The selection of a structure of a neural network model for predicting the flow parameters of transport systems

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Abstract

The selection of a structure of a model for predicting flow parameters of a distributed transport system of the conveyor type is considered in this paper. The rationale for using a neural network to model a transport system consisting of a large number of individual sections is given. The analysis of transport conveyor models is carried out. It is shown that the model of a transport system, which is based on a neural network, can be successfully applied to predict the flow parameters of a transport system consisting of a very large number of sections. The architecture of the neural network and the technique of forming a data set for its training are proposed. To train the neural network, the back propagation method of error was used. A comparative analysis of models of conveyor-type transport systems based on multilayer neural networks of different structures is carried out. Various neural network structures were studied on various test tasks. An analysis of the neural network learning rate with logistic and linear activation functions is given.

Keywords

conveyor, distributed system, control

1. Introduction

One of the important problems of the leading enterprises of the mining industry is the reduction of costs for the extraction and transportation of minerals. The conveyor type transport system is the main method of transporting material [1–3]. The average share of the cost of transporting a unit mass of material is 20% of the total cost of coal mining [4]. Costs are especially noticeable for long multi-sectional transport systems and branched transport systems. As the length of the transport system increases, transportation costs increase too. Uneven coming of material at the input of the transport system leads to an uneven distribution of material along the transportation route. It's the one of the main reason for the inefficient use of transport conveyor.

Reduced transportation costs is achieved by increasing the level of congestion with the material of the transport system [1, 5]. To increase the level of congestion of the transport

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system, control the speed of the conveyor belt or the value of the output stream from the accumulating hopper entering the input of a separate section is used [6-8]. The design of the control system is simplified if the transport conveyor is divided into sections [1, 2]. In this case, control of flow parameters can be carried out within a separate section. For the design of a control system for flow parameters of the transport system, transport conveyor models are most often used, which are based on the finite element method [3, 9-12] and the finite difference method [13, 14]. For a qualitative analysis of the parameters of transport systems, equations of system dynamics [7] and aggregated equations [15] are used.

2. Formal Problem Statement

Dividing a long transport conveyor into separate sections and using transport systems with an extensive internal route containing a large number of converging and diverging sections ensures an increase in the capacity and length of transport systems. However, in this case, the use of finite element and finite difference methods for modelling conveyor-type transport systems is not effective due to the large amount of calculations [2, 10, 13]. To model a transport system consisting of a large number of sections, the analytical model of a transport conveyor [16] can be successfully applied. An analytical model of the main multi-section conveyor is presented in [17]. If the conveyor belt speed for each section of the transport system, consisting of a very large number of sections, is constant, then this models are an excellent tool for simulating such a transport system. If the speed of the conveyor belt changes over time, then the analytical model will require significant computational resources. This circumstance imposes a limitation on the maximum number of sections of the transport system, for the description of which an analytical model can be used. The maximum number of sections is determined from the condition that the calculation time should be less than the maximum permissible value. This value is limited by the time allotted for controlling the parameters of the transport system. If the number of sections reaches several dozen separate sections, then a more advanced model of the conveyor is required to design an effective control system for the flow parameters of the transport conveyor.

This paper proposes the use of a neural network (NN) for modelling a multi-section conveyor. It should be noted that the researchers of conveyor systems have already shown interest in this class of models. Regression models [18-20] and NN models [21, 22, 23] were used to analyse the strength characteristics of the transport conveyor. The feasibility of using the regression model of the conveyor section for the design of the belt speed control system was studied in paper [19]. In [21], a model based on NN is considered to control the speed of movement of the conveyor belt. The advantage of these papers is that the regression model and the model based on NN were built in accordance with the actual experimental measurement. However, when designing multi-section transport conveyors, the ability to use an experimental data set is associated with great difficulties. This greatly complicates the use of NN for modelling a multi-section transport conveyor. This work is devoted to the construction of a model based on NN to describe the state of the flow parameters of a multi-section conveyor and the following analysis of these parameters.

3. An Analytical Model of the Conveyor Section

A conveyor is a type of production line [23]. Consider the approximation that the conveyor belt is not extensible. For this assumption, the rock material moves along the transportation route at the same speed equal to the speed of the belt. The system of equations for modelling the movement of material along the transport route has the form [8, 16]:

$\frac{\partial [\chi]_0(t,S)}{\partial t} \frac{\partial [\chi]_0(t,S)}{\partial S}(S)$	(1)
$[\chi]_1(t,S)=a(t)[\chi]_0(t,S)$	(2)

under the initial conditions:

$[\chi]_0(t_0,S)=H(S)\Psi(S)$,	(3)
$\int_{-\infty}^{+\infty}\delta(S)ds=1$, $H(S)=¿0,S<0;¿¿¿¿$	(4)

where the parameters $[\chi]_0(t,S)$ (t/m), $[\chi]_1(t,S)$ (t/h) - the linear density of the rock and the flow of the rock at time *t* (h) at the point of the route determined by the coordinate *S* (m), $S\in[0,S_d]$, S_d is the length of the conveyor line. Flow parameters $[\chi]_0(t,S)$, $[\chi]_1(t,S)$ are linked coefficient $a=a(t)$ (m/h), which determines the conveyor belt speed of the conveyor line; $\lambda(t)$ - the intensity of the arrival of the rock on the conveyor line at the point with the coordinate S=0; $\delta(S)$ is Dirac function.

Let's write the next expressions using dimensionless variables [16]:

$\tau=\frac{t}{T_d}$, $\xi=\frac{S}{S_d}$,	(5)
$\theta_0(\tau,\xi)=\frac{[\chi]_0(t,S)}{\Theta}$, $\psi(\xi)=\frac{\Psi(S)}{\Theta}$, $\gamma(\tau)=\lambda(t)\frac{T_d}{S_d\Theta}$,	(6)
$g(\tau)=a(t)\frac{T_d}{S_d}$, $\vartheta(\tau)=\sigma(t)\frac{T_d}{S_d\Theta}$, $\Theta=\max\left\{\Psi(S),\frac{\lambda(t)}{a(t)}\right\}$,	(7)
$\delta(\xi)=S_d\delta(S)$, $H(\xi S_d)=H(S)$.	(8)

Rewrite the system of equations (1) – (3) in the dimensionless form:

$\frac{\partial\theta_0(\tau,\xi)}{\partial\tau} \frac{\partial\theta_0(\tau,\xi)}{\partial\xi}(\xi)$,	(9)

$\theta_0(0,\xi)=\mathrm{H}(\xi)\cdot\psi(\xi)$,	(10)

where T_d is the time during which the rock passes the entire transportation route, from the moment it enters the conveyor belt and up to the point of unloading from the conveyor.

The system of equations (5), (6) corresponds to a system of characteristics:

$\frac{d\xi}{d\tau}=g(\tau)$, $\xi\|_{\tau=0}=\beta$,	(11)
$\frac{d\theta_0(\tau,\xi)}{d\xi}=\delta(\xi)\frac{\gamma(\tau)}{g(\tau)}$, $\theta_0(0,\beta)=\mathrm{H}(\beta)\cdot\psi(\beta)$.	(12)

Integration of the system of equations (11), (12) allows to obtain a general solution in the form:

$\theta_0(\tau,\xi)=\left[H(\xi)-H(-G(\tau_\xi))\right]\frac{\gamma(\tau_\xi)}{g(\tau_\xi)}+H(-G(\tau_\xi))\psi(-G(\tau_\xi))$,	(13)
$\tau_\xi=G^{-1}(G(\tau)-\xi)=\tau-\Delta\tau_\xi$, $G(\tau)=\int_0^\tau g(\omega)d\omega$, $G^{-1}(G(\tau))=\tau$,	(14)

where $\Delta\tau_\xi$ is the value of the transport delay.

The obtained solution (13) allows to determine the output parameters of the single conveyor's section. For a conveyor's section whose length is $\xi=1$, the output parameters can be calculated using the following formulas:

$\theta_0(\tau,1)=(1-H(1-G(\tau)))\frac{\gamma(\tau-\Delta\tau_\xi)}{g(\tau-\Delta\tau_\xi)}+H(1-G(\tau))\psi(1-G(\tau))$,	(15)
$\theta_1(\tau,1)=(1-H(1-G(\tau)))\frac{\gamma(\tau-\Delta\tau_\xi)}{g(\tau-\Delta\tau_\xi)}g(\tau)+H(1-G(\tau))\psi(1-G(\tau))g(\tau)$.	(16)

For the steady-state mode, expressions (15) and (16) have a simpler form:

$\theta_0(\tau,1)=\frac{\gamma(\tau-\Delta\tau_\xi)}{g(\tau-\Delta\tau_\xi)}$,	(17)
$\theta_1(\tau,1)=\frac{\gamma(\tau-\Delta\tau_\xi)}{g(\tau-\Delta\tau_\xi)}g(\tau)$.	(18)

In the initial period of movement of the conveyor belt $(1-G(\tau))>0$ the output parameters of the conveyor section are determined by condition (10):

$\theta_0(\tau,1)=\psi(1-G(\tau))$,	(19)

$\theta_1(\tau,1)=g(\tau)\psi(1-G(\tau))$.	(20)

The obtained expressions for calculating the output parameters $\theta_0(\tau,1)$ and $\theta_1(\tau,1)$ of the conveyor section (17) – (20) will be used to form a data set for training NN of a multi-section conveyor.

4. Conveyor Section Model Using a Neural Network

The conveyor-type transport system provides directional movement of material from the place of mining to the place of processing or the point of loading for subsequent transportation. The route diagram of a branched conveyor system consisting of several dozen separate sections is given in [24]. Constructing a model of a transport conveyor using NN, let's use a simplified diagram of the transport route shown in Figure 1.

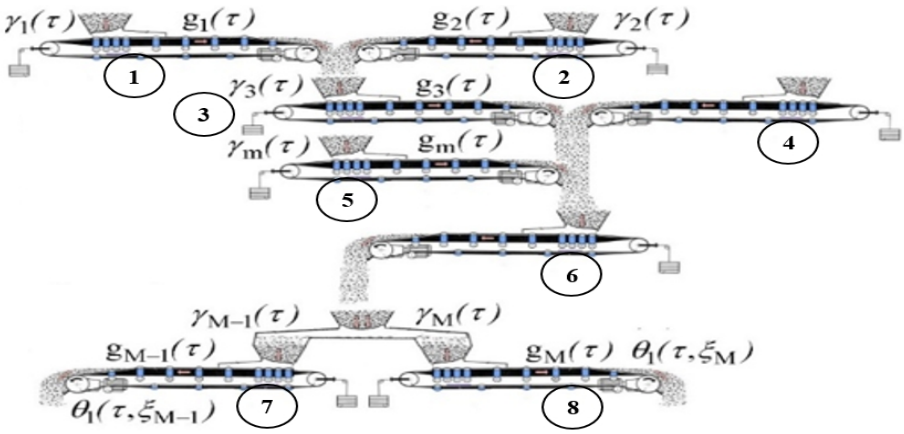


Figure 1: Diagram of a branched conveyor transport route.

The transport route diagram contains four input conveyors (section m = 1,2,4,5) and two output conveyors (section m = 7,8). The material coming from the previous section into the bunker instantly leaves it and enters the next section. The bunker only provides the required direction of movement of the material. Regulation of the value of the material flow is carried out with a change in the speed of the conveyor belt (18), (20). The model under consideration, as will be shown below, can be expanded without any problems to an arbitrary number of sections, which allows to simulate transport routes of a rather complex configuration.

To describe the functioning of a separate conveyor section of the transport system, we use dimensionless variables (5)–(8) of the model (9), (10), which allow to determine the state of the flow parameters of the individual conveyor section at a time τ : $\gamma_m(\tau)$ is the intensity of the input flow of material; $g_m(\tau)$ is conveyor belt speed; ξ_m is length of the m –th transport section. An additional parameter of the section may be the value of the transport delay $\Delta\tau_{\xi m}$:

$$\xi_m = \int_{\tau-\Delta\tau_{\xi m}}^{\tau} g(\omega)d\omega.$$	(21)

However, the measurement of the transport delay in production conditions is associated with a number of difficulties. As a result, the calculation of the value of the transport delay is performed by measuring the value of the conveyor belt speed, which is equivalent to solving (21). But solving (21) leads to the fact that the advantage of using a model based on NN is lost in comparison with the analytical model. It is the cost of computing resources associated with solving (21) that makes it difficult to use an analytical model to describe a transport system consisting of a large number of sections and opens the prospects for using a model based on NN. Therefore, if in real production conditions it is not possible to directly measure the amount of transport delay, this parameter is not advisable to include in a set of parameters for an individual section. Similar considerations can be given for the parameters of the input material flow $\gamma_m(\tau)=\theta_{1m}(\tau,0)$ and the material output flow $\theta_{1m}(\tau,1)$ for the inner sections (17), (20), the values of which are determined through the value of the transport delay $\Delta\tau_{\xi m}$. In addition, it should be pointed out that for calculating the parameters $\gamma_m(\tau)=\theta_{1m}(\tau,0)$, $\theta_{1m}(\tau,1)$ of the inner sections, the information should be stored on their values and values of the conveyor belt speed $g_m(\tau)$ for the time interval $(\tau-\Delta\tau_{\xi m};\tau)$.

Taking into account the above arguments, as the nodes of the input layer of NN, we choose the intensity of the input stream of the material and the speed of the conveyor belt of the input sections (m = 1,2,4,5). The values of the nodes of the output layer of NN will correspond to the values of the output flow for the final sections (m = 7, 8).

$$\frac{\gamma_2(\tau)}{\gamma_3(\tau)}=const,\ \gamma_3(\tau)\neq 0.$$	(22)

The architecture of NN for constructing an aggregated model is a feed-forward, a full-connected and three layer. We introduce the notation for the parameters of the input layer of NN:

$x_{3m-2}=\gamma_m(\tau)$, $x_{3m-1}=g_m(\tau)$, $x_{3m}=\xi_m$, μ=1,...,M.	(23)

where m is the number of the conveyor section (Figure 1). For the model of the transport system, we will use the input parameters $\gamma_m(\tau)$, $g_m(\tau)$, ξ_1 of the input sections m = 1,2,4,5 (Figure 1).

Let's introduce the notation for the parameters of the output layer of NN:

$y_1=\theta_{17}(\tau,\xi_7)$, $y_2=\theta_{18}(\tau,\xi_8)$.	(24)

The output parameters y_1 and y_2 correspond to the output material flows for sections m = 7, 8 of the transport system of Figure 1. The parameter system (23), (24) is an example of a set of NN parameters for a transport system of eight sections. Using a similar approach, we can determine the input and output parameters for an aggregated model of a transport system with an arbitrary number of sections.

5. Results

Two types of activation functions were used for the selection of a structure of NN model [25]: the linear or ReLU (25) and the logistic (26):

$$f(x)=bx, \quad \begin{cases} f(x)=a, & \text{if } x \geq a/b, \\ f(x)=bx, & \text{if } a/b > x > 0, \end{cases} \tag{25}$$

$$f(x)=\frac{a}{1+\exp(-bx)}. \tag{26}$$

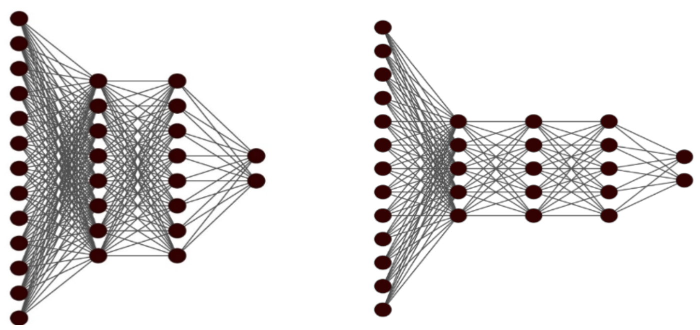
Within one layer, for all nodes, the same activation function is set with coefficients fixed for each node of the layer a, b. For different layers, the form of the activation function and the coefficients that determine it may differ.

For the transport system we had considered two models a multilayer NN with structure 13–$N_L L$–2, containing L-hidden layers and N_L nodes in each layer: 13-8-8-2 and 13-5-5-5-2. The considered structures contain approximately the same number of hidden nodes $N_h = N_L L \sim 15$ with the number of weights

$$N_w = (N_i + N_o) N_L + (L-1) N_{L^2}, \tag{27}$$

that determine the computational complexity of the learning algorithm. When analyzing structures with the same number of neurons in the input N_i, output N_o and hidden layers N_h the formula that determines the number of weight coefficients for the structure $N_i - N_L L - N_o$ (Figure 2) takes the form

$$N_w = (N_i + N_o) N_L + (L-1) N_{L^2} = \frac{N_{h^2}}{L}\left(1 - \frac{1}{L} + \frac{N_i + N_o}{N_h}\right). \tag{28}$$



a) b)

Figure 2: The neural network structure: a) 13-8-8-2; b)13-5-5-5-2

With an increase in the number of hidden layers L the value of the function $N_w(L)$ decreases for L>1. The sign of the derivative of the function $N_w(L)$ is determined by the expression:

$$\frac{\partial N_w}{\partial L} \sim \left(\frac{2}{L} - \frac{N_i + N_o + N_h}{N_h} \right) < 0 \text{, for } L>1. \tag{29}$$

Thus, at constant values of N_i, N_o, N_h the complexity of the computational algorithm for determining the values of the output flow parameters of the transport system in accordance with (28) is inversely proportional to the number of hidden layers. The main characteristics of NN used to build a model of the transport system are presented in Table 1.

Table 1
Characteristics of neural networks for modelling the transport system

id	Structure (hidden layer)	Activation function	Coeff. "a" (HL)	Coeff. "b" (HL)	Coefficient "a" (output layer)	Speed learning	MSE	Number of epochs
711	8-8	Logistic	2,0	1,0	2,0	10^{-4}	0,39	103
712	8-8	Logistic	2,0	1,0	4,0	10^{-4}	0,19	1,2*103
713	5-5-5	Logistic	2,0	1,0	4,0	10^{-4}	0,51	1,2*103
911	8-8	Linear (ReLU)	100	0,1	4	10^{-4}	0,08	68*103
9112	8-8	Linear (ReLU)	100	0,1	4	10^{-3}	0,05	78*103
921	5-5-5	Linear (ReLU)	2,0	1,0	2,0	10^{-4}	0,41	28*103
9212	5-5-5	Linear (ReLU)	2,0	1,0	2,0	10^{-3}	0,08	28*103

Each option is represented by the same and constant learning rate $\alpha_{km} = 10^{-4}$ which allows you to compare the training durations of NN used to build different models of transport systems. The value of the coefficient "b" for the output layer is equal to 1,0 for all studied cases. In model 711 with structure 13-8-8-2, the same activation function is defined for each node. The results of predicting the output flow $\theta_{17}(\tau, 3/2)$ using this model are presented in Figure 3. The quality of the prediction is estimated at MSE = 0,390. A doubling of the scale factor in the activation function of the output layer led to a halving of the MSE value (MSE = 0,197) with the same number of learning epochs.

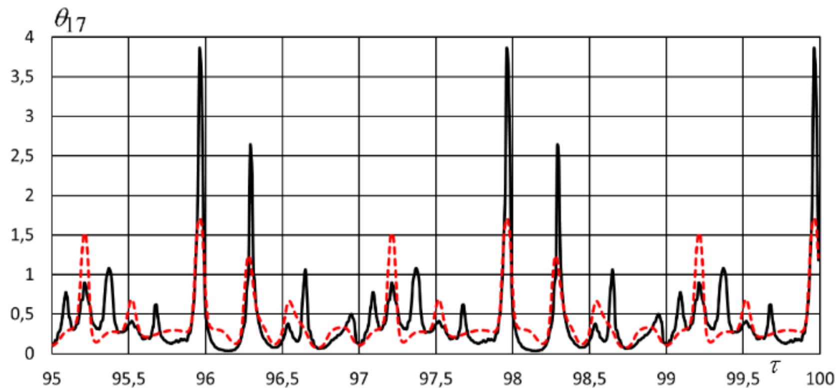


Figure 3: Predicted material output flow $\theta_{17}(\tau,1.5)$, Model 711.

Subsequent migration from 13-8-8-2 (Model 712) to 13-5-5-5-2 (Model 713) did not result in a decrease in MSE. The reason is explained by the development of instability in the learning process of NN. The next step of the study was the transition in model 712 from the logistic activation function (1) to the linear activation function (2). With the value of the coefficients for the hidden layer $a=4$, $b=1$ and for the hidden layer $a=4$, $b=1$ the learning process was not stable. When changing the coefficients for the hidden layer $a=100$, $b=0,1$ the learning process became stable. The learning process lasted ~68*103 epochs and was stopped with MSE~0,08 and $\Delta MSE \sim 7 \cdot 10^{-7}$. Then, to speed up the learning process, the learning rate was increased from a value $\alpha_{km}=10^{-4}$ to a value $\alpha_{km}=10^{-3}$ for all nodes. This made it possible to continue the learning process in an accelerated mode, reaching ~78*103 epochs with an MSE~0,053. Further training was interrupted due to the development of instability in the training process. At the same time, the value MSE~0,390 and MSE~0,197 was reached at ~6*103 and ~15*103 epochs, respectively. This allows one to compare the training required by the three for logistic activation function and linear activation function (ReLU) for the given parameters for NN (Table 1) as a ratio of ~10 : 1.

The final stage of the study was the transition from structure 13-8-8-2 (Model 911) to structure 13-5-5-5-2 (Model 921), Table 1. The presence of an additional hidden layer did not lead to a decrease in the MSE value in model 921 compared to the 911. However, it is worth noting the presence of oscillatory processes of the MSE value relative to value ~ 0,082. The results of prediction the output flow parameters $\theta_{17}(\tau,1.5)$, $\theta_{18}(\tau,0.6)$ of the transport system are presented in Figure 4, Figure 5. Comparison of the prediction results shows that the use of the ReLU activation function for training NN makes it possible to obtain a more accurate forecast of stream parameters with a lower MSE value than when using the Logistic activation function. A significant disadvantage of using the Linear activation function (ReLU) compared to using the Logistic activation function is a significant increase in the time that needs to be spent on training NN. A comparative analysis of the prediction quality criterion for those considered in this work is shown in Figure 6.

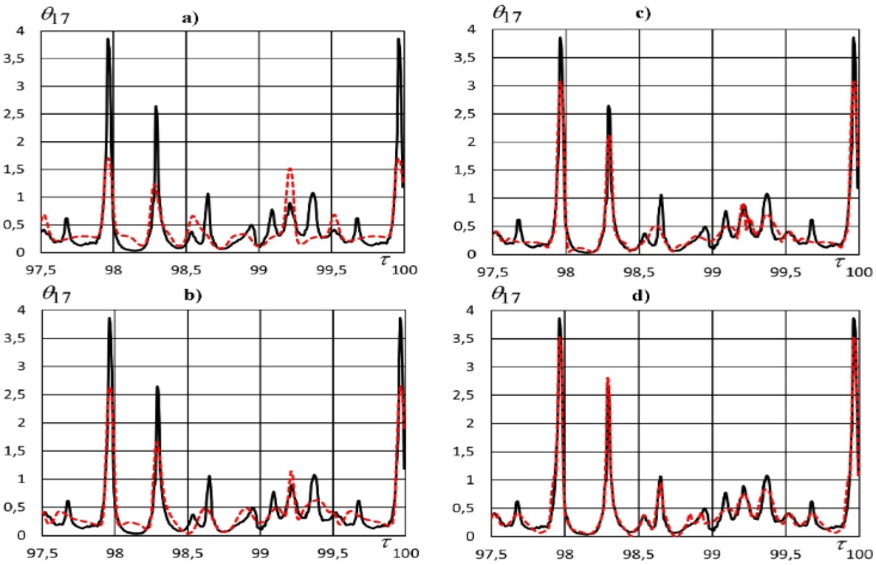


Figure 4: Predicted material output flow $\theta_{17}(\tau,3/2)$: a) model 711; b) model 721; c) model 911; d) model 721.

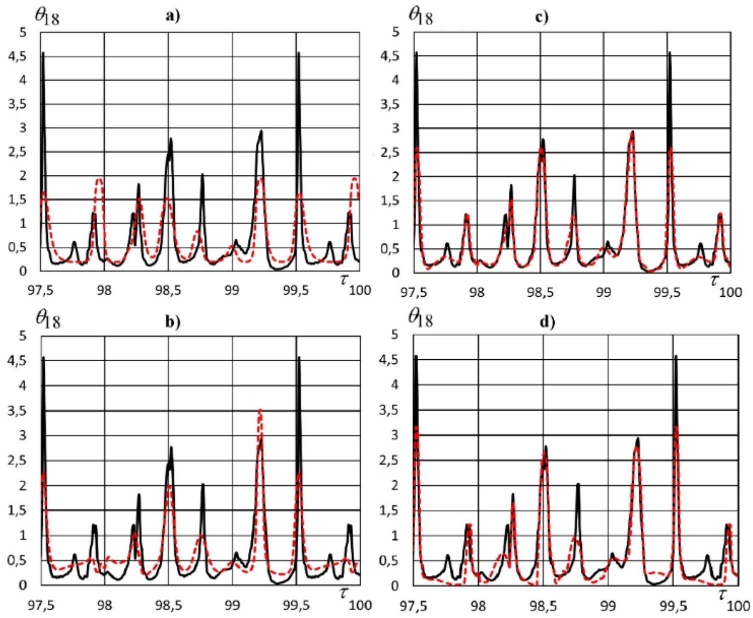


Figure 5: Predicted material output flow $\theta_{18}(\tau,0.6)$: a) model 711; b) model 721; c) model 911; d) model 721.

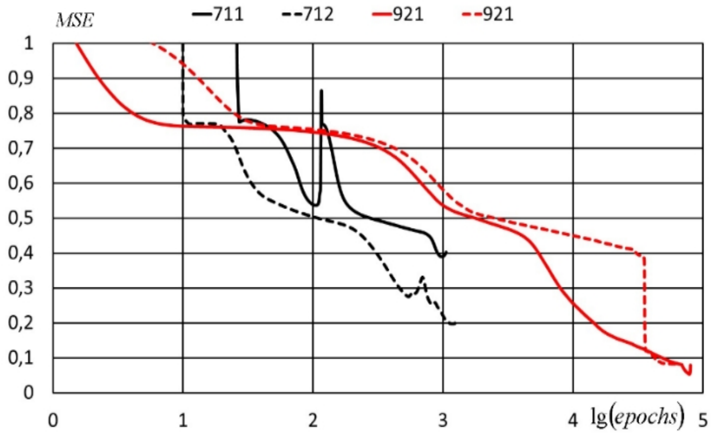


Figure 6: Prediction quality criterion.

Multilayer NN based on linear (ReLU) demonstrated a more robust learning process and gave lower MSEs than NN based on logistic activation functions. An increase in the number of hidden layers with a constant number of neurons in them led to the emergence of instabilities during the learning process of NN for the logistic activation function and the appearance of oscillatory processes in the case of using the ReLU activation function. It should be noted that an increase in the number of hidden layers, on the one hand, leads to a decrease in the quality of the forecast (an increase in the MSE value), on the other hand, it makes it possible to obtain a significant increase in the accuracy of predicting the peak values of the flow parameters of the transport system, which is clearly shown in Figure 4, Figure 5.

6. Conclusion

A model using NN can be a fairly good tool for predicting the state of the output flow parameters of a branched transport system consisting of a large number of individual sections. However, the accuracy of such a model depends on many factors, including the architecture and the structure of such a model.

In this work, a comparative analysis of transport conveyor models based on multilayer NN is carried out. The main focus is on NN with the logistic activation function and the ReLU activation function. NN with a logistic activation function demonstrated a shorter learning time for equal MSE values, which is explained by the distributed form of nonlinearity and high connectivity. However, it should be noted that the learning process of NN with and linear (ReLU) activation function is more stable, which allows achieving lower MSE values in the learning process. The influence of the structure of NN on the duration of their training was also studied.

The work touches upon many issues that are important from the point of view of constructing models of conveyor-type transport systems. The estimation of the method of initialization of the weight coefficients providing the connection between the nodes of NN is carried out and the rationale for the preparation of a normalized data set for training NN is given. The importance of the last question is emphasized by the fact that the values of the nodes of the input and output layers are positive, which leads to a simultaneous increase or decrease in the weight coefficients that ensure the connection of the nodes of the input layer with the nodes of the hidden layer, and, as a consequence, to the occurrence of oscillatory processes.

A method for increasing the accuracy of the learning process as a result of removing values from the data set is demonstrated, which characterize the transient mode of operation of the transport system.

This article does not discuss the importance of hidden neurons as detectors of factors that determine the behavior of the flow parameters of the transport system. Also, the problem of reducing the order of a multilayer NN with losing the quality of the model prediction is not considered.

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