Predicting the Parameters of the Output Flow of Conveyor Systems

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Abstract— In this article, the problem of constructing models of multi-section conveyor-type transport systems using a neural network is considered. The analysis of models of long-distance multi-section transport systems, which are used to design control systems of the flow parameters from the point of view of reducing the unit costs of material transportation, is presented. The areas of the models' application and associated limitations are demonstrated. The advantages of using neural networks for developing multi-section transport systems models are shown. The influence of the initial distribution of materials along the transport route and the presence of a transport delay in the system on the quality of predict of the transport system flow parameters are estimated. The effect of the use of speed sensors located on the inner and output sections in order to improve the quality of predict of the transport system flow parameters is analyzed. It is shown that the use of speed sensors in conveyors with belt speed control can significantly improve the quality of predict.

Keywords—multi-section conveyor, transport delay, PDE conveyor model, belt speed control, conveyor model, ANN, process efficiency.

I. INTRODUCTION

The key task directly related to the use of artificial intelligence in enterprises with a flow method of organizing production is mainly the task of operational management. Special attention is paid to this issue at mining enterprises [1], [2], in particular, to solve the problem of minimizing energy costs when transporting material from the place of production to the place of shipment. As the main means of transportation, a conveyor is used, which is one of the most economical ways of transporting material and allows you to move material through difficult terrain [3], [4], [5]. By a material loading factor of the transport section of 0.5–0.7 [6], transport costs are 20% of the total cost of the extracted material for a medium-length transport route (5–15 km) [7]. For the longest transport systems, the length of which usually reaches 100 km [8], the cost of transporting material increases in proportion to the length of the transport route. With an uneven loading of the transport system, the material, the load factor of the transport system can significantly decrease, that leads to a significant increase in the specific energy consumption by the material transportation per unit length. One of the ways to reduce energy consumption for the transportation process is increasing the level of material loading of the transport system [9]-[11]. It is achieved by using a control system for the material flow coming from the accumulating bunker to the inlet of the conveyor section [12]-[14], the speed of the conveyor belt [15], or a combined control system. To construct control systems, conveyor models are most often used, which are based on the equations of system dynamics [14], the aggregated equation of state [16], Lagrange equations, finite element method [3], [17], [18]. Models containing Lagrange equations and the finite element method allow one to take into account the uneven distribution of material along the transportation route. However, when designing control systems for a multi-section transport conveyor, their use is difficult due to the high cost of computing resources. The development of an analytical model (PiKh–model) of the conveyor-or section [19] made it possible to design control systems for a multi-section conveyor [20]. However, if the number of sections reaches several tens, then the use of an analytical model also leads to computational difficulties [8]. One of the solutions to this problem is the use of a neural network and multiple regression equations to model the transport system. This article focuses on the development of the shown approach.

II. PROBLEM STATEMENT

The trend in the development of the mining industry is the use of a multi-section transport system [21]-[23]. The use of a neural network for predicting the flow parameters of a multi-section transport system is presented in [8]. As a test case for the analysis, a conveyor structure consisting of 8 separate sections was used (Fig. 1).

Each m–th section corresponds to the parameters: $g_m (r)$ — the conveyor belt speed; $\gamma_m (r)$ — the material flow at the section input; $\delta_m$ — the section transport route length; $\theta_m (r, \delta_m)$ — the output material flow from the section. The transport system has bunkers for combining the input flow of material and for decoupling the output flow of material [24]. There is no control of material flows from the bunker.
The output flow of material from the sixth bunker is distributed in the ratio $\gamma_7(\tau) / \gamma_8(\tau) = 2/3$.

The value of eight input nodes is determined by the state of the parameters $x_{3m-2} = \gamma_m(\tau), \; x_{3m-1} = g_m(\tau), \; x_{3m} = \xi_m, \; \mu = 1..M,

$y_1 = \theta_1(\tau, \xi_7), \; y_2 = \theta_2(\tau, \xi_8)$.

The weights of the neural network are initialized with random values.

![Fig. 1. Structural diagram of the conveyor](image)

![Fig. 2. Input and output parameters of the neural network](image)

This article continues research [8], [25] devoted to modelling a multi-section transport system using a neural network. Monitoring of flow parameters on a conveyor belt comes to the fore for the current trend of further development of a multi-section transport conveyor. The development of machine vision technology and digital image processing algorithms makes it possible to create non-contact sensors for measuring the belt speed and material flow at an arbitrary place in the conveyor section [26], [27]. The measurement of parameters based on machine vision and digital image processing algorithms is characterized by a satisfactory accuracy of changing parameters and a relatively low cost [28]. To measure the material flow, it is necessary to set several sensors along the section, since the material is unevenly distributed along the transportation route [9]. One sensor per section is sufficient to measure the belt speed since the conveyor belt speed is constant throughout the section. In this regard, this paper focuses on further improving the transport multi-section conveyor model using a neural network and increasing the accuracy of predicting the output flow parameters of the transport system due to:

a) a dataset used to train the neural network that contains information about the belt speed. Belt speed information can be obtained by using non-contact sensors that measure belt speed;

b) reducing the prediction error associated with the presence of a transition period of the transport system functioning. During this period of time, the output flow of a separate section depends on the material distribution along the conveyor section at the moment of the start of measurements, which introduces an error when training the neural network.

III. LITERATURE REVIEW

Recently, sufficient attention is paid to the development of transport conveyor models based on the use of a neural network [29], [30] or a regression equation [31]-[33]. Most of the models are used to describe single-section transport systems. A model based on a neural network with 13-5-1 architecture (13 nodes in the input layer, 4 nodes in the hidden layer and one node in the output layer) was proposed for diagnosing the state of wear of a conveyor belt [29]. In [30], a neural network-based main conveyor model is presented to control the process of material extraction and transportation. A neural network with 3-4-3 architecture is used to design a belt speed control system for a conveyor section start mode and belt acceleration [34]. In the paper [31], an experimental data set for constructing a regression model was formed based on the analysis of 18 conveyor sections. Preparing a dataset for training a neural network or constructing a regression equation is a key point, on which the accuracy of predicting the flow parameters of a transport system depends significantly. In order for a model based on a neural network to ensure a satisfactory prediction accuracy for the values of the flow parameters of the transport system, training the neural network requires a set of relevant data in sufficiently large quantities and a wide range of changes in the flow parameters of the transport system. For this, it is necessary that the data set supposes the functioning modes of the transport system, which can differ significantly from the normative ones. Such modes are characterized, as a rule, by excessive resources consumption, which is economically unprofitable and not permissible for the enterprise. If the transport system consists of several tens of sections, then the number of all possible combinations that characterize the full modes set of operation of the transport system becomes so large that the forming of a data set for training is impossible. It is a significant barrier to the use of neural networks and regression equations in models for describing multi-section transport conveyors. A solution method for this problem limiting the use of neural networks for modelling transport systems was proposed in paper [25]. In this paper, the training dataset is formed on the basis of an analytical PDE-model of the conveyor without direct interaction with the functioning transport system. In this work, the issue of improving the accuracy of prediction flow parameters for transport systems equipped with sensors for measuring belt speed is investigated.
IV. MODELLING OF A MULTI-SECTION TRANSPORT SYSTEM

A. Analytical Model of a Multi-Section Transport System

To describe the section of the transport system, let’s use the dimensionless PDE model [13], [19]:

\[
\frac{\partial \theta_0(t, \xi)}{\partial \tau} + g(t) \frac{\partial \theta_0(t, \xi)}{\partial \xi} = \delta(\xi) \psi(t), \quad \theta_0(0, \xi) = \psi(\xi). \quad (2)
\]

To describe the flow parameters state of the transport system at the moment in time \( t \) at the point of the transport route with the coordinate, let’s introduce dimensionless parameters:

\[
\tau = \frac{t}{T_d}, \quad \xi = \frac{S}{S_d},
\]

\[
\theta_0(t, \xi) = \frac{[\chi]_0(t, S)}{\Theta}, \quad \psi(\xi) = \frac{\Psi(S)}{\Theta}, \quad \gamma(t) = \frac{\lambda(t)}{T_d} \frac{T_d}{S_d} \frac{S_d}{\Theta},
\]

\[
\Theta = \max \left\{ \Psi(S), \frac{\lambda(t)}{a(t)} \right\}, \quad g(t) = a(t) \frac{T_d}{S_d},
\]

\[
[\chi](t, S) = a(t) [\chi](t, S), \quad \delta(\xi) = S_d \delta(S), \quad H(\xi) = H(S),
\]

where \( S_d \) is the section length; \( T_d \) is the characteristic time of the transportation process; \([\chi]_0(t, S), [\chi](t, S)\) are the linear density of the material and the material flow at the moment in time \( t \) at the point of the route with the coordinate \( S \in [0, S_d] \); \( \Theta \) is the maximum permissible value of the linear density of the material; \( \Psi(S) \) is the initial distribution of material along the length of the section; \( \lambda(t) \) is the flow of material from the bunker coming to the input of the conveyor section; \( a(t) \) is the belt speed; \( \delta(S) \) is Delta function; \( H(S) \) is Heaviside function.

To equation (2) with the initial conditions \( \psi(\xi) \) the solution corresponds [19]:

\[
\theta_0(t, 1) = (1 - H(1 - G(t))) \frac{\gamma(G^{-1}(G(t) - 1))}{g(G^{-1}(G(t) - 1))} + H(1 - G(t)) \psi(1 - G(t)), \quad (3)
\]

\[
G(t) = \int_0^t g(\alpha) d\alpha, \quad \theta_1(t, 1) = g(t) \theta_0(t, 1).
\]

Expression (3) allows calculating the values of the output flow from the conveyor section depending on the value of the input flow and the speed of the conveyor belt.

B. Training Dataset

To train the neural network, let use the dataset, which is presented and described in detail in the papers [8], [25]. To form a data set, an analytical model of a multi-section transport system (2), (3) was used. The dependence of the material flow \( \gamma_m(t) \) for the input sections \( m = 1, 2, 4, 5 \) (Fig. 3), also the belt speed \( g_m(t) \) (Fig. 4), and the initial distribution of the material \( \psi_m(t) \) along the length of the m-section of the transport system are presented periodically by the function

\[
\gamma_m(t) = \gamma_{0m} + \gamma_{1m} \sin \left( \frac{m\pi t}{4} - \frac{m\pi}{4} \right), \quad (4)
\]

\[
g_m(t) = g_{0m} + g_{1m} \sin \left( \frac{m\pi t}{4} + \frac{m\pi}{4} \right), \quad (5)
\]

\[
\psi_m(t) = \psi_{0m} + \psi_{1m} \sin \left( \frac{m\pi t^3}{4} + \frac{m\pi}{4} \right). \quad (6)
\]

Fig. 3. Belt speed for m-th in second

Fig. 4. Material flow at the input of the m-th section

The material flow for the input sections of the transport system and the belt speed of each section change during the operation of the transport system from zero to the maximum allowable value. The value of the time-varying material flow entering the transport system can be represented as a Fourier series expansion. Dependences (4)-(6) are an approximation of such a decomposition, allows to get a qualitative idea of the process of formation of the output material flow and the dependence of its value on the input material flow to the transport system and the speed of the section belt. It should be noted that the initial distribution \( \psi_m(t) \) (6) is the noise that affects the quality of the prediction of the output parameters. This circumstance has to be taken into account in the process of training the neural network. The dataset is prepared for a transport system with section lengths

\[
x_{3m} = \frac{\xi}{S_m} = \{1.0; 0.5; 0.7; 0.8; 1.5; 1.0; 1.5; 0.6\},
\]

which allows the transport delay to be simulated for each section of the conveyor.

The value of the input material flow \( \gamma_m(t) \) for the intermediate sections 3, 6 and the output sections 7 and 8 is calculated according to the formulas (2). A detailed description and analysis of the flow parameters of the transport system are presented in [25].
V. RESULTS

Let us consider sequential actions allowing to increase the accuracy of prediction of the output flow parameters in the model [8] of the transport system (Fig. 1). In the transport system model [1], which let's take as a zero approximation, a neural network with an architecture of 9-3-2 (9 nodes in the input layer, 3 nodes in the hidden layer and 2 nodes in the output layer) and an activation function (1) is used. Neural network training is based on a data set [25] with a number of elements \( N_e \approx 10^4 \), which was generated using the PDE-model of a branched transport system (2). The quality of training and the predicting accuracy of the zero approximation model is characterized by the value of MSE (mean squared error)

\[
MSE = \frac{1}{N_e} \sum_{n=1}^{N_e} \left( (y_{1n} - y_{1\text{ref}, n})^2 + (y_{2n} - y_{2\text{ref}, n})^2 \right)
\]

equal to MSE=0.445, where \( y_{1n} \), \( y_{2n} \) are the test values of the output parameters, \( y_{\text{ref}, n} \), \( y_{2\text{ref}, n} \) are the predicted values of the output parameters.

To improve the accuracy of predicting flow parameters, let us consider three steps.

As a first step to improve the prediction accuracy of the values of the transport system output parameters (Fig.1), let us consider changing the architecture of the neural network directly by increasing the number of nodes in the hidden layer. The increase in the number of hidden layer nodes for the transition to the 9-15-2 network architecture made it possible to construct a model for predicting the flow parameters of the transport system with the value MSE = 0.17 (the model of the transport system in the first approximation). Comparative analysis of the simulation results is shown in Fig.5 (solid line is analytical model; dashed line is model using a neural network). The MSE value decreased by three times when the nodes of the hidden layer were increased by 5 times. In this work, let's will not search for criteria for the optimal architecture of a neural network. This issue is supposed to be solved separately in the future. The architecture 9–15–2 will be used in this paper as a basic architecture for analyzing various methods for improving the prediction quality of the output flow parameters of a multi-section transport system (Fig.1).

As the next step in increasing the accuracy of prediction the parameters of the transport system, let's consider the influence of the initial conditions. In according with (3), the value of the output flow \( \theta_{1m}(\tau,1) \) of the conveyor section length \( \xi_m \) is determined through the value of the input flow \( \gamma_m(\tau) \) with a delay \( \Delta \tau_m \)

\[
\xi_m = \int_0^{\Delta \tau_m} g(\alpha) d\alpha.
\]

Thus, for the m-th section during the period of time \( 0 \leq \tau \leq \Delta \tau_m \), the value of the output flow \( \theta_{1m}(\tau,1) \) is determined by the distribution of material \( \gamma_m(\xi) \) along the section

\[
\theta_{1m}(\tau,1) = H(1-G(\tau))\gamma_m(1-G(\tau))g_m(\tau).
\]

Thus, the output material flow value of the transport system is determined through the value of the material flow coming the input of the transport system with a delay. This transport delay is equal to the sum of all sections delays through which the transport route passes. During the initial period of time, equal to the total transport delay, the value of the output flow of material of the output sections \( \theta_{17}(\tau,\xi_7) \), \( \theta_{18}(\tau,\xi_8) \) does not depend on the value of the input flow \( \gamma_1(\tau), \gamma_2(\tau), \gamma_4(\tau), \gamma_5(\tau) \) (Fig. 1). The presence of this data in the training set leads to an additional prediction error of the output parameters \( \theta_{17}(\tau,\xi_7), \theta_{18}(\tau,\xi_8) \). Taking into account the estimated calculation of the transport delay \( \Delta \tau_m \) of the m-th section [21], the estimate of the value of the total transport delay for the transport system is be obtained

\[
\Delta \tau_S = \Delta \tau_1 + \Delta \tau_3 + \Delta \tau_6 + \Delta \tau_7 \approx 2.0 + 0.9 + 0.9 + 1.2 \approx 5.
\]

Let’s exclude from the training set [21] the data corresponding to the time interval of the transient mode of the transport system functioning \( 0 \leq \tau \leq \Delta \tau_S \approx 5 \). The exclusion of the specified data from the training set made it possible to increase the prediction accuracy, which is characterized by the value MSE=0.154 (model of the transport system in the second approximation). The data corresponding to the transition period is 5% (\( \Delta \tau_S/100 \)) of the total data, which allowed to reduce the MSE value by 10% (14\% \( \approx 1,07/1,154 \)). The comparative analysis of the simulation results is presented in Fig.6 (solid line is analytical model; dashed line is model using a neural network).

Comparing the predicting results of the output flow for the first approximation model (Fig.5) and for the second approximation model (Fig. 6), one can see a slight difference in behavior for the predicted flow \( \theta_{18}(\tau,\xi_8) \) despite the
The last step of the research is to improve the prediction accuracy of the parameters of the transport system as a result of adding information to the training set about the belt speed of intermediate and output sections \(g_3(r), g_6(r), g_7(r), g_8(r)\). This information can be obtained using non-contact speed sensors (third approximation model). Supplemented the dataset with information about the belt speed of the intermediate and output sections led to the threefold decrease in the MSE value compared to the second approximation model (MSE=0.051). Comparative analysis of the results of prediction the output flow \(\theta_7(r, \xi_7)\), \(\theta_8(r, \xi_8)\) is presented in Fig.7 and Fig.8 (solid line is analytical model; dashed line is model using a neural network). Fig.8 demonstrates significant differences between the second and third approximation models. The predicted flows values \(\theta_7(r, \xi_7)\), \(\theta_8(r, \xi_8)\) for the model of the third approximation, fairly well approximate the behavior of the flow parameters of the transport system. There is an acceptable accuracy of prediction the flow parameters for the peak values of the functions \(\theta_7(r, \xi_7)\), \(\theta_8(r, \xi_8)\). It should be noted that the result was obtained for the modified architecture of the neural network. The third approximation model with the addition of four input nodes \(g_3(r), g_6(r), g_7(r), g_8(r)\) corresponds to the neural network architecture 13-15-2, while the models of the first and second approximations (Fig.5, Fig.6) are based on the neural network with the architecture 9-15-2.

Adding new factors to the model leads to an increase in the prediction accuracy both by adding additional information and by directly modifying the neural network architecture. A separate study should be devoted to the question of the influence of the network structure on the prediction accuracy. Preliminary numerical experiments related to changes in the network structure allow us to conclude that the main contribution to improving the prediction accuracy of the output parameters is made directly by adding to the set of information on the intermediate and output sections belt speed \(g_3(r), g_6(r), g_7(r), g_8(r)\). The characteristic of the prediction quality for the model of the 0,1,2,3-th approximation, depending on the number of learning epochs \(N_p\), is shown in Fig.9.

A back-propagation algorithm was used to train the neural network. The correction of the values of neural network nodes is performed using the gradient descent method with a constant step \(\lambda = 10^{-3}\). The required number of epochs for training a neural network for models considered in the article is approximately the same and is \(N_p \sim 10^5\). After a sharp drop in the MSE value for the first several tens of learning epochs, a rather gradual decrease in the MSE value follows.

VI. CONCLUSION

The use of artificial intelligence methods makes it possible to design information systems for the efficient management of multi-section transport conveyors. The use of artificial intelligence methods is of particular importance when constructing models of a transport network consisting of several tens or even hundreds of interconnected sections. In this case, analytical models cease to be attractive, and models containing the Lagrange equations, finite element method become simply difficult to implement for describing such transport systems. An effective solution in this case is the development of models of a multi-section transport system based on a neural network. At the same time, the use of various kinds of monitoring systems based on machine vision and digital image processing algorithms makes it possible to conduct training of a neural network quite effectively. This paper shows as the additional use of contactless belt speed sensors can significantly improve the accuracy of predicting the output flow parameters of a conveyor-type transport system. A further development of this research is the analysis of the application of systems for monitoring the parameters of the transport conveyor containing contactless sensors of the material flow. In contrast to the case of using belt speed sensors, when one sensor is enough to record the belt speed, several non-
contact material flow sensors can be placed for a separate section, which supposedly should signficantly improve the accuracy of predicting the output parameters of the transport system. By in the same time, it is necessary to separately assess the increase in prediction accuracy associated with a change in the architecture of the neural network.

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