https://doi.org/10.33271/nvngu/2024-4/121

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DESIGNING THE PREDICTIVE CONTROL OF A DRUM DRYER USING MULTI-AGENT TECHNOLOGY

Purpose. To increase the efficiency of drying lines for bulk products by automating control using intelligent technology to determine the state of the product and predict its initial moisture content by analyzing a series of control signals and messages in the time domain.

Methodology. The author's model of a drum dryer with axial and furnace burners for drying charge used for the production of iron ore concentrate – pellets – was used. The model was used to generate training and control examples. The performance of the multi-agent technology and the accuracy of predicting the initial moisture content were researched.

Findings. The article analyses the factors that complicate the high-quality automatic control of the process of drying bulk products in drum dryers rotating in a furnace with burners. A model of an intelligent predictor is proposed, which identifies the state of the product and predicts its output moisture content on the basis of available control and feedback signals. The operability of the multi-agent system model and of the calculating algorithms for the predicted moisture value was proved. The possibility of using the technology to ensure automatic control of the technological process and high-quality stabilization of the controlled parameter are demonstrated.

Originality. The predictor is implemented as a peer-to-peer multi-agent system. This multi-agent system stores and works signal vectors with values placed by the time delays between the change in the corresponding signal and the change in product moisture at the dryer outlet. Each agent contains a description of a specific situation in the dynamics. The technology provides for automatic adjustment of the multi-agent system by analyzing arrays of signals over a long time period and generating new agents in cases where a situation is detected which cannot be described by an array of existing agents.

Practical value. The technology provides the initial moisture content calculation by an array of agents and allows the dryer automatic control by levelling the time delay in the feedback channel.

Keywords: *bulk products drying, automated control, model experiments*

Introduction. In the current realities of the processing industry (including iron ore concentrate production, carbon black production, feed additive production and construction mix production), operational staff try to achieve acceptable sustainable mode. They try to avoid changing the operating modes as there is a risk of not keeping critical product quality parameters within acceptable limits [1].

Drum dryers belong to a specific class of objects that require special structures and models for automatic control. In dryers rotated inside the furnace, the number of control influences can be more than ten. There is no possibility of direct measurement of the humidity and temperature for the product inside the drum. Time delay between the change in the control influence and the change in the humidity of the product at the drum outlet can be several tens of minutes. In addition, the set capacity can vary throughout the day, and raw materials have different initial moisture content and drying kinetics at different times. All these factors make it impossible to use classical PID control structures.

Problem statement. The paper considers the type of industrial furnaces of cylindrical shape with rotation about the longitudinal axis, in particular, drum furnaces. Such furnaces are designed to heat bulk materials for the purpose of their physical and chemical treatment. The material and flue gas are fed into the drum furnace both in parallel with the movement of the product and in the opposite direction. The heat sources are burners with burn powdered, solid, liquid or gaseous fuels.

For the purpose of this study we have chosen a furnace that processes the charge for the production of iron ore concentrate. The scheme of the technological equipment is shown in Fig. 1.

The metal drum is installed on support rollers at a slight angle to the horizon. In some cases, the diameter of the drum is made variable in length. The drum is rotated (1–6 rpm) by an electric motor through a gearbox and an open gear. The charge is fed through a metering device and a controlled capacity feeder (usually a frequency controlled electric drive). Slag in the form of pulp is fed in bulk or through nozzles. To improve the heat transfer conditions, the drum is equipped with various heat exchange devices such as blades, shelves, chain loops, nozzles, etc. For the same purpose, in some cases, the drum lining is made of complex shapes, such as cellular. The main dimensions of the drum vary considerably: the length from 20 to 130 m and the diameter from 3 to 7.5 m. When the drum rotates, the material is poured over the internal nozzles and moves along the axis of the drum to the outlet. It is influenced by fuel gases supplied from the same end and heat from the drum walls.

The finished product is discharged on the other side and flows into the transport and cooling system. The steam-gas mixture is removed from the center of the drum by a fan that maintains a constant vacuum level in the piping. The mixture is cleaned of dust (fines) in the filtration system.

For the selected scheme, the heat sources are an axial burner and two furnace burners located along the drum. Each burner has a built-in control system regulating the supply of fuel and compressed air to the nozzle depending on the set output. The technological system has energy feedback: the hot gases in the chimney heat the compressed air for the burner, which is fed to the burners. This increases the temperature of the flame.

The exhaust gas from the furnace is transferred to the outlet of the drum through an exhaust hood, which creates differential pressures inside the drum and removes liquid vapors and fumes from the system.

Drying occurs under the furnace gases come into contact with the raw material in three ways:

1) when the raw material falls from the blades, blown by the flue gases;

2) from the surface of the material piled on the bottom of the drum;

3) by contact with more heated surfaces (walls, blades).

The plant's capacity reaches 150 tons per hour (finished product). The technological process is energy-intensive, and the quality of the final product, which includes the dried material, depends on it. For continuous production, it is important to maintain quality indicators within narrow limits.

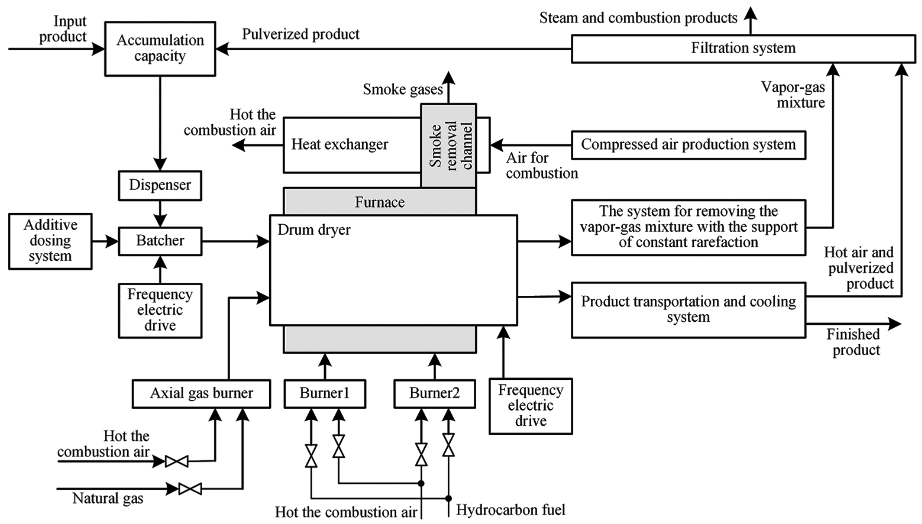

Fig. 1. Scheme of technological equipment

Literature review. Studies in the field of applied intelligent technologies show the insufficient adaptability of formal models of artificial neural networks, fuzzy logic controllers, and expert systems to optimize and automatically control technological processes in real time. Works [2, 3] describe neural controllers for technological processes. Satisfactory synthesis results are achieved if private optimal solutions for individual process states have already been found. Neural controllers approximate training examples to all possible states, but they do not provide the search for optimal solutions.

Works [4, 5] describe a model of a fuzzy controller and a method for selecting the settings and parameters of the accessory functions. The fuzzy controller acts as an additional module that adjusts the settings of the PID controller and gives the controller nonlinear properties that improve the transient process.

We can generalize: the proposed models of neural network and fuzzy automatic control systems also work on the basis of an inconsistency signal and do not implement full-fledged predictive control. They have very limited self-tuning properties and require the participation of experts to improve the quality of control [6].

The absence of a universal approach to the use of advanced intelligent technologies forces the synthesis of specialized methods and models for each installation individually, and sometimes it is necessary to supplement and modify the control system even for individual technological modes [7, 8]. Also, many improved automatic control methods for optimizing control algorithms require an analytical description of control processes and adequate computational models [9].

Sources [10, 11] define the technology of multi-agent systems as promising for solving the problems of optimal control of multiconnected systems.

Therefore, it is important to initially determine the mode with highest efficiency within the specified productivity of the production line for the selected product brand. After that, the task is to achieve and stabilize it. Works [12, 13] describe methods for controlling and forecasting a continuous dynamic process using a multiagent system (MAS) with a set of peer objects that classify the current state of the process according to temporary reports of technological signals. Such MAS is focused on determining parameters that cannot be directly measured. In essence, the MAS should act as a predictor that identifies the regulated parameter at the next control cycles.

The positive effect of using predictors and state observers in automatic control processes is described in [14, 15]. Paper [16] describes the use of a neural network to identify the state and control a nonlinear dynamic object using the "control system design" framework. In this example, the neural network matches the current situation with optimized control actions, which provides advantages over traditional control systems.

Unsolved aspects of the problem. The proposed models of neural network and fuzzy automatic control systems also work on the basis of an inconsistency signal and do not implement full-fledged predictive control. They have very limited self-tuning properties and require the participation of experts to improve the quality of control [17]. The lack of a universal approach to the use of known intelligent technologies forces the synthesis of specialized methods and models for each installation individually [18], and sometimes it is necessary to supplement and modify the control system even for individual technological modes. Also, many improved automatic control methods for optimizing control algorithms require an analytical description of control processes and adequate computational models. Sources [19, 20] define the technology of multiagent systems as promising for solving problems of optimal control of multichain systems.

Purpose and tasks statement. The purpose of the work is to increase the efficiency of technological lines for drying bulk products by automating control using intelligent technology for determining the state of the product and predicting its initial moisture content using the analysis of an array of control and message signals in the time domain.

The following tasks were formulated to achieve the purpose:

- development of a model of a drum dryer as a technological control object, generation of experimental data;
- development of structural elements of the multiagent system;
- development of an algorithm for setting up and operating a multi-agent predictor;
- experimental study of the performance and quality of the multi-agent forecasting technology.

Description of the research methodology. In order to generate an array of experimental data and debug the multi-agent technology, it is advisable to develop a computer model of a technological installation that reproduces the drying process in compliance with the dynamic characteristics of real equipment.

The modeling assumes that the product moves along the drum discretely from one conditional link to another. The model is based on two parallel circuits of memory elements that correspond to the product and moisture in the conditional section of the drum (Fig. 2).

The input signals are the product flow and moisture content, on the basis of which the "Calculating the mass of material and water" block generates separate dry product and water flows, which are integrated into the material and water mass, which is on average at the beginning of the drum. The memory elements store the values of the mass of the substance and transfer them from the previous to the next one according to the speed of the substance movement, depending on the drum rotation speed. The "Reset and download signal generation module" (Fig. 2) generates sig-

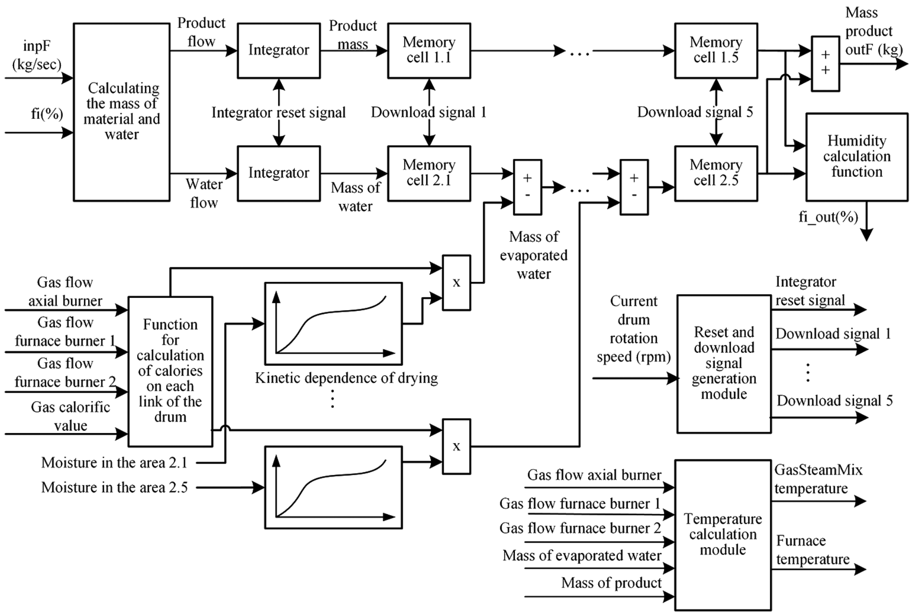

Fig. 2. Scheme of modeling the drying process

nals for the memory elements to fix and memorize the input value. Such a scheme allows subtracting the mass of evaporated moisture from the mass of water in the area at each step.

The "Function for calculation of calories on each link of the drum" calculates the calories delivered to each drum link based on the fuel consumption. Based on information about the moisture content of the product and on the basis of kinetic dependencies, the mass of evaporated moisture is calculated.

A separate module "Temperature calculation module" calculates the signals from the furnace temperature sensors and the temperature of the vapor-gas mixture at the drum outlet based on the product weight, evaporated water weight, and fuel consumption of each burner. The computational model considers and displays the time delays between changes in the process state and their detection by temperature sensors. The model serves as a generator of training and control data to study the quality of the multi-agent system.

Results. The final form of the automatic prognostication system structure depends on the configuration of the technological equipment. In the considered configuration, the input signals of the multiagent system are selected:

- rotational speed of the drum, rpm;
- gas flow to the axial gas burner, m^3/h;
- gas flow rate to the first furnace gas burner, m^3/h;
- gas consumption to the second gas burner, m^3/h;
- input product flow rate into the drum, kg/s;
- moisture content of the input product, %;
- temperature of the vapor-gas mixture, °C;
- temperature of the upper part of the furnace, °C.

Each input signal passes through a delay link, which corresponds to the time that elapses from the change in the corresponding signal to the change in humidity at the output. Thus, a simple one-dimensional vector describes the situation in dynamics to facilitates the identification task. Fig. 3 shows the formation of the input vector (signals y_c^i).

The multi-agent system consists of an ensemble of peer agents. Each agent contains its own memorized vector (y_p^i), similar to the input vector. Also, the agent stores the moisture content of the output product under the conditions specified by the input vector. The number of agents depends on the number of identified situations.

The agent also stores an array of weights for each component of the vector w^i. Each agent calculates the weighted distance between the input and the stored vectors, which allows adequately assessing the degree of difference between situations. The basic principle of weighting coefficients is next: if a small change in the input signal leads to a significant change in the predicted value, the coefficient is chosen to be greater than one, and if a significant change in the input signal leads to a slight change in the predicted value, the coefficient is chosen to be less than one.

The agent structure provides the calculation of a weighted

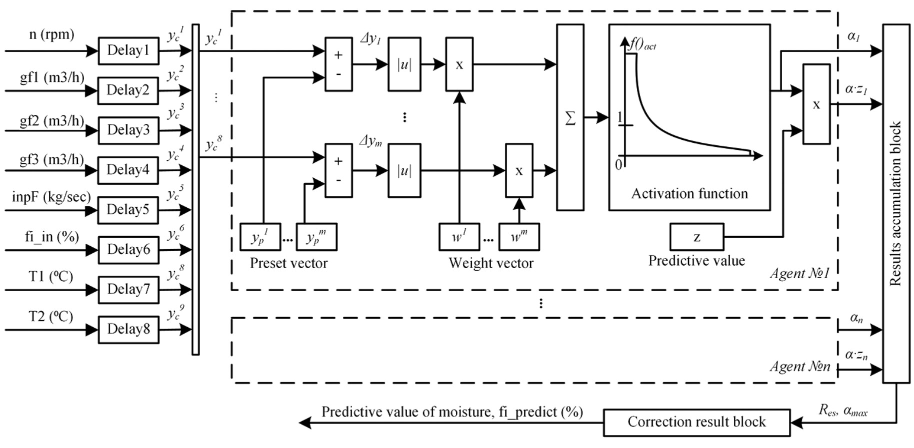

Fig. 3. Structure of the multi-agent predictor in the forecasting mode

modulo difference sum. Based on the sum of the difference, the output of the activation function (α) is calculated, which is inversely proportional to the difference between the vectors. The value of "α" corresponds to the degree of similarity between the input and the vectors stored in the agent. Also, the agent calculates the product of the predicted value z and the degree of similarity α, forming the output signal ($\alpha \cdot z$).

The "Results accumulation block" for the selected agents calculates the result using the 0^{th}-order Sugeno defuzzification method

$$R_{es} = \frac{\sum_{i=1}^{n} z_i \cdot f_{tr}(\alpha_i, \alpha_{max}) \cdot f_{act}\left(\sum_{j=1}^{m}\left(\left|y_c^j - y_{pi}^j\right|\right) w_i^j\right)}{\sum_{i=1}^{n} f_{tr}(\alpha_i, \alpha_{max}) \cdot f_{act}\left(\sum_{j=1}^{m}\left(\left|y_c^j - y_{pi}^j\right|\right) w_i^j\right)}, \quad (1)$$

where f_{act} is the output of the activation function of the i^{th} agent; f_{tr} is the logical function of selecting agents according to the threshold of α_i, depending on the maximum value of α across the entire set of agents, the activation function is described by the expression

$$f_{tr} = \begin{cases} 1, \alpha_i \geq threshold \\ 0, \alpha_i < threshold \end{cases},$$

where *threshold* is the adaptive threshold for selecting calculating agents.

Thus, an adaptive selection of agents is realized to form the final forecast. The approach is as follows: the higher the maximum value of α_{max}, the higher the threshold for agents whose output will be considered. Thus, for certain situations, the influence of those agents that are inadequate to the current situation is leveled. The threshold for the f_{tr} function can be set in a tabular way (Table 1).

The "Correction result block" is used for a low value of α_{max}. If a low degree of any agent correspondence to the current situation is observed, the output value is corrected by the a priori formed dependence of the proportional influence of the input signal vector components on the output humidity value

Table 1

Dependence of the *threshold* for selecting agents on the maximum degree of compliance

No.	α_{max}	*threshold*
1	0.001	0.03
2	0.003	0.04
3	0.006	0.1
4	0.008	0.15
5	0.01	0.2
6	0.015	0.25
7	0.03	0.3
8	0.05	0.35
9	0.10	0.4
10	0.4	0.45
11	0.7	0.5
12	1.0	0.9

$$fi_{predict} = R_{es} + \frac{0.12}{\alpha_{max}} \sum k_j \cdot \Delta y_j, \quad (2)$$

where Δy_i is the deviation of the j^{th} vector component for the agent with the maximum value of α; k_j is the coefficient of influence for the j^{th} component on the final result.

Algorithm for setting up and operating a multi-agent predictor. The functioning of the multiagent system can be represented as a UML states diagram of a single procedure (Fig. 4). The procedure is cyclical, performed in constant steps. At each step, a vector of input signals is generated for the multiagent predictor. At the same time, the moisture content of the output product is correlated with the past values of the input vector and, if these data differ from the existing ones by more than

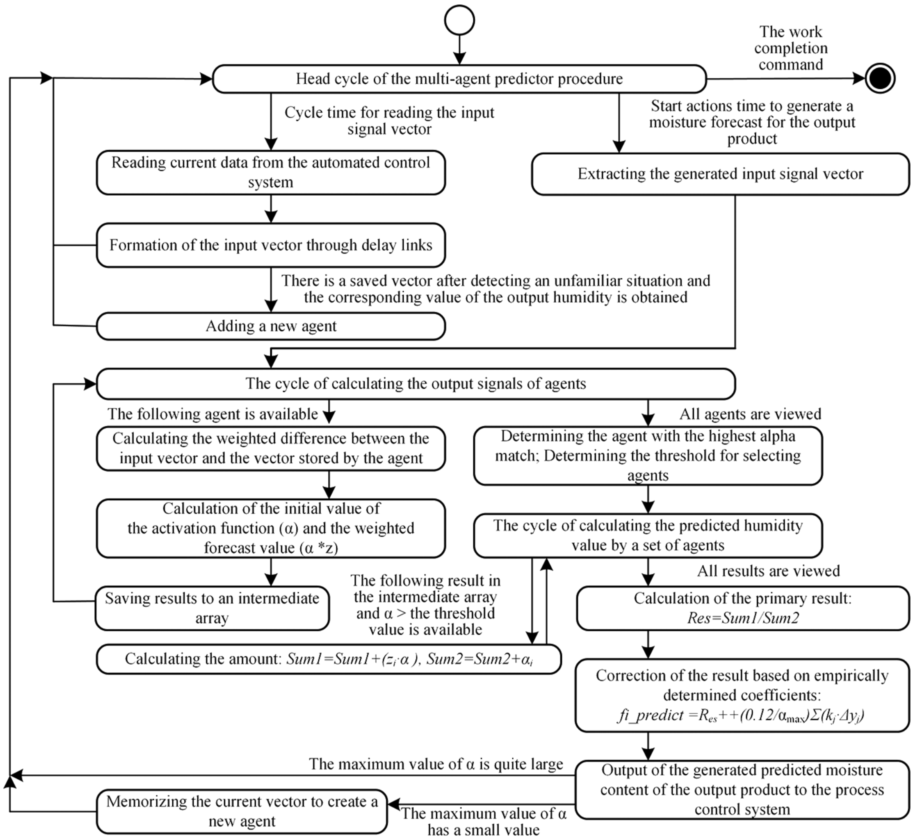

Fig. 4. UML state diagram of the procedure for calculating the predicted humidity value by the multi-agent system

a given threshold, a new agent is added to the collection. This is how the self-learning property is realized.

When it is time to calculate the forecast, the output signals of all agents α and $(\alpha \cdot z)$ are calculated. When all agents have been reviewed, the maximum value of α and the number of such an agent are determined, as well as the *threshold* for including a particular agent in the calculation.

Next, the result is calculated using formula (1). The final predicted value of the product moisture content $fi_{predict}$ is calculated by formula (2), with the result adjusted in proportion to the deviation between the components of the input vector and the components of the agent vector α_{max}.

Experimental study of the multiagent forecasting technology quality. Based on the developed model of the technological process, several modes were formed, which differed in initial humidity and gas flow to the burners. The rotational speed of the drum and the material flow into the drum remained constant. It was also assumed that the product brand was constant and had constant kinetic properties of moisture evaporation. Each control variable was changed after the transient process was completed.

The multiagent system was implemented as a procedure in the same simulation environment in which the model of the technological plant was designed. During the modeling process, the multiagent system processed information. If situation that differed from those already described by existing agents based on signal vectors was identified, the MAS also formed agents.

The list of input and control influences during the training period is shown in Table 2.

The criterion for adding an agent was the expression

$$\alpha_{max} < 2.$$

Based on the results of observing the object's operation, the system automatically generated 739 agents.

In order to study the performance of the developed technology, controlling influences were formed within the observed values, but in such combinations, which are not found in existing agents.

Fig. 5 shows the change in the initial humidity, which is calculated by the model of the technological installation and is experimental data. Also, Fig. 5 shows a variant of the multi-agent system without the correction operation according to formula (2). In the interval from 600 to 1,750 seconds and from 2,800 to 3,750 seconds, a significant error is observed, reaching 32 % in determining the initial moisture content. This is due to the fact that the combination of input signals causes a significant change in humidity, but is not familiar to the multi-agent system.

The next step was to apply the correction operation according to formula (2) based on empirically determined coefficients. In the course of the experiments, the values indicated in Table 3 were selected: C1 is the number of the vector component (signal designation); C2 is the value of the coefficient.

For the rest of the signals, the coefficients are equal to zero.

In Fig. 6, we can see the comparative results of the forecast on the same example with the application of the correction operation.

The next step was to allow the multiagent system to add new agents when a significant prediction error occurs and the α_{max} value is less than 0.1. Fig. 7 shows the results of the predictor for the studied modes.

Discussion of the experimental results. In the course of the study, the raw material consumption and the rotational speed of the drum were not changed to reduce the number of combinations of input conditions. This allows us to test the possibility of self-learning and approximation of multidimensional dependencies under working with one-dimensional signal vectors describing dynamic processes, within the local area. Changing four input influences (input product moisture, gas consumption/performance of the axial burner, and two furnace burners) made it possible to identify the advantages and disadvantages of the multi-agent technology.

Table 2

Composition of the input signal vector

No.	n (rpm)	gf1 (m^3/h)	gf2 (m^3/h)	gf3 (m^3/h)	inpF (kg/s)	fi_in (%)
1	4	100	60	60	5	20
2	4	100	70	60	5	20
3	4	100	70	70	5	20
4	4	150	70	70	5	20
5	4	170	70	70	5	20
6	4	130	60	60	5	18
7	4	100	60	60	5	22
8	4	100	60	70	5	22
9	4	100	70	70	5	22
10	4	150	70	70	5	22
11	4	170	70	70	5	22
12	4	160	60	65	5	23
13	4	110	60	65	5	23
14	4	110	60	65	5	17
15	4	110	40	65	5	17
16	4	110	40	45	5	17
17	4	130	40	45	5	17
18	4	150	60	65	5	24
19	4	120	60	65	5	24
20	4	120	60	65	5	18
21	4	120	60	55	5	18
22	4	120	45	55	5	18
23	4	140	60	60	5	22
24	4	110	60	60	5	22
25	4	110	60	60	5	19.5
26	4	110	60	25	5	19.5
27	4	110	45	25	5	19.5
28	4	170	77	45	5	22
29	4	170	77	72	5	22
30	4	80	77	72	5	22
31	4	80	77	72	5	19.5
32	4	80	77	89	5	19.5
33	4	80	112	89	5	19.5
34	4	80	67	89	5	19.5
35	4	175	60	40	5	22
36	4	135	60	40	5	22
37	4	135	60	40	5	19.5
38	4	135	60	65	5	19.5
39	4	135	45	65	5	19.5

Table 3

Correction factors for calculating the final moisture value

C1	2 (gf1)	3 (gf2)	4 (gf3)	5 (inpF)	6 (fi_in)	7 (T1)	8 (T2)
C2	0.6	0.5	0.5	0.2	0.25	0.05	0.05

Modeling studies have shown the general operability of the proposed technology, the fundamental possibility of approximating the multidimensional dependence of the output of a dynamic object on the set of input and disturbing influences of an agent ensemble. Each agent stores a description of a separate dynamic situation in the form of a signal vector of input signals and a constant of the predicted humidity value.

On a set of control examples, the predictor correctly identified the direction of change in the controlled variable, if each

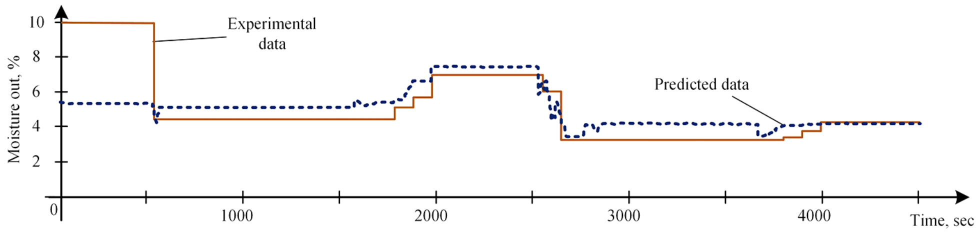

Fig. 5. A control example of studying the operation of the multi-agent system without a correction operation

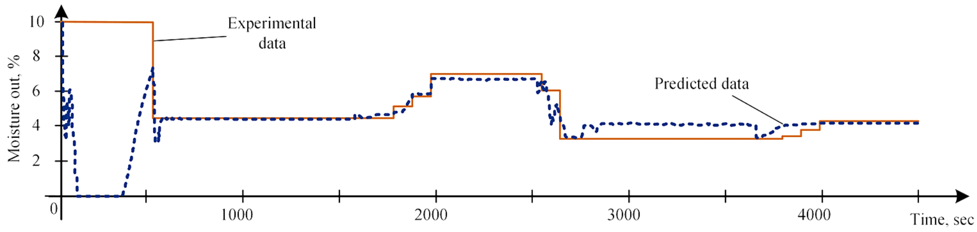

Fig. 6. Control example of studying the operation of the multi-agent system with a correction operation

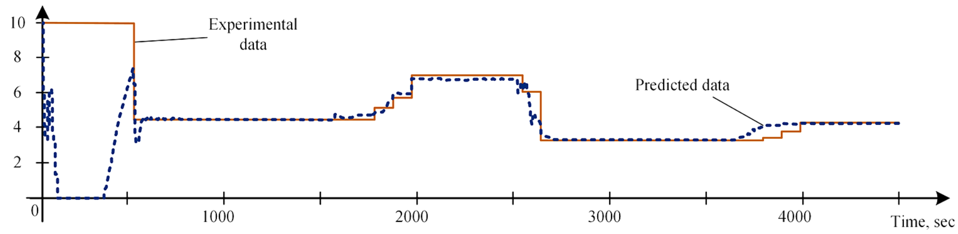

Fig. 7. Control example of studying the operation of the multi-agent system with an adjustment operation and adding a new agent

of the components of the input vector was within the range of situations considered in the past, even if it was significantly off the exact value.

Experiments have shown that the complexity of the application is due to the fact that the technology involves calculating the Hamming distance between vectors to select ones for forecast formation. This approach requires an expanded set of agents for an accurate result, otherwise, as shown in Fig. 5, the forecast has a significant error. Using weighting coefficients to calculate the weighted Heming distance, selecting agents by the threshold of "recognizing" the situation (signal α) improves the result only partially.

This is fixed by applying a correction. The coefficients of the correction function can be calculated by analyzing the data for the entire array of agents through regression analysis.

Automatic addition of an agent, in cases of appearing situation that is not recognized by any agent, allows one not only to accurately determine the initial humidity under these conditions, but also to improve the accuracy of the forecast for other situations, as can be seen in Fig. 7. After 2,600 seconds, we can notice a difference from the similar fragment in Fig. 6, which proves the impact of the new agent on the result in other situations.

Conclusions and prospects for further development. Drum dryers, in the context of automatic control, require the introduction of special models of automation systems that will provide PID control loops with up-to-date and accurate information about the state of the process, and will allow timely changes in control influences. In most drum dryers rotated inside the furnace, there can be more than a dozen control influences. For high-quality process control, in addition to the software and hardware of the process control system, it is necessary to have qualified operational personnel, who prevent the rejects occurrence or unprofitable modes.

The large range and individual characteristics of dryers, as well as the variety of product characteristics, make it very important to develop an intelligent technology with automatic learning and adaptation to a specific dryer.

Experimental studies confirm the following:

1. Multi-agent technology involves the use of a passive industrial experiment for its training, what is safe for the enterprise's operation.

2. Observation of the technological process allows the developed technology to automatically form a limited set of agents for reliable operation of the predictor. In cases where an unfamiliar situation is encountered, the technology allows generating the appropriate agent, when the quality indicator at the output of the technological unit becomes known.

3. For modes characterized by intermediate values of input signals, the ensemble of agents generates a collective forecast, in which the contribution of agents with a higher degree of compliance (situation recognition) is considered with greater weight. The procedure of excluding agents with a low level of correspondence allows reducing the forecast error. Otherwise, a situation may arise when a large number of agents with a low level of compliance "overpower" a single agent with a high level of compliance.

4. The quality of forecasting depends significantly on the accuracy of determining the time delays between changes in the input signal and the output humidity. The use of time delay blocks allows us to adequately describe the state of a dynamic process with a one-dimensional vector and reliably identify the current situation.

5. The use of the function of correcting the output result, at a low level of identification for the current situation based on the calculated values of the consistency between the same components of the input and the most appropriate vectors, can significantly improve the accuracy of the forecast.

6. The absolute error in predicting the moisture content of the output product in the studied examples does not exceed 5 %, which makes it possible to implement automatic stabilization of the product moisture content.

The achieved results are relevant for a wide range of objects characterized by the impossibility of direct measurements, non-stationarity of characteristics, long transportation delays, and a multitude of possible states. The implementation of the proposed technology allows ensuring the proper quality of automatic control by identifying and predicting the quality of products. The use of the predictor will allow one to implement classical control loops, compensate for the delay in the control loop and ensure timely correction of control influences before the product characteristic goes beyond the permissible limits.

The property of self-learning is realized by adding a new agent to the collection when an input signal vector with a high degree of difference from all vectors stored in the agents is detected. Under working with vectors composed of signal reports in the direct control channel and the feedback channel, it becomes possible to use the multi-agent system to perform predictive control of a dynamic object. The model experiments demonstrate the efficiency of the multi-agent control system.

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Мультиагентна технологія побудови предиктору для керування барабанною сушаркою

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Мета. Підвищення ефективності технологічних ліній сушіння сипучих продуктів шляхом автоматизації керування із застосуванням інтелектуальної технології визначення стану продукту та прогнозування його вихідної вологості з використанням аналізу масиву сигналів керування й повідомлення в часовій області.

Методика. Використана авторську модель барабанної сушарки з аксіальними й топковими пальниками для сушіння шихти, що використовується для виробництва залізорудного концентрату – окотків. На моделі виконана генерація навчальних і контрольних прикладів. Проведене дослідження працездатності мультиагентної технології та оцінка точності прогнозування вихідної вологості.

Результати. У роботі проаналізовані фактори, що ускладнюють якісне автоматичне керування процесом сушіння сипучих продуктів у барабанних сушарках, які обертаються всередині топки з пальниками. Запропонована модель інтелектуального предиктору, що ідентифікує стан продукту та прогнозує його вихідну вологість за доступними керуючими сигналами й сигналами зворотного зв'язку. Доведена працездатність моделі мультиагентної системи та алгоритмів обчислення прогнозного значення вологості, можливість використання технології для забезпечення автоматичного керування технологічним процесом і якісної стабілізації керованого параметра.

Наукова новизна. Предиктор реалізується у вигляді однорангової мультиагентної системи, що зберігає та проводить роботу з сигнальними векторами, в яких значення сигналів розміщене з урахуванням часових затримок між зміною відповідного сигналу та зміною вологості продукту на виході сушарки. Кожний агент містить опис окремої конкретної ситуації в динаміці. Технологія передбачає автоматичне налаштування мультиагентної системи шляхом аналізу масивів сигналів на тривалому проміжку часу й генерацію нових агентів у випадках, коли фіксується ситуація, яку неможливо описати масивом існуючих агентів.

Практична значимість. Технологія забезпечує розрахунок вихідної вологості масивом агентів і дозволяє реалізувати автоматичне керування сушаркою з нівелюванням часової затримки в каналі зворотного зв'язку.

Ключові слова: *сушіння сипучих продуктів, автоматичне керування, модельні експерименти*

The manuscript was submitted 13.02.24.