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# CONSTRUCTING GENERATORS OF VALUES OF AN INPUT MATERIAL FLOW OF CONVEYOR-TYPE TRANSPORT SYSTEMS

**Abstract:** **Object of research** is stochastic stationary input flow of material of a conveyor-type transport system. **Subject of research** is development of a method for generating a training data set for a neural network in a transport conveyor model. **Goal of the research** consists in the development of a random value generator for constructing an implementation of the input flow of material of a transport conveyor, which has specified statistical characteristics, calculated on the basis of the results of previously performed experimental measurements. **The results obtained.** The article considers a class of stochastic material flows of a transport system, for which it is possible to approximate the experimental implementation of a random process by an implementation corresponding to the simplest flow for the model of a random telegraph wave. A method is presented for generating values of the input material flow in order to form a data set for training a neural network in a branched transport conveyor model. The basic principles for constructing a generator of input material flow values are defined. The use of a single experimental implementation of a stochastic input material flow to calculate statistical characteristics for constructing a generator of input material flow values is justified. Dimensionless parameters have been introduced to simplify the description of stochastic input material flows and to determine similarity criteria for stochastic input material flows. The implementation of a stochastic input flow of material is presented in the form of a series expansion in coordinate functions. The law of distribution of the length of the time interval between two events of the simplest flow of events, used to approximate the implementation of the input material flow, is determined. A comparative analysis of correlation functions for experimental, approximated and generated implementations of the input material flow was carried out. The length of the time interval required to carry out experimental changes in the input material flow is justified. Estimates of the statistical characteristics of the implementations of the input material flow are given.

**Keywords:** transport conveyor; neural network; stochastic process; dataset generator; realization.

## Introduction

Conveyor-type transport systems in the mining industry have a significant impact on reducing the cost of material extraction [1–3]. Reducing the unit costs of transporting material is achieved as a result of uniform loading of material along the entire transportation route. This allows us to ensure the maximum value of the material loading factor of the transport conveyor [4, 5]. The uneven loading of material in the transport system is caused both by the presence of a stochastic input flow of material arriving at the input of the transport system, and as a result of the use of imperfect systems for the control of the conveyor belt speed [6, 7] or of the material flow from the storage bin [8–10]. This also applies to combined control systems [11, 12], in which the speed of the conveyor belt and the flow of material from the accumulating hopper are controlled simultaneously. The imperfection of control systems is explained by the fact that a conveyor-type transport system is a complex dynamic system with a variable transport delay [13]. The use of control systems for the flow parameters of a separate conveyor makes it possible to ensure a quasi-uniform loading of the conveyor belt with material as a result of changing the speed of the conveyor belt, which accordingly leads to a change in the flow of material at the output of the transport conveyor [14]. This dynamic flow of material enters the following conveyor, causing uneven distribution of material along the transport route on this conveyor [15]. To design control systems for the flow parameters of conveyors consisting of one or several sections, models based on numerical methods (finite element method, FEM [16]; finite difference method, FDM) or system dynamics equations [17] were used. For branched transport systems, including several dozen conveyors, an analytical conveyor model is used [10, 18].

To design control systems for transport conveyors with a branched structure, it is advisable to use models based on regression equations [19, 20] and neural networks [21–23]. However, both for constructing regression equations and for training neural networks, sufficiently large training data sets are required [24], containing the values of the input and output flow parameters of the transport system. To build adequate models of a functioning transport system, it is necessary to collect experimental data for a fairly wide range of changes in the values of the flow parameters of the transport conveyor. It is impossible to obtain such data under operating conditions of a real transport system, since changes in transportation modes will lead to malfunctions in the system. This task is further complicated by the fact that for highly ramified transport systems, a large number of combinations of modes of operation of the transport system arise. For a transport system consisting of only 30 sections of conveyors, each of which can operate only in a two-speed mode, it is necessary to perform experimental measurements for $\sim 10^9$ combinations of modes of operation of the transport system. Additional difficulties are imposed by the very fact of the presence of a stochastic input flow of material.

Thus, using a functioning system to construct a training dataset based on experimental measurements is not a feasible task. However, in some cases, it is still possible to build a training data set if you split the original problem into two subtasks: a) perform an analysis of the statistical characteristics of the input material flows in order to build a generator input material flows with the given statistical characteristics; b) use an analytical model of a transport conveyor when calculating the values of the output material flow of an extensive transport system for the generated values of the input material flow. The solution to the first problem is to calculate the statistical characteristics of the input material flows based on experimental data for the operating system. To ensure satisfactory calculation accuracy, it is necessary to have a sufficiently large number of realizations of input material flows with a given interval length during which it is necessary to measure the values of the input material flow. The solution to the first problem can be significantly simplified if the experimentally obtained implementation of the input material flow is approximated by a stationary flow with ergodic properties. In this case, to determine the statistical characteristics, it is sufficient to have a single implementation of the input material flow, constructed on the basis of experimental measurements for a time interval of a given length. Based on the statistical characteristics of the experimental implementation of the input material flow, a generator of a stochastic input material flow can be constructed. This generator subsequently serves as a source for generating the required number of implementations of the input material flow on a time interval of a given length. To solve the second problem, we will use the analytical model of the transport conveyor [25]. The boundary conditions for the analytical model equations are the generated realizations of the input material flow. It should be noted that in highly branched transport systems for the formation of a training data set, the computational costs for calculating the values of the output flow of material using an analytical model are comparable to the computational costs associated with training a neural network. A simplified model of a branched transport system based on a neural network is presented in [26]. This work demonstrates a method for generating a data set for a deterministic input material stream. It should be noted that to calculate the statistical characteristics of the input material flow generator, the results of research works devoted to the analysis of experimental measurements of input material flows can be used [12, 27–30]. The presented works discuss individual implementations of stochastic material flow, which can be used to analyse and develop the foundations of the theory of typification of input material flows of a transport conveyor. Additionally, it should be noted that when experimentally measuring the input material flow, it is necessary to exclude the influence of the initial distribution of the material flow along the route on the value of the output material flow.

## Problem statement

We consider a class of stochastic material flows of a transport system, for which it is possible to approximate by experimental implementation a random process that corresponds to the simplest flow with alternating two given values of the input material flow between events (the model of a random telegraph wave [31]). A typical representative of this class is the stochastic input flow of material of a transport conveyor, which operates in a mode when the input flow is absent or takes on a quasi-constant value. To describe the random flow of material $\lambda(t)$ arriving at the entrance of the transport conveyor at time interval $t \in [t_{\min}, t_{\max}]$, let us introduce dimensionless parameters:

$$\gamma(\tau) = \frac{\lambda(t) - m_\lambda(t)}{\sigma_\lambda}, \ \gamma_f(\tau) = \frac{\lambda(t)}{\sigma_\lambda},$$

$$m_f = \frac{m_\lambda(t)}{\sigma_\lambda}, \ \tau = 2\frac{t - t_{\min}}{t_{\max} - t_{\min}} - 1, \tag{1}$$

$$\tau \in [-1,1], \ \vartheta = \frac{2\eta}{t_{\max} - t_{\min}},$$

$$m = M\left[\frac{\lambda(t) - m_\lambda(t)}{\sigma_\lambda}\right] = M[\gamma(\tau)] = 0,$$

$$\sigma^2 = M\left[\left(\frac{\lambda(t) - m_\lambda(t)}{\sigma_\lambda}\right)^2\right] = M\left[\gamma^2(\tau)\right] = 1, \tag{2}$$

$$k(\vartheta) = M[\gamma(\tau)\gamma(\tau - \vartheta)],$$

where $m_\lambda(t)$, $\sigma_\lambda$ are mathematical expectation and standard deviation for the values of a random input material flow $\lambda(t)$ with characteristic correlation time $\eta$. Let us consider the dimensionless centered stochastic input flow $\gamma(\tau)$ as a centered stationary random process. With a limited set of sample data specified by a single implementation of a centered stationary random process, time averaging for stationary process $\gamma(\tau)$ can be replaced by averaging of a totality:

$$m = \frac{1}{2}\int_{-1}^{1}\gamma(\tau)d\tau = \frac{1}{N+1}\sum_{n=0}^{N}\gamma(\tau_n) = 0,$$

$$\sigma^2 = \frac{1}{2}\int_{-1}^{1}\gamma^2(\tau)d\tau = \frac{1}{N+1}\sum_{n=0}^{N}\gamma^2(\tau_n) = 1, \tag{3}$$

$$k(\vartheta_i) = \int_{-1}^{1}\frac{\gamma(\tau)\gamma(\tau+\vartheta_i)}{2}d\tau = \sum_{n=N/2}^{N} 2\frac{\gamma(\tau_n)\gamma(\tau_n - \vartheta_i)}{N+1}, \tag{4}$$

$$\vartheta_i = 2\frac{i}{N}, \ k(\vartheta_i) = k(-\vartheta_i).$$

A sufficient condition for the fulfillment of equalities (3) – (5) is the limit equality:

$$\lim_{\vartheta \to \infty} k(\vartheta) \to 0. \tag{5}$$

Let us approximate the implementation of a centered stationary random process $\gamma(\tau)$ by an implementation that is represented by a sequence of random values of the material flow, constant in value during random time intervals $T_n$:

$$\gamma(\tau) = \sum_{n=0}^{\infty}(-1)^n\Theta\rho_n(\tau), \ \Theta_n = (-1)^n\Theta, \tag{6}$$

$$\rho_n(\tau) = H(\tau_n - \tau) - H(\tau_{n-1} - \tau), \ \tau_{-1} = 0;$$

$$H(S) = \begin{cases} 0, & S < 0, \\ 1, & S \ge 0, \end{cases} \quad \tau_n = \sum_{k=0}^{n} T_k, \ \tau_{-1} = 0. \tag{7}$$

where $\Theta$ is constant; $T_n$ is independent random variables with standard deviation $\sigma_{Tn}$ and mathematical expectation $m_{Tn}$; $H(x)$ is Heaviside function. Functions $\rho_n(\tau)$ are orthogonal functions on interval $\tau \in [\tau_{n-1}, \tau_n]$

$$\frac{1}{\tau_n - \tau_{n-1}} \int_{\tau_{n-1}}^{\tau_n} \rho_n(\tau)\rho_k(\tau)d\tau = \begin{cases} 1 & \text{if} \quad n = k, \\ 0 & \text{if} \quad n \neq k. \end{cases} \quad (8)$$

A centered stationary random process $\gamma(\tau)$ alternately takes values $\pm\Theta$ on interval $T_n$ upon the occurrence of the next event. Obviously, the one-dimensional distribution law of a centered stationary random process $\gamma(\tau)$ is discrete and has a distribution series

$$\gamma(\tau) : \left| \begin{array}{c|c} -\Theta & \Theta \\ \hline 0.5 & 0.5 \end{array} \right|. \quad (9)$$

For the presented approximation of random process $\gamma(\tau)$, it is necessary to build a generator that generates a random flow with statistical characteristics (3) – (5) that determine the centered stationary random process $\gamma(\tau)$.

## Construction of a generator of input material flow values

The sequence of values of random variables $((-1)^n \Theta, T_n)$ form the implementation of a centered stationary random process

$$\gamma(\tau) = H(\tau_0 - \tau)\Theta + ... = \Theta , \quad 0 \leq \tau < \tau_0 , \quad (10)$$

$$\gamma(\tau) = H(\tau_0 - \tau)\Theta + \left(H(\tau_1 - \tau) - H(\tau_0 - \tau)\right)(-\Theta) + ... =$$

$$= -\Theta , \quad \tau_0 \leq \tau < \tau_1 ,$$

$$\gamma(\tau) = H(\tau_0 - \tau)\Theta + ... = (-1)^n \Theta , \quad \tau_{n-1} \leq \tau < \tau_n .$$

Let us consider on the dimensionless time axis $[0, \tau]$ the simplest flow of events $T(\tau)$ with intensity $1/m_{Tn}$. At the moment of the occurrence of the event, the random process $\gamma(\tau)$ takes on the value $(-1)^n\Theta$, keeping it constant until the occurrence of the next event. We assume that the random variables $T_0$, $T_1$, $T_2$,… $T_n$, which determine the length of the time interval between events, have the same probability distribution density of the random variable $f_T(T)$ and are independent.

Let us determine the characteristics of a centered stationary random process $\gamma(\tau)$. Since the random variables $T_n$ are independent, taking into account the distribution series (9), we get

$$m(\tau) = -\Theta \cdot 0.5 + \Theta \cdot 0.5 = 0 , \quad (11)$$

$$\sigma^2 = (-\Theta)^2 \cdot 0.5 + \Theta^2 \cdot 0.5 = \Theta^2 .$$

The product $\Theta_n\Theta_{n+i}$ takes the value $\Theta_n\Theta_{n+i} = \Theta^2$ if in interval $\vartheta$ the value $i$ is even, and the value $\Theta_n\Theta_{n+i} = -\Theta^2$ otherwise. We will assume that the flow of events of switching values $\Theta_n$ is stationary, ordinary and without aftereffect. Such a stream of events is a Poisson stream of events, for which the probability of occurrence of $i$ events on an interval $\vartheta$ is determined by the expression

$$P_i(\vartheta) = \frac{1}{i!}\left(\frac{\vartheta}{m_T}\right)^i \exp\left(-\frac{\vartheta}{m_T}\right), \quad (12)$$

Then the probability that in interval $\vartheta$ value $i$ is even, and therefore $\Theta_n\Theta_{n+i} = \Theta^2$ can be represented as the sum over even values $i = 2k$

$$P_{\Theta_n\Theta_{n+i} = \Theta^2} = \sum_{k=0}^{\infty} P_{2k} = \sum_{k=0}^{\infty} \frac{1}{2k!}\left(\frac{\vartheta}{m_T}\right)^{2k} \exp\left(-\frac{\vartheta}{m_T}\right) =$$

$$= \exp\left(-\frac{\vartheta}{m_T}\right) \sum_{k=0}^{\infty} \frac{1}{2k!}\left(\frac{\vartheta}{m_T}\right)^{2k} . \quad (13)$$

To simplify the writing of this expression, we use the Taylor series expansion for the hyperbolic cosine

$$\frac{1}{2}\left(\exp\left(\frac{\vartheta}{m_T}\right) + \exp\left(-\frac{\vartheta}{m_T}\right)\right) = \sum_{k=0}^{\infty} \frac{1}{2k!}\left(\frac{\vartheta}{m_T}\right)^{2k} , \quad (14)$$

As a result, we obtain the final records of the probabilities that on the interval $\vartheta$ the value $i$ is either even or odd

$$P_{\Theta_n\Theta_{n+i} = \Theta^2} = \sum_{k=0}^{\infty} P_{2k} = \exp\left(-\frac{\vartheta}{m_T}\right) \frac{1}{2}\left(\exp\left(\frac{\vartheta}{m_T}\right) + \right.$$

$$\left. + \exp\left(-\frac{\vartheta}{m_T}\right)\right) = \frac{1}{2}\left(1 + \exp\left(-\frac{2\vartheta}{m_T}\right)\right); \quad (15)$$

$$P_{\Theta_n\Theta_{n+i} = -\Theta^2} = 1 - P_{\Theta_n\Theta_{n+i} = \Theta^2} = \frac{1}{2}\left(1 - \exp\left(-\frac{2\vartheta}{m_T}\right)\right). \quad (16)$$

To determine the correlation function of a random process $\gamma(\tau)$, we use the following formula

$$k(\vartheta) = M[\gamma(\tau)\gamma(\tau - \vartheta)] = M\left[\left(\sum_{n=0}^{\infty} \Theta_n \rho_n(\tau)\right)\left(\sum_{i=0}^{\infty} \Theta_i \rho_i(\tau + \vartheta)\right)\right] =$$

$$= \Theta^2 P_{\Theta_n\Theta_{n+i} = \Theta^2} + \left(-\Theta^2\right) P_{\Theta_n\Theta_{n+i} = -\Theta^2} =$$

$$= \Theta^2 \frac{1}{2}\left(1 + \exp\left(-\frac{2\vartheta}{m_T}\right)\right) + \left(-\Theta^2\right)\frac{1}{2}\left(1 - \exp\left(-\frac{2\vartheta}{m_T}\right)\right) =$$

$$= \Theta^2 \exp\left(-\frac{2\vartheta}{m_T}\right). \quad (17)$$

Correlation function $k(\vartheta)$ for flow $\gamma(\tau)$ (6) satisfies the limit equality (5), which is a sufficient condition for the fulfilment of equalities (3) and (4), which are used to calculate the statistical characteristics of the approximated random process $\gamma(\tau)$.

The probability that more than one event will not occur in section $\vartheta$ can be written in the following form

$$P_0(\vartheta) = \exp\left(-\frac{\vartheta}{m_T}\right). \quad (18)$$

Then the distribution law for the length of the interval $T_n$ between two events in the simplest stream of events can be found from the relation

$$F_T(T) = P(T < \tau) = 1 - P(T \geq \tau) = 1 - P_0(T) =$$

$$= 1 - P_0(T) = 1 - \exp\left(-\frac{T}{m_T}\right) \qquad (19)$$

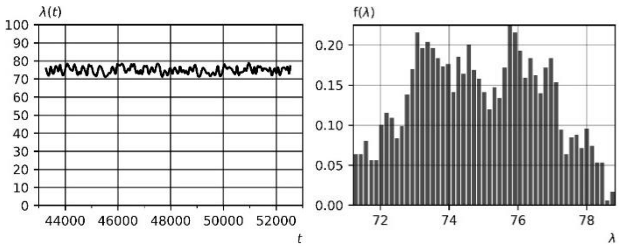
$$f_T(T) = \frac{dF_T(T)}{dT} = \frac{1}{m_T}\exp\left(-\frac{T}{m_T}\right),$$

$$1 = \int_0^\infty \frac{1}{m_T}\exp\left(-\frac{T}{m_T}\right)dT, \; m_T = M[T]. \qquad (20)$$

We use the resulting distribution law to generate the length of the time interval $T_n$ between two events in the canonical representation of the stochastic flow of material (6), (7).

## Analysis of results

As an example, consider the construction of a generator of input material flow values, which allows you to simulate the material flow entering the entrance of the main conveyor of the Hong Thai coal company (Vietnam) mine when operating in the mode of four treatment areas. To analyse the loading and movement of coal along scraper and belt conveyors during explosive breaking of coal by several working faces of the transport system of the Hong Thai coal company (Vietnam) mine, field observations of the loading of the main conveyor were carried out (02/17/2017). The mine operated in four treatment areas. The volume of coal was recorded using conveyor scales at intervals close to a minute. The experiment was carried out for 3 hours. The experimental observations presented in Fig. 1 were used and processed in the research paper of Bui Trung Kien (Vietnam) when checking the adequacy of the developed mathematical model for loading and moving coal along scraper and belt conveyors. The model result for a given material flow implementation assumed a constant value of $\lambda(t) = 75$ for the time interval shown in Fig. 1. This result can be taken as a zero approximation when modelling the movement of material along the transportation route.




a b

**Fig. 1**: Results of experimental observation of the loading of the main conveyor of the Hong Thai coal company (Vietnam) mine during the operation of four treatment areas: a – implementation of the input material flow; b – histogram of the distribution of values λ of the input material flow

The next approximation is the approximation of the implementation of a stationary random process $\lambda(t)$ by implementation, represented by a sequence of random values of material flow, constant in value during random time intervals and having the statistical characteristics of the original implementation, which improving the accuracy of modelling a conveyor-type transport system.

Fig. 2 shows the input flow of material $\lambda(\tau)$ in dimensionless form $\gamma_f(\tau)$, taking into account dimensionless parameters (1), (2). Let us approximate the implementation of the dimensionless material flow $\gamma_f(\tau)$ by an implementation represented by a sequence of random values of the material flow (6), constant in value during random time intervals $T_n$.

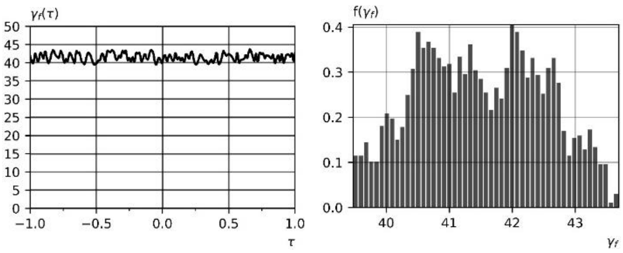



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**Fig. 2**: Dimensionless input material flow $\gamma_f(\tau)$: a – implementation of the input material flow; b – histogram of the distribution of values $2\gamma_f$ of the input material flow

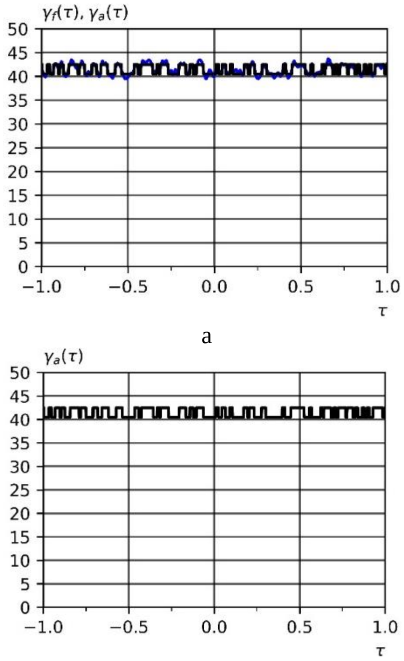
When approximating the implementation of a dimensionless material flow $\gamma_f(\tau)$, we use the following rule:

$$\begin{cases} \gamma_a(\tau) = m_0 + \Theta, & \gamma(\tau) \geq 0; \\ \gamma_a(\tau) = m_0 - \Theta, & \gamma(\tau) < 0. \end{cases} \qquad (21)$$

The result of the approximation for the implementation of dimensionless material flow $\gamma_f(\tau)$ is shown in Fig. 3. The error of approximation $\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau)$ of the implementation of the dimensionless flow of material $\gamma_f(\tau)$ is presented in Fig. 4.

For comparison, the approximation error was studied for the zero approximation $\varepsilon(\tau) = \gamma_f(\tau) - m_f = \gamma(\tau)$. Also, to compare two approximation options, Q-Q plots (Quantile-to-Quantile) were built (Fig. 5). The external similarity of the two graphs is explained by the fact that during intervals $T_n$ the value of the material flow remains a constant value. The presence of tails indicates a deviation from the normal distribution law and the presence of restrictions on the lower and upper values of the material flow realization.

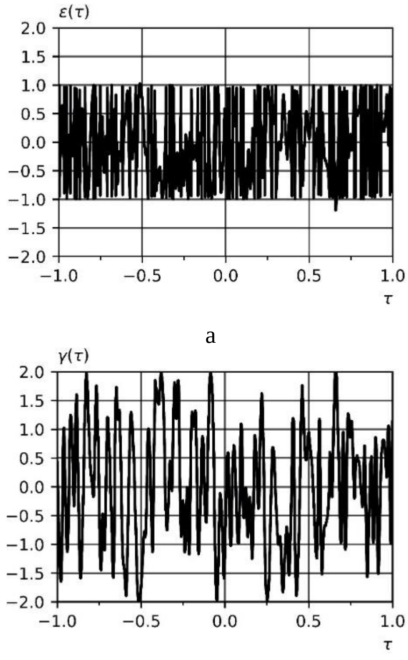
The distribution histogram for the simplest flow of events $T(\tau)$, constructed based on the results of approximation of the implementation of the dimensionless flow of material $\gamma_f(\tau)$, is presented in Fig. 6., a. When approximating the experimental implementation of the dimensionless material flow $\gamma_f(\tau)$ in interval $\tau \in [-1,1]$, 68 elements $T_n$ were used. Then, for comparative analysis in interval $\tau \in [-1,1]$, a material flow was generated in accordance with expression (6), which contains 60 elements $T_n$. The histogram of the distribution of values $T_n$ is presented in Fig. 6, b. Analysis of the results obtained indicates that the number of elements used to approximate and generate the flow of material is insufficient to conclude that the simplest flow of events $T(\tau)$ has an exponential distribution law.




a

b

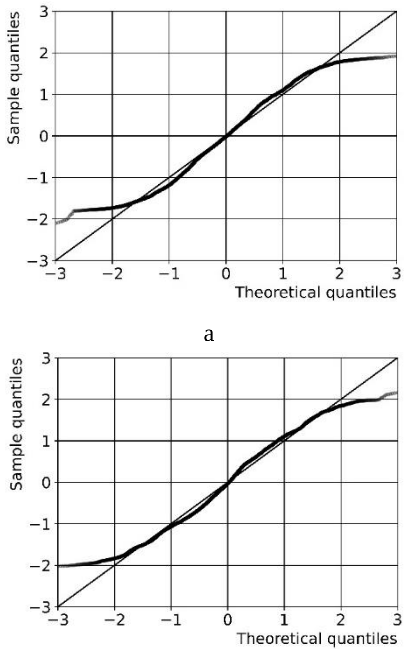
**Fig. 3**: Dimensionless input material flow: a – comparative analysis of implementations $\gamma_a(\tau)$, $\gamma_f(\tau)$ of the input material flow; b – implementation of input material flow $\gamma_a(\tau)$




a

b

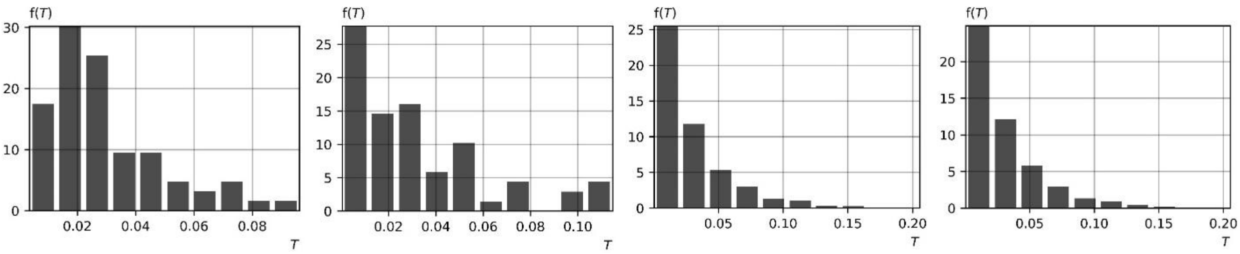
**Fig. 4**: Approximation error for the implementation of dimensionless material flow $\gamma_f(\tau)$: a – $\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau)$; b – $\varepsilon(\tau) = \gamma_f(\tau) - m_f$




a

b

**Fig. 5**: Q-Q plots (Quantile-to-Quantile): a – $\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau)$; b – $\varepsilon(\tau) = \gamma_f(\tau) - m_f$

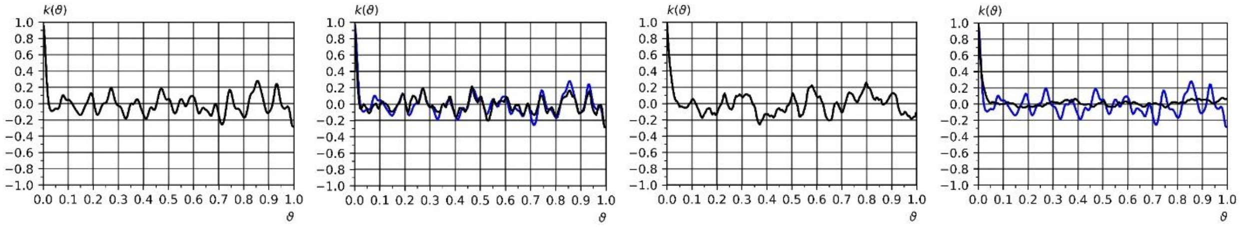



a b c d

**Fig. 6**: Distribution histogram for the simplest flow of events $T(\tau)$:
a) the result of approximation of the implementation of a dimensionless flow of material $\gamma_f(\tau)$ on interval $\tau \in [-1; 1]$;
b) the result of generating the simplest stream of events $T(\tau)$ on interval $\tau \in [-1; 1]$;
c) the result of generating the simplest stream of events $T(\tau)$ on interval $\tau \in [-1; 15]$;
d) the result of generating the simplest stream of events $T(\tau)$ on interval $\tau \in [-1; 31]$

Thus, it follows that to perform the approximation, an experimental implementation of the material flow is required for a time interval containing from 500 to 1000 elements $T_n$. Histograms for the simplest flow of events $T(\tau)$, generated at intervals $\tau \in [-1; 15]$ and $\tau \in [-1; 31]$, containing from 500 to 1000 elements $T_n$ are presented in Fig. 6, c and 6, d, respectively. With an increase in the number of elements $T_n$, and, accordingly, the length of the interval for the implementation of the input flow of material, the distribution histogram takes on a characteristic form for the exponential distribution law.

A comparative analysis of correlation functions for the experimental, approximated and generated implementations of the input material flow is presented in Fig. 7. The correlation function for approximated implementation $\gamma_a(\tau)$ (Fig. 7, b) repeats the function for experimental implementation $\gamma_f(\tau)$ with a sufficient degree of accuracy. High accuracy is achieved in interval $\vartheta \in [0;\ m_T]$, where $m_T \approx 0.029$ is achieved for the experimental implementation of the input material flow. The correlation time for the experimental implementation of the input material flow, as follows from theoretical calculations, is approximately equal to the mathematical expectation of the random variable $T_n$. A similar conclusion can be made for the correlation function of the generated implementation of the input material flow (Fig. 7.c). The correlation function for the generated implementation of the input material flow at time interval $\tau \in [-1; 1]$ has periodic fluctuations around the zero value. When the length of the interval increases to a size containing from 500 to 1000 elements $T_n$, the correlation function takes on a pronounced exponential dependence, determined by theoretical calculations (Fig. 7, d). The amplitude of periodic oscillations of the implementation correlation function for time interval $\tau \in [-1; 31]$ is significantly less than for time interval $\tau \in [-1; 1]$. The correlation function, like the distribution histogram, approaches the form determined by theoretical calculations.




a b c d

**Fig. 7**: Correlation function $k(\vartheta)$ for the implementation of the input material flow:
a) initial implementation of the input material flow;
b) comparison of the original and approximated implementations of the input material flow;
c) generated implementation of the input material flow at interval $\tau \in [-1; 1]$;
d) comparison of the original and generated implementations of the input material flow at interval $\tau \in [-1; 31]$

Comparative analysis of statistical characteristics for the experimental, approximated and generated implementation of the input material flow for time interval $\tau \in [-1; 1]$ is presented in Table 1. The mathematical expectation and standard deviation for the experimental, approximated and generated implementation of the input material flow have fairly close values, which indicates the quality of the experimental approximation process implementation.

The generated implementation of the input material flow and the correlation function for it are presented in Fig. 8.

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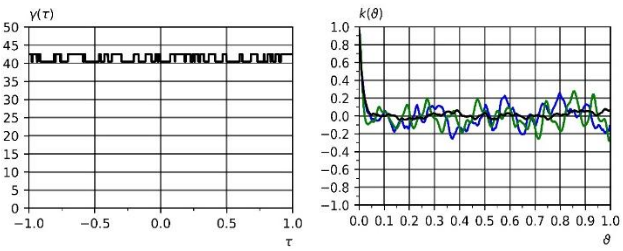
*Table 1* – **Characteristics of the implementation of the input material flow**

| Parameter | Original implementation | Approximate implementation | The generated implementation |
|---|---|---|---|
| Mathematical expectation | 41.4953177 | 41.4758254 | 41.4518000 |
| Standard deviation | 1.0 | 0.99992330 | 0.99916590 |
| Maximum value | 43.6898579 | 42.4953177 | 42.4953177 |
| Minimum value | 39.4717485 | 40.4953177 | 40.4953177 |




a b

**Fig. 8**: Input material flow $\gamma(\tau)$: a) implementation of the input material flow generated; b) comparative analysis of correlation functions for the experimental, approximated and generated implementation of the material flow on interval $\tau \in [-1; 31]$

For a time interval for generating values of the input material flow that satisfies the condition of the minimum permissible number of elements $T_n$, the correlation function for implementing the input material flow corresponds with sufficient accuracy to the theoretical correlation function. The accuracy of the approximation directly depends on the length of the time interval required to perform experimental measurements of the input material flow values.

## Conclusions

This study addresses the current problem of generating a training data set for training a neural network in a model of a branched, extended transport pipeline. Transport systems are considered whose input stream implementations allow an approximation in the form of a simple stream of events. The approximation of the material flow is represented by alternating two given constant values of the input material flow between events at interval $T_n$. During the approximation, it was assumed that the flow of events characterizing the process of material receipt at the input of the transport system is stationary, ordinary and without aftereffect.

To generate a training set of data obtained as a result of the generated implementation of the input stream of material, a two-stage method is proposed. At the first stage, using the canonical expansion for given coordinate functions, the experimental implementation of the input material flow is approximated on interval $\tau \in [-1; 1]$. At the second stage, the statistical characteristics of the approximation implementation of the input material flow are calculated. These characteristics are further used to generate random values of the input material flow for the transport conveyor. A justification for the validity of approximating experimental data by a given sequence of two alternating values of material flow is presented. The analysis of the correlation functions, mathematical expectation and standard deviation indicates satisfactory accuracy of the process of generating values of the input material flow. The assessment of the minimum permissible length of the time interval for performing experimental measurements deserves special attention.

When generating random values that form the implementation of the input material flow, the statistical characteristics of the generated implementation correspond to the statistical characteristics of the experimental implementation.

It is shown that the length of the time interval has a significant impact on the statistical characteristics of the constructed implementation of the input material flow. If the interval length is unsatisfactory, the statistical characteristics of the experimental implementation may have a significant deviation from their actual values, which leads to low quality of the generated data set, which is used to train the neural network.

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## Основні принципи побудови генератора значень вхідного матеріального потоку транспортних систем конвеєрного типу

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**Анотація. Об'єкт дослідження –** стохастичний стаціонарний вхідний потік матеріалу транспортної системи конвеєрного типу. **Предметом дослідження** є розробка методу генерації навчального набору даних для нейронної мережі в моделі транспортного конвеєра. **Мета дослідження** полягає в розробці генератора випадкових значень для побудови реалізації вхідного потоку матеріалу транспортного конвеєра, який має задані статистичні характеристики, розраховані за результатами попередньо проведених експериментальних вимірювань. **Отримані результати.** У статті розглядається клас стохастичних матеріальних потоків транспортної системи, для яких можна апроксимувати експериментальну реалізацію випадкового процесу реалізацією, що відповідає найпростішому потоку з чергуванням двох заданих значень вхідного матеріального потоку між подіями. Представлено метод генерації значень вхідного матеріального потоку з метою формування набору даних для навчання нейронної мережі в моделі розгалуженого транспортного конвеєра. Визначено основні принципи побудови генератора величин вхідного матеріального потоку. Обгрунтовано використання єдиної експериментальної реалізації стохастичного вхідного матеріального потоку для розрахунку статистичних характеристик для побудови генератора значень вхідного матеріального потоку. Безрозмірні параметри були введені для спрощення опису стохастичних потоків вхідних матеріалів і для визначення критеріїв подібності для стохастичних потоків вхідних матеріалів. Реалізація стохастичного вхідного потоку матеріалу представлена у вигляді розкладу в ряд за координатними функціями. Визначено закон розподілу довжини інтервалу часу між двома подіями найпростішого потоку подій, який використовується для апроксимації реалізації вхідного матеріального потоку. Проведено порівняльний аналіз кореляційних функцій для експериментальної, апроксимованої та згенерованої реалізацій вхідного матеріального потоку. Обгрунтовано тривалість інтервалу часу, необхідного для проведення експериментальних змін потоку вхідного матеріалу. Наведено оцінки статистичних характеристик реалізацій вхідного матеріального потоку.


**Ключові слова:** транспортний конвеєр; нейронна мережа; випадковий процес; генератор набору даних; реалізація.