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STUDYING THE ADEQUACY OF THE NEURAL NETWORK LEVEL CONTROLLER IN THE AUTOMATED CONTROL SYSTEM OF AN EVAPORATOR

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The aim of the study is to substantiate the use of neural network control of beet juice level in an evaporator by evaluating the accuracy and adequacy of the model. This allows us to assess how well the model properties describe the course of the real process. The use of mathematical statistics methods is the most common way to test models for adequacy. In the automation scheme of level control, capacitive level gauges are used as a sensor. The actuators are pneumatic seat valves with a built-in throttle and an electro-pneumatic converter. The use of neural network controllers is found only in some specific cases of intelligent control of the evaporation process, and there are no data comparing the use of intelligent controllers with classical ones. In this paper, the Durbin-Watson *d*-criterion is used to assess the adequacy of the model. Statistical data on the behavior of the level control system circuits in different operating modes using intelligent and classical controllers were collected and a model of the evaporator unit operation was built. The advantage of the Durbin-Watson criterion is its simple and fast implementation, which does not require large economic and energy costs. The accuracy of the model was also evaluated. The static error of the control quality for the levels in the five enclosures of 25–65 % (in 10 % increments) is within the range of no more than 0,2 %. The proposed model of the evaporator station operation is generally characterized by high accuracy.

Keywords: computer science, automation, neural networks, modeling.

Introduction

The automatic control system of an evaporation plant can be characterized as requiring the intervention of a process operator who, in the course of operation, makes adjustments to the setting parameters of the regulators responsible for temperature and material flows. Such adjustments can be explained both by changes in the technological and quality indicators of the components at the input of the evaporator station and by the need to change them at the output of the section. When making changes to the automation system, the operator must take into account how adjacent sections affect the operation of the evaporator station, as well as the impact of the evaporator station on the operation of adjacent areas of the plant [1].

To implement a modern automation system, it is necessary to use modern software and hardware. Since the perfection of the evaporation process is a rather important task. In study [2], the author considers a model of the evaporation process that takes into account the balance of mass and energy at the evaporation stages. However, this study leaves unresolved issues related to the occurrence of nonlinearity and the problem of fluid flow deviation. In addition, this study did not consider the possibility of using intelligent controllers in the evaporation process. The reason for this may be the difficulties arising from the need to use special software. The study [3] considers the process of linearization of a nonlinear model consisting of 14 nonlinear levels of beet juice of the first order, which is a dynamic model of the evaporator. In this study, the function of the change in product concentration on the deviation of the fluid flow rate was first revealed. However, no research has been conducted on the use of intelligent controllers. This may be due to the lack of a suitable neural network training model.

Evaporators for the sugar industry are usually equipped with evaporators with natural circulation. If the optimal regime is not observed during the evaporation process, alkalinity decreases due to the decomposition and caramelization of sucrose, which leads to the decomposition of amides such as aspargin [4]. The juices of condensates (ammonia water) and vapors from the evaporator contain carbon dioxide, carbon monoxide, and ammonia. Sugar juice contains glucose ($C6H12O6$), and the above factors cause changes in its properties. When the temperature of glucose reaches 160° C and remains unchanged for a long time, one of the two water molecules is split off, i.e., glucose anhydride ($C6H10O5$) is obtained, from which the formation of crystallized sugar is impossible. When the temperature is further raised to 220° C (from animal and vegetable products), the sugar juice produces tasteless caramel or bitter assamar, which are not capable of fermentation. Therefore, the formation of sugar from such substances is impossible [5]. Therefore, the best quality control parameters should be ensured to prevent sugar syrup from being over-extracted and overheated.

The need to update the existing control systems is indicated in [6], and some approaches used for the distributed level of process control are presented. An explanation of these approaches is useful for a better understanding of the processes that occur during the formation of the control influence, especially when software developers for industrial control systems use a large number of settings for system operation. This approach is only available to qualified specialists with significant work experience [6]. However, knowledge of these processes by specialists can also provide more flexible work when structuring data [7]. However, this publication does not address the use of intelligent regulators in the evaporation process. This may be due to the complexity of the calculations [8].

This paper investigates the use of methods for regulating the level of beet juice in an evaporator, which will improve the accuracy of level control and thus increase the efficiency of the evaporation plant [9].

The aim of the study is to substantiate the use of neural network control of beet juice level in the evaporator by evaluating the accuracy and adequacy of the model [10]. This allows us to assess how well the model properties describe the course of the real process. The use of mathematical statistics methods is the most common way to test models for adequacy. The use of neural network controllers will increase the efficiency of the evaporator station.

Materials and methods

Paper [11] describes the control of several evaporation stations with full integration of fuzzy control and the use of wireless network sensors and actuators. However, the comparison of the use of neuro-fuzzy controllers with other types of intelligent control and justification of the feasibility or inexpediency of using this type of control in the case of the possibility of implementing a system with another type of intelligent control is not made. In addition, neuro-fuzzy control in this study is not applied to all control loops. The reason for this may be the high complexity and cost of conducting such a study.

Paper [12] also considers options for improving the evaporation process and performs complex calculations. In [13], the authors prove that the evaporation rate decreases markedly with time and perform a calculation that shows that diffusion in the liquid phase is the rate-limiting step for this system, unlike the evaporation of pure water. In [14], a generalized steady-state mathematical model is developed to simulate a multichannel evaporator system. Paper [15] considers the problems of detecting malfunctions in industrial processes using dynamic neural networks on the example of an evaporator. The considered neural network has a multi-level feedforward structure. In [16], the author investigates the application of real-time optimization in the evaporation section using methods that reduce the time for model development. In [17], the authors consider the use of genetic algorithms in sugar production. Study [18] analyzes the development of the structure of an automated control system using tensor methods in sugar production. However, the authors of these works also do not apply intelligent control. The reason for this may be the high complexity of the calculations or the lack of the necessary hardware or software.

In [6], the author argues that using intelligent control, it is possible to ensure a faster decrease in the temperature of the housing and achieve more stable control of overheating in the first evaporator tank. However, this work also does not address the issue of using intelligent controllers to regulate other parameters (e.g., pressure, beet juice level, consumption). In addition, this paper considers only the possibility of using intelligent controllers in other cases than the first one. This may be due to the high complexity of calculations and the need to use specific software. The problem of controlling other parameters of the evaporation process was considered in [7]. In this work, it is proved that evaporation control can be realized by recirculating the liquid in the evaporation section or by supplying only liquid to the evaporator; the issue of using intelligent regulators in the evaporation process is not considered.

A five-hull evaporator station of a sugar plant was used as a test setup. Fig. 1 shows the automation scheme of the level control circuits in the first building of the evaporator. Capacitive level sensors are used as sensors in the first building (LE 1a, LT 1b). The silicone-compounded electronic circuit is housed in an enclosure with an IP65 to IP68 rating, depending on the electrical connection selected. KD140M manufactured by Lviv Instrument-Making Plant was chosen as a secondary instrument (LIA 1c). They are designed to work in conjunction with non-interchangeable primary transducers (sensors) that convert the measured non-electrical quantities (pressure, flow, level, vacuum) into an AC output signal (340 ± 30 mV (at 250 mA) per 1 mm of sensor plunger movement.

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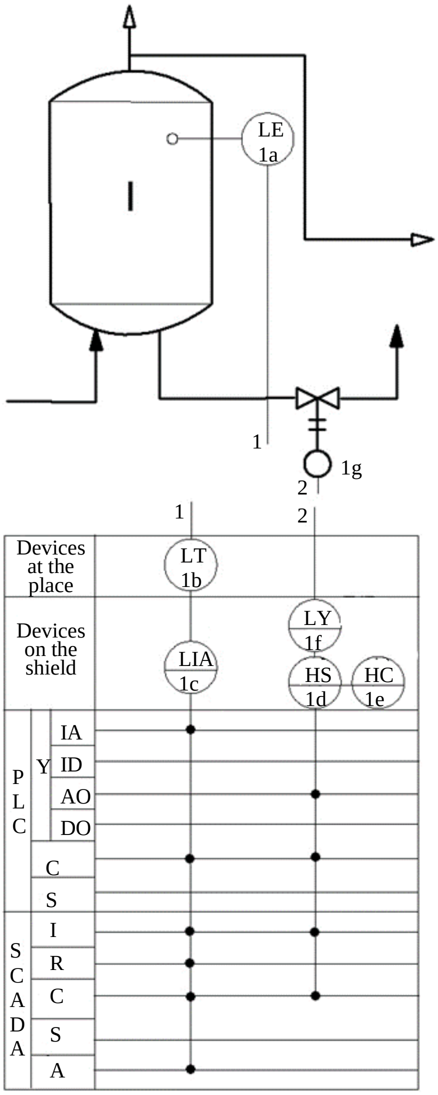

Fig. 1

The signal is sent to the controller (PLC) on the control unit (intersection with C), as well as to the human-machine interface (SCADA), which displays the level value in the evaporator housings on the screen of the operator's automated workstation (computer) (intersection with I). The obtained data is stored in the memory (R). These data (actual level values in the evaporator tanks) are used to conduct this experiment. If the level value in the evaporator vessels exceeds the set limits, an alarm signal (A) is generated. The control signal output by the controller (AO) is sent to the electropneumatic converter (LY 1f), which converts an analog unified electrical signal. In turn, the actuator (e.g., 1g) changes the position of the control valves. The operator can control the position of the controller in the remote (manual) mode (intersection with C — remote control from the SCADA operator). To switch the «Manual/Auto» mode (HS 6c, HC 6c), manual control units of the BRU-17 model are used, which are used for manual control of an analog signal and an analog actuator. It has one analog input with support for a standardized signal of 0–5 mA, 0–20 mA or 0–10 V and one analog output with support for a standardized signal of 0–5 mA, 0–20 mA or 0–10 V. It supports RS-485 and ModBus network interfaces and protocols. The controller used is the Modicon M340, an industrial logic controller for machine manufacturers, small and medium-sized automation systems. It supports 4 MB of memory for saving programs and 256 KB for saving data. It is equipped with built-in communications such as CANopen bus, supports Ethernet TCP/IP, RTU serial interface, and ASCII character interface. Danfoss VFG33 pneumatic seat valves (6e) with a built-in throttle and an electro-pneumatic converter are used as actuators [4].

Development of a mathematical model of a five-hull evaporator

Fig. 2 shows the structure of the model of a five-hull evaporator with a neural network controller, where $Y_z(t)$ is the task signal, $Y(t)$ is the output signal, and $Y_{zz}(t)$ is the feedback signal.

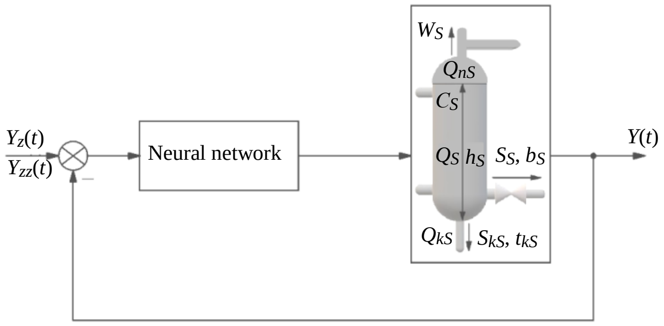

Fig. 2

As can be seen from Fig. 2, the structure of a system with a neural network controller is similar to that of a system with a classical controller. The only difference is the use of a neural network controller trained with the help of a reference model instead of classical controllers. Thus, we can conclude that this structure is suitable for the operation of the system model with a neural network controller.

The data for the neural network were obtained in production from a representative sample created by experts based on the processing of data from systems with classical controllers.

To filter the data from the experimental study of the sample, the simple moving average (SMA) method was chosen [19]. This method consists in converting time series into series of dependent estimates (values) according to formula (1).

$$\hat{h}_i = \frac{1}{w} \sum_{j=i-w}^{i+m} z_j , \tag{1}$$

where $\hat{h}$ — moving average; w — the size of the anti-aliasing window; j — serial number of the smoothing window; i — serial number of the item; z — number of ordinates; $m = (w-1)/2$.

Often, when conducting real-time research, there may be cases when it becomes necessary to calculate a moving average for the last point rather than the average. Then the formula for the calculation will look like (2).

$$\hat{h}_i = \frac{1}{w} \sum_{j=i-w}^{i} z_j . \tag{2}$$

There is a recursive formula (3) that aims to simplify the calculations.

$$\hat{h}_i = \hat{h}_{i-1} + \frac{1}{w}(z_i - z_{i-w}). \tag{3}$$

More details on the operation of this filtering algorithm can be found in [20].

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To train the neural network, we used the method of backward error propagation.

In order to preserve the variables that characterize the regulated system performance at one point of operation, it is necessary to linearize the model around the equilibrium point. The nature of the modeling is set in accordance with the real process and performed in the MatLab environment.

Fig. 3 shows a comparison of the results of level control in the first case using classical PID-controllers (X1), fuzzy controllers (X2), and neural network controllers (X3).

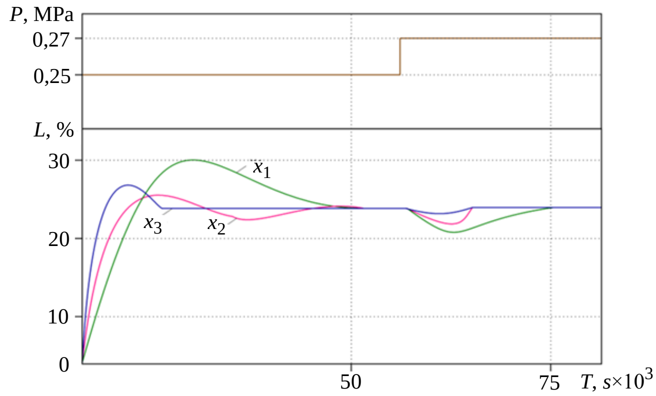

Fig. 3

After that, we evaluate the accuracy of the system. We start the automation system of a five-body evaporator station (see Fig. 1), select the type of control, and take transient graphs and setpoints from the SCADA system.

Comparing the data obtained as a result of modeling (Table 1), we can conclude that the use of neural network controllers (X2) significantly reduces the control time compared with the use of classical (X1) and fuzzy (X2) controllers. However, the use of fuzzy controllers (X2) provides a smaller oscillation amplitude than the use of classical and neural network controllers and allows to get rid of the static error.

Table 1

N corps	*a*	*b*	*c*	*d*
PID-regulator				
1	25	27	26,5	1,5
2	35	38	37,3	2,3
3	45	47	2	4
4	55	53	2	3,6
5	65	63	2	3
Fuzzy regulator				
1	25	26	1	4
2	35	33	2	5,7
3	45	44	1	2
4	55	56	1	1,8
5	65	66	1	1,5
Neural network regulator				
1	25	25	0	0
2	35	35,1	0,1	0,3
3	45	44,9	0,1	0,2
4	55	55	0	0
5	65	65,2	0,2	0,3

Consider the notation: *a* — set point, %, *b* — measured value, %; *c* — absolute error, %; *d* — relative error, %.

The absolute error value (A) is calculated by the formula

$$A = \left| Z(t) - \tilde{Z}(t) \right| \tag{4}$$

where $Z(t)$ — the actual value of the time series, $\tilde{Z}(t)$ — predicted value of the time series.

The value of the relative error (V) for each value of a time series point is calculated using the formula:

$$V = \frac{\left| Z(t) - \tilde{Z}(t) \right|}{Z(t)} \times 100\,\%. \tag{5}$$

The closer the relative error approaches 0 %, the more accurate the model is [9]. From Table 1, we can conclude that the highest model accuracy is achieved when using a neural network controller.

Next, we compare the quality indicators of the PID controller, fuzzy controller, and neural network controller [14] (Table 2).

Table 2

a	*b*	*c*	*d*	*e*
PID-regulator				
1	15	52	2,98	97,3
2	12	51	2,95	97
3	10	53	2,89	97,2
4	15	55	2,91	95,3
5	13	54	2,92	96,1
Fuzzy regulator				
1	9	50	2,62	82,6
2	8	49	2,63	83,4
3	9	51	2,67	85,4
4	6	54	2,69	81,2
5	7	53	2,61	82,3
Neural network regulator				
1	3	20	2,47	73,1
2	2	21	2,45	73,2
3	2	23	2,43	73,9
4	2	21	2,41	73,5
5	2	20	2,42	72,9

Let us consider the notation: *a* — case number, *b* — maximum dynamic deviation, %; *c* — setup time, *c**103; *d* — quadratic integral quality criterion, *e* — sum of squares of residuals.

According to all the above indicators, it can be concluded that the quality of the level control process increases when using neural network controllers compared to the use of classical and fuzzy controllers [14].

The quality of the level control directly affects the energy costs for heating the evaporated syrup in the evaporator building, since when the level of syrup in the evaporator building increases, it is necessary to increase the consumption of heating steam to maintain the required syrup temperature. In addition, deviations from the set level of

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syrup in the vessel affect the pressure change in the vessel, which in turn affects the change in the boiling point of the syrup and leads to a disruption of the technological process [1].

Assessment of the adequacy of the developed model

In addition to checking the accuracy of the model, it is also necessary to check its adequacy. This allows to assess how well the model properties describe the course of the real process [21].

The use of mathematical statistics is the most common way to test models for adequacy. The actual value of the object under study, according to the methods of mathematical statistics, can be represented as (6):

$$y_i = \hat{y}_i + \varepsilon_i. \tag{6}$$

where $\hat{y}_i$ — the value obtained in the modeling process; ε_i — random (residual) component.

Fig. 4 shows a comparison of the course of the real process and the modeling results: *a*) PID-controller, *b*) fuzzy controller, *c*) neural network controller (1 — the graph of the real process, 2 — the graph of the model).

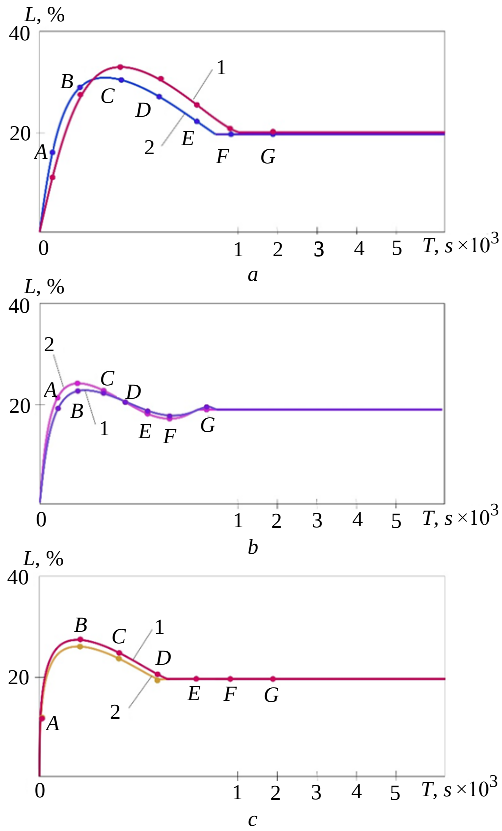

Fig. 4

One of such methods for an evaporator is considered in [21]. This is the Durbin-Watson *d*-criterion. A comparison of the simulation and the course of the real process is shown in Fig. 4.

The accuracy of predicting numerical values was calculated using formula (7) [22].

$$\delta = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - x_i'}{x_i}\right| \le \varepsilon, \tag{7}$$

where x_i — actual value; x_i' — model value; ε — random (residual) component.

Since the model's accuracy index δ (Table 3) does not exceed its maximum value $\delta\max = 0,9$, we can conclude that the system is adequate [23, 24].

Table 3

a	b	c	d	e
PID-regulator				
A	9	17	0,9	<10
B	25	25,9	0,03	<10
C	31	29,3	0,05	<10
D	27	24,6	0,10	<10
E	24	22,3	0,08	<10
F	20,5	19,5	0,05	<10
G	19,8	19,5	0,02	<10
Fuzzy regulator				
A	19	21	0,1	<10
B	23	25	0,09	<10
C	22,5	23	0,02	<10
D	20	20	0	<10
E	19	18,5	0,03	<10
F	18,3	18	0,02	<10
G	20	21	0,05	<10
Neural network regulator				
A	10	10	0	<10
B	23	24	0,04	<10
C	22	23	0,05	<10
D	20	21	0,05	<10
E	20	20	0	<10
F	20	20	0	<10
G	20	20	0	<10

Let's look at the notation: *a* — name of the point, *b* — x_i; *c* — x_i'; *d* — absolute error of the model, %, *e* — comparison with the maximum permissible error $\varepsilon = 10$.

Thus, to assess the adequacy of the model, we used the d_a method to check whether all the values of absolute errors correspond to the permissible level set for model construction: $\varepsilon_i = 10$ (8).

$$d_a = \frac{1}{n}\sum_{t=1}^{n} \Delta x_t$$
$$\Delta x_t = \begin{cases} 1, \text{ if } |\varepsilon_t| > d, \\ 0, \text{ if } |\varepsilon_t| \le d. \end{cases} \tag{8}$$

From Fig. 4 and formula (8), we can conclude that the model is adequate according to the criterion d_a, since $d_a = 0$.

Conclusion

As a result of the study of a great number of sources, it was concluded that most of the problems of intelligent control in the evaporation process remain unresolved. The use of neural network controllers occurs only in certain specific cases.

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The results of this study showed that when using a neural network controller, the system is stable, but a small static error occurs. However, the advantage of this type of control is much higher speed of regulation than when using classical or fuzzy controllers. Therefore, in order to remedy this situation, it is possible to combine the operation of neural network and fuzzy controllers, namely: it is possible to use the evaporation system in the neural network control mode to reduce the control time, and then switch to the control mode using a fuzzy controller in order to get rid of the static error. In order to avoid emergency situations when combining the operation of regulators, it is necessary to develop a model for predicting the operation of the fuzzy and neural network control system. In addition, such a model will also allow to take into account the influence of a huge number of external factors that can affect the system.

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ДОСЛІДЖЕННЯ АДЕКВАТНОСТІ РОБОТИ НЕЙРОМЕРЕЖЕВОГО РЕГУЛЯТОРА РІВНЯ В АВТОМАТИЗОВАНІЙ СИСТЕМІ КЕРУВАННЯ ВИПАРНИМ АПАРАТОМ

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Мета дослідження — обґрунтування використання нейромережевого регулювання рівня бурякового соку у випарному апараті шляхом оцінки точності та адекватності моделі. Це дозволяє оцінити, наскільки якісно властивості моделі описують перебіг реального процесу. Використання методів математичної статистики є найбільш поширеним способом перевірки моделей на адекватність. У схемі автоматизації регулювання рівня як датчик використовуються ємнісні рівнеміри. Виконавчими механізмами служать пневматичні сідельні клапани з вбудованим дроселем та електропневмоперетворювачем. Нейромережеві регулятори використовуються лише в окремих специфічних випадках інтелектуального керування процесом випарювання, відсутні дані порівняння застосування інтелектуальних регуляторів з класичними. У даній роботі використано *d*-критерій Дарбіна–Уотсона для оцінки адекватності моделі. Зібрано статистичні дані поведінки контурів системи регулювання рівня у різних режимах роботи з використанням інтелектуальних та класичних регуляторів і побудовано модель роботи випарної станції. Перевага критерію Дарбіна–Уотсона — легка і швидка його реалізація, яка не потребує великих економічних та енергетичних затрат. Також оцінено точність отриманої моделі. Статична похибка якості регулювання для рівнів в п'яти корпусах 25–65 % (з кроком 10 %) знаходиться в межах, що не перевищує 0,2 %. Запропонована модель для роботи випарної станції характеризується високою точністю в цілому.

Ключові слова: комп'ютерні науки, автоматизація, нейронні мережі, моделювання.

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