Development of a Method for Generating Material Input Flow for Transport Conveyor Using Experimental Data

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Abstract

This work is devoted to the development of a method for generating values of the input material flow of a transport conveyor based on experimental data. The experimental data are represented by a single realization of the material flow for a sufficiently large observation time interval. The statistical characteristics of the implementation of the input material flow are studied. To determine the values of the correlation function, the numerical integration method was used. To analyze statistical characteristics, dimensionless parameters are introduced that can be used to construct similarity criteria for input material flows. When constructing the generator of the input material flow, the canonical expansion of the random process in orthogonal functions is used. This decomposition allows transformations to be carried out over a stochastic input flow of material. It is assumed that the implementation of the input material flow is formed for the steady state of material extraction. As a zero approximation when constructing generators of the input material flow values, it is stipulated that random measurements in the canonical expansion have a normal distribution law. Orthogonal functions are represented by a normalized Fourier series. It is shown that centered random variables of the canonical expansion have dispersion values that are defined as expansion coefficients of the correlation function in a Fourier series. Analysis of the generated material flow realization shows that its values have a distribution close to the normal distribution. An example of realization using a random value generator for the input material flow is presented. The accuracy of the realization is determined by the number of terms in the Fourier series expansion and the accuracy of the numerical integration method

Keywords

Belt conveyor, input material flow, dataset generator, stochastic material flow, normal distribution, stochastic process realization, statistical characteristic, correlation function, ergodic process

1. Introduction

The modern mining industry is inextricably linked with technological and engineering innovations that are aimed at increasing the efficiency of the mining process [1]. In this context, belt conveyors play an important role in the technological process, providing automated movement of material along the transport route [2,3]. Traditional conveyor belt control models assume that input material flows are deterministic flows [4, 5]. However, as experimental studies demonstrate, the input material flow is a stochastic flow [6, 7]. This complicates the management of flow parameters of the transport system [8]. Designing highly efficient control systems requires both the construction of new types of transport conveyor models that would take into account the stochastic characteristics of the input material flow and the modification of existing models [9, 10]. One of the ways to analyze the quality of control systems for the flow parameters of a transport conveyor is to use generators of random values of the

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input material flow [11]. The generator of input material flow values must be able to create implementations of the input material flow with given statistical characteristics and correlation functions. One of the areas of application of such generators is the construction of data sets for training neural networks that are built into a transport system model [12, 13, 14]. One of the methods for simplifying the modeling of stochastic input material flows is the use of various types of distribution of random variables [15, 16]. Among these distributions, the most commonly used is the normal distribution, which is characterized by unbounded tails of the probability density function [17]. However, this approach, as a rule, does not take into account the specific patterns of formation of input flows, which are determined by a number of technical and technological factors. This limits the application of such models in environments where precise control of material flows is critical. To develop more accurate mathematical models for controlling material flows, it is necessary to conduct experimental studies based on real data [18, 19]. This requires a variety of conveyors with different characteristics of the incoming material, which is a difficult task in practice [20].

At the same time, there are experimental works [20, 21], that present a graphical realization of stochastic material flows entering the sections of working transport conveyors. These stochastic flow realizations serve as a valuable resource for building mathematical models and analyzing the statistical characteristics of input material flows.

The presence of a methodology for analyzing realizations of the input material flow will make it possible to determine the functional connections between the statistical characteristics of random variables of the material flow, which can be used as the basis for a generator of input material flow values. This approach can significantly improve the accuracy of models and the efficiency of material flow management in manufacturing. This paper explores the possibility of constructing a generator of stochastic material flow values based on functional connections between the statistical characteristics of the realization of the input material flow, constructed on the basis of the experimental data.

2. Problem statement

With a limited set of sample data specified by a single realization of a random process, time averaging for a stationary process $\lambda(t)$ can be replaced by averaging over the values set:

$$m_\lambda = \frac{1}{t_{\max} - t_{\min}} \int_{t_{\min}}^{t_{\max}} \lambda(t)dt = \int_{\lambda_{\min}}^{\lambda_{\max}} \lambda f_\lambda(\lambda)d\lambda\ , \quad (1)$$

$$\sigma_\lambda{}^2 = \frac{1}{t_{\max} - t_{\min}} \int_{t_{\min}}^{t_{\max}} (\lambda(t) - m_\lambda)^2 dt = \int_{\lambda_{\min}}^{\lambda_{\max}} (\lambda - m_\lambda)^2 f_\lambda(\lambda)d\lambda\,, \quad (2)$$

$$\lambda_{\max} = \max(\lambda(t)), \quad \lambda_{\min} = \min(\lambda(t)), \quad (3)$$
$$t_{\max} = \max(t), \quad t_{\min} = \min(t),$$

where $f_\lambda(\lambda)$ is the distribution density of the random variable of the input material flow:

$$1 = \int_{-\infty}^{\infty} f_\lambda(\lambda)d\lambda\ . \quad (4)$$

The correlation function of a stationary ergodic process $\lambda(t)$ is given by the expression:

$$k_\lambda(\eta) = \frac{1}{t_{\max} - t_{\min}} \int_{t_{\min}}^{t_{\max}} (\lambda(t) - m_\lambda)(\lambda(t+\eta) - m_\lambda)dt\,, \quad k_\lambda(\eta) = k_\lambda(-\eta)\,. \quad (5)$$

A sufficient condition for the fulfillment of equalities (1), (2) is the limit equality:

$$\lim_{\eta\to\infty} k_\lambda(\eta) \to 0 . \tag{6}$$

To describe the flow of material incoming at the input of the transport conveyor, let us introduce dimensionless parameters:

$$\gamma(\tau) = \frac{\lambda(t) - \lambda_{\min}}{\lambda_{\max} - \lambda_{\min}}, \quad \gamma(\tau) \in [0,1], \quad t \in [t_{\min}, t_{\max}], \tag{7}$$

$$\tau = 2\frac{t - t_{\min}}{t_{\max} - t_{\min}} - 1, \quad \tau \in [-1,1], \tag{8}$$

$$\eta = t_i - t_j = \frac{t_{\max} - t_{\min}}{2}\left(\tau_i - \tau_j\right) = \frac{t_{\max} - t_{\min}}{2}\vartheta, \tag{9}$$

$$\vartheta = \frac{2\eta}{t_{\max} - t_{\min}},$$

$$m = \frac{m_\lambda - \lambda_{\min}}{\lambda_{\max} - \lambda_{\min}}, \quad \sigma = \frac{\sigma_\lambda}{\lambda_{\max} - \lambda_{\min}} . \tag{10}$$

Taking into account the entered parameters, the material flow and its statistical characteristics are presented in dimensionless form:

$$1 = \int_{-\infty}^{\infty} f_s(\gamma) d\gamma , \tag{11}$$

$$m = \frac{1}{2}\int_{-1}^{1} \gamma(\tau) d\tau = \frac{1}{N+1}\sum_{n=0}^{N} \gamma(\tau_n), \quad \tau_n = \frac{2n}{N} - 1, \quad n = \overline{0, N}, \tag{12}$$

$$\sigma^2 = \int_{-\infty}^{\infty} (\gamma - m)^2 f(\gamma) d\gamma = \frac{1}{2}\int_{-1}^{1} (\gamma(\tau) - m)^2 d\tau = \frac{1}{N+1}\sum_{0}^{N} (\gamma(\tau_n) - m)^2 , \tag{13}$$

$$k_s(\vartheta_i) = \frac{1}{2}\int_{-1}^{1} (\gamma(\tau) - m)(\gamma(\tau + \vartheta_i) - m) d\tau = \int_{0}^{1} (\gamma(\tau) - m)(\gamma(\tau - \vartheta_i) - m) d\tau =$$

$$= \frac{2}{N+1}\sum_{n=N/2}^{N} (\gamma(\tau_n) - m)(\gamma(\tau_n - \vartheta_i) - m), \quad \vartheta_i = 2\frac{i}{N}, \quad i = \overline{0, \frac{N}{2}}, \tag{14}$$

$$k_s(\vartheta) = k_s(-\vartheta) .$$

The distribution density $f_s(\gamma)$ can be obtained by approximating the histogram of the distribution of the values of the input material flow.

It is required, using the presented characteristics of the implementation of the input material flow (11)–(14), to build a generator of values for the input material flow of a conveyor-type transport system.

3. Main material. Building a generator of the input material flow values

Let us present the expression for the input material flow $\gamma(\tau)$ in the form of an expansion:

$$\gamma(\tau) = m(\tau) + \sum_{n=0}^{\infty} \Theta_n \rho_n(\tau), \tag{15}$$

where Θ_n are centered independent random variables with standard deviation σ_n; $\rho_n(\tau)$ are non-random orthogonal functions; $m(\tau) = m$ is the mathematical expectation of the values of the material flow incoming in the input of the conveyor. This decomposition allows transformations to be carried out over a stochastic input material flow. The decomposition for a fixed point in time is represented by a linear combination of random variables Θ_n, which simplifies the determination of the statistical characteristics of the stochastic input material flow. All time dependence is concentrated in deterministic functions $\rho_n(\tau)$, which is the basis for determining the correlation function of material flow. Thus, the same correlation function $k(\vartheta)$ can correspond to a large number of expansion methods (15), presented as a composition of elementary random processes $\Theta_n \rho_n(\tau)$.

Let us determine the characteristics of the stochastic flow of material $\gamma(\tau)$. Since the time dependence is concentrated in a deterministic function $\rho_n(\tau)$, and random behavior in a random variable Θ_n, it follows:

$$M[\gamma(\tau)] = M\left[m(\tau) + \sum_{n=0}^{\infty} \Theta_n \rho_n(\tau)\right] = m + \sum_{n=0}^{\infty} M[\Theta_n \rho_n(\tau)] = m + \sum_{n=0}^{\infty} \rho_n(\tau) M[\Theta_n] = m, \tag{16}$$

$$D[\gamma(\tau)] = D\left[m(\tau) + \sum_{n=0}^{\infty} \Theta_n \rho_n(\tau)\right] = D\left[\sum_{n=0}^{\infty} \Theta_n \rho_n(\tau)\right] = M\left[\left(\sum_{n=0}^{\infty} \Theta_n \rho_n(\tau)\right)^2\right] =$$

$$= \sum_{n=0}^{\infty} \rho_n^2(\tau) M\left[\Theta_n^2\right] = \sum_{n=0}^{\infty} \rho_n^2(\tau) \sigma_n^2, \tag{17}$$

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

$$= M\left[\sum_{n=0}^{\infty}\sum_{i=0}^{\infty} \Theta_i \Theta_n \rho_i(\tau+\vartheta) \rho_n(\tau)\right] = M\left[\sum_{n=0}^{\infty} \Theta_n^2 \rho_n(\tau+\vartheta) \rho_n(\tau)\right] = \sum_{n=0}^{\infty} \sigma_n^2 \rho_n(\tau+\vartheta) \rho_n(\tau), \tag{18}$$

where $M[\Theta_i \Theta_n] = 0$, due to the fact that centered random variables Θ_n are independent random variables.

Expansion (15) is the canonical expansion of a stochastic process $\gamma(\tau)$ in coordinate functions $\rho_n(\tau)$. Centered random variables Θ_n act as coefficients of the canonical expansion.

It is assumed that the implementation of the input material flow is formed for the steady state of material extraction. Therefore, we will assume that the probabilistic characteristics of the stochastic process do not depend on time. Thus, the one-dimensional distribution density of the values of the stochastic input material flow (4) does not depend on time, and the mathematical expectation and dispersion of the stochastic material flow are constant values.

Let us present the decomposition of the stochastic flow of material (15) in the following form:

$$\gamma(\tau) = m + A_0 + \sum_{n=0}^{\infty} \left(A_n \cos(\pi\tau) + B_n \sin(\pi\tau)\right), \tag{19}$$

where random variables A_0, A_n, B_n are independent variables:

$$M[A_j B_n]=0 \ , \ \text{ and } M[A_j A_n]=M[B_j B_n]=0 \quad \text{if } j \neq n , \tag{20}$$

with mathematical expectations equal to zero and standard deviations σ_0, σ_n:

$$M[A_0]=M[A_n]=M[B_n]=0 , \tag{21}$$

$$D[A_0]=\sigma_0^2 , \ D[A_n]=D[B_n]=\sigma_n^2 . \tag{22}$$

The correlation function (18) for the stochastic material flow (19) taking into account equalities (20), (21) can be represented as:

$$k(\vartheta)=\sigma_0^2+\sum_{n=1}^{\infty}\sigma_n^2\cos(\pi(\tau+\vartheta))\cos(\pi\tau)+\sigma_n^2\sin(\pi(\tau+\vartheta))\sin(\pi\tau)=$$

$$=\sigma_0^2+\sum_{n=1}^{\infty}\sigma_n^2(\cos(\pi(\tau+\vartheta))\cos(\pi\tau)+\sin(\pi(\tau+\vartheta))\sin(\pi\tau))=\sigma_0^2+\sum_{n=1}^{\infty}\sigma_n^2\cos(\pi\vartheta) . \tag{23}$$

Unknown values of expansion coefficients σ_0^2, σ_n^2 can be found from the correlation function $k_s(\vartheta)$ (14), the values of which are determined taking into account the stochastic flow of material in the realization $\gamma(\tau)$:

$$\sigma_0^2=\frac{1}{2}\int_{-1}^{1}k_s(\vartheta)d\vartheta=\int_{0}^{1}k_s(\vartheta)d\vartheta , \tag{24}$$

$$\sigma_n^2=\int_{-1}^{1}k_s(\vartheta)\cos(\pi n\vartheta)d\vartheta=2\int_{0}^{1}k_s(\vartheta)\cos(\pi n\vartheta)d\vartheta , \tag{25}$$

$$\sigma^2=k(0)=\sigma_0^2+\sum_{n=1}^{\infty}\sigma_n^2 . \tag{26}$$

Expansion coefficients σ_0^2, σ_n^2 depend on the specific type of correlation function $k_s(\vartheta)$ (14). As a zero approximation, it is assumed that the independent random variables A_0, A_n, B_n have a normal distribution law:

$$A_0 \Rightarrow f(a_0)=\frac{1}{\sigma_0\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{a_0}{\sigma_0}\right)^2\right) , \tag{27}$$

$$A_n \Rightarrow f(a_n)=\frac{1}{\sigma_n\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{a_n}{\sigma_n}\right)^2\right) , \tag{28}$$

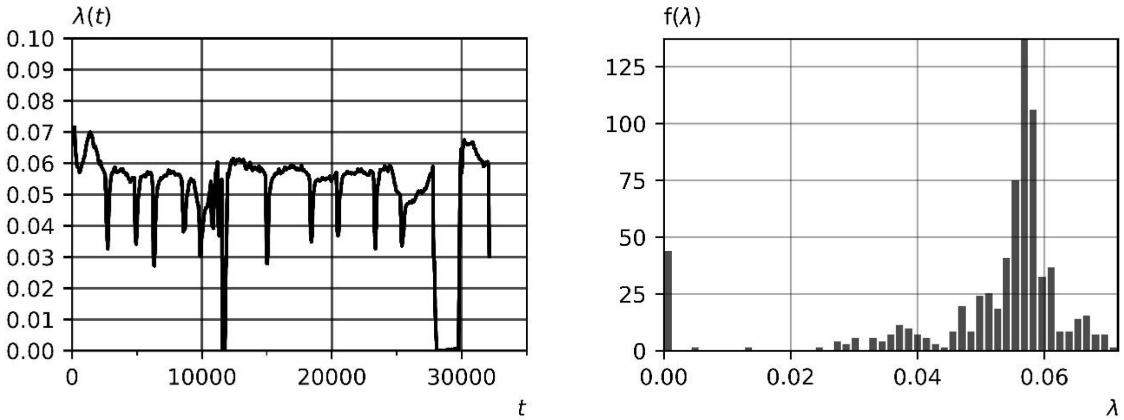
$$B_n \Rightarrow f(b_n)=\frac{1}{\sigma_n\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{b_n}{\sigma_n}\right)^2\right) .$$

When decomposing a random process $\gamma(\tau)$ the following circumstances should be taken into account: a) the functions $\rho_n(\tau)$ are orthogonal and normalized functions. The type of coordinate functions can be chosen in a large number of ways; b) canonical expansion (15) does not allow determining the distribution law of the values of the stochastic flow of material $\gamma(\tau)$. The canonical expansion may have different distribution laws depending on the chosen distribution laws for random variables Θ_n; c) practical methods for constructing the canonical expansion (15) should be based on data represented by realizations of the stochastic input material flow $\gamma(\tau)$.

Statistical data presented by material flow realizations make it possible to determine the coefficients of expansion of the correlation function $k(\vartheta)$ into a series of coordinate functions $\rho_n(\tau)$.

4. Analysis of results

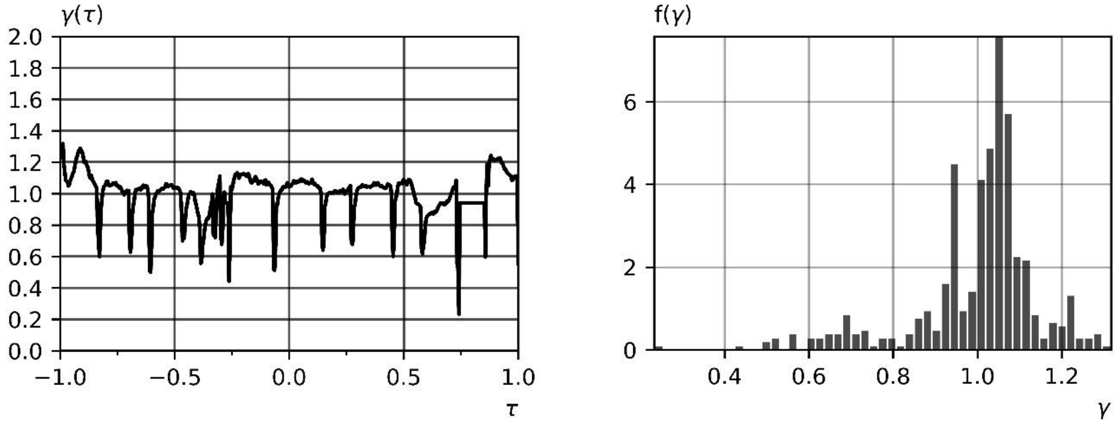
Let's consider the input flow of material arriving at the entrance of the transport conveyor (NCC Industry, Sweden) Figure 1 [21]. To measure the material flow, mass-measuring devices connected to the cloud solution were used. The collected experimental data was recorded in cloud storage at a frequency of 0.1–0.2 Hz.



a) b)

Figure 1: Input material flow $\lambda(t)$ (NCC Industry, Sweden, [21]): a) realization of the input material flow; b) histogram of distribution the input material flow values λ.

Taking into account dimensionless parameters (7)–(10), the input material flow $\lambda(t)$ is presented the in dimensionless form $\gamma(\tau)$ (Figure 2), which will be used to build a generator of material flow values incoming at the input of the transport system.



a) b)

Figure 2: Dimensionless input material flow $\gamma(\tau)$: a) realization of the input material flow; b) histogram of distribution the input material flow values γ.

Based on experimental data, let us construct the correlation function (14) for the dimensionless implementation of the input material flow $\gamma(\tau)$. The correlation function $k_s(\vartheta)$ obtained in this way is used to determine the expansion coefficients σ_0^2, σ_n^2 (24)–(26). The spectrum for expansion coefficients σ_0^2, σ_n^2 and correlation functions $k_s(\vartheta)$ presented in Figure 3.

For the spectrum calculated on the basis of experimental data, represented by expansion coefficients σ_0^2, σ_n^2, in accordance with expression (23), an approximation correlation function is constructed. The accuracy of approximation of the correlation function (14) by the Fourier series (23) with expansion coefficients σ_0^2, σ_n^2 (24), (25), is demonstrated in Figure 4.

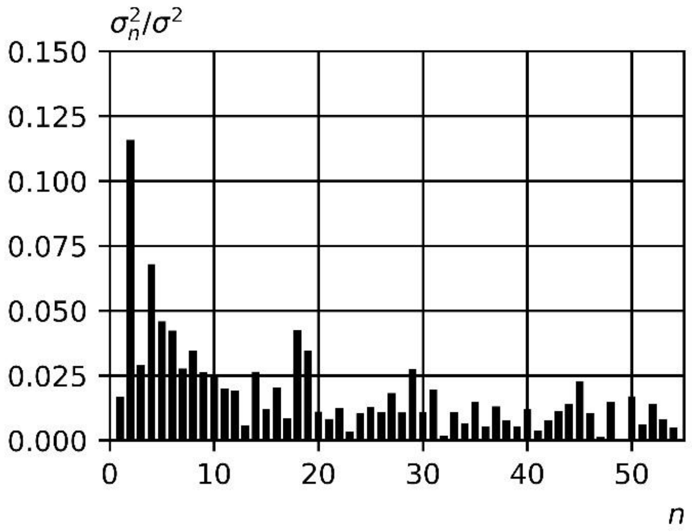


Figure 3: Spectrum of expansion coefficients σ_0^2, σ_n^2 and the correlation function $k_s(\vartheta)$

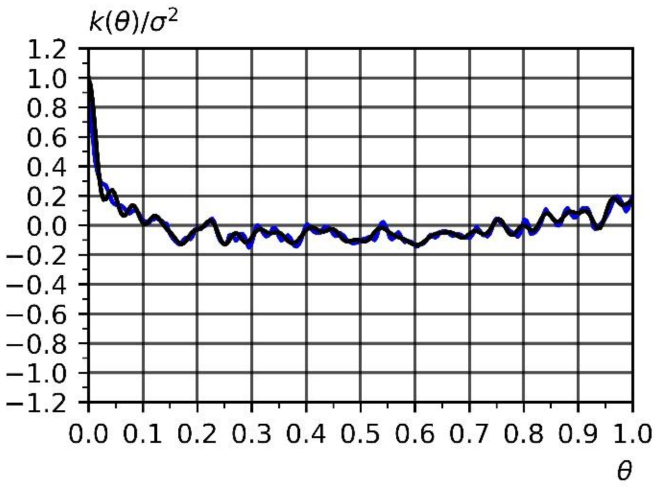
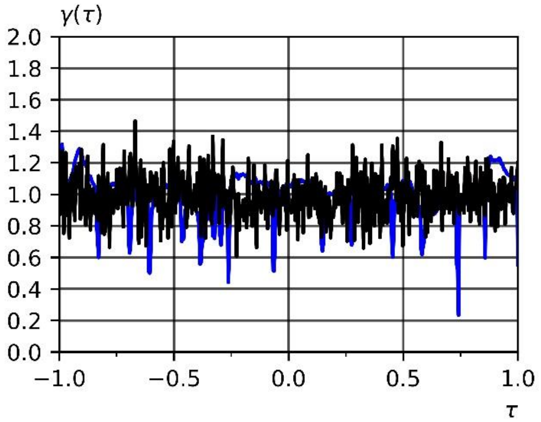
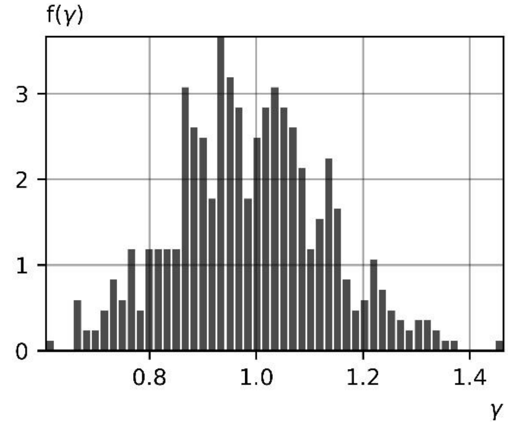


Figure 4: The correlation function $k_s(\vartheta)$ (blue line) and its representation by a Fourier series with the expansion coefficients σ_0^2, σ_n^2 (black line)

Let us generate values for the dimensionless input material flow $\gamma(\tau)$ in accordance with the canonical representation of the stochastic process (19). As a zero approximation, as emphasized above, it is assumed that the random variables A_0, A_n, B_n are the centered random variables and have a normal distribution law (27), (28) with the values of the standard deviations σ_0, σ_n, the square of which is presented in the form of an expansion spectrum of the experimental correlation function $k_s(\vartheta)$ (Figure 3). An example of the realization of the input material flow values and the histogram of the distribution of these values are presented in Figure 5.



a)



b)

Figure 5: The generated input material flow $\gamma(\tau)$: a) the realization of the input material flow (the blue line is the realization of the input material flow based on experimental data; the black line is the generated implementation of the input material flow); b) the distribution histogram for the generated material input flow values.

Two realizations of the input material flow have close values for the mathematical expectation and standard deviation, as well as, with a sufficient degree of accuracy, the same dependences of the correlation function on the correlation time (Figure 4). Characteristics of the input material flow for the realization constructed on the basis of experimental data and for the generated input material flow values are presented in Table 1. The difference in the values of statistical characteristics is explained by the limited number of terms of the Fourier series and the error in numerical integration.

Table 1
The characteristics of the realization of the input material flow

Parameter	Realization of input material flow values based on experimental data	The generated realization of input material flow values
Mathematical expectation	1.0	0.9880261
Standard deviation	0.1454249	0.1409089
Maximum value	1.3173883	1.4635336
Minimum value	0.2329674	0.6062985

As one would expect, the distribution law for the generated material flow values is close to the normal distribution law. Indeed, for a fixed point in time, the generated value of the input material flow in accordance with expression (19) is a linear function of uncorrelated normally distributed centered random variables A_0, A_n, B_n with standard deviations σ_0, σ_n. Consequently, the random value of the material flow $\gamma(\tau)$ is distributed according to the normal distribution law. However, despite the fact that two implementations of the input material flow (formed on the basis of experimental data and generated values) have the same type of correlation function (Figure 4) and similar values of statistical characteristics (Table 1), the material flows, that they represent are sufficiently differ considerably. The type of distribution law for the values of the input material flow has a significant impact on the form of realization of the input material flow.

5. Conclusions

When constructing a generator of the realization of the input material flow values for the NCC Industry option (Sweden, [21]), the assumption is made that the random variable that determines the average value of the input material flow over an interval of the measure has a normal distribution law. The analysis of the generated material flow based on the statistical characteristics of the experimental realization of the material flow $\lambda(t)$ shows:

a) the mathematical expectation, standard deviation and maximum (minimum) value of the generated material flow correspond to these values for the realization of the material flow based on experimental data;

b) the expansion coefficients of the correlation function σ_0^2, σ_n^2, in accordance with expressions (23), (24) make it possible to construct an approximation correlation function for the implementation of the input material flow The accuracy of the approximation is determined by the number of terms in the Fourier series expansion and the accuracy of the numerical integration method;

c) the canonical expansion (19) does not indicate what distribution law the centered random variables A_0, A_n, B_n should have, but only indicates the values of the standard deviations σ_0, σ_n for the centered random variables A_0, A_n, B_n. In this regard, the choice of the distribution law for the centered random variables A_0, A_n, B_n becomes important when constructing a generator for the realization the input material flow values;

d) the use of the assumption of a normal distribution law for the values of the input material flow when modeling conveyor-type transport systems requires additional analysis of the cases when such an assumption is justified.

The prospect for further research is the development of methods for determining the law of distribution of values of the material input flow of a transport conveyor based on the statistical characteristics of the realization of the material flow, constructed on the basis of the experimental data.

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