Neural network-based approach for predicting the flow material in transport systems

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Abstract

This article addresses the problem of effectively training a neural network to predict parameters of the output flow of a conveyor system. It discusses the problems of obtaining a complete set of data for complex branched structures of multi-section conveyor systems with different section lengths. The problem of generating a data set for training a neural network is solved using an analytical model of a transport system. The input parameters for the model include approximations of the incoming material flow and conveyor belt speed allowing to consider the oscillatory behavior of the transport system's parameters. The study also examines the impact of peak loads on the material flow at the system's entry point. The findings demonstrate that the predictive model enables effective analysis of dynamic changes in the transport system's parameters, including peak flow values.

Keywords

control, PDE-model, distributed system, conveyor

1. Introduction

A transport conveyor designed for moving bulk materials is a complex dynamic system with a transport delay [1–3]. The system includes many long conveyors [4–6] and accumulating bunker located between them [7, 8]. The conveyor is an important component of the transport infrastructure of a mining enterprise, offering versatility, easy of automation and high productivity. Transporting bulk materials represent a significant proportion of the total cost of materials extraction [9, 10] and increasing the efficiency of the transport conveyor provides a significant reduction in this cost. A common method for reducing transport costs is to optimize the loading factor of bulk material on a transport conveyor, based on the use of belt speed control systems [11–13] and regulation of the volume of material flow coming from the accumulating bunker [14–17]. To construct a training data set, this work uses an analytical model of the transport system [16]. The model reflects the oscillatory nature of the system parameters and allows taking into account variable transport delay.

The novelty of this work lies in the integration of neural network techniques with traditional conveyor system models, which enhances the ability to predict and optimize transportation systems performance under varying conditions. This approach not only contributes to solving problems in the field of transport systems, but also offers practical recommendations for the mining industry, ensuring more efficient and cost-effective transportation of materials.

2. Formal problem statement

The process of transporting material on a belt conveyor is characterized by its complex and non-linear nature and as a result, the mathematical models developed for this process consist of sets of

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highly complex and non-linear PDEs [18]. It requires highly complicated numerical techniques to solve them. Therefore, these models are not suitable for control system design. Recently, researchers in the field of conveyor systems have shown increased interest in neural network models due to their advantages such as adaptation, fault tolerance and speed of operation. For example, authors in the study [19] develops five artificial neural network models to predict conveyor belt damage using 11 parameters. In the paper [20] proposed a deep learning-based conveyor belt damage detection method. An intelligent control system of transporting material on a belt conveyor utilizing the capabilities of neuro-fuzzy systems is presented in the paper [18]. The papers [21, 22] are devoted to the development of instrumental and methodological support for the study of conveyor transport systems with neural network models. However, the authors of these and other articles do not consider neural network models for branched multi-section conveyor systems.

The purpose of this study is to build an effective model for predicting the values of the output flow parameters of a branched conveyor transport system. Analysis of experimental studies [23-25] allows us to make the assumption that, with a sufficient degree of accuracy, the input flow of the material can be represented in the form of a Fourier series expansion with a limited number of terms of the series [26]. To ensure a quasi-constant fill factor of the conveyor, it is necessary to synchronize the value of the input material flow and the belt speed [27]. It follows from this that the value of the input material flow and the value of the belt speed must be proportional. This allows us to represent the speed of the belt in the form of an expansion in a Fourier series with the same limited number of terms in the series. To simplify the demonstration of the analysis of results, the input material flow and belt speed are presented in the form of a series limited by one term. This approximation of the flow parameters of the transport system is the basis for the formation of the input parameters of the analytical model. The use of an analytical model allows for each series of values of input parameters to calculate a series of values of output parameters of the transport conveyor. Accordingly, it possible to generate a data set for training a neural network in the model for predicting the flow parameters of the transport conveyor. The input parameters are represented by harmonic functions containing the phase shift. This approach is used to model situations when peak values of material flow occur in a transport system. Special attention is paid to the analysis of these situations in this study. The proposed model makes it possible to predict the occurrence of such situations that leads to increased load on the conveyor belt and its gradual destruction.

3. Preparation of a data set for training a neural network

A set of training data is needed for supervised training of a neural network. In our case, these data represent examples of input data and their corresponding outputs for solving specific problems of managing an existing transport system. It is difficult to obtain such a data set in the conditions of real operation of transport systems. This is due to the following reasons: 1) each transport system is unique in design and sections of one transport system have different lengths; 2) the functioning of the transport system is carried out in a narrow range of flow parameters, in which economic feasibility is ensured, but the training data set must be generated in a wide range of values; 3) lack of measuring sensors in the required places of the transport route; 4) confidentiality of production information. Therefore, to generate a data set for training a neural network, we use an analytical model of the transport system [16]. To build this model, we used a simplified transport route diagram presented in Figure 1. The transport route diagram contains four input conveyors (section m = 1,2,4,5) and two output conveyors (section m = 7,8). Also, for simplicity, we assume that for a node that contains an input material stream and two outgoing material flows, the ratio of the values of the output flows is constant (Figure 2).

Consider such values of the parameters of the transport system: $\gamma_m(\tau)$ is the intensity of the input flow of material and $g_m(\tau)$ is conveyor belt speed. This values are oscillatory in nature and limited by the minimum and maximum values. The experience of using periodic functions to analyze the accuracy of approximation of predicted results using a neural network is described in [28-30].

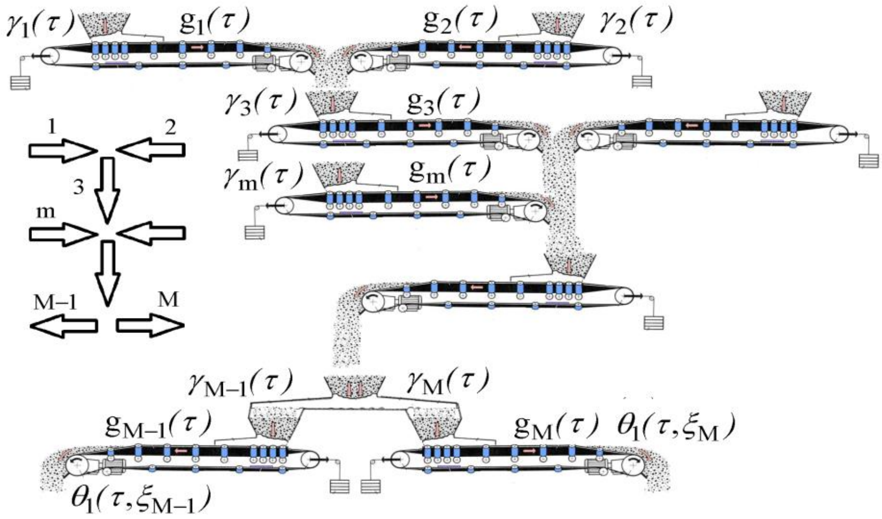

Figure 1: Diagram of a branched conveyor transport route.

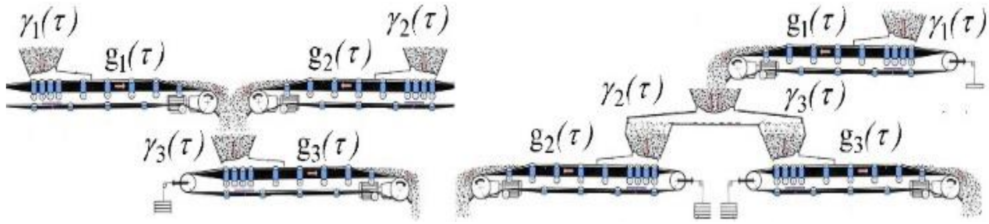

Figure 2: Schemes for calculating the balance of flows in the nodes of the conveyor transport route: a) converging node; b) diverging node.

Given this experience flow parameters $\gamma_m(\tau)$, $g_m(\tau)$, that determine the state of the transport system, and initial condition $\psi m(t)$, that determine the initial distribution of material along the length of the section, were represented as:

$$\gamma_m(\tau) = \gamma_{0m} + \gamma_{0m} \sin\left(m\pi\tau - \frac{m\pi}{4}\right), \; \gamma_{0m} = \frac{3+m}{24}, \tag{1}$$

$$g_m(\tau) = g_{0m} + \frac{g_{0m}}{2} \sin\left(m\pi\tau + \frac{m\pi}{3}\right), g_{0m} = \frac{3+m}{8}, \tag{2}$$

$$\psi_m(t) = \psi_{0m} + \psi_{0m} \sin\left(m\pi\xi + \frac{m\pi}{4}\right), \; \psi_{0m} = \frac{3+m}{24}. \tag{3}$$

The values $\gamma m(\tau)$ and $g m(\tau)$ of the input sections m=1,2,4,5 for the interval $0 \le \tau \le 2$ are shown in Figure 3 and Figure 4.

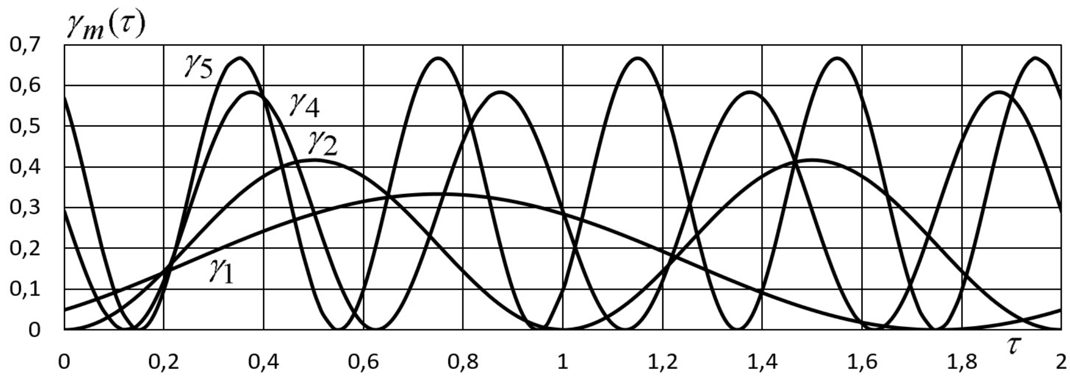

Figure 3: The intensity of material flow $\gamma_m(\tau)$ incoming to m–th section.

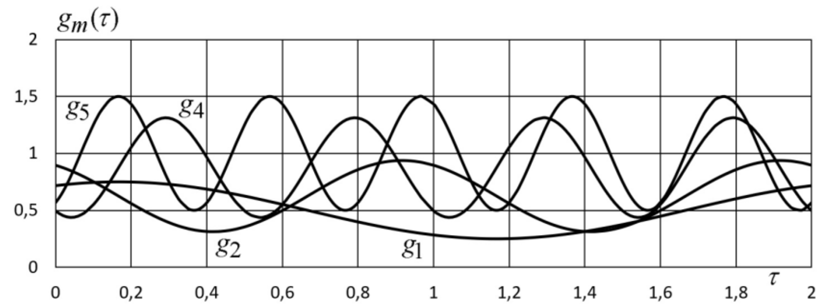

Figure 4: The belt speed $g_m(\tau)$ for m–th section.

The data set for training the neural network is generated by using the analytical model [16]. The data set satisfies the transport route in Figure 1. Let's take a time interval $0 \le \tau \le 2$. The material output flow $\theta_{1m}(\tau,\xi_m)$ describes as:

$$\theta_{1m}(\tau,\xi_m) = \frac{\gamma_m(\tau-\Delta\tau_{\xi_m})}{g_m(\tau-\Delta\tau_{\xi_m})} g_m(\tau)\,,\ \xi_m \le G_m(\tau)\,, \tag{4}$$

$$\theta_{1m}(\tau,\xi_m) = g_m(\tau)\psi_m(\xi_m - G(\tau))\,,\ \xi_m > G_m(\tau)\,, \tag{5}$$

were ξ_m is the length of the m-th section; $\Delta\tau_{\xi_m}$ is the transport delay time; $G_m(\tau)$ is an end point of the transition mode of the m-th section of the conveyor line. The values the material output flow θ_{1m} for sections m = 1,2,4,5 is shown in Figure 5. This behavior of the output flow of the material θ_{1m} is explained by the presence of a transition period during which the value of the output flow is determined by the distribution of the material with a linear initial density $\psi_m(\xi)$ along the m-th section. The arrows indicate the point in time when the transition period is completed $\xi_m = G_m(\tau)$.

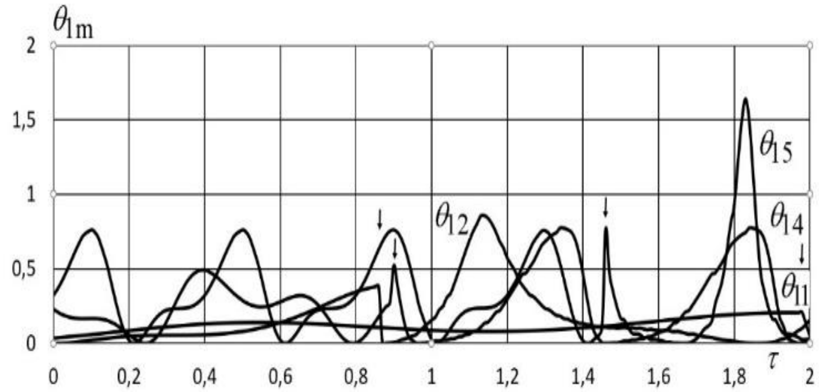

Figure 5: The material output flow $\theta_{1m}(\tau,\xi_m)$ for m-th section.

The change in the linear material density at the output of a section (m = 1,2,4,5) describes as:

$$\theta_{0m}(\tau,\xi_m) = \frac{\gamma_m(\tau-\Delta\tau_{\xi_m})}{g_m(\tau-\Delta\tau_{\xi_m})}\,,\ \xi_m \le G_m(\tau)\,, \tag{6}$$

$$\theta_{0m}(\tau,\xi_m) = \psi_m(\xi_m - G_m(\tau))\,,\ \xi_m > G_m(\tau)\,. \tag{7}$$

The changes are shown in Figure 6 and Figure 7. Arrows in Figure 6 and Figure 7 indicate the point of separation of the time interval into two parts, the left part of which corresponds to the transitional mode of the conveyor line $\xi_m > G_m(\tau)$, the right part of which often corresponds to the established mode of the conveyor line $\xi_m \le G_m(\tau)$. The profile of the linear density $\theta_{0m}(\tau,\xi_m)$ is formed by two parameters, intensity in-coming material flow $\gamma_m(\tau)$ and the speed $g_m(\tau)$ separated section. The value of the output flow $\theta_{1m}(\tau,\xi_m)$ determines the value of the input flow $\gamma_m(\tau)$ for the next section.

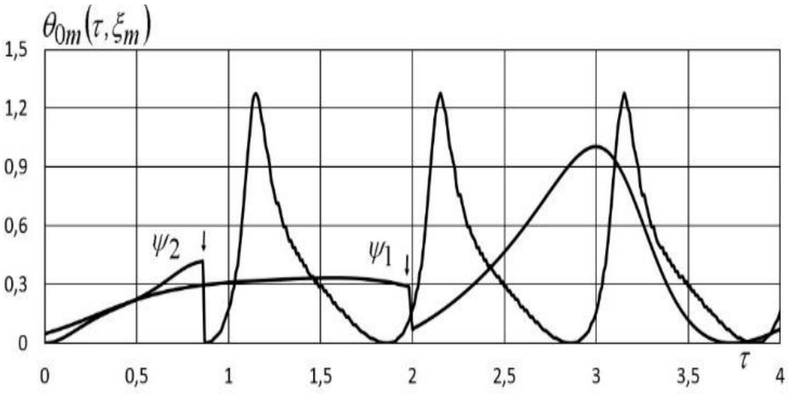

Figure 6: The linear density $\theta_{0m}(\tau,\xi_m)$ at the output of the first and second sections.

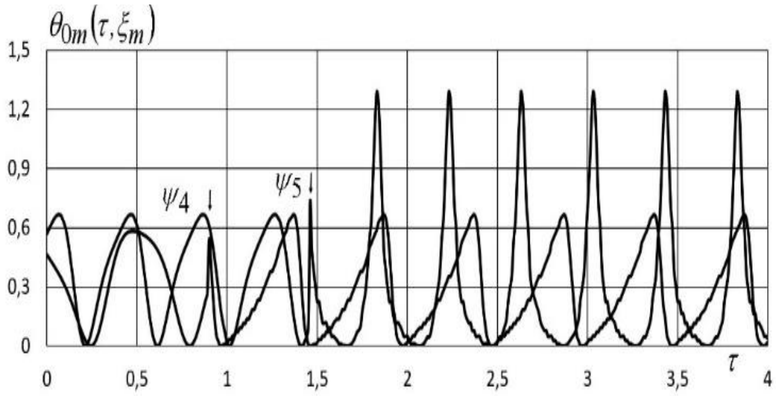

Figure 7: The linear density $\theta_{0m}(\tau,\xi_m)$ at the output of the fourth and fifth sections.

The duration of the transition period $\tau_{tr\,m}$ is determined by the speed $g_m(\tau)$ of the conveyor belt and the length of the section ξ_m

$$\xi_m = \int_0^{\tau_{tr\,m}} g_m(\omega)d\omega \,. \tag{8}$$

In the case under consideration (Figure 6, Figure 7), the maximum duration of the transition period has section number one, $\tau_{tr\,1} \sim 2$. For the transition period, the output flow of the material with the conveyor section $\theta_{1\mathrm{m}}(\tau,\xi_m)$ is not related to the input flow of the material $\gamma_m(\tau)$ and the speed of the belt $g_m(\tau)$. The transition period of the *m*-th section is characterized by the average transport delay time $\tau_{tr\,m} \sim \Delta\tau_{\xi_m}$ for this section (Figure 8). The transition period for the considered transport system (Figure 1) can be estimated by the value

$$\tau_{tr\,\Sigma} \sim \max\left(\max(\tau_{tr\,1},\tau_{tr\,2}) + \tau_{tr\,3},\tau_{tr\,4},\tau_{tr\,5}\right) + \tau_{tr\,6} + \max(\tau_{tr\,7},\tau_{tr\,8})\,. \tag{9}$$

Substituting the values $\tau_{tr\,m} \sim \Delta\tau_{\xi_m}$ in (9) allows us to obtain the transition period for the transport system

$$\tau_{tr\,\Sigma} \sim \tau_{tr\,1} + \tau_{tr\,3} + \tau_{tr\,6} + \tau_{tr\,7} \approx 5\,. \tag{10}$$

The values of the parameters of the transport system of the time interval $0 \le \tau < \tau_{tr\,\Sigma}$ that corresponds to the time of the transition period should be excluded from the data set intended for training the neural network. The reason is that during this period of time the output material flow $\theta_{1\mathrm{m}}(\tau,\xi_m)$ is determined by the initial distribution of the material $\psi_m(\xi)$ along the transport route [16], and not by the parameters $\gamma_m(\tau)$ and $g_m(\tau)$, when the output flow of the transport system is independent of the initial distribution of the material. The value of the output flow for m=1, 2, 4, 5 of the section is shown in Figure 9. It should be noted that the value of the output flow of the 5-th section has pronounced peak values, which are determined by expressions (4), (5).

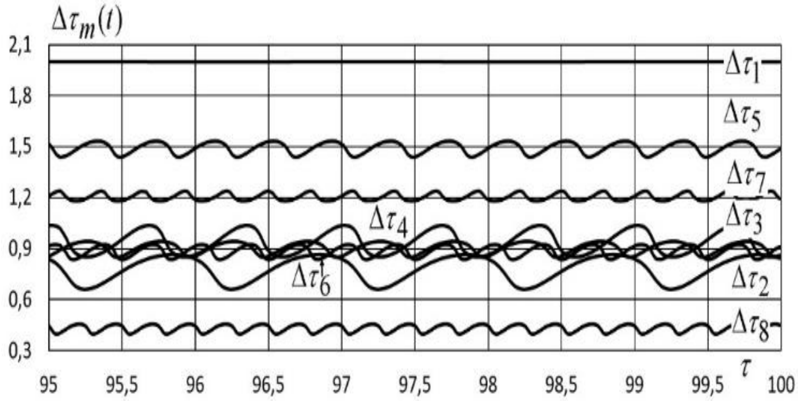

Figure 8: Transport delay value $\Delta\tau_{\mathrm{m}}(\tau)$ for the m–th section, $\tau >> \tau_{tr\,\Sigma}$.

The appearance of peak values is a consequence of the periodic nature of the supply of raw materials to the input of the section and the periodic law of change in the speed of movement of the conveyor belt. Thus, peak loads can occur not only as a result of an uneven random cargo flow of material incoming to the entrance of the transport system. They can also form inside the transport system itself. Peak loads in the transport system can occur when the material flows smoothly into the transport system by virtue of equation (4). The presence of peak values in the data set complicates the training of the neural network.

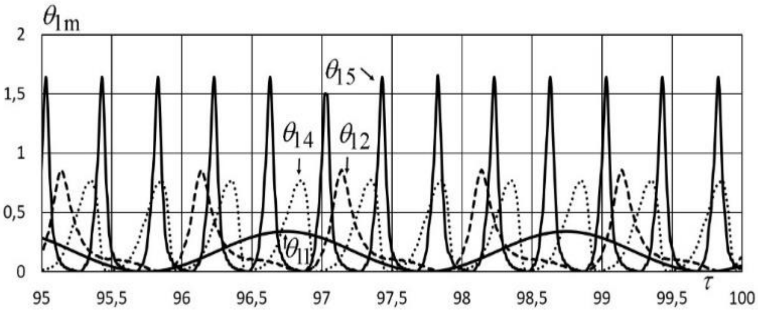

Figure 9: The output flow $\theta_{1\mathrm{m}}(\tau,\xi_m)$ for the m–th section, $\tau >> \tau_{tr\,\Sigma}$.

The transport system (Figure 1) is a distributed system. Such a system is characterized by transport delay. Transport delay in a distributed system plays an important role in generating output values of flow parameters. The value of the transport delay $\Delta\tau_m(\tau)$ for the m–th section depending on the time τ is shown in Figure 8. The value of transport delay for sections m = 5…8 can be considered constant. Thus, the absence of transport delay in the data set for training the neural network should not lead to a significant error.

4. Prediction model analysis

For training the neural network, a data set was used, which was formed in accordance with the provisions of the previous partition. This data set is pushed in [31]. Figure 3, Figure 4, Figure 7, Figure 9 demonstrate that the values of training the neural network are presented in a wide range of values. The neural network is built in accordance with the architecture based on a model from article [32]. To calculate the weight coefficients of the neural network, the back propagation method of error was used. The updated weight value for each era is calculated based on its old value and error determined by the parameters of the output layer

$$W_{j,k,n+1} = W_{j,k,n} - \alpha \nabla E_{j,k,n}, \tag{11}$$

where the learning rate is equal $\alpha = 10^{-5}$.

The error $E_{j,k,n}$ was distributed between the nodes in proportion to the values of the weight coefficients. For analysis, the process of training a neural network, the data order for training was unchanged. This allowed to lead multiple repetitions of training with various network parameters and compares the effect from changing parameters. Weight coefficients were initialized with random values in the range $[0.0;1.0]$ with uniform distribution density. For some parameter options, the learning process reached 300,000 eras. As the input nodes of the neural network for modelling the transport system, the characteristics $\gamma_m(\tau)$, $g_m(\tau)$ of the input sections 1,2,4,5 on the interval $0 \le \tau \le T_k = 100$ are used. The prediction of the values of the output flow parameters $\theta_{1\mathrm{m}}(\tau, \xi_m)$ for sections *m*=1, 2, 4, 5 is shown in Figure 10. The results obtained correspond to a neural network with an architecture of 3–10–1 (the input layer contains three nodes with values 1, $g_m(\tau)$, $\gamma_m(\tau)$; the output layer contains one node $\theta_{1\mathrm{m}}(\tau, \xi_m)$; the hidden layer contains 10 nodes). The prediction error is estimated by the indicator

$$MSE_m = \frac{1}{N_r} \sum_{r=1}^{N_r} (z_{m,r} - y_{m,r})^2, \tag{12}$$

where N_r = 9000 is the amount of data for testing a neural network. The indicator value is

$\{MSE_1; MSE_2; MSE_4; MSE_5\} = \{10^{-3}; 0{,}009; 10^{-3}; 0{,}0173\}$.

MSE_5 value is significantly higher than MSE_1, MSE_2, MSE_4.

A high value MSE_5 corresponds to the presence of peak values of the output flow θ_{15} (Figure 10). Figure 11 and Figure 12 show the prediction of the output stream from the transport system, *m* = 7.8. The prediction error is $MSE_{78} = 0{,}22$. A model provides a satisfactory prediction for peak values of the output flow of the material $\theta_{18}(\tau,1)$. For the output flow $\theta_{17}(\tau,1)$, the model averages the peak small values of the function, while trying to repeat the behavior of the function for peak maximum values.

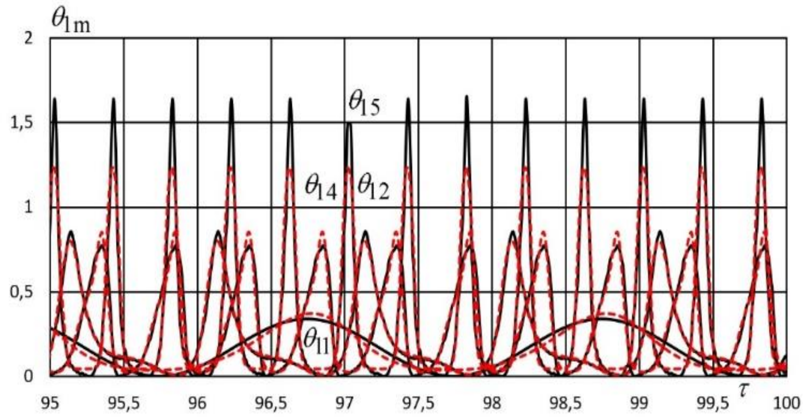

Figure 10: Prediction of the output flow of material $\theta_{1\mathrm{m}}(\tau, \xi_m)$, *m*=1, 2, 4, 5.

We explain the difference in the prediction for flow $\theta_{17}(\tau,1)$ and $\theta_{187}(\tau,1)$ by the fact that the output flow $\theta_{17}(\tau,1)$has a significant spread between the height of the group of maximum peak values and the group of minimum peak values.

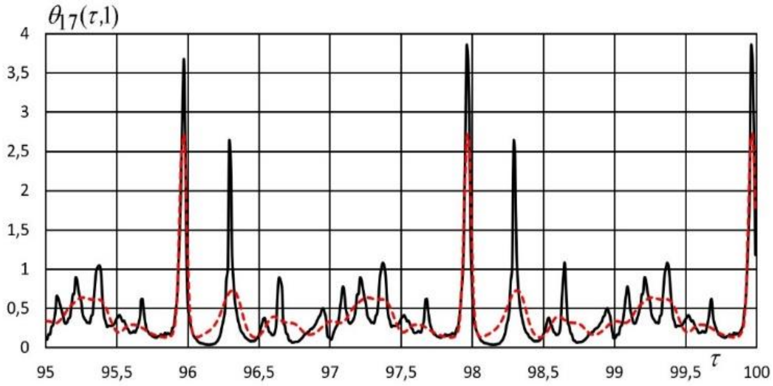

Figure 11: Prediction of the output flow of material $\theta_{17}(\tau,1)$.

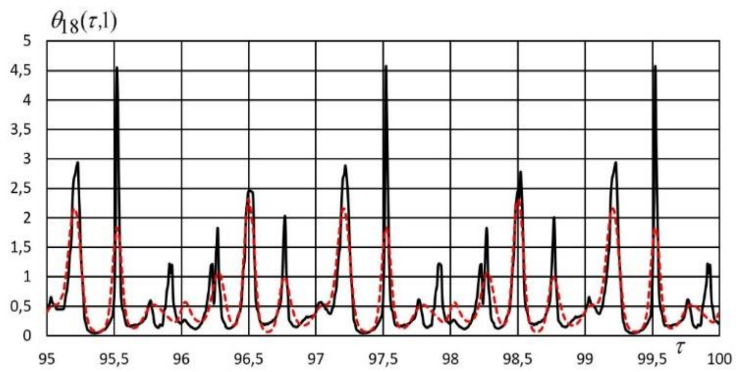

Figure 12: Prediction of the output flow of material $\theta_{18}(\tau,1)$.

The approximation of the output flows $\theta_{13}(\tau,1)$, $\theta_{16}(\tau,1)$ is fairly well presented, for the intermediate sections m = 3 and m = 6. The prediction results are given in Figure 13 and Figure 14. The prediction error MSE_3 is 0,022 and MSE_3 is 0,25. The value MSE for each subsequent section increases by one order of magnitude. The exception is the last sections. For these sections, the prediction error remains at the same level as the prediction error of the previous section. We attribute this fact to the fact that the flows after the sixth section diverge, and the total prediction error also decreases.

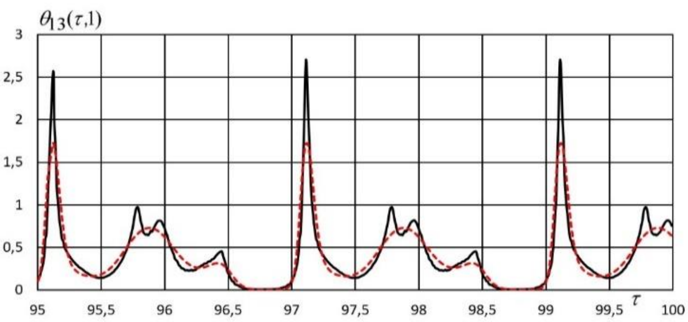

Figure 13: Prediction of the output flow of material $\theta_{13}(\tau,1)$.

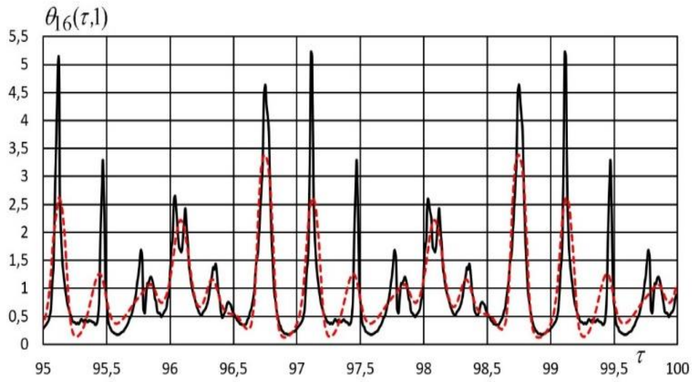

Figure 14: Prediction of the output flow of material $\theta_{16}(\tau,1)$.

5. Conclusion

The results of the analysis the model using a neural network show that the neural network is a good enough tool for predicting the value of flow parameters of an industrial transport system, which consists of a very large number of divided sections. The prediction model allows us to determine the peak values of the parameters of the transport system. An important consequence of the analysis of the PiKh−model of the transport system [16] is that peak loads in the transport system also arise for the case of a smooth change in the magnitude of the incoming material flow $\gamma_m(\tau)$ and the speed $g_m(\tau)$ of the conveyor belt. The peak value is many times bigger than the amplitude of the background wave. The simplest explanation of the peak value effect can be built on the analysis of the simple superposition of the waves different length. This effect increases in case periodical change of the value of the belt conveyor. The occurrence of this effect is one of the causes of damage to transport systems. One of the problems in studying the influence of the appearance of peak values on the parameters of the transport system is the difficulty of obtaining them under industrial conditions due to the unpredictable nature of the occurrence. The prediction model allows you to identify these situations and ensure their elimination by controlling the flow parameters of the transport system, for example, conveyor belt speed. To reduce the prediction error in the formation of the data set for training the neural network, the data that corresponds to the transition mode should be excluded. In this paper, the technique is given for the estimate the value of the duration transitional mode for the many sections transport system. The analysis of the transport system model shows that the reduction of prediction errors can be achieved by including as an additional node into the input layer the flow parameter, which is the speed of the conveyor belt. An important result of the conducted research is the conclusion that for transport systems with a high frequency of oscillation of the conveyor belt speed, the oscillation amplitude of the transport delay value is significantly less than the average value of the transport delay. This allows us to consider the duration of the transport delay as a constant value and, accordingly, to conclude that this parameter has a negligible effect on the prediction results. Such an assumption provides a reason why transport delay is optional for inclusion in the set of parameters of the input layer of the neural network. The assumptions obtained in this paper determine the prospects for further research.

References

[1] Ensure an efficient and safe mining transportation, Siemens Mining industry, SIMINE Conveyor. URL: https://xcelerator.siemens.com/global/en/industries/mining-industry/transport.html

[2] J. Cornet, Head and tail controls in long overland conveyors, Bulk Materials Handling by Conveyor Belt 4 (2002) 55-67.

[3] B. Karolewski and P. Ligocki, Modelling of long belt conveyors. Maintenance and reliability 16 (2014) 179–187.
[4] O. Pihnastyi, V. Khodusov and A. Kotova, Mathematical model of a long-distance conveyor, Mining Science 30 (2023) 27–43. doi:10.37190/msc233002
[5] M. Thompson and A. Jennings, Impumelelo coal mine is home to the world's longest belt conveyor, Mining Engineering, 68 10 (2016) 14–35.
[6] X. Mathaba and N. Xia, A parametric energy model for energy management of long belt conveyors, Energies 8 12 (2015) 13590–13608. doi:10.3390/en81212375
[7] M. Bajda, R. Błażej, L. Jurdziak, Analysis of changes in the length of belt sections and the number of splices in the belt loops on conveyors in an underground mine, Engineering Failure Analysis 101 (2019) 439–446. doi:10.1016/j.engfailanal.2019.04.003
[8] M. Koman and Z. Laska, The constructional solution of conveyor system for reverse and bifurcation of the ore flow, Rudna mine KGHM Polska Miedź SA," CUPRUM 3 72 (2014) 69–82.
[9] G. Wheatley, R. Rubel, Analysis of conveyor drive power requirements in the mining industry. Acta logistica 8 1 (2021) 37-43. doi:10.22306/al.v8i1.200
[10] D. Więcek, A. Burduk and I. Kuric, The use of ANN in improving efficiency and ensuring the stability of the copper ore mining process, Acta Montanistica Slovaca 24 1 (2019) 1–14.
[11] I. Halepoto, M. Shaikh and B. Chowdhry, Design and Implementation of Intelligent Energy Efficient Conveyor System Model Based on Variable Speed Drive Control and Physical Modeling, Control and Physical Modeling International, Journal of Control and Automation 9 6 (2016) 379-388. doi:10.14257/ijca.2016.9.6.36
[12] D. He, Y. Pang, G. Lodewijks and X. Liu, Healthy speed control of belt conveyors on conveying bulk materials, Powder Technology 327 (2018) 408-419. doi:10.1016/j.powtec.2018.01.002
[13] H. Lauhoff, Speed Control on Belt Conveyors – Does it Really Save Energy? Bulk Solids Handling Publ 25 (2005) 368-377.
[14] V. Korniienko, S. Matsiuk and I. Udovyk, Adaptive optimal control system of ore large crushing process, Radio Electronics, Computer Science, Control 1 (2018) 159–165. doi:10.15588/ 1607-3274-2018-1-18
[15] R. Kiriia and L. Shyrin, Reducing the energy consumption of the conveyor transport system of mining enterprises, in: Proceedings of International Conference Essays of Mining Science and Practice, vol. 109, 2019, pp. 1–8. doi:10.1051/e3sconf/201910900036
[16] O. Pihnastyi, G. Kozhevnikov and V. Khodusov, Conveyor model with input and output accumulating bunker, in: Proceedings of IEEE 11-th International Conference on Dependable Systems, Services and Technologies (DESSERT), 2020, pp. 253–258. doi:10.1109/DESSERT50317.2020.9124996
[17] W. Kung, The Henderson Coarse Ore Conveying System, A Review of Commissioning, Start-up, and Operation, Bulk Material Handling by Belt Conveyor, Society for Mining, Metallurgy and Exploration, Inc., 2004, pp. 1-7.
[18] O. Lutfy, N. Mohd, M. Marhaban, K. Abbas, Non-linear modelling and control of a conveyor-belt grain dryer utilizing neuro-fuzzy systems. in: Proceedings IMechE, vol. 225 Part I: Systems and Control Engineering, 2016, pp. 611-623. DOI: 10.1177/2041304110394559.
[19] P. Parmar, L. Jurdziak, A. Rzeszowska and A. Burduk, Predictive Modeling of Conveyor Belt Deterioration in Coal Mines Using AI Techniques. Energies 17 (2024) 3497-3503. doi:10.3390/en17143497
[20] M. Zhang, Y. Zhang, M. Zhou, K. Jiang, H. Shi, Y. Yu and N. Hao, Application of Lightweight Convolutional Neural Network for Damage Detection of Conveyor Belt. Appl. Sci. 11 (2021) 7282-7291. doi:10.3390/app11167282
[21] O. Druzhinina, O. Masina and A. Petrov, Modeling of the belt conveyor control system using artificial intelligence methods, in: Journal of Physics: Conference Series, Vol 2001, Measuring Techniques and Instrumentation, 2021, pp. 1-11. doi:10.1088/1742-6596/2001/1/012011

[22] A. Zolkin, E. Vereschagina, A. Bityutskiy, M. Grigoriev, V. Kalyakina, Synthesis of a neuro-fuzzy system for a conveyor line control using a superscalar approach, in: Proceedings of the AIP Conf. Proc, vol. 2632, 2022, pp. 1-6. doi:10.1063/5.0099220
[23] A. Curtis and R. Sarc, Real-time monitoring volume flow, mass flow and shredder power consumption in mixed solid waste processing, Waste Management 131 (2021) 41–49. doi:10.1016/j. was-man.2021.05.024
[24] F. Zeng, C. Yan, Q. Wu and T. Wang, Dynamic behaviour of a conveyor belt considering non-uniform bulk material distribution for speed control, Applied Sciences, 10 13 (2020) 31–19. doi:10. 3390/app10134436
[25] M. Vasic, N. Miloradovic and M. Blagojevic, Speed control high power multiple drive belt conveyors, Research and Development in Heavy Machinery 27 (2021) 9–15. doi:10.5937/ IMK2101009V
[26] O. Pihnastyi and M. Sobol, Method for determining statistical characteristics of input material flows of transport conveyor, in: Proceedings of the Information Control Systems & Technologies, September 21-23, 2023, Odesa, Ukraine, pp. 375-381.
[27] O. Pihnastyi, V. Khodusov and A. Kotova, The problem of combined optimal load flow control of main conveyor line, Acta Montanistica Slovaca 27 1 (2022) 216–229. doi:10.46544/AMS. v27i1.16
[28] A. Kirjanow, The possibility for adopting an artificial neural network model in the diagnostics of conveyor belt splices, Interdisciplinary issues in mining and geology 6 (2016) 1–11.
[29] L. Xinglei and Yu. Hongbin, The Design and Application of Control System Based on the BP Neural Network, in: Proceedings of the 3rd International Conference on Mechanical Engineering and Intelligent Systems (ICMEIS 2015), 2015, pp. 789-793. doi:10.2991/icmeis-15.2015.148
[30] X. Pingyuan and S. Yandong, Application Research on BP Neural Network PID Control of the Belt Conveyor, JDIM 9 6 (2011) 266-270.
[31] O. Pihnastyi, Test data set for the conveyor transport system, Mendeley Data 2 (2020) 234-241. doi:10.17632/4vcb843t76.5
[32] O. Pihnastyi and G. Kozhevnikov, Control of a Conveyor Based on a Neural Network, in: Proceedings of IEEE International Conference on Problems of Infocommunications Science and Technology, PICS&T, 2021, pp. 295–300.