An Analytical Method for Generating a Data Set for a Neural Model of a Conveyor Line

Oleh Pihnastyi
Department of distributed information systems and cloud technologies, National Technical University "KPI" Kharkiv, Ukraine
pihnastyi@gmail.com

Georgii Kozhevnikov
Department of distributed information systems and cloud technologies, National Technical University "KPI" Kharkiv, Ukraine
kozhevnikov.gk@gmail.com

Tetiana Bondarenko
Department of computer information technologies and mathematics Ukrainian Engineering-Pedagogies Academy Kharkiv, Ukraine
bondarenko_tca@uipa.edu.ua

Abstract—Models using neural networks are a rather promising class of models for designing highly efficient control systems for a dynamic distributed transport system of the conveyor type. An important problem in constructing a model of a conveyor-type transport multi-section system is the formation of a data set for training a neural network. This study discusses a method for generating data for training a neural network based on an analytical model of a conveyor-type transport system. A detailed analysis of the most common models of the transport conveyor is performed and the choice of an analytical model for the formation of a training data set is theoretically justified. An algorithm for calculating the flow parameters of individual sections of the transport system is proposed. An estimation of the transition period is given. Graphical representation of a data set for training a neural network using an analytical model of a transport system is demonstrated.

Keywords—conveyor, flow control, artificial intelligence, dynamic distributed system, ANN model

I. INTRODUCTION

Industry 4.0 represents a new round of the industrial revolution, which is characterized by the transition to a fully automated digital production, controlled by intelligent systems in real-time in constant interaction with the external environment and the prospect of joining a global industrial network. Artificial intelligence along with additive, predictive technologies is an integral part of the new industrial revolution: Industry 4.0. Currently, the key tasks of artificial intelligence in enterprises are mainly organizational management. Particular attention is paid to this issue at enterprises with a continuous method of organizing production [1]. An integral element of such systems is the transport conveyor.

Conveyor-type transport systems are especially widespread in the mining industry [2–6]. The total length of the modern transport system exceeds 100 km, and the length of a separate section is up to 20 km. The main characteristics of modern conveyor-type transport systems are presented in [7]. Despite its apparent simplicity, a transport conveyor is a complex dynamic distributed system, which implies a transport delay (the time interval between two events: the flow of material to the input of the system and the output of material from the transport system). Significant flow parameters of the transport conveyor, which have a significant impact on the energy costs of the transport system, are the linear density distribution of the material along the transport route and the magnitude of the material flow along the transport route.

The main models that are used to design optimal control systems for the flow parameters of the transport conveyor are numerical models. The foundation of these models is the finite element method [5, 8–12]; finite difference method [12,13]; Lagrange method [13]; a method using the aggregated equation of state [14]; system dynamics method [15]. A detailed review of models of conveyor systems shows that these models are used to determine the dynamics of changes in the flow parameters of an individual conveyor section [16]. It should be noted that the use of numerical models for the design of algorithms for optimal control of the flow parameters of the transport system causes significant difficulties and requires significant computational resources. The transition from a conveyor model consisting of one section to a conveyor model containing tens or hundreds of separate sections becomes a difficult problem to overcome. This is one of the reasons that explain the almost absence of publications devoted to the problem of modelling transport systems, even consisting of several sections.

The advent of the analytical model of the conveyor system (PiKh – model) [17] seemed to open up the prospects of designing optimal control systems for the flow parameters of a multi-section conveyor. Using the analytical model, a description is given of a multi-section main conveyor (sections of the main conveyor are placed sequentially one after another) [7] and a two-section conveyor (an additional section of the conveyor is attached to the main section at an arbitrary point on the transportation route) [18]. The PiKh–model is a successful tool for describing transport systems consisting of dozens of conveyor sections. The model of an individual section contains, as a rule, two basic equations. The first differential equation determines the distribution of material along the transport route, the second differential equation determines the state of the material in the bunker at the entrance to a separate section. Estimated, a transport system containing one hundred separate sections is described by a model of two hundred equations. Such a model requires significant computational, and most importantly, time resources. The reaction time of the control system, which is based on an analytical model for such a number of sections, may exceed the maximum allowable. Thus, the analytical model did not solve the problems that arose when using numerical models but
moved the applicability of the model to a much larger number of conveyor sections.

II. NEUROMODELLING OF CONVEYOR TYPE TRANSPORT SYSTEMS

Along with the numerical models considered above [5, 8–12], there are a sufficient number of studies devoted to the use of neural networks [19–21] and regression equations for modelling the conveyor section [21, 22]. In a mathematical sense, a neural network is a universal nonlinear approximation for functions of many variables

\[ y = f(x), \quad y = \{y_1, y_2, ..., y_n\}, \quad x = \{x_1, x_2, ..., x_m\} \]  

(1)

where \( x \) is the input data of the model; \( y \) is the input data of the model. Neural models are used to display complex relationships between the input and output data of a model.

In [19], a neural model 13-5-1 was proposed for diagnosing the state of wear of a conveyor belt. Studies in [20] are devoted to neural modelling of the process of extraction and transportation of rock. The purpose of constructing the ANN model is to provide control of the process of mining and transportation of rock, which will ensure the output value of the material flow in accordance with a given planned value. Control of the transport system according to this criterion is one of the main directions of research of conveyor systems of transport type [23].

In [21], a control system was considered that uses a 4-6-3 neural network (back-propagation algorithm) as a control object. To build a regression model [22], data for the training set were collected from 18 conveyor sections.

Neural network training is a major determinant of model quality. High-quality training of a neural network that is capable of simulating a specific transport system requires the collection of relevant data in large quantities [19–22]. In addition, the range of data changes should be wide, covering the possible values of the input and output parameters of the transport system. Data collection requires a significant investment of enterprise resources takes a lot of time. In many cases, collecting data for training is not possible. This is because, in order to collect data in a number of ranges of changes in the values of input and output factors, it is necessary to operate the transport system in economically unfavorable conditions that require significant expenditures of material resources, or in conditions that can lead to the destruction of transport equipment.

The most important advantage of control systems based on models using a neural network is that the response time of a control system is much smaller than for numerical models [5, 8–12]. By virtue of relation (1), with a significant increase in the number of sections, the duration of the calculation of the output parameters can be significantly shorter than for an analytical multi-section model of a conveyor system. A model using a neural network can be successfully applied to describe multi-section conveyor systems, if there is data for training the neural network. Thus, the possibility of using neural networks for modelling a multi-section pipeline reduces to the problem of developing methods for generating data for training a neural network. The relevance of this problem determined the purpose of this study.

III. ANALYTICAL MODEL OF CONVEYOR TYPE TRANSPORT SYSTEM

To describe the conveyor section (see Fig. 1) we will use the classic dynamic distributed model of the conveyor in a dimensionless form (PiKh-model) [17]:

\[ \frac{\partial \theta_0(\tau, \xi)}{\partial \tau} + g(\tau) \frac{\partial \theta_0(\tau, \xi)}{\partial \xi} = \delta(\xi) \gamma(\tau) \]  

(2)

\[ \theta_0(0, \xi) = H(\xi) \wp(\xi) \]  

(3)

The state of the stream 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:

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

(4)

\[ \theta_0(\tau, \xi) = \left[ \frac{\lambda(t)}{\Theta} \right]_0(t, S), \quad \wp(\xi) = \frac{\Psi(S)}{\Theta}, \]  

(5)

\[ \gamma(\tau) = \lambda(t) \frac{T_d}{S_d \Theta}, \quad \gamma_\lambda(\tau) = \frac{\lambda(t)}{T_d} \frac{T_d}{S_d}, \]  

(6)

\[ \gamma_{\lambda, \max} = \lambda_{\max} \frac{T_d}{S_d \Theta}, \quad g(\tau) = a(t) \frac{T_d}{S_d}, \]  

(7)

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

(8)

\[ \left[ \chi \right]_0(t, S) = a(t) \left[ \chi \right]_0(t, S), \]  

(9)

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

(10)

where \( S_d \) is the length of the conveyor line; \( T_d \) is characteristic transit time of the material along the transport route; \( \left[ \chi \right]_0(t, S) \) 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 limit value of the linear density of the material for the analysed conveyor section; \( \Psi(S) \) is initial distribution of material along the process route; \( \lambda(t) \) is the intensity of the flow of material into the accumulating 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; \( \delta(\tau) \) is the predicted output flow from the conveyor section; \( \delta(S) \) is delta function; \( H(S) \) is Heaviside function.
Equation (2) with initial conditions (3) corresponds to the solution [17]:

\[ \theta_0(\tau, l) = \left(1 - H(1 - G(\tau))\right)G^{-1}(G(\tau) - I) + \]

\[ + H(1 - G(\tau))G^{-1}(1 - G(\tau)) - \int_0^{\tau} g(\alpha) d\alpha \quad (11) \]

\[ \theta_1(\tau, l) = g(\tau)\theta_0(\tau, l). \quad (12) \]

Expressions (11), (12) determine the state of the flow parameters at the output from the conveyor section, depending on the magnitude of the input flow and the speed of movement of the conveyor belt. The value of the output parameters determines the state of the flow parameters at the input of the subsequent section, which in turn makes it possible to calculate the values of the output parameters of the section.

IV. TEST DATA GENERATION METHOD FOR TRAINING A NEURAL NETWORK

The analytical model (2), (3) is not suitable for the design of conveyor transport control systems with an extremely large number of sections. This limitation is due to the fact that the calculation time of the output parameters of the transport system may exceed the maximum permissible time determined by the control parameters. However, for this model, successful use can be found as a tool for generating data in an arbitrary range for training a neural network. As a test case, we use the conveyor-type transport system architecture shown in Fig. 2. The construction of an analytical model will be done for a multi-section conveyor consisting of eight sections \( M = 8 \). To calculate the conveyor section, we need to know the values of the material flow at the input of the conveyor section. For intermediate sections, the value of the input flow is determined by the value of the output flows of the conjugate conveyor sections. The calculation of the parameters of a multi-sectional transport system, we will begin by calculating the output sections of the transport system using the method of walking the tree in depth (Fig. 3). The state of the flow parameters of an individual section can be represented as a superposition of harmonic functions. To ensure a wide range of values of the flow parameters of the transport system, we will represent the speed of the tape of the \( m \)-th section as a harmonic function (Fig. 4):

\[ g_m(\tau) = g_{0m} + g_{1m} \sin \left( \frac{m\pi\tau}{4} + \frac{m\pi}{4} \right), \quad (13) \]

We also set the input material flow \( \gamma_m(\tau) \) for sections 1, 2, 4 and 5. Taking into account the previous considerations, we use periodic functions for the input flow

\[ \gamma_m(\tau) = \gamma_{0m} + \gamma_{1m} \sin \left( \frac{m\pi\tau - m\pi}{4} \right). \quad (14) \]

![Diagram of a multi-section transport conveyor](image1)

![The sequence of calculation of sections of the transport conveyor](image2)

The value of the input material flow \( \gamma_m(\tau) \) for the intermediate sections 3, 6 and the output sections 7 and 8 can be calculated by the formulas (11), (12), if the values of the output material flow from the previous sections are known. The input flow of the third section is equal to the total material flow of the first and second sections. The values of the material flow into the transport system for sections 1, 2, 4 and 5 are shown in Fig. 5. The input material flow into the transport system for intermediate sections, calculated according to formulas (11), (12), is shown in Fig. 6. The initial distribution of material before starting the transport system is set by periodic functions (15):

\[ \psi_m(\tau) = \psi_{0m} + \psi_{1m} \sin \left( \frac{m\pi\tau}{4} + \frac{m\pi}{4} \right). \quad (15) \]
Fig. 4. The speed of the tape of the m-th section.

The initial distribution of material along the m-th section (15) of the transport conveyor determines the magnitude of the output flow of the m-th section during the transition mode. Fig. 7 gives an estimate of the duration of the transition period, the value of which is 2. On the interval $\tau \geq 2$ a steady state is observed, the dynamics of which is represented by a periodic function.

Fig. 5. The input flow of material into the transport system for the m-th section.

Fig. 6. Input material flow for the intermediate m-th section (transient mode).

Fig. 7. Input material flow for the intermediate m-th section (steady-state batch mode).

Of substantial practical interest is the value of the density of the material along the conveyor section. The value of the density of the material at the inlet of 1, 2, 4 and 5 of the conveyor section is shown in Fig. 8. The dynamics of the magnitude of the linear density of the material at the entrance to the section determines the uneven loading of the material along the transportation route [14, 16, 17]. To reduce the cost of transporting the material, it is necessary to ensure uniform loading of the material along the transport route with the maximum allowable value. The value of the linear density of the material at the inlet of the intermediate section, calculated by the formula (11) for the transitional and steady-state modes, is presented in Fig. 9 and Fig. 10. In the interval $0 < \tau < \theta$ the dynamics of the value of the linear density of the material $\theta_{lm}(\tau,0)$ at the input of the section for the steady-state periodic mode of operation of the transport system is showed. The dynamics of changes in the flow quantities $\theta_{lm}(\tau,0)$ and (Fig. 7, Fig. 10) is determined by the magnitude of the material flow entering the input of the transport system and the speed of the conveyor belt (Fig. 4, Fig. 5). An important factor that can be used to train a neural network is the amount of transport delay (Fig. 11). Figure 11 shows the quasi–stationary value of the transport delay for the steady-state operating mode of the m-th section. The output material flow with sections 7 and 8 is shown in Fig. 12. The dynamics of the magnitude of the output flow of sections 7 and 8 is determined by the magnitude of the input flow of sections 1, 2, 4, 5 (Fig. 5) and the speeds of conveyor belts of individual sections (Fig. 4).

Fig. 8. The density of the material for 1,2,4,5 sections.

Fig. 9. The linear density of the material at the inlet of the intermediate m-th section (transient mode).

Fig. 10. The linear density of the material at the input of the intermediate m-th section (steady-state periodic mode).
methodology considered in this paper. A neural network, which is formed according to the model of a transport system using a set for training a stationary value. The transport delay has a quasi-periodic function, leading to peak values of the transport system may be due to the superposition of the stochasticity of the material flow at the output from the conveyor belt speed given by smooth periodic functions. Thus, the stochasticity of the material flow at the output from the transport system may be due to the superposition of the material flows of the individual conveyor sections. At the same time, the value of the transport delay has a quasi-stationary value.

The prospect of further research is the construction of a model of a transport system using a set for training a neural network, which is formed according to the methodology considered in this paper.

REFERENCES

[1] O. Pihnastyi, "Statistical theory of control systems of the flow production", LAP LAMBERT Academic Publishing, Beau Bassin, p. 436, 2018.
[2] Siemens, "Innovative solutions for the mining industry" 2018; www.siemens.com/mining.
[3] "ConveyorBeltGuide Engineering: Conveyor components"; http://conveyorbeltguide.com/engineering.html.
[4] 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.
[5] M. Alspaugh, "Latest developments in belt conveyor technology", MINEXpo, New York, Las Vegas, NV, USA, 2004.
[6] M. Alspaugh, "Longer Overland Conveyors with Distributed Power," Rockwell Automation Fair, St Louis, MO USA, 2005.http://www.overlandconveyor.com/pdf/Longer_Overland_C onveyors_with_Distributed_Power.pdf
[7] O. Pihnastyi and V. Khodusov, "Model of a composite magistral conveyor line," IEEE International Conference on System analysis & Intelligent computing (SAIC 2018), pp. 68-72, 2018.
[8] L. Nordell and 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, 1984; http://www.ckt.co.za/secure/conveyor/papers/toughed/transient/tr ansient-belt-stresses.htm
[9] 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. 8(3), pp. 206-211, 2006; http://dx.doi.org/10.7763/IJET.2016.V8.886
[10] B. Karolewski and P. Ligocki, "Modelling of long belt conveyors," Maintenance and reliability, vol. 16 (2), pp. 179-187, 2014; ya.yadda.icu.edu.pl/yadda/element/bwmeta1.element.baztech-ee355084-3e77-46eb-b46f-f6131e77b30
[11] R. Pascual, V. Merauane and G. Barrientos, "Analysis of transient loads on cable-reinforced conveyor belts with damping consideration," XXVII Iberian Latin-American Congress on Computational Methods in Engineering, pp.1-15, 2005.
[12] C. Wheeler, "Predicting the main resistance of belt conveyors," BELTCON 12 - International Materials Handling Conference, 2003; http://www.saimh.co.za/beltcon/beltcon12/paper1208.htm
[13] T. Mathaba and X. Xia, "A parametric energy model for energy management of long belt conveyors," Energies, vol. 8(12), 2015, 13596–13608.
[14] A. Reutov, "Simulation of load traffic and steeped speed control of conveyor," in: IOP Conference Series: Earth and Environmental, vol. 87, pp. 1-4, 2017.
[15] E. Wolstenholme, "Designing and assessing the benefits of control policies for conveyor belt systems in underground mines," Dynamics, vol. 6(2), pp. 25-35, 1980.
[16] O. Pihnastyi, "Control of the belt speed at unbalanced loading of the conveyor," Scientific bulletin of National Mining University, vol. 6(6), pp. 122-129, 2019; https://doi.org/10.29202/mbnu/2019-6/18
[17] O. Pihnastyi and 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 (4), pp. 64-77, 2017, https://doi.org/10.14529/mmp170407.
[18] O. Pihnastyi and 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, no. 4 (166), pp. 138-146, 2018;
[19] 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
[20] D. Więcek, A. Burduk, I. Kuric, "The use of ANN in improving efficiency and ensuring the stability of the copper ore mining process," Acta Montanistica Slovaca, vol. 24, pp. 1-14, 2019
[21] Xi Pingyuan and Song Yandong, "Application Research on BP Neural Network PID Control of the Belt Conveyor," JDIM, vol. 9(6), pp. 266-270, 2011.
[22] M. Andrejeova and 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
[23] O. Pihnastyi and V. Khodusov, "Optimal Control Problem for a Conveyor-Type Production Line," Cybern. Syst. Anal. Springer US, vol. 54, no. 5, pp. 744-753, 2018; DOI:https://doi.org/10.1007/s10559-018-0076-2
[24] O. Pihnastyi, "Test data set for the conveyor transport system," Mendeleev Data, vol. 4, 2020. 
http://dx.doi.org/10.17632/4vb843t76.4