

Control of a Conveyor Based on a Neural Network

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Abstract— The present study is devoted to the design of main flow parameters a conveyor control system with a large number of sections. For the design of the control system, a neural network is used. The architecture of the neural network is justified and the rules for the formation of nodes for the input and output layers are defined. The main parameters of the model are identified and analyzed. The data set for training the neural network is formed using the analytical model of the transport system. The criterion for the quality of the transport system is written. For the given criterion for the quality of the transport system, the Pontryagin function is defined and the adjoint system of equations is given. It allows calculating optimal control of the transport system. For calculation is used additional model of the transport system with output nodes which are controls. A graphical representation of the results of the study is given.

Keywords—*PDE-model production; PiKh-model; distributed system; optimal control.*

I. INTRODUCTION

The flow method of organizing production assumes the use of a conveyor system [1]. The conveyor is the main means of transporting material in mining enterprises. [2-6]. The average share of the cost of transporting a unit mass of material is 20% of the total cost of coal mining [7]. The main advantage of conveyor-type transport systems is the continuity of the transportation process. Modern transport conveyor systems are characterized by relatively large power consumption, intensive material flow, extended in separate sections, high-speed conveyor belts [8]. One of the methods to increase the efficiency of conveyor transport is to increase the uploading of the transport system with material and ensure uniform distribution of material along the transport route [9-11]. The operation of the conveyor with a nominal upload is the most cost-effective. An increase in the upload of the transport system to the rated operating power reduces the share of unproductive consumption, which leads to a decrease in the specific value of energy spent on the transportation of material of a unit mass. Nominal uploading of the transport system can be achieved by using a system for controlling the intensity of incoming material from an accumulating bunker or a belt speed control system. The use of input bunkers is a simple and effective way to increase the efficiency of the transport system [12-14]. To control the input material flow, bunkers with a capacity of 100–500 m³ are used [7]. The availability of accumulating bunkers allows stopping the main conveyors for the duration of their filling and transferring their work to periods with lower payment for electricity (differential daily rates). However, it is often

not possible to install a bunker or its capacity is insufficient to ensure effective control. This is one of the reasons for using conveyor belt speed control systems [9-11].

II. FORMAL PROBLEM STATEMENT

To design optimal control systems for the flow parameters of a separate section of the transport system, models are used that are based on methods: finite element method [15–20]; finite difference method [20,21]; Lagrange method [21]; aggregated equation of state [22]; system dynamics [12]. The development of the analytical model (PiKh-model) of the conveyor-type transport system [16] has expanded the possibilities of designing control systems for a multi-section conveyor.

The prospect of further development of the transport system associated with the increase in the number of sections of the transport conveyor complicates the use of the analytical PDE-model. The constraint is due to the fact that an increase in the number of sections leads to a proportional increase in the number of equations that make up the model of the transport system. For a transport system with 50-100 sections, it becomes difficult to use an analytical PDE-model to design a control system for flow parameters. This article proposes one of the ways to solve this problem: using a neural network-based model to develop a control system for a multi-section transport system.

III. LITERATURE REVIEW

Recent works devoted to modelling a separate section of a conveyor using a neural network [23–27] and multiple regression [28–30] are of particular interest for designing control systems with a large number of sections [31]. This class of models is of particular importance for the design of control systems for a transport conveyor consisting of hundreds of sections. In the absence of experimental data for training a neural network in modeling a transport system, an analytical model can be used [16, 32, 33]. In this regard, in this work, we will pay attention to the construction of an optimal control system for the flow parameters of the assembly line using the neural network.

IV. CONVEYOR SECTION MODEL

The state of the flow parameters of the transport system at a point in time t at the point of the transport route with the coordinate S is described by dimensionless variables [14]:

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

$$[\chi]_1(t, S) = a(t)[\chi]_0(t, S), \quad (1)$$

$$g(\tau) = a(t) \frac{T_d}{S_d}, \quad \gamma(\tau) = \lambda(t) \frac{T_d}{S_d \Theta}, \quad \gamma_b(\tau) = \lambda_b(t) \frac{T_d}{S_d \Theta},$$

$$\gamma_{\max} = \lambda_{\max} \frac{T_d}{S_d \Theta}, \quad (2)$$

$$\delta(\xi) = S_d \delta(S), \quad H(\xi) = H(S), \quad \vartheta(\tau) = \sigma(t) \frac{T_d}{S_d \Theta},$$

$$0 \leq \lambda(t) \leq \lambda_{\max}, \quad (3)$$

where S_d is conveyor line length; T_d is the characteristic time the material takes 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 $S \in [0, S_d]$; Θ is limit value of the linear density of the material for the analyzed conveyor section; $\Psi(S)$ is the initial distribution of material along the 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 λ_{\max} ; $a(t)$ is conveyor belt speed; $\sigma(t)$ is the predicted material output from the conveyor section; $\delta(S)$ is delta function; $H(S)$ is Heaviside function.

The analytical model [14] allows you to write an expression for the density of the material and for the material flow at the output from the conveyor section:

$$\theta_0(\tau, 1) = (1 - H(1 - G(\tau))) \frac{\gamma(G^{-1}(G(\tau) - 1))}{g(G^{-1}(G(\tau) - 1))} + H(1 - G(\tau)) \psi(1 - G(\tau)), \quad (4)$$

$$\theta_1(\tau, 1) = g(\tau) \theta_0(\tau, 1), \quad G(\tau) = \int_0^\tau g(\alpha) d\alpha. \quad (5)$$

The solution of the equation

$$G(\tau_{tr}) - 1 = 0 \quad (6)$$

determines the duration of the transition period during which the flow of material at the output from the transport system is determined by the initial distribution of the material $\psi(\xi)$ along the conveyor section. The transport delay time

$$\tau \geq \tau_{tr}, \quad \tau_1 = G^{-1}(G(\tau) - 1). \quad (7)$$

allows you to determine the relationship of input and output flow parameters of the conveyor section

$$\theta_0(\tau, 1) = \frac{\gamma(\tau - \Delta\tau_1)}{g(\tau - \Delta\tau_1)} = \theta_0(\tau - \Delta\tau_1, 0), \quad \tau \geq \tau_{tr}, \quad (8)$$

$$\theta_1(\tau, 1) = \frac{\gamma(\tau - \Delta\tau_1)}{g(\tau - \Delta\tau_1)} g(\tau) = g(\tau) \theta_0(\tau - \Delta\tau_1, 0), \quad \tau \geq \tau_{tr}, \quad (9)$$

The value of the linear density at the output of the conveyor section is equal to the value of the linear density at the input of the conveyor section with a delay $\Delta\tau_1$. Consider the construction of a control system for a branched transport system [34], (Fig.1), consisting of eight separate sections. When designing the control system, let's use a model that has the architecture of the neural network shown in Fig.2 with input and output parameters:

$$x_{3m-2} = \gamma_m(\tau), \quad x_{3m-1} = g_m(\tau), \quad x_{3m} = \xi_m, \quad \mu=1..M, \quad (10)$$

$$y_1 = \theta_1(\tau, \xi_7), \quad y_2 = \theta_1(\tau, \xi_8), \quad (11)$$

where $\gamma_m(\tau)$ is the intensity of the input flow of material; $g_m(\tau)$ is the belt speed; ξ_m is section transport route length. The output parameters y_1 and y_2 (Fig.2) correspond to the output flow of the material for $m=7, 8$ sections of the transport system Fig.1. A neural network contains one hidden layer with three nodes, 9 input nodes and two output nodes. The value of the eight input nodes is determined by the state of the parameters $x_{3m-2} = \gamma_m(\tau)$, $x_{3m-1} = g_m(\tau)$ for sections $m=1, 2, 4, 5$. The value of the ninth node is 1. The choice of 9-3-2 architecture is justified by studies of the models of the conveyor section performed in [35–37]. As the activation function for the neural model, the Logistic-function is selected:

$$f(x) = \frac{a}{1 + \exp(-bx)} \quad (12)$$

Weights initialized with random values.

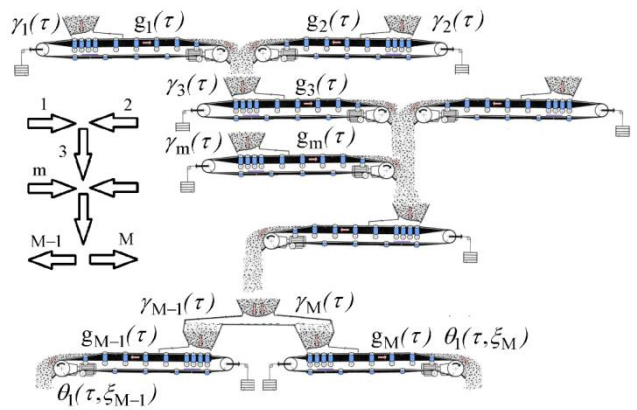


Fig. 1. Diagram of a branched conveyor transport route

V. THE PROBLEM OF THE OUTPUT FLOW OPTIMAL CONTROL

Let's formulate the problem of constructing the optimal control for the flow of material $\lambda(\tau) = u(\tau)$, entering the conveyor sections 1, 2, 4, 5 from the bunker for the steady-state operation of the conveyor line, $\tau \geq \tau_{tr}$ (7). It is

required to determine the material flows $y_1(\tau) = \theta_{17}(\tau, \xi_7)$, $y_2(\tau) = \theta_{18}(\tau, \xi_8)$ from the transport system for a period of time $\tau = [0, \tau_k]$ the input material flow continuous control $u_1(\tau) = x_1 = \gamma_1(\tau)$, $u_2(\tau) = x_4 = \gamma_2(\tau)$, $u_4(\tau) = x_{10} = \gamma_4(\tau)$, $u_5(\tau) = x_{13} = \gamma_5(\tau)$, incoming from the accumulating bunker to the input of the conveyor section, which minimize the functional:

$$\int_0^{\tau_k} \left((y_1(\tau) - g_1(\tau))^2 + (y_2(\tau) - g_2(\tau))^2 \right) d\tau \rightarrow \min \quad (13)$$

with differential connections

$$\frac{dn_{03m-2}(\tau)}{dt} = \gamma_{b3m-2}(\tau) - u_m(\tau),$$

$$n_{03m-2}(0) = n_{003m-2}, \quad (14)$$

linear density constraints

$$0 \leq \theta_{03m-2}(\tau, 0) \leq \theta_{0\max 3m-2}, \quad (15)$$

restrictions on the amount of material in the storage bunker

$$0 \leq n_{03m-2}(\tau) \leq n_{b3m-2}, \quad (16)$$

control restrictions input layer

$$u_{\min m} \leq u_m(\tau) \leq u_{\max m}. \quad (17)$$

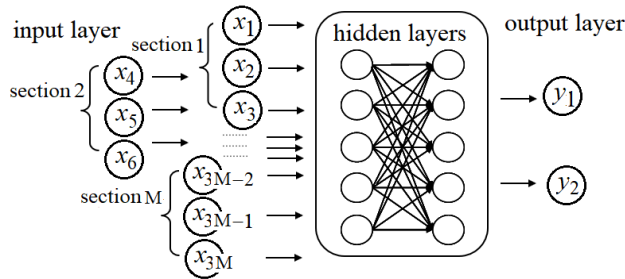


Fig. 2. Neural network architecture

The Pontryagin function and the adjoint system of equations for the problem (13) - (17) have the form:

$$H = -(y_1(\tau) - g_1(\tau))^2 - (y_2(\tau) - g_2(\tau))^2 +$$

$$+ \sum_m \psi_m (\gamma_{b3m-2}(\tau) - u_m(\tau)), \quad (18)$$

$$\frac{d\psi_m}{d\tau} = -\frac{\partial H}{\partial n_{03m-2}} = 0, \quad \psi_m(\tau_k) = 0. \quad (19)$$

If the accumulating bunker is large enough that overflow or emptying of the bunker is not achieved during the control process, then, by solving equation (19) follows $\psi_m(\tau) = 0$ and the Pontryagin function can also be written as follows

$$H = -(y_1(\tau) - g_1(\tau))^2 - (y_2(\tau) - g_2(\tau))^2 \rightarrow \max, \quad (20)$$

where

$$y_1(\tau) = \theta_{17}(\tau, \xi_7) = \theta_{18}(u_1, x_2, u_2, x_5, u_4, x_{11}, u_5, x_{14}), \quad (21)$$

$$y_2(\tau) = \theta_{18}(\tau, \xi_8) = \theta_{18}(u_1, x_2, u_2, x_5, u_4, x_{11}, u_5, x_{14}) \quad (22)$$

Data set [1] was used for neural network training. Thus, the system of equations (21), (22) gives predictive control, which determines the state of the parameters of the transport system $\theta_{17}(\tau + \Delta\tau_{17}, \xi_7)$, $\theta_{18}(\tau + \Delta\tau_{18}, \xi_8)$ at the time $(\tau + \Delta\tau_{18})$. From the maximum condition for the Pontryagin function, we determine the optimal controls u_m

$$\frac{\partial H}{\partial u_m} = \sum_m (-y_1(\tau) + g_1(\tau)) \frac{\partial \theta_{17}(u_1, x_2, u_2, x_5, u_4, x_{11}, u_5, x_{14})}{\partial u_m} +$$

$$+ \sum_m (-y_2(\tau) + g_2(\tau)) \frac{\partial \theta_{18}(u_1, x_2, u_2, x_5, u_4, x_{11}, u_5, x_{14})}{\partial u_m} = 0. \quad (23)$$

The equations (23) determines the transport system optimal control (Fig.1). If equality is not satisfied, then optimal control is achieved on the upper or lower constraint for control $u_m(\tau)$ (27). Consider the options when (23) are zero. The practical interest is the option

$$\theta_{17}(u_1, x_2, u_2, x_5, u_4, x_{11}, u_5, x_{14}) - g_1(\tau) = 0, \quad (24)$$

$$\theta_{18}(u_1, x_2, u_2, x_5, u_4, x_{11}, u_5, x_{14}) - g_2(\tau) = 0. \quad (25)$$

for which the quality criterion is zero. The other solutions of the system of equations (23) determine the local minima of the Pontryagin function with the controls u_m . Optimal control is determined by the choice of values u_m at which the minimum value of the quality criterion is achieved (13). In this study, we will assume that the optimal control u_m is determined by the system of equations (23), (24). The values of the output flows θ_{17} , θ_{18} is given through the coefficients of the nodes of the neural network (Fig.2) with the Logistic-activation function (12). The functions θ_{17} , θ_{18} are non-linear. This causes difficulties in solving the system of equations (24), (25). Let's construct functions u_m , which inverse to the functions θ_{17} , θ_{18}

$$u_1 = u_1(\theta_{17}, \theta_{18}, x_2, x_5, x_{11}, x_{14}),$$

$$u_2 = u_2(\theta_{17}, \theta_{18}, x_2, x_5, x_{11}, x_{14}), \quad (26)$$

$$u_4 = u_4(\theta_{17}, \theta_{18}, x_2, x_5, x_{11}, x_{14}),$$

$$u_5 = u_5(\theta_{17}, \theta_{18}, x_2, x_5, x_{11}, x_{14}). \quad (27)$$

To determine the controls u_m let's use a neural network with 7-10-4 architecture. The input layer has 7 nodes: $1, \theta_{17}, \theta_{18}, x_2, x_5, x_{11}, x_{14}$. Output nodes are u_1, u_2, u_4, u_5 . The Logistic-activation function (12) was chosen as the activation function. The neural network is trained in the test sample [38], which was used to train the main model (10), (11).

VI. ANALYSIS OF THE RESULTS

When training a neural network, a recurrence relation was used

$$W_{j,k,n+1} = W_{j,k,n} - \alpha \frac{\partial E}{\partial W_{j,k,n}},$$

$$E = \frac{1}{2} \sum_{m=1}^{N_m} (z_m - y_m)^2, \quad (28)$$

where is the updated weight value $W_{j,k,n+1}$ (for the epoch $n+1$) is calculated based on its old value and the error $E = E(z_m, y_m)$, determined by the parameter error value by the total number N_m of the output layer between the test data z_m and the values of the model based on a neural network (Fig.2). For model (10), (11), the coefficient value is $\alpha = 10^{-5}$, $n < 0.64 \cdot 10^6$; $\alpha = 10^{-4}$, $0.64 \cdot 10^6 \leq n < 0.9 \cdot 10^6$; $\alpha = 10^{-3}$, $0.9 \cdot 10^6 \leq n < 1.076 \cdot 10^6$. Fig.3 and Fig.4 show the results of applying the model using a neural network to predict the output flow of material from the transport system (Fig.1). The value of MSE (Mean squared error) depending on the number of training epochs

$$MSE = \frac{1}{R} \sum_{r=1}^R ((z_1 - y_1)^2 + (z_1 - y_1)^2), \quad (29)$$

is shown in Fig.5, where R is the number of rows in the training set.

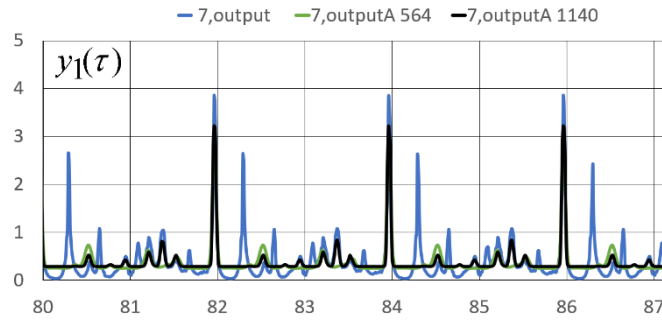


Fig. 3. The predicted output material flow for section 7

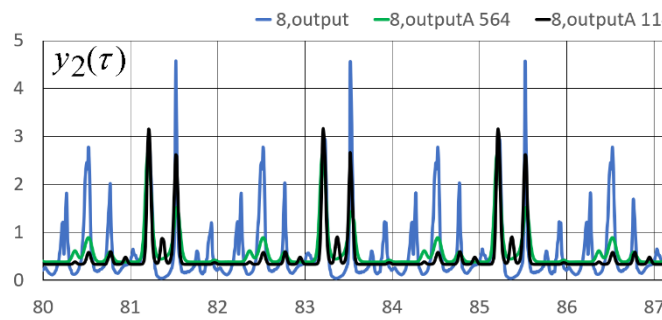


Fig. 4. The predicted output material flow for section 8

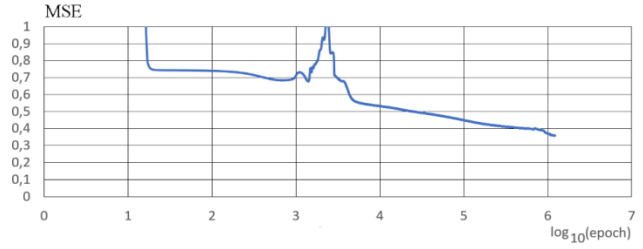


Fig. 5. Mean squared error for the summary output flow

The solution of the system of equations (26), (27) is given in Fig. 6–Fig. 9. The solution of the system of the equations is obtained for the neural net architecture 7-10-4 and for the number of the epochs is equals $n = 0.108 \cdot 10^6$. The coefficient α is constant and is equals $\alpha = 10^{-5}$. The obtained solution defines the optimal controls u_1, u_2, u_4, u_5 , for which the value MSE is 0,0176.

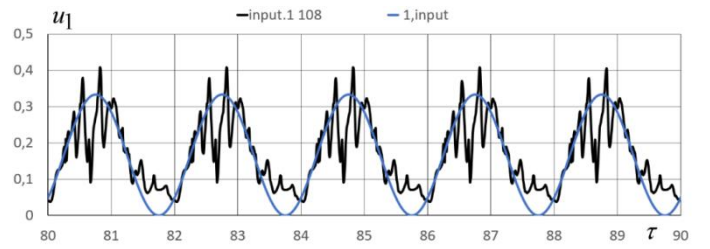


Fig. 6. Optimal bunker №1 input flow control

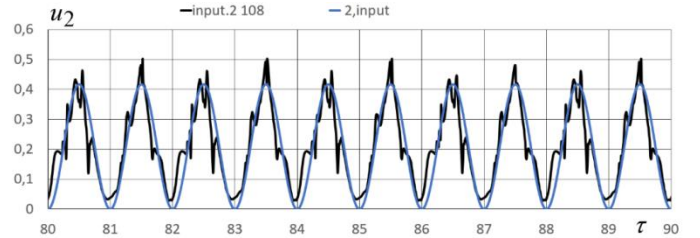


Fig. 7. Optimal bunker №2 input flow control

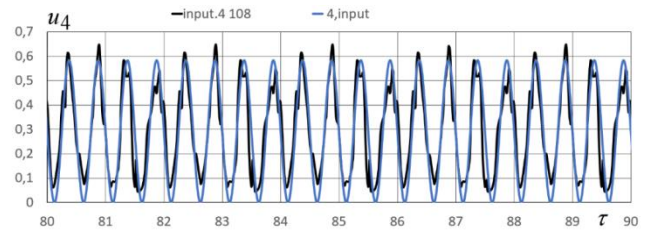


Fig. 8. Optimal bunker №4 input flow control

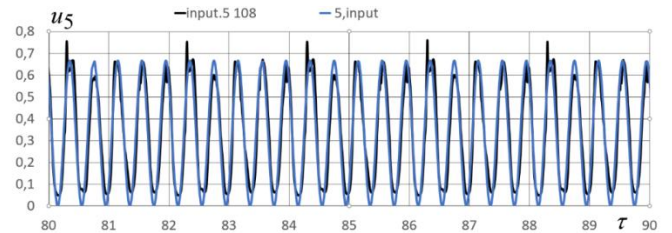


Fig. 9. Optimal bunker №5 input flow control

As expected, the accuracy of the solution for the nearest conveyor sections is higher than for the remote sections. The Fig.6– Fig.9 show a comparison of the exact

solution and the solution obtained using the model (26), (27).

In this paper, we consider the use of a model of a transport system based on a neural network. For the design of the control system, an example of a transport system consisting of eight separate sections was used. The advantage of the proposed approach increases significantly when we consider a transport system consisting of several dozen separate sections [40]. To simulate such transport systems, the application of the finite element method [15–17] becomes practically impossible; the use of an analytical model becomes complicated. It is for such kind of transport systems that the considered model based on neural network is promising. It is important to note that the proposed model is scalable. The architecture of the neural network (Fig.2) allows you to specify an arbitrary number of nodes in the input layer without changing the algorithm for constructing the model and the algorithm for constructing optimal control of its parameters. An increase in the number of inner sections does not lead to a significant increase in the number of nodes in the input layer. This is because this current section output flow is the next section input flow. In contrast to this, the analytical model and the model based on the finite element method require the calculation of the flow parameters of each section.

VII. CONCLUSION

When designing effective control systems for a transport conveyor with a large number of separate sections, models are required that allow not only a sufficiently accurate description of the conveyor but also the determination of its parameters for a given time. Using a neural network to design models of transport systems allows us to solve this problem. The analytical PiKh-model [12] made it possible to generate test data that are necessary for training a neural network. Applying the methodology for constructing models of a transport system using a neural network, a method for determining the optimal flow parameter control of the transport system is proposed. Using the classical approach for the design of transport system control systems [1, 39], which includes the formation of a control quality criterion and the construction of the Pontryagin function, optimal material flow control incoming from the input bunker is synthesized. To determine the optimal controls, a method based on a model of a transport system using a neural network is proposed. The precision of synthesized controls is characterized by the value of MSE. The prospects for further research are to determine the class of activation functions and analyze their parameters with the aim of learning the neural network.

REFERENCES

1. O. Pihnastyi, *Statistical theory of control systems of the flow production*. Beau Bassin, LAP LAMBERT: Academic Publishing, 2018.
2. Conveyorbeltguide Engineering: Conveyor components, <http://conveyorbeltguide.com/examples-of-use.html>
3. W. Kung, "The Henderson Coarse Ore Conveying System," A Review of Commissioning, Start-up, and Operation, Bulk Material Handling by Belt Conveyor 5, Society for Mining, Metallurgy and Exploration, Inc., 2004
4. M. Alspaugh, "Latest developments in belt conveyor technology," In: MINEexpo 2004, New York, Las Vegas, NV, USA, 2004.
5. Siemens. Innovative solutions for the mining industry, www.siemens.com/mining
6. M. Alspaugh, "Longer Overland Conveyors with Distributed Power," In: Overland Conveyor Company, Lakewood, USA, 2005.
7. Ju. Razumnyj, A. Ruhlov, and A. Kozar, "Povyshenie jenergoeffektivnosti konvejernogo transporta ugol'nyh shaht," *Girnichia elektromehnika ta avtomatika*. vol. 76, pp. 24–28, 2006. <https://docplayer.ru/64655888-Povyshenie-energoeffektivnosti-konvejernogo-transporta-ugolnyh-shaht.html>
8. O. Pihnastyi, "Largest conveyor transport systems," *Mendeley Data*, vol. V1, 2020, <http://dx.doi.org/10.17632/2tf5ynzt2x.1>
9. Continuous conveyors. Belt conveyors for loose bulk materials. Basics for calculation and dimensioning. DIN 22101:2002-08. 2002.
10. O. Pihnastyi, "Control of the belt speed at unbalanced loading of the conveyor," *Scientific bulletin of National Mining University*. vol.6, pp. 122–129, 2019. <https://doi.org/10.29202/nvngu/2019-6/18>
11. A. Semenchko, M. Stadnik, P. Belitsky, D. Semenchko, and O. Stepanenko, "The impact of an uneven loading of a belt conveyor on the loading of drive motors and energy consumption in transportation," *Eastern European Journal of Enterprise Technologies*, vol. 82, 4/1, pp. 42–51, April 2016. <https://doi.org/10.15587/1729-4061.2016.75936>
12. E. Wolstenholm, "Designing and assessing the benefits of control policies for conveyor belt systems in underground mines." *Dynamica*. vol. 6(2), 25–35 June 1980.
13. H. Lauhoff, "Speed Control on Belt Conveyors – Does it Really Save Energy?," *Bulk Solids Handling Publ.* vol. 25(6), 368–377, 2005
14. O. Pihnastyi, V. Khodusov, Model of conveyor with the regulable speed. *Bulletin of the South Ural State University. Ser. Mathematical Modelling, Programming and Computer Software* vol. 10, 64–77 (2017). <https://doi.org/10.14529/mmp170407>
15. L. Nordell, Z. Ciozda, "Transient belt stresses during starting and stopping," *Elastic response simulated by finite element methods. Bulk Solids Handling* vol. 4(1), pp. 99–104, April 1984. <http://www.ckit.co.za/secure/conveyor/papers/troughed/transient/transient-belt-stresses.htm>
16. D. He, Y. Pang, G. Lodewijks, and X. Liu, "Determination of Acceleration for Belt Conveyor Speed Control in Transient Operation," *International Journal of Engineering and Technology* vol. 1.8(3), pp. 206–211, 2016. <http://dx.doi.org/10.7763/IJET.2016.V8.886>
17. M. Alspaugh, "Latest Developments in Belt Conveyor Technology." Overland Conveyor Co., pp.1–11 In: MINEexpo 2004 Las Vegas, NV, USA, 2004. [http://www.overlandconveyor.com/pdf/Latest Developments in Belt Conveyor Technology.pdf](http://www.overlandconveyor.com/pdf/Latest%20Developments%20in%20Belt%20Conveyor%20Technology.pdf)
18. B. Karolewski, P. Ligocki, "Modelling of long belt conveyors. Maintenance and reliability," *Eksplotacja i Niezawodność* vol. 16, no. 2, pp. 179–187, 2014. <http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.baztech-ce355084-3e77-4e6b-b4b5-ff6131e77b30>
19. R. Pascual, V. Meruane, and G. Barrientos, "Analysis of transient loads on cable-reinforced conveyor belts with damping consideration," In: the XXVI Iberian Latin-American Congress on Computational Methods in Engineering (CILAMCE-2005), pp.1–15, Santo, Brazil 2005. <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.494.34&rep=rep1&type=pdf>

20. C.Wheeler, "Predicting the main resistance of belt conveyors," In International Materials Handling Conference (Beltcon) 12, Johannesburg, South Africa (2003).
<http://www.saimh.co.za/beltcon/beltcon12/paper1208.htm>
21. X.Mathaba and Xia, "A parametric energy model for energy management of long belt conveyors," *Energies* vol. 8(12) pp. 13590–13608, 2015. DOI: <https://doi.org/10.3390/en81212375>
22. A. Reutov, "Simulation of load traffic and steeped speed control of conveyor," In: IOP Conference Series: Earth and Environmental, 87, pp.1–4. 2017. <https://doi.org/10.1088/1755-1315/87/8/082041>.
23. A.Kirjanów, "The possibility for adopting an artificial neural network model in the diagnostics of conveyor belt splices," *Interdisciplinary issues in mining and geology* vol. 6, pp. 1–11, 2016.
24. 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* vol. 24(1). pp. 1–14, 2019.: <https://actamont.tuke.sk/pdf/2019/n1/1wiecek.pdf>
25. Li, W., Wang, Z., Zhu, Zh., Zhou, G., "Design of Online Monitoring and Fault Diagnosis System for Belt Conveyors Based on Wavelet Packet Decomposition and Support Vector Machine." *Advances in Mechanical Engineering* vol. 5, pp.1–10, January 2013. <https://doi.org/10.1155/2013/797183>
26. Xinglei L., Hongbin, Yu.: 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). pp. 789–793. (2015). <https://doi.org/10.2991/icmeis-15.2015.148>
27. Pingyuan, Xi, Yandong, Song: "Application Research on BP Neural Network PID Control of the Belt Conveyor." *JDIM* vol. 9(6), pp. 266–270, 2011.
<https://www.questia.com/library/journal/1G1-338602055/application-research-on-bp-neural-network-pid-control>
28. M. Andrejiova, D. Marasova, "Using the classical linear regression model in analysis of the dependences of conveyor belt life," *Acta Montanistica Slovaca* vol. 18(2). pp. 77–84, 2013.
<https://actamont.tuke.sk/pdf/2013/n2/2andrejiova.pdf>
29. Yan Lu, Q. Li, "A regression model for prediction of idler rotational resistance on belt conveyor," *Measurement and Control* vol. 52(5), pp. 441–448, June, 2019.
<https://doi.org/10.1177/0020294019840723>
30. A. Grincova, D. Marasova, Experimental research and mathematical modelling as an effective tool of assessing failure of conveyor belts. *Maintenance and reliability*. vol. 16 (2), pp. 229–235, 2014. Available: <http://www.ein.org.pl/sites/default/files/2014-02-09.pdf>
31. Bastian Solutions Conveyor System Design Services, <https://www.bastiansolutions.com/solutions/technology/conveyor-systems/design-services>
32. O. Pihnastyi, V. Khodusov, "Calculation of the parameters of the composite conveyor line with a constant speed of movement of subjects of labour," *Scientific bulletin of National Mining University*, vol. 4 (166), pp. 138–146, 2018.
<https://doi.org/10.29202/nvngu/2018-4/18>
33. O. Pihnastyi, V. Khodusov, "Model of a composite magistral conveyor line," In IEEE International Conference on System analysis & Intelligent computing (SAIC 2018), pp.68–72. Ukraine, Kyiv, 2018. <https://doi.org/10.1109/saic.2018.8516739>
34. R. Zimroz, R. Krol, "Failure analysis of belt conveyor systems for condition monitoring purposes," *Mining Science* vol. 128(36), pp.255–270, 2009.
<http://www.miningscience.pwr.edu.pl/Failure-analysis-of-belt-conveyor-systems-for-condition-monitoring-purposes,59825,0,2.html>
35. S. Abdollahpor, A. Mahmoudi, A. Mirzazadeh, "Artificial neural network prediction model for material threshing in combine harvester," *Elixir Agriculture*, vol. 52, pp. 11621–11626, 2012. [https://www.elixirpublishers.com/articles/1353477517_52%20\(2012\)%2011621-11626.pdf](https://www.elixirpublishers.com/articles/1353477517_52%20(2012)%2011621-11626.pdf)
36. Y. Yuan, W. Meng, X. Sun, "Research of fault diagnosis of belt conveyor based on fuzzy neural network," *The Open Mechanical Engineering Journal*, vol. 8, pp. 916–921, 2014.
<https://doi.org/10.2174/1874155X01408010916>
37. N. Selcuk, Y. Birbir, "Application of artificial neural network for harmonic estimation in different produced induction motors", *Int. J. of Circuits, Systems and Signal Processing*, vol. 4(1), pp. 334–339 2007.
<https://pdfs.semanticscholar.org/ba2f/6d5ea4c91720be4044e0f3544efb60fd6bb4.pdf>
38. O. Pihnastyi, "Test data set for the conveyor transport system", *Mendeley Data*, V2, 2020.
<https://doi.org/10.17632/4vc843t76.5>
39. O. Pihnastyi, V. Khodusov, "Optimal Control Problem for a Conveyor-Type Production Line," *Cybern. Syst. Anal.* vol. 54(5), pp. 744–753, 2018. <https://doi.org/10.1007/s10559-018-0076-2>
40. Robert Krol, Witold Kawalec, Lech Gladysiewicz: An effective belt conveyor for underground ore transportation systems. In: IOP Conference Series: Earth and Environmental Science, 95(4), pp. 1–4, 2017. <https://doi.org/10.1088/1755-1315/95/4/042047>