweight drilling fluids with and without solids to improve the technological and technical and economic development indicators when drilling wells in difficult conditions, as well as when killing gas wells on the period of production of repair work at the fields

References

1. Ivakhnenko A.G., Zaichenko Yu.P., Dimitrov V.D. Decision making based on self-organization. - M.: Science. - 1976. - 280 p.
2. Rastrigin L.A. Statistical search methods. - M.: Nauka. - 1969. - 376 p.
3. Rastrigin L.A. Extreme control systems. - M.: Science. 1974. - 630 p.
4. Suvonov O.O. Mathematical model of control of a hydrodynamic object with distributed parameters (on the example of oil fields). Central Asian journal of mathematical theory and computer sciences http://cajmtcs.centralasianstudies.org/index.php/CAJMTCS Volume: 03 Issue: 04 | Apr 2022 ISSN: 2660-5309. 5 pages.