# Neural model of conveyor type transport system

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**Abstract.** In this paper, a model of a transport conveyor system using a neural network is demonstrated. The analysis of the main parameters of modern conveyor systems is presented. The main models of the conveyor section, which are used for the design of control systems for flow parameters, are considered. The necessity of using neural networks in the design of conveyor transport control systems is substantiated. A review of conveyor models using a neural network is performed. The conditions of applicability of models using neural networks to describe conveyor systems are determined. A comparative analysis of the analytical model of the conveyor section and the model using the neural network is performed. The technique of forming a set of test data for the process of training a neural network is presented. The foundation for the formation of test data for learning neural network is an analytical model of the conveyor section. Using an analytical model allowed us to form a set of test data for transient dynamic modes of functioning of the transport system. The transport system is presented in the form of a directed graph without cycles. Analysis of the model using a neural network showed a high-quality relationship between the output flow for different conveyor sections of the transport system.

**Keywords:** conveyor, PDE– model, distributed system, transport delay.



## 1 Introduction

The transport conveyor is a complex dynamic stochastic distributed system. The transport conveyor is an integral part of the technological process at enterprises with the flow method of organizing production [1]. Conveyor transport is widely used in the mining industry [2–6]. Table 1 shows a number of basic characteristics of conveyor-type transport systems. One way to save energy, which is necessary for the functioning of such systems, is to increase the level of congestion of the conveyor line [7–9]. To reduce the energy costs required to move one ton of material along the transportation route, systems are used to control the speed of the belt or the intensity of the material at the entrance of the conveyor section from the input bunker [10–12]. The effectiveness of the conveyor control system is largely determined by the model of the transport system. This fact acquires special significance when designing control systems for a transport system consisting of a large number of sections.

**Table 1.** Characteristics of long-ranged conveyor transport system

| Conveyor name | Length (km) | sections | Power (kW) | Speed (m/sec) | Capacity (t/h) |
|---|---|---|---|---|---|
| From the Bu Craa mine to the coast at El Aaiún, Western Sahara, [2] | 128.7 | 11 | | | 2000 |
| Sasol's Impumelelo project in South Africa (2015), [2] | 27.5 | 1 | | 6.5 | 2400 |
| The Henderson Coarse Ore Conveying System, the North American Continental Divide (2000), [3,4] | 24.0 | 3 | 12700 | 4.5 | 2270 |
| Çöllolar Lignite Open Pit Mine, Turkey (2011), [5] | 17.4 | 26 | 46300 | | 9350 |
| From a mine in India to a cement plant in Bangladesh (2005), [2] | 16.5 | 1 | | 6.5 | |
| Neyveli Lignite Corp., India (2007), [5] | 14.0 | 8 | 2520 | 5.4 | |
| Open Cast Mine Reichwalde, Germany (2010), [5] | 13.5 | 6 | 19350 | 5.5 | 6000 |
| Coarse ore conveyor system Minera Los Pelambres, Chile (1998), [5] | 12.7 | 3 | 25000 | | 8700 |
| Tianjin China Port Authority, China (2005) [6] | 8.98 | 1 | 4x 1500 | 5.6 | 6000 |
| Baumgartner Tunnel, the Metropolitan St. Louis (Missouri) , USA [6] | 6.18 | | | 2.54 | 200 |
| Barcelona Tunnel (the Metro (Train) Extension Project), Spain (2005) [6] | 4.71 | 1 | 3.5 | | 1500 |

## 2 Literature review

To build the models on which the systems for controlling the speed of the belt or the intensity of material input at the entrance of the conveyor section from the input bunker are based, use the finite element method [13–18]; finite difference method [18,19]; Lagrange method [19]; a method using the aggregated equation of state [20]; system dynamics method [10]; multiple regression method [26–28]. Most often used in models for calculating flow parameters a finite element method. This method allows you to determine the value of the flow parameters of the conveyor section for dynamic transient conditions, taking into account the distribution of material along the transportation route. The finite element method, before the advent of the analytical model (PiKh–model) of the conveyor-type transport system [12], was perhaps the main method used by researchers to construct the conveyor model. The use of neural network methods and multiple regression methods to describe flow parameters was less promising than the finite element method. One of the reasons is that the researchers focused on modelling a single section of the conveyor. Another, no less important reason is the lack of test data in the right amount for training a neural network or for building a regression model. When considering a model of a transport system, which consists of a large number of separate conveyor sections, the use of the finite element method is unreasonable even when modelling a transport system consisting of several dozen separate sections. A good tool, in this case, is the PiKh– conveyor system model. In this case, a separate model is built for each separate section. Combining sections into a common system leads to a system of equations [29, 30]. In the event that a separate section does not include an accumulating bunker, the number of equations of the system is equal to the number of sections. In [29], a model of a conveyor system consisting of 2 sections is presented. In [30], the principles of constructing a model of the main conveyor are considered.

## 3 Formal problem statement

If the transport system is a conveyor [31], which consists of tens or even hundreds of separate sections, and each section has a system for controlling the rate of material input from the input bunker and a belt speed control system, then using analytical models can be associated with significant difficulties. In this case, the application of methods using the neural network and multiple regression methods is of scientific and practical interest for solving the problem. The more the number of sections in the transport system, the stronger the interest of researchers in applying methods using the neural network and multiple regression methods. In this regard, in this work, we will pay attention to constructing a model of an assembly line using a neural network.

## 4 Conveyor section model

To describe the conveyor section (Fig. 1) let us use the classic dynamic distributed model of the conveyor in a dimensionless form (PiKh-model) [12]:

$$\frac{\partial \theta_0(\tau,\xi)}{\partial \tau} + g(\tau)\frac{\partial \theta_0(\tau,\xi)}{\partial \xi} = \delta(\xi)\gamma(\tau) \tag{1}$$

$$\theta_0(0,\xi) = \mathrm{H}(\xi)\psi(\xi) . \tag{2}$$

The state of the flow parameters of the conveyor line at a point in time $t$ at the point of the transport route with the coordinate $S$ is described by dimensionless variables:

$$\tau = t / T_d \ , \ \xi = S / S_d \ , \tag{3}$$

$$\theta_0(\tau,\xi) = [\chi]_0(t,S)/\Theta , \ \psi(\xi) = \Psi(S)/\Theta , \tag{4}$$

$$\gamma(\tau) = \lambda(t)\frac{T_d}{S_d\Theta} , \ \gamma_b(\tau) = \lambda_b(t)\frac{T_d}{S_d\Theta} , \ \gamma_{\max} = \lambda_{\max}\frac{T_d}{S_d\Theta} , \tag{5}$$

$$g(\tau) = a(t)T_d / S_d , \ \Theta = \max\{\Psi(S), \lambda(t)/a(t)\} , \ \delta(\xi) = S_d\delta(S) , \ H(\xi) = H(S) , \tag{6}$$

$$[\chi]_1(t,S) = a(t)[\chi]_0(t,S) , \ \vartheta(\tau) = \sigma(t)\frac{T_d}{S_d\Theta} , \ 0 \le \lambda(t) \le \lambda_{\max} , \tag{7}$$

where $S_d$ is length of the conveyor line; $T_d$ is the characteristic time of the passage of the material along the transport route; $[\chi]_0(t,S)$, $[\chi]_1(t,S)$ is the linear density of material distribution and material flow at a point in time $t$ at the point of the transport route with the coordinate $S \in [0, S_d]$; $\Theta$ is the limit value of the linear density of the material for the analyzed conveyor section; $\Psi(S)$ is the initial distribution of material along the technological route; $\lambda_b(t)$ is the intensity of the flow of material into the bunker; $\lambda(t)$ is the output flow of material from the bunker to the input of the conveyor section, limited by $\lambda_{\max}$; $a(t)$ is conveyor belt speed; $\sigma(t)$ is the predicted output flow of the material from the conveyor section; $\delta(S)$ is delta function; $H(S)$ is Heaviside function.

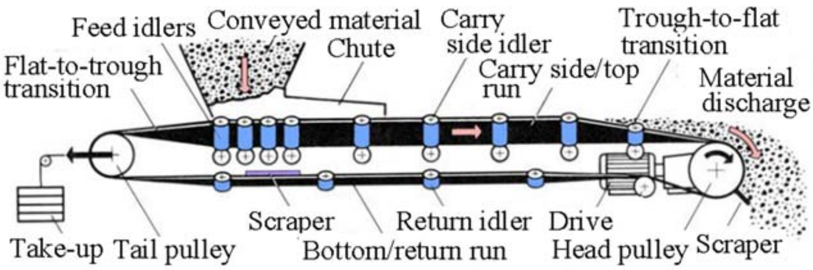


**Fig. 1.** Schematic diagram of the conveyor line [2]

Equation (1) with initial conditions (2) corresponds to the solution [12]:

$$\theta_0(\tau,\xi) = \left(H(\xi) - H(\xi - G(\tau))\right)\frac{\gamma(G^{-1}(G(\tau)-\xi))}{g(G^{-1}(G(\tau)-\xi))} + \mathrm{H}(\xi - G(\tau))\psi(\xi - G(\tau)) \tag{8}$$

$$\theta_1(\tau,\xi) = g_0\theta_0(\tau,\xi) = \gamma(\tau - \xi / g_0),\ G(\tau) = \int_0^\tau g(\alpha)d\alpha\,. \tag{9}$$

The system of equations (8), (9) determines the behaviour of the flow parameters of the conveyor. The linear density of the material along the transport route $\theta_0(\tau,\xi)$ at an arbitrary point in time $\tau$ can be determined if the intensity $\gamma(\tau)$ of the rock entering the conveyor line entrance and the speed of the conveyor belt $g(\tau)$ are known. The linear density of the material $\theta_0(\tau,1)$ and the material flow $\theta_1(\tau,1)$ at the output from the transport conveyor system $\xi = 1$ is determined by the expressions

$$\theta_0(\tau,1)=\begin{cases}\dfrac{\gamma(G^{-1}(G(\tau)-1))}{g(G^{-1}(G(\tau)-1))}, & G(\tau)-1\ge 0;\\ \psi(1-G(\tau)), & G(\tau)-1<0;\end{cases}\quad \theta_1(\tau,1)=\theta_0(\tau,1)g(\tau). \tag{10}$$

Equation solution

$$G(\tau_{tr})-1=0 \tag{11}$$

allows you to calculate the duration of the transition period $\Delta\tau_{tr}=\tau_{tr}-\tau_0$, during which the material flow at the exit from the transport system is determined by the type of expression of the linear density of the material $\psi(\xi)$ at the initial time $\tau_0$. The linear density of the material $\theta_0(\tau,\xi)$ at an arbitrary point $\xi$ at the time $\tau\ge\tau_{tr}$ is related to the linear density of the material $\theta_0(\tau_\xi,0)$ at the input of the transport system at the time $\tau=\tau_\xi$

$$\theta_0(\tau,\xi)=\gamma(\tau_\xi)/g(\tau_\xi)=\theta_0(\tau_\xi,0),\ \tau\ge\tau_{tr},\ \tau_\xi=G^{-1}\big(G(\tau)-\xi\big). \tag{12}$$

If we introduce a definition for the delay time $\Delta\tau_\xi=\tau-\tau_\xi$, then expression (13) can be represented as follows

$$\theta_0(\tau,\xi)=\frac{\gamma(\tau-\Delta\tau_\xi)}{g(\tau-\Delta\tau_\xi)}=\theta_0(\tau-\Delta\tau_\xi,0). \tag{13}$$

The delay time $\Delta\tau_\xi$ sets the period of time during which the element of material received at the entrance of the transport system at a time $\tau_\xi$ passes the path along the transportation route equal to $\xi$. When $\xi=1$, the expression

$$\theta_0(\tau,1)=\frac{\gamma(\tau-\Delta\tau_1)}{g(\tau-\Delta\tau_1)}=\theta_0(\tau-\Delta\tau_1,0)=\theta_0(\tau_1,0),\ \tau\ge\tau_{tr}, \tag{14}$$

determines the relationship between the linear density of the material at the input and output. The value of the linear density at the output is equal to the value of the linear density at the input with a delay $\Delta\tau_1$.

## 5 Conveyor section model using a neural network.

The system of equations (8), (9) determines the linear density of the material along the transportation route and allows you to calculate the material flow at an arbitrary location of the transport path of a separate conveyor section. At a constant speed of movement of the conveyor belt, the expression determining the linear density of the material $\theta_0(\tau,\xi_m)$ and the material flow $\theta_1(\tau,\xi_m)$ at the time $\tau$ at the output of the transportation route $\xi = \xi_m$ takes a simple form with a constant time value of the delay time $\Delta\tau_{\xi\, m} = \tau - \tau_{\xi\, m}$ . If the speed of the belt is not constant in time, then to calculate the flow parameters of the conveyor transport system, it is necessary to determine the value of the delay time $\Delta\tau_{\xi\, m}$ for each m-th section from the equation

$$\tau_{\xi\, m} = G_m^{-1}\left(G_m(\tau) - \xi_m\right),\ G_m(\tau) = \int_{\tau_{0\,m}}^{\tau} g_m(\alpha) d\alpha . \tag{15}$$

If the transport system consists of a large number M of individual sections, then it is required to solve the M-equations (8), (9). Additional restrictions are imposed due to the complexity of constructing an analytical system of equations that determines the flow of material from the place of production to the place of processing [32, Fig.1 and Fig.2]. Therefore, with a large number M of individual sections, it is advisable to build aggregated models of transport systems. One of the approaches to designing aggregated models of conveyor transport systems is the use of neural networks [32–37]. To describe the functioning of a separate conveyor section of the transport system, we use dimensionless variables (4) - (7) of the model (1), (2), which allow us to determine the state of the flow parameters of the individual conveyor section at a time $\tau$ : $\gamma_m(\tau)$ is the intensity of the input flow of material; $g_m(\tau)$ is conveyor belt speed; $\xi_m$ is section transport route length. Let's move on to the construction of a neural network using the example of a branched transport system. As an option for analysis, we will use the structure of the transport conveyor shown in Fig. 2, which consists of 8 separate sections (M = 8). It should be noted that the state of the flow parameters at the output sections (section m = 7.8) is determined by the parameters of the 4 input sections (section m = 1,2,4,5). The transport system has nodes where the material flows converge (Fig. 5.a) and nodes where the material flows diverge (Fig. 3). When considering, let's assume that there is no bunker control. The amount of material flow through the bunker remains unchanged. This situation is common, it represents the case when the parameters of the bunker are not controlled. In this case, the bunker at the entrance of a separate section does not contain material. For nodes in which the material flows converge, the intensity of the input material flow is determined through the parameters of the converging sections. For the case when the node contains two incoming flows and one outgoing (Fig. 3), the balance relation holds:

$$\gamma_3(\tau) = \gamma_1(\tau - \Delta\tau_{\xi 1}) \frac{g_1(\tau)}{g_1(\tau - \Delta\tau_{\xi 1})} + \gamma_2(\tau - \Delta\tau_{\xi 2}) \frac{g_2(\tau)}{g_2(\tau - \Delta\tau_{\xi 2})}, \tag{16}$$

$$\Delta\tau_{\xi\, m} = \tau - \tau_{\xi\, m} = \tau - G_m^{-1}\left(G_m(\tau) - \xi_m\right). \tag{17}$$

For nodes in which the material flows diverge, the intensity of the input material flow is also determined through the parameters of the converging sections. For the case when the node contains an incoming flow and two outgoing flows (Fig. 3), the balance ratio has the form:

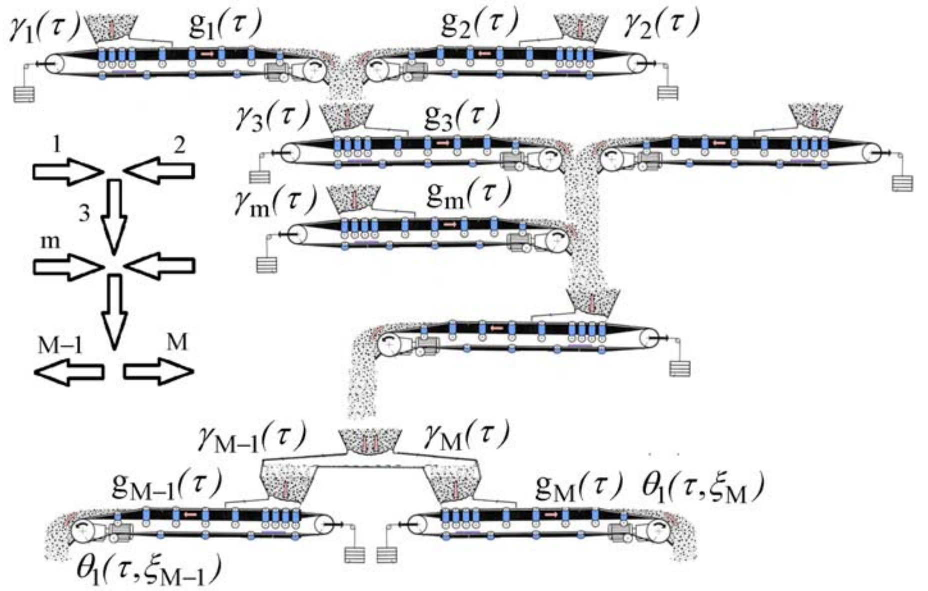


**Fig. 2.** Diagram of a branched conveyor transport route

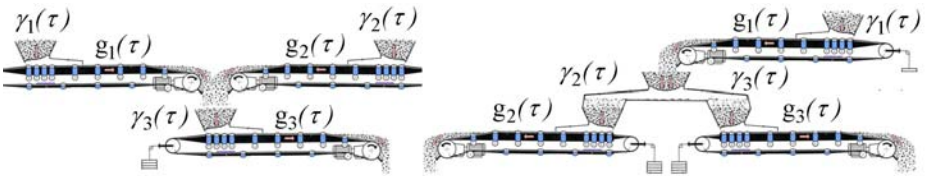


**Fig. 3.** Schemes for calculating the balance of flows in the nodes of the conveyor transport route: a) converging node; b) diverging node

$$\frac{\gamma_2(\tau)}{\gamma_3(\tau)} = \gamma_{23} = const, \ \gamma_3(\tau) \neq 0 . \tag{18}$$

Let us assume that the state of the transport system is determined at a moment in time $\tau$, if at that moment in time the parameters of each individual conveyor section are determined: $\gamma_m(\tau)$, $g_m(\tau)$. When constructing an aggregated model of a conveyor transport system in the absence of control, we exclude from consideration the parameters $\gamma_m(\tau)$ of the internal nodes, which can be determined through the flow parameters of the mated sections.
The architecture of the neural network to build an aggregated model (Fig. 4.) Let us introduce the notation for the parameters of the input layer of the neural network

$$x_{3m-2} = \gamma_m(\tau),\ x_{3m-1} = g_m(\tau),\ x_{3m} = \xi_m,\ m=1..M, \tag{190}$$

where m is the number of the conveyor section (Fig. 2). For the transport system model in Fig. 2, the input parameters (20) $x_7 = \gamma_3(\tau)$, $x_{16} = \gamma_6(\tau)$, $x_{19} = \gamma_7(\tau)$, $x_{22} = \gamma_8(\tau)$ are excluded. Similarly, let us exclude the velocities for sections m=3,6 from the input layer. We introduce the notation for the parameters of the output layer

$$y_1 = \theta_{17}(\tau, \xi_7),\ y_2 = \theta_{18}(\tau, \xi_8). \tag{20}$$

The output parameters $y_1$ and $y_2$ correspond to the output material flow for m=7,8 sections of the transport system Fig. 2.

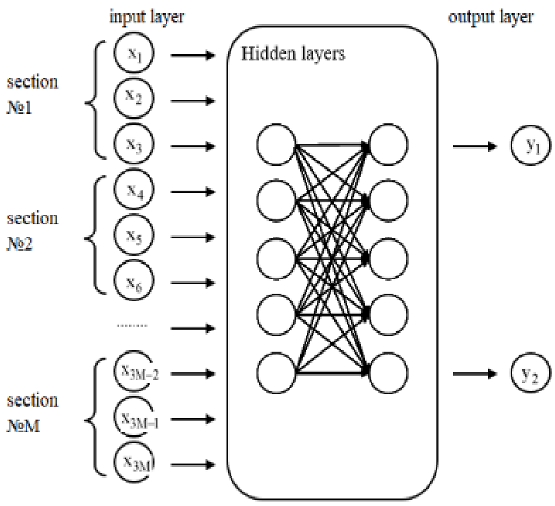


**Fig. 4.** Neural network architecture

The topology of the hidden layer of the neural network for models of the conveyor section using part of the parameters (20) was considered in [34]. For forecasting, one hidden layer with six nodes was used. As an activation function, the Logistic function was selected:

$$f(x) = \frac{a}{1 + \exp(-bx)} \tag{21}$$

Weights are initialized with random values. In [33], a 4-20-1 conveyor system model was considered to study the dependence of the output material flow on 4 input parameters, among which an important parameter is $g_m(\tau)$. The inner layer contains 20 nodes. In [35], the topology of a neural network of the form ($m_1$ - $m_2$ -14)=

$(4-9-14)$ was considered, where $m_2 = 2m_1 + 1$ is the number of hidden layers; $m_1 = 4$ is the number of nodes in the input layer. In this paper, let's focus on the topology 9-3-2. This architecture corresponds to the transport system model of 4 sections with parameters (20) $x_{3m-2} = \gamma_m(\tau)$, $x_{3m-1} = g_m(\tau)$ and one node whose value is one. The hidden layer contains 3 nodes. The output layer contains 2 nodes (21). The activation function has the form (22). The length of the conveyor is different.

## 6 Preparation of test data

As noted above, for existing transport systems it is almost impossible to obtain complete experimental data for training a neural network for transient modes. For training of the neural network, test data is required that contain a wide range of values. However, the functioning of the transport system in such a range of flow parameters is associated with high energy costs. Additionally, the lengths of the sections of the existing transport system are defined and cannot be changed. In this regard, let's use the PiKh – model (1), (2) [12] to prepare the test data, which allows us to construct an exact solution that determines the state of the flow parameters of the transport system. Let us believe that the intensity of the material flow $\lambda_m(\tau)$ to the input of the m-th non-node section of the conveyor and the belt speed $a_m(t)$ m-th section is known:

$$a_m(t) = a_{0\,m} + a_{1\,m}\sin(\omega_{a\,m}t + \varphi_{a\,m}), \tag{22}$$

$$\omega_{a\,m} = \frac{m\pi}{T_a},\ \varphi_{a\,m} = \frac{m\pi}{4},\ a_{0\,m} = a_{1\,m} = a_0\frac{3+m}{8}, \tag{23}$$

$$\lambda_m(t) = \lambda_{0\,m} + \lambda_{1\,m}\sin(\omega_{\lambda\,m}t + \varphi_{\lambda\,m}), \tag{24}$$

$$\omega_{\lambda\,m} = \frac{m\pi}{T_\lambda},\ \varphi_{\lambda\,m} = -\frac{m\pi}{4},\ \lambda_{0\,m} = \lambda_{1\,m} = \lambda_0\frac{3+m}{8}, \tag{25}$$

at the initial linear density along the route of the conveyor section

$$\Psi_m(t) = \Psi_{0\,m} + \Psi_{1\,m}\sin(k_m S + \varphi_{\Psi\,m}), \tag{26}$$

$$\varphi_{\Psi\,m} = \frac{m\pi}{4},\ \Psi_{0\,m} = \Psi_{1\,m} = \Psi_0\frac{3+m}{8}. \tag{27}$$

To go to dimensionless coordinates, we choose the characteristic size $S_d$, the characteristic process time $T_d$ for the transport system

$$S_d = S_6,\ T_d = T_6. \tag{28}$$

The choice of characteristic quantities is arbitrary and is used to select the scale of the scale for measuring system parameters for conducting a numerical experiment. We assume that the 6th section will be one of the most loaded elements of the system, or at least for a functioning transport system this section will be in operation for maximum time. To simplify the dependencies $\lambda_m(\tau), a_m(t)$, $\Psi_m(t)$, used to form test data, we assume

$$T_a = T_d\ ,\ T_\lambda = T_d\ ,\ S_\lambda = S_d\ . \tag{29}$$

Let us also introduce the characteristic flow of material in the network $\lambda_{kh} = 3\lambda_0$. The value of the characteristic flow is equal to the sum of the average values $\lambda_{0\,m}$ of the non-nodal sections. It should be noted that the choice of characteristic values is arbitrary and also determines the scale of the variables $\lambda_{0\,m}$ of the problem under consideration. Taking into account (30), should write

$$\tau = t / T_d\ , \xi_{d\,m} = S_{d\,m} / S_d\ , \tag{30}$$

$$g_{0\,m} = g_{1\,m} = a_{0\,m}\frac{T_d}{S_d}\ ,\ \gamma_{0\,m} = \gamma_{1\,m} = \frac{\lambda_{0\,m}}{\lambda_{kh}}\ ,\ \psi_{0\,m} = \psi_{1\,m} = \frac{\Psi_{0\,m}}{\lambda_{kh}}\frac{S_d}{T_d}\ , \tag{31}$$

$$g_m(\tau) = a_m(t)\frac{T_d}{S_d} = g_{0\,m} + g_{1\,m}\sin\left(m\pi\tau + \frac{m\pi}{4}\right), \tag{32}$$

$$\gamma_m(\tau) = \lambda_m(t)\frac{T_d}{S_d\Theta} = \gamma_{0\,m} + \gamma_{1\,m}\sin\left(m\pi\tau - \frac{m\pi}{4}\right), \tag{33}$$

$$\psi_m(t) = \frac{\Psi_m(t)}{\Theta} = \psi_{0\,m} + \psi_{1\,m}\sin\left(m\pi\xi + \frac{m\pi}{4}\right). \tag{34}$$

Since the choice $T_d$ is arbitrary, the parameter $T_d$ is defined in such a way that equality

$$1 = a_0 T_d / S_d\ , \tag{35}$$

then dimensionless coefficients can be written as

$$g_{0\,m} = \frac{3+m}{8}\ ,\ \gamma_{0\,m} = \frac{3+m}{24}\ ,\ \psi_{0\,m} = a_0\frac{\Psi_0}{\lambda_0}\frac{3+m}{24}\ . \tag{36}$$

For training the neural network, test data were used [38]. Test data was generated on the foundation of the model (1) - (7) [12] in accordance with the scheme of the transport system of Fig. 3 and the architecture of the neural network shown in Fig. 4. Test data is based on an analytical model (PiKh-model). The parameters of the analytical model correspond to conditions (23)–(37).

## 7 Analysis of the results

Fig.5 shows the output flow of section 8 of the transport system (Fig. 2, Fig. 4) for the analytical model and the neural network model. The calculation of the parameters of the output flow for the neural network model is performed for the number of epochs equal to 300,000 and the learning coefficient $\alpha = 10^{-5}$

$$W_{j,k,n+1} = W_{j,k,n} - \alpha \nabla E\ ,\ E = \frac{1}{2}\sum_{m=1}^{N_m}(z_m - y_m)^2\ , \tag{37}$$

where the updated weight value $W_{j,k,n+1}$ (for an epoch $n+1$) is calculated on the basis of its old value and the error $E = E(z_m, y_m)$, determined by the $N_m$ parameters of the output layer between the test data $z_m$ and the values $y_m$ of the neural network model (Fig. 4). To analyze the process of training a neural network, data from a test run comes in a strictly specified order. This allows for multiple repetitions of training

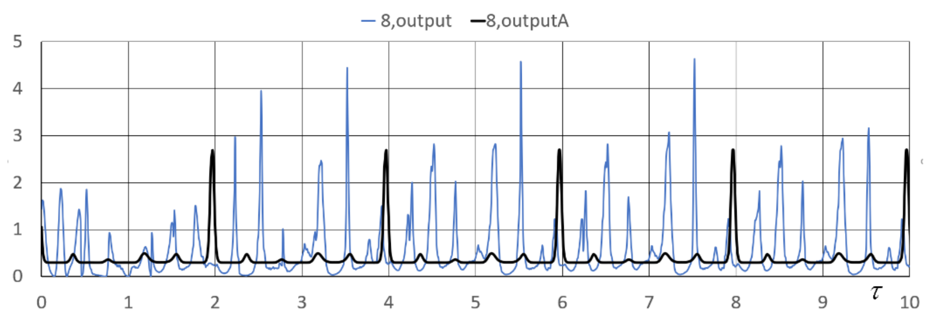


**Fig. 5.** The value of the output flow of section 8, calculated using the analytical model (8, output) and the neural network model (8, outputA)

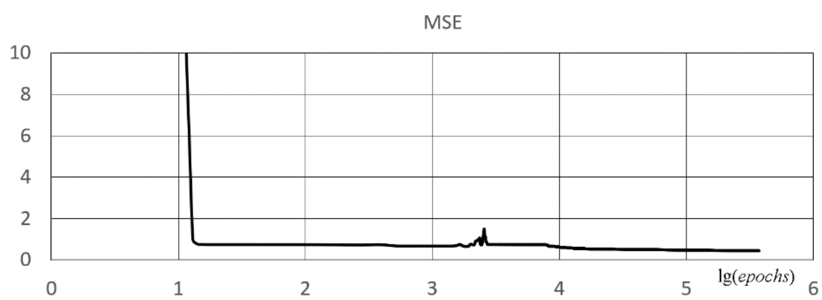


**Fig. 6.** The magnitude of the MSE error depending on the number of training epochs

with various parameters of the network architecture and compares the effect of changing parameters. The value of MSE (Mean squared error) depending on the number of training epoch is shown in Fig. 6. For training with 375000 epochs and a test sample of 9000 lines, the MSE is 0.445 [38]. The learning results show that the predicted values of the output flow of section 8 obtained using the neural model are different from the values of the flow parameters of the test sample (analytical model). This result is explained by a rather large MSE value. Further comparative qualitative

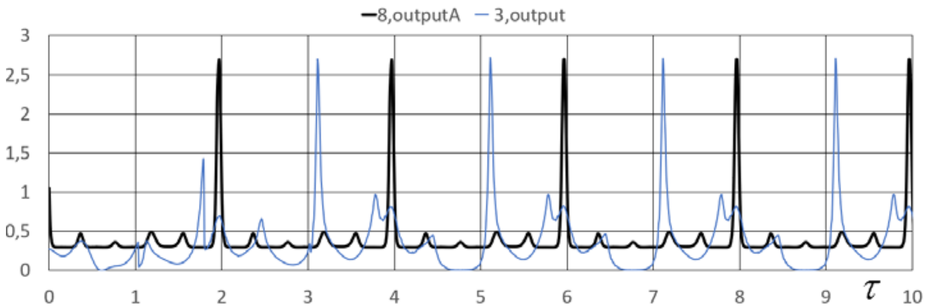


**Fig. 7.** The value of the output stream of section 3 calculated using the analytical model (3, output) and the output flow of section 8 calculated using the neural network model (8, outputA)

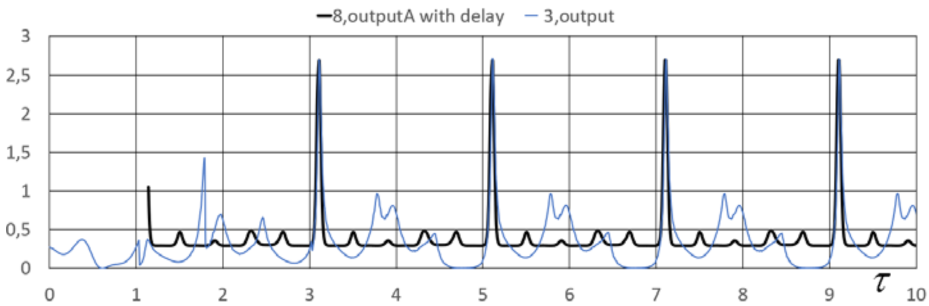


**Fig. 8.** The value of the output flow of section 8 with an offset by the delay $\Delta\tau_{68} = 1.15$

analysis of the output streams of material from two different sections gave a rather interesting result. The value of the parameter of the output flow of section 8 (neural model) qualitatively repeats the values of the parameter of the output flow of section 3 (neural network model). Repetition is carried out with some delay (Fig. 7). The delay value is the value $\Delta\tau_{68} = 1.15$ ( Fig.7) [38]. This value can also be calculated using the test data table [38]. On the other hand, using test data, let's calculate the average delay for section 6 and section 8. Material that leaves section 3 should go through section 6 and section 8 until it reaches the output of section 8 of the transport system. Thus, it should be assumed that the delay between the value of the material flow in section 6 and in section 8 is $\Delta\tau_{68} \approx \Delta\tau_6 + \Delta\tau_8$. Test data allow us to determine the average value of the delay for sections 6 and 8: $\langle\Delta\tau_6\rangle = 0.8754$, $\langle\Delta\tau_8\rangle = 0.4287$, $\langle\Delta\tau_{68}\rangle = 1.3041$, which is pretty close to the value synthesized by the neural model ( $\Delta\tau_{68} = 1.15$ ).The offset of the output flow of section 8 is shown in Fig. 8.

The developed model of a transport system using the neural network opens up new prospects for the design of control systems for a multi-section conveyor. Also, one of the differences between this work and works [21–25] is that a new method of data preparation for training a neural network is proposed. This allows you to significantly expand the field of study of the behaviour of the parameters of the transport system for various established operating modes of individual sections. A separate area of further research is the definition of similarity criteria for transport systems. Such an approach will make it possible to determine the basic models for various operating modes of the transport conveyor and to study in detail the characteristics of the flow of the material for individual sections.

## 8 Conclusion

A model of a conveyor transport system using a neural network is one of the tools for research a transport system with a large number of separate sections. The advent of the analytical PiKh–model [12] made it possible to generate test data that are necessary for training a neural network. The lack of a test data set is one of the problems that impede the process of constructing neural models. In many cases, the formation of a set of test data in the required range of parameter changes is an insurmountable obstacle. In this regard, an important result of this work is the development of a method for generating a set of test data for training a neural network that simulates conveyor-type transport systems. A distinctive feature of the modelling of transport systems is that they are complex dynamic distributed systems in which the signal propagates with a delay. And this article presents the first results of constructing a neural model on the foundation of an analytical model. Using the simple architecture of a neural network (9-3-2) as an example, a qualitative relationship between the output flows of the material of different sections is shown. The qualitative relationship between the output flow parameters of section 3 and section 8 is shown. A quantitative assessment of the estimated time of movement of the material through the sections of the transport system is given.

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