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Automated methods of controlling the flow of syrup in the evaporation station with subsystems of decision support and forecasting

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Abstract

Introduction. The purpose of the presented study is to substantiate the methods of regulating the consumption of syrup in the evaporation station with a forecasting subsystem, which will allow to predict the behavior of the system and the decision-making subsystem, which will reduce the influence of the human factor on the course of the evaporation process.

Materials and methods. The work of the evaporation station with the subsystem of forecasting and decision support when regulating the consumption of syrup was researched. In the automation scheme for regulating the flow rate of syrup, induction flow meters are used as a sensor. Pneumatic saddle valves with a built-in throttle and an electro-pneumatic converter were used as actuators.

Results and discussion. The use of neural sensors occurs only in certain specific cases of intelligent control of the evaporation process, there is no data comparing the use of intelligent regulators with classical ones, the possibility of combining the work of several types of intelligent regulators, as well as clear means of predicting their work and supporting decision-making. Therefore, in this paper, a decision-making subsystem has been justified, which made it possible to assess the priorities of user requests when using a human-machine interface. The highest priority was given to the request to display information on possible changes to the adjustment parameters of other control circuits. The forecasting method was also used to compare the methods of regulating the flow rate of syrup in the apparatus, which made it possible to predict the behavior of the system during the formation of the control action and display the finished forecast on the operator's screen and, thus, increase the efficiency of the evaporation station. Statistical data on the behavior of the contours of the automation system in different modes of operation using intelligent and classical regulators were collected, a model for predicting the operation of an evaporation station by the method of local tendency was built and a forecasting algorithm was developed. The accuracy of the obtained forecasting model is also evaluated. The accuracy of the forecasting model was 98% for the PID controller, 95% for the neural fuzzy regulator and 96% for the neural network.

Conclusions. The model for predicting the operation of the evaporation station is characterized by high accuracy in general, but during the occurrence of oscillations in the transition process, there is an insignificant delay in predicting these fluctuations. The most important in the output of information by the decision-making subsystem is the function of displaying information about the possible changes to the parameters of regulation of other control circuits.

Introduction

The system of automatic control of the evaporation station can be described as a system that requires the intervention of an operator-technologist, who in the course of his work makes adjustments to the tasks of regulators responsible for temperature and material flows. Such adjustments can be explained both by a change in the technological and quality indicators of the components at the inlet of the evaporation station, and by the need to change them at the exit of the section. When making changes to the operation of the automation system, the operator must take into account how adjacent sections affect the operation of the evaporation station, as well as the impact of the evaporation station on the operation of adjacent sections of the plant (Hrama et al., 2019).

Perfection of the evaporation process is quite an important task. In the study (Chantasiriwan, 2021), the author considers a model of the evaporation process that takes into account the balance of mass and energy in the stages of the evaporation process. However, this study did not consider the possibility of using intelligent regulators in the evaporation process. The reason for this may be the difficulties arising from the need to use special software. Research (Verma et al., 2018) makes it possible to overcome the problem of its occurrence. This paper explores the process of linearization of a nonlinear model consisting of 14 nonlinear levels of primary order, which is a dynamic model of the evaporator. This study for the first time revealed the function of changing the concentration of the product from the deviation of the flow rate of a liquid (Garcés et al., 2021). However, no research has been conducted on the use of intelligent regulators in this study. This may be due to difficulties in developing rule bases for neural fuzzy regulators or the lack of an appropriate neural network training model (Said et al., 2021).

Evaporation stations for the sugar industry are equipped, as a rule, with stations with natural circulation (Petrenko et al., 2022). In which, in case of non-compliance with the optimal mode in the evaporation process, there is a decrease in alkalinity due to the decomposition and caramelization of sucrose, which leads to the decomposition of amides such as aspargin (Hrama et al., 2019). Juices of condensate (ammonia water) and vapors from the evaporation station contain carbon dioxide, carbon monoxide and ammonia. Sugar juice contains glucose ($C_6H_{12}O_6$), the above factors cause a change in its properties. When the glucose temperature reaches 160 °C and leaves it unchanged for a long time, one of the two water molecules is cleaved, that is, glucose anhydride is formed ($C_6H_{10}O_5$), from which the formation of crystallized sugar is impossible. With a further increase in temperature to 220 °C, tasteless caramel or bitter assamar (a substance formed when heating products of animal and vegetable origin) is formed from sugar juice, which are not capable of fermentation. Therefore, the formation of sugar from such substances is impossible (Hrama et al., 2019). Therefore, in order to prevent overexposure and overheating of the sugar syrup, it is necessary to ensure the best quality control parameters.

The need to update existing control systems is indicated in the work (Sidletskyi et al., 2020). The paper presents some approaches used for a distributed level of control of technological processes. But this work does not reveal the issue of using intelligent regulators in the evaporation process. Perhaps this is due to the complexity of the calculations.

In the works (Garcés et al., 2021) the author claims that with the help of intelligent control, it is possible to ensure a faster decrease in tank temperature and achieve more stable overheating control in the first evaporator tank. But in this paper there is also no disclosure of the issue of using intelligent regulators to regulate other parameters (for example, pressure, syrup level, flow rate). In addition, this paper considers only the possibility of using intelligent regulators in buildings other than the first. The problem of controlling other parameters of the evaporation process is considered in the work (Verma et al., 2018). In this paper, it is proved that evaporation control can be implemented by recirculation of fluid in the evaporation section or by supplying only liquid to the evaporator. But this paper also does not address the use of intelligent regulators in the evaporation process. In the paper (Cao et al., 2020), the authors research decision-making subsystems and argue that their use in automation systems can improve the quality of automation processes by reducing the human factor, but for the correct operation of the decision-making subsystem, it is also necessary to develop a forecasting subsystem. However, the work does not consider the evaporation process.

The paper explores the use of methods for regulating the consumption of syrup in an evaporator with a subsystem of forecasting and decision support, which will allow to predict the behavior of the system and derive a ready-made forecast, which will thus increase the efficiency of the evaporation station.

The aim of the work is to substantiate the methods of regulating the consumption of syrup in the evaporator with the forecasting subsystem and the decision-making subsystem. This will make it possible to predict the behavior of the system during the formation of the control action and display the finished forecast on the operator's screen, increasing the efficiency of the evaporation station by reducing the influence of the human factor on the process.

Materials and methods

Object and subjects

As the station on which the study was conducted, a five-corps evaporation station of the sugar factory was taken. Figure 1 shows the scheme of automation of the contours for regulating the flow rate of the syrup. In the syrup flow control circuits, induction flow meters COMACCAL FLOW 28 are used as a sensor (FE 14a, FIT 14b). Induction flow meters are used for instantaneous and total measurement of water and conductive fluids in filled pipelines. The principle of their operation is based on the phenomenon of electromagnetic induction. With the help of electrodes isolated from the pipe and recessed into a level with an insulating layer, the electromotive force is removed, which in the measuring unit is amplified and converted into a unified current signal of 0 – 5 mA. Measurement error ±1.5%. As secondary display devices (FIS 14c) selected KD140M manufactured by "LPZ Lviv Instrument-Making Plant". These devices are designed to work complete with non-interchangeable primary transducers (sensors) that convert the measured non-electric quantities (pressure, flow rate, level, vacuum) into an AC output signal (340 ± 30) mV (at a current of 250 mA) by 1 mm of movement of the sensor plunger. The signal goes to the controller (PLC) to the control unit (intersection with C), as well as to the human-machine interface (SCADA) in which the syrup flow value is displayed on the screen of the automated workplace of the operator (computer) (intersection with I). The resulting data is stored in memory (R). These data (the actual values of the syrup consumption) are used to conduct this experiment. If the syrup consumption value exceeds the set limits, then an alarm (A) is generated. The control signal output by the controller (AO) goes to the electropneumatic converter (LY 14e), which converts an analog unified electrical signal. In turn, the actuator (for example, 9f) changes the position of the control valves. The operator can control the position of the regulator in remote (manual) mode (intersection with C – remote control from the SCADA operator). To switch the "Manual/Automatic" mode (HS 14d, HC 14d), the

BRU-17 manual control units were used. It has one analog input with support for a unified signal of 0-5 mA, 0-20 mA or 0-10 V and one analog output with support for a unified signal of 0-5 mA, 0-20 mA or 0-10 V. Supports interfaces and protocols of the RS-485 and ModBus network. Modicon M340 is used as a controller. Modicon M340 is an industrial logic controller for machine manufacturers, small and medium-sized automation systems. Supports 4 MB of memory for saving programs and 256 KB for data storage. It is equipped with built-in communications such as the CANopen bus, supports TCP/IP Ethernet network, RTU serial interface, and ASCII character interface. This controller uses the BMX AMI 0810 input module and the BMX AMO 0410 output module The pneumatic saddle valves (14f) Danfoss VFG33, with a built-in throttle and an electro-pneumatic converter, were used as actuators (Hrama et al., 2019).

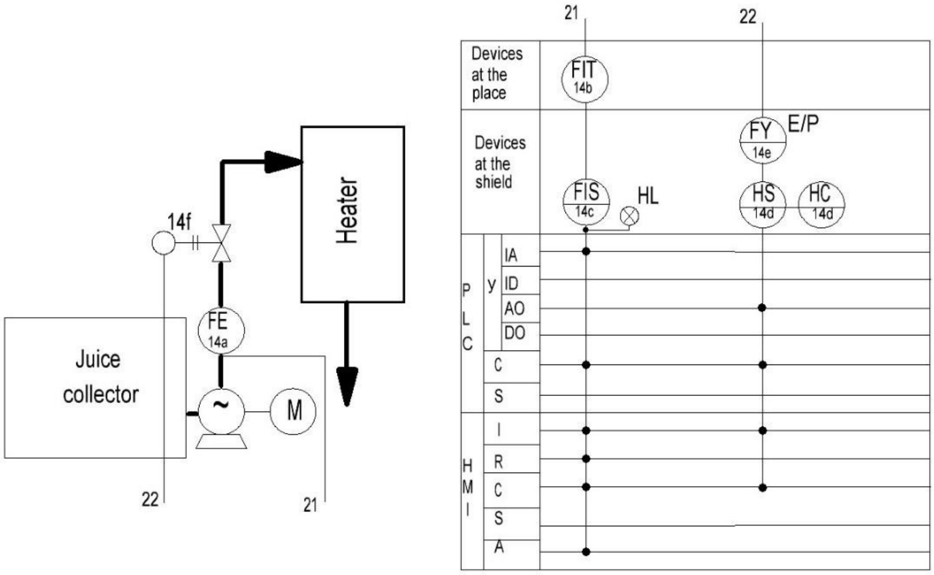

Figure. 1. Automation of the control circuit of the flow rate of the evaporation station syrup

Description of the methodology for developing a decision-making subsystem

In this paper, a method of calculating and forecasting user priorities for the development of a decision-making subsystem was chosen.

To work with this technique, it is necessary to obtain information about users (U), their requests (Q) and their requests for modification (D). Obtaining this data allows you to form time series of changes in priority estimates (1) (Piazzoni et al., 2020):

$$X = \{x_t, t = t', \ldots N\} \qquad (1)$$

where t is the observation number, , $t \in (1,\ldots N)$

t' – the number of observation in which the user's request was first recorded,

x_t – the value of the priority of the user's request at the time of the start of iteration with the number t,

N – the number of iterations during which monitoring and prioritizationof user requests is carried out.

The result of the chosen methodology is to obtain recommendations P_j in the form of estimates of requests for changes in the human-machine interface (2) (Zgurovsky et al., 2018), ranked by the degree of importance:

$$P_j = F(x_{N+1,j}, B(X_j)), j = 1,...,L \tag{2}$$

where x_{N+1} is the projected priority score of the user's request,

j – user request identifier,

L – the number of user requests to make changes to the human-machine interface,

$B(X_j)$ – assessment of the trend of changing the priority of the user request, obtained by the time series X_j,

F – the procedure for integrating point predictive $x_{N+1,j}$ and temporal $B(X_j)$ estimates of the priority of user requests for changes to the human-machine interface.

This technique of prioritizing user requests to make changes to the human-machine interface consists of several of the following steps (Rajan et al., 2017):

1. Stage of data extraction and transformation. The provided stage is the removal of data from the database of records of user requests for changes. Converting these hits to a modification of the human-machine interface. At this stage, information is generated about users (U), their requests (Q) and their requests for modification (D). Next, a matrix of relations of user requests (R) is formed. After that, point and temporal estimates of the priorities of modification requests (X_j and $B(X_j)$) are calculated.
2. At the second stage, there is a modeling and forecasting of estimates of priorities for the time series X_j. First you need to build models of fuzzy time series using linguistic variables. Next, the forecasting of point estimates of priorities based on fuzzy models is carried out.
3. At the third stage, recommendations are formed for the decision-making subsystem. The basis for this is the linguistic summary of temporal and predictive estimates of the priorities of user requests.

For the correct development of the decision-making subsystem, it is necessary to collect data (Lin et al., 2019). Input data are the key characteristics of human-machine interface users and information about their actions. Data on the main characteristics of users can be recorded in the following form (3) (Talebi et al., 2019):

$$U = \{u_i, i = 1,...,M\} \tag{3}$$

where u_i is the key characteristic of the user; i – user ID; M – number of users.

Only those data that are necessary for the study and correspond to the declared period during which the data will be processed are uploaded from the database. To do this, the human-machine interface must contain the ability to identify users (Lin et al., 2008). The list of requests (Q) to make changes to the human-machine interface can be written as follows (Cao et al., 2020) (4):

$$\begin{gathered} Q = \{q_k, k = 1,...,K\} \\ q_k = \{i, j, t\} \end{gathered} \tag{4}$$

where q_k is a description of user requests for changes in the human-machine interface.

k – hit index,

K – number of hits,

i – user ID,

j – user hover identifier,

t – iteration number of the development.

It is also necessary to classify user appeals in order to separate changes to change the type of regulation (Talebi et al., 2019). The list of requests for changes to the human-machine interface can be written as follows (Lakhno et al., 2017) (5):

$$D=\{d_j, j=1,...,L\} \tag{5}$$

where d_j – description of the user's request; j – user hover identifier; L – the number of user requests to make changes to the human-machine interface.

Another important parameter is the date and time when the user makes changes to the human-machine interface (Piazzoni et al., 2020). This parameter is necessary for the formation of time series of estimates of the priorities of requests for changes to the human-machine interface (Zgurovsky et al., 2018).

The priority of a human-machine interface change request can be calculated as follows (6) (Talebi et al., 2019):

$$R=\{r_{i,j}\}$$
$$r_{i,j}=\begin{cases} t', \text{ if } \{i,j,t\}\in Q, \\ 0 \end{cases} \tag{6}$$

where R is the relationship matrix, $r_{i,j}$ – iteration number of development t'.

Next, it is necessary to calculate the point and temporal estimates of the priorities of modification requests for each problem, which are received from users in the form of time series (Rajan et al., 2017). The calculation of these estimates allows you to display information on requests for changes in the human-machine interface in more detail (Piazzoni et al., 2020). After that, the user's priority score is calculated and a temporal assessment is formed, which is considered as a fuzzy trend (Talebi et al., 2019). To this end, it is necessary to develop a special algorithm for assessing the priority of user requests based on the data obtained according to the methodology described above (Zgurovsky et al., 2018).

On the basis of this method of developing a decision-making subsystem, the basic requirements for the functioning of the software for the operation of the evaporation station are formed (Piazzoni et al., 2020). Several iterations of software development were carried out. The development involved 20 users who made approximately 100 requests. The results of the survey after processing according to the algorithm (Figure 3) were entered in Table 4. Fragments of data received from users are given in Tables 1–3:

Table 1

Description of user requests for software modification

a	b
1	The possibility of changing the regulation regime.
2	Revision of regulation forecasting using different types of regulators.
3	Derivation of recommendations for changing the regulatory regime.
4	Display information on possible changes to the adjustment parameters of other control circuits.

where a is the user request ID, j. Set in random order (Piazzoni et al., 2020); b – description of user requests, d.

Table 2

Description of key user characteristics

a	**b**
1	Director
2	Engineer
3	Engineer
4	Operator
...	...
20	Operator

where a is the user request index, i. Set in order from the highest position to the lowest (Piazzoni et al., 2020); b – key characteristic of the user.

Table 3

Description of user requests

a	**b**	**c**
2	1	1
3	1	1
4	2	3
5	4	2
...	...	...
1	3	4

where a is the user request index, i; b – user request identifier, j; c is the iteration number of software development, t. Installed in the order of software development from the first iteration to the last (Piazzoni et al., 2020).

Description of forecasting by local trends

Forecasting the operation of an evaporation station using the method of local trends occurs using fuzzy time series models (Jolly et al., 2000).

To obtain a predictive local trend, a fuzzy time series model is generated (Lahtinen., 2001). For this purpose, a model (Figure 4) of a fuzzy dynamic process with a fuzzy increment is used, which looks like this: – a universal set for which fuzzy sets are defined $X_t(t=1,2,...) \subset R^1$ $\tilde{x}_t^{\,i},(i=1,2,...)$, $\tilde{v}_t^{\,j},(j=1,2,...)$, $\tilde{a}_t^{\,s},(s=1,2,...)$ (Dong et al., 2017).

Next, the parameter value of the first-order time series model is set (Lei et al., 2016) and the sum of the intensities of fuzzy elementary trends for each interval is calculated by creating an algorithm of fuzzy local trends for this case (Dong et al., 2017).

To predict the operation of an automated evaporation station, the following algorithm was used: first, it is necessary to convert the initial time series into a fuzzy time series. The next step is to convert the resulting fuzzy time series into a time series of fuzzy elementary tendency and dephase the intensity center of gravity method of each fuzzy elementary trend for each time series $a_t = DeFuzzy(\tilde{a}_t)$ (Anghinoni et al., 2019).

Analysis of the stability of the forecasting model is as follows. The automation system of the five-corps evaporation station is launched (Figure 1), after which the transient graphs and projected values during the operation of the station are removed from the SCADA system (Dong et al., 2017). They are shown in Figure 6. Further, the graphs are divided into an arbitrary number of equal time intervals (González-Potes et al., 2016). Each time interval is separated from the next by a point with the name in Latin letter. The value to which the transient corresponds to at a given time is the actual value, and the value that corresponds to the graph with the projected values at a given time is the predicted value. All these values are recorded in Table 1. The values of the absolute and relative forecasting error for each point are also calculated and recorded in Table 1 (Dong et al., 2017).

The value of absolute error (A) is calculated by the formula (7).

$$A = \left| Z(t) - \tilde{Z}(t) \right| \tag{7}$$

where $Z(t)$ is the actual value of the time series,

$\tilde{Z}(t)$ – forecast value of the time series

The relative error value (V) for each time series point value is calculated using the following formula (8):

$$V = \frac{\left| Z(t) - \tilde{Z}(t) \right|}{Z(t)} \times 100\% \tag{8}$$

The next step is to assess the accuracy of the system. The automation system of the five-corps evaporation station is launched (Figure 1), the type of regulation is selected, after which the transient graphs and predicted values during the operation of the station are removed from the SCADA of the system. They are shown in Figure 6. Further, the graphs are divided into an arbitrary number of equal time intervals (González-Potes et al., 2016). Each time interval is separated from the next by a point with the name in Latin letter. The value to which the transient corresponds to at a given time is the actual value, and the value that corresponds to the graph with the projected values at a given time is the predicted value. All these values are recorded in Table 1. The values of absolute errors are calculated using the formula (7). The average error (SP) is calculated by the formula (9) (Dong et al., 2017):

$$SP = \frac{1}{n} \sum_{t=1}^{n} (Z(t) - \tilde{Z}(t)) \tag{9}$$

where SP is the average error of the forecast value of the time series,

n – the number of intervals of the time series, $Z(t)$ – the actual value of the time series, $\tilde{Z}(t)$ – forecast value of the time series (Lei et al., 2016).

The average absolute error (SAP) is calculated by the formula (10).

$$SAP = \frac{1}{n} \sum_{t=1}^{n} \left| Z(t) - \tilde{Z}(t) \right| \tag{10}$$

The average relative forecasting error (SVP) is calculated by the formula (11) (Lei et al., 2016).

$$SVP = \frac{1}{n} \sum_{t=1}^{n} \frac{\left| Z(t) - \tilde{Z}(t) \right|}{Z(t)} \times 100\% \tag{11}$$

The accuracy of the forecasting model (T) is calculated by the formula (12)

$$T = 100\% - \frac{1}{n} \sum_{t=1}^{n} V \tag{12}$$

The closer to 100% the accuracy index of the model (T) approaches, the more accurate the model is (Lei et al., 2016).

Results and discussion

Analysis and synthesis of control action using forecasting methods in the control system of the evaporation station

We propose to use a block diagram of regulation (Hrama et al., 2022), modifying it in such a way as to include the possibility of forecasting (Lei et al., 2016) and decision-making subsystems (Piazzoni et al., 2020).

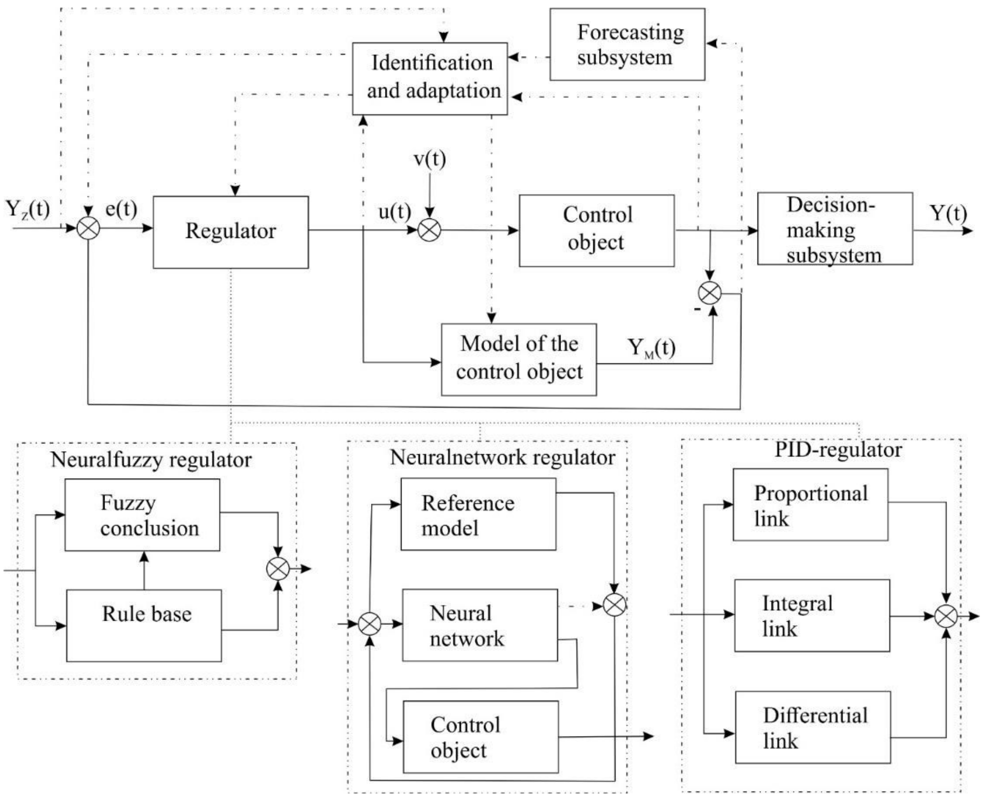

Figure. 2. Figure of the structural scheme of regulation

The block diagram of the regulation is shown in Figure 2, where $Y_z(t)$ is the signal of the task, e(t) is the disagreement between the task signal and the feedback, u(t) is the control signal, v(t) is the external perturbation, Y(t) is the output signal, $Y_M(t)$ is the output signal from the object model.

In more detail, the work of intelligent regulators, on the example of fuzzy ones, is discussed in the work (Tang et al., 2001). In this work, a fuzzy PID controller was researched as a discrete version of a conventional PID controller, so it retains the same structure, but has an independent adjustable control factor. It is proved that it is possible to improve the classic PID controller with a certain adaptive control ability. But this regulator cannot be considered a full-fledged neural fuzzy regulator. In addition, this paper also does not consider the use of other types of intelligent regulators. A possible reason for this may be the costly part in conducting research. The problems of using neural obfuscive regulators are discussed in more detail in the work (Chantasiriwan, 2017). This work presents a new PID controller of fuzzy logic. This regulator is a fuzzy PID controller with a computational efficient analytical scheme. The author proves that the controller is stable with limited input / limited output However, this regulator is very difficult to implement, and this paper does not provide the possibility of using other types of intelligent regulators. In addition, there is no possibility of using this regulator for some adjustment parameters. Also, none of the above works has any justification for updating existing automation systems for the evaporation station. A possible reason for this may also be the costly part in conducting research. The use of neural sensors is considered in the work (Sidletskyi et al., 2019). The data says that one of the advanced methods of improving control systems is the addition of fuzzy and neural fuzzy logic. Methods of dynamic power control were analyzed using fuzzy logic and adaptive neural networks. One of the possible options for regulating power is the use of fuzzy conclusions (the so-called fuzzy system). The control action is formed by checking the consistency of fuzzy rules for the actual parameters of the system. Rules are created in accordance with the experience of the operator, which reflects his / her actions when changing technological parameters. But this work does not consider the use of neural regulators in the evaporation process. In addition, it also does not address other types of intellectual regulation.

Synthesis of the algorithm of the decision-making subsystem

To assess the priority of user requests to make changes to the human-machine interface and the formation of time series with their help, a special algorithm was developed (Figure 3).

The first step of this algorithm is to determine the iteration number of the development of a human-machine interface. To do this, determine the value of t', at which the value of the vector $\{r_i\}$ will be minimal, but not zero (Zgurovsky et al., 2018). A zero value means that users of a human-machine interface do not address a given function or problem (Rajan et al., 2017).

The next step is to determine the estimate of the priority x_t of some user request to make changes to the human-machine interface (Talebi et al., 2019). This calculation occurs according to the formula (6). In this algorithm, the intensities of fuzzy trends of various types are grouped, followed by the formation of linguistic rules of the main trend of time series. The implementation of this algorithm allows you to form a set of estimates of the priorities of requests. In this study the following estimates are used: "Increase in request priorities", "Decrease in request priorities", "Priorities remain stable", "Uncertainty of changes in priorities", "Fluctuations in changes in priorities", "Increase in request priorities with fluctuation", "Decrease in query priorities with fluctuation". If you apply this algorithm for each user request to make changes to the human-machine interface of the evaporation station and attribute each request to its corresponding time series, you can determine the linguistic term that carries information about changes in priorities (Rajan et al., 2017). This information allows you to form recommendations of the decision-making subsystem (Piazzoni et al., 2020).

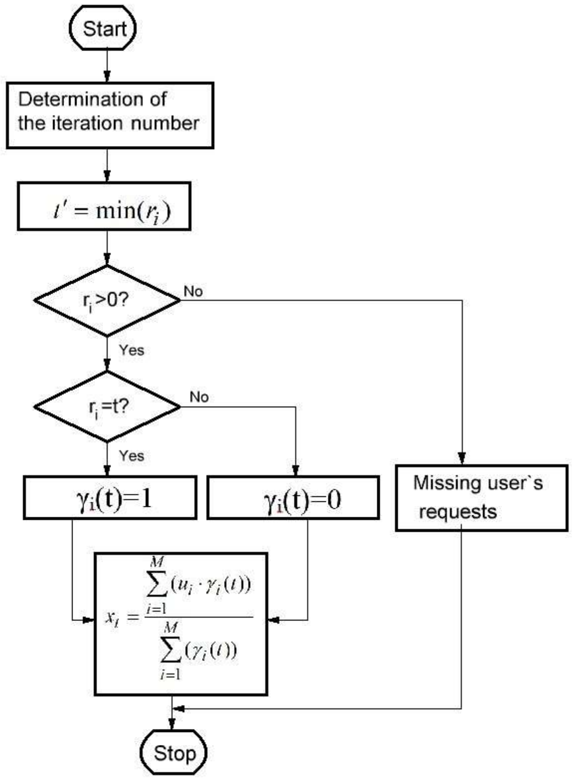

Figure. 3. Special algorithm for assessing the priority of user requests

The next step, according to formula (1), we form time series for changing priority estimates (Talebi et al., 2019). The following is the time series for displaying information about possible changes to the adjustment parameters of other control circuits (13):

$$X_1 = \{3,1;2,2;1,3;1,4\} \tag{13}$$

So, from the time series X_1 we can say that at the first observation, the function of displaying information about the possible changes to the parameters for regulating other control circuits among users had a third priority, but with further observations, the priority of this function increased and after the third observation took first place (Zgurovsky et al., 2018). From this we can conclude that the projected priority of users of this function will be high (Piazzoni et al., 2020).

Therefore, according to the formula (2), you can get recommendations P and in the form of ranked estimates of queries (Talebi et al., 2019). For the function of displaying information about the possible changes to the parameters of regulation of other control circuits, the following series has the form (14):

$$P_1 = F(1, \text{"Very important"}) \tag{14}$$

According to the formula (3), data on the main characteristics of users can be written in the following form (15):

$$U = \{\text{"}director\text{"},1;\ \text{"}engineer\text{"},2;\ \text{"}engineer\text{"},3;...;\text{"}operator\text{"},20\} \tag{15}$$

Next, the formula (4) creates a list of requests for changes to the human-machine interface:

$$q_1 = \{1, 5, 2\} \quad (16)$$

According to formula (5), it is necessary to classify user appeals in order to separate the introduction of changes to change the type of regulation (Lin et al., 2008):

$$D = \{\text{"change of regulation type"}, 5\} \quad (17)$$

Next, using the formulas (1) and (2), the relationship matrix is filled in to determine the priorities of the queries. The formula (6) calculates the determination of priority estimates (Piazzoni et al., 2020). The results are listed in Table 4.

Table 4

Determination of priority assessments

a	b	c	d	e	f
X_1	2	1	Important	Oscillation	Very important
X_2	3	2	Important	Height	Very important
X_3	4	3	Important	Height	Important
X_4	1	4	Important	Height	Very important

where a is the time series (1); b – user request identifier (table 1); c – assessment of the priority of the request (13); d – linguistic evaluation of the request (6); e – tendency to change the priority of the request (2); f – Recommendation for creating functional requirements (14).

According to Table 4, it can be concluded that the most important in the output of information by the decision-making subsystem is the function of displaying information about the possible changes to the parameters of regulation of other regulatory circuits, since it has the highest priority rating (Zgurovsky et al., 2018). Also very important is the availability of the function of reviewing the forecasting of regulation using different types of regulators (Rajan et al., 2017). Therefore, during the operation of the decision-making subsystem, these functions will have the highest priority.

Synthesis of the algorithm of local trends

We will develop an algorithm for local trends of the evaporation station. The paper (González-Potes et al., 2016) describes the management of several evaporation stations with full integration of fuzzy control and the use of wireless network sensors and actuators. But in this paper there is no comparison of the use of neural sensors with other types of intelligent regulation and there is no justification for the expediency or inexpediency of using this type of regulation in case of the possibility of introducing a system with another type intelligent control. In addition, neural fuzzy regulation in this study does not apply to all regulatory circuits. The reason for this may be the high complexity and cost of conducting such a study. The authors of the study also meet with similar problems (Tang et al., 2001). In this paper, the control of evaporator overheating using a fuzzy sliding mode controller is considered. In addition, this study does not disclose the use of fuzzy regulation for other circuits of regulation of the evaporation station.

It is necessary to improve the model of forecasting the operation of the evaporation station by the method of local tendency and the forecasting algorithm and determine the influence of the algorithm on the accuracy and stability of the obtained forecasting model.

To work with the algorithm of local trends, we set the following parameter dependencies (Lei et al., 2016):

$$\tilde{x}_i = Fuzzy(x_i),$$
$$\tilde{\upsilon}_i = TTend(\tilde{x}_i, \tilde{x}_{i-1}),$$
$$\tilde{\upsilon}_{i+1} = \tilde{f}_{\tilde{\upsilon}}(\tilde{\upsilon}_i),$$
$$\tilde{a}_i = RTend(\tilde{a}_i, \tilde{a}_{i-1}),$$
$$\tilde{a}_{i+1} = \tilde{f}_{\tilde{a}}(\tilde{a}_i),$$
$$\tilde{x}_{i+1} = Comp(\tilde{x}_{i+1}, \tilde{\upsilon}_{i+1}, \tilde{a}+1),$$
$$x_{i+1} = DeFuzzy(\tilde{x}_{i+1}) + \varepsilon_{i+1},$$

Figure. 4. First-order time series model

Where Fuzzy is the operation of the phase of the scale, TTend is the operation to determine the type of difference, RTend is the operation to identify the intensity of the difference, Comp is the operation to calculate the new fuzzy assessment, DeFuzzy is the operation of defasification of the scale. $\tilde{f}_{\tilde{\upsilon}}, \tilde{f}_{\tilde{a}}$ – fuzzy dependencies are presented in the form of a composite implication rule, $x_{i+1}, \varepsilon_{i+1}$ – numerical estimate and error of the predicted level of the time series.

In this model, an absolute fuzzy estimate $\tilde{x}_i$ is determined by phasifying the scale according to the value of the object being evaluated x_i. Next, an operation takes place to determine the type of differences and the next step is the process of determining the intensity of the differences. After that, a new absolute fuzzy estimate is calculated (Xu et al., 2020). The final step is the defasification of the scale according to the definition of the object x_i being evaluated according to an absolute fuzzy estimate $\tilde{x}_i$.

A two-stage algorithm for selecting a time series forecasting model has been developed (Dong et al., 2017). It is calculated the sum of the intensities of fuzzy elementary trends for each interval (Figure 5).

Using the algorithm (Figure 5), it is possible to evaluate local trends using linguistic and numerical forms (Anghinoni et al., 2019). To work this algorithm, it is necessary to convert the initial time series to a fuzzy time series (Mehmood et al., 2021) using the model shown in Figure 1. The next step in the implementation of this algorithm is to divide the resulting time series into a certain number of intervals. At each interval, the sum of the intensities of the same type of fuzzy elementary trends is calculated. Further, comparing the time intervals with growth (ST_{up}) and decrease (ST_{down}) of the time intervals of the length of a fuzzy trend, the type of local trend ("Stable", "Growing", etc.) is chosen (Xu et al., 2020).

This algorithm does not require additional interpretation by the user. The disadvantage of this algorithm is the limitation of its operation by the number of predetermined time intervals, which is why the number of identified local trends will be equal to the number of intervals specified by the developer (Anghinoni et al., 2019). This algorithm allows you to get time series, which can be used in the future to predict local trends. The advantage of this algorithm is the ability to reduce the knowledge base, which can be represented as a set of rules that are generated by a fuzzy time series (Dong et al., 2017).

$$
\begin{aligned}
&if\ P_{up}(\tau_t) = true\ then\ ST_{up} = ST_{up} + a_t,\\
&if\ P_{down}(\tau_t) = true\ then\ ST_{down} = ST_{down} + a_t,\\
&if\ ST_{up} = 0\ and\ ST_{down} = 0\ then\\
&\tilde{\upsilon}=\text{"Stable",a=0},\\
&if\ ST_{up} \geq 2 \cdot ST_{down}\ then\\
&\tilde{\upsilon}=\text{"Up",a=abs}(ST_{up} - ST_{down}),\\
&if\ ST_{down} \geq 2 \cdot ST_{up}\ then\\
&\tilde{\upsilon}=\text{"Down",a=ads}(ST_{up} - ST_{down}),\\
&if\ 0{,}9 \cdot ST_{up} \leq ST_{down} \leq 1{,}2 \cdot ST_{up}\\
&or\ 0{,}9 \cdot ST_{down} \leq ST_{up} \leq 1{,}2 \cdot ST_{down}\\
&then\ \tilde{\upsilon}=\text{"Regular",a=}(ST_{up} + ST_{down})/2\\
&else\ \tilde{\upsilon}=\text{"Chaos",a=abs}(ST_{up} - ST_{down}),\\
&\tilde{a} = Fuzzy(a).
\end{aligned}
$$

Figure. 5. Algorithm of local trends for research
P – the finite set of points on the interval n (the finite set of tendencies);
ST – the time interval of the length of a fuzzy trend.

Result of the syrup flow forecasting algorithm with the decision-making subsystem

The result of the algorithm execution (Figure 5.) Forecasting of an automated syrup consumption system using intelligent regulation and a decision-making subsystem is shown in Figure 5. Forecasting of an automated syrup consumption system using intelligent regulation and a decision-making subsystem is shown in Figure 5. Forecasting of an automated syrup consumption system using intelligent regulation 6. Table 5 shows the results of calculations for the consumption of syrup using PID, neural fuzzy, and neural network regulators. Based on the results presented in the table, we can conclude that, since the value of SP is negative, the forecast was overestimated relative to the actual data (Lei et al., 2016). This is true, since the forecast shows a small absolute error of 1% when using neurone-fuzzy regulation. And with the actual use of this type of regulation, it is absent. However, this overestimation is insignificant, as can be seen from the indicator of the average relative error of forecasting (Dong et al., 2017).

In theory, when applying the average relative error in assessing the accuracy of the model for predicting the evaporation process, the value of forecast accuracy can reach 100% (Lei et al., 2016). This will mean that the selected forecasting model describes the process with absolute accuracy (Anghinoni et al., 2019). In practice, such a phenomenon is almost impossible, since the forecast cannot take into account absolutely all the factors that affect the automation system (Xu et al., 2020). In the case when the value of forecast accuracy approaches 0%, then this model does not describe the predicted process at all (Butt et al., 2020).

Table 5

Indicators for assessing the error of forecasting the consumption of syrup

№	a	b	c	d	e	f	g
PID regulator							
1	A	0	0	0			
2	B	222	223	1			
3	C	217	215	2			
4	D	215	214	1	-0,8	0,8	2
5	E	215	214	1			
6	F	215	214	1			
7	G	215	214	1			
Accuracy of the forecasting model (12):						98%	
Neural obscure regulator							
1	A	0	0	0			
2	B	214	216	2			
3	C	215	214	2			
4	D	215	214	2	-0,9	0,9	5
5	E	215	214	1			
6	F	215	214	1			
7	G	215	214	1			
Accuracy of the forecasting model (12):						95%	
Neural network regulator							
1	A	0	0	0			
2	B	217	216	1			
3	C	215	214	1			
4	D	215	214	1	-0,9	1,27	4
5	E	215	214	1			
6	F	215	214	1			
7	G	215	214	1			
Accuracy of the forecasting model (12):						96%	

where a – Point name, b – Actual value, m^3/h, c – Predicted value, m^3/h, d – Absolute error, %, e – mean error (SP) (9), f – mean absolute error (SAP) (10), g – average relative forecasting error (SVP) (11).

The forecast accuracy indicator is also used to select the optimal forecasting model. The optimal model is the model whose accuracy is closest to 100% (Lei et al., 2016), since it is more likely to make a more accurate forecast.

Since, in our case, the value of the average relative error is 5%, it follows that the accuracy of the model is 95%, which is a very high assessment of the quality of our forecasting system. Since the accuracy of the forecasting model is very close to 100%, it can be considered optimal (Dong et al., 2017).

In order to correctly understand how much, you can trust the obtained algorithm for predicting the evaporation process, it is also necessary to assess the accuracy of the forecast obtained (Lei et al., 2016). In Figure 4 shows a comparison of the predicted value of the change in the flow rate of syrup using PID, neurone-fuzzy and neural network regulators and the actual change in syrup consumption.

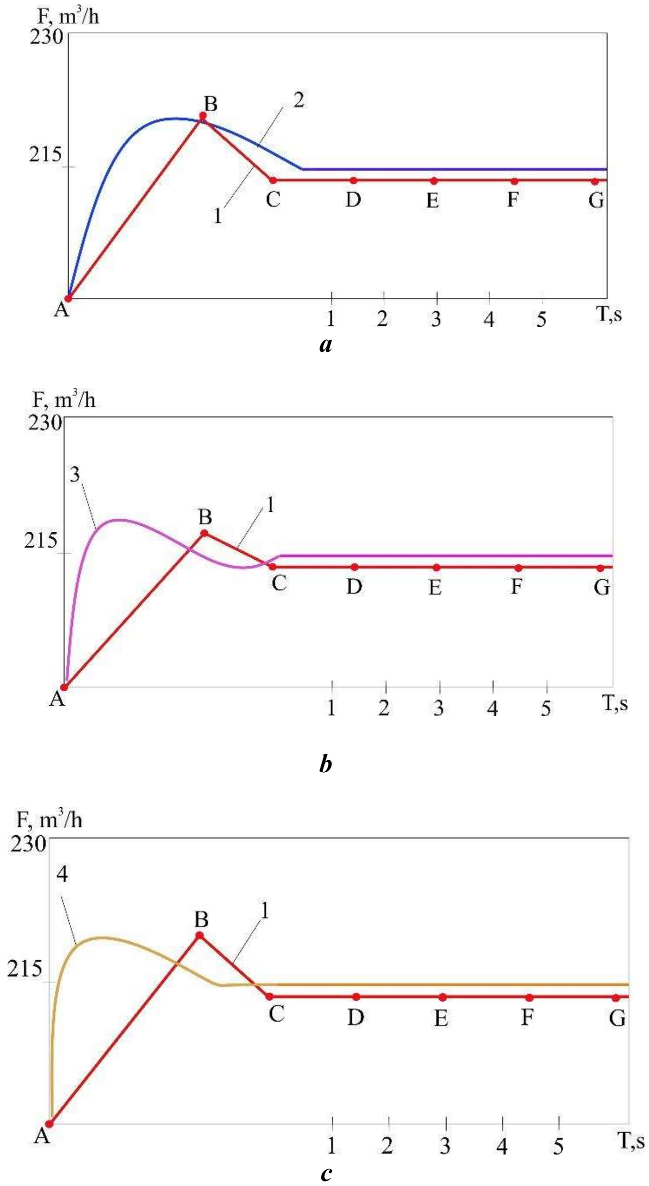

Figure 6. Comparison of the transients of the predicted and actual consumption of the syrup in the first building of the evaporation station using:

a – PID;
b – neurone-fuzzy;
c – neural network regulators;
1 (▬) – the projected value of the syrup consumption;
2 (▬) – the actual value of the syrup consumption (PID-regulator);
3 (▬) – the actual value of the syrup consumption (neurone-defunt regulator);
4 (▬) – actual value of syrup consumption (neural network regulator);
AB, BC, CD, ..., JK – time series intervals.

In this study, a forecasting method was used to compare methods for regulating the flow rate of syrup in the apparatus, which makes it possible to predict the behavior of the system during the formation of the control action and display the finished forecast on the operator's screen and, thus, increase the efficiency of the evaporation station. The advantage of this method is its easy and quick implementation, which does not require large economic and energy costs. The disadvantage of this method is the need to break the transient process into separate time intervals of the number series manually and the direct dependence of the accuracy of the model on the number of elements of the time series.

In other studies, most of the problems of intelligent control in the process of evaporation remain unresolved. The use of neural regulators occurs only in certain specific cases. In addition, there is no comparison of the use of intelligent regulators with classic ones. There is also no coverage of the possibility of combining the work of several types of intelligent regulators if necessary. In addition, there are no clear means of forecasting the work of intelligent regulators and decision-making subsystems.

Conclusions

1. After researching a large number of sources, it was concluded that in other studies, most of the problems of intelligent control in the evaporation process remain unresolved. The use of neural regulators occurs only in certain specific cases. Therefore, a model for predicting the operation of an evaporation station by the method of local tendency was built and a forecasting algorithm and an algorithm for the decision-making subsystem were developed.
2. An algorithm for assessing the priority of user requests according to the method of calculating and forecasting priorities was developed. The result of this algorithm was the determination of priority estimates, which showed that the most important in the output of information by the decision-making subsystem is the function of displaying information about the possible changes to the parameters of regulation of other regulatory circuits, since it has the highest priority rating.
3. A model of forecasting the operation of an evaporation station by the method of local tendency is constructed and a forecasting algorithm has been developed. The accuracy of the obtained forecasting model is also evaluated. The accuracy of the forecasting model was 98% for the PID controller, 95% for the neural non-fuzzy regulator and 96% for the neural network, which are high rates The advantage of this model is its high accuracy in general, but the disadvantage is that during the occurrence of oscillations in the transition process, there is an insignificant delay in predicting these fluctuations.
4. Statistical data of the behavior of the contours of the automation system in different modes of operation using intelligent and classical regulators were collected, a model for predicting the operation of an evaporation station by the method of local tendency was built and a forecasting algorithm was developed. The advantage of this method is its easy and quick implementation, which does not require large economic and energy costs. The disadvantage of this method is the need to break the transient process into separate time intervals of the number series manually and the direct dependence of the accuracy of the model on the number of elements of the time series.

References

Anghinoni L., Zhao L., Zheng Q., Zhang J. (2018), Time series trend detection and forecasting using complex network topology analysis, *International Joint Conference on Neural Networks*, 2018, pp. 1–7, DOI: 10.1109/IJCNN.2018.8489167.

Cao H., Li M., Zhao S., Song, X. (2020), Decision making, planning, and control strategies for intelligent vehicles, *Synthesis Lectures on Advances in Automotive Technology*, 4(3), pp. 1–138, DOI: 10.2200/s01019ed1v01y202006aat012.

Chantasiriwan S. (2017), Distribution of juice heater surface for optimum performance of evaporation process in raw sugar manufacturing, *Journal of Food Engineering,* 195, pp. 21–30, DOI: 10.1016/j.jfoodeng.2016.09.014

Dong Q., Sun Y., Li P. (2017), A novel forecasting model based on a hybrid processing strategy and an optimized local linear fuzzy neural network to make wind power forecasting: A case study of wind farms in China, *Renewable Energy,* 102, pp. 241-257, DOI: 10.1016/j.renene.2016.10.030.

Garcés R., Lomas J., Pilatasig J. G., Andaluz, V., Tutasig A., Zambrano A., Varela-Aldás J. (2021), Virtual control of a double effect evaporator for teaching-learning processes, *Lecture Notes in Computer Science*, pp. 690–700, DOI: 10.1007/978-3-030-87595-4_50.

González-Potes A., Mata-López W.A., Ochoa-Brust A.M., Pozo C.E. (2016), Smart control of multiple evaporator systems with wireless sensor and actuator networks, *Energies, 9*, pp. 1–24, DOI: 10.3390/en9030142.

Hrama M., Sidletskyi V., Elperin I. (2019), Justification of the neuro-fuzzy regulation in evaporator plant control system, *Ukrainian Food Journal, 8*, pp. 873–890, DOI: 10.24263/2304-974x-2019-8-4-17

Hrama M., Sidletskyi V., Elperin I. (2022), Intelligent automatic control of sugar factory evaporator operation using behavior prediction subsystem, *Ukrainian Food Journal,* 11(1), pp. 148–163, DOI: 10.24263/2304-974X-2022-11-1-14.

Jolly P.G., Tso C.P., Chia P.K., Wong Y. (2000), Intelligent control to reduce superheat hunting and optimize evaporator performance in container refrigeration, *HVAC&R Research,* 6, pp. 243-255, DOI: 10.1080/10789669.2000.10391261

Lahtinen S. (2001), Identification of fuzzy controller for use with a falling-film evaporator. *Food Control*, *12,* pp. 175–180, DOI: 10.1016/S0956-7135(01)00004-4.

Lakhno V., Boiko Y., Mishchenko A., Kozlovskii V., Pupchenko O. (2017), Development of the intelligent decision-making support system to manage cyber protection at the object of informatization, *Eastern-European Journal of Enterprise Technologies,* 2(9 (86)), pp. 53–61, DOI: 10.15587/1729-4061.2017.96662.

Lei H., Xia Y., Qin X. (2016), Estimation of semivarying coefficient time series models with ARMA errors, *Annals of Statistics, 44*, pp. 1618-1660, DOI: 10.1214/15-AOS1430.

Lin C., Wu W. (2008), A causal analytical method for group decision-making under fuzzy environment, *Expert Systems With Applications*, 34(1), pp. 205–213, DOI: 10.1016/j.eswa.2006.08.012.

Lin L., Wang F., Luo B. (2019), An optimization algorithm inspired by propagation of yeast for fleet maintenance decision making problem involving fatigue structures, *Applied Soft Computing*, 85, pp. 105–117, DOI: 10.1016/j.asoc.2019.105755.

Mehmood B., Hussain L., Mahmood A., Lone K. (2020), Artificial Intelligence based accurately load forecasting system to forecast short and medium-term load demands, *Mathematical Biosciences and Engineering,* 18(1), pp. 400-425, DOI: 10.3934/mbe.2021022.

Petrenko V., Maslikov M., Boyko V., Miroshnik M. (2022), Speed of temperature relaxations on evaporator stations in transitional modes, *Scientific Works of National University of Food Technologies*, 28(1), pp. 104–116, DOI: 10.24263/2225-2924-2022-28-1-11.

Piazzoni A., Cherian J., Slavik M., Dauwels J. (2020), Modeling perception errors towards robust decision making in autonomous vehicles, *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence.* DOI: 10.24963/ijcai.2020/483.

Rajan B., Chandra V. (2017), ABC metaheuristic based optimized adaptation planning logic for decision making intelligent agents in self adaptive software system, *Data Mining and Big Data*, pp. 496–504, DOI: 10.1007/978-3-319-61845-6_49.

Said A, Ishak N., Tajjudin M., Kasuan N. (2021), ARX Modeling and FPID with model reference controller design of a hot air blower system. *2021 IEEE 9th Conference on Systems, Process and Control (ICSPC 2021),* DOI: 10.1109/icspc53359.2021.9689080.

Sidletskyi V., Korobiichuk I., Ladaniuk A., Elperin I., Rzeplińska-Rykała K. (2020). Development of the structure of an automated control system using tensor techniques for a diffusion station, *Automation 2019. Advances in Intelligent Systems and Computing*, 920, pp. 175–185, DOI: 10.1007/978-3-030-13273-6_18

Talebi S., Simaan M., Qu Z. (2019), Decision-making in complex dynamical systems of systems with one opposing subsystem, *2019 18th European Control Conference (ECC)*, DOI: 10.23919/ecc.2019.8796292.

Tang K., Man K., Chen G., Kwong S. (2001) An optimal fuzzy PID controller, *IEEE Transactions on Industrial Electronics*, 48(4), pp. 757–765, DOI: 10.1109/41.937407.

Verma O., Gaurav M., Vinay K. (2018), Simulation and control of a complex nonlinear dynamic behavior of multi-stage evaporator using PID and Fuzzy-PID controllers, *Journal of Computational Science, 25*, pp. 238–251. DOI: 10.1016/j.jocs.2017.04.001.

Xu D., Cheng W., Zong B., Song D., Ni J., Yu W., Liu Y., Chen H., Zhang X. (2020), Tensorized LSTM with adaptive shared memory for learning trends in multivariate time series, *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(02), pp. 1395-1402, DOI: 10.1609/aaai.v34i02.5496.

Zgurovsky M., Pavlov A. (2018), The four-level model of planning and decision making, *Combinatorial Optimization Problems in Planning and Decision Making*, pp. 347–406, DOI: 10.1007/978-3-319-98977-8_8.

Анотації

Харчові технології

Вплив рисового борошна на конформаційні перетворення в тісті при виробництві пшеничного хліба

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Вступ. Метою роботи було визначення впливу рисового борошна на конформаційні перетворення в структурі тіста для виготовлення пшеничного хліба, до складу якого внесено лецитин.

Матеріали і методи. Було досліджено рисове борошно, його хімічний склад та фракційний склад білків. Конформаційні перетворення структурних елементів в тісті та хлібі були досліджені методом інфрачервоної спектроскопії у ближній інфрачервоній області.

Результати і обговорення. У рисовому борошні загальний вміст білків на 47% нижчий, ніж у пшеничному борошні, вміст харчових волокон у 8,5 разів нижчий. Фракційний склад білків показав вищий вміст альбуміну, проламіну та нерозчинних білків в пшеничному борошні, ніж в рисовому на 11, 90 та 75% відповідно. За вмістом глобулінів та глютелінів переважає борошно рисове на 7 та 183% відповідно, однак склад глютелінів у досліджуваних зразках різний. У пшеничному борошні це глютенін, який є клейковинним білком, утворює гетерогенну суміш полімерів через дисульфідні зв'язки поліпептидів. У рисовому борошні представником глютелінів є орізенін. Інфрачервоні спектри відбивання пшеничного та рисового борошна показали подібний характер спектрів: екстремуми спостерігаються на однакових довжинах хвиль, спектри між собою розташовані паралельно та відрізняються лише за інтенсивністю відбивання. Спектр лецитину соняшникового значно відрізняється через відмінний хімічний склад. Також на деяких довжинах хвиль на спектрі лецитину помітні зміщення екстремумів як в коротко-, так і довгохвильову область. Вторинна структура глютену зазнала змін в хлібі після впливу температури шляхом просування α-спіралей і β-поворотів і сприяла утворенню дисульфідних зв'язків.

Висновки. Проведені дослідження свідчать про доцільність застосування рисового борошна в технології хлібобулочних виробів на заміну пшеничного з метою мінімізувати вміст клітковини в хлібі.

Ключові слова: *хліб, рис, борошно, лецитин, ІЧ спектроскопія.*

Зменшення вмісту акриламіду в формованих картопляних чіпсах підвищеної харчової цінності

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Вступ. Метою дослідження є визначення оптимальних температурних режимів випікання-висушування картопляного тіста для зменшення акриламіду в формованих картопляних чіпсах з підвищеною харчовою цінністю.

Матеріали і методи. В якості досліджуваної сировини обрано: картопляну крупку, висівки жита, ячменю, жмих гарбузового насіння, кріопорошки броколі та червоного буряка. Визначали кількість аспарагінової кислоти, редукувальних цукрів в основній та додатковій сировині, а також кількість утвореного акриламіду в процесі температурного оброблення тістової картопляної маси.

Результати і обговорення. Для підвищення харчової цінності формованих картопляних чіпсів розширено традиційну сировинну базу за рахунок застосування різних висівок зернових, жмиху, харчових волокон, порошків овочів, тощо. Рекомендовані оптимальні параметри оброблення картопляного тіста при температурі 125°С та тривалості 4,5 хв без застосування рослинних олій на відміну від традиційних способів виробництва формованих картопляних чіпсів. Визначено кількість аспарагінової кислоти – 190,5 мг/г білка і редукувальних цукрів – 0,6 % в картопляній крупці. У висівках жита та ячменю кількість аспарагінової кислоти 77,5 та 72,6 мг/г білка відповідно, у жмиху гарбузового насіння – 80,5 мг/г білка, у кріопорошках броколі та червоного буряка – 72,5 та72,9 мг/г білка відповідно. Масова частка редукувальних цукрів у висівках жита та ячменю складає 0,74 та 0,8 %, у жмиху гарбузового насіння – 0,5 %, у кріопорошках броколі та червоного буряка – 0,3 та0,5 %відповідно. Отримані кінцеві продукти, в яких не виявлено акриламіду завдяки зміни класичної технології і параметрів виробництва формованих картопляних чіпсів. Досліджено, що при застосуванні класичної технології формованих картопляних чіпсів кількість акриламіду у готових виробах становила 61 мкг в 100 г продукту. В формованих картопляних чіпсах без додавання висівок, жмиху та кріопорошків, які випікалися-висушувалися,кількість акриламіду була 9,35 мкг в 100 г продукту.

Висновки. Утворення акриламіду залежить від хімічного складу сировини, тривалості та температури випікання-висушування та технології виробництва формованих картопляних чіпсів.

Ключові слова: *картопляна крупка, чіпси, висівки, кріопорошок, акриламід.*

Вплив знакозмінних імпульсів тиску на сенсорні характеристики в бродильній технології

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Вступ. Метою наукової роботи є дослідження впливу знакозмінних імпульсів тиску в харчових виробництвах під час одержання дослідних зразків вина, кріпленого вина та асоційованих водних систем і розчинів на сенсорні характеристики та дегустаційне оцінювання.

Матеріали та методи. Було виконано аналіз зміни фізико-хімічних параметрів зразків вина, кріпленого вина та асоційованих водних систем і розчинів під час оброблення із застосуванням знакозмінних імпульсів тиску з використанням різних технологічних режимів. В роботі використані загальнонаукові та спеціальні методи досліджень, а саме електрохімічні методи. Окрім цього в роботі використаний метод сенсорного аналізу зразків вина, кріпленого вина та асоційованих водних систем і розчинів.

Результати і обговорення. В результаті застосування знакозмінних імпульсів тиску під час одержання кріпленого вина, загальний дегустаційний бал підвищився на 7,3%, у порівнянні з контрольними зразками, що є досить вагомим показником якості готового продукту. Під час проведення оброблення знакозмінними імпульсами тиску варіювалось число кавітації від 0.1 до 0.5, що дозволило одержати під час дегустаційного оцінювання найвищий загальний бал 8.8. Обгрунтовано технологію одержання кріпленого вина, що полягає у дробленні винограду, гребеневідділенні, настоюванні сусла на м'яззі, пресування, зброджування сусла, купажування, спиртування. Спиртування вина проводять із застосуванням знакозмінних імпульсів тиску в умовах гідродинамічної кавітації з числом кавітації 0,3, швидкістю зсуву потоку $2{,}6 \cdot 105 c^{-1}$ та напруженням зсуву потоку 260 Па.

Висновки. Загальний бал зразків вина та кріпленого вина, які були одержані в умовах знакозмінних імпульсів тиску, мав підвищені показники якості у порівнянні з контрольними зразками. Це позитивним чином впливає на якість готового продукту.

Ключові слова: *випробування, аналіз, рідкий, оброблення, тиск.*

Біотехнологія, мікробіологія

Вплив наночастинок подвійного дво- та тривалентного оксиду заліза на бактеріостатичні властивості насіння льону

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Вступ. Вивчено вплив наночастинок подвійного дво- та тривалентного оксиду заліза (НЧ $FeO \times Fe_2O_3$ – наномагнетиту) на бактеріостатичні (захисні) властивості насіння льону проти грибкових інфекцій та встановлено залежність бактеріостатичних властивостей від кількості наномагнетиту (НЧ $FeO \times Fe_2O_3$).

Матеріали і методи. Мікросопічне визначення морфологічних та культуральних особливостей мікроміцетів (культури дріжджів *Saccharomyces cerevisiae* та міцеліальних грибів *Mucor racemosus*) на агаризованому живильному середовищі. Дослідні зразки мікроміцетів одержували шляхом посіву стандартного мікробного препарату у вигляді суспензії (вихідне *розведення мікробної суспензії* 1:100) в чашки Петрі (чашковий метод).

Результати і обговорення. Відзначено здатність наночастинок подвійного дво-та тривалентного оксиду заліза (НЧ $FeO \times Fe_2O_3$ – наномагнетиту) сприяти покращенню бактеріостатичних (захисних) властивості насіння льону: додавання 0,1%; 0,15%; 0,2% наномагнетиту в (8–20 разів) пригнічує розвиток мікрофлори (мікроміцетів) у зразках насіння льону.

Встановлено зменшення (порівняно з контролем): кількості в (8–10) разів та розміру в (10–20) разів колоній мікроміцетів (дріжджів *Saccharomyces cerevisiae* та міцеліальних грибів *Mucor racemosus*). Визначено раціональний вміст наночастинок подвійного дво- та тривалентного оксиду заліза (НЧ $FeO \times Fe_2O_3$ – наномагнетиту) – 0,15% від маси рецептурної суміші.

Запропонована математична модель дозволяє прогнозувати ефективність використання НЧ $FeO \times Fe_2O_3$ – наномагнетиту в пригніченні росту міцеліальних грибів (мікроміцетів) для забезпечення бактеріостатичних властивостей сировинних інгредієнтів, зокрема насіння льону.

Висновок. Вперше досліджено вплив наночастинок подвійного дво- та тривалентного оксиду заліза (НЧ $FeO \times Fe_2O_3$ – наномагнетиту) на бактеріостатичні (захисні) властивості насіння льону.

Ключові слова: *насіння, льон, наночастинка, $FeO \times Fe_2O_3$, наномагнетит, бактеріостатичний.*

Процеси, обладнання і системи контролю

Автоматизовані методи керування витрати сиропу у випарному апараті з підсистемами підтримки прийняття рішень та прогнозування

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Вступ. Мета представленого дослідження – обґрунтування методів регулювання витрати сиропу у випарному апараті з підсистемою прогнозування, що дозволить спрогнозувати поведінку системи та підсистемою прийняття рішень, яка дозволить знизити вплив людського фактору на перебіг процесу випарювання.

Матеріали і методи. Досліджується робота випарної установки з підсистемою прогнозування та підтримки прийняття рішень при регулюванні витрати сиропу. В схемі автоматизації регулювання витрати сиропу в якості датчика використовуються індукційні витратоміри. В якості виконавчих механізмів використано пневматичні сідельні клапани, з вбудованим дроселем та електро-пневмоперетворювачем.

Результати і обговорення. Використання нейронечітких регуляторів відбувається лише в окремих специфічних випадках інтелектуального керування процесу випарювання, відсутні дані порівняння застосування інтелектуальних регуляторів з класичними, можливості комбінування роботи кількох типів інтелектуальних регуляторів, а також чітких засобів прогнозування їх роботи та підтримки прийняття рішень. Тому у даній роботі обгрунтовано підсистему прийняття рішень, яка дозволила оцінити пріоритети запитів користувачів при використанні людино-машинного інтерфейсу. Найвищий пріоритет отримав запит на виведення інформації про можливе внесення змін до параметрів регулювання інших контурів регулювання. Також було використано метод прогнозування для порівняння методів регулювання витрати сиропу в апараті, що дозволило спрогнозувати поведінку системи при формуванні управляючого діяння та вивести готовий прогноз на екран оператора та, таким чином, підвищити ефективність роботи випарної станції. Було зібрано статистичні дані поведінки контурів системи автоматизації у різних режимах роботи з використанням інтелектуальних та класичних регуляторів і побудовано модель прогнозування роботи випарної станції методом локальної тенденції та розроблено алгоритм прогнозування. Також оцінено точність отриманої моделі прогнозування. Точність моделі прогнозування склала 98% для ПІД-регулятора, 95% для нейронечіткого регулятора та 96% для нейромережевого.

Висновки. Модель для прогнозування роботи випарної станції характеризується високою точністю в цілому, але під час виникнення коливань у перехідному процесі виникає несуттєве запізнення прогнозування цих коливань. Найбільш важливою при виведенні інформації підсистемою прийняття рішень є функція виведення інформації про можливе внесення змін до параметрів регулювання інших контурів регулювання.

Ключові слова: *випарювання, витрата, сироп, система, прогнозування.*