Artificial Intelligence Research and Applications (AIra)
https://www.ijaira.org/ Online ISSN: 3108-3889
S. Valtchev et al., Vol. 2, No. 1, March, 2026 Research Article

Neural Networks in Control Systems for Multi-Drive Facilities of Metallurgical Enterprises

Stanimir Valtchev *‡, Tatyana Sinyukova **‡, Alexey Sinyukov **

* FCT-UNINOVA-CTS, University NOVA of Lisbon, Portugal.
** Institute of Computer Science, Department of Automated Electric Drives and Robotic, Lipetsk State Technical University, Russian Federation.

(ssv@fct.unl.pt, stw0411@mail.ru, zeitsn@yandex.ru)

‡ Corresponding Authors: Stanimir Valtchev and Tatyana Sinyukova, ssv@fct.unl.pt and stw0411@mail.ru.

Received: 07.02.2026, Revised: 28.02.2026, Accepted: 06.03.2026

Abstract- Metallurgical plants use mechanisms with multiple motors, and their control systems must account for the specifics of the process and the impact of external and internal disturbances. Standard controllers don't always achieve the desired results, especially when systems contain various uncertainties, such as signal, parametric, and structural ones. Therefore, it has been proposed to integrate neural network-based control systems to account for and minimize nonlinearities and disturbances present in the systems. The study developed an algorithm for creating a nonlinear control system that takes into account processes occurring in the mechanical part of the object, as well as random disturbances. An algorithm for creating neural controllers for multi-drive systems was developed. Compared to a standard neural controller, its use allowed for a reduction in the number of neurons in the inner layer and the number of internal layers, reducing the training set by approximately 28 percent. The proposed universal structure of neural controllers and observers enables the creation of stable control systems for multi-drive mechanisms, while maintaining the operational capability of the devices and ensuring high-quality process control even when unmeasured parameters or distorted signals are involved in their formation.

Keywords: Neuroregulators, multi-drive systems, neuroobservers, nonlinear control system.

1. Introduction

Metallurgical plants utilize production machinery that incorporates multiple motors. Cranes and rolling mills are among the most common types of such machinery.

In complex structures of devices containing multi-motor mechanisms, elastic deformations, play, gaps, friction, and dynamic impacts occur in the mechanical part. There is a high probability of exposure of the control system to disturbances, which can arise both externally and within the mechanisms [1, 2]. Currently, there is no clear algorithm that takes into account the characteristics of transient processes in nonlinear systems.

In devices containing multiple drives, the interconnection between them occurs through mechanical structures and the object being moved (load)/processed (metal). To achieve effective control, closed-loop feedback loops must be introduced into the control system [3, 4]. Ensuring both specified and required indicators in dynamics at industrial facilities is achieved by reconfiguring the parameters of the mechanism, as a response to changes in the parameters of the control signal, by means of a regulator [5, 6].

Overhead cranes operate by moving loads on flexible suspensions, the swaying of which has a negative impact on the entire structure. In continuous rolling mills, the material being processed moves through several units (stands)

Cite this article as: S. Valtchev, T. Sinyukova, and A. Sinyukov, "Neural Networks in Control Systems for Multi-Drive Facilities of Metallurgical Enterprises," *Artificial Intelligence Research and Applications (AIra)*, Vol. 2, No. 1, pp. 41–54, March, 2026, https://doi.org/10.20508/pt40b183.

simultaneously during the rolling process, which can result in elastic deformations in the stand components [7, 8].

The objects in question have complex electromechanical systems that are affected by both internal and external interference; the load on these mechanisms is often variable, which leads to the conclusion that due to the uncertainties present in the mechanisms in question, it is advisable to introduce neural network technologies into their structure, in particular, observers and regulators based on them [9, 10].

When constructing control systems, it is necessary to take into account that in addition to load and disturbance effects, their structure contains elements such as electric motors, during the operation of which parametric disturbances are formed as a consequence of constantly changing electromagnetic moments [11, 12].

Often, when formulating requirements for electric drives, both for crane mechanisms and rolling mills, the primary focus is on regulating or maintaining the speed of the mechanism at the required values, maintaining the accuracy of the operations performed (accuracy of load positioning, accuracy of metal rolling to ensure a given strip thickness), real-time monitoring of changing process parameters, and compensation for the influence of disturbing effects [13, 14].

Regardless of the type of motor used (DC or AC), their internal systems are nonlinear, since during operation the state (parameters) of electrical machines changes as a response to existing and random internal and external influences [15].

In practice, without complicating the system, the main motor parameters that can be monitored (measured) include voltage, current, and speed. The process of determining the necessary but unknown parameters usually occurs indirectly, using various types of observers [16].

Large industrial mechanisms are multi-mass systems with a significant number of degrees of freedom. Elastic vibrations are observed in the subsystems of these objects due to the flexibility of the mechanical elements. However, during research, without significantly distorting the results, multi-mass systems are simplified to two- or three-mass systems, which allows for the development of more suitable models for research [17].

Recently, electronic converters have become widespread in industrial machinery. These can be with or without rectifier control, with autonomous current or voltage inverters, as well as frequency converters with direct galvanic coupling to the grid or with a DC link in the form of a "rectifier-filter" circuit. The use of frequency converters often results in disturbances that affect not only the converter's dynamic characteristics but also its operational stability, resulting in interference, errors, and so on. The use of neural networks helps avoid these problems [18].

Neural networks are becoming widespread in many areas due to their high demand and are being actively developed and improved. This has resulted in the emergence of neural networks that use supervised and unsupervised learning, with fixed and dynamic weight settings, with discrete and analog input information, single-layer and multi-layer, with and without feedback, synchronous and asynchronous, and many others [19].

An analysis of work in the field of electric drive control systems showed that recurrent neural networks containing dynamic multilayer perceptrons in their structure are most often used in these systems; a feature of these networks is the presence of feedback [20].

The most optimal structures for multi-drive electric drives, according to the research conducted, are:

- Elman neural network, which is a neural network with feedback and the ability to learn due to the presence of hidden neurons that record their previous states.
- The NARX neural network, which is a multi-layer network, is capable of storing information about previous system indicators, as well as predicting the state of output signals in the future, this network is also trainable.

The process of developing control systems for multi-drive objects using neural networks is directly related to determining the required number of neural layers in the neural network and the number of neurons in each layer. It is necessary to determine these parameters due to the fact that the resulting system, resulting from an incorrect selection of layers and neurons, may become excessively complex, may require retraining, and may introduce an output parameter error due to the lack of a training stage in the original neural network. Various methods exist to prevent these errors. For example, work [21] proposes algorithms for estimating the error that arises during neural network training.

Also, an important factor in the synthesis of neural networks is the correct choice of parameters of the initial weighting coefficients [22-24]. The most acceptable approaches are those based on:

- on the random selection of weighting coefficients, in this case, when using high-dimensional data, an increase in computing resources is observed;
- depending on the activation function, the method is simple to implement and does not require large computing resources.

Developments in neural networks and fuzzy logic have enabled efficient control of multi-motor mechanisms by compensating for disturbances arising both within the controlled object and outside the object but affecting its operation. Optimization of control systems is observed in both static and dynamic modes, due to reduced error detection time and timely adjustment of the control signal.

During the study of multi-drive control systems, it was discovered that classical control methods are used, with developments primarily focused on solving specific problems. The research objectives in this paper included developing control systems for multi-drive mechanisms using classical methods and neural network theory, considering the nonlinearities inherent in the mechanical components of industrial mechanisms, disturbances, and the interrelationships between output variables.

This study developed an industrial mechanism control algorithm that accounts for disturbances arising during the operation of the plant, the nonlinearity of the control system, and so on. Algorithms for generating universal observers and controllers based on neural networks were developed, which require less time to respond to control inputs. In the practical implementation of unified models of the mechanical components of multi-drive systems with elastic links, the use of transfer matrices that link output data in analytical form is relevant.

When synthesizing control systems for multi-drive mechanisms using neural networks, the problem arises related to the correct selection of the number of neural layers and neurons in each layer. Overestimating these parameters complicates the implementation of neural controllers and neural observers. Increasing the complexity of the neural network structure may necessitate retraining the neural network. Adjusting the number of input signals arriving at the input of a neural controller or neural observer without training the network with the new signal increases the likelihood of increasing the error in the output parameter.

Equally important when synthesizing neural network-based blocks is the correct selection of weighting coefficients. The most appropriate approach is a method based on sequencing the control parameters according to their importance, depending on the degree of their impact on the output parameter.

2. Sequence of Neuroregulator Development

2.1. Development of an Algorithm for Generating a Nonlinear Control System

Before introducing neural controllers into the control system of a multi-drive object, an algorithm for synthesizing a nonlinear system was proposed. This algorithm is based on accepted functional properties, making it possible to obtain non-measurable parameters and parameters that are generated with distortion. The developed algorithm improves the dynamic performance of the object.

Algorithm Synthesis:

- Generating initial parameters: operating modes of interconnected mechanisms, initial data for electric drives, etc.
- Description of the interconnected part of the mechanical system, taking into account the geometry and parameters of the gears, sensor location, and the elastic properties of the object being moved/processed. At this stage, the design (initial) data for the mechanical part of the control system is adjusted to regulate the mechanism's moment of inertia, stiffness, and damping coefficient. Models of the electrical part of the electric drives are also developed.
- Applying decomposition: If the final mathematical model being developed becomes too complex, horizontal and/or vertical decomposition must be applied to the system.
- Forming a quality criterion or criteria that take into account the synthesis objectives.
- Synthesizing a nonlinear control system taking into account quality criteria, constraints, and disturbances.
- Forming a basic version of the control system.
- Developing interconnected electromagnetic and mechanical subsystems. Refinement of the mechanical subsystem to improve the dynamic characteristics of the drives.
- Developing an interconnected multi-drive system.
- Checking the resulting system for compliance with the technical specifications: if the system complies, the algorithm execution is considered complete; if not, the initial data must be adjusted and a step-by-step development of the nonlinear system with the adjusted parameters must be performed.

2.2. Development of an Algorithm for Generating a Nonlinear Control System

When synthesizing the neuroregulator, nonlinearities present in control systems and in the electric drives themselves were taken into account; a deterministic method was used as the basis for choosing the architecture.

It is proposed to select the initial parameters of the neuroregulator for interconnected multi-drive systems in several stages:

- Synthesis of a multi-drive model based on the reference model, taking into account the control signals (*u(t)*), the transfer functions of the controller (*Wreg(p)*), the transfer functions of the linear multi-drive model (*Wmo(p)*), the changing output signal (*V(t)*), and the matrix reflecting the disturbances present in the system (*d(t)*). The reference model has the following form: F(u(t), Wreg(p), Wmo(p), d(t), V(t)).
- Checking the stability of a multi-drive system based on the analysis of transient processes obtained in a nonlinear control system. If the transient processes are stable, then we proceed to the next step; if not, then we return to the first stage and adjust the controller parameters.
- Acceptance of assumptions (at the initial stage of developing a neuroregulator, we assume that the impact of external and internal disturbances on the object is not significant).
- We accept that the value of the output signal can vary within a certain range from the minimum to the maximum value.

It is proposed to develop a neuroregulator according to the following algorithm:

- Bringing the controller transfer function (Wreg(p)) to a discrete form (Wreg(z)), where the sampling step (Δt) depends on the transient time (t_{tt}), which ranges from

10 to 20 of the small time constant of the link in the drive control system, therefore the step is determined as $\Delta t = t_{tt} /(10\div12)$.

The proposed sampling step is sufficient to ensure a stable synthesis of the controller architecture. Also at this stage, it is necessary to compare the dynamic characteristics formed in the linear system and obtained using the controller described in this section. If the difference is not 10% [25], then when moving to the next stage, if the specified values are observed to be exceeded, then it is necessary to make adjustments to the observation time.

- Introduction of a discrete controller into the structure of a multi-motor electric drive.
- Synthesis of a neuroregulator ($W^*reg(z)(NN)$) using the linear function *purelin*. Also at this stage, it is necessary to enter the number of the current layer and the neuron in the layer; it is necessary to take into account that the gain coefficients are numerically equal to the values of the weight coefficients of the neural network.
- Transformation of the neural controller architecture ($NN \rightarrow NN^*$) – depends on the neural network layers and the number of neurons in each layer. It is proposed to add the same number of neurons to the first layer as to the second layer.

  Next, instead of the *purelin* activation function, we use the hyperbolic tangent *tanh(n)*, which allows us to approximate the linear function at the origin. At this stage, the weighting coefficients are adjusted. If the activation of each layer reduces the number of layers in the neural network, the number of layers must be increased by one.
- To ensure stable operation of the entire system, it is necessary to determine the changing parameters of the output value (V(t)). It is proposed to use a random number generator operating according to the law of uniform distribution over the entire range of the activation function, but we should also consider that, as noted above, the output signal value can vary within a certain range from the minimum to the maximum value.

  If the dynamic characteristics of the object are stable at this stage, the controller synthesis process is considered complete, and we proceed to its training. If stability is not achieved, gradually increase the controller coefficients using the hyperbolic tangent function, first by a factor of two, then by the same amount, increasing the V(t) gain. Check the transient stability of the control system. If it is achieved, the controller is synthesized and can be trained. If not, sequentially prove the transient stability.
- It is necessary to generate a training data set taking into account the object's control tasks, ensuring system control within a given control signal range: $data=\{u_m e_m\}^s_{m=0}$, where *m* is the current training sample parameter, *s* is the finite number of training sample elements, u_m is the current input parameter, and e_m is the current output error parameter in the control system. Experience shows that high-quality training of a neural controller occurs using training, validation, and test sets. The data volume depends on the complexity of the object.
- It is necessary to generate a training data set taking into account the object's control objectives, so as to ensure system control within a given control signal range: Experience shows that high-quality training of a neural controller occurs using training, validation, and test samples. The data volume depends on the complexity of the object.

The structural diagram of the developed algorithm is shown in Fig. 1.

Different approaches are used in training the neuroregulator:

- The backpropagation algorithm using gradient descent minimizes the error function by adjusting network weights in the direction opposite to the gradient of the function. The error gradient of each network weight is calculated from the output layer to the input layer, with the weight adjusted so that the error tends to a minimum. Training occurs online, and this method utilizes sigmoid activation functions, including the hyperbolic tangent.
- The algorithm for backpropagation of errors using the gradient descent method with perturbation is based on the principle described above. The disadvantages include the duration of data processing, and when using this method, finding the global minimum is not guaranteed.
- The Levenberg-Marquardt backpropagation algorithm [26] is a damped least squares method that provides a balance between convergence speed and stability. The disadvantages include complex calculations that require an increase in the time required to train the algorithm.
- The backpropagation algorithm of Bayesian regularization—network weight adjustments are based on the difference between predicted and actual data, considering a priori information about the distribution of weight coefficients. Disadvantages include inefficiency in the presence of local minima forming on the surface of the error function.
- The imitation learning method – learning occurs based on the dynamics of the original controller using feedback data. Upon completion of training, the neural controller functions identically to the original controller. This method is most often used for initial training.

For training, the backpropagation algorithm using the gradient descent method was selected.

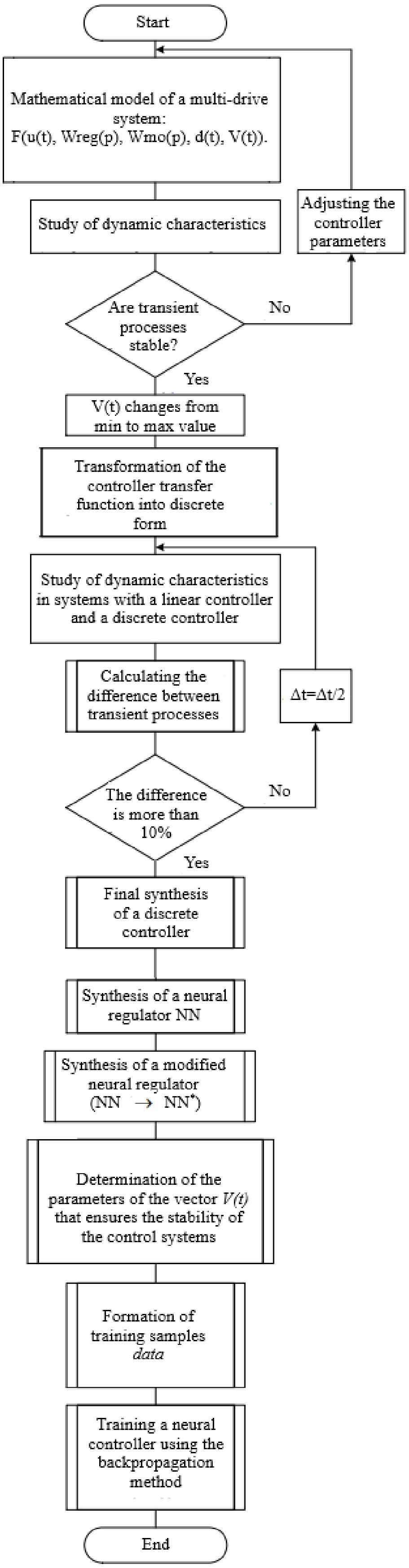

Fig. 1. Structural diagram of the developed algorithm.

2.3. Development of Discrete Predictive Control for A Multi-Engine System

Interconnected multi-mass mechanical systems, which represent multi-drive production mechanisms, are characterized by a large number of inputs and outputs. The mathematical description of these objects includes the physical processes that form during the object's operation as separate subsystems.

The process of controlling output signals involves regulating mechanical variables and, through them, electromagnetic parameters. This leads to the formation of types of assessments of control quality indicators for parameters at each level.

Each subsystem with multiple inputs and outputs can be represented as:

$$\begin{cases} x = F(a,b,c,t) = A(x,t)a + B(x,t)b + C(x,t)c \\ -\text{this non-little function is continuously differentiable;} \\ y = z(x) = D(x,t). \end{cases} \quad (1)$$

All presented vectors of state variables *a*, control *b*, disturbance *c*, measured variables *y*, are time-varying values that are influenced by both external and internal factors. By *t* we mean time, which is a discrete quantity. *A(x,t)* is the state matrix, *B(x,t)* is the control matrix, *C(x,t)* is the disturbance matrix, *D(x,t)* is the scaling matrix

When developing systems of this kind, it is proposed to use the predictive control method, the main advantages of which are:

- Possibility of controlling electromechanical mechanisms of different types (linear and non-linear).
- Possibility of application in multidimensional and multichannel control systems, even in the presence of delay.
- Correction of the control signal when various types of disturbing influences occur.
- Possibility of controlling a multi-drive mechanism using data on the technological process of the object recorded in the memory of the control controller.

The assumptions made at the stage of developing the control methodology are the system under study has feedback, the quantities involved in the control process are measurable, the differential equations describing the system are continuous and real, the equilibrium point of the nonlinear function *F* is formed at $x=0$ $(a_{equ}=0, b_{equ}=0)$.

Discrete control algorithm using predictive models (sampling time $t=nT_s$):

- Carrying out the linearization of a nonlinear object to a pseudolinear model, for this, the differential equation (1), considering all types of disturbing effects and the equilibrium point, is written in the form:

$$\begin{cases} x(y) == A_p(x)a(t) + B_p(x)b(t) + (F(a,b,c,t) - \\ -A_p(x)a(t) + B_p(x)b(t)); \\ \qquad y(t) = D_p(x)a(t), \end{cases} \quad (2)$$

where $A_p(x) = \left.\frac{\partial F}{\partial a^T}\right|_{\substack{a=a_{equ}\\b=b_{equ}}}$ – matrix of state variables;

$B_p(x) = \left.\frac{\partial F}{\partial b^T}\right|_{\substack{a=a_{equ}\\b=b_{equ}}}$ – control variable matrix;

$D_p(x) = \left.\frac{\partial z}{\partial a^T}\right|_{\substack{a=a_{equ}\\b=b_{equ}}}$ – matrix of observation variables.

Using Euler's method, we will reduce it to a discrete form (n is the iteration number, n=0,1,2…k-1).

$$\begin{cases} x(n+1) == A(n)a(n) + B(n)b(n) + (F(a,b,c,t) - \\ -A(n)a(n) + B(n)b(n)); \\ \qquad y(n) = D(n)x(n). \end{cases} \quad (3)$$

where $A(n)=I+TsA_p(x)$ is a discrete matrix of state variables, $B(n)=TsB_p(x)$ is a discrete matrix of control variables, $D(n)=TsD_p(x)$ is a discrete matrix of disturbance variables.

- Development of a predictive model, at this stage it is necessary to determine the state variables for the entire prediction horizon (N_p):

$$\begin{aligned} &\hat{x}(n+1|n) = A(n|n)\hat{a}(n) + B(n|n)b(n|n) + B_d(n|n)\hat{d}(n); \\ &. \\ &. \\ &. \\ &\hat{x}(n+N_p|n) = A(n+N_p-1|n)\hat{a}(n+N_p-1|n) + \\ &+B(n+N_p-1|n)b(n+N_p-1|n) + B_d(n+N_p-1|n)\hat{d}(n). \end{aligned} \quad (4)$$

Control action:

b(n|n)=b(n-1)+Δb(n|n);
b(n+1|n)=b(n-1)+Δb(n|n)+ Δb(n+1|n);
.
.
.
$b(n+N_c-1|n)=b(n-1)+\Delta b(n|n)+ \ldots+\Delta b(n+ N_c-1|n)$.

- Optimization of the model by the quality functional (*u*) using the nonlinear programming method allows to reduce the prediction error.

  Optimization of the quality functional occurs taking into account the vector of desired output parameters ($y_{zad}(n)$) of the control object at iteration n, the weight matrices of the state (Q(n)) and control (R(n)>0) of the control system of the multi-drive object.

$$J(n) = \left[y_{zad}(n) - y(n)\right]^T Q(n)\left[y_{zad}(n) - y(n)\right] + \Delta u(n)^T R(n)\Delta u(n). \quad (5)$$

- Calculation of predicted output signals:

$$\begin{bmatrix} \hat{y}(n+1)|n \\ \hat{y}(n+2)|n \\ . \\ . \\ . \\ \hat{y}(n+N_p)|n \end{bmatrix} = \begin{vmatrix} C(n+1|n) & 0 & ... & 0 \\ 0 & C(n+2|n) & ... & 0 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ 0 & 0 & ... & C(n+N_p|n) \end{vmatrix} x$$

$$x \begin{bmatrix} \hat{x}(n+1)|n \\ \hat{x}(n+2)|n \\ . \\ . \\ . \\ \hat{x}(n+N_p)|n \end{bmatrix} \quad (6)$$

- Determination of the optimal control action (*Nc* – control horizon).

The process described is iterative; during the study, the model parameters are updated over the entire forecast range; the data obtained during the previous forecast iteration are the basis for subsequent iterations. Let's consider the development of a discrete predictive speed controller for a rolling mill (Fig. 2).

The discrete control method involves obtaining current parameters from the controlled object. The combination of a Kalman filter and training data obtained using an artificial neural network allows for work with systems in which an incomplete database of controlled signals is available.

During the prediction stage, the state variable is updated and the relationship between the estimated state variable and the actual measured value is calculated. The optimization algorithm, an iterative process, enables optimal values for the parameters of the multi-drive system.

The stages of development of a predictive controller are shown in Fig. 3.

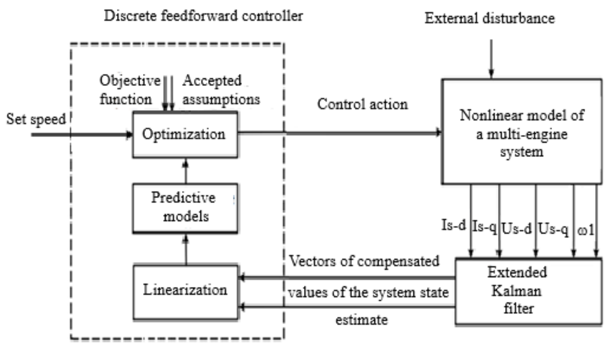

Fig. 2. Speed controller.

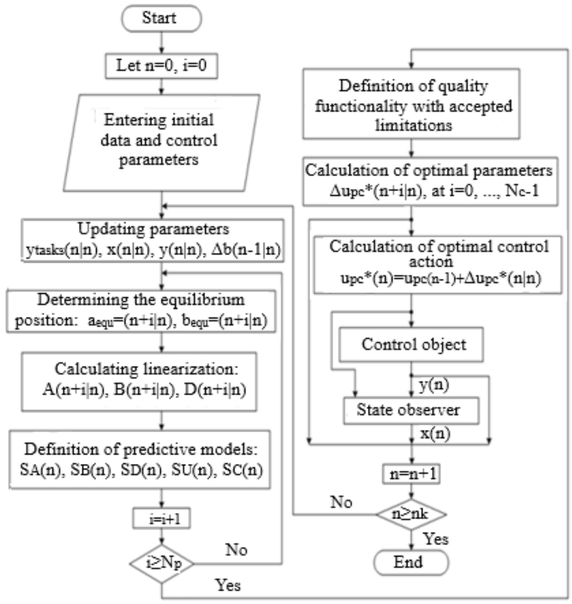

Fig. 3. Stages in regulator development.

In operating machinery, it is often necessary to obtain information about an object in real time. This requires all the data necessary for optimal operation, but this data is not always available. In this case, the use of observers becomes relevant. Fig. 4 shows a state observer proposed for use in a multi-mass rolling mill stand control system. Angular velocity sensors are included in the system to record the angular velocities of the first (equivalent mass on the rolling mill motor shaft) and fourth masses (the upper roll of the rolling stand, while the third mass is the lower roll of the rolling stand).

The control signal is sent to the input of the first mass speed control unit. The system evaluates the speed control error of the fourth mass. The observer development process is shown in Fig. 5. Fig. 6 shows transient processes that clearly demonstrate the influence of changing controller parameters during operation, which directly depend on the parameters of the controlled object (dynamic characteristics), for different values of the prediction horizon *Np* and control *Nc*. The presented graphs indicate that the proposed observer operates effectively, providing the required dynamic characteristics for Np = 20 and Nc =10 and 15. The training sample declined by approximately 28 percent.

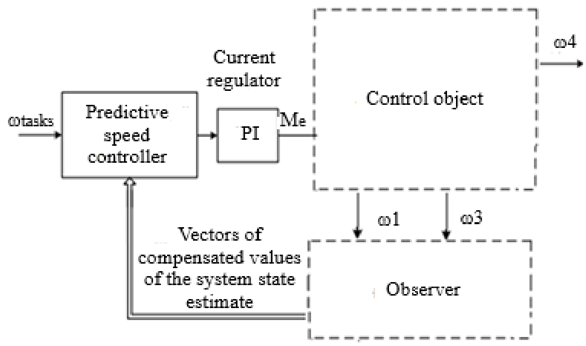

Fig. 4. State observer.

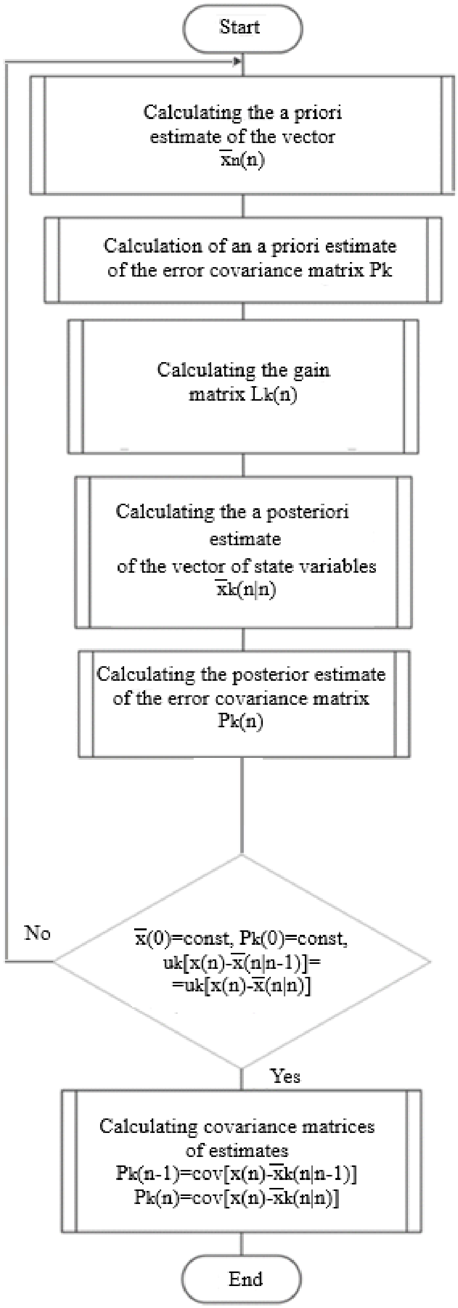

Fig. 5. Stages of observer development.

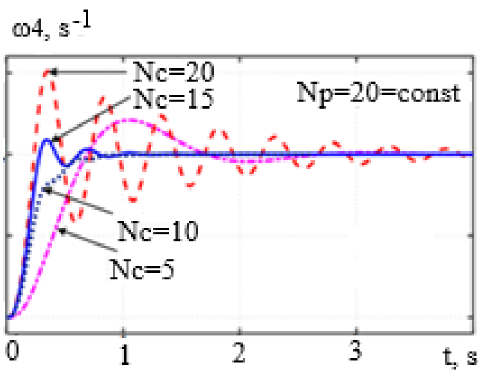

Fig. 6. Formation of transient processes.

2.4. Identification of Parameters Using a Neural Network

Due to the presence of various types of uncertainties in multi-drive mechanisms and their control systems, there is a need to apply identification methods; the use of the NARX neural network architecture is proposed (Fig. 7).

NARX is a multilayer perceptron consisting of two layers with direct data exchange between them. The hidden layer of the neural network under consideration contains k neurons, and the output layer contains one neuron. The network has one input, which contains a delay memory block consisting of du elements, and one output of do elements, which is connected to the input via a delay memory block. These two memory blocks feed the input layer of the perceptron. Fig. 6 shows the network state for the nth iteration.

In the study, a neural network with one hidden layer z_u=z_y=2 was used, the architecture of this neural network is shown in Fig. 8.

For the objects under consideration, the priority is to obtain an identification model $\hat{F}(u)$ with parameters accessible for determination, with a given accuracy *F(u)* for all control signals *u(n)*, where *n=1, 2, ..., k*, while the outputs of the models are designated as and *y*, and *e* is taken to be the root mean square error (Fig. 9).

The functioning of the neural network occurs according to the diagram shown in Fig. 10.

At the activation stage, when performing identification, it is proposed to use the hyperbolic tangent and logistic function. For training, it is proposed to use the algorithm of inverse recognition in time with Bayesian regularization. When minimizing the quality function, it is proposed to use the gradient descent method; at this stage, the weighting coefficients are adjusted.

Fig. 11 shows a system with one input and one output, where $\hat{y}(n+1)$ is an estimate of the output parameter of the multi-drive control system y(n+1). The optimal response is y(n+1); if an error occurs, the synaptic weights of the neural network are adjusted.

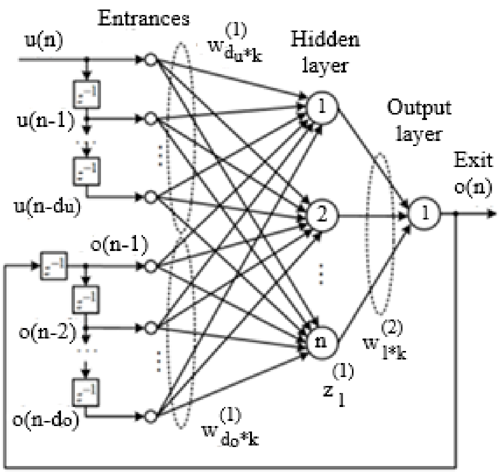

Fig. 7. How NARX works.

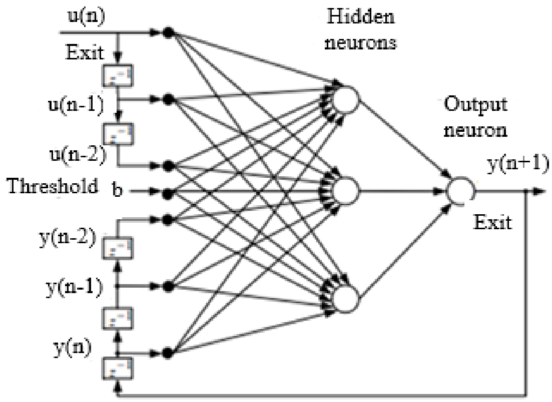

Fig. 8. NARX structure with one hidden layer.

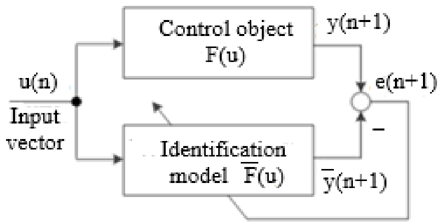

Fig. 9. Explanation of the process of parameter setting using the NARX-based identification technique.

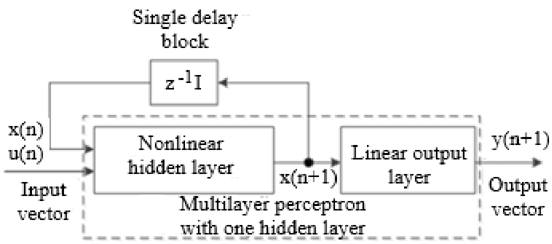

Fig. 10. NARX operation.

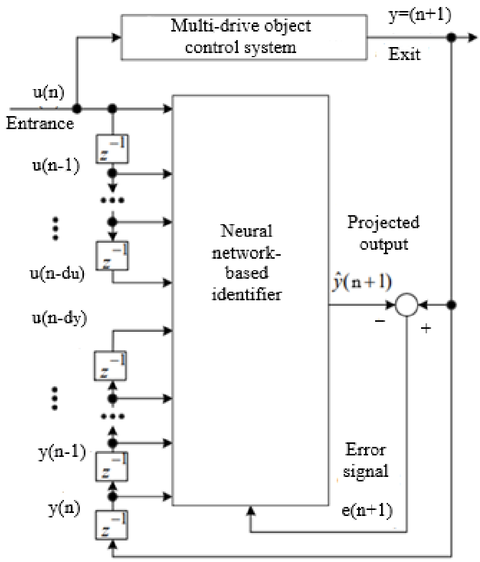

Fig. 11. Introducing NARX to the facility management system.

3. Introduction of a Neuroregulator Operating According to the Developed Algorithm into the Control System of Multi-Drive Mechanisms

As mentioned above, a rolling mill is a multi-drive system, the operation of which requires control of variables such as rolling speed in the stands, rolling force, strip tension, etc.

The process of strip rolling may be accompanied by a change in pressure between the pressure rolls, which leads to the appearance of elastic deformations in the components of the stand and, as a consequence, causes a change in the thickness of the rolled metal as a result of inaccuracies that may arise in any of the processes of forming a metal strip.

Often, the deviation of the thickness of the rolled metal strip from the required parameters is formed in the finishing group of stands, and is influenced by:

- Characteristics of the rolled strip.
- Characteristics of the cages.

The control system under study (Fig. 12) considers data from sensors measuring the speed, thickness of the rolled metal between stands, and the thickness of the metal at the mill exit. In the structural diagram shown, h_i*-1* is the strip thickness at the entrance h_i is the thickness of the rolled metal after *i* pressure rolls, σ_i*-1* is the rear tension, σ_i is the front tension, and υ is the rolling speed of the metal.

Fig. 13 shows the structural diagram of the control of adjacent stands of a rolling mill.

Using a classic speed and thickness controller in the control system, the characteristics shown in Figs. 14-15 were obtained. The graphs show that the deviation from the set value occurs in the form of oscillations, with a minimum value of approximately 0.026 mm and a maximum of 0.032 mm, both in the direction of increasing and decreasing the set value of the metal strip thickness. Strip tension is established at approximately 0.4 seconds, and the process is oscillatory in nature.

At the next stage of the research, instead of the classical controller, a standard NN Predictive Controller was used, the structural diagram of the system using which is shown in Fig. 16.

Further research was carried out using a regulator in the control system developed according to the algorithm proposed above (Fig. 17).

The results of modeling with a standard neuroregulator are shown in Fig. 18-19, with a neuroregulator developed according to the proposed algorithm, in Fig. 20-21.

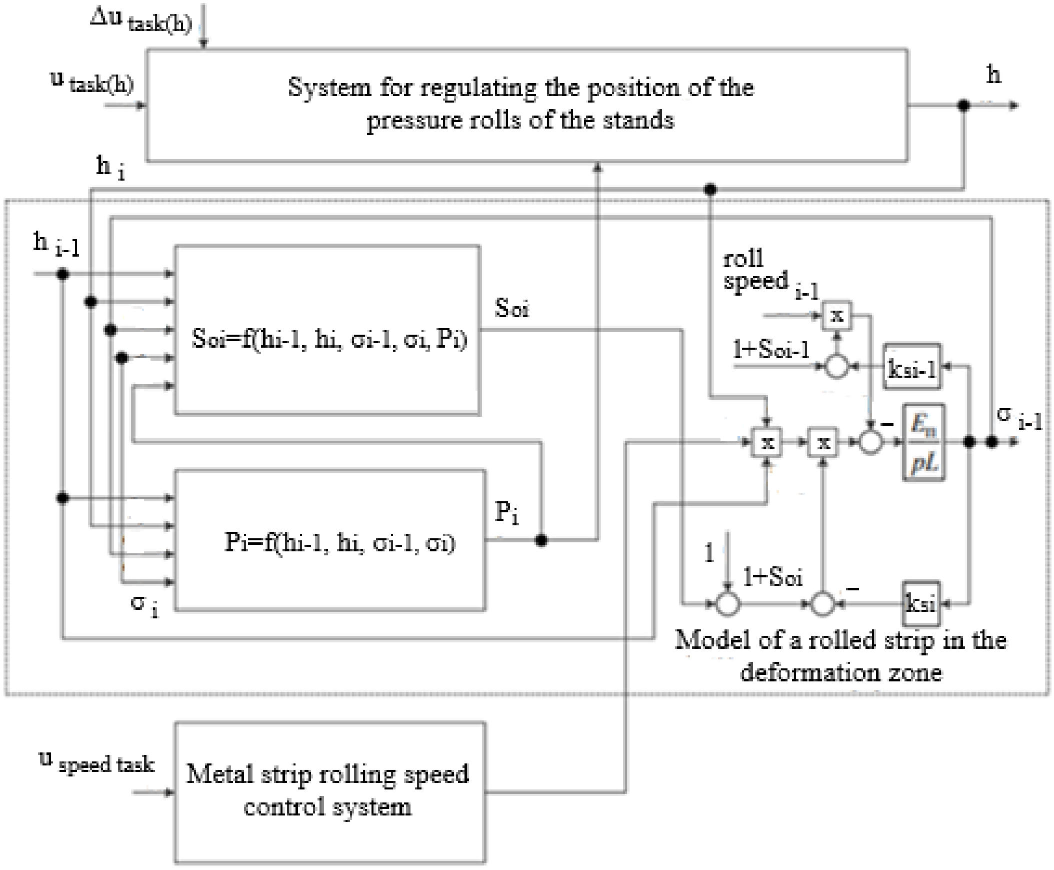

Fig. 12. Finishing stand roll control system.

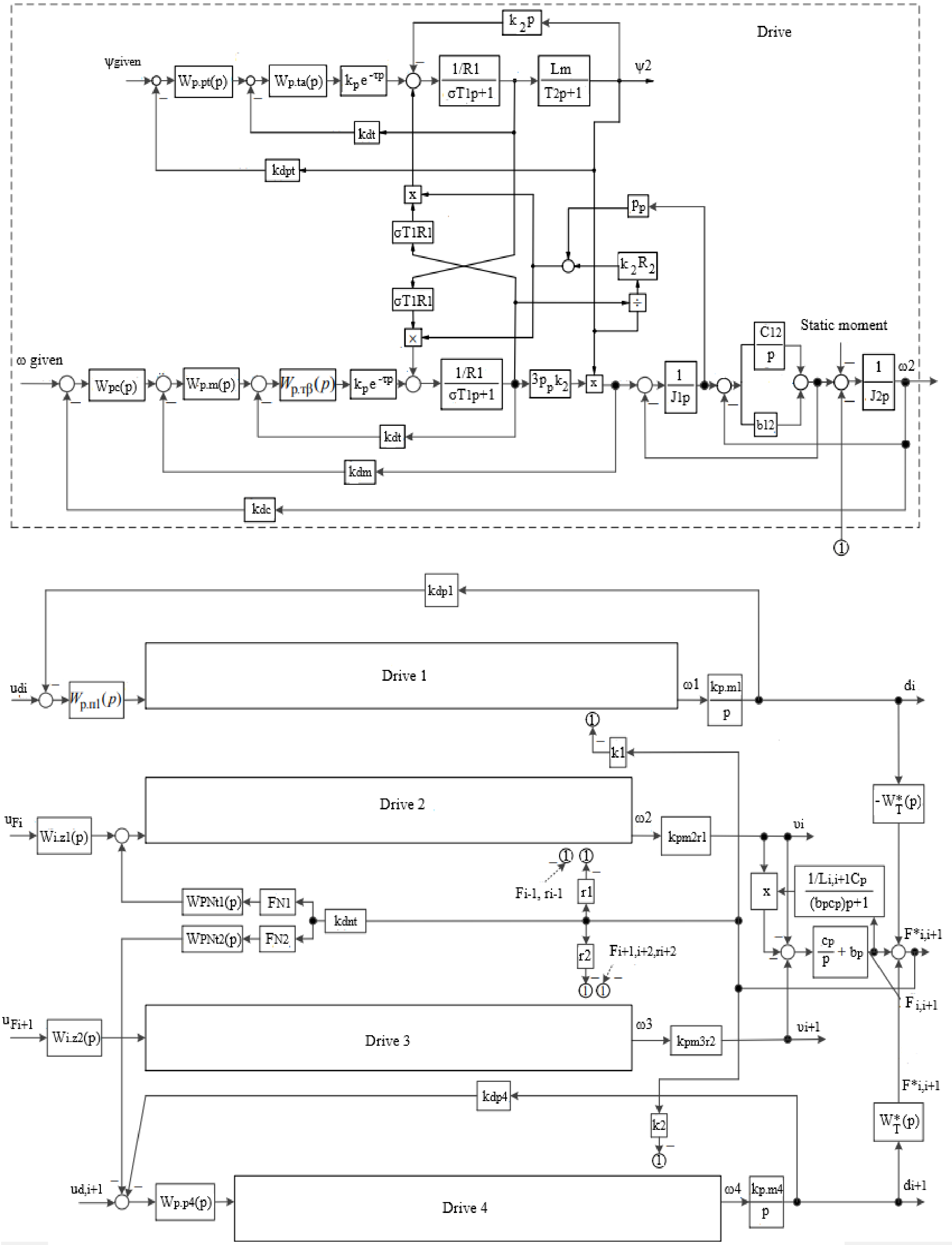

Fig. 13. Adjacent cage control system.

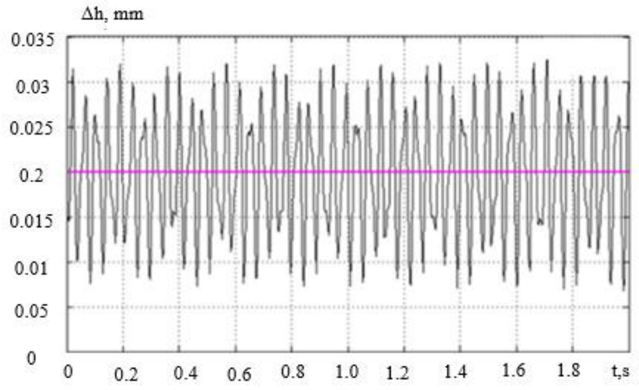

Fig. 14. Graph of deviation of metal strip thickness from a given value in a system with a classic regulator.

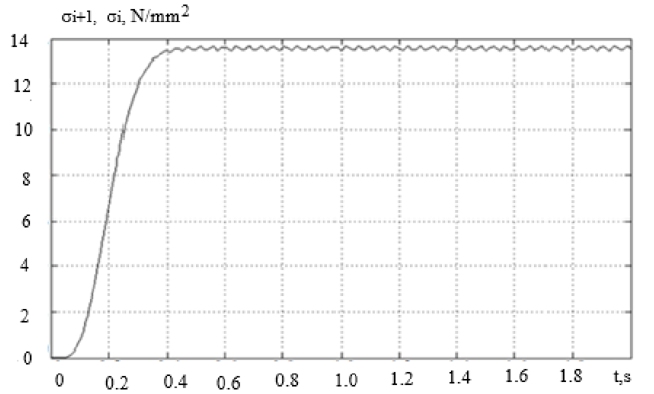

Fig. 15. Formation of strip tension in a system with a classic regulator.

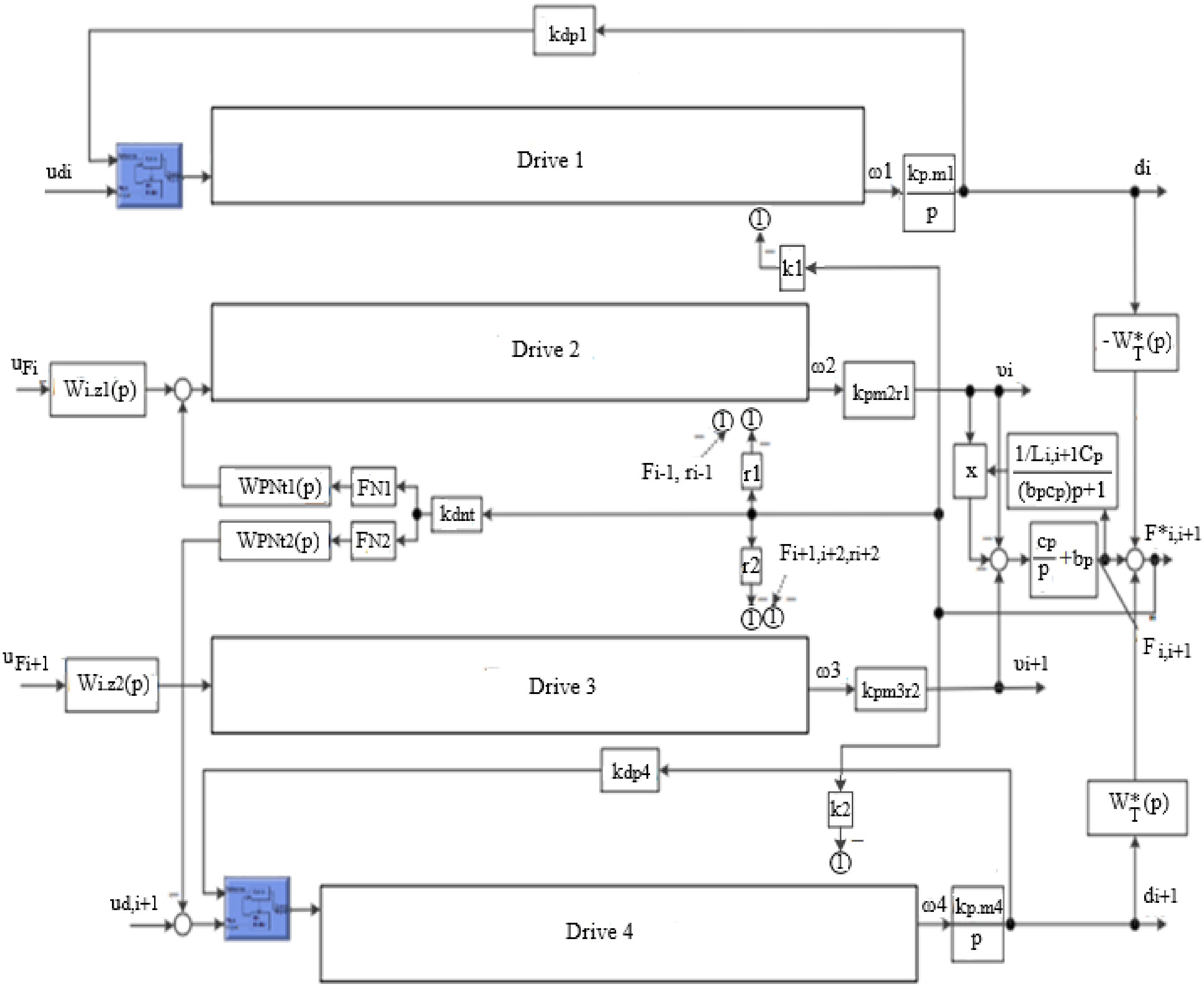

Fig. 16. System with NN predictive controller.

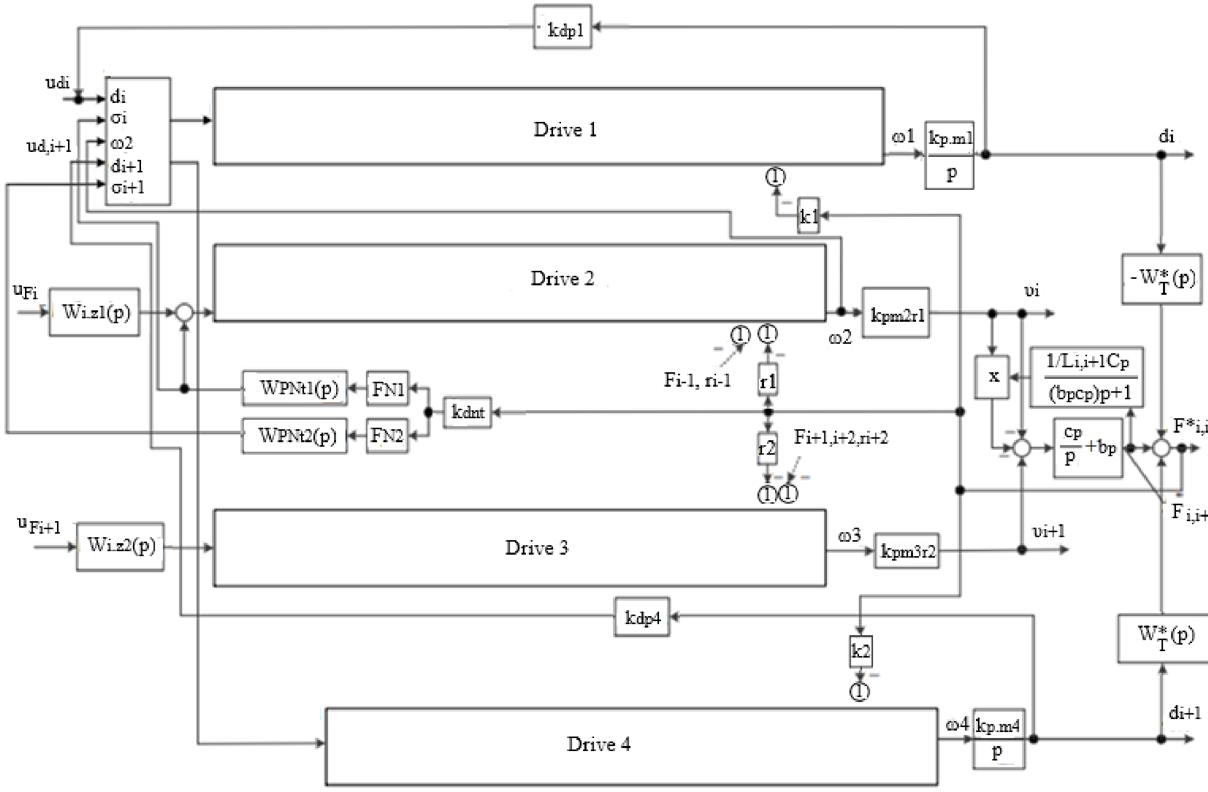

Fig. 17. System with developed algorithm.

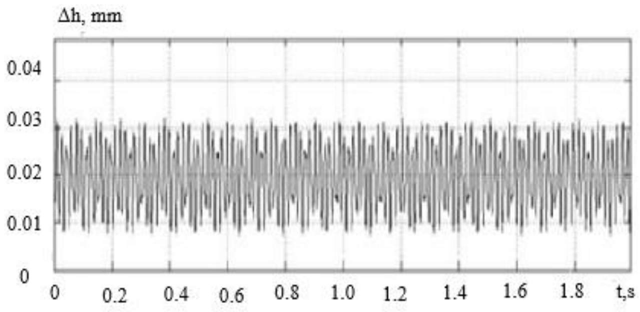

Fig. 18. Graph of deviation of metal strip thickness from a given value in a system with NN predictive controller.

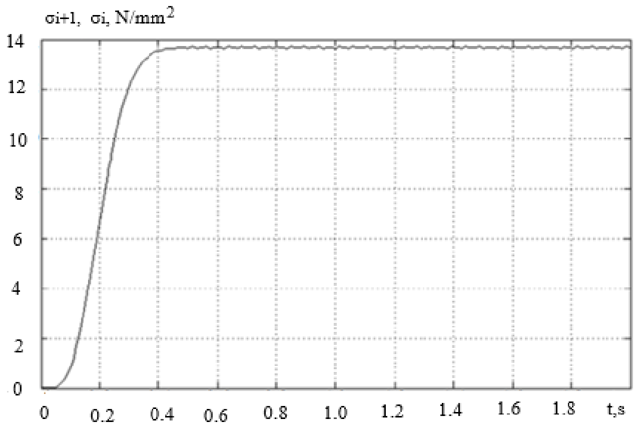

Fig. 19. Formation of strip tension in a system with NN predictive controller.

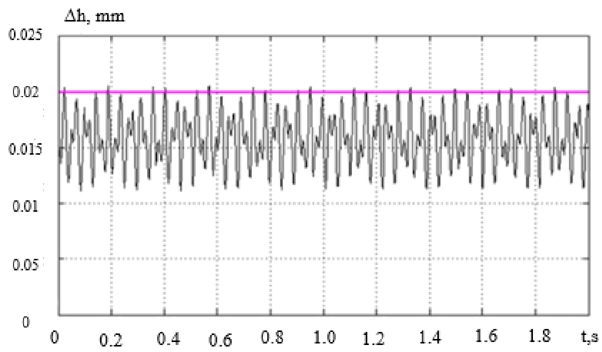

Fig. 20. Graph of the deviation of the thickness of a metal strip from a given value in a system with a neuroregulator operating according to the developed algorithm.

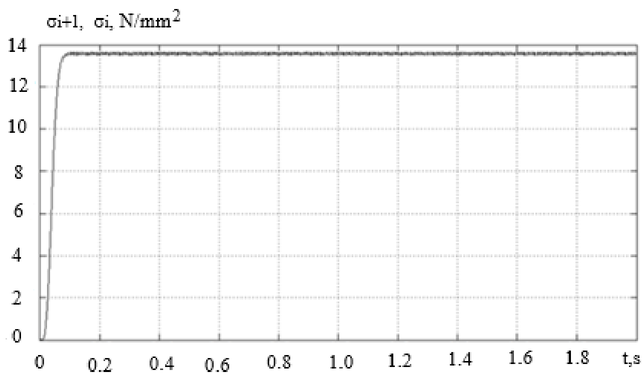

Fig. 21. Formation of band tension in a system with a neuroregulator operating according to the developed algorithm.

When using the NN Predictive Controller speed and thickness control system, the obtained characteristics indicate that deviations from the set value occur as oscillations, with a minimum value of approximately 0.005 mm and a maximum of up to 0.012 mm, both in the direction of increasing and decreasing the set value of the metal strip thickness. Strip tension is established at approximately 0.4 seconds, with a noticeable reduction in oscillations.

When using a speed and thickness neural controller in the control system, operating according to the developed algorithm and the presented characteristics, it can be concluded that deviations from the set value are generated as oscillations. The minimum oscillation value is approximately 0.001 mm for increasing rolled metal thickness, and the maximum is up to 0.02 mm for decreasing the set value of the metal strip thickness. Strip tension is generated at approximately 0.08 seconds.

4. Conclusion

Neural networks are currently widely used, but there is no universal neural network structure suitable for use in multi-drive mechanism control systems. The proposed method for identifying multi-drive mechanism control system parameters using neural networks enables the reconstruction of multi-drive system data in the presence of uncertainties (signal, parametric, or structural) and the identification of control system parameters. The proposed algorithm for synthesizing a neural controller and neural observer reduces the number of neurons in the inner layer, the number of inner layers, and the training sample. This is all made possible by using a mathematical description of the processes and taking into account various types of influences affecting the control system, which are considered during controller synthesis. The proposed neural network-based controllers and observers require less training time, which improves the speed of mechanism operation when responding to control inputs.

The developed neural controller was used to regulate the rolling process in adjacent stands, improving the accuracy of rolled metal thickness control by more than 10 percent. The proposed model considers the processes occurring in metal during rolling. The results obtained, allow to conclude that the proposed algorithm is effective.

Further testing of the proposed method, which improves the dynamic performance of the object, is planned for use on multi-drive crane systems

Author Contributions

S.V. conceptualized and supervised the study; T.S. performed the data analysis; A.S. drafted the manuscript; all authors reviewed and approved the last version.

Acknowledgements

N/A

Conflict of Interest

The authors declare no conflict of interest.

References

[1] M. Zhang, X. Ma, X. Rong, X. Tian, and Y. Li, “Adaptive tracking control for double-pendulum overhead cranes subject to tracking error limitation, parametric uncertainties and external disturbances,” Mechanical Systems and Signal Processing, vol. 76–77, pp. 15–32, Aug. 2016, doi:10.1016/j.ymssp.2016.02.013.

[2] S. P. Sayali, W. Vijayraj, P. D. Shendge, and S. B. Phadke, “Sliding mode and inertial delay based direct yaw moment control for AGVs,” in Proc. 6th Int. Conf. Convergence in Technology (I2CT), Maharashtra, India, Apr. 2–4, 2021, doi:10.1109/I2CT51068.2021.9418161.

[3] L. A. Chumakova, D. A. Argunov, A. V. Matveev, and P. A. Maksimov, “Dynamic loads in the drive of a reduction mill stand,” Steel, no. 10, pp. 56–57, 2018.

[4] F. Zhang, Y. Zhang, J. Hou, and B. Wang, “Thickness control strategies of plate rolling mill,” International Journal of Innovative Computing, Information and Control, vol. 11, no. 4, pp. 1227–1237, 2015.

[5] J. Sun, S.-Z. Chen, H.-H. Han, X.-H. Chen, Q.-J. Chen, and Z. Hua, “Identification and optimization for hydraulic roll gap control in strip rolling mill,” Journal of Central South University, vol. 22, no. 6, pp. 2183–2191, 2015, doi:10.1007/s11771-015-2742-0.

[6] V. R. Gasiyarov, A. A. Radionov, A. S. Karandaev, V. Khramshin, and B. Loginov, “Improving the algorithm of automated gage control during shaped feed rolling on a plate mill,” in Proc. IEEE 11th Int. Conf. Mechanical and Intelligent Manufacturing Technologies (ICMIMT), Cape Town, South Africa, Jan. 20–22, 2020, doi:10.1109/ICMIMT49010.2020.9041207.

[7] S. Valtchev, A. V. Sinyukov, V. N. Meshcheryakov, and T. V. Sinyukova, “Development of a fuzzy controller for damping oscillations of a flexible suspended load in electromechanical systems of crane mechanisms,” Electricity, no. 4, pp. 13–27, 2025, doi:10.24160/0013-5380-2025-4-13-27.

[8] A. V. Sinyukov, E. Y. Abdullazyanov, T. V. Sinyukova, N. N. Zaruckiy, and E. I. Gracheva, “Using a fuzzy logic-based apparatus for damping vibrations of a flexible load,” Power Engineering: Research, Equipment, Technology, vol. 26, no. 3, pp. 33–49, 2024, doi:10.30724/1998-9903-2024-26-3-33-49.

[9] S. V. Langraf, A. I. Sapozhnikov, and A. S. Glazyrin, “Dynamics of an electric drive with a fuzzy controller,” Bulletin of Tomsk Polytechnic University, vol. 316, no. 4, pp. 168–173, 2010.

[10] Y. Niu, H. Li, and F. Liu, “A loss-aware continuous Hopfield neural network (CDN)-based mapping

algorithm in optical network-on-chip," in Proc. 20th Int. Conf. Optical Communications and Networks (ICON), 2022.

[11] W. M. Haddad, V. Chellaboina, J. L. Fausz, and A. Leonessa, "Optimal nonlinear robust control for nonlinear uncertain systems," International Journal of Control, vol. 73, no. 4, pp. 329–342, 2000.

[12] S. H. Asgari, M. Jannati, T. Sutikno, and N. R. N. Idris, "Vector control of three-phase induction motor with two stator phases open-circuit," International Journal of Power Electronics and Drive Systems, vol. 6, no. 2, pp. 282–292, 2015, doi:10.11591/ijpeds.v6.i2.

[13] P. J. Shaija and E. D. Asha, "An intelligent speed controller design for indirect vector-controlled induction motor drive system," Procedia Technology, vol. 25, pp. 801–807, 2016, doi:10.1016/j.protcy.2016.08.177.

[14] L. A. Amézquita-Brooks, C. E. Ugalde-Loo, E. Licéaga-Castro, and J. Licéaga-Castro, "In-depth cross-coupling analysis in high-performance induction motor control," Journal of the Franklin Institute, vol. 355, pp. 2142–2178, 2018, doi:10.1016/j.jfranklin.2018.01.002.

[15] B. Kada, M. Hebali, I. F. Bouguenna, B. Ibari, and M. Bennaoum, "High-performance inverse artificial neural network controller for asynchronous motor control," The Journal of Engineering and Exact Sciences, vol. 10, no. 9, p. 20857, 2024, doi:10.18540/jcecvl10iss9pp20857.

[16] H. Sudheer, S. F. Kodad, and B. Sarvesh, "Improvements in direct torque control of induction motor for wide-range of speed operation using fuzzy logic," Journal of Electrical Systems and Information Technology, vol. 5, pp. 813–828, 2018.

[17] Y. Yao and B. Zhang, "Influence of the elastic modulus of a conveyor belt on the power allocation of multi-drive conveyors," PLoS ONE, vol. 15, no. 7, e0235768, 2020.

[18] D. A. Dementev, E. D. Maximova, I. A. Sysoletin, and S. V. Mezin, "Research of the influence of feedback signals in the neuroregulator on the quality of regulation," Journal of Physics: Conference Series, vol. 1889, no. 2, p. 022053, 2021, doi:10.1088/1742-6596/1889/2/022053.

[19] R. D. Diwan, "Induction motor testing using MATLAB/Simulink," International Research Journal of Engineering and Technology, vol. 8, no. 6, pp. 1810–1815, 2021.

[20] D. Rai, S. Sharma, and V. Bhuria, "Fuzzy speed controller design of three phase induction motor," International Journal of Emerging Technology and Advanced Engineering, vol. 2, pp. 145–149, May 2012.

[21] S. Haykin, Neural Networks: A Complete Course. Moscow: Williams, 2016.

[22] A. J. da Silva, W. R. de Oliveira, and T. B. Ludermir, "Weightless neural network parameters and architecture selection in a quantum computer," Neurocomputing, vol. 183, pp. 13–22, 2016.

[23] A. M. Bruckstein, D. L. Donoho, and M. Elad, "From sparse solutions of systems of equations to sparse modeling of signals and images," SIAM Review, vol. 51, no. 1, pp. 34–81, 2009.

[24] M. Hyder, M. Shahid, M. Kashem, and M. Islam, "Initial weight determination of a MLP for faster convergence," Journal of Electronics and Computer Science, pp. 1–6, 2009.

[25] V. A. Besekersky and E. P. Popov, Theory of Automatic Control Systems. St. Petersburg: Profession, 2003.

[26] Y. Bengio, P. Simard, and P. Frasconi, "Learning long-term dependencies with gradient descent is difficult," IEEE Transactions on Neural Networks, vol. 5, no. 2, pp. 157–166, 1994.