MODELING, FORECASTING OF SYSTEMS IN THE PROCESS OF BIOGAS PRODUCTION

Kh.Abdullayev PhD student, National Research University "Tashkent Institute of Irrigation and Agricultural Mechanization Engineers"

Abstract

The article deals with the problems of forecasting related to the insufficient quality and quantity of initial data, changes in the environment in which the process takes place, the impact of subjective factors. The process of formation of a mathematical model is analyzed, and the prediction of obtaining biogas in the fermentation process for a part of the bioreactor, which will facilitate the study of various processes occurring in this installation. A daptive neuro-fuzzy system of conclusions is discussed, which implements a fuzzy output system in the form of a five-layer neural network of direct signal propagation, as well as mathematical modeling of thermal processes in a biogas plant.

Key words: *forecasting, mathematical model, neuro-fuzzy system, neural network, modeling of the thermal process.*

Introduction. Mathematical modeling is an important stage of scientific research, because it allows you to imagine the physics of the process occurring in a particular object. The most accurate and complete model helps to simplify the process of analyzing the dynamic characteristics of a physical phenomenon or process occurring in the object of study, subject to verification for adequacy to the real process [1]. The expediency of mathematical modeling is due to the high cost of conducting experiments on a real biogas production unit (bioreactor). , subject to the need for its design and manufacture, and significant time costs, due to the high inertia of a number of processes, on the example of obtaining biogas from various agricultural wastes by anaerobic fermentation in the bioreactor, due to the large overall dimensions of the installation.

Material and methods. Consider the process of forming a mathematical model, and predicting the production of biogas during fermentation for a part of the bioreactor, which will facilitate the study of various processes occurring in this installation.

Forecasting is one of the most popular, but at the same time one of the most difficult tasks of data mining. Forecasting problems are associated with insufficient quality and quantity of initial data, changes in the environment in which the process takes place, the impact of subjective factors. The forecast is always made with some error, which depends on the forecast model used and the completeness of the initial data [2].

As the information resources used in the model increase, the accuracy of the forecast increases, and the losses associated with uncertainty in decision-making decrease.

Various forecasting methods are known and widely used: algorithms for extrapolating experimental data in simple engineering calculations and software products, as well as more cumbersome statistical methods using parametric models.

Four methods of identifying the nonlinear dependence of output are considered - using a linear regression model, a quadratic regression model, a fuzzy knowledge base and a neural-paring model. To solve this problem, consider a class of adaptive networks functionally equivalent to fuzzy reasoning systems. An important task is to determine the network inputs.

The adaptive neuro-fuzzy inference system is one of the first variants of hybrid neuro-fuzzy networks - a neural network of direct signal propagation of a special type. The architecture of a neuro-fuzzy network is isomorphic to a fuzzy knowledge base. Neuro-fuzzy networks use differentiated implementations of triangular norms (multiplication and probabilistic OR), as well as smooth membership functions. This makes it possible to use fast neural network training algorithms based on the method of backpropagation of errors to configure neuro-fuzzy networks [3, 4]. The adaptive neuro-fuzzy system of conclusions implements a fuzzy output system in the form of a five-layer neural network of direct signal propagation. The purpose of layers is as follows:

the first layer - the terms of the input variables;

the second layer - antecedents (parcels) of fuzzy rules;

the third layer is the normalization of the degrees of implementation of the rules;

the fourth layer is the conclusion of the rules;

the fifth layer is the aggregation of the result obtained according to various rules.

For a fuzzy system having two inputs x and one output y, fuzzy reasoning is shown in fig. 1, a, and the corresponding equivalent adaptive neuro-fuzzy network - in fig. 1, b.

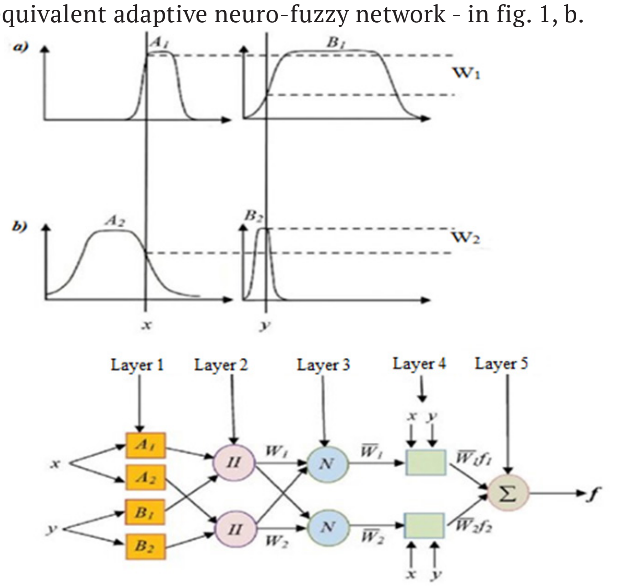

Figure 1. Fuzzy reasoning (a) and equivalent adaptive neuro-fuzzy network (b).

The knowledge base of such a system contains two fuzzy rules if

Rule 1: If $x = A_1$ и $y = B_1$ то $f_1 = p_1x + q_1y + r_1$,

Rule 2: Ifx $= A_2$ и $y = B_2$ то $f_2 = p_2x + q_2y + r_2$.

Layer 1: Each node in this layer is an adaptive node with the following node function:

$$O_i^1 = \mu_{A_i}(x),$$

where x is the input signal of node i, A_i is a linguistic variable associated with a given node function. In other words, is the membership function of the variable $O_i^1 A_i$, which determines the degree to which a given x satisfies A_i. Normally, a bell-shaped function is chosen as:$\mu_{A_i}(x)$

$$\mu_{A_i}(x) = 1 \Big/ \left(1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}\right),$$

where $\{a_i, b_i, c_i\}$ is the set of parameters of this layer. The parameters of this layer refer to the so-called *prerequisite parameters*.

Layer 2: Each node in a given layer is a fixed node that multiplies the input signals, the output value of the node being the weight of some rule:

$$\omega_i = \mu_{A_i}(x) * \mu_{B_i}(x), i = 1,2. \quad (3)$$

Layer 3: Each i-th node of a given layer determines the ratio of the weight of the i-th rule to the sum of the weights of all the rules:

$$\overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} \quad (4)$$

The output signals of the 3rd layer is *called normalized weights*.

Layer 4: The nodes of this layer are defined by linear (for a Model of the Sugeno type) functions of the output variable membership:

$$O_i^4 = \overline{\omega_i} f_i = \overline{\omega_i}(p_i x + q_i y + r_i), \quad (5)$$

Where is the output signal of the 3rd layer and is the set of parameters of this layer (the so-called $\overline{\omega_i}(p_i x + q_i y + r_i)$*output parameters*).

Layer 5: The only node in this layer is a fixed node in which the total output value of the adaptive network is calculated as the sum of all input signals:

$$O_1^5 = \sum_i \overline{\omega_i} f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \quad (6)$$

Obviously, for the given values of the prerequisite parameters, the total output value (Fig. 2) is a linear combination of the output parameters:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_1 = \overline{\omega_1} f_1 + \overline{\omega_2} f_2 =$$
$$= (\overline{\omega_1} x) p_1 + (\overline{\omega_1} y) q_1 + (\overline{\omega_1}) r_1 + (\overline{\omega_2} x) p_2 + (\overline{\omega_2} y) q_2 + (\overline{\omega_1}) r_2 \quad (7)$$

where $p_1, q_1, r_1, p_2, q_2, r_2$ are the output parameters.

Typical training procedures for neural networks can be used to configure an adaptive neuro-fuzzy network since it uses only differentiated functions. Usually, a combination of gradient descent is used in the form of an error backpropagation algorithm and the method of least squares. The backpropagation algorithm configures the parameters of the antecedents of the rules, i.e. the membership functions. Each iteration of the configuration procedure is performed in two steps. At the first stage, a training sample is fed to the inputs, and the optimal parameters of the nodes of the fourth layer are found by an iterative method by the interaction between the desired and actual behavior of the network. At the second stage, the residual residual residual is transmitted from the network output to the inputs, and the parameters of the nodes of the first layer are modified by the method of backpropagation of the error. At the same time, the coefficients of the conclusions of the rules found at the first stage do not change. The iterative configuration procedure continues until the residualness exceeds the preset value.

Consider a typical prediction algorithm carried out using neural networks.

Selection of significant factors. At the first stage, the maximum number of significant factors affecting the forecast is allocated. Such additional factors affecting the behavior of the predicted value are called exogenous (external) or artifacts. Here, the observation interval (sliding window) is selected, that is, it is found out by how many previous values of the time series the forecast is made.

Data preprocessing. At the second stage, insignificant, according to the expert, and not affecting the forecast, data are eliminated. If necessary, the missed information is also restored. Skillfully carried out data preprocessing can significantly improve the quality of the forecast.

Build the model. At the next stage, the most suitable paradigm and structure of the neural network, as well as the algorithm and parameters of its training, are selected for this analyzed process.

Actual *forecasting (obtaining the result).* Experiments are carried out according to a scheme similar to the one in which the training was carried out.

Results

Consider theathematic modeling on the example of thermal processes in a biogas plant. According to Newton's law, the force of internal friction opposing motion between water particles moving at different speeds is determined by the formula:

$$s = \mu \frac{dw}{dn}. \quad (8)$$

Consequently, the heat transfer process is represented in this way.

Each particle moves at a different speed: the particle velocity decreases towards the wall of the bioreactor of the biogas plant, and the velocity of the particles adhered to the wall of the bioreactor is zero. Considering the law of thermal conductivity, this makes it possible to determine the heat flow through the layer of water near the wall.

$$q = -\lambda_b \left(\frac{dT}{dy}\right)_{y=o}. \quad (9)$$

Where: λ_b is the coefficient of thermal conductivity of water; T is the current temperature.

Differential equation for a moving particle of liquid has the form:

$$\frac{dT}{d\tau} + \omega_x \frac{dT}{dx} + \omega_y \frac{dT}{dy} + \omega_z \frac{dT}{dz} = \alpha\left(\frac{d^2T}{dx^2} + \frac{d^2T}{dy^2} + \frac{d^2T}{dz^2}\right) + \frac{W}{c\rho}. \quad (10)$$

Where: τ – time, from; $\omega_x, \omega_y, \omega_z$ - components of water velocity; m/s; W is the amount of heat absorbed by a unit volume per unit time, J/s; $c\rho$ - specific volumetric heat capacity,
J/ (m³ · K); *x, y, z* - current coordinates.

The heat transfer law can be used to determine the heat capacity,
J/ (m³ · K); *x, y, z* - current coordinates.

The heat transfer law can be used to determine the heat transfer process. However, it is necessary to know the kind of temperature field function in a liquid, which is described by the differential equation (10).

This equation contains the components of the velocity that can be determined from the system of equations:$\omega_x, \omega_y, \omega_z$

$$\frac{d\omega_x}{d\tau} + \omega_x \frac{d\omega_x}{dx} + \omega_y \frac{d\omega_x}{dy} + \omega_z \frac{d\omega_x}{dz} = v\left(\frac{d^2\omega_x}{dx^2} + \frac{d^2\omega_x}{dy^2} + \frac{d^2\omega_x}{dz^2}\right) + \left(g_x - \frac{1}{\rho}\frac{dP}{dx}\right), \quad (11)$$

$$\frac{d\omega_y}{d\tau} + \omega_x \frac{d\omega_y}{dx} + \omega_y \frac{d\omega_y}{dy} + \omega_z \frac{d\omega_y}{dz} = v\left(\frac{d^2\omega_y}{dx^2} + \frac{d^2\omega_y}{dy^2} + \frac{d^2\omega_y}{dz^2}\right) + \left(g_y - \frac{1}{\rho}\frac{dP}{dy}\right) \quad (12)$$

$$\frac{d\omega_z}{d\tau} + \omega_x \frac{d\omega_z}{dx} + \omega_y \frac{d\omega_z}{dy} + \omega_z \frac{d\omega_z}{dz} = v\left(\frac{d^2\omega_z}{dx^2} + \frac{d^2\omega_z}{dy^2} + \frac{d^2\omega_z}{dz^2}\right) + \left(g_z - \frac{1}{\rho}\frac{dP}{dy}\right) \quad (13)$$

After solving equations (11–13), we get:

$$\frac{d\rho}{d\tau} + \frac{d(\rho\omega_x)}{dx} + \frac{d(\rho\omega_y)}{dy} + \frac{d(\rho\omega_z)}{dz} = 0. \quad (14)$$

Discussion

Equation (14) is called the flow continuity condition. Equations (11-13) and (14) outline the relationship between physical parameters. To fully describe thermal processes, the system of equations in question must contain additional equations. These equations must contain physical, geometric, time and boundary conditions. Thus, solving the considered system of equations is a difficult task. Therefore, only experimental studies will help to obtain numerical values of the desired variables, after which equations are drawn up that describe the results of the experiments [5]. In this regard, it will be necessary to make a computational experiment.

Conclusion

As a result of the study, a method for forecasting output is proposed, based on the construction of approximate models in the form of adaptive neuro-fuzzy networks trained on samples of real data for past periods. Based on the proposed method, an approximating model of the forecast was created.

The considered features of the use of fuzzy sets and neural networks, which show their *advantages* in comparison with other existing methods when choosing a forecast model.

References:

1.Zadeh L. The Information principle // In Proc. the 15th IEEE International Conference on Information Reuse and Integration, San Francisco, CA, USA; August 13-15, 2014.

2. Zadeh L., Neshat N., Kazemi A., Saberi M.Predictive control of drying process using an adaptive neuro-fuzzy and partial least squares approach // International Journal of Advanced Manufacturing Technology, 58 (5-8), 2012, pp. 585-596.

3. Jowers L.J., Buckley J.J., Reilly K.D. Simulating continuous fuzzy systems // Information Sciences 177 (2007), P p.436–448.

4. Muhamediyeva D.T. and Sayfiyev J. Approaches to the construction of nonlinear models in fuzzy environment// IOP Conf. Series: Journal of Physics: Conf. Series 1260 (2019) 102012 DOI: 10.1088/1742-6596/1260/10/102012

5. Siddikov I. Kh., Kalandarov P. I., Yadgarova D. B. Engineering Calculation and Algorithm of Adaptation of Parameters of a Neuro-Fuzzy Controller The American Journal of Applied sciences (2021)3 (09), 41–49.