

STRUCTURAL AND PARAMETRIC IDENTIFICATION OF RECYCLING SYSTEMS

Khusan Igamberdiev

Madina Mirxalilovma Fozilova

Follow this and additional works at: <https://ijctcm.researchcommons.org/journal>



Part of the [Complex Fluids Commons](#), [Controls and Control Theory Commons](#), [Industrial Technology Commons](#), and the [Process Control and Systems Commons](#)



STRUCTURAL AND PARAMETRIC IDENTIFICATION OF RECYCLING SYSTEMS

Kh.Z.Igamberdiev¹, M.M.Fozilova²

¹Doctor of Technical Sciences, Professor, Academician of the Academy of Sciences of the Republic of Uzbekistan, Tashkent State Technical University named after Islam Karimov. Address: 2 Universitetskaya st., 100095, Tashkent city, Republic of Uzbekistan;

²Research Institute for the Development of Digital Technologies and Artificial Intelligence under the Ministry of Digital Technologies of the Republic of Uzbekistan. Tashkent city, Republic of Uzbekistan.
Email: fozilovamm85@gmail.com.

Abstract. The issue of identifying recirculation systems with a specific control loop, in which information and control information about various technological processes circulate, is being considered. A methodology for identifying recirculation systems has been developed, based on algorithms for structural identification of the model based on the results of assessing the sensitivity of the optimum of control parameters and a fuzzy inference algorithm based on production rules that contribute to solving the problem of parametric identification.

Key words: recirculation systems, mathematical, structural-parametric, optimization and control systems.

Annotatsiya. Har xil turdagi texnologik jarayonlar to'g'risida ma'lumotlar oqimi va boshqaruv ma'lumotlari aylanadigan ma'lum bir boshqaruv zanjiri bilan aylanma tizimlarini aniqlash masalasi muhokama qilingan. Nazorat parametrlarining optimal sezgirligini baholash natijalari asosida modelni tizimli identifikatsiyalash algoritmlari va parametrik muammoni hal qilishga yordam beradigan ishlab chiqarish qoidalariga asoslangan loyqa xulosalar algoritmi asosida retsirkulyatsiya tizimlarini aniqlash metodologiyasi ishlab chiqilgan.

Tayanch so'zlar: retsirkulyatsion (aylanmali) tizimlar, matematik, tuzilmaviy parametrik, optimallashtirish va boshqarish tizimi

Аннотация. Обсуждается проблема идентификации рециркуляционных систем со специфическим контуром управления, в котором циркулируют потоки осведомительной и управляющей информации о различных технологических процессах. Разработана методика идентификации рециркуляционных систем, базирующаяся на алгоритмах структурной идентификации модели по результатам оценки чувствительности оптимума управляющих параметров и алгоритма нечеткого вывода на основе продукционных правил, способствующих решению задачи параметрической идентификации.

Ключевые слова: рециркуляционные системы, математические, структурно-параметрические системы, оптимизация и управление.

Introduction

In control problems of recirculation systems, a situation arises when some state parameters are directly measured or determined by an indirect method. For the observed object with known parameters, the following equation is valid:

$$\frac{dx}{dt} = Ax + Bu, x(t_0) = x(0), \quad (1)$$

$$Y = Cx. \quad (2)$$

The state of the control object can be assessed using a mathematical model

$$\frac{d\bar{x}}{dt} = A\bar{x} + Bu. \quad (3)$$

If the model is adequate to the real state, the application of the state of the model $x(0)$ and the object $x(0)$ results coincide, ..., just as the results of solving equation (1) coincide with the results of solving model (3).

Otherwise, if $x(0) \neq \bar{x}(0)$ then the identification error will be

$$e(t_0) = x(0) - \bar{x}(0) \quad (4)$$

and will depend on the accuracy of the measurement method, experimental data processing procedures, and so on [1].

Various methods and approaches have been proposed for error assessment [2], and their advantages and disadvantages have been sufficiently analyzed in works [3,4].

For example, a frequently used parametric identification method in the form of "Least Squares Methods" for operating technological objects is characterized by the correlation of noise over time. This is due to a shift in parameter estimates, an increase in the dispersion of these estimates, and a decrease in the quality of management [5,6].

Research Methods and the Received Results

In [3], the features of identifying closed systems are noted, characterized by changes in control variables depending on the observed variables at the output - control is carried out in a closed loop. Identification in closed-loop control is carried out with object noise and additional noise is introduced into the closed loop. In addition, complex structured real production facilities are also characterized by a delay in recycled material flows [7], which leads to a shift in input parameters and causes additional errors.

Thus, the noted noise, measurement inaccuracies, and uncertainties in the input and output parameters of the object require special approaches to the identification of recycling processes.

The error represented by equation (4) reflects the presence of output measurement error and accuracy in model parameter estimates, as well as the magnitude of the lag.

$$e(t) = y(t) - y(t - \tau),$$

where, is the measurement at the moment of time; $y(t - \tau)$ - measurement value at moment $(t - \tau)$.

Many large-scale industrial facilities are characterized by a similar shift in parameter estimates. This in turn causes a decrease in the quality of control systems [8].

Solving problems using parametric identification methods given in several works [9] provides that the parameters of the signals characterizing the state of the object and the measurement errors over the observation period are assumed to be constant. Although they are affected by external disturbances that directly affect the identification error [2].

It was noted in [5] that parametric identification methods make it difficult to solve many practical problems due to the inability to accurately establish certain types of signal distribution functions and errors.

It was noted [3] that statistical methods are not resistant to deviations of the initial data from the expected ones. This also reduces the efficiency of statistical data processing procedures and thereby ultimately reduces the accuracy of the control system.

It can be noted that in reality, the error distribution density tends to the normal law. But at the same time, anomalous errors distort the appearance of the normal law.

Analysis of the discrepancy between the mathematical model and the real process mainly depends on the characteristics of the control object.

The recirculation systems under consideration belong to the class of control objects that are difficult to formalize, characterized by structural complexity, multiparameter, poor knowledge of the connections between standard technological operators, and also the presence of interference; Some of the control variables change depending on those observed at the output - (the presence of a recycled material flow and a significant measurement error. This all leads to errors and complicates the solution of the identification problem.

One of the ways to overcome these difficulties is to use combined methods depending on the specifically solved problems.

For structural and parametric identification of control parameters of recirculation systems, a hybrid method is proposed that combines the main algorithm for assessing the sensitivity of the optimum and fuzzy logic.

Structural identification is carried out according to the proposed algorithm for assessing the sensitivity measure of the optimum of control parameters, as a result of which insignificant control parameters are excluded and the structure of the model is formed based on significant control parameters.

Parametric identification is carried out according to the algorithm [7] and after determining the parameters and constructing membership functions, a base of fuzzy rules is formed [9].

Structure identification

Sensitivity research is associated with the need to identify the parameters that most strongly influence the accuracy of the model and the choice of control actions when synthesizing a control system [3]. Most often used:

- sensitivity of output parameters

$$\zeta_y = \frac{\partial y}{\partial x};$$

- sensitivity of state variables

$$\zeta_x = \frac{\partial x}{\partial u};$$

- sensitivity to optimum

$$\zeta_\phi = \frac{\partial \phi}{\partial u};$$

where are x - the state parameters; u - control parameters; y - output parameters; ϕ - optimum criterion.

The control action represents the dependency

$$u = (x(0), y, t, \zeta)$$

if there is a circulating flow in the system

$$u = f(x(0), x, y, t, \zeta)$$

Typically, the optimal values of control parameters obtained using a mathematical model will have deviations from the true value. In this regard, it is necessary to estimate the sensitivity of the optimum to a small change in the control action Δu_i .

Optimum sensitivity $-\zeta_\phi$ characterizes the magnitude of the relative change in the optimality criterion ϕ when the control action deviates Δu_i from its optimal value u_i^{opt} . The work [3] defines the sensitivity of the optimum relative to the specified criterion. It also has a direct relationship with other parameters of the model.

Let's turn to "Sensitivity of the optimum" in relation to the control parameters - u_i^{opt} . If the control object is at the optimal value u_i^{opt} ($i = (1, m)$), optimality criterion ϕ takes maximum value.

$$\phi = \phi(x, u, y) \rightarrow \max$$

Although the optimality criterion depends on the input, output, and control parameters, when solving optimization problems it is directly related to the control parameters. From the above, we can write

$$\phi = \phi(u_1, u_2, \dots, u_m) \rightarrow \max$$

In conditions of deviation of control parameters from optimal values - u_i^{opt} to Δu_i , then the optimality criterion will also change by the amount $\Delta\phi$

$$\Delta\phi = \phi\left(\sum_{i=1}^n (u_i^{opt} \pm \Delta u_i)\right) - \left(\sum_{i=1}^n u_i^{opt}\right). \quad (5)$$

In case of deviation u_i to Δu_i change assessment $\Delta\phi$ will be [10]

$$\Delta\phi = \sum_{i=1}^m \frac{\partial\phi}{\partial u_i} \Delta u_i + \frac{1}{2} \sum \sum \frac{\partial^2\phi}{\partial u_i \cdot \partial u_R} \Delta u_i \Delta u_R.$$

Optimal control is achieved when

$$\frac{\partial\phi}{\partial u_i} = 0, \quad i = \overline{1, m}. \quad (6)$$

At this value the change ϕ equal

$$\Delta\phi = \frac{1}{2} \sum_{i=1}^n \sum_{R=1}^r \frac{\partial^2\phi}{\partial u_i \cdot \partial u_R} \Delta u_i \Delta u_R. \quad (6a)$$

Let us assume that the maximum deviation $\Delta u_i \leq \zeta_i$. Then we can accept that

$$\Delta u_i \Delta u_R \leq \zeta^2. \quad (7)$$

From expressions (6a) and (7) one can estimate the magnitude of the change:

$$|\Delta\phi| \leq \frac{1}{2} \zeta^2 \sum_{i=1}^r \sum_{R=1}^r \left| \frac{\partial^2\phi}{\partial u_i \cdot \partial u_R} \right|. \quad (8)$$

Since with a permissible change in value Δu_i optimality criterion ϕ will also change according to $\Delta\phi$, and the value estimate - ζ_ϕ from the condition $\Delta u_{i\max} - u_{i\text{opt}} \geq \zeta_\phi$ can be determined from the equation

$$\zeta_\phi = \sqrt{\frac{2|\Delta\phi|}{\sum_{i=1}^r \sum_{R=1}^r \left| \frac{\partial^2\phi}{\partial u_i \cdot \partial u_R} \right|}}. \quad (9)$$

A simplified form of equation (9) is

$$\zeta_\phi = \sqrt{\frac{2|\Delta\phi|}{\left| \frac{\partial^2\phi}{\partial u_R} \right|}}. \quad (10)$$

Using expression (10), we estimate the measure of the sensitivity of the optimum for each control parameter separately.

Sensitivity assessment, along with the identification of significant control parameters when carrying out structural identification of a recirculation system model, also makes it possible to establish the limits of permissible deviation of operating parameters, the range of variation of model coefficients, and, on the basis of ... to form optimization and control algorithms.

Parameter identification

Structural-parametric identification of recirculation systems in the most general form is presented as a process of constructing a model with the establishment of patterns of connections between input parameters $x = \{x_1, x_2, \dots, x_n\}$ and output parameter y . The number of input parameters is established during structural identification based on estimates of the optimum sensitivity measure

The use of natural language statements “If..., then...”, followed by their formalization based on the theory of fuzzy sets, makes it possible to adequately reflect the “inputs and outputs” of a controlled object without resorting to complex differential-integral computational procedures [11-12].

“Input-output” relationships are established using the Gaussian membership function [13] in the following form:

$$\varphi_i(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - x_{i2}}{\delta_i}\right)^2\right], i = 1, \bar{n},$$

where x_i - parameter value: x_i^* - average parameter value: δ_i - dispersion.

The choice of the Gaussian membership function is due to flexibility and simplicity (specified by two parameters).

The neuro-fuzzy model using the algorithm [7] includes five layers. Neural network, with n input parameters and m rules, the total number of configurable parameters of the neural network is $m(n+1)$. Setting the parameter values of the neuro-fuzzy model is carried out in accordance with the learning algorithm for adaptive fuzzy backpropagation systems [7, 13], based on the gradient descent method.

Conclusion

To train the model, you can use one of the optimization methods, for example, the descent method, gradient, or hybrid algorithms [9], the latter are more effective since all parameters are refined in parallel and simultaneously.

When solving the optimization problem, a genetic algorithm was used, which is quite flexible and does not require the calculation of derivatives taking into account other characteristics [9].

When implementing a genetic algorithm, you must:

- determine optimized parameters;
- choose the method of encoding information;
- set the objective function;
- determine the rules for initializing the initial population;
- select selection, crossing, and mutation operators, as well as set their parameters;
- perform a given number of iterations to achieve an error that is less than a given one.

After specifying the parameters, the process starts until the parameters of the technological process under study are stabilized.

References:

1. Pegat, A. (2009). Nechetkoe modelirovanie i upravlenie [Fuzzy Modeling and Control]. M.: BINOM, 798 p. (in Russian).
2. Izerman, R. (1984). Sifrovie sistemi upravleniya [Digital control systems]. M.: Mir, 541 p. (in Russian).
3. Semenov, A.D., Artamonov, D.V., Bryuxachev, A.V. (2003). Identifikatsiya ob'ektov upravleniya [Identification of control objects]. Penza: Izd. Penz. gos. un-t., 211 p. (in Russian).

4. Bobsov, A.A., Kremlev, A.S., Pirkin, A.A. (2011). Kompensatsiya garmonicheskogo vozmusheniya dlya parametricheskogo i funktsional'no neopredelennogo nelineynogo ob'ekta [Compensation of harmonic disturbance for parametric and functionally uncertain nonlinear object]. *Avtomatika i telemekhanika*, 1, 121-129. (in Russian).
5. Igamberdiev, X.Z., Mamirov, U.F. (2018). Regularizovannie algoritmi identifikatsii neopredelennix dinamicheskix ob'ektov upravleniya [Regularized algorithms for identifying uncertain dynamic control objects]. *Jurnal «Vestnik Tash GTU»*. 2, 16-21. (in Russian).
6. Igamberdiev, H.Z., Yusupbekov, A.N., Zaripov, O.O., Sevinov, J.V. (2017). Algorithms of adaptive identification of uncertain operated objects in dynamical models. *Procedia Computer Science*, 120, 854 - 861.
7. Ismailov, M.A., Kaipberganov, B.T., Fayzullaev, B.A. (2022). Intellekturnie sistemi diagnostiki proizvodstvennix ob'ektov [Intelligent diagnostic systems for production facilities]. *NIU «TNIMMSX»*. 2022, 114 p.
8. Kuksa, P.P. Sintez i optimizatsiya nelokal'nykh interpretiruemix lingvisticheskix neyro-nechetkix modeley [Synthesis and optimization of non-local interpretable linguistic neuro-fuzzy models]. E-mail: pkouxa@yahoo.com www.geocities.com/pkouxa. (in Russian).
9. Muxamedieva, D.T., Primova, X.A., Xasanov, U.U. (2016). Neyro-nechetkiy algoritmi identifikatsii i nastroyki parametrov sistem nechetkogo vivoda [Neuro-fuzzy algorithm for identifying and setting parameters of fuzzy inference systems]. *Uzbek Journal of the problems of informatics and energetic*. 3, 21-27. (in Russian).
10. Boyarinov, A.I., Kafarov, V.V. (1969). *Metodi optimizatsii v khimicheskoy tekhnologii* [Optimization methods in chemical technology]. M.: Izd. «Ximiya», 564 p. (in Russian).
11. Shtovba, S.D. *Vvedenie v teoriyu nechetkix mnojestv i nechetkuyu logiku* [Introduction to fuzzy set theory and fuzzy logic]. <http://www.matlab.exponenta.ru>. (in Russian).
12. Kudinov, Yu.I., Kudinov, I.Yu., Baykov, S.V.. Identifikatsiya i obucheniye v nechetkix sistemax [Identification and learning in fuzzy systems]. *Avtomatizatsiya i informatika*. (in Russian).
13. Xodashinskiy, I.A. (2008). Tekhnologiya identifikatsii nechetkix modeley tipa singleton i Mamdani [Identification technology for singleton and mamdani type fuzzy models]. *Tr. VII mezhdunarodnoy konferentsii. Identifikatsiya sistem i zadach upravleniya «SICPRO» 081. Institut problem upravleniya*. 137-163. (in Russian).