DYNAMIC SYSTEMS MODELING USING ARTIFICIAL NEURAL NETWORKS FOR AGRICULTURAL MACHINES

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МОДЕЛИРОВАНИЕ ДИНАМИЧЕСКИХ СИСТЕМ С ИСПОЛЬЗОВАНИЕМ ИСКУССТВЕННОЙ НЕЙРОННОЙ СЕТИ ДЛЯ СЕЛЬСКОХОЗЯЙСТВЕННЫХ МАШИН

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ABSTRACT

The tasks of designing complex dynamic systems (an agricultural machine, a car, a metalworking machine) are always multi-criteria, since choosing a reliable option needs taking into account many various requirements for the technical systems. The methodologies and methods of dynamic systems research are currently improving due to the need in developing a functional component that takes into account the unlimited possibilities of computers, in some cases changing over to "virtual reality". The purpose of the study is to reveal the essence of a promising heuristic approach to the assessment of functional relationships between the functioning elements of dynamic systems and variables describing the state of a given system.

Technological production processes can be considered as a dynamic system containing resistance forces. In dynamic systems (machines), a transitory phenomenon occurs when starting and stopping, when switching from one mode to another, as well as when resetting or increasing the working load. In many cases, when studying transitory phenomena in dynamic systems, it is convenient to use not the classical method of integrating differential motion equations, but an operational calculus based on a promising area of applied mathematics – artificial neural networks, and one of the promising methods for the development and design of various dynamic systems is simulation by artificial neural networks.

The technological process model for onion harvesting machines presented by artificial neural networks is able to assess the qualitative indicators, separate functioning elements of the cleaning machine performance out of input factors with different physical nature, while further research is based on previous model constructions.

The methodology for modeling working processes of dynamic systems by using artificial neural networks in the form of reality objects significantly expands the opportunities for arrangement and reuse of the results obtained, makes it possible to use the analytical apparatus of the information theory (message transmission in the presence of interference) for searching and optimizing the design and operating parameters of the machines under development.

РЕЗЮМЕ

Задачи проектирования сложных динамических систем (сельскохозяйственная машина, автомобиль, металлообрабатывающий станок), всегда являются многокритериальными, поскольку при выборе достоверного варианта приходится учитывать множество различных требований, которые предъявляются к техническим системам. Совершенствование методологий и методов исследований динамических систем в настоящее время обусловлено необходимостью разработки функциональной составляющей, учитывающей неограниченные возможности вычислительных машин, переходящих в ряде случаев в «виртуальную реальность». Цель исследования – раскрыть суть перспективного эвристического подхода к оценке функциональных связей между функционирующими элементами динамических систем и переменными, описывающих состояние данной системы.

Технологические процессы производства можно рассматривать как динамическую систему, содержащую силы сопротивления. В динамических системах (машинах) переходный процесс

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возникает при пуске и остановке, при переходе с одного режима на другой, а также при сбросе или увеличении полезной нагрузки. Во многих случаях при исследовании переходных процессов в динамических системах удобно пользоваться не классическим методом интегрирования дифференциальных уравнений движения, а операционным исчислением, в основе которого лежит перспективная область прикладной математики – искусственные нейронные сети, а одним из перспективных методов разработки и проектирования различных динамических систем является метод моделирования искусственными нейронными сетями.

Модель технологического процесса работы машины для уборки лука, представленная искусственными нейронными сетями имеет возможность оценки качественных показателей работы отдельных функционирующих элементов уборочной машины от входных факторов, обладающих разной физической природой, при этом дальнейшее исследования базируются на предшествующих модельных построениях.

Методология моделирования рабочих процессов динамических систем применением искусственных нейронных сетей в виде объектов реальной действительности значительно расширяет возможности систематизации и повторного использования полученных результатов, обеспечивает возможность применения аналитического аппарата теории информации (передачи сообщений при наличии помех) для поиска и оптимизации конструктивных и режимно-технологических параметров разрабатываемых машин.

INTRODUCTION

At the present moment, the most common method for designing and assessing the performance of dynamic systems is system analysis. In the context of dynamic systems development, the following are traditionally used: conceptual, physical, structural-functional, mathematical (logical-mathematical), simulation modeling (*Komashinsky I.V., 2003).* Modeling of dynamic systems based on a systemic approach is reduced to building a model based on a "black box" principle *(Shchennikov V.N., Shchennikova E.V., Sannikov S.A., 2017).* These models do not reveal the mechanism of the phenomena and therefore can only be used when considering a specific process on an actual machine; hence they are not effective enough for in-depth studies at the subsystem level and finding new design solutions *(Garina S.V., Lyupayev V.M., Nikishin M.B., 2015).* When studying individual processes performed by dynamic systems and assessing their effectiveness based on entropy criteria as an indicator of randomness or irregularity, there are various approaches to effectiveness assessment *(Garina S.V., Lyupayev V.M., Nikishin M.B., 2015).*

The use of entropy quality assessment indicators when separating mixed volumes of heterogeneous particles is considered as a measure of heterogeneity of this mixture's composition *(Kamaletdinov R.R., 2012):*

$$\mathrm{H_x} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{x_i} \log_2 \mathrm{x_i}, \qquad (1)$$

where m– number of components, pcs;

x_i– component concentration.

The logical development of analytical descriptions for processes based on an entropy criterion is the information model for separation of grain mixtures proposed by A.P. Iofinov *(Kamaletdinov R.R., 2012).* In this case, it is suggested that the degree of the composition change (equalization) is evaluated as the amount of relative information E obtained after the mixture passes through the separator *(Kamaletdinov R.R., 2012).* Neural networks have an advantage over the more traditional methods considered above, on the assumption that when exact description of all existing interconnections is impossible, a certain set of indicators characterizing the phenomenon under investigation can be defined. When no clear conceptual model is available, it is not possible to apply regression methods *(Kostenko M.Yu., Kostenko N.A., 2009).*

MATERIALS AND METHODS

In machines, a transitory phenomenon occurs when starting and stopping, when switching from one mode to another, as well as when resetting or increasing the working load (*Komashinsky I.V., 2003).*

The qualitative indicators of the performance of dynamic systems, including an agricultural machine, are influenced by a decent number of factors: soil and climatic conditions, types of the functioning elements used (executive devices), technological and operating parameters of the machine *(Lobachevsky Ya.P., Emelyanov P.A., Aksenov A.G., Sibirev A.V., 2016).* An artificial neural network transforms the vector of input signals (X impacts) into the vector of output signals Y. An artificial neuron imitates, at a first approximation, the properties of a natural brain nerve cell (*Komashinsky I.V., 2003).* An artificial neural network is a mathematical model of a system containing simple elements (artificial neurons) connected and interacting with each other. It is known that any natural or artificial system that comprises initial state (input message/signal) *X (t)* and final state (output message) *Y (t)* is a classic understanding of the working processes of the machines, which is confirmed by the generalized scheme of an artificial neuron (*Komashinsky I.V., 2003).* Each neuron, including an artificial one, must have some inputs to receive a signal. The signals arriving on the inputs are multiplied by their weights. The first input signal is multiplied by the weight corresponding to this input. Then all products are transmitted to the summation unit, which summarizes all input signals multiplied by the corresponding weights. The activation function converts the weighted sum which is the output of the neuron. As activation function of neural elements, the hyperbolic tangent or sigmoid function is usually used. If the corresponding elements have the same activation function, the network is called homogeneous, otherwise – heterogeneous (*Komashinsky I.V., 2003).*

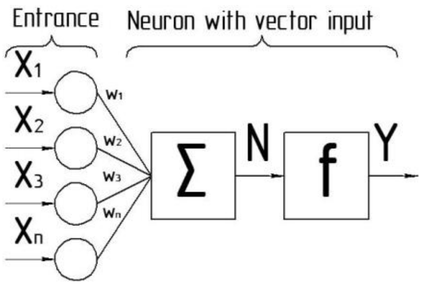

Fig. 1 – Generalized scheme of an artificial neuron

The principal distinction of a neural network from other statistical models is that it is not programmed in the usual sense of the word, it is trained (*Komashinsky I.V., 2003).* The training principle is to adjust the parameters of all neurons using the developed algorithm so that the network behaviour meets the desired requirements, which is identical when setting up agricultural machines for optimal operation. Due to its non-linear nature and fundamental similarity with brain activity, neural networks as they undergo training can identify the most complex relationships between the parameters of the input vectors, without requiring vast expenditures on computing resources. It is most appropriate to use neural networks as a statistical model due to the large number of their advantages. A neural network is hardware and software set of artificial neurons taking the vector parameters as input, multiplying them by appropriate weights, then summarizing the values obtained and determining the output value according to the established activation function. The intended purpose of machine operation, for example, an agricultural machine, is to transform the initial properties of the material interacting with the machine's executive devices into the required ones, which *(Sibirev A.V., Aksenov A.G., Dorokhov A.S., 2018)*, by analogy with an artificial neural network, represents transformation of an input signal into a specific output signal. The technological process of agricultural machine operation is a technological chain consisting in parallel and/or successive individual operations performed by functioning elements, including a set of technological actions for transformation of mechanical, energetic, physical, biological and other indicators in a particular object (*Kuzmin V.A., Fedotkin R.S., Kryuchkov V.A., 2017*). The beginning of agricultural machine executive body interaction with the material being processed should be considered as an artificial neuron's input. Later on, this signal, depending on how the process progresses, is subjected to transformation. Each signal is multiplied by the corresponding weight, which, by analogy with the actual technological process of an agricultural machine, corresponds to the effect of technological and operating parameters of the executive device on the processing quality of the interacting material.

The executive devices of an agricultural machine affect the material being processed in order to change its properties, which corresponds to the meaning of the activation function transforming the weighted sum of input signals into the desired neuron output. Activation functions (transfer functions) of a neuron may be presented in various ways *(Borisova L.V., Dimitrov V.P., 2017).*

RESULTS

Using an exponential, logistic or any S-shaped function (according to *V.P. Goryachkin*), it is possible to determine the total duration of individual development periods of the phenomenon (process) under study, the intensity of its development at any given time, which is displayed by the process development diagram presented in Figure 2.

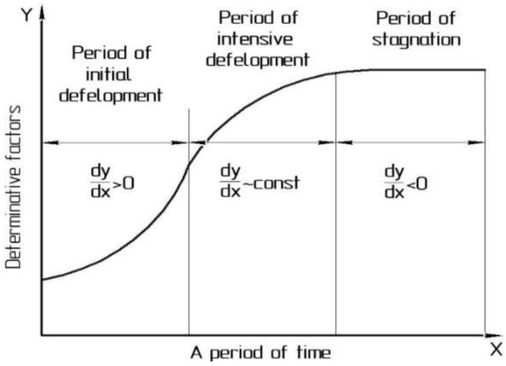

Fig. 2 – Graphical representation of the development of the agricultural process

When neural network is trained, training data is fed to the input network layer. This stage is called the forward motion of the back propagation algorithm. During the forward motion, each node in the hidden layer receives values from all other nodes in the input layer, then these values are multiplied with suitable weight coefficients and added up. The output signals of neurons are nonlinear transformations of the activation function.

In the same way, each output node receives the resulting values from all neurons in the hidden layer, these values are also multiplied with suitable weight coefficients and added up. The output of each output neuron is the non-linear transformation function of the activation function. The output values for the final layer are compared with the ideal output values. Ideal output values are output training data.

Table 1

Objects (processes) - analogues of artificial neural networks and agricultural machines

Seq. No.	Object (process) – analogue (artificial neural network)		Object (process) under study	
	Operation	Function	Operation	Function
1	Artificial neural network training	Configuring weights and thresholds for all layers	Adjustment of the agricultural machine under study	Configuring the functioning elements of the agricultural machine to a quasi-optimal operation mode
2	Reproduction by the artificial neural network	At the reproduction stage, information is processed after training, with the weights and thresholds, as a rule, remaining unchanged.	Technological operation process of an agricultural machine	The influence of the executive devices in an agricultural machine is aimed at processing or reprocessing the material to change its properties or state
3	A multilayer artificial neural network (perceptron) consists of 3 layers: first input, second hidden and third output	The first input layer receives and transmits the input signal to the second hidden layer. The second hidden layer converts the input signal and transmits it to the output layer. The third output layer generates signals for the interpreter and the user.	An agricultural machine includes a set of heterogeneous functioning elements (executive devices) representing the machine as an integrated dynamic system.	The functioning element (executive device) of an agricultural machine is designed to perform useful work.
4	Operation of an artificial neural network is based on topology – the architecture of layers and connections between the neurons.	Artificial neurons can be connected to each other using various methods, which creates a variety of neural networks with different architectures, training rules and capabilities.	The functioning elements (executive devices) of an agricultural machine have different designs and arrangements depending on interaction with the agricultural environment.	The design of the functioning elements (executive devices) depends first of all on the purpose of the agricultural machine and its operating conditions.

Based on the assumptions made, it follows that when a complex multi-functional system is developed, including an agricultural machine, which is a technical object consisting of interconnected functional parts (artificial neurons), it can be viewed as an artificial neural network – a multilayer perceptron with direct signal propagation (without feedbacks), having identical processes and objects with agricultural machinery, as presented in Table 1.

A multilayer perceptron functions according to the following formulas (*Komashinsky I.V., 2003):*

$$g_j = f\left(\sum_{i=1}^{n} v_{ij}x_i + Q_j\right) \tag{2}$$

where:

v_{ij} – is the connection weight of the i-th neuron's hidden layer to the j-th;

x_i – input signal;

Q_j – threshold array of the neuron's hidden layer.

$$y_k = f\left(\sum_{j=1}^{h} w_{jk}g_j + T_k\right) \tag{3}$$

where:

w_{jk} – is the connection weight of the i-th neuron's hidden layer to the k-th;

g_j – output signal of the neuron's hidden layer;

T_k – threshold array of the neuron's output layer.

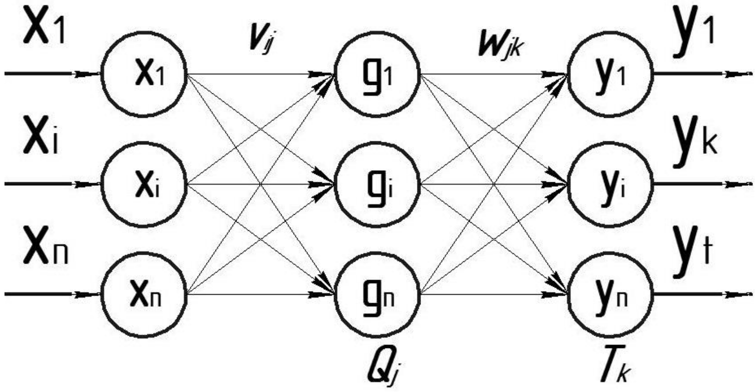

Fig. 3 – Multilayer perceptron

To provide high operation quality of technical equipment when planting and harvesting root crops and onions, it is necessary to ensure that technological operations are performed in compliance with agrotechnical requirements. In order to assess the qualitative indicators of the developed technical means as parameters of each vector most accurately, you must take into account perturbation factors of the external environment (X), state of the executive devices (Z) and factors conditioned by the optimal operation mode (U). Due to the fact that the qualitative indicators of the technological process of technical equipment operation related to cultivating and harvesting root crops and onions are not assessed by just a single qualitative indicator of operation but by at least two or even three, the dynamic system under study (sowing machine, combine harvester) is an individual case of Kohonen artificial neural networks (*Komashinsky I.V., 2003).* The input arguments for such a neural network are vectors, the numerical parameters of which represent the physical and mechanical properties of root crops and the state of the external environment, therefore each individual vector is a set of environmental disturbance factors (X). An agricultural machine is designed, depending on the type of the functioning elements used (artificial neurons), to perform basic technological operations: planting root crops, undercutting (digging up) root crops, separating them from the soil, removing the tops and plant matter, spreading over the surface of the harvested field or loading root crops into vehicles (*Komashinsky I.V., 2003).*

Most of the harvesters for root crops and onions, depending on the type of crop being harvested, consist of the following major functioning elements of various design (*Kamaletdinov R.R., 2012*): the undercutting executive device (П), the initial separation executive device (УП), as well as the executive device intensifying the separation process of the products being harvested from large soil lumps (УК); besides, modern designs of harvesting machines include devices for secondary separation of root crops from soil lumps and an unloading conveyor/roller (УТ). In order to most accurately assess the operation quality of the machine for harvesting seed onions, which is a complex dynamic system, it makes sense to consider the functioning elements of the harvesting machine separately.

During operation of the machine for harvesting root crops and onions, the resulting indicators (Y) of its operation will be affected by changing parameters of external and internal impacts, which may vary within the following values *(Kamaletdinov R.R., 2012):*

$$\begin{cases} X_{max} \le X \le X_{min} \\ Z_{max} \le Z \le Z_{min} \\ U_{max} \le U \le U_{min} \end{cases} \tag{4}$$

where:

X_{max}, X_{min} – are maximum and minimum values of external influence parameters with regard to the machine for harvesting root crops and onions;

Z_{max}, Z_{min} – maximum and minimum values of internal non-adjustable parameters of external influence on the machine for harvesting root crops and onions;

U_{max}, U_{min} – maximum and minimum values of internal adjustable parameters of external influence on the machine for harvesting root crops and onions.

As activation function of neural elements, the hyperbolic tangent or sigmoid function is usually used *(Makarov A.N., 2017).*

To ensure effective operation of an artificial neural network, it must be trained. The training algorithm consists in sequential processing of input vectors. The implementation of this artificial neural network training algorithm implies a change in the connection weights of neural networks, in our case, the internal adjustable parameters (U) of the functioning elements of the harvesting machine.

The varying connection weights of neural networks within the established values entail a change in the qualitative indicators (Y) of the harvester's functioning elements, the analytical dependencies of which are known, as a result of previous studies of the harvesters' executive devices.

The range of the qualitative indicator value (Y), the value of which must be obtained depending on the input vector (X), is reported to the neural network, based on which the neural network adapts the parameters of its neurons so that after training algorithm is passed, its behaviour corresponds to the solution of the specified task. The basic principle of neural network operation is to configure the neuron's parameters so that the network behaviour corresponds to a certain desired behaviour.

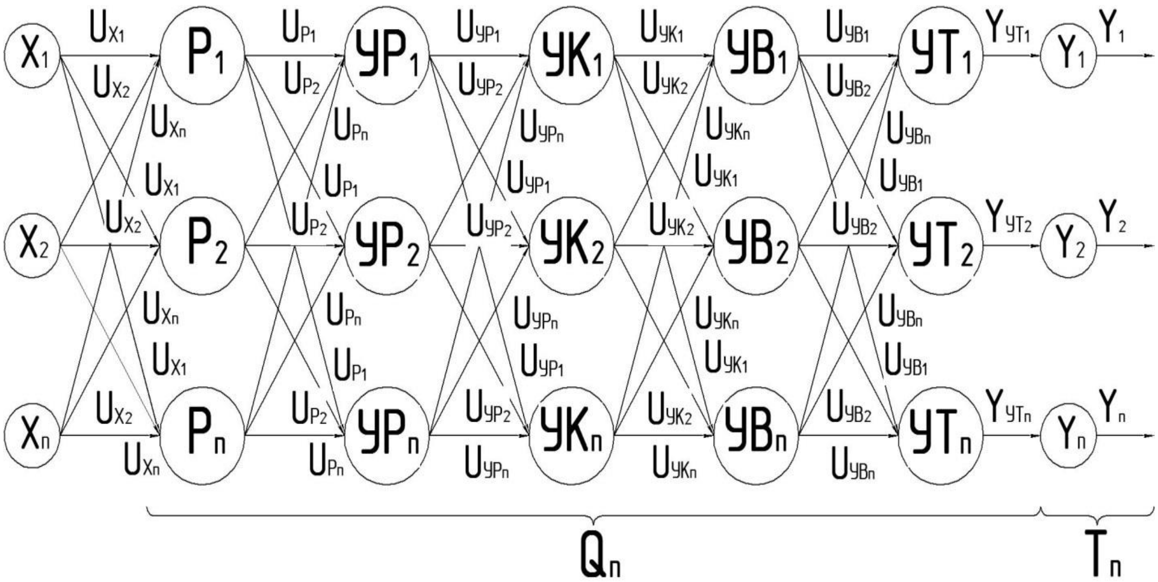

Fig. 4 – Functional diagram of the machine for harvesting root crops and onions for digging type for single-phase cleaning or the first phase of harvesting as a multilayer neural network:

P_1, P_2, Пn – design type of an undercutting executive device; $УP_1$, $УP_2$, УPn – design type of an initial separation executive device; УК1, УК2, УКn – design type of an initial separation executive device with an intensifier; $УВ_1$, $УВ_2$, $УВ_n$ – design type of a secondary separation executive device with an intensifier; $УТ_1$, $УТ_2$, УТn – design type of a swathing device or an unloading conveyor; X_1, X_2 и X_n – artificial neuron input; U_p, U_{yp}, Uук, Uув and Uут – control action functions for the undercutting executive device, initial separation executive device, initial separation executive device with a separation intensifier, secondary separation executive device and swathing device; Zр, Zур, Zук, Zув and Zут – state functions for the functioning element of the undercutting executive device, initial separation executive device, initial separation executive device with a separation intensifier, secondary separation executive device and swathing device;Yр, Yур, Yук, Yув и Yут – resulting parameters of the undercutting executive device, initial separation executive device, initial separation executive device with a separation intensifier, secondary separation executive device and swathing device

By adjusting weights and displacement parameters, an artificial neural network can be trained to perform a particular job; it is also possible that the network itself will adjust its parameters to achieve the result required.

The increase in the number of analytical dependencies used to determine qualitative indicators of the functioning elements' operation leads to a more accurate prediction of artificial neural networks. This requires using both standard and secondary performance indicators of the functioning elements as parameters for each vector.

In this case, to determine the resulting parameters (Y) of the harvester's functioning element, we'll use a random search method, according to which, when the input signal (X) passes from the previous executive device N_{n-1} to the next one, N_n a step is taken $j \cdot \xi$, where ξ is the single vector indicating the direction for the selected change of optimized parameters of the machine for harvesting root crops and onions; j – is the step size conditioned by the state of the internal adjustable parameters (U) of the harvester's functioning elements.

Therefore, each output parameter (Y) of the harvester's functioning element is determined by a system of qualitative performance indicators. Qualitative indicators of the machine for harvesting root crops and onions are assessed by a system of indicators: damage to root crops and bulbs Π_K,%; separation completeness of root crops and bulbs ν_K,%; loss of root crops and bulbs P_K,%.

At the same time, the qualitative indicators of the technological process of harvesting root crops and onions must comply with the agrotechnical requirements, i.e. they must remain in the range of values:

$$Y_{min} \leq Y_i \leq Y_{max} \tag{5}$$

where Y_i is the value of the i-th qualitative indicator of harvesting root crops and bulbs;

Y_{min}, the minimum value of the qualitative indicator of harvesting root crops and bulbs not exceeding the agrotechnical requirements;

Y_{max}, the maximum value of the qualitative indicator of harvesting root crops and bulbs not exceeding the agrotechnical requirements.

If the indicators of harvesting root crops and onions specified by agrotechnical requirements comply with the indicated range, as defined by equation, the artificial neural network output receives a value equal to 1, otherwise it receives 0, i.e.:

$$\Delta Y_i \begin{cases} 0, \text{ if } Y_i \leq Y_{min} \\ 1, \text{ if } Y_{min} \leq Y_i \leq Y_{max} \end{cases} \tag{6}$$

Table 2

The main indicators of the evaluation of machines for harvesting root crops and onions in accordance with agrotechnical requirements

Indicators	Vegetable root crops	Bulb onion	Seed onion	Garlic
Completeness of harvesting root crops and bulbs, at least, %	96	97	95	98
Contamination of a pile of root crops and bulbs, max, %	18	20	20	20
Damaged root crops and bulbs, max, %	8	2	2	3

To simulate the technological process of harvesting root vegetables and onions as closely as possible, we must take into account environmental factors, which are the input vectors X of the artificial neural network affecting the qualitative indicators of the harvesting machine, including: X_1 – sowing width of root crops and onions; X_2 – density of standing crops; X_3 – depth of root crops and bulbs; X_4 – sizes of root crops and bulbs; X_5 – physical and mechanical properties of the soil (soil moisture and hardness); X_6 – friction coefficient of root crops and bulbs against various surfaces.

The totality of input vectors arriving to the input of an artificial neural network (in our case, an agricultural machine) for transformation, shall be represented as a matrix:

$$X^{(i)} = \begin{bmatrix} X_1 & X_2 & X_3 \\ X_4 & X_5 & X_6 \end{bmatrix} \tag{7}$$

The topology of the same functioning elements of a harvester is determined by various designs of the executive devices within one layer of the artificial neural network.

Consequently, the weight coefficients determining the efficiency of the root crops and onion harvester artificial neural network hidden layer functioning elements are determined by a column vector, the elements of which are internal adjustable parameters (U) of the executive devices of the root crops and onion harvester:

$$W^{(i)} = \begin{bmatrix} U_{(П_1,УР_1,УК_1,УВ_1)} \\ U_{(П_2,УР_2,УК_2,УВ_2)} \\ U_{(П_n,УР_n,УК_n,УВ_n)} \end{bmatrix} \tag{8}$$

where $U_{(П_n,УР_n,УК_n,УВ_n)}$ means control action functions for the undercutting executive device, initial separation executive device, initial separation executive device with a separation intensifier and secondary separation executive device;

n – is the design type of the root crops and onion harvester functioning element.

Due to the fact that the threshold of an artificial neural network is a characteristic specifying the initial activity level of a neuron, it is necessary that the structural parameters of the executive device in the functioning element of the agricultural machine correspond to the operation performed, in order to ensure the initial stage of the agricultural operation (plowshare/coulter penetration, bar elevator movement).

Consequently, the internal non-adjustable parameters (Z) of a root crops and onion harvester functioning element are a threshold, the quantitative values of which define the qualitative performance of the technological operation.

The internal non-adjustable parameters of the artificial neural network hidden layer (Z) in the functioning elements of the root crops and onion harvester shall be represented as a column vector $Q^{(i)}$:

$$Q^{(i)} = \begin{bmatrix} Z_{(П_1,УР_1,УК_1,УВ_1)} \\ Z_{(П_2,УР_2,УК_2,УВ_2)} \\ Z_{(П_n,УР_n,УК_n,УВ_n)} \end{bmatrix} \tag{9}$$

where $Z_{(П_n,УР_n,УК_n,УВ_n)}$ – means state functions for the undercutting executive device, initial separation executive device, initial separation executive device with a separation intensifier and secondary separation executive device;

n – is the design type of the root crops and onion harvester functioning element.

The technological process analytical description for the functioning elements of the root crops and onion harvester based on the theory of artificial neural networks for the hidden layer shall be written as (*Komashinsky I.V., 2003):*

$$g_i = f\left(\sum_{i=1}^{n} w_{ij}x_i + Q_n\right) = f(x) = \frac{1}{1+e^{-\alpha x}} \cdot \left(\sum_{i=1}^{n} W^{(i)} \times X^{(i)} + Q^{(i)}\right) \tag{10}$$

where:

w_{ij} is the connection weight of the i–th neuron to the *j*–th;

x_i – is the input signal;

Q_n – is the hidden layer threshold array (functioning elements of the machine for harvesting vegetable crops).

According to equation (9), the technological process of a root crops and onion harvester operation, taking into account the output layer of the artificial neural network - the swathing device/unloading conveyor, shall be written as (*Komashinsky I.V., 2003):*

$$y_k = f(x) = \frac{1}{1+e^{-\alpha x}} \cdot \left(\sum_{j=1}^{h} W^{(j)} \times f\left(\sum_{i=1}^{n} W^{(i)} \times X^{(i)} + Q^{(i)}\right) + T^{j}\right) \tag{11}$$

The weight coefficients determining the efficiency of the swathing device/unloading conveyor (output layer) of a root crops and onion harvester are determined by the column vector:

$$W^{(i)} = \begin{bmatrix} U_{(,УТ_1)} \\ U_{(,УТ_2)} \\ U_{(,УТ_n)} \end{bmatrix} \tag{12}$$

where: $U_{(УТ_n)}$ is the control action function of the swathing device/unloading conveyor;

n, is the design type of the swathing device/unloading conveyor of the root crops and onion harvester.

The internal (Z) non-adjustable parameters of the artificial neural network output layer – the swathing device/unloading conveyor of the root crops and onion harvester shall be represented as a column vector for the neuron output layer threshold $T^{(j)}$:

$$T^{(j)} = \begin{bmatrix} Z_{(yT_1)} \\ Z_{(yT_2)} \\ Z_{(yT_n)} \end{bmatrix} \quad (13)$$

where $Z_{(yT_n)}$ –is the state function of the swathing device/unloading conveyor;

n – is the design type of the swathing device/unloading conveyor of the root crops and onion harvester.

To implement training process of the artificial neural network under study – the root crops and onion harvester simulated by a multilayer perceptron without feedbacks, training according to Hebb's rule or Δ –rule is used. Artificial neuron training according to Hebb's rule is advisable on condition that the neuron activation function is bipolar-threshold: Y -1; 1), or W vector is normalized, including the threshold.

The Hebb's rule is unsuitable for training an artificial neural network simulating operation of an agricultural machine, because the activation function during all agricultural processes is a form of sigmoid function, and not a threshold function, as required by this rule.

Therefore, the artificial neural network under study must be trained according to the Δ –rule. However, when training an artificial neural network by the Δ –rule, we must have information not only on the values of the current inputs of neurons X, but also the required correct values of Y.

For a multilayer network, these correct values are only available for neurons of the output layer. The required output values for the hidden layer neurons are unknown, which limits application of the Δ-rule.

To determine qualitative indicators of the root crops and onion harvester functioning elements, experimental studies were conducted, the results of which were used to obtain the input (X) and output (Y) parameters of the onion harvester functioning elements necessary to carry out training of an artificial neural network.

The data of the studies conducted were processed on a personal computer and represented in the form of diagrams in Figure 5, which allow us to determine the predicted output parameters of the root crops and onion harvester functioning elements necessary to conduct training of an artificial neural network.

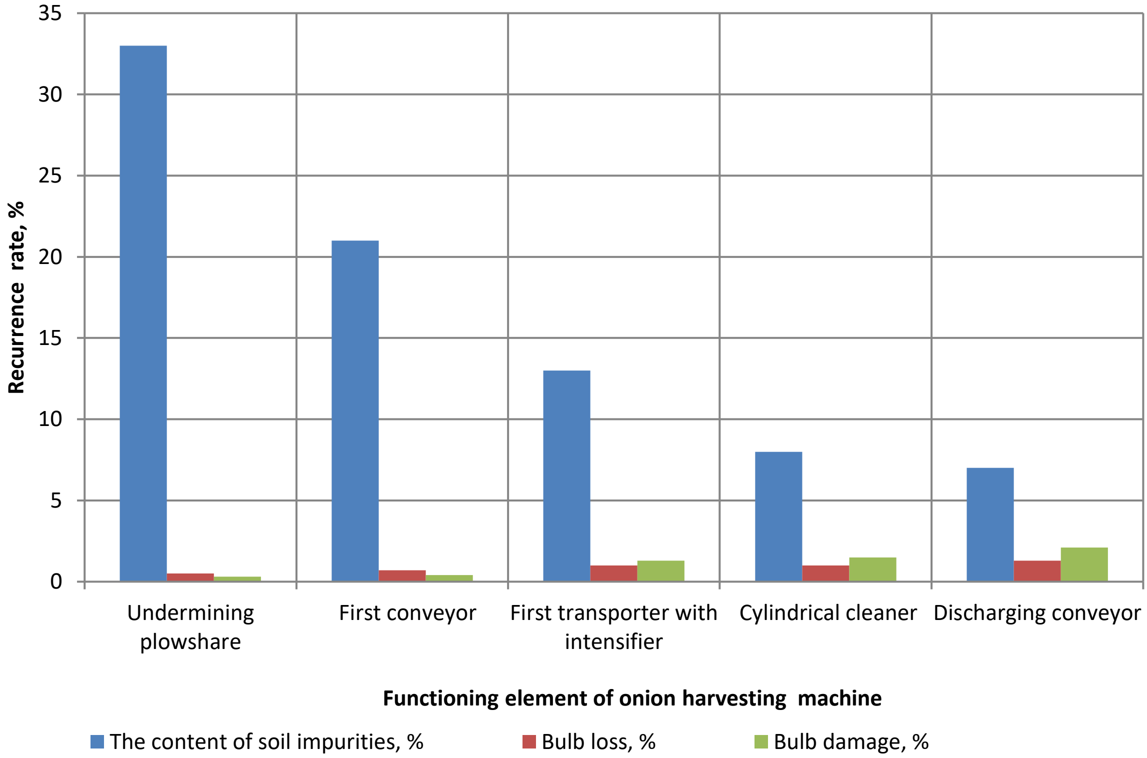

Fig. 5 – Technological process qualitative indicators of the onion harvester functioning elements operation

Along the abscissa axis, the studied functioning elements of the onion harvester are indicated – the undercutting blade, the first, second and unloading conveyors, as well as the secondary separation device - a cylindrical soil impurity cleaner; along the ordinate axis – the recurrence probability of performance qualitative indicators of the seed onion harvester functioning elements.

Table 3

Prognosis of an artificial neural network – root crops and onion harvester

Harvester functioning element	Harvester functioning element resulting parameters (Y)		
	Damaged root crops and bulbs	**Separation completeness of root crops and bulbs**	**Loss of root crops and bulbs**
Undercutting executive device (P)	$\text{П}_{\text{К(Р)}} = \left(\frac{\text{G}_{\text{РОВ}}}{\text{G}_{\text{СТ}} - \text{G}_{\text{РОВ}}}\right) \times 100\%$	$\text{К}_{\text{К(Р)}} = \left(\frac{\text{H}_{\text{R}}}{\text{H}_{\text{P}}}\right) \times 100\%$	$\text{P}_{\text{К(Р)}} = (1 - \text{W}) \times \left(\frac{\text{H}_{\text{P}} - \text{H}_{\text{SR}}}{\sigma_{\text{н}}}\right) \times 100\%$
Initial separation executive device (УР)	$\text{П}_{\text{К(УР)}} = \text{П}_{\text{К(Р)}} \times \left(\frac{\text{G}_{\text{РОВ}}}{\text{G}_{\text{СТ}} - \text{G}_{\text{РОВ}}}\right) \times 100\%$	$\nu_{\text{К(УР)}} = \text{К}_{\text{К(Р)}} \times \left(\frac{\nu_{\text{P}}^{\text{I}} - \nu_{\text{P}}^{\text{К}}}{\nu_{\text{P}}^{\text{I}}}\right) \times 100\%$	$\text{P}_{\text{К(УР)}} = \text{P}_{\text{К(Р)}} \times \left[100 - \left(\frac{\text{G}_{\text{L1}}}{\text{G}_{\text{L1}} + \text{G}_{\text{L2}}}\right) \times 100\right]$
Initial separation executive device with a separation intensifier (УК)	$\text{П}_{\text{К(УК)}} = \text{П}_{\text{К(УР)}} \times \left(\frac{\text{G}_{\text{РОВ}}}{\text{G}_{\text{СТ}} - \text{G}_{\text{РОВ}}}\right) \times 100\%$	$\nu_{\text{К(УК)}} = \nu_{\text{К(УР)}} \times \left(\frac{\nu_{\text{P}}^{\text{I}} - \nu_{\text{P}}^{\text{К}}}{\nu_{\text{P}}^{\text{I}}}\right) \times 100\%$	$\text{P}_{\text{К(УК)}} = \text{P}_{\text{К(УР)}} \times \left[100 - \left(\frac{\text{G}_{\text{L1}}}{\text{G}_{\text{L1}} + \text{G}_{\text{L2}}}\right) \times 100\right]$
Secondary separation executive device (УВ)	$\text{П}_{\text{К(УВ)}} = \text{П}_{\text{К(УК)}} \times \left(\frac{\text{G}_{\text{РОВ}}}{\text{G}_{\text{СТ}} - \text{G}_{\text{РОВ}}}\right) \times 100\%$	$\nu_{\text{К(УВ)}} = \nu_{\text{К(УК)}} \times \left(\frac{\nu_{\text{P}}^{\text{I}} - \nu_{\text{P}}^{\text{К}}}{\nu_{\text{P}}^{\text{I}}}\right) \times 100\%$	$\text{P}_{\text{К(УВ)}} = \text{P}_{\text{К(УК)}} \times \left[100 - \left(\frac{\text{G}_{\text{L1}}}{\text{G}_{\text{L1}} + \text{G}_{\text{L2}}}\right) \times 100\right]$
Swathing device or unloading conveyor (УТ)	$\text{П}_{\text{К(УТ)}} = \text{П}_{\text{К(УВ)}} \times \left(\frac{\text{G}_{\text{РОВ}}}{\text{G}_{\text{СТ}} - \text{G}_{\text{РОВ}}}\right) \times 100\%$	$\nu_{\text{К(УТ)}} = \nu_{\text{К(УВ)}} \times \left(\frac{\nu_{\text{P}}^{\text{I}} - \nu_{\text{P}}^{\text{К}}}{\nu_{\text{P}}^{\text{I}}}\right) \times 100\%$	$\text{P}_{\text{К(УТ)}} = \text{P}_{\text{К(УВ)}} \times \left[100 - \left(\frac{\text{G}_{\text{L1}}}{\text{G}_{\text{L1}} + \text{G}_{\text{L2}}}\right) \times 100\right]$

$P_{\text{К}}$ – bulb damage on the functioning element, %; $G_{\text{РОВ}}$ – is the weight of the damaged standard root crops and bulbs in a pile, kg; $G_{\text{СТ}}$ –is the weight of the separated root crops and bulbs in a pile, kg; $\text{К}_{\text{К}}$ – is the purity of the tailings heap when the soil layer is undercut, %; H_R –is the depth of unconsolidated soil layers, m; H_P – undercutting depth, m; $\text{P}_{\text{К}}$ – is the loss of root crops and bulbs on the functioning element, %; W – is the Laplace function; H_{SR} – is the depth of the cut soil layer, m; $\sigma_{\text{н}}$ – is the standard deviation of the depth of the lower root crops and bulbs; $\nu_{\text{К}}$ – is the separation completeness of a pile on the functioning element, %; ν_P^I – is the weight of soil impurities in the original pile of root crops and bulbs, kg; $\nu_P^{\text{К}}$ – is the weight of non-isolated soil impurities, kg; G_{L1} – is the weight of root crops and bulbs collected to the container before interaction with the executive device, kg; G_{L2} – is the weight of root crops and bulbs collected in the container after interaction with the executive device, kg.

Predicted $\text{П}_{(\text{ПР})\text{К}}$damage to root crops and bulbs:

$$\text{П}_{(\text{ПР})\text{К}} = \text{П}_{(\text{ПР})\text{К}_\text{Р}} + \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left[\left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right] + \text{П}_{\text{К(ук)}} \cdot \left[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right] + \text{П}_{(\text{ПР})\text{К}_{\text{УВ}}} \cdot \Big[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left[\left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right] - \text{П}_{\text{К(ук)}} \cdot \left[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right]\Big] + \text{П}_{(\text{ПР})\text{К}_{\text{УТ}}} \cdot \Big[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left[\left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right] - \text{П}_{\text{К(ук)}} \cdot \left[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right] - \text{П}_{(\text{ПР})\text{К}_{\text{УВ}}} \cdot \Big[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left[\left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right] - \text{П}_{\text{К(ук)}} \cdot \left[1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}} - \text{П}_{(\text{ПР})\text{К}_{\text{УР}}} \cdot \left(1 - \text{П}_{(\text{ПР})\text{К}_\text{Р}}\right)\right]\Big]\Big], \tag{14}$$

where $\text{П}_{(\text{ПР})\text{К}_\text{Р}}$ is the predicted damage to root crops and bulbs on the undercutting executive device, %;
$\text{П}_{\text{К(ур)}}$ is the predicted damage to root crops and bulbs on the primary separation executive device, %;
$\text{П}_{\text{К(ук)}}$, the predicted damage to root crops and bulbs on the primary separation executive device with a separation intensifier, %;
$\text{П}_{\text{К(ув)}}$, the predicted damage to root crops and bulbs on the secondary separation executive device, %;
$\text{П}_{\text{К(ут)}}$, the predicted damage to root crops and bulbs on the swathing device/unloading conveyor, %.

The damage to root crops and bulbs on the harvester functioning element was determined by the formula *(Kostenko M.Yu., Kostenko N.A., 2009):*

$$\Pi = \frac{G_{POB}}{G_{CT} - G_{POB}} \cdot 100\% \tag{15}$$

where G_{POB} is the weight of damaged standard root crops and bulbs in a pile, kg;

G_{CT}, the weight of the total amount of root crops and bulbs in a pile, kg.

The predicted $\nu_{(\Pi P)K}$ separation completeness of root crops and bulbs:

$$\nu_{(\Pi P)K} = 1 - \left(\nu_{(\Pi P)K_{\Pi}} \cdot \nu_{(\Pi P)K_{yP}} \cdot \nu_{(\Pi P)K_{yK}} \cdot \nu_{(\Pi P)K_{yB}} \cdot \nu_{(\Pi P)K_{yT}}\right) \tag{16}$$

where:

$\nu_{(\Pi P)K_P}$ is the predicted separation completeness of root crops and bulbs on the undercutting executive device, %;

$\nu_{K(yp)}$, the predicted separation completeness of root crops and bulbs on the primary separation executive device, %;

$\nu_{K(yp)}$, the predicted separation completeness of root crops and bulbs on the primary separation executive device with a separation intensifier, %;

$\nu_{K(yB)}$, the predicted separation completeness of root crops and bulbs on the secondary separation executive device, %;

$\nu_{K(yT)}$, the predicted separation completeness of root crops and bulbs on the swathing device/unloading conveyor, %.

The separation completeness ν of a pile of root crops and bulbs is determined by the formula *(Kostenko M.Yu., Kostenko N.A., 2009):*

$$\nu = \frac{\nu_P^I - \nu_P^K}{\nu_P^I} \cdot 100\% \tag{17}$$

where:

ν_P^I is the weight of soil impurities in the original pile, kg;

ν_P^K, the weight of soil impurities in the container (non-isolated impurities), kg.

Predicted $P_{(\Pi P)K}$ loss of root crops and bulbs:

$$P_{(\Pi P)K} = P_{(\Pi P)K_P} + P_{(\Pi P)K_{yP}} + P_{(\Pi P)K_{yK}} + P_{(\Pi P)K_{yB}} + P_{(\Pi P)K_{yT}} \tag{18}$$

where:

$P_{(\Pi P)K_P}$ is the predicted loss of root crops and bulbs on the undercutting executive device, %;

$P_{K(yp)}$, the predicted loss of root crops and bulbs on the primary separation executive device, %;

$P_{K(yp)}$, the predicted loss of root crops and bulbs on the primary separation executive device with a separation intensifier, %;

$P_{K(yB)}$ is the predicted loss of root crops and bulbs on the secondary separation executive device, %;

$P_{K(yT)}$, is the predicted loss of root crops and bulbs on the swathing device/unloading conveyor, %.

Loss P_L beyond the harvester functioning element was determined by the following formula *(Kostenko M.Yu., Kostenko N.A., 2009):*

$$P_L = 100 - \left(\frac{G_{L1}}{G_{L1} + G_{L2}}\right) \cdot 100 \tag{19}$$

where:

G_{L1} is the weight of root crops and bulbs collected in the container before interaction with the executive device, kg;

G_{L2}, the weight of root crops and bulbs collected in the container after interaction with the executive device, kg.

CONCLUSIONS

After the dynamic system under study (root crops and onion harvester) completed training, the harvester functioning elements were adjusted to the optimal operating modes by varying function (U) of the internal adjustable parameters in the range determined by the structural and technological parameters of the functioning elements – function (Z) of the internal non-adjustable parameters of the functioning element.

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