УДК 681.5.017
DOI: 10.17277/vestnik.2024.03.pp.414-425

INTELLIGENT INFORMATION-MEASURING SYSTEM OF DRUM DRYING UNIT

S. V. Artemova[1], M. A. Kamenskaya[2], P. I. Karasev[1], N. S. Ershov[1], Vu Tri Chien[3] A. A. Domornikova[1]

Department of Data Protection (1), karasev@mirea.ru;
Department of Instruments and Information-Measuring Systems (3);
MIREA – Russian Technological University, Moscow, Russia;
Department of Power Engineering (2); Tambov State Technical University, Tambov, Russia

Keywords: information-measuring system; drying; relative humidity; neural networks; network knowledge model.

Abstract: The article discusses an intelligent information-measuring system of a drum drying unit. A generalized block diagram of a drum-type drying installation is given. The construction of a model for operational humidity assessment is described. The model is a neural network with a multilayer perceptron architecture trained using the backpropagation method. It is the basis of an indirect measurement method that makes it possible to determine the moisture content of stillage during its drying in a drum drying unit. Particular attention is paid to the methodology for constructing intelligent information-measuring systems and the network model of knowledge representation.

Introduction

Drying is a widespread process in various industries. Drying units belong to the energy-intensive technological devices.

In the drum drying units (**DDU**), a convective drying process is realized. This type of equipment is used for drying fine bulk and wet materials. The drum drying unit consists of a cylinder installed at an inclination of about 3–6° relative to the horizontal plane, with two belts, with the rotation of the shaft, which slides on support rollers. The distance between the rollers can be adjusted to change the angle of inclination of the shaft. The shaft rotates thanks to a tight fit on the housing, the gears are connected to the motor through a gearbox. In this system, the drying material is actively mixed in contact with the drying agent. Significant heat exchange is carried out, there is a fast drying speed and a high uniformity of the product.

The drum drying unit operates with high productivity at atmospheric pressure and is well suited for technology of processing during the production of feeding alcoholic stillage. The drying in the drum drying unit is characterized by high stability, the quality of the product being dried and meets the technical requirements [1].

An important indicator of the drying process is the quality of the stillage being dried. Monitoring of moisture content in the mode of the real time drying process and making timely decisions on the management of this process has a significant impact not only on the quality of the material being dried, but also on the energy performance of the entire production in whole. The development and implementation of an intelligent information-measuring system (**IMS**) for the DDU helps to reduce the loss of quality of drying of the distiller's grain.

Method of indirect measurement of relative humidity of the stillage in the process of its drying in the DDU

The object for which the information-measuring system is realized is a drum shell-and-tube drying plant manufactured by VetterTec GmbH. Generalized block diagram of the DDU is presented in Fig. 1.

The composition of the DDU includes a fixed housing with a rotating drum located inside. Inside the drum there are two head parts of two pipe slabs and pipes flared in them. The drum with the material is heated by the steam supplied from the factory boiler room. In the tubes inside the drum, the steam moves in the direction opposite to the direction of material movement. At the same time, the quantity, the length and the diameter determine the heating power of the drying unit. At a pressure of 5 – 7 atmospheres in the system, the steam temperature ranges from 160 to 180 °C. The amount of steam supplied is regulated by automatic sealing steam heads.

The material for the drying in the DDU is the distiller's grain, which is a product left from the raw material after distillation for the producing of the alcohol or the beer. It is a kind of sediment with a strong odor and often cloudy color, as well as impurities.

The stillage can be used to feed the livestock. The mass fraction of distiller's dried grains is usually (96 ± 1), (93 ± 2), (90 ± 1) %. If the temperature of the material is higher than 120 degrees, then it begins to burn. This adversely affects the quality and the price of the finished product. When the thin stillage is supplied to the inlet of the DDU, it must be diluted with already dried stillage on a mixing screw. This provides that there is no accumulation of intermediate products at the plant.

Residual moisture content of distiller's dried grains is the main target quality indicator. Traditionally, its humidity content is monitored every 2 hours in the conditions of the laboratory. When determining of the humidity, additional time is required, resulting in a time lag. In order to achieve the required quality of the stillage at the output of the drum drying unit, it is required to know its moisture content in order to make timely decision on controlling the drying process. In order to eliminate this disadvantage it is supposed to use the developed IMS for the DDU.

The IMS is a comprehensive systems that possess information and measurement flows. This complex is accompanied by a multitude of measurement channels, which are of the greatest interest. The power of the measurement channel is determined by the magnitude of the arrangements which are subject to control using the available transducers. The functioning of the created IMS is based on the method of indirect

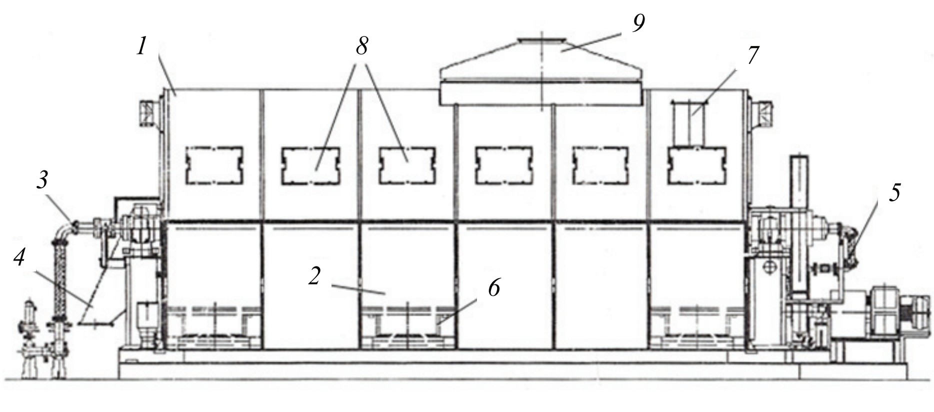

Fig. 1. Generalized block diagram of the drum type drying unit:
1 – housing; *2* – drum; *3* – steam supply; *4* – dry material outlet; *5* – steam outlet; *6* – blades; *7* – supply of material for drying; *8* – air-inlet windows; *9* – vapor-drain

measurement of relative humidity of the stillage in the process of its drying in the DDU on the basis of neural networks. The IMS includes the following primary measuring transducers:

– three primary measuring transducers of the temperature in different zones of the DDU;

– one primary measuring pressure transducer for systems with the supply of heat transfer agent in the form of steam directly into the working area of the DDU;

– primary measuring transmitter of oxygen content;

– distribution primary measuring transducer, which is pointed at the separation of thin and dried stillage;

– pulse-width devices located in the production processes control system (**PPCS**) and responsible for regulating the operation of the exhaust fan;

– transducer, which is also located in the PPCS and provides the determination of the loading level of the electric motor of the drying unit.

For each primary measuring transducer a separate channel is provided for transmission of information flows directly to the information-measuring system. The created system has eight measurement channels.

To estimate the relative humidity of the material in the mode of the real time in the IMS of the DDU models represented in the form of neural networks are used. The drying of the stillage is a nonlinear complex process, which is difficult to accurately express and control using traditional methods. An artificial neural network is not only capable of processing nonlinearities, realizing a self-organizing tuning and adaptive learning to provide a fault-tolerant noise protection, but also can effectively cope with nonlinear and complex fuzzy processes.

The network inputs are the following values: x_1 – initial moisture content of the stillage at the drying unit inlet, % of the dry matter; x_2 – stillage temperature at the dryer outlet, °C; x_3 – heat transfer agent pressure in atmospheres; x_4 – air temperature in the drying unit, °C; x_5 – exhaust fans power, %; x_6 – oxygen content in the drying unit air, %; x_7 – vapor temperature, °C; x_8 – drying unit electric motor load, %.

Each input parameter usually has different physical values and dimensionalities, and each input sample is equally important. Therefore all input variables are presented in the range [0; 1], and the initial range should cover all possible values of input parameters in the normal mode of operation of the system. The normalization of values is done by the formula:

$$x_{iN} = \frac{x_i - \mu_i}{\sigma_i}; \qquad (1)$$

$$f : T \times U \times X \times S \to Y,$$

where x_{iN} is the normalized value of the i-th variable, x_i is value of the i-th variable, μ_i is the mathematical expectation of the i-th variable, σ_i is the variance of the i-th variable.

The neural network training is organized according to the technological parameters reference metrics in the adaptive range of the drying unit with a fixed accuracy.

The analytical model for evaluating and monitoring the moisture content of the material in a drum drying unit is an artificial neural network, which is presented as a multilayer perceptron, trained using an errors back propagation algorithm. It can be written as follows:

$$\varphi = 100 - f_4\left(\sum_{h=1}^{m_3} f_3\left(\sum_{k=1}^{m_2} f_2\left(\sum_{j=1}^{m_1} f_1\left(\sum_{i=1}^{n} x_{iN} W_{i,j}^{(1)} + b_j\right) W_{i,k}^{(2)} + b_k\right) W_{k,h}^{(3)} + b_h\right) W_h + b^{\text{out}}\right), \qquad (2)$$

where φ is the estimate of the material humidity; x_{iN} is the normalized value of the i-th input variable.2; f_1, f_2, f_3 are the activation functions – ReLu-function:

$$f_1 = \max\left(0, \sum_{i=1}^{n} x_i\, W_{i,j}^{(1)} + b_j\right); \tag{3}$$

$$f_2 = \max\left(0, \sum_{j=1}^{m_1} \max\left(0, \sum_{i=1}^{n} x_i\, W_{i,j}^{(1)} + b_j\right) W_{j,k}^{(2)} + b_k\right); \tag{4}$$

$$f_3 = \max\left(0, \sum_{k=1}^{m_2} \max\left(0, \sum_{j=1}^{m_1} \max\left(0, \sum_{i=1}^{n} x_i\, W_{i,j}^{(1)} + b_j\right) W_{j,k}^{(2)} + b_k\right) W_{k,h}^{(3)} + b_h\right); \tag{5}$$

$$f_4 = \max\left(0, \sum_{h=1}^{m_3} \max\left(0, \sum_{k=1}^{m_2} \max\left(0, \sum_{j=1}^{m_1} \max\left(0, \sum_{i=1}^{n} x_i W_{i,j}^{(1)} + b_j\right) W_{j,k}^{(2)} + b_k\right) W_{k,h}^{(3)} + b_h\right) W_h + b^{\text{out}}\right), \tag{6}$$

n is the number of input variables (in our case $n = 8$), ($i = 1, \ldots, n$); m_1 is the number of neurons in the 1st hidden layer (in our case $m_1 = 36$) ($j = 1, \ldots, m_1 = 36$); m_2 is the number of neurons in the 2nd hidden layer (in our case $m_2 = 36$) ($k = 1, \ldots, m_2 = 36$); m_3 is the number of neurons in the 3rd hidden layer (in our case $m_3 = 36$) ($h = 1, \ldots, m_3 = 36$); x_i is the value of the i-th input variable; $W_{i,j}^{(1)}, W_{j,k}^{(2)}, W_{k,h}^{(3)}, W_k^{\text{out}}$ are hidden and output weighting coefficients:

$$W_{i,j}^{(1)} = \begin{pmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,m_1} \\ W_{2,1} & \cdots & \cdots & W_{2,m_1} \\ \vdots & \vdots & \vdots & \vdots \\ W_{n,1} & \cdots & \cdots & W_{n,m_1} \end{pmatrix}; \tag{7}$$

$$W_{j,k}^{(2)} = \begin{pmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,m_2} \\ W_{2,1} & \cdots & \cdots & W_{2,m_2} \\ \vdots & \vdots & \vdots & \vdots \\ W_{m_1,1} & \cdots & \cdots & W_{m_1,m_2} \end{pmatrix}; \tag{8}$$

$$W_{k,h}^{(3)} = \begin{pmatrix} W_{1,1} & W_{1,2} & \cdots & W_{1,m_3} \\ W_{2,1} & \cdots & \cdots & W_{2,m_3} \\ \vdots & \vdots & \vdots & \vdots \\ W_{m_1,1} & \cdots & \cdots & W_{m_1,m_3} \end{pmatrix}; \tag{9}$$

$$W_h^{\text{out}} = \begin{pmatrix} W_1 \\ W_2 \\ \cdots \\ W_{m_3} \end{pmatrix}; \tag{10}$$

$b_j^{in}, b_k, b_h, b^{\text{out}}$ are the displacement vector for the input layer, the displacement vector for the 1-hidden layer, the displacement vector for the 2-hidden layer and the displacement vector for the output layer:

$$b_j^{in} = \begin{pmatrix} b_1 & b_2 & b_3 & \dots & b_{m_1} \end{pmatrix}; \tag{11}$$

$$b_k = \begin{pmatrix} b_1 & b_2 & b_3 & \dots & b_{m_2} \end{pmatrix}; \tag{12}$$

$$b_h = \begin{pmatrix} b_1 & b_2 & b_3 & \dots & b_{m_3} \end{pmatrix}. \tag{13}$$

The used analytical model (2) makes it possible to make an evaluation the humidity of the material in scale of the real time in the drying unit in the process of its drying with a relative error, less than 2 %.

To estimate and monitoring of the humidity of the material during its drying in the drying unit, it is necessary to set up the system once. Using arrays of statistical data obtained from the transducers installed in the drying unit, we train a neural network. The obtained network parameters $W_{i,j}^{(1)}, W_{j,k}^{(2)}, W_{k,h}^{(3)}, W_k^{\text{out}}$, $b_j^{in}, b_k, b_h, b^{\text{out}}$ are recorded in the database system, and the resulting analytical model is recorded in the knowledge base. In the database is also stored the information which is coming from the transducers in the process of the system functioning.

The method allows for real-time operational assessment of humidity of the stillage in the process of its drying. The operative assessment of the humidity makes it possible, in the case of the deviation of the value of the humidity from the ideal humidity in the drying unit, to set up the parameters of the drying unit opportunely in order to increase the quality of the released material.

In the developed model of relative humidity estimation the fully connected neural network architecture is used. The proposed architecture has five layers with the corresponding number of neurons in the layers: 8-36-36-36-1. When compared with the experimental measurements, the predicted values followed the law of variation and the size of the experimental values, and the relative error of AARE (Average Absolute Relative Error) does not exceed 2 %. Hence, the neural network model can successfully predict the relative material humidity estimation during the drying process.

At the same time, there are no feedbacks and no connections between neurons in the same layer are utilized. The neurons in each layer are only connected to the neurons in the neighboring layer. The ReLU function was chosen as the activation function in the hidden layers and a linear function was used for the output layer [2].

The performance of the model was evaluated using the correlation coefficient – R_{cc}, Mean Square Error (**MSE**) and Mean Relative Error (**MRE**) of the training sample.

The correlation coefficient is defined as

$$R_{\text{cc}} = \frac{\sum_{i=1}^{N}((\varepsilon_i - \varepsilon)(\rho_i - \rho))}{\sqrt{\sum_{i=1}^{N}(\varepsilon_i - \varepsilon)^2 \sum_{i=1}^{N}(\rho_i - \rho)^2}}.$$

Mean Square Error is calculated as

$$\text{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\varepsilon_i - \rho_i)^2}.$$

Mean Relative Error

$$\mathrm{MRE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\varepsilon_i - \rho_i}{\varepsilon_i}\right| \times 100 ,$$

where ε_i and ρ_i are the experimental and predicted value respectively, and N is the total number of data used in the study. The coefficient R_{cc} is in [0, 1], and the closer the value is to 1, the better is the model performance, and the closer it is to 0, the worse is the model performance. The smaller is the selective root mean square error, the better is the quality of the prognostication and the model performance [2].

The architecture of the obtained artificial neural network was selected experimentally. From the analysis of the subject area, the number of neurons in the input layer was set to eight in accordance with the parameters that have a significant impact on the drying process in the drum drying unit, and the number of hidden layers and neurons in them was determined based on the accuracy and performance of the model during its training [2].

The optimal number of neurons in each layer was selected using comparative analysis. When the number of hidden layer nodes is equal to 36, the smallest training error is set at the level 0.1896 % and the number of epochs is equal to 50,000. These results show that the neural network model has good generalization ability.

The correlation coefficient R_{cc}, the MSE for the training data set are 99.18 %, 0.1609 % respectively.

The values of the correlation coefficient R_{cc}, the MSE for the set of the testing data are 98.94, 0.1896 % respectively.

The final artificial neural network model was tested on the test data not used in training (Figs. 2, 3).

The method for indirectly measuring the relative humidity of the stillage during its drying process in the DDU is as follows:

Step 1. Interrogate the transducers of the drying unit and calculate the input values of the neural network.

Step 2. Check the conditions of the ingoing measured values in the adaptive ranges of values used in training the neural network. If the condition is not met, the data is written to the database and a message is sent to the user.

Step 3. Normalize the obtained values (1).

Step 4 Calculate the humidity of the material using analytical model of the neural network (2).

Step 5. Save the calculated value in the database.

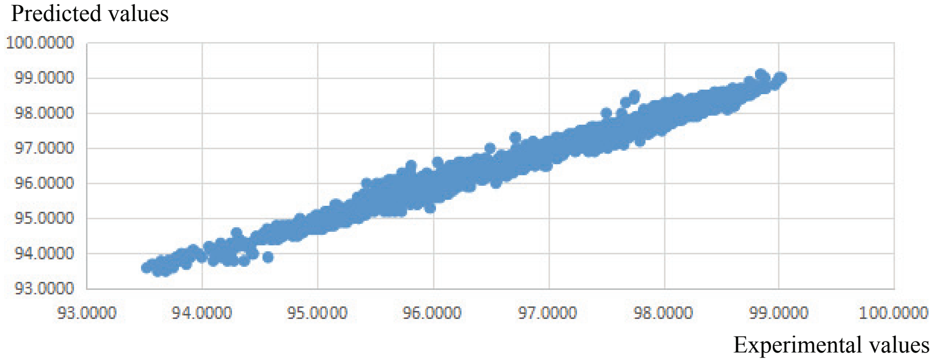

Fig. 2. Correlation between experimental and predicted humidity data during the training

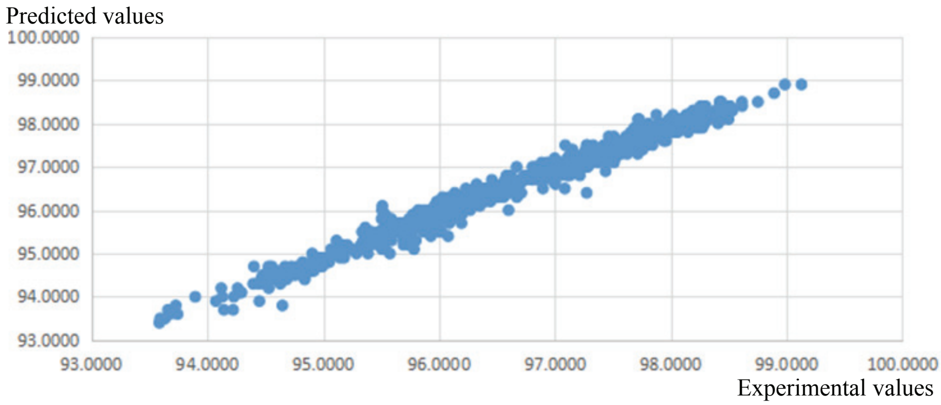

Fig. 3. Correlation between experimental and predicted humidity data during the testing

Table 1

Estimation of the material humidity using the example of a random sample of data

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	Reference metric φ	Estimation of the humidity from the model φ
80.6	117	6.47	114	44	5.5	108.3	75	97.0	96.85234
73.4	115	4.82	109	63	5.4	100.8	75	97.2	97.35859
72.7	115	7.28	117	71	5.8	106.6	77	97.4	96.82810
73.6	116	7.21	111	70	6.2	106.7	76	96.7	96.63859
74.6	116	5.22	107	70	7.4	101.5	77	97.5	97.46047
76.0	115	7.03	131	69	4.6	108.5	75	96.2	96.49960
75.8	106	4.67	125	82	4.9	105.5	70	95.1	95.57700
73.6	106	4.67	123	81	5.4	103.4	71	96.2	96.44693
75.6	98	3.78	115	85	4.4	100.5	75	95.5	95.53036
74.5	114	6.82	119	57	5.1	103.1	80	96.0	95.97664

Estimation of the material humidity using the example of a random sample of data shown in Table 1.

In Table 1, the maximum absolute inaccuracy of humidity monitoring by model (2) is < 0.6 and the relative error is < 0.6 %. To analyze the data, the correlation coefficient was used, which was equal to 0.9894. This result shows that the experimental and predicted values match well. The neural network model with error back-propagation algorithm has good performance and can explain the coincidence of 98.94% of the above experimental values and the values calculated by the model. Based on this, it can be concluded that the obtained artificial neural network can model and predict the change in humidity of the stillage during its drying.

The information-measurement system of the drum drying units

The information-measurement system is realized in the form of a separate program module integrated into the PPCS, which allows determining promptly in real time the humidity of dried stillage at the outlet of the drying unit.

The block diagram of the developed information-measurement system is shown in Fig. 4. The center of this system are knowledge and data bases. In the first case,

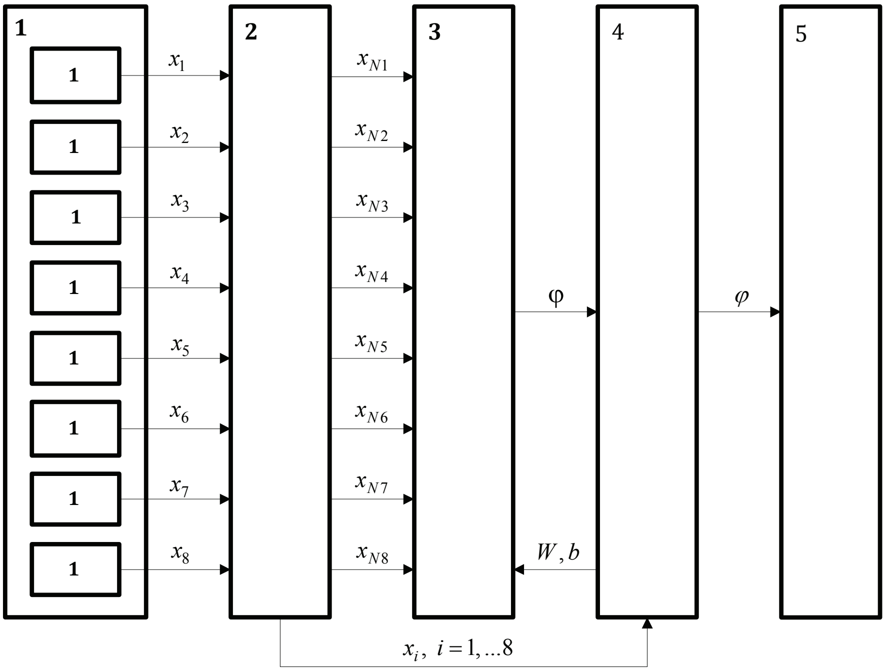

Fig. 4. Structural diagram of the IMS of the relative humidity of the material

it is supposed to locate a sufficient amount of information, which is needed to build analytics and decision making.

1. Drying unit of drum type.

1.1 – 1.8. Aggregate of primary measuring transducers of technological parameters of drying process.

2. Means of calculation of input variables.
3. Means of calculation of humidity.
4. Database.
5. Graphical and textual means of the information displaying.
6. Control system of the technological process.

The information-measurement system uses the frame model of the knowledge base [3], which contains the neural network model of the drying process in the DDU. The workflow is defined by the following key points: the humidity calculation module has primary knowledge from pre-collected data and knowledge bases. The latter are formed through neural training and augmented over time. Among the key criteria, the coefficient of normalization of primary information and the acceptable range of characteristics are highlighting. The primary measuring transducers located in the DDU request information through the PPCS: output product temperature, input product humidity, hot steam pressure, evaporation temperature, exhaust fans power, oxygen content in the air, load on the electric motor of the drying unit. The information obtained is also recorded in thedatabase and then sent to the calculation module of humidity estimation. Here, the data are normalized and the calculation and analysis of the material humidity level is performed. The obtained results are recorded in the database. The results are transmitted to the PPCS. The operator of the PPCS can control the drying process in drying units equipped with the IMS on the monitor screen.

The proposed methodology of the IMS construction contains the following stages:

1. Creation of the system requirement taking into account the key control tasks.
2. Technological characteristics determination which have an effect on the level of the stillage relative humidity.
3. The realization of the data collection for the knowledge base about the stillage relative humidity.
4. Division of the information flows into the test and training components.
5. Defining the architecture of the neural traning system.
6. Performing the verification operations regarding the adequacy of the applied model.
7. Development of the algorithmic support and the software.

The information base of the IMS is used to form a system of declarative type, in which the storage and the use of information flows for the work of a special module and of the system as a whole are performed through direct implementation in the PPCS.

The core of the IMS are the knowledge base (KB) and the database (DB).

In the IMS a network model of the KB is used. It contains neural network models of operational estimation of humidity in the process of the material drying in the drying unit. The knowledge here is represented in the following form:

$$S_r = \left\{x_n, W^{(1)}_{n,m_1}, W^{(2)}_{m_1,m_2}, W^{(3)}_{m_2,m_3}, W^{\text{out}}_{m_3}, b^{\text{in}}_{m_1}, b_{m_2}, b_{m_3}, b^{\text{out}}, c_{m_1}, c_{m_2}, c_{m_3}, f_1, f_2, f_3, f_4\right\},$$

where S is a network model; r is a network model number; x_n is a multitude of elements of the input layer of the network; $W^{(1)}_{n,m_1}$ is a connection matrix (synapse weights of the neurons of the first hidden layer), with the dimension $n \times m_1$; $W^{(2)}_{m_1,m_2}$ is a connection matrix (synaptic weights of the neurons of the second hidden layer), with the dimension $m_1 \times m_2$; $W^{(3)}_{m_2,m_3}$ is a connection matrix (synaptic weights of the neurons of the third hidden layer), with the dimension $m_2 \times m_3$; Σ_1 is a multitude of states of the neurons of the 1st hidden layer, here, the power of the multitude is determined by the calculation number of neurons of the 1st hidden layer equal to m_1; Σ_2 is a multitude of states of neurons of the 2nd hidden layer, here, the power of the multitude is determined by the calculation number of neurons of the 2nd hidden layer equal to m_2; Σ_3 is a multitude of states of neurons of the 3rd hidden layer, here, the power of the multitude is determined by the calculation number of neurons of the 3rd hidden layer equal to m_3; c_{m_1} is a multitude of neurons of the 1st hidden layer, the power of the multitude is equal to m_1; c_{m_2} is a multitude of neurons of the 2nd hidden layer, the power of the multitude is equal to m_2; c_{m_3} is a multitude of neurons of the 3rd hidden layer, the power of the multitude is equal to m_3; $W^{\text{out}}_{m_3}$ is a vector of links (vector of weight coefficients of the output layer); $b^{in}_{m_1}, b_{m_2}, b_{m_3}, b^{\text{out}}$ are the displacement vector for the 1-hidden layer, the displacement vector for the 2-hidden layer and the displacement vector for the output layer; f_1, f_2, f_3 are activation functions ReLu, f_4 is a linear function of the activation.

Conclusion

The use of the IMS of the DDU allows to perform estimation of the relative humidity of the distiller's grain in mode of the real time. The implementation of the IMS of the DDU for estimation and monitoring of material humidity in the process of drying in the drum dryer at Talvis JSC in Novaya Lyada allowed raising the output of quality product. Thus, the assigned technical task has been reached by obtaining a real-time operational assessment of the material humidity during the drying process to control this process in order to ensure the specified quality of the released product.

References

1. Lykov M.V. *Sushka v khimicheskoy promyshlennosti* [Drying in the chemical industry], Moscow: Khimiya, 1970, 432 p. (In Russ.)
2. Artemova S.V, Vu Chi Chiyen, Kamenskaya M.A. *Sposob otsenki vlazhnosti materiala v protsesse sushki v barabannoy sushil'noy ustanovke* [A method for assessing the moisture content of a material during drying in a drum drying installation], Russian Federation, 2022, Pat. № 2766517 (In Russ.)
3. Artemova S.V., Ladynin A.I., Shmeleva A.G., Vu Tri Chien, Kamenskaia M.A., Ryabchik T.A. Technological Processes Operational Assessment Frame Model in Automated Control Systems, *Proc. of IV International Conference on Control in Technical Systems*, St. Petersburg, 21-23 September 2021. St. Petersburg, 2021, pp. 27-29. doi: 10.1109/CTS53513.2021.9562783
4. Khaykin S. *Neyronnyye seti: polnyy kurs* [Neural networks: complete course], Moscow: Vil'yams, 2006, 1104 p. (In Russ.)
5. Gafarov F.M., Galimyanov A.F. *Iskusstvennyye neyronnyye seti i ikh prilozheniya* [Artificial neural networks and their applications], Kazan: Izdatel'stvo Kazanskogo universiteta, 2018, 121 p. (In Russ.)
6. Kumar A., Zhang Z.J., Lyu H. Object Detection in Real Time Based on Improved Single Shot Multi-Box Detector Algorithm, *EURASIP Journal on Wireless Communications and Networking*, 2020, vol. 2020, no. 204, pp. 1-18.: doi: 10.1186/s13638-020-01826-x
7. [Image segmentation]: TensorFlow Core. available at: https://www.tensorflow.org/tutorials/images/segmentation (accessed 15 January 2024).
8. Galushkin A.I. *Nejronnye seti: osnovy teorii* [Neural networks: basic theory], Moscow: Gorjachaja linija – Telekom, 2017, 496 p. (In Russ.)
9. Gromov Yu.Yu., Karasev P.I., Titov M.Yu., Sari F.A. [Comparison of fuzzy image processing methods], *Pribory i sistemy. Upravlenie, kontrol', diagnostika* [Devices and systems. Management, control, diagnostics], 2021, no. 7, pp. 55-61. doi: 10.25791/pribor.7.2021.1279 (In Russ., abstract in Eng.)
10. Ince T. Unsupervised Classification of Polarimetric SAR Image with Dynamic Clustering: An Image Processing Approach, *Advances in Engineering Software*, 2010, vol. 41, no. 4, pp. 636-646. doi: 10.1016/j.advengsoft. 2009.12.004
11. Vinogradov S.Yu. [Component model of fuzzy clustering based on the c-means algorithm], *Matematicheskiye metody v tekhnike i tekhnologiyakh – MMTT* [Mathematical methods in engineering and technology – MMTT], 2014, no. 6(65), pp. 111-113. (In Russ., abstract in Eng.)
12. Mask R-CNN: architecture of a modern neural network for segmenting objects in images: Habr, available at: https://habr.com/ru/articles/421299/ (accessed 15 January 2024).

Интеллектуальная информационно-измерительная система барабанной сушильной установки

С. В. Артемова[1], М. А. Каменская[2], П. И. Карасев[1], Н. С. Ершов[1], Ву Чи Чиен[3], А. А. Доморникова[1]

Кафедры: КБ-1 «Защита информации» (1), karasev@mirea.ru; КБ-6 «Приборы и информационно-измерительные системы» (3), ФГБОУ ВО «МИРЭА – Российский технологический университет», Москва, Россия; кафедра «Электроэнергетика» (2), ФГБОУ ВО «ТГТУ», Тамбов, Россия

Ключевые слова: информационно-измерительная система, сушка, относительная влажность, нейронные сети, сетевая модель знаний.

Аннотация: Рассмотрена интеллектуальная информационно-измерительная система барабанной сушильной установки (БСУ). Приведена обобщенная структурная схема сушильной установки барабанного типа. Дано описание построения аналитической модели оперативного определения относительной влажности послеспиртовой барды в процессе ее сушки в БСУ. Модель представлена в виде обученной многослойной нейронной сети, имеющей архитектуру многослойного перцептрона, обученного по алгоритму обратного распространения ошибки. Данная модель является основой приведенного метода косвенного измерения, позволяющего определять влажность барды. Особое внимание уделено методике построения интеллектуальных информационно-измерительных систем и сетевой модели представления знаний.

Список литературы

1. Лыков, М. В. Сушка в химической промышленности / М. В. Лыков. – М. : Химия, 1970. – 432 с.
2. Пат. № 2766517 С1 РФ, МПК F26B 25/22. Способ оценки влажности материала в процессе сушки в барабанной сушильной установке / Артемова С. В, Ву Чи Чиен, Каменская М. А. ; заявитель ФГБОУ ВО «МИРЭА – Российский технологический университет». – № 2021112482 ; заявл. 29.04.2021; опубл.. 15.03.2022, Бюл. № 8. – 12 с.
3. Technological Processes Operational Assessment Frame Model in Automated Control Systems / S. V. Artemova, A. I. Ladynin, A. G. Shmeleva, Vu Tri Chien, M. A. Kamenskaia, T. A. Ryabchik // Proc. of IV International Conference on Control in Technical Systems, St. Petersburg, 21 – 23 September 2021. St. Petersburg, 2021. – P. 27 – 29. doi: 10.1109/CTS53513.2021.9562783
4. Хайкин, С. Нейронные сети: полный курс: пер. с англ. / С. Хайкин. – 2-е изд. – М. : Вильямс, 2006. – 1104 с.
5. Гафаров, Ф. М. Искусственные нейронные сети и их приложения / Ф. М. Гафаров, А. Ф. Галимянов. – Казань : Изд-во Казанск. ун-та, 2018. – 121 с.
6. Kumar, A. Object Detection in Real Time Based on Improved Single Shot Multi-Box Detector Algorithm / A. Kumar, Z. J. Zhang, H. Lyu // EURASIP Journal on Wireless Communications and Networking. – 2020. – Vol. 2020, No. 204. – P. 1 – 18. doi : 10.1186/s13638-020-01826-x
7. Сегментация изображения: TensorFlow Core. – Текст: электронный. – URL: https://www.tensorflow.org/tutorials/images/segmentation (дата обращения: 15.01.2024).
8. Галушкин, А. И. Нейронные сети: основы теории / А. И. Галушкин. – М. : Горячая линия – Телеком, 2017. – 496 с.

9. Сравнение нечетких методов обработки изображений / Ю. Ю. Громов, П. И. Карасев, М. Ю. Титов, Ф. А. Сари // Приборы и системы. Управление, контроль, диагностика. – 2021. – № 7 – С. 55 – 61. doi: 10.25791/pribor.7.2021.1279

10. Ince, T. Unsupervised Classification of Polarimetric SAR Image with Dynamic Clustering: An Image Processing Approach / T. Ince // Advances in Engineering Software. – 2010. – Vol. 41, No. 4. – P. 636 – 646. doi: 10.1016/j.advengsoft. 2009.12.004

11. Виноградов, С. Ю. Компонентная модель нечеткой кластеризации на основе алгоритма с-средних / С. Ю. Виноградов // Математические методы в технике и технологиях – ММТТ. – 2014. – № 6(65). – С. 111 – 113.

12. Mask R-CNN: архитектура современной нейронной сети для сегментации объектов на изображениях : Habr. – URL: https://habr.com/ru/articles/421299/ (дата обращения: 15.01.2024).

Intelligentes Informations- und Messsystem der Trommeltrockner

Zusammenfassung: Es ist ein intelligentes Informations-Messsystem einer Trommeltrocknungsanlage (TTA) betrachtet. Es ist ein verallgemeinertes Blockdiagramm der Trommeltrocknungsanlage vorgestellt. Beschrieben ist der Aufbau eines analytischen Modells zur betrieblichen Bestimmung der relativen Feuchte von Nachalkoholschlempe während der Trocknung in einer Trocknungsanlage. Das Modell ist in Form eines trainierten mehrschichtigen neuronalen Netzwerks mit der Architektur eines mehrschichtigen Perzeptrons vorgestellt, trainiert unter Verwendung des Backpropagation-Algorithmus. Dieses Modell ist die Grundlage der oben genannten Methode der indirekten Messung, die es ermöglicht, den Feuchtigkeitsgehalt von Schlempe zu bestimmen. Besonderes Augenmerk ist auf die Methodik zum Aufbau intelligenter Informations- und Messsysteme und ein Netzwerkmodell der Wissensrepräsentation gelegt.

Système intelligent d'information et de mesure du séchoir à tambour

Résumé: Est examiné le système intelligent d'information et de mesure de l'unité de séchage à tambour (UST). Est cité un schéma structurel généralisé de l'installation de séchage à tambour. Est donnée une description de la construction d'un modèle analytique pour la détermination opérationnelle de l'humidité relative du barde post-alcool dans le processus de séchage dans UST. Le modèle se présente sous la forme d'un réseau neuronal multicouche apprentis, doté de l'architecture d'un perceptron multicouche formé à l'aide d'un algorithme d'inversion d'erreur. Ce modèle est à la base la méthode de mesure indirecte permettant de déterminer l'humidité de la barde. Une attention particulière est accordée à la méthodologie de la construction des systèmes intelligents d'information et de mesure et à un modèle de présentation des connaissances en réseau.

Авторы: ***Артемова Светлана Валерьевна*** – доктор технических наук, заведующий кафедрой КБ-1 «Защита информации», ФГБОУ ВО «МИРЭА – Российский технологический университет», Москва, Россия; ***Каменская Мария Анатольевна*** – кандидат технических наук, доцент кафедры «Электроэнергетика», ФГБОУ ВО «ТГТУ», Тамбов, Россия; ***Карасев Павел Игоревич*** – кандидат технических наук, доцент кафедры КБ-1 «Защита информации»; ***Ершов Никита Сергеевич*** – преподаватель кафедры КБ-1 «Защита информации»; ***Ву Чи Чиен*** – аспирант кафедры КБ-6 «Приборы и информационно-измерительные системы», институт кибербезопасности и цифровых технологий; ***Доморникова Анна Александровна*** – студент, ФГБОУ ВО «МИРЭА – Российский технологический университет», Москва, Россия.