

8-2-2019

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### Recommended Citation

Yunusova, S. T. (2019) "SIMULATION OF A TRAINED TRAINED NEURAL NETWORK OF A FUZZY LOGIC REGULATION SYSTEM BASED ON THE COTTON DRYING PROCESS," *Technical science and innovation*: Vol. 2019: Iss. 2, Article 7.

DOI: <https://doi.org/10.51346/tstu-01.19.2.-77-0027>

Available at: <https://btstu.researchcommons.org/journal/vol2019/iss2/7>

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UDC 681.5.015.3

**SIMULATION OF A TRAINED TRAINED NEURAL NETWORK OF A FUZZY LOGIC REGULATION SYSTEM BASED ON THE COTTON DRYING PROCESS****S. T. Yunusova***Tashkent State Technical University***Abstract**

*The article discusses the modeling of a fuzzy-logical system of regulation of the process of drying of raw cotton. The tasks of overcoming uncertainties arising in the process of operation of technological units at the enterprises of the cotton-cleaning industry are presented. An example of solving such a problem by using an artificial neural network is given. Mathematical models based on the neural network have been developed that are used to formalize the process of drying raw cotton and determine the optimal tuned parameters of the fuzzy-logical PID controller, allowing the fate of changing the operating modes of the technological units of the drying drum. A method for determining the number of synoptic weights of artificial neural networks is proposed, which minimizes the number of trainings and increases the speed of management decisions. To train the neural network weights use the reverse spreading error method. The range of variation of the regulator parameter is justified, taking into account the features of the cotton drying process. As a result, the proposed model was used in the control system of the drying process in terms of quality indicators, which led to an increase in the accuracy of the technological process.*

**Key words:** *neural model, neural network, dynamic model of an object, dryer, process, PID controller, cotton drying, fuzzy logic controller.*

**Introduction**

One of the most important processes at cotton processing enterprises is the process of drying raw cotton, which is a complex and multi-criteria task, characterized by the presence of a large number of uncertainties associated with changes in the variety, moisture and grade of dried cotton that arise in the process of cotton processing. One way to solve this problem is to use the methods of the theory of fuzzy sets. In this case, the construction of a fuzzy model is based on a formal representation of the characteristics of the system under study in terms of linguistic variables.[1,2,14,16].

In the general case, the goal of control is to determine the values of control variables based on the analysis of the current state of the dryer drum and the processed cotton, the implementation of which allows us to ensure the desired behavior or condition of the control object.

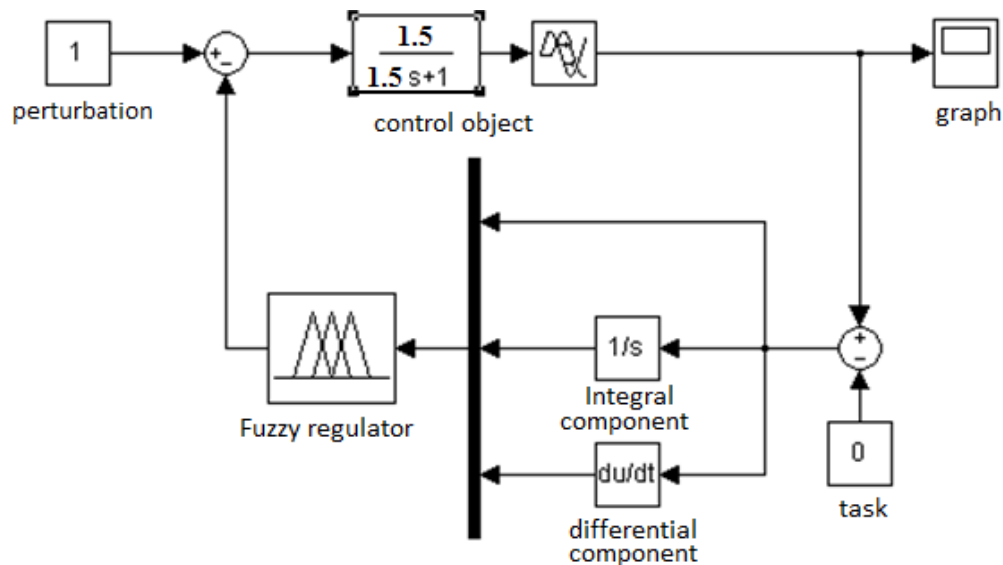
**Research results**

Recently, to solve such problems, methods of intelligent control, in particular artificial neural network (ANN), are widely used. When constructing a system of intelligent control of dynamic objects operating in real conditions, it is necessary to take into account the presence of uncorrelated disturbances, for example, the weediness and humidity of the cotton on the control object, as well as model values of the control system parameters that differ from the parameters of the working system [6,8,10,15].

Consider the practical use of artificial neural networks as an inverse neural model (INM) used to control the drying process of raw clap.

When creating an inverse model based on ANN, it should be borne in mind that the accuracy of reproducing the dynamics of the control object by a neuromodel depends on the choice of input network signals, the number of hidden layers and neurons that they contain [3.5, 8, 18].

To synthesize an OSI system, it is necessary to obtain experimental characteristics of its operation. For this, the drying process as a control object can be represented in the form of a block diagram using a PID - like fuzzy - controller (Fig. 1).



**Fig. 1.** Model of a single-circuit automatic control system with a PID-like fuzzy-controller.

It can be seen from Fig. 1 that the control object is a serial connection of typical automation links: an a periodic first-order link and a pure delay link. In this case, the transfer function of the control object has the form:

$$W_0(s) = \frac{1.5}{1.5s + 1} \cdot e^{-r \cdot s}$$

The transfer function of the PID controller is:

$$y(t) = k_s \cdot \varepsilon(t) + \frac{1}{T_I} \cdot \int \varepsilon(t) dt + T_D \cdot \frac{d\varepsilon(t)}{dt}$$

where  $k_s$  is the gain,  $T_I$  is the integration time,  $T_D$  is the differentiation time,  $\varepsilon(t)$  is the error signal. For the input variables of the controller, symmetric ranges of change are recommended, while:

$$x_1 \in \left[ -\frac{1}{P}; \frac{1}{P} \right], x_2 \in \left[ -\frac{1}{I}; \frac{1}{I} \right] \text{ и } x_3 \in \left[ -\frac{1}{D}; \frac{1}{D} \right],$$

where P is the proportional component; I- integral component; D is the differential component.

For the output variable of the regulator, it is recommended to take the range of variation in the form  $y \in [0; C]$  where the upper limit C for a single step action varies from 1.1 to 2 so that the output signal of the regulator can compensate for this disturbance. As the value of C increases, the dynamic error decreases, but the regulation time and the number of transient oscillations increase. Therefore, it is recommended that C be taken equal to 2 when the optimal ratio between the magnitude of the dynamic error, the regulation time and the number of

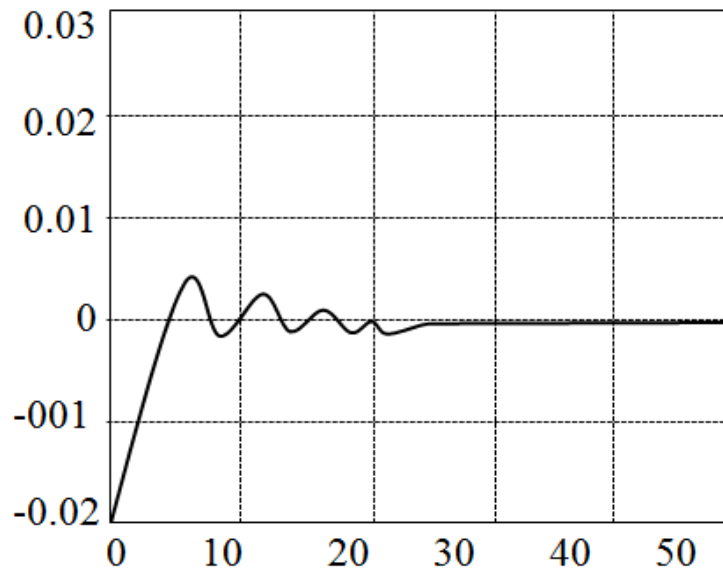
oscillations is observed [4.7].

Let the ranges of change of variables:

- $x_1 = [-0.9155; 0.915]$
- $x_2 = [-1.163; 1.163]$
- $x_3 = [-1; 1]$  (originally)
- $y = [0; 2]$

A more precise adjustment of the range of variation of the D-component is carried out by the selection method. For example, for a given object  $[-0.16; 0.16]$ .

The graph of the transition process of a model with a PID-like fuzzy controller is presented in Fig. 2.



**Fig. 2.** Transient graph of a model with a PID-like fuzzy controller.

Next is the synthesis of ANN, for which the structure based on the trained neural network of the created ANN is indicated with the type of activation functions of the neurons of the hidden and output layers.

For this purpose we use the MATLAB software environment.

In this case, it is proposed to use a two-layer ANN with back propagation of error, in which an iterative gradient learning algorithm is used to minimize the standard deviation of the current output and the desired network output. To estimate the required number of synoptic weights  $L\omega$  in a two-layer network with a sigmoidal transfer function, we use the formula:

$$\frac{m \cdot N}{1 + \log_2 N} \leq L\omega \leq m \left( \frac{N}{m} \right) + 1 \cdot (n + m + 1) + m,$$

where  $n$  is the dimension of the input signal;  $m$  is the dimension of the output signal;  $N$  is the number of elements in the training set.

$$12,5 \leq L\omega \leq 277.$$

(1)

The number of neurons in the hidden layer  $L$  is calculated by the formula [4]:

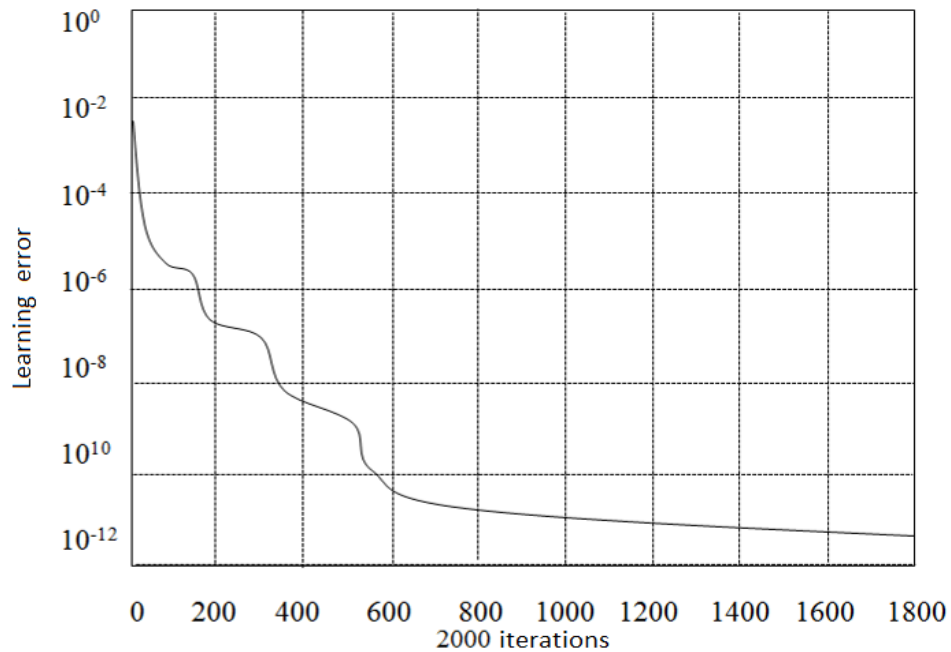
$$L = \frac{L\omega}{n + m}. \quad (2)$$

Knowing the minimum and maximum number of synoptic weights of the network (1) and using (2), we determine that the number of neurons in the hidden layer  $L$  lies within [3,5,6].

When training the neural network “with the teacher”, the deviation of the values of the

degree of sodium utilization at the output neuron from the real indicators and the reverse passage of these deviations to the elements that generated it are calculated in order to correct the error. At each era, we feed all the training observations to the network input, which are compared with target values and errors are calculated. The error value is used to adjust the network weights. The analysis shows that in this case it will be possible to maintain these quality indicators with a deviation of 1-2% from the required values.

In fig. Figure 3 shows a graph of the variation of the mean square error of reproducing the generated ANN properties of the inverse model of the system in the process of its training (minimizing the NS error).



**Fig.3.** Schedule of the MNS training process (minimization of error AND NS).

The values of the adjustable parameters (b.s) of membership functions, as well as the weights of fuzzy rules are given in Tables 1 and 2.

**Table. 1.**

**Membership Function Parameters**

Thermal conditions		A <sub>1</sub>	A <sub>2</sub>	A <sub>3</sub>	A <sub>4</sub>	A <sub>5</sub>	A <sub>6</sub>
Before training	b	0	0,15	0,4	0,6	0,85	1
	c	0,3	0,3	0,3	0,3	0,3	0,3
After training	b	0	0,13	0,41	0,63	0,85	1
	c	0,02	0,04	0,05	0,05	0,04	0,01

**Table. 2.**

**Weights rules**

Link Weight	W <sub>11</sub>	W <sub>25</sub>	W <sub>33</sub>	W <sub>44</sub>	W <sub>52</sub>	W <sub>66</sub>
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Before training	1	1	1	1	1	1
After training	0,999	0,9985	0,9988	0,9985	0,9984	0,9975

## Conclusion

Using the proposed model in the drying process control system in terms of quality indicators, which will lead to an increase in the accuracy of maintaining quality indicators.

## References

1. Cotton: World Statistics. Bulletin of the International Cotton Advisory Committee, NY, November 2015. <http://www.ICAC.org>. <http://www.USDA.gov>
2. Rojkov. S.A., Ternova T.I., Edinovich M.B. Problemi avtomatizovanogo rozbrakovannya tkanin. // Problemy legkoy i tekstilnoy promyshlennosti Ukrainy, 2004. №2(9), S.204-211.
3. Parpiev.A.R., Usmanqulov.A va boshq. Chigitli paxtani quritish,-T.,:“Fan va texnologiyalar”, 2009 y.B.34-36.
4. Zarubin V.S. Matematicheskoe modelirovanie v texnike- Moskva: izd. MVTU, 2003 g. S. 56-60
5. Paxta xom ashyosini quritish. Darslik Parpiev A., Axmatov- M. S., Usmonqulov A.B., Mo‘minov M, - Toshkent, “CHO‘lpon”, 2009 y. S 70-78.
6. Sinyavskaya E.D. Analiz tochnosti raboty nechetkoy modeli i optimizatsiya ee parametrov na primere upravleniya temperaturoy v xlebopekarnoy kamere. // Materialy II Vserossiyskoy nauchno-prakticheskoy konferensii «Molodyoj, nauka, innovatsii»- Groznyy, 2013.S. 95-100.
7. Siddikov I. X., Setmetov N.U. Metodologicheskaya osnova i prinsipy sozdaniya kompyuternoy sistemy podderjki prinyatiya resheniy dlya xlopkoochistitelnyx zavodov // Problemy tekstilya. Tashkent .2008№1 S.11-14
8. Gostev V. I. Proektirovanie nechetkix regulyatorov dlya sistem avtomaticheskogo upravleniya – SPb.: BXV – Peterburg, 2011.- 416 s.
9. Pegat A. Nechetkoe modelirovanie i upravlenie. M.: Binom. Laboratoriya znaniy, 2009-798 s.
10. Yunusova. S.T. Nechetkaya model upravleniya texnologicheskimi parametrami teplogeneriruyushix ustanovok.// Problemy energo - i resursoberejeniya -T,: 2017 g. № 3-4. S. 118-122
11. Alp Yanar T., Akyurek Z., 2011 Fuzzy model tuning using simulated annealing, Expert Systems with Applications.№38:8159-8169.
12. Mamatov A.Z. Modelirovanie texnologii sushki xlopka-syrsa s selyu povysheniya kachestvo volokna // Diss. Na soiskanie uchenoy stepeni. d.t.n. Tashkent. 1995g. S.248.
13. Igamberdiev X.Z. Issledovanie voprosov matematicheskogo modelirovaniya i upravleniya protsessom sushki xlopka – syrsa: Avtoref. dis. kand.tex.nauk. –Tashkent: 1974. -26 s.
14. Polyakov K.A. Polyakov A.E. Reshenie zadachi optimizatsii energosberegayushix rejimov tekstilnogo oborudovaniya. // Izv. Vuzov. Texnologiya tekstilnoy promyshlennosti, 2005. -№1. – s. 124-127.
15. Artukov R.D. Povыshenie effektivnosti protsessa podgotovki xlopka k pererabotki putem optimizatsii temperaturnogo rejima sushki. // Diss. na soiskanie uchenoy stepeni kand. texn. Nauk Tashkent 1998. S.36.
16. Karsukova A. V. Intensifikatsiya sushki xlopka-syrsa s primeneniem sushilnogo agenta vysokoy vlajnosti i temperatury: Dis. kand.tex.nauk. –Tashkent: 1984. -163s.

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17. Xolmatov D.A., YUnusova S.T. Setmetov N.U.,Xujanazarov U.O. Software tool monitoring process of processing raw cotton. International Journal of Advanced Research in Science, Engineering and Technology Vol. 6, Issue 2 , March 2019.

18. S.T. YUnusova. Nechetkaya model upravleniya texnologicheskimi parametrami teplogeneriruyushchix ustanovok –«Проблемы энерго i resursosberejeniya».-Toshkent -№ 3-4,2017 g.118-122s.

19. YUnusova S.T. O formalizatsii kriteriya optimizatsii protsessa ochildki xlopka-syrsa ToshDTU xabarlari .2013 y . №3- ,35-40.

20. Xolmatov D.A., Yunusova S.T. Setmetov N.U.,Xujanazarov U.O. Information and algorithmic technological monitoring system algorithmic processes processing of raw cotton. WCIS -2014., Eighth World Conference on Intelligent Systems for Industrial Automatik..Toshkent .261-264bet.