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Intelligent automatic control of sugar factory evaporator operation using behavior prediction subsystem

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Abstract

Introduction. The aim of the presented research was to substantiate the intelligent automatic control of the sugar juice evaporation with the subsystem for behavior prediction, which allows to determine the behavior of the automatic system.

Materials and methods. The operation of the evaporator unit with system behavior prediction to regulate the sugar juice level was investigated. Capacitive level gauges were used as a sensor in the automation scheme of sugar juice level control. Pneumatic seat valves with a built-in throttle and an electro-pneumatic converter were used as actuators.

Results and discussion. The use of neuro-fuzzy regulators occurs only in some specific cases of intelligent control of the evaporation process. There is no data comparing the use of intelligent regulators with classical ones and the possibility of combining several types of intelligent regulators, as well as clear means of predicting their work. Therefore, in the present study, a prediction method was used to compare methods to regulate the level of sugar juice in the evaporator. This 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, which made it possible to increase the efficiency of the evaporative station. Statistical data on the behavior of the automation system contours in various operating modes were collected using intelligent and classical controllers, and a model was built to determine the operation of the evaporator using the local trend method and the modified algorithm of prediction. The advantage of this method is its easy and fast implementation, which does not require large economic and energy costs. The accuracy of the prediction model was 98% for the PID-controller, 95% for the fuzzy-controller and 96% for the neural network. The obtained model of the system prediction is stable because the absolute error does not change when dividing the time series into intervals.

Conclusions. The proposed system of intelligent automated control of the evaporation of sugar juice with a modified prediction method based on local trends has an insignificant delay, while prediction is performed with high accuracy and stability.

Introduction

The evaporation process is one of the main operations in the sugar factory. However, the high temperature conditions of evaporation results in unwanted sucrose losses. High-quality automatic control of the evaporator operation is of the highest importance in the sugar production because it ensures adherence to the temperature regime, prevents overheating of the sugar juice, and increases the overall efficiency of the sugar factory.

System of automatic control of the evaporating plant can be described as a one requiring the intervention of the operator who makes adjustments to the tasks for regulators responsible for maintaining temperature and material flows.

Such adjustments are required because of the instability of the technological and quality indicators of sugar juice at the inlet to the evaporation plant, as well as of the need to change them at the outlet (Hrama et al., 2019a). When making changes to the automated control system, the operator must take into account both the impact of the work of adjacent sections on the process of sugar juice concentration in the evaporation station, and the impact of changes in sugar juice indicators on the activity of subsequent equipment (Hrama et al., 2019b).

To ensure an effective automation system, the use of modern software and hardware is needed. However, the use of intelligent systems in automating the sugar evaporation process provides a large number of options, some of which can lead to extraordinary and emergency situations. It is very important to prevent their occurrence in time (Chantasiriwan, 2017). To predict the possibility of insufficient situations, it is proposed to introduce a forecasting module into automation systems. This will allow predicting the state of the system and making operational decisions (Verma et al., 2018).

Improving the evaporation process is rather an important task. Chantasiriwan (2017) proposed a model of the evaporation process that takes into account the balance of mass and energy. However, the issues related to the occurrence of nonlinearity and the problem of fluid flow deviation remain unresolved. In addition, the possibility of using intelligent regulators in the evaporation process was not considered in this exploration. The reason for this may be the difficulties that arise due to the need to use special software.

Verma with co-authors (2018) studied the process of linearization of a nonlinear model of an evaporator plant consisting of 14 first order nonlinear differential equations. The change of the product concentration from the deviation of the liquid flow rate was found y for the first time, but intelligent controllers were not used. This may be due to the difficulty of developing rule bases for neural fuzzy regulators or the lack of an appropriate neural network training model.

The need to upgrade existing control systems was shown (Sidletskyi et al., 2016). The authors presented some approaches that are used for the distributed level of process control, but application of intelligent controllers in the evaporation process were also not disclosed.

The main objective of the present research was to study the possibility of using intelligent methods for regulating the level of sugar juice in an evaporator with a prediction subsystem, which will allow foreseeing the behavior of the system and getting a ready forecast, and thus improve the efficiency of the evaporator station.

Materials and methods

A five-corps sugar evaporator was used. The scheme of automation of sugar juice level control is shown in Figure 1.

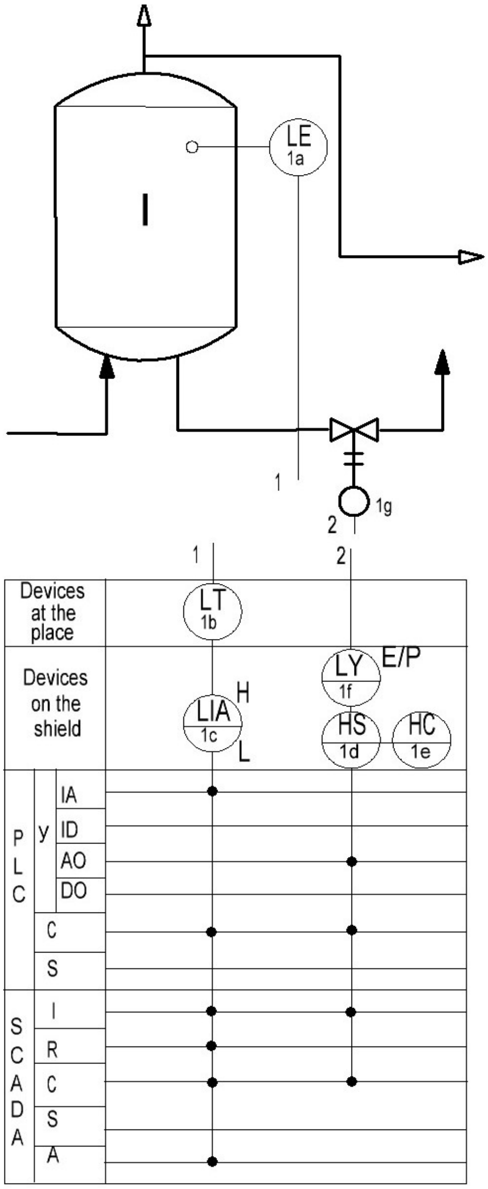

Figure. 1 Automatic liquid level control in evaporation station

Capacitive equalizers (LE 1a, LT 1b) are used as sensors in sugar juice level control circuits. Single channel microprocessor-based indicator ITM-110 (Mikrol, LLC, Kharkiv) was used as a secondary indicating device (LIA 1c). The signal is sent to the regulator (PLC) on the control unit (intersection with C), as well as to the human-machine interface (SCADA), which displays the level of sugar juice value on the screen of the automated operator's workplace (computer) (intersection with I). The obtained data is stored in memory (R). This data (actual level of sugar juice values) is used for conducting the experiment. In case the level of sugar juice value exceeds the set limits, an alarm signal (A) is generated. The control signal, which is output by the regulator (AO), is sent to an electro-pneumatic converter (LY 1f), which converts an analog unified electrical signal. In turn, the actuator (e.g. 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 of the SCADA operator). БРУ-17 manual control units are used for switching the "Manual/Automatic" mode (HS 1d, HC 1e). Modicon M340 is used as a regulator. Pneumatic seat valves (1g) J4SPG1805 KRAFTt-AIR, with integrated choke and electro-pneumatic converter (Hrama et al., 2019b) are used as actuator.

Description of prediction using the method of local tendencies

Prediction the operation of the evaporating station using the method of local tendencies can be carried out using fuzzy time series models (Jolly et al., 2000). A fuzzy time series model is generated to obtain the forecasted local tendency (Lahtinen, 2001). To do this, the model of fuzzy dynamic process with fuzzy increment is used (Fig. 1). This increment looks in the following way: $X_t(t=1,2,...)\subset R^1$ – a universal set for which fuzzy sets $\tilde{x}_t^i,(i=1,2,...)$, $\tilde{v}_t^j,(j=1,2,...)$, $\tilde{a}_t^s,(s=1,2,...)$ are defined (Dong et al., 2017). Next, there is a need to set the values of the parameters of the time series model of the first order (Lei et al., 2016) and calculate the sum of the intensities of fuzzy elementary tendencies for each interval by creating an algorithm for fuzzy local tendencies for this case (Dong et al., 2017). The algorithm, which first converts the initial time series to a fuzzy time series, was used to forecast the operation of the automated evaporating station. The next step is to convert the obtained fuzzy time series into a time series of fuzzy elementary tendencies and to perform defuzzification using the method of the center of gravity of intensity of each fuzzy elementary tendency for each time series

$a_t = DeFuzzy(\tilde{a}_t)$ (Anghinoni et al., 2018).

The analysis of the stability of the prediction model is as follows. The automation system of the five-hull evaporator station is launched (Fig. 1), after which the SCADA system is removed from the graphs of the transition process and the predicted values during the operation of the installation (Dong et al., 2017). They are shown in Fig. 6. Next, the graphs are divided into any number of equal time intervals (González-Potes et al., 2016). Each time interval is separated from the next by a dot called a Latin letter. The value that corresponds to the transition process at a given time is the actual meaning, and the number that corresponds to the graph with the predicted meanings at this time is the predicted value. All these numbers are entered in Table 1. Also calculated and entered in Table 1 the meanings of absolute and relative prediction error for each point (Dong et al., 2017).

The value of the absolute error (A) is calculated by formula (1):

$$A = \left|Z(t) - \tilde{Z}(t)\right| , \tag{1}$$

where $Z(t)$ is the actual value of the time series, $\tilde{Z}(t)$ is forecasted value of the time series (Lei et al., 2016).

The value of the relative error (V) for each value of the time series point is calculated by the following formula (2):

$$V = \frac{\left|Z(t) - \tilde{Z}(t)\right|}{Z(t)} \times 100\% \tag{2}$$

For stability analysis, this compares the dependence of the relative error when the noise level changes (i.e. the change or the absolute error). To do this, a graph of the dependence of the relative error on the absolute (González-Potes et al., 2016). This graph shows the points in Table 1 at the same time intervals into which the transition process was divided (Dong et al., 2017). Graphs of changes in relative and absolute errors over time are built on these points. The values of absolute and relative errors are also taken from Table 1. If the values of relative error do not change when the absolute error does not change, the prediction system is stable (Zhang et al., 2011).

The next step is to assess the accuracy of the system. The automation system of the five-hull evaporator station is launched (Figure 1), the type of control is selected, after which the SCADA system is removed from the graphs of the transition process and the predicted values during the operation of the installation. They are shown in Fig. 6. Next, the graphs are divided into a free number of equal time intervals (González-Potes et al., 2016). Each hour interval is separated from the next dot by a Latin letter. The value that corresponds to the transition process at a given time is the actual value, and the value that corresponds to the graph with the predicted values at that time is the predicted value. All these values are entered in Table 2. The values of absolute errors are calculated by formula (1). The average error (SP) calculated by formula (3) (Dong et al., 2017):

$$SP = \frac{1}{n}\sum_{t=1}^{n}(Z(t) - \tilde{Z}(t)), \tag{3}$$

where SP is the mean error of the forecasted value of the time series, n is the number of time series intervals, $Z(t)$ is the actual value of the time series, $\tilde{Z}(t)$ is forecasted value of the time series (Lei et al., 2016).

The average absolute error (SAP) was calculated by formula (4):

$$SAP = \frac{1}{n}\sum_{t=1}^{n}\left|Z(t) - \tilde{Z}(t)\right| \tag{4}$$

The mean relative error of prediction (SVP) was calculated by formula (5) (Lei et al., 2016):

$$SVP = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|Z(t) - \tilde{Z}(t)\right|}{Z(t)} \times 100\% \tag{5}$$

The mean standard error (SKP) was calculated by formula (6) (Chowdhury et al., 2015):

$$SKP = \frac{1}{n}\sum_{t=1}^{n}(Z(t) - \tilde{Z}(t))^2 \tag{6}$$

The square root of mean standard error (SQSKP) was calculated by formula (7):

$$SQSKP = \sqrt{SKP} \tag{7}$$

The standard deviation (SV) was calculated by formula (8):

$$SV = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Z(t) - SKP)^2} \tag{8}$$

Accuracy of prediction model (T) was calculated by formula (9):

$$T = 100\% - \frac{1}{n}\sum_{t=1}^{n}V \tag{9}$$

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

Results and discussion

Synthesis of the algorithm of local tendencies

Let's consider the operation of the algorithm of prediction based on high-order fuzzy time series (Chen, 2002) and the operation evaporating station. A description of control of several evaporating stations with full integration of fuzzy control and the use of wireless network sensors and actuators was shown (González-Potes et al., 2016). Though, the comparison of the use of neural fuzzy regulators with other types of intelligent control was not included. There is also no justification for the feasibility or unreasonableness of using this type of control in case of the possibility of implementing a system with another type of intelligent control. In addition, neural fuzzy control is not used in all control circuits. The reason for this may be the high complexity of such study. The authors faced similar problems (Zhang et al., 2011). This research contains a consideration of the control of evaporator overheating using a fuzzy slider mode regulator. In addition, this paper does not address the use of fuzzy control for other control circuits of the evaporating station.

The paper (Lavarack et al., 2004) features the consideration of the methodology of increasing the efficiency of steam use. However, modern types of control are not used in it. That is why there is a high probability that the use of intelligent regulators can further increase the efficiency of steam. This work also contains the consideration of options for improving the evaporation process (Srivastava et al., 2013). These studies also feature complex calculations. In the exploring, the authors prove that the rate of evaporation decreases noticeably over time (Roger et al., 2018). They perform a calculation and demonstrate that diffusion in the liquid phase is a step, which limits the rate for this system, in contrast to the evaporation of pure water. A generalized stationary mathematical model for modeling a multichannel evaporator system was developed in the paper (Srivastava et al., 2013). Patan with co-authors (2005) have considered the problems of detection of malfunctions of industrial processes using dynamic neural networks on the example of an evaporating station. The considered neural network had a multilevel feed structure. In the exploration, Merino with co-authors (2018) investigated the application of real-time optimization in the evaporation section of a sugar refinery using methods that reduce the time for developing models. Polupan with co-authors (2018) proposed to use of genetic algorithms in sugar production. The paper (Sidletskyi et al., 2019) features the consideration of the development of the structure of an automated control system using tensor methods in sugar production. However, the authors of these studies also did not use intelligent control. This may so due to the high complexity of the calculations or the lack of necessary hardware or software.

It was claimed that by using intelligent control it is possible to provide a faster decrease in housing temperature and achieve more stable control of overheating in the first evaporator tank (Jolly et al., 2000. Though, this examine also does not disclose the use of intelligent regulators for regulating other parameters (e.g., pressure, level of beet juice, consumption). In addition, only the possibility of using intelligent regulators in other housings than the first one is considered in this study. This may be so due to the high complexity of the calculations and the need of using the specific software. The paper (Lahtinen, 2001) features the consideration of the problem of control of other parameters of the evaporation process. In this exploration, it is proved that the control of evaporation can be implemented by recirculation of liquid in the evaporation section or by feeding only liquid to the evaporator. However, this article also does not address the use of intelligent regulators during the evaporation process.

It is necessary to improve the model of prediction the operation of the evaporator station using the method of local tendency and prediction algorithm and determine the impact of the algorithm on the accuracy and stability of the obtained prediction model.

The following dependences of parameters was used to work with the algorithm of local tendencies (Lei et al., 2016):

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

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

In this model, the definition of the absolute fuzzy estimate $\tilde{x}_i$ is determined using the fuzzification of a scale according to the value of the estimated object x_i. Next goes the operation to determine the type of differences. The process of determining the intensity of differences would be the next step. It is followed by the calculation of a new absolute fuzzy estimate (Xu et al., 2020). The last step is defuzzification of the scale according to the definition of the evaluated object x_i by an absolutely fuzzy estimate $\tilde{x}_i$.

A two-stage algorithm for selecting a time series prediction model has been developed. Let's calculate the amount of the intensities of fuzzy elementary tendencies for each interval by the following way (Dong et al., 2017):

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

where P is a final set of points in the n interval (final set of tendencies), ST is a time interval of the fuzzy tendency length.

With the developed algorithm, local tendencies are assessed. The next step is to use language and numerical forms in the algorithm (Anghinoni et al., 2018). For the operation of this algorithm it is necessary to convert the initial time series into a fuzzy time series (Mehmood et al., 2020) using the model shown in Figure 2. The next step in this algorithm is to divide the obtained time series into a number of intervals. The amount of the intensities of the same type of fuzzy elementary tendencies is calculated at each interval. Next, the type of local trend ("Stable", "Ascending", etc.) can be selected by comparing the time intervals during the increase (ST_{up}) and decrease (ST_{down}) of time intervals of the fuzzy tendency length (Xu et al., 2020).

This algorithm does not require additional user interpretation. This algorithm has a disadvantage due to the limitation of its operation by the number of predefined time intervals. Therefore, the number of identified local tendencies will be equal to the number of intervals specified by the developer (Anghinoni et al., 2018). This algorithm allows obtaining time series that can be used in the future to forecast local tendencies. 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 over a fuzzy time series (Dong et al., 2017).

Analysis and synthesis of control action using prediction methods in the evaporating station control system

It is suggested using the flow chart of control (Tang et al., 2001), modifying it so as to include the possibility of prediction (Lei et al., 2016), and changing the type of control (Lapin et al., 2016) (Figure 2).

Flow chart of control is shown in Figure 2, where $Y_Z(t)$ is a task signal, e(t) is a mismatch between task signal and feedback, u(t) is control signal, v(t) is external disturbance, Y(t) is output signal, and $Y_M(t)$ is output signal from the object model.

The paper (Tang et al., 2001) contains a more detailed consideration of the work of intelligent regulators, on the example of fuzzy regulators. In this exploration, the fuzzy PID-regulator is investigated as a discrete version of an ordinary PID-regulator. Therefore, it retains the same structure but has an independently adjustable control factor. It is proven that it is possible to improve the classic PID-regulator with a certain adaptive control ability. Though this regulator cannot be considered to be a full-fledged neural fuzzy regulator. In addition, the use of other types of intelligent regulators is not considered in this study. The cost of research may be a possible reason for this. The article (Carvajal, 2000) contains a more detailed consideration of the issue of using neural fuzzy regulators. This analysis presents a new PID-regulator of fuzzy logic. This regulator is a fuzzy PID-regulator with a computable efficient analytical circuit. The author proves that the regulator is stable with limited input/limited output. However, it is very difficult to implement this regulator, and this paper does not provide the possibility of using other types of intelligent regulators. In addition, it is not possible to use this type of regulator for some control parameters. Also, none of the above-mentioned studies justify the need for upgrading existing evaporating station automation systems. The cost of research may also be a possible reason for this. The paper (Sidletskyi et al., 2019) features a consideration of the issue of using neural fuzzy regulators. This exploration states that the addition of fuzzy and neural fuzzy logic is one of the advanced methods of improving control systems. Methods of dynamic power control were analyzed using fuzzy logic and adaptive neural networks. The use of fuzzy inferences (so-called fuzzy systems) may be one of the possible options for power control. The control action is formed by checking the coordination of fuzzy rules with the actual parameters of the system. Rules are created according to the experience of the operator, which reflects his/her actions when changing technological parameters. Though this paper does not contain the consideration of the use of neural fuzzy regulators in the evaporation process. In addition, it also does not address other types of intelligent regulation.

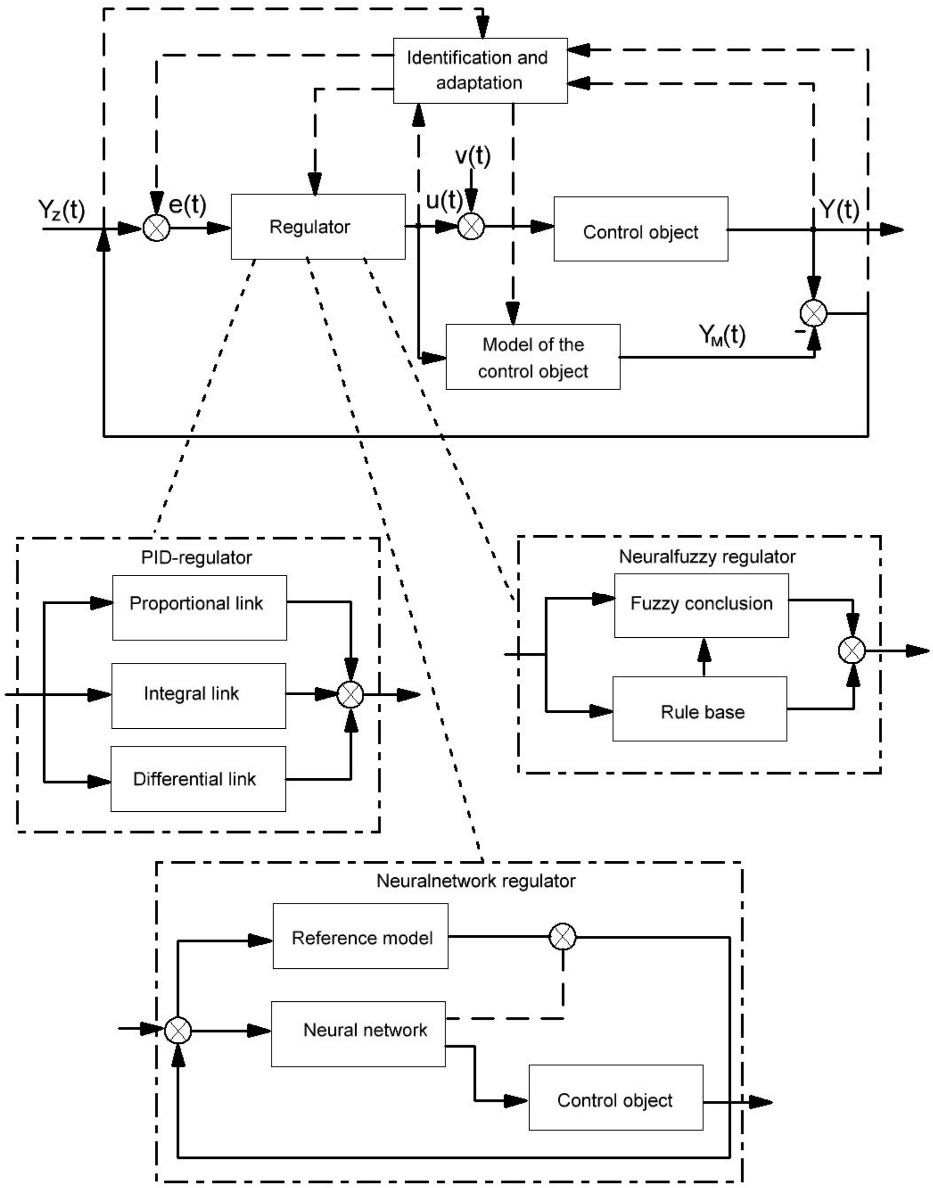

Figure 2. Flow chart of control

Analysis of the prediction model stability

The results of the study of the prediction model stability were shown (Table 1).

Table 1

Absolute and relative errors of the evaporating station level of sugar juice prediction model

a	b	c	d	e
A	0	0	0	0
B	28	26	2	7.7
C	24	26	2	7.7
D	27	25	2	8
E	26	25	1	4
F	26	25	1	4
G	26	25	1	4
H	26	25	1	4
I	26	25	1	4
J	26	25	1	4
K	26	25	1	4

Note: *a is the point name; b is the forecasted value,% ; c is the actual value,% ; d is the absolute error (1), %; e is the relative error (2), % .

The dependence of the relative error on the absolute errors is shown in Figure 3.

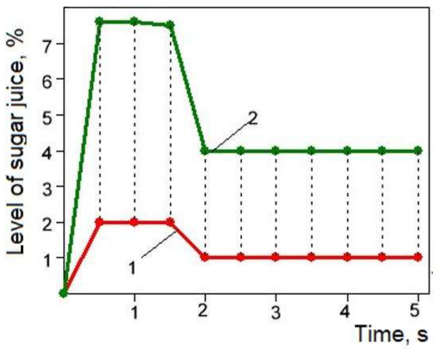

Figure 3. The dependence of relative error on absolute errors:
1 (—) – absolute error variation, 2 (—) – relative error variation.

This graph indicates that the relative error does not exceed 8%. In addition, it is apparent that in the case of dividing the time series into intervals, the accuracy of measurements remains stable if the absolute error does not change. This fact allows asserting that the obtained model of system prediction is stable and can be used to predict the operation of the evaporating station (Lei et al., 2016). Problems of the complexity of calculations are widely revealed in research (Xiao-Yang, 2007). The research (Liu et al., 2013) features development of a mathematical model of control of overheating of the electronic evaporator system of the expansion valve with the investigated control strategy. The authors of this article conducted the and modeling of the electronic expansion valve of the evaporator with fuzzy regulation were carried out in the exploration. The model is identified by the least-squares algorithm based on the minimized sum of square residues. The research (Zhong et al., 2007) features a consideration of fuzzy control for evaporator overheating. The lack of development of intelligent regulators for the system as a whole is a common problem of these studies. Such problems can also arise due to the high complexity of calculations, lack of necessary hardware and software, and high cost of research. The analysis of the robust controller use in the evaporation process was done (Normey-Rico et al., 2005). The author conducted a comparative analysis of this type of controller with the PID-regulator and concluded that the suggested controller provides better performance. However, the comparison of the use of classical regulators and intelligent regulators was not conducted in this study. The cost of research may be the reason for this.

Analysis of the level of sugar juice prediction algorithm operation

The result of the implementation of the prediction algorithm for the level of beet juice in the first case of the evaporating station using neural fuzzy control is shown in Fig. 3. Table 2 indicates the results of calculations for the level of sugar juice in the first case of the evaporating station using PID, fuzzy, and neural network regulators. In Table 2: a is a point name, b is forecasted value,% , c is actual value,% , d is absolute error,% , e is mean error (SP) (formula 3), f is mean absolute error (SAP) (formula 4), g is mean relative prediction error (SVP) (formula 5), h is mean standard error (SKP) (formula 6), i is square root of the mean standard error (SQSKP) (formula 7), j is standard deviation (SV) (formula 8).

Based on the results shown in the table, it can be concluded that, since the value of SP is negative, the forecast was overestimated relative to the actual data (Lei et al., 2016). This is true because the forecast shows a small absolute error of 1% when using fuzzy control. Though it is absent in the actual use of this type of control. However, such an overestimation is insignificant, as can be seen from the mean relative prediction error (Dong et al., 2017).

Theoretically, when using the mean relative error in estimating the accuracy of the evaporation process prediction model, the value of the accuracy of the forecast can reach 100% (Lei et al., 2016). This will mean that the selected prediction model describes the process with absolute accuracy (Anghinoni et al., 2018). In practical terms, such a phenomenon is almost impossible, because the forecast cannot take into account all the factors that affect the automation system (Xu et al., 2020). In case when the value of the forecast accuracy is close to 0%, this model does not describe the forecasted process.

The forecast accuracy indicator is also used in order to select the optimal prediction model. The model with the accuracy closest to 100% (Lei et al., 2016) is considered optimal because it is more likely to make a more accurate forecast.

So far as in our case, the value of the mean relative error is 5%, consequently, the accuracy of the model is 95%. This is a very high assessment of the quality of our prediction system. Since the accuracy of the prediction model is very close to 100%, it can be considered optimal (Dong et al., 2017). In order to correctly understand how much one can trust the obtained evaporation process prediction algorithm, it is also necessary to evaluate the accuracy of the obtained forecast (Lei et al., 2016). Figure 4 shows a comparison of the forecasted value of the level of sugar juice change in the first case of the evaporating station using PID, fuzzy and neural network regulators, and the actual level of sugar juice change.

Table 2

Prediction error estimation indicators for the first evaporating station body

a	b	c	d	e	f	g	h	i	j
PID-regulator									
A	0	0	0						
B	49	50	1						
C	28	28	0						
D	27	28	1						
E	27	28	1						
F	27	28	1	0.8	0.8	2	0.8	0.89	24.18
G	27	28	1						
H	27	28	1						
I	27	28	1						
J	27	28	1						
K	27	28	1						
Accuracy of prediction model (9):								98%	
Neural fuzzy regulator									
A	0	0	0						
B	28	25	2						
C	24	25	2						
D	27	25	2						
E	26	25	1						
F	26	25	1	-0.9	0.9	5	0.002	0.045	24.02
G	26	25	1						
H	26	25	1						
I	26	25	1						
J	26	25	1						
K	26	25	1						
Accuracy of prediction model (9):								95%	
Neural network regulator									
A	0	0	0						
B	26	25	1						
C	26	25	1						
D	26	25	1						
E	26	25	1						
F	26	25	1	-0.9	1.27	4	0.9	0.94	21.87
G	26	25	1						
H	26	25	1						
I	26	25	1						
J	26	25	1						
K	26	25	1						
Accuracy of prediction model (9):								96%	

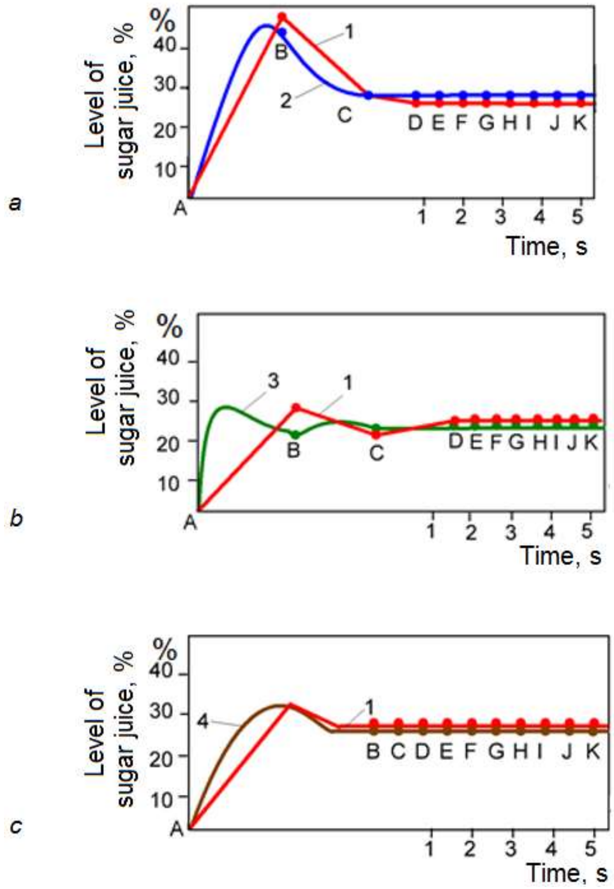

Figure 4. Comparison of transients of forecasted and actual levels of sugar juice in the first body of the evaporating station using:
a – PID-regulator,
b – neural fuzzy regulator and
c – neural network regulator
1 (—) – forecasted level of sugar juice value,
2 (—) – actual level of sugar juice value (PID-regulator),
3 (—) – actual level of sugar juice value (neural fuzzy regulator),
4 (—) – actual level of sugar juice value (neural network regulator),
AB, BC, CD, …, JK – time series intervals

In other studies, most of the problems of intelligent control in the evaporation process remain unresolved (Chantasiriwan, 2021; Lahtinen, 2001; Sidletskyi et al., 2016; Verma et al., 2018.) The use of neural fuzzy regulators takes place only in some specific cases. In addition, there is no comparison of the use of intelligent regulators with the use of classic regulators. There is also no explanation of the possibility of combining the work of several types of intelligent controllers if necessary. In addition, there is no clear means of prediction the operation of intelligent regulators.

In this study, the prediction method was used to compare the methods of level of sugar juice control in the device. This allows prediction the behavior of the system during the formation of the control action and displaying the finished forecast on the operator's screen, thus, increasing the efficiency of the evaporating station. This method has an advantage due to its easy and fast implementation, which does not require large economic and energy costs. The disadvantages of this method are the need to divide the transition process into separate time intervals of the numerical series manually and the direct dependence of the accuracy of the model on the number of elements of the time series.

Conclusions

1. According to the conducted studies of literary sources, it was determined that there is an unresolved part of the problems of intelligent control in the evaporation process – this is the use of neuro-fuzzy controllers in some specific cases.
2. Statistical data on the behavior of the automation system circuits in transient operating modes were collected using intelligent and classical controllers, and a model was built to predict the operation of the evaporator plant using the local trend method and a prediction algorithm was developed. The advantage of this method is its easy and fast implementation, which does not require large economic and energy costs. The disadvantage of this method is the need to divide the transient process into separate intervals of the time series manually and the direct dependence of the model accuracy on the number of elements of the time series.
3. In the work, a modification of the forecasting model by the local trend method was performed and an algorithm for predicting the operation of the evaporator plant was developed. The accuracy of the prediction model was 98% for the PID controller, 95% for the neuro-fuzzy controller and 96% for the neural network, which are high rates. the resulting system prediction model is stable and can be used to predict the operation of the evaporative plant
4. Analysis of the study data indicated that when fluctuations occur in the transient, an insignificant delay occurs, while the advantage of the model is its high accuracy and stability, which satisfies its use.

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.

Carvajal J., Chen G., Öğmen H. (2000), Fuzzy PID controller: Design, performance evaluation, and stability analysis, *Information Sciences, 123(*3–4*)*, pp. 249–270, DOI: 10.1016/S0020-0255(99)00127-9.

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

Chen S. (2002), Forecasting enrollments based on highorder fuzzy time series, *Cybernetics and Systems*, 33(1), pp. 1–16, DOI: 10.1080/019697202753306479.

Chowdhury J., Nguyen B., Thornhill D. (2015), Modelling of evaporator in waste heat recovery system using finite volume method and fuzzy technique, *Energies, 8*, pp. 14078–14097, DOI: 10.3390/en81212413.

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.

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. (2019a), Comparison between PID and fuzzy regulator for control evaporator plants, *IEEE 39th International Conference on Electronics and Nanotechnology (ELNANO), 2019, Kyiv, Ukraine. Conference Proceedings*, pp. 54–59.

Hrama M., Sidletskyi V., Elperin I. (2019b), 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

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.

Lapin M., Sidletskyi V. (2016), Vykorystannia system nechitkoi lohiky dlia dynamichnoho upravlinnia potuzhnistiu parovykh kotloahrehativ, *Scientific Works of National University of Food Technologies*, 22(4), pp. 24–31.

Lavarack B., Hodgson J., Broadfoot R., Vigh S., Venning J. (2004), Improving the energy efficiency of sugar factories: Case study for Pioneer Mill, *International Sugar Journal*, *106*, pp. 337-342.

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.

Liu T., Wang Y., Yang Q., Yang X. (2013), Optimal fuzzy control of electronic expansion valve-evaporator system, *BioTechnology: An Indian Journal*, 8, pp. 586–594.

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.

Merino A., Acebes L., Alves R., de Prada C. (2018), Real Time Optimization for steam management in an evaporation section, *Control Engineering Practice, 79*, pp. 91–104. DOI:10.3390/pr7080537.

Normey-Rico J., Merino A., Cristea S., de Prada C. (2005), Robust dead-time compensation of a evaporation process in sugar production, *IFAC Proceedings,* 38(1), pp. 460–465, DOI: 10.3182/20050703-6-CZ-1902.01651.

Patan K., Parisini T. (2005), Identification of neural dynamic models for fault detection and isolation: the case of a real sugar evaporation process, *Journal of Process Control,* 15(1), pp. 67–79, DOI:10.1016/j.jprocont.2004.04.001.

Polupan, V., Sidletskyi V. (2018), Genetic algorithm usage for optimization of saturator operation, *Ukrainian Food Journal, 7*(4), pp. 754–762, DOI: 10.24263/2304-974X-2018-7-4-18.

Roger K., Sparr E., Wennerström H. (2018), Evaporation, diffusion and self-assembly at drying interfaces, *Physical Chemistry Chemical Physics,* 20, pp. 10430–10438, DOI: 10.1039/c8cp00305j.

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

Sidletskyi V., Elperin I., Polupan V. (2016), Analiz ne vymiriuvalnykh parametriv na rivni rozpodilenoho keruvannia dlia avtomatyzovanoi systemy, obiektiv i kompleksiv kharchovoi promyslovosti, *Scientific Works of National University of Food Technologies*, *22*(3), pp. 7–15.

Srivastava D., Mohanty B., Bhargava. R. (2013), Modeling and simulation of mee system used in the sugar industry, *Chemical Engineering Communications,* 200, pp. 1089–1101, DOI:10.1080/00986445.2012.737876.

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.

Zhong Y., Han J., He X. (2007), Fuzzy control for superheat of evaporator based on variable-universe method, *Journal of Guangxi University of Technology*, *2,* pp. 25-28.

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.

Zhang J., Wenfang Z., Ying L., Guolian H. (2011), Design of evaporator control system using fuzzy sliding mode controller, *The 2011 International Conference on Advanced Mechatronic Systems, August 11–13*, *2018,* Zhengzhou, China, pp. 508-512.