A New Approach to Evaluation of the Material Cutting Using the Artificial Neural Networks

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***Abstract* – Article deals with the process of accurate measurements and evaluation, i.e. the monitoring of the technological process of the material cutting using the Abrasive Water Jet and process control while using the artificial neural network, and a suggestion of process steps, particularly by a thorough application of mathematical modelling principles. An important mission of this article is to document, in an easy and comprehensible way, a tool intended for the creation of good control properties for multiple axes of the material cutting head support (using the AWJ, Plasma, acetylene burner, etc.). A desired objective is to achieve the best possible or optimal quality of the surface of the cut material, while using the properties of modern cutting technologies. To achieve those objectives, one of several known options was applied, in particular the advantages of the artificial neural networks and their beneficial properties. A simple task will be used to practically document the behaviour of an artificial neural network and a selected model execution.**

***Keywords* – Artificial neural network, Neuron, Multiaxial head support, Multi-parameter control.**

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1. Introduction

The introductory part of the present article provides a framework description of selected conventional as well as more up-to-date principles and technical approaches focused on the creation of continuous and smooth control. One of the state-of-the-art optimization strategies is the introduction of an artificial neural network in place of a more time-consuming numerical tool to compute the cost function [1]. The tasks focused on the creation of the control (trajectories) for equipment supporting technological heads have often been discussed in papers by several authors [2]. They are aimed at providing a required method of control in determined conditions and other disturbing effects and various requirements. The requirements include elimination, suppression of the effects that deteriorate the quality of a used technology, under static conditions and also in the situation of variable (dynamic) processes. Creation of the desired control is assumed in the real time [2]. Zhou focused on the problem of neural-network-based decentralized adaptive output-feedback control for a class of nonlinear strict-feedback large-scale stochastic systems [3]. In particular, specific or non-specific failures occurring in the control environment, a contactless [4] (touch-free) control of supported technological head, or pre-programming (rough control template) is preferred and subsequently carried out by a mechanic support [5]. Many current papers deal also with the applications in the field of robotics where several disturbing effects must be addressed [6-8]. Some innovative approaches to trajectory planning are cumbersome and demanding in terms of calculation, especially in the real state of the environment. Li and Bui [9] proposed a fluid-based model of trajectory planning in the static environment by using a fluid model, by the application of Poisson's equations and heuristic principles. To suppress the collisions of a multiaxial manipulator, a bit map model (technique) is used. Ong and Gilbert [10] describe a model determining the distances between the objects on the platform of potential collision states instead of searching for an appropriate, free way. Their algorithm determines the index of the overlap of the manipulator (or any other object) and an obstacle, whereas only the zero overlap trajectory is accepted as a safe one. There are also certain states where the procedure may be supplemented or the used trajectory design algorithms may be completely changed. By applying the artificial neural networks, we will find a potential application for models generating a trajectory in the real time by means of learning. Ritter [11] proposes the Kohonen's autonomously organized map based on artificial neural networks for the purpose of learning (acquiring) the transformation (conversion) from the Cartesian coordinate reference system into the manipulator's working space. The kinematics and the dynamics of the support arm are learned by the neighbouring neurons through cooperation. Fujii [12] proposes a multi-layer model with inadequate algorithm for the suppression of collisions in the (dynamic) environment containing several manipulators and several obstacles, whereas the created trajectories are not optimized, especially in the initial learning phase. Choi [13] introduced an algorithm for the creation of an arm trajectory by applying the neural activity determining the learning level based on previous solutions. An artificial neural network consists of two parts – one for the movement control and one for the static position control. The input layer has learnt to switch between these networks. A very operative solution can be found with the application of a multi-agent system. This system comprises the implemented algorithm of an ant colony, herd, flock, clan, crowd, wad, batch, school, gaggle, and hive where collisions do not happen in real natural conditions and at very high rates and extremely fast changes to the environmental and to the dynamics [14].

Practically all of the above listed options, solutions, and methods facilitate the supplementation of the control creation process not only with kinetic variables but also with technological variables, variables affecting the process and product quality. Process complexity will change significantly, in terms of economy and efficiency, if we also supplement the control with energetic, time, logistic, and distribution parameters [15],[16],[17].

With regard to cutting technologies, important variables affecting the control creation, and thus required for this process, include mainly the production of a resulting product, i.e. the quality of the cut surface [18]. For the quality and accuracy of the surface of the cut area, in the case of technologies (AWJ, plasma, acetylene burner, etc.) these parameters include: jet homogeneity, stability, jet modulation, movement and distribution of abrasives in the jet, direction of water and abrasive particles, "coherency", oscillations added to the basic movement (transversal, longitudinal, shaped, directional, combined, continuous, pulse, ..) and other parameters that can be monitored, measured, and controlled. It is advisable to include them in the identification before they are accepted or excluded, in order to determine the effect of a particular parameter on the change of notable quality indicators. By omitting any of the quality indicators or parameters, the values and relevancy of achieved properties will significantly decrease due to the absence of beneficial synergies.

2. Material and methods

Technological procedures, for example material cutting processes, are to a large extent determined by the functions of the inspection and information and control systems used for the control of technological machinery, auxiliary and manipulation equipment, complexes, cells, etc. Inspection and information and control systems have a certain HW structure and SW designed with regard to number of requirements specified by the manufacturer and user for the use thereof at a real workplace in the real time. The requirements are arranged in a pre-determined hierarchy and are fulfilled by means of number of regulating mechanisms [24],[25]. Regulators work independently in regulation mechanisms or in mutual relationship or conditionality. They are of the SW nature and facilitate the access to their own technological process with the aim to achieve the desired or optimal parameters of final results of the technological process. The most important and intensively monitored parameters of the results of technological process include quality indicators in the entire structure characteristic their own process or a final result of the technological process. To achieve the required parameters of a technological process and subsequently also of a product, regulation models or mechanisms, able to operate in the real time, are improved or new ones are developed concurrently with the technological process so that a user may access the on-line mode of monitoring the technological process course, process control using the selected factors accurately documenting the ongoing process.

2.1. Problem formulation

The survey object within the specified area is the analysis of the option of on-line monitoring or control of the material cutting technological process. The method of cutting with the abrasive water jet (AWJ) seems to be appropriate as well. When the AWJ is engaged, it is usually required to adhere to the optimal quality of the cut surface, mainly the parameters of flatness and roughness of the cut surface. When examining the AWJ technology options for material cutting, primarily metal materials, it is important to examine the forces developed by a working tool and affecting the object of a manufacturing operation, being the material to be subjected to longitudinal or transversal cutting. The AWJ working tool consists of two main components. A carrying medium is high-pressure water supplied to the working head, being a mixing pipe at the end of the technological flow; the second working medium is homogenized abrasive supplied via the pipeline into the mixing head where it is then dragged down by a water jet. This mixture leaves the technological head and impacts the surface of the cut material and by means of high kinetic energy it destructs the cut material and gradually forms a cut fissure on the cut material. Due to the fact that the main force factor of the interaction between the working tool and the cut material represents the impacts of abrasive particles onto the cut material, contacts of solid objects continuously occur. Even though the flow of the high-pressure water from the working head is continuous, impacts of the abrasive onto the cut material is of chaotic – stochastic nature. The material cutting technological process using the AWJ method thus results also in the occurrence of accompanying physical phenomena that accurately frame and indirectly document the technological process course. These accompanying physical phenomena include:

- vibration emission
- acoustic emission
- change to the inductance of the cut material, mainly metal material
- thermal emission production

2.2. Description of the measurement experiment

For the purpose of accurate measurements and evaluation, i.e. the monitoring of the technological process course, it is advisable to measure and analyse the data from the vibration and acoustic emission. The use of a well-arranged set of sensors – acceleration meters provides, in the on-line mode, a sufficient amount of relevant data on the creation and properties of the vibration and acoustic emissions during the AWJ technological process. By applying the specified SW (e.g. LabView) the measured data are processed, digitalized, and entered into an appropriate regulation frame. Regulation limits are determined on the basis of the results of final outputs defined by quality parameters, e.g. by the quality of the surface of the cut material. Possible appropriate parameters for defining the regulation limits to achieve the required or optimal quality include, for example, the data on RMS (Root Mean Square) values or an effective value, data on the topography of the cut material, or the data on the material surface roughness R_a. According to the hypothesis, we have performed a measurement experiment (Fig.1.).

3. Theory/calculation

The use of the self-regulating mechanism, while using the appropriately modelled and applied feedback, is only a partial possibility how to use autonomously learning regulating or control mechanisms for the control of kinematic sets in the dynamic mode. It is continuous control of 1 to x – axial sets, containing also the supplemented control of at least one technological parameter, which are mutually interrelated [19]. Within this interrelation, one parameter is superior to other parameters or individual parameters are arranged in a descending order. Their significance then determines also the importance of the regulation of the controlled parameter value with the use of the pre-specified regulation mechanism.

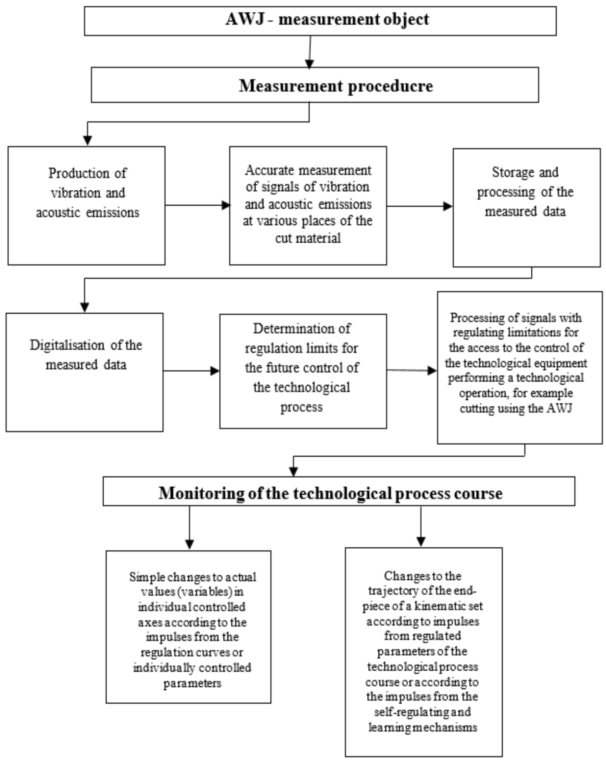


Figure 1. Procedure of measurement experiment for modelling the artificial neural network

Various types of regulation mechanisms are known to be applied in practice but the theory and also application of artificial neural networks in the field of control of kinematic sets and the control of technological processes is becoming more and more used in the last years. The above mentioned method of monitoring and control of technological processes, while using and processing the accompanying physical phenomena, is an example of the partial use of the simple feedback [20]. This example is an example of a simple self-regulating neuron or a simple neural structure.

A neuron model for the control activities may be chosen from several options and properties suitable for the task solved. One of the possible representatives is [21].

On the basis of conventional information sources on neuron characteristics, a generalized equation (1) with the parameters that will be changed (adjusted) during the solution process can be selected as the fundamentals for the creation of the artificial neural network model.

$$\frac{d_{xi}}{d_t} = -A_{xt} + (B - x_t)S_t^+(t) - (D + x_t)S_t^-(t) \qquad (1)$$

Where:

x_i is the neural activity (membrane potential) of the *i* neuron,

A, B, D	are non-negative constants representing the attenuation rate and the upper and the lower limits of the neural activity,
S_t^+, S_t^-	are actuating and damping neuron inputs

3.1. Structure of the artificial neural network and its layers in the application to the AWJ and the accompanying phenomena

From the synthesis point of view, the most frequently used structure is the multi-layer structure of the artificial neural network, as shown in Figure 2. Outputs from the *i* layer are conducted to the inputs in the *i* +1 layer. The first layer is designated as the input layer or the distributing layer, intended for the receipt of the values from the surrounding environment, process them and lead the outputs to the input of each neuron of the following layer. The last layer is called the output layer or the action layer and the values at its outputs represent the response (reaction) of the entire network to the input samples. Internal layers are usually called hidden layers. The number of layers and the number of neurons in individual layers depend on the complexity of the function we require from the network.

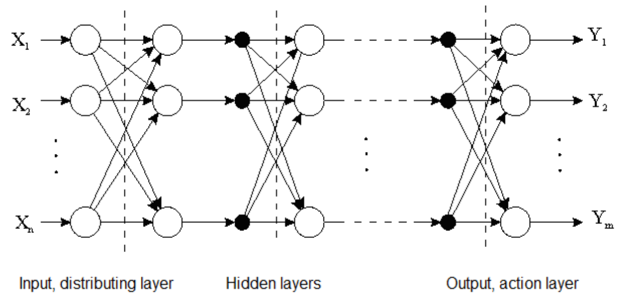


Figure 2. Multi-layer structure of the artificial neural network [13,4 edited by the author].

By adding the required properties of neuron elements, we ensure the preconditions to continue with the model creation.

3.2. Model algorithm

With regard to the neuron environment and the polarity of input neuron signals, the equation (1) may be adjusted as follows [2],[27]:

$$\frac{d_{x_i}}{d_t} = -A_{x_i} + (B - x_i)\left([I_i]^+ + \sum_{j=1}^{N} w_{ij}[x_i]^+\right) - (D + x_i)[I_i]^- \qquad (2)$$

Where:

N - total number of neurons in the artificial neural network,

$[I_i]^+ + \sum_{j=i}^{N} w_{ij}[x_i]^+ a[i_i]^-$ is actuating and damping inputs,

I_i external input into *i* neuron defined as:

$I_i = E$, if the goal lies here
$I_i = -E$, if an obstacle lies here
$I_i = 0$, in any other case
$E >> B$ – positive constant

The matrix of weighs of interconnections between the *i* neuron and the *j* neuron is symmetrical and defined as

$$w_{ij} = f(d_{ij}) \qquad (3)$$

Variable $d_{i,j}$ represents the Euclid distance between the neuron *i* and the neuron *j* in the status space S. Each neuron is only interconnected in the limited space with the nearest neurons and not with the total number of neurons *N*. Neuron neighbourhood is most frequently *k=2*.

4. Results

In this planned task we examine a multiaxial working space of the manipulation device, in our case it is a support of a technological tool above the working surface.

4.1 Modelling the processes of the artificial neural network

The artificial neural network creates the control with the required properties. For a simple task, we will use the network of 22×24 neurons arranged in a rectangular structure, neurons are interconnected with the neighbouring ones. The function of the target neuron for the entire network is expressed by the activity of each neuron towards the nearest surrounding environment and by the weight coefficients between the neighbouring neurons. The searched trajectory, if there is one, is usable (most appropriate, optimized, ...) with regard to the required control properties. For the purpose of network identification, several combinations of parameters (A, B, D, E) were chosen. Within the further examination, the parameters will have to be subjected to more appropriate setting and a thorough optimization process. The activity of neurons of the learned network in the stabile environment is shown in Figure 2. The interconnection of the target neuron changes the activity of the surrounding neurons, whereas the size of the neuron's surrounding area is selected as $k = 2$. The activity expressing the effects of neurons is adjusted as follows:

$$f(x_y) = \begin{Bmatrix} x_{ij/a} \\ 0 \end{Bmatrix} \tag{4}$$

if the n_{ij} neuron belongs to the surrounding environment,
if the n_{ij} neuron does not belong to the surrounding environment.

Where: a is defined as:

$$a = \max\left\{\sum_{j=1}^{N} w_{ij}[x_i]^+\right\} \tag{5}$$

i – number of neurons belonging to the surrounding environment.

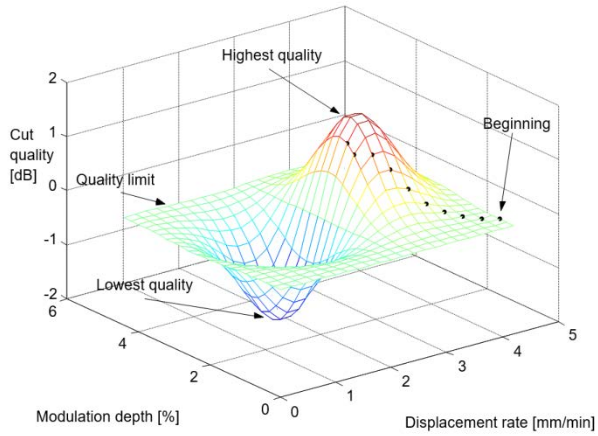


Figure 3. Activity of neurons and generated control in the static environment (source: Matlab).

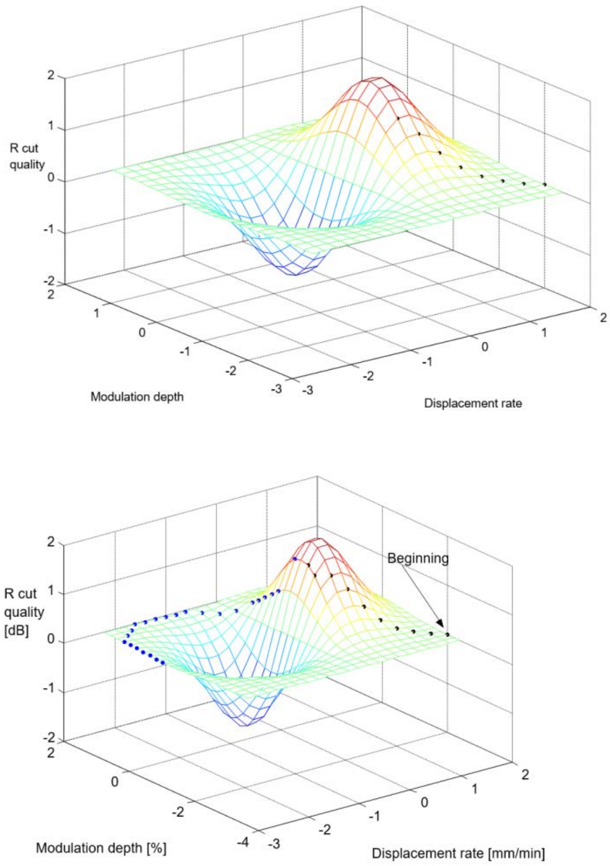
In order to find the control compliant with the required properties, control statuses must be located at sites with the lowest level of undesirable effects on the quality of the performed technology. Negative activity of neurons remembering the statuses of inappropriate properties cannot affect the surrounding neurons to prevent the information on the undesired quality of technology from spreading to the neighbouring neurons through which the control of the technology (manipulator) will not move. The found control statuses are shown in Figure 3. and represent one of the possible solutions with regard to the required technology properties [26],[27]. The values of control statuses and activities of the target neuron are spreading along the entire network thanks to the neural interconnection and searches for the neurons with the highest value of this information. If the current position is p_a then the following position p_n is determined by the selection:

$$p_n \Leftarrow x_{p_n} = \max\{x_i, i = 1,2,....k\} \tag{6}$$

where:

k – determines the number of neurons neighbouring with the neuron with the p_a position.
If the neighbouring neurons do not have higher activity, the actual positions remains unchanged and the technology control does not change. In the relationship (3) the activity increases with the intensity determined by the formula $(B - x_i)S_i^+$. It applies at the identical input S_i^+ that the closer x_i is to B, the less the activity of x_i increases. If $x_i \langle B$ the actuating relationship is positive and x_i is increasing. If $x_i = B$, the activity does not increase; if $x_i \rangle B$ the activity is pushed back to the B value. Neural activity is thus ranging in a narrow interval of

values around *B.* A similar situation is with the value *D* that determines the lower activity limit. If the x_i activity is located within the interval of values $\langle -D, B \rangle$, it is guaranteed that it will remain in this interval for any values of actuating and damping signals. Stability and direction of the designed model can also be verified using the Ljapun theory of stability [2],[26]. For the dynamic simulation with variable process properties, the neural activity changes together with the technology properties and the created control is shaped as smooth functions. In this case, an important parameter is a relative rate of the change of the environment's property and the ongoing technological process, i.e. the objective of the created control [22]. If the changes to the technology property are performed slower than the reactions of the artificial neural network, the situation is then appropriate for the real finding of good results of the monitored desired value of the process. In the case that the generated control is slower than the change to the dynamic environment, then the created control is not able to reach the required properties. In such situation, it is necessary to stabilize the technology more efficiently and create thus the conditions for achieving the desired properties. Neural activity for the dynamic and variable environment and selected technologies is shown in Figure 4.



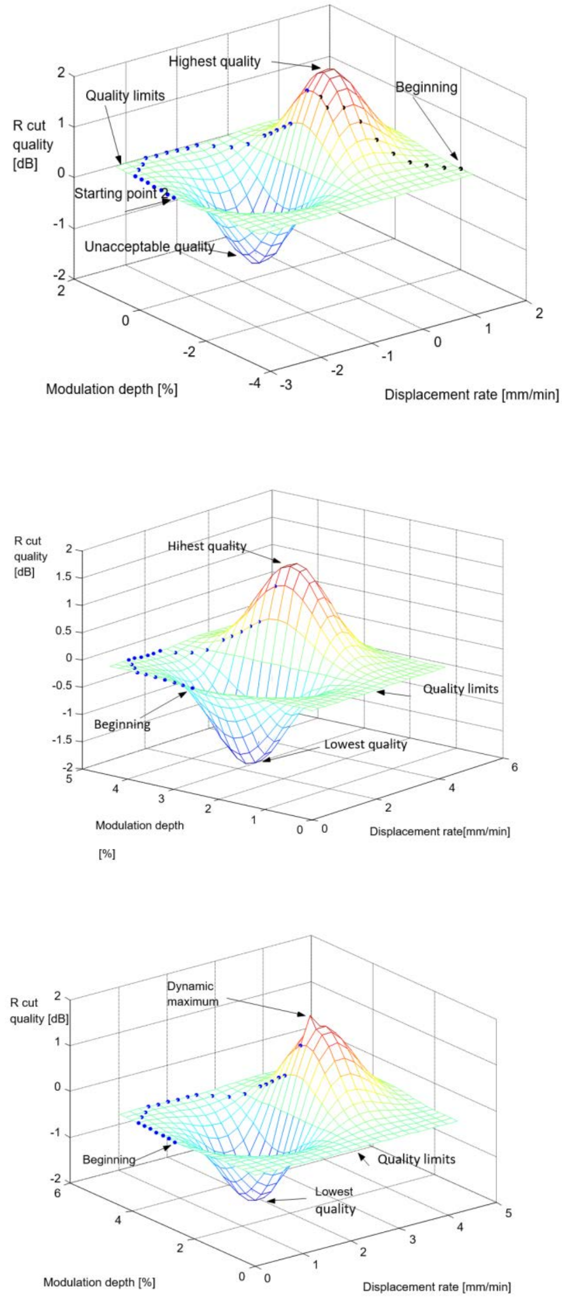


Figure 4. *Neural activity and generated control in the dynamic environment.*

4.2 Discussion

Change to the properties of the technology and the environment causes the change to neural activity with regard to the actual value of the desired variable. However, only the actual target neuron itself showed the highest possible activity $x_i = 1$. Generating the following control status p_n is affected by the current status. The information on this status is communicated through weight matrixes to the entire network. As a result, the created control does not have to appear as the best one (optimized, optimal, effective, ...), if we consider only the resulting static status. In such case, the properties of the environment and of the technology do not change, which never occurs in the real technology of cutting with a water jet, plasma... . At the time of creating the control of the following status, however, the selection thereof is determined by the relationship (8).

The presented example is carried out for a pair of parameters with the experimental function of the relationship between the quality and the position of parameters in the control space. The task can be applied to any number of parameters and also input variables for the activity of the artificial neural network. An independent analysis can be used to create an appropriate structure and select efficient variables of inputs for the artificial neural network.
In cases of limited network space, a problem appears in the initial stage of learning and the network activity is reaching its limits. An unspecified parameter value can repeatedly reach its limits as well. In such situation, it might be advisable to consider and change the appropriate selection of the space size and number of neurons in the network.

5. Conclusion

Process control created while using the artificial neural networks and self-learning mechanisms offer a tool that facilitates reaching the acceptable parameters of control processes in the conditions of variable changes and in the technological environment.

Examined static and dynamic environment with the requirement to create the required control in variable technology properties is an example of how to apply it also in other cases. Behaviour of the selected artificial neural network in similar elementary tasks can be adjusted according to the specific requirements [23]. Many theories are currently being developed for various types and sorts of artificial neural networks, suitable also for the discussed task or situation; minor modifications of the described algorithm facilitate the solution not only of the model tasks but also the cases when optimal control solutions are found in the learning stage, whether with or without a teacher. In the testing stage, it is possible to propose the control properties also for unlearned input parameters.

To achieve optimal solutions for the process control for each particular task, it is necessary to carry out the analysis of the complete chain. The process starts with physical scanning, adjustment, transformation, digitalization, processing of working and disturbing variables of the technology. It then continues with the selection of an appropriate type of the artificial neural network and ensuring the essential properties of the optimization of individual members of the control chain, creating thus the preconditions for achieving satisfactory results.

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