UDC:62-50:681.3.06:519.876.5

METHOD OF IDENTIFICATION BASED ON THE ASSOCIATIVE SEARCH MODEL FOR DETERMINING THE UNKNOWN COEFFICIENTS OF A LINEAR DYNAMIC SYSTEM MODEL

Karshi State Technical University
Associate Professor of the Department of "Automation and Control of Technological Processes"
Bekqulov Jahongir Sherboyevich
Karshi State Technical University
Student of the Department of Automation and Control of Technological Processes
Turaev Orzubek Amirbek ugli

Annotatsiya. *Mazkur maqolada chiziqli dinamik tizim modelining noma'lum koeffitsiyentlarini aniqlash muammosi ko'rib chiqiladi. Ushbu muammoni hal etishda assotsiativ qidirish modeli asosida taklif etilgan yondashuv asosiy vosita sifatida qo'llaniladi. Taklif etilgan metod yordamida tizim parametrlarini identifikatsiyalash aniqligi oshiriladi hamda tizim modelining real obyektga yaqinligi ta'minlanadi. Tadqiqotda nazariy asoslar, matematik model, algoritm tavsifi va eksperiment natijalari keltirilgan.*

Annotation.*In this article, the problem of determining the unknown coefficients of the model of a linear dynamical system is considered. In solving this problem, the proposed approach based on the associative search model is used as the main tool. With the help of the proposed method, the accuracy of system parameter identification is increased, and the proximity of the system model to the real object is ensured. The study presents the theoretical foundations, mathematical model, description of the algorithm, and experimental results.*

Keywords: *Linear dynamic system, identification, unknown coefficients, associative search model, regression, least squares method, MATLAB/Simulink, forecasting, technological process, virtual analyzer*

Introduction. Most modern technical and technological systems have a complex dynamic character, and precise mathematical models are necessary for their effective management and modeling. Especially in linear dynamic systems, the identification of unknown parameters or coefficients is an important stage of system identification. Determining parameters by traditional methods usually requires a lot of time and computational resources. Therefore, approaches based on elements of artificial intelligence, including associative search models, are relevant for solving this problem[1].

Therefore, the problem of identifying unknown coefficients of a linear dynamic system is solved on the basis of associative search models, which ensures high accuracy and flexibility in determining system parameters. Let's consider the algorithm for determining the unknown coefficients of a linear dynamic model. Without limiting the generality of the function, we can rewrite the model as follows:

$$y_{\varphi} = \sum_{i=1}^{M} \zeta \hat{x}_i \tag{1}$$

where: $\hat{x} = (\hat{x}_1, \hat{x}_2, ...\hat{x}_r), k = m + nS, \hat{x}$ - extended input vector, for which:

$\{\hat{x}_1, \hat{x}_2, ...\hat{x}_m\} = \{y_{\varphi-1}, y_{\varphi-2}, ..., y_{\varphi-m}\}; (\hat{x}_{m+1}, \hat{x}_{m+2}, ...\hat{x}_{m+n,k}) = (\hat{x}_{\varphi-1}, \hat{x}_{\varphi-2}, ...\hat{x}_{\varphi-1,k} ....\hat{x}_{\varphi-n,k}).$

ζ - extended vector of input coefficients, for which:

$\{\zeta_1, \zeta_2, ..., \zeta_m\} = \{a_1, a_2, ..., a_m\}; \{\zeta_{m+1}, \zeta_{m+2}, ..., \zeta_{m+n,k}\} = \{b_{1,1}, b_{1,2}, ...b_{1,k}, ...b_{n,k}\}.$

(1) When modeling and identifying the parameters of the technological process, the information in the knowledge base archive is structurally represented in the form of spatial vectors. In order to ensure the minimization of general errors in the process of determining optimal control or model parameters, it is considered a scientifically and practically acceptable approach to determine the archival vector closest to the vector reflecting the current state according to Euclidean or other metric criteria and make decisions based on it [1,2].

Based on the selected representative vectors, a structured matrix containing extended vector descriptions of input parameters is formed, which forms the main analytical basis of the information base for subsequent stages of identification or modeling:

$$\hat{X} = \begin{pmatrix} \hat{x}_1^1 & . & . & . & \hat{x}_{\zeta}^1 \\ . & . & & & . \\ . & & . & & . \\ . & & & . & . \\ \hat{x}_1^P & . & . & . & \hat{x}_{\zeta}^P \end{pmatrix}, P >> \zeta \tag{2}$$

To determine the set of coefficients in the process of identifying the parameters of model (1), it is necessary to form a system of equations reflecting the linear relationships between them and find an analytical or numerical solution to this system.

$$\hat{X}\zeta = \hat{y}, \tag{3}$$

where $\hat{y}$ represents the set of parameters predicting the future state of the system. If the full rank condition of the matrix X is met and its rank is considered equal to $\hat{X} = k$, then the least squares method is used as the main evaluation tool for determining the estimate $\hat{\zeta}$ as a solution to the numerical expression (3), which allows identifying the system parameters with optimal accuracy.

$$(\hat{y} - \hat{X}\hat{\zeta})^T(\hat{y} - \hat{X}\hat{\zeta}) = \min \alpha(\hat{y} - \hat{X}\hat{\zeta})^T(\hat{y} - \hat{X}\hat{\zeta}). \tag{4}$$

The condition of necessary extremum (minimality), determined by the parameter vector ζ, based on the requirement of stationarity of the functional, forms the corresponding system of linear algebraic equations:

$$\hat{X}^T\hat{X}\zeta = \hat{X}^T\hat{y}. \tag{5}$$

Assuming that the matrix $\hat{X}$ is completely colored, i.e., its color is maximal, based on this condition, we obtain the following analytical result:

$$\hat{\zeta} = (\hat{X}^T\hat{X})^{-1}\hat{X}^T\hat{y}. \tag{6}$$

Expression $\hat{\zeta}$ is an estimate obtained on the basis of the least squares method (LSM) and, according to the Gauss-Markov theorem, has the smallest variance among all classes of non-offset linear estimators with respect to parameter ζ [2-8]. At the same time, in cases where the $\hat{X}^T\hat{X}$ matrix does not have sufficient accuracy, the evaluation method carried out through expression (6) cannot provide a reliable result.

Due to the existing statistical correlation between the components belonging to the extended input vectors of dynamic system models, the identification matrices representing them often turn out to be low-color or quantitatively ill-conditioned. This situation significantly reduces the accuracy of calculations and limits the possibility of reliable estimation using traditional algebraic approaches. In this regard, it is advisable to use a generalized inversion procedure based on the Moore-Penrose (Moore-Penrose) pseudo-solution concept in the evaluation process. In cases where the numerical uniqueness of matrix $\hat{X}^T\hat{X}$ is violated, or in the case of a system of linear algebraic equations for expression (5), where there exists an infinite set of solutions of parameters $\hat{\zeta}$, a solution is selected by determining an estimate that satisfies the predetermined optimality criterion (for example, the minimum of the norm).

$$\hat{\zeta}_0{}^T\hat{\zeta}_0 = \min \hat{\zeta}^T\hat{\zeta} \ . \tag{7}$$

The minimization of the estimate ζ, determined by expression (4), is ensured only if and only if the parameter vector $\hat{\zeta}$ satisfies the following condition, i.e., in this case, based on this optimality criterion, there exists an extremum value of the functional:

$$\hat{\zeta} = \hat{X}^+\hat{y} + (I - \hat{X}^+\hat{X})p. \tag{8}$$

Here p – r is a random vector of a given dimension, defined in a probability space and characterized by statistical properties (mathematical expectation, covariance matrix). Under these conditions, the estimate of the parameter vector $\hat{\zeta}_0$ is determined based on the following analytical expression, which serves to obtain an optimal estimate:

$$\hat{\zeta}_0 = \hat{X}^+\hat{y}. \tag{9}$$

Also, expression (9) in its content represents a functional equivalent of the evaluation principle based on the least squares method, i.e., this approach can be considered as a generalized form of the classical EQQ methodology. In the process of determining the unknown coefficients of the linear model and assessing their real values, a model built on memory-based search algorithms was used. This approach is aimed at optimizing the functioning of a virtual analyzer that determines the product quality at the output of a drum dryer, and within the framework of the study, an associative linear model of product quality based on forecasting was developed. Based on the main technological parameters influencing the potassium chloride drying process, the possibilities of product quality forecasting were analyzed. To assess the statistical relationships, Pearson correlation coefficients were calculated, and based on their results, informationally significant input variables were identified. Then, based on these selected variables, an associative linear regression model was formed, and a functional forecasting system for determining product quality was developed [3].

$$Q(t) = \sum_{i=1}^{6} \beta_i x_i(t) \tag{10}$$

where $Q(t)$ - quality indicator of the product (amount of residual moisture after drying potassium chloride); x_1, x_2, x_3, x_5 - consumption of drying agent, primary and secondary air, material, respectively; x_4 and x_6 - humidity of the material and air at the inlet, respectively; $\beta_i, i = 1,2,3,4,5,6$ - coefficients.

The proposed associative model is built on the basis of a linear structure, and its conceptual distinguishing feature is that it relies on a knowledge base about the technological object, which is updated and adaptively improved over time. This knowledge base serves as a data archive containing historical observations of the parameters of the technological process and allows for the formalization of an updated local model for each functional cycle. As a result of the analysis based on the statistical and dynamic characteristics of the process, the need to select input vectors corresponding to the current state from the archive of the technological process to form a reliable forecast estimate using the associative model at each time point (in particular, in the minute interval) was determined [2-12]. Computational experiments of the model were carried out on the Simulink platform in the MATLAB environment based on simulation modeling. A practical experimental database obtained from a real industrial object - a technological line for the production of potassium fertilizers - was used as initial parameters. This served to ensure the dynamic assessment of the modeled process in accordance with real technological conditions.

In the computational experiment, signals of technological parameters of drying agent consumption (X1), primary air consumption (X2), secondary air consumption (X3), material input moisture (X4), material consumption (X5), and air input moisture (X6) are received at the input of the simulation model (Fig. 1). These technological variables are defined as the main information inputs of the model, reflecting the physical and dynamic characteristics of the drying process.

A complex simulation model of a virtual analyzer for assessing the technological process of drying potassium chloride (KCl) and the moisture content of the product at its output was created using Simulink in the MATLAB environment, the block-schematic structure of which is shown in Fig. 1. This model integratedly represents the heat and mass transfer of the drying system, the change in signal flux over time, and prediction algorithms.

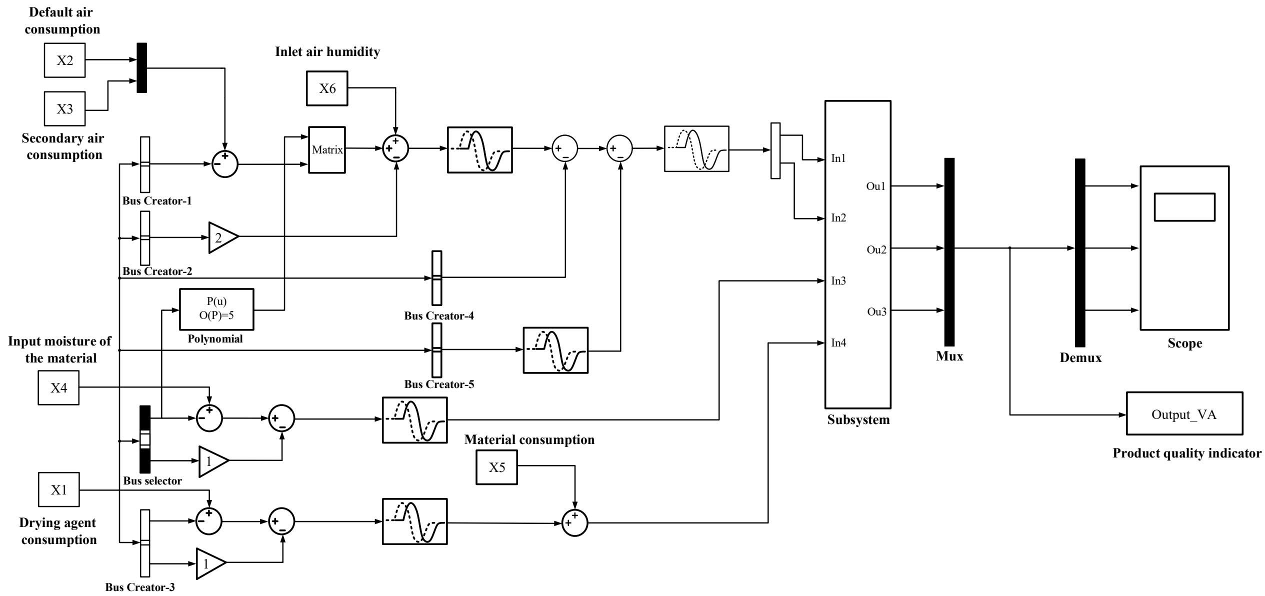

Figure 1. Simulation model of a virtual analyzer built using the MATLAB program

Within the framework of the analysis of the technological process of drying potassium chloride, a computational stage was carried out, aimed at forecasting product quality for 70 functional cycles (one cycle corresponds to one day of production activity). This approach to forecasting is organized based on the structure of a model that integrates the classical linear model and the associative search mechanism based on memory. The results of modeling based on the symbiosis of these two approaches are graphically presented in Fig. 2, which reflect the reliability of the forecasting algorithm in accordance with the dynamics of the technological process parameters over time.

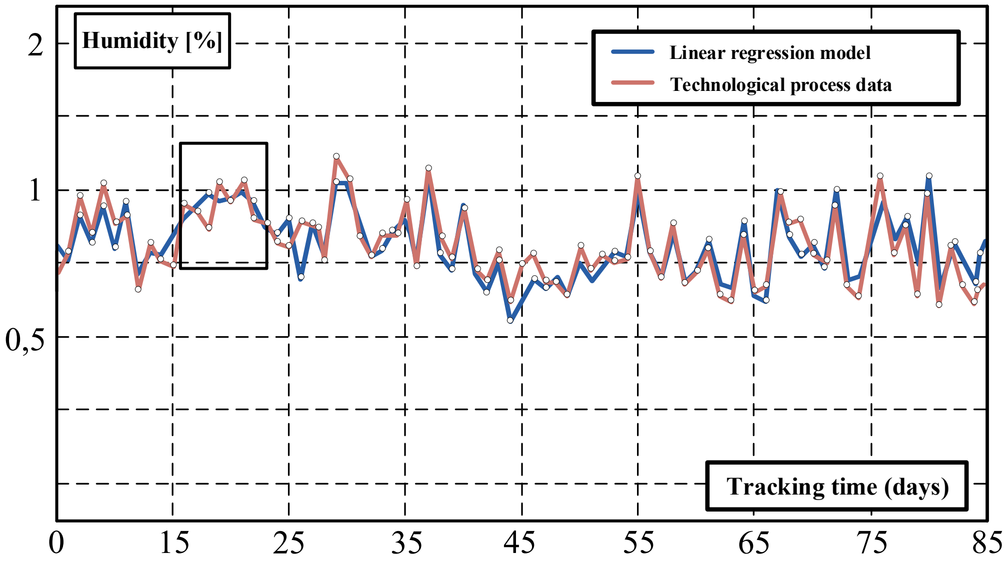

Figure 2. Forecast graph of the quality indicator of manufactured products

To calculate the accuracy of forecasting, the average absolute error is used, which is determined as follows.

$$y_{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_i(t) - \tilde{y}(t)\right|, \tag{11}$$

where: $y_i(t)$ - actual value; $\tilde{y}(t)$ - value obtained as a result of forecasting; N - number of studied cycles. In addition, the root mean square error was studied.

$$y_{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left|(y_i(t) - \tilde{y}(t))^2\right|. \tag{12}$$

To avoid large errors in product quality forecasting, the root mean square error was also used. The analysis results for the above technological process are presented in Table 1.

Table 1

Error	Linear model	Associative model	Explanation
Average Absolute Error (AVR)	0.6	0.201	The result of the associative model is more accurate than the linear one.
Mean squared error (MSE)	0.61	0.279	The prediction of the associative model has less error than the prediction of the linear model
Pearson correlation coefficient	0.548	0.87	The prediction of the associative model has a similarity dynamic of the object relative to the prediction of the

			linear model.

The possibility of using an auxiliary model in a virtual analyzer Based on the results obtained using a computational experiment conducted on a simulation model of the KCl drying process in drum dryers, a predictive linear regression model is constructed, which has the following form.

$$K(t) = a_0 + a_1 M(t) + a_2 P(t) + a_3 T_1(t) + a_4 T_2(t) \quad (13)$$

where $K(t)$ - product moisture content (promising quality indicator); $P(t)$ - pressure of the drying agent; $T_1(t)$ - temperature of the drying agent $T_2(t)$ - temperature of the drying agent at the outlet of the dryer; a_0 - free term of the linear regression model; a_1, a_2, a_3, a_4 – coefficients of the model. As a result of the calculations, the values of the coefficients obtained for the model are equal to the following.

$$a_0 = 0{,}95, a_1 = 0{,}31, a_2 = -0{,}154, a_3 = -0{,}243, a_4 = -0{,}513$$

A simulation model of the technological process of drying KCl in drum dryers and a virtual analyzer for measuring residual moisture using MATLAB instruments has been developed. Based on the developed simulation model, a computational experiment was conducted, and linear regression models were trained [4-10]. In the computational experiment, a sample of process parameters with a volume of 810 points of observation time (days) was tended. Figure 3 shows the result of the linear regression model.

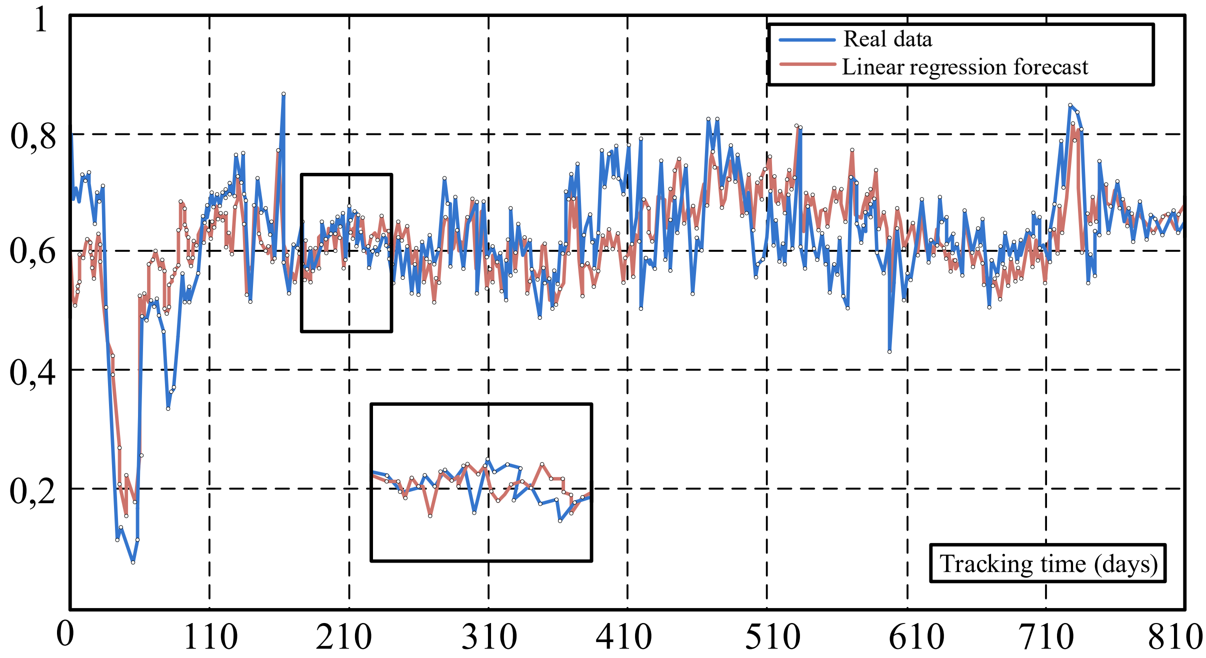

Figure 3. Linear regression model result

When assessing the quality of the developed model, the mean absolute error, the root mean square error, and Pearson's correlation coefficient were used. The results of the model are presented in Table 2.

Table 2

Xatolik	Real ma’lumotlar	Chiziqli regressiya modeli	Izoh
O‘rtacha absolyut xatolik	0,895	0,8	Chiziqli regressiya modeli bashoratining natijasi real ma’lumotlar miqdoriga deyarli teng
O‘rtacha kvadratik xatolik	0,081	0,079	
Pirson koeffitsiyenti	0,591	0,586	

Conclusion

In this article, a method of identification based on the associative search model, aimed at determining unknown coefficients of linear dynamic systems, was developed and practically substantiated. The proposed approach allows for the formation of the most appropriate regression model for each observation cycle, taking into account the statistical relationships in the data archive. This creates conditions for adaptive assessment of system parameters that change over time in real time.

In the identification process, information vectors were selected for the parameters included in the model using the associative search mechanism. As a result, using optimization based on the least squares method, minimal variance estimates of unknown coefficients were obtained. Simulation experiments were conducted in the MATLAB/Simulink environment, and it was proven that the proposed method has high accuracy, stability, and predictability.

The obtained results showed that regression methods based on the associative search approach can be used as an effective identification tool for industrial technological processes, including the modeling of chemical and thermal processes, as well as automatic control systems.

Reference:

1.Емеьянов С.В., Коровин С.К., Рыков А.С., и др., Методы идентификации промышленных объектов в системах управления. Кемерово: Кузбассизндат,2007.- 307с.

2.Kothare M. V., V. Balakrishnan, and M. Morari, Robust constrained model predictive control using linear matrix inequalities // Automatica. 1996. Vol. 32. No. 10. P. 1361-1379.

3.Qin, S.J. and Badgwell, T.A. (2003). A survey of industrial model predictive control technology. Control engineering practice, 11(7), 733-764.

4.Gavrilov A.V. (2002). The Model of Associative Memory of Intelligent System. In: Preprints of the 6-th Russian-Korean International Symposium on Science and Technology. Volume no 1, pp. 174-177.

5.Ильин В.В. Система управления качеством. Российский опыт.-СПб.: Невский проспект; Вектор, 2015. — 224 с.

6.Материалы по продуктам MATLAB&Toolboxes [Электронный ресурс]. – Режим доступа: http://matlab.exponenta.ru

7.Piotr Tatjewski. Advanced Control of Industrial Processes//Structures and Algorithms. Springer-Verlag London Limited 2007. Library of Congress Control Number: 2006936016

8.Маллаев А.Р., Беккулов Ж.Ш., Норбоев О. Н., Эшонкулов М Н. Программа для отображения на экран данных, полученных с виртуальных анализаторов/Агентство по интеллектуальной собственности Республики Узбекистан. № DGU 09820.2021 г.

9.Nurullaevich, K. S., & Sherboyevich, B. J. (2024). Abstract boiling on the example of an improved control system for the combustion of natural gas (potassium chloride) in the calorifier of the dryer. *American Journal of Innovation in Science Research and Development*, *1*(7), 18-27.

10.Sherbaevich, B.J. (2024). ADAPTIVE CONTROL SYSTEM FOR A FLUIDIZED BED DRYER. *American Journal Of Applied Science And Technology*, *4*(12), 47-56.

11.Sherboyevich, B. J., & Askarovna, A. S. (2024). The conceptual structure of the APC-an improved system for monitoring and controlling technological processes for the production of mineral (potash) fertilizers. *American Journal of multifunctional publishing*, *1*(7), 26-35.

12.Sherboyevich, B. J. (2022). Mineral o ‘g ‘itlar sifatini aniqlashda qo ‘llaniluvchi virtual analizatorlar. *Инновационные подходы, проблемы, предложения и решения в науке и образовании*, *1*(1), 79-83.