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STATIONARY STOCHASTIC INPUT FLOW MODELING OF BRANCHED CONVEYOR SYSTEMS

Abstract: The object of research is stochastic stationary input material flow of a conveyor-type transport system. Subject of research is a method for generating realizations of a stationary stochastic input flow of material on the basis of experimental data. **The goal** of the research consists in the development of a random value generator for constructing an implementation of the input material flow of a transport conveyor, which has specified statistical characteristics, calculated on the basis of the previously performed experimental measurements results. **The results** obtained. The stationary stochastic input flow of material is represented by a canonical expansion as a sum of harmonic oscillations with random amplitudes at various non-random frequencies. A two-stage approach is proposed for forming realizations of the input material flow. At the first stage, using the canonical expansion in given coordinate functions, the experimental realization of the input material flow for a given interval is approximated. At the second stage, statistical characteristics of the implementations of the input material flow are calculated. The conducted analysis showed that the application of the smoothing method for the realizations of the material flow, based on the canonical decomposition of the realizations of the input material flow, ensures a sufficiently accurate reproduction of the statistical characteristics like a flow, which is important when designing effective systems for managing the flow parameters of a transport system. A comparative analysis of correlation functions for experimental, approximated and generated implementations of the input material flow is figured out. The length of the time interval required to carry out experimental changes in the input material flow is justified. **Conclusion.** The methods of generating input flows based on experimental data proposed in the paper allow increasing the accuracy of modeling and control of conveyor systems, which in the long term can lead to a decrease in operating costs and an increase in the productivity of conveyor-type transport systems.

Keywords: material flow; stochastic process; random variable generator; approximation error.

Introduction

Conveyor systems are key elements in the mining industry and play a vital role in increasing the efficiency of production processes and reducing material transportation costs. Reducing the cost of resource extraction is possible, in particular, by reducing the specific costs of raw material transportation, which is achieved through optimal and uniform loading of materials along the entire length of the transport line [1,2,3]. Efficient use of conveyor systems allows achieving maximum loading factor of the transport conveyor, which significantly improves system performance and reduces maintenance costs [4,5]. However, one of the main problems remains the uneven loading of the material, which occurs for several reasons. Firstly, it is the stochastic nature of the input flow of material arriving at the entrance of the transport system [6]. Secondly, the use of control systems to regulate the speed of the conveyor belt or the flow of material from the storage bins [7].

The problem of uneven loading becomes even more complex when using combined control systems, which simultaneously regulate the speed of the conveyor belt and the feed of material from the bunkers [8]. These control systems do not always provide ideal balancing of material flows due to the complexity of process dynamics and the presence of variable time lags in the transport system [9]. As a result, this leads to a decrease in the efficiency of flow parameter control systems, especially for long and highly branched transport routes.

In order to minimize the unevenness of the material flow at each stage of transportation, control systems for individual conveyor sections are used. These systems allow the belt speed to be adapted depending on the current loading conditions, which makes it possible to achieve a quasi-uniform feed of the material and thus the required values for the output flow of the material [10]. However, the quasi-stationary flow entering the next conveyor section usually causes uneven material flow at subsequent stages of transportation, which leads to a decrease in the efficiency of the entire system [3].

When designing control systems for such complex transport systems, various mathematical models are used. One of the most common approaches is the use of the finite element method [11], which allows modeling the behavior of traffic flows taking into account time delays and other features of the transport system. For more complex branched transport networks consisting of several dozen conveyors, preference is given to analytical models [3, 12], which have the ability to take into account a large number of variables and interactions between system elements. However, despite the effectiveness of these methods, designing control systems for transport conveyors with a branched structure is an extremely complex problem. One of the most promising approaches is the use of models based on regression equations [13], as well as models using neural networks [14, 15].

These methods allow modeling complex relationships between various system parameters and predicting the behavior of transport flows in real time. However, their successful application requires the availability of a large volume of data that contains the values of the input and output parameters of the transport system flows under various operating modes. The formation of adequate training data sets becomes especially important for creating models capable of effectively managing the transport system [16]. This requires collecting a large amount of experimental data covering a wide range of changes in the flow parameters of the transport conveyor. Using the existing transport system as a source for forming a training data set in a sufficiently wide range of values based on experimental measurements causes serious difficulties and is not always possible. Nevertheless, the problem of forming a training data set is relevant and requires an effective solution. The solution to this problem is associated with the solution of two interrelated subproblems. The first subproblem is to analyze the statistical characteristics of the input material flow with the subsequent construction of a flow value generator with predetermined statistical properties. The second subproblem involves the use of an analytical model of a transport conveyor [2] to calculate the values of the output material flow based on the generated values of the input flows in a branched transport system [9].

The solution to the first subproblem is reduced to calculating the statistical parameters of the input flows based on experimental data collected for a real system. To achieve high calculation accuracy, it is necessary to have a large number of implementations of the input material flows, each of which should be recorded over a certain time interval. The process of forming a sufficient number of implementations requires a large volume of experimental data, which can significantly complicate the problem. However, this stage can be simplified if we assume that the obtained experimental realization of the input flow can be approximated as a stationary flow with ergodic properties. In some cases, this assumption allows to significantly reduce the number of necessary experimental realizations. Based on the statistical characteristics of a limited set of experimental realizations of the input flow of material, a generator of random values of the input flows of material of a highly branched transport conveyor is constructed. The generator is used to form the required number of input material flow realizations necessary for the transport conveyor model, which is the foundation for designing effective transport system control. To solve the second problem, related to calculating output material flows, an analytical model of the transport conveyor is used [2]. This model is based on equations whose boundary conditions are formed by the generator of input material flow values. It is important to point out that in highly branched transport systems with numerous conveyors, the computational costs of modeling output material flows are often comparable to the costs of training a neural network. In this case, the analytical model is only needed to prepare the training data set, and the neural network serves as the foundation of the transport system model. Neural network-based transport system models are an alternative approach to calculating output material flow values for highly branched conveyor-type transport systems [17, 18, 19].

In this study, the results of studies devoted to the analysis of experimental data [20, 21, 22] were used to develop a generator of input material flow values. These papers consider individual implementations of stochastic input material flows entering the transport system, which are the basis for creating and refining theoretical models when typifying input material flows in transport systems. The flow of material entering the input of the transport conveyor, depending on the operating conditions of the transport system, can be either a continuous flow of material or interrupted at individual time intervals [23]. The implementation of the input flow of material and the analysis of the statistical characteristics of the input flow of material are presented in [24].

Main parameters of the input material flow

Let us consider a class of stochastic input material flows for which the statistical characteristics of the input material flow do not depend on time. This means that the statistical characteristics of an arbitrary implementation do not depend on the start time of the experimental changes in the values of the input material flow. To analyze the statistical characteristics of a stationary stochastic input material flow $\lambda(t)$, dimensionless parameters are introduced:

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

$$\tau=2\frac{t-t_{\min}}{t_{\max}-t_{\min}}-1,\ \ \vartheta=\frac{2\eta}{t_{\max}-t_{\min}},\qquad(1)$$

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

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

$$k(\vartheta)=M[\gamma(\tau)\gamma(\tau-\vartheta)],\ \tau\in[-1,1],$$

where m_λ is the mathematical expectation of the values of the stationary stochastic flow of material $\lambda(t)$; σ_λ is the standard deviation of the values of the stationary stochastic flow of material $\lambda(t)$. Using dimensionless parameters, the stationary stochastic input flow of material $\lambda(t)$ in dimensionless form $\gamma_f(\tau)$ is represented as:

$$\gamma_f(\tau)=m_f+\gamma(\tau).\qquad(3)$$

The dimensionless stochastic input flow $\gamma(\tau)$ is a centered stationary random process with mathematical expectation $m=0$ and standard deviation $\sigma=1$. The correlation function of the input material flow $\gamma(\tau)$ is a normalized function satisfying the equality

$$k(0)=1.\qquad(4)$$

Decomposition of a stationary material flow and verification of ergodicity conditions

Let us represent a stationary centered random process $\gamma(\tau)$ on a fixed time interval $\tau\in[-1,1]$ in the form of a canonical expansion:

$$\gamma(\tau)=\sum_{j=1}^{\infty}\Theta_{cj}\cos(\omega_j\tau)+\Theta_{sj}\sin(\omega_j\tau),\ \ \omega_j=\pi j,\qquad(5)$$

where Θ_{cj}, Θ_{sj} are centered random variables with mathematical expectation $M[\Theta_{cj}]=M[\Theta_{sj}]=0$ and standard deviation $M\left[\left(\Theta_{cj}\right)^2\right]=M\left[\left(\Theta_{sj}\right)^2\right]=\sigma_j^2$. Let us define the statistical characteristics of the dimensionless stationary stochastic input material flow $\gamma(\tau)$:

a) mathematical expectation

$$M[\gamma(\tau)]=M\left[\sum_{j=1}^{\infty}\Theta_{cj}\cos(\omega_j\tau)+\Theta_{sj}\sin(\omega_j\tau)\right]=$$

$$=\sum_{j=1}^{\infty}\cos(\omega_j\tau)M[\Theta_{cj}]+\sin(\omega_j\tau)M[\Theta_{sj}]=0; \quad (6)$$

b) standard deviation

$$\sigma^2=M\left[\gamma^2(\tau)\right]=M\left[\left(\sum_{j=1}^{\infty}\Theta_{cj}\cos(\omega_j\tau)+\Theta_{sj}\sin(\omega_j\tau)\right)^2\right]=$$

$$=\sum_{j=1}^{\infty}\cos^2(\omega_j\tau)M\left[\Theta_{cj}{}^2\right]+\sum_{j=1}^{\infty}\sin^2(\omega_j\tau)M\left[\Theta_{sj}{}^2\right]=$$

$$=\sum_{j=1}^{\infty}\left(\cos^2(\omega_j\tau)+\sin^2(\omega_j\tau)\right)\sigma_j^2=\sum_{j=1}^{\infty}\sigma_j^2=1; \quad (7)$$

c) correlation function

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

$$=M\left[\begin{array}{c}\left(\sum_{j=1}^{\infty}\Theta_{cj}\cos(\omega_j\tau)+\Theta_{sj}\sin(\omega_j\tau)\right)\\ \left(\sum_{j=1}^{\infty}\Theta_{cj}\cos(\omega_j(\tau+\vartheta))+\Theta_{sj}\sin(\omega_j(\tau+\vartheta))\right)\end{array}\right]=$$

$$=\sum_{j=1}^{\infty}\cos(\omega_j\tau)\cos(\omega_j(\tau+\vartheta))M\left[\Theta_{cj}{}^2\right]+$$

$$+\sum_{j=1}^{\infty}\sin(\omega_j\tau)\sin(\omega_j(\tau+\vartheta))M\left[\Theta_{sj}{}^2\right]=$$

$$=\sum_{j=1}^{\infty}\left(\cos(\omega_j\tau)\cos(\omega_j(\tau+\vartheta))+\sin(\omega_j\tau)\sin(\omega_j(\tau+\vartheta))\right)\sigma_j^2=$$

$$=\sum_{j=1}^{\infty}\left(\cos(\omega_j\tau-\omega_j(\tau+\vartheta))\right)\sigma_j^2=\sum_{j=1}^{\infty}\cos(\omega_j\vartheta)\sigma_j^2. \quad (8)$$

From the condition

$$\lim_{T\to\infty}\frac{1}{T}\int_0^T\left(1-\frac{\vartheta}{T}\right)k(\vartheta)d\vartheta=0, \quad (9)$$

where

$$\int_0^T\left(1-\frac{\vartheta}{T}\right)k(\vartheta)d\vartheta=\int_0^T\left(1-\frac{\vartheta}{T}\right)\sum_{j=1}^{\infty}\cos(\omega_j\vartheta)\sigma_j^2d\vartheta=$$

$$=\sum_{j=1}^{\infty}\int_0^T\left(1-\frac{\vartheta}{T}\right)\cos(\omega_j\vartheta)\sigma_j^2d\vartheta=\sum_{j=1}^{\infty}\frac{\sigma_j^2}{T\omega_j{}^2}\left(1-\cos(\omega_jT)\right),$$

it follows that the canonical expansion (5) of the stationary random process $\gamma(\tau)$ is ergodic with respect to the mathematical expectation. Satisfaction of condition (9) makes it possible to use integration over time on the interval $\tau\in[-1,1]$ to determine the mathematical expectation of the random process $\gamma(\tau)$.

$$\frac{1}{2}\int_{-1}^{1}\gamma_f(\tau)d\tau=m_f, \quad \frac{1}{2}\int_{-1}^{1}\gamma(\tau)d\tau=0. \quad (10)$$

To check the fulfillment of the ergodicity condition with respect to the standard deviation, the stationary centered random process is considered

$$\gamma_\sigma(\tau)=\gamma^2(\tau)-\sum_{j=1}^{\infty}\sigma_j^2=\gamma^2(\tau)-1, \quad (11)$$

with mathematical expectation determined in accordance with formula (7):

$$M[\gamma_\sigma(\tau)]=M\left[\gamma^2(\tau)\right]-\sum_{j=1}^{\infty}\sigma_j^2=0. \quad (12)$$

Let's represent random process $\gamma_\sigma(\tau)$ by a canonical decomposition of the form:

$$\gamma_\sigma(\tau)=\gamma^2(\tau)-\sum_{j=1}^{\infty}\left(\cos^2(\omega_j\tau)+\sin^2(\omega_j\tau)\right)\sigma_j^2= \quad (13)$$

$$=\sum_{j=1}^{\infty}\left(\Theta_{cj}^2-\sigma_j^2\right)\cos^2(\omega_j\tau)+\left(\Theta_{sj}^2-\sigma_j^2\right)\sin^2(\omega_j\tau)+$$

$$+\sum_{j=1}^{\infty}\Theta_{cj}\Theta_{si}\cos(\omega_j\tau)\sin(\omega_i\tau)+$$

$$+\sum_{j=1}^{\infty}\sum_{i=1,j\neq i}^{\infty}\left(\begin{array}{c}\Theta_{cj}\Theta_{ci}\cos(\omega_j\tau)\cos(\omega_i\tau)+\\ +\Theta_{sj}\Theta_{si}\sin(\omega_j\tau)\sin(\omega_i\tau)\end{array}\right)+$$

$$+\sum_{j=1}^{\infty}\sum_{i=1,j\neq i}^{\infty}\Theta_{cj}\Theta_{si}\cos(\omega_j\tau)\sin(\omega_i\tau).$$

The decomposition of a random process $\gamma_\sigma(\tau)$ corresponds to the correlation function

$$k_\sigma(\vartheta)=M[\gamma_\sigma(\tau)\gamma_\sigma(\tau+\vartheta)]=\sum_{j=1}^{\infty}\left(\cos(\omega_j\vartheta)\right)^2\sigma_{Dj}^2, \quad (14)$$

$$\sigma_{Dj}^2=M\left[\left(\Theta_{cj}^2-\sigma_j^2\right)^2\right]=M\left[\left(\Theta_{sj}^2-\sigma_j^2\right)^2\right]=\mu_{4j}-\sigma_j^4, \quad (15)$$

which is constructed by analogy with the expression for the correlation function (8). From the condition

$$\lim_{T\to\infty}\frac{1}{T}\int_0^T\left(1-\frac{\vartheta}{T}\right)k_\sigma(\vartheta)d\vartheta=\frac{1}{4}\sum_{j=1}^{\infty}\sigma_{D_j}^2\neq 0, \quad (16)$$

where $\frac{1}{T}\int_0^T\left(1-\frac{\vartheta}{T}\right)\sum_{j=1}^{\infty}\left(\cos\left(\omega_j\vartheta\right)\right)^2\sigma_{D_j}^2 d\vartheta=$

$$=\sum_{j=1}^{\infty}\left(\left(1-\cos\left(2\omega_j T\right)\right)\Big/\left(8\omega_j^2T^2\right)+\frac{1}{4}\right)\sigma_{D_j}^2,$$

it follows that for a dimensionless stationary stochastic input flow $\gamma(\tau)$ the ergodicity condition for the standard deviation is not satisfied.

To check the ergodicity condition for the correlation function, the random process is considered.

$$\gamma_{kor}(\tau)=\gamma(\tau)\gamma(\tau+\vartheta)-k(\vartheta),\ \ \vartheta=\mathrm{const} \quad (17)$$

with mathematical expectation defined by expression (8):

$$M\left[\gamma_{kor}(\tau)\right]=M\left[\gamma(\tau)\gamma(\tau+\vartheta)\right]-k(\vartheta)=0. \quad (18)$$

Let us write down the correlation function that corresponds to a random process $\gamma_{kor}(\tau)$:

$$k_{kor}(\varphi)=M\left[\gamma_k(\tau)\gamma_k(\tau+\varphi)\right]-k^2(\vartheta)=$$
$$=M\left[\gamma(\tau)\gamma(\tau+\vartheta)\gamma(\tau+\varphi)\gamma(\tau+\vartheta+\varphi)\right]-k^2(\vartheta). \quad (19)$$

When constructing an analytical expression for the correlation function, it is necessary to calculate moments up to the fourth order. For simplicity, it is assumed that random variables Θ_{cj}, Θ_{si} have a normal distribution law. Then, expressing the central moment of the fourth order of function $\gamma(\tau)$ through the correlation function $k(\vartheta)$, the expression for the correlation function $k_{kor}(\varphi)$ of the random process $\gamma_{kor}(\tau)$ is obtained

$$k_{kor}(\varphi)=k^2(\varphi)+k(\varphi+\vartheta)k(\varphi-\vartheta). \quad (20)$$

From the condition

$$\lim_{T\to\infty}\frac{1}{T}\int_0^T\left(1-\frac{\varphi}{T}\right)k_{kor}(\varphi)d\varphi=\sum_{j=1}^{\infty}\frac{1+\cos\left(2\omega_j\vartheta\right)}{4}\sigma_{D_j}^2\neq 0, \quad (21)$$

where $\frac{1}{T}\int_0^T\left(1-\frac{\varphi}{T}\right)\left(k^2(\varphi)+k(\varphi+\vartheta)k(\varphi-\vartheta)\right)d\varphi=$

$$=\frac{1}{T}\int_0^T\left(1-\frac{\phi}{T}\right)\sum_{j=1}^{\infty}\begin{pmatrix}\cos^2\left(\omega_j\phi\right)+\cos\left(\omega_j\left(\phi+\vartheta\right)\right)\times\\ \times\cos\left(\omega_j\left(\phi-\vartheta\right)\right)\end{pmatrix}\sigma_{D_j}^2 d\phi=$$

$$=\frac{1}{T}\int_0^T\left(1-\frac{\varphi}{T}\right)\sum_{j=1}^{\infty}\left(\frac{1+\cos\left(2\omega_j\vartheta\right)}{2}+\cos\left(2\omega_j\varphi\right)\right)\sigma_{D_j}^2 d\varphi=$$

$$=\sum_{j=1}^{\infty}\left(\frac{1+\cos\left(2\omega_j\vartheta\right)}{4}+\frac{1-\cos\left(2\omega_j T\right)}{\omega_j^2T^2}\right)\sigma_{D_j}^2,$$

it follows that for a dimensionless stationary stochastic input flow $\gamma(\tau)$ the ergodicity condition with respect to the correlation function $k(\vartheta)$ is not satisfied. This conclusion is obtained for a random process for which random variables Θ_{cj}, Θ_{si} have a normal distribution law. A similar conclusion regarding the ergodicity condition can be obtained for a random process $\gamma_{kor}(\tau)$ at $\vartheta=0$ with an arbitrary distribution law of random variables Θ_{cj}, Θ_{si}. Indeed, at $\vartheta=0$ equality $\gamma_{kor}(\tau)\big|_{\vartheta=0}=\gamma_\sigma(\tau)$ follows, for which the correlation function is represented by expression (14) and the ergodicity condition (21) takes the form (16).

Thus, for $\gamma(\tau)$, the ergodicity condition is not satisfied with respect to the correlation function $k(\vartheta)$, and accordingly, condition (21) as a whole is not satisfied. An important conclusion follows from this: due to the fulfillment of the ergodicity condition for the random process $\gamma(\tau)$, the value of the mathematical expectation m_f is determined based on formula (10) using a single implementation of the random process $\gamma_f(\tau)$. To determine the mean square value σ and the correlation function $k(\vartheta)$ of the random process $\gamma_f(\tau)$, a sufficiently large number of implementations of the random process is required. Thus, the problem of constructing a generator of input material flow values is divided into two separate subproblems:

a) determination of the distribution law of random variables Θ_{cj}, Θ_{si} in the canonical expansion (5) of a stationary random process $\gamma(\tau)$;

b) determination of the standard deviation σ and the type of correlation function $k(\vartheta)$ of a stationary random process $\gamma(\tau)$ for calculating the values of the standard deviations σ_j of random variables Θ_{cj}, Θ_{si} in the canonical expansion (5) of a stationary random process $\gamma(\tau)$.

This paper examines in detail the solution of these subproblems.

Modification of the decomposition of a stationary random flow of material and calculation of statistical characteristics

When choosing the expansion of the stationary random process $\gamma(\tau)$ in the form (5), it is assumed that a single realization of the input flow of material would be used to calculate the statistical characteristics of the stationary random process. However, as was substantiated above, for the stationary random process $\gamma(\tau)$, the ergodicity condition is satisfied only with respect to the mathematical expectation. This circumstance requires that a sufficiently large number of realizations of the random process $\gamma(\tau)$ be used to calculate the statistical characteristics of the stationary random process $\gamma(\tau)$. In this regard, expansion (5) of the stationary random process $\gamma(\tau)$ is modified to the following form

$$\gamma(\tau)=\Theta_0+\sum_{j=1}^{\infty}\Theta_{cj}\cos(\omega_j\tau)+\Theta_{sj}\sin(\omega_j\tau),\ \omega_j=\pi j, \quad (22)$$

where Θ_{0i}, Θ_{cj}, Θ_{si} are random variables with mathematical expectation and standard deviation

$$M[\Theta_0]=0,\quad M[\Theta_{cj}]=0,\quad M[\Theta_{sj}]=0, \quad (23)$$

$$M\left[\Theta_0{}^2\right]=\sigma_0^2,\quad M\left[\Theta_{cj}{}^2\right]=M\left[\Theta_{sj}{}^2\right]=\sigma_j^2.$$

Let us expand the realization $\gamma_n(\tau)$ of the stationary random process $\gamma(\tau)$ (22) on the interval $\tau\in[-1,1]$ into a Fourier series

$$\gamma_n(\tau)=\frac{\theta_{0n}}{2}+\sum_{j=1}^{\infty}\theta_{cnj}\cos(\omega_j\tau)+\theta_{snj}\sin(\omega_j\tau),\ \omega_j=\pi j, \quad (24)$$

where θ_{0n}, θ_{cnj}, θ_{snj} are constant expansion coefficients.

The correlation function can be defined as the averaging of correlation functions over individual realizations $\gamma_n(\tau)$ of a random process $\gamma(\tau)$

$$k(\vartheta)=\frac{1}{N}\sum_{n=0}^{N}\frac{1}{2}\int_{-1}^{1}\gamma_n(\tau)\gamma_n(\tau+\vartheta)d\vartheta=$$

$$=\sum_{n=1}^{N}\frac{\theta_{0n}^2}{4N}+\sum_{j=1}^{\infty}\cos(\omega_j\vartheta)\sum_{n=1}^{N}\left(\frac{\theta_{cnj}^2}{2N}+\frac{\theta_{snj}^2}{2N}\right)+$$

$$+\sum_{j=1}^{\theta_{snj}\theta_{cnj}}\sin(\omega_j\vartheta)\sum_{n=1}^{N}\left(\frac{\theta_{snj}\theta_{cnj}}{2N}-\frac{\theta_{cnj}\theta_{snj}}{2N}\right)=$$

$$=\sum_{n=1}^{N}\frac{\theta_{0n}^2}{N}+\sum_{j=1}^{\infty}\cos(\omega_j\vartheta)\sum_{n=1}^{N}\left(\frac{\theta_{cnj}^2}{2N}+\frac{\theta_{snj}^2}{2N}\right), \quad (25)$$

where $\int_{-1}^{1}\cos(\omega_j\tau)\cos(\omega_i(\tau+\vartheta))d\vartheta=\begin{cases}\cos(\omega_j\vartheta), & j=i;\\ 0, & j\neq i;\end{cases}$

$$\int_{-1}^{1}\sin(\omega_j\tau)\sin(\omega_i(\tau+\vartheta))d\vartheta=\begin{cases}\cos(\omega_j\vartheta), & j=i;\\ 0, & j\neq i;\end{cases}$$

$$\int_{-1}^{1}\sin(\omega_j\tau)\cos(\omega_i(\tau+\vartheta))d\vartheta=\begin{cases}-\sin(\omega_j\vartheta), & j=i;\\ 0, & j\neq i;\end{cases}$$

$$\int_{-1}^{1}\cos(\omega_j\tau)\sin(\omega_i(\tau+\vartheta))d\vartheta=\begin{cases}\sin(\omega_j\vartheta), & j=i;\\ 0, & j\neq i.\end{cases}$$

From conditions (23) for a stationary random process $\gamma(\tau)$ (22), it follows

$$\sigma_0^2\cong\frac{1}{N}\sum_{n=1}^{N}\frac{\theta_{0n}^2}{4},\ \sigma_j^2\cong\frac{1}{N}\sum_{n=1}^{N}\theta_{cnj}^2=\frac{1}{N}\sum_{n=1}^{N}\theta_{snj}^2, \quad (26)$$

from where the expression for the correlation function is finally determined

$$k(\vartheta)=\sigma_0^2+\sum_{j=1}^{\infty}\sigma_j^2\cos(\omega_j\vartheta). \quad (27)$$

and also the value of the standard deviation σ for the distribution function of the values of the input material flow

$$\sigma^2=\sigma_0^2+\sum_{j=1}^{\infty}\sigma_j^2. \quad (28)$$

In practical calculations in this paper, the Fourier series expansion for the first ten terms of series is used $j\in[1,J=10]$. It is also assumed that that the material flow realizations represented by a set of N-intervals are independent.

If a single realization of a random stationary process $\gamma(\tau)$ is used to calculate statistical characteristics, then in accordance with (26) the standard deviation σ_0, σ_j, at $N=1$ takes on a random value

$$\sigma_0^2\cong\frac{\theta_{01}^2}{4},\ \sigma_j^2\approx\frac{\theta_{c1j}^2+\theta_{s1j}^2}{2}, \quad (29)$$

which is determined by the values θ_{0n}, θ_{cnj}, θ_{snj} of random variables Θ_0, Θ_{cj}, Θ_{sj}. It follows that the correlation function (27), determined by random values σ_0 and σ_j, is a random function.

Thus, a single realization of a stationary random process $\gamma(\tau)$, even of a sufficiently long duration, cannot be used to calculate the standard deviation and correlation function of the stationary random process $\gamma(\tau)$, since it leads to a distortion of the statistical characteristics of the random process. The required number of realizations of a centered stationary random process $\gamma(\tau)$ can be determined by the following formula

$$P\{|m_x|<\varepsilon_x\}=2\Phi\left(\frac{\varepsilon_x\sqrt{N}}{\sigma_x}\right),\quad N=\frac{t^2\sigma_x^2}{\varepsilon_x^2}, \quad (30)$$

where $t=1.96$ для $P\{|m_x|<\varepsilon_x\}\approx 0.95$; X is a centered random variable Θ_0, Θ_{cj}, Θ_{sj}; ε_x is the permissible error for determining the mathematical expectation of a centered random variable X; $M[X^2]\approx\sigma_x^2$.

Construction of a generator of input material flow values

Each realization $\gamma_n(\tau)$ of a stationary stochastic process $\gamma(\tau)$ corresponds to values θ_{0n}, θ_{cnj}, θ_{snj} of random variables Θ_0, Θ_{cj}, Θ_{sj}, $1\le n\le N$. If there are N realizations $\gamma_n(\tau)$, for each random variable $X=[\Theta_0,\Theta_{cj},\Theta_{sj}]$ a histogram of the distribution of values of the random variable can be constructed. Taking into account the histogram of the distribution of values of a random variable, we construct a statistical distribution function of a random variable $F(x) = P\{X < x\}$. Then, using the inverse function method, we obtain a sequence of values of $\theta_{0n}, \theta_{cnj}, \theta_{snj}$ random variables $\Theta_0, \Theta_{cj}, \Theta_{sj}$:

$$\theta_{0n} = F_0^{-1}(u_{0n}), \tag{31}$$

$$\theta_{cnj} = F_{cj}^{-1}(u_{cnj}), \ \ \theta_{snj} = F_{sj}^{-1}(u_{snj}),$$

with statistical distribution functions:

$$F_0(\theta_0) = P_0\{\Theta_0 < \theta_0\}, \tag{32}$$

$$F_{cj}(\theta_{cj}) = P_{cj}\{\Theta_{cj} < \theta_{cj}\}, \ F_{sj}(\theta_{sj}) = P_{sj}\{\Theta_{sj} < \theta_{sj}\}.$$

Functions $F_0^{-1}(u_{0n}), \ F_{cj}^{-1}(u_{cnj}), \ F_{sj}^{-1}(u_{snj})$ are inverse functions of functions $F_0(\theta_{0n}), \ F_{cj}(\theta_{cnj}), \ F_{sj}(\theta_{snj})$, where $u_{0n}, \ u_{cnj}, \ u_{snj}$ are sequences of values of independent random variables U_0, U_{cj}, U_{sj} with uniform distribution law for the range $[0.0; 1.0]$.

The general operating principle of the input material flow value generator is as follows: a) values u_{01}, u_{c1j}, u_{s1j} of random variables U_0, U_{cj}, U_{sj} are generated; b) based on the inverse function method in accordance with formulas (31), the values θ_{01}, θ_{c1j}, θ_{s1j} are calculated; c) the values θ_{01}, θ_{c1j}, θ_{s1j} are used in formula (24) to construct the implementation $\gamma_1(\tau)$ of the stochastic stationary process $\gamma(\tau)$ on a fixed time interval $\tau \in [-1;1]$.

The given computational procedures are repeated for time intervals $\tau \in [-1 + 2(n-1); 1 + 2(n-1)]$, $n > 1$ corresponding to realizations $\gamma_n(\tau)$. The stationary stochastic process $\gamma(\tau)$ is thus represented as an infinite sequence of realizations $\gamma_n(\tau)$.

Analysis of results

Let us consider the process of constructing realizations for a stationary stochastic input material flow using the developed generator of input flow values. It is assumed that the realizations of the stochastic material flow formed using the generator will find wide application for simulating the input material flow on a transport conveyor in problems of designing effective control systems for flow parameters in transport systems. In this paper, a generator built on the basis of experimental data is used to demonstrate the methodology for forming realizations of the input material flow.

The experimental data were obtained by analyzing the flow of material entering the input of an operating conveyor [25]. The main focus was on reproducing the key statistical characteristics of the experimental input flow of material. The results obtained made it possible to form an approximate model of the input flow of material, which is an important step in studying the problems of optimizing the operation of a transport conveyor. In the paper [25], a non-uniform bulk material distribution model based on bulk material flow measurement data from a laser scanner is proposed. The influence of the stochastic material flow characteristics on the speed control parameters of the transport conveyor belt is studied in detail. It is also worth noting that a limitation is imposed on the maximum value of the conveyor belt acceleration, exceeding which can cause the destruction of the conveyor belt [26].

Experimental values obtained from material flow measurements cannot be used directly in energy-efficient belt speed control models. A solution to this problem can be obtained by developing input material flow models based on statistical characteristics of the input flow. The main difficulty in constructing such models is in calculating statistical characteristics. One way to solve this problem is to form the required set of experimental data, which is a set of measurements of the input material flow values. Another problem is how to evaluate and test the models directly in production conditions. One of the options for solving this problem is based on conducting simulation experiments. These experiments should use models of statistical characteristics of the material flow that coincide with the statistical characteristics of the material flow of the operating system.

In general, the calculation of statistical characteristics of the input material flow can be made on the basis of experimental implementations of the input material flow of operating transport conveyors. This paper considers a method for calculating statistical characteristics based on the presence of a sufficiently large number of implementations of the input material flow. The results of calculating statistical characteristics are the foundation for constructing a generator of input material flow values with specified statistical characteristics. The input material flow realizations required for calculating statistical characteristics are formed as a result of conducting independent experimental measurements of the input material flow values or dividing a single, but sufficiently large, experimental realization of the input material flow into a sufficiently large number of time intervals.

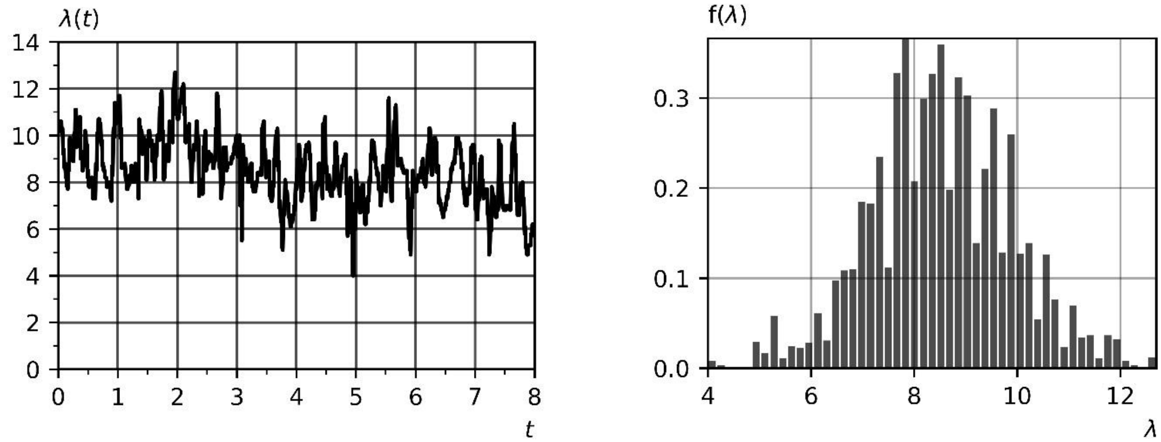
The experimental implementation of the input material flow used in this study for dividing into time intervals, as well as the distribution function of the input material flow values, are shown in Fig. 1. To form a dimensionless implementation of the input material flow in accordance with the dimensionless parameters (1), (2), the mathematical expectation and standard deviation for the input material flow values are calculated. To calculate the statistical characteristics of the material flow, the implementation of the material flow (Fig. 1) is divided into twenty intervals (N = 20).

For each n-interval, the constant expansion coefficients are calculated, and the mathematical expectation and standard deviation of random variables are determined. Summing up the squares of the standard deviation for all harmonics in accordance with formula (28), we obtain the standard deviation for the distribution function of the input material flow values. The value of the standard deviation is used to calculate the dimensionless parameters of the input material flow (1), (2).

Fig. 2 shows the dimensionless realization of the material flow and the dimensionless density distribution of the material flow values. The approximation of the dimensionless stationary stochastic input material flow $\gamma(\tau)$ is shown in Fig. 2. This approximation is based on the first ten harmonics of the expansion $j \le J = 10$ and is performed in accordance with formula (24). The approximated realization $\gamma_a(\tau)$ of the dimensionless input material flow is shown in Fig. 3.

Approximated realization $\gamma_a(\tau)$ is used to estimate the statistical characteristics of the dimensionless input material flow. The main goal of the approximation is to replace the original experimental material flow with a theoretical material flow with well-studied properties, the statistical characteristics, distribution function and correlation function of which correspond to the experimental material flow with a given accuracy. The number of terms in the expansion (24) when approximating the dimensionless realization of the input material flow $\gamma_n(\tau)$ is selected from the condition of ensuring a given accuracy of the approximation.

It is also important to point out that during approximation, the experimental realization of the input material flow is smoothed. The degree of smoothing (the degree of averaging), as well as the accuracy of approximation, is specified by the number of terms in the expansion of the canonical representation (24). Each term in the expansion is determined by the statistical characteristics of the input material flow.



a b

Fig. 1: The measured data of instantaneous non-uniform iron ore powder distribution with a flow of 8.911 kg/s (3L/s) at a stable speed of 1.0 m/s [22]: a – realization of the input material flow; b – histogram of the distribution of values λ of the input material flow.

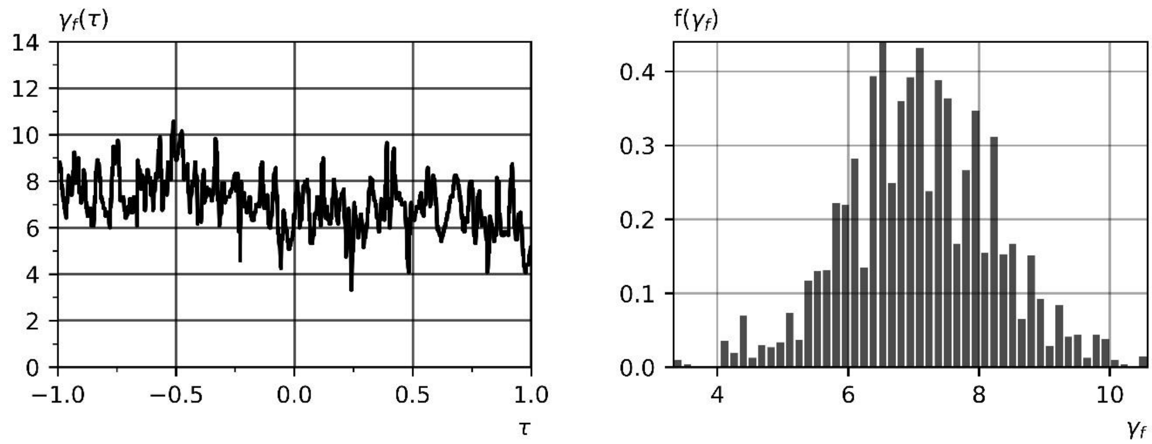


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Fig. 2: Dimensionless input material flow $\gamma_f(\tau)$:
a – realization of the input material flow; b – histogram of the distribution of values γ_f of the input material flow

Along with smoothing the realization of the experimental input material flow, as a result of approximation, smoothing of the distribution density of the values of the experimental realization of the input material flow occurs (Fig. 3, b). Smoothing (averaging) of data during approximation reduces the level of noise and errors, which is critical for accurate calculations and forecasting the dynamics of the material flow under uncertainty. The approximation error $\varepsilon(\tau)$ is determined by the expression representing the difference between the measured values of the experimental realization $\gamma_f(\tau)$ and the values of the approximated realization $\gamma_a(\tau)$ at the same moment in time τ

$$\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau). \quad (33)$$

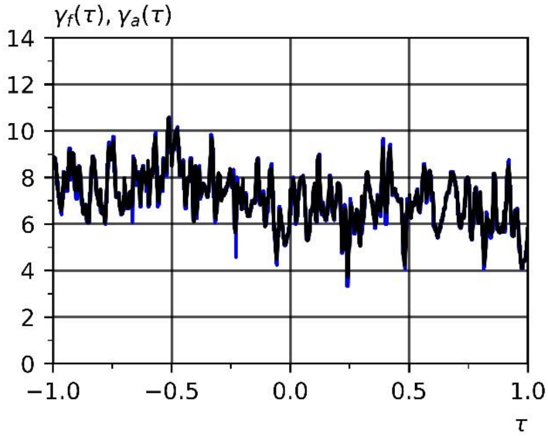
Function ε (τ) allows quantitative analysis of the deviation of the approximated implementation $\gamma_a(\tau)$ from the experimental implementation $\gamma_f(\tau)$. This function is a criterion for assessing the improvement of the stochastic input material flow model. Estimation of the approximation error allows identifying differences between the experimental and approximated values of the material flow over time intervals, which provides an understanding of the system dynamics by identifying areas of the experimental implementation with increased uncertainty.

It should be noted that the values of experimental implementation $\gamma_f(\tau)$ contain both random and systematic errors, which have a significant impact on the approximation results.

To analyze the distribution of the approximation error of the dimensionless material flow, Q-Q (Quantile-to-Quantile) graphs were constructed. This analysis method made it possible to compare the distribution density of the approximation error with the theoretical distribution density of the error (with a normal error distribution law) and visually assess the deviations. Q-Q graphs clearly demonstrate the degree of correspondence between the actual and theoretical error distributions.

According to the results of the analysis, the distribution law of the approximation error is close to the normal distribution law, which indicates that random errors occur mainly due to the summation of a large number of small independent factors. The normal distribution law of the error will allow the use of well-developed statistical methods in future studies to assess the accuracy of measurements, construct confidence intervals and test hypotheses.

The approximation error $\varepsilon(\tau)$ for the implementation of the dimensionless material flow $\gamma_f(\tau)$ is shown in Fig. 4. The graphical representation allows us to evaluate the nature of systematic and random errors and makes it possible to determine the most important parameters that affect the accuracy of the model.



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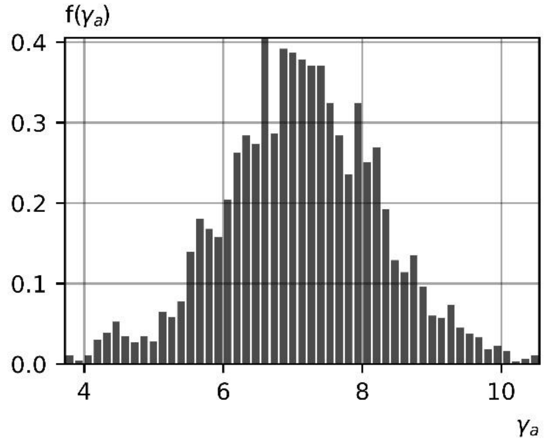
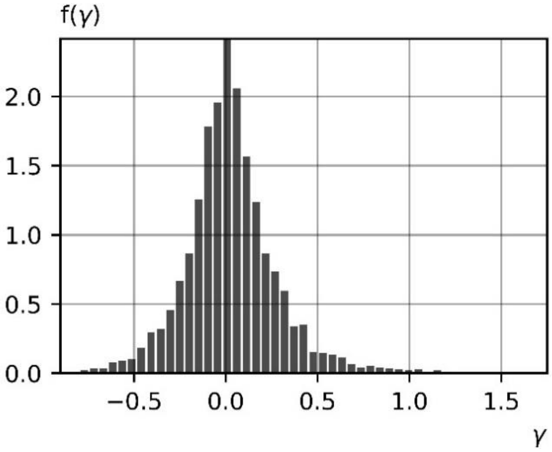


b

Fig. 3: Dimensionless input material flow: a – comparative analysis of realizations $\gamma_a(\tau)$, $\gamma_f(\tau)$ of the input material flow; b – histogram of the distribution of values $\gamma_a(\tau)$ of the input material flow



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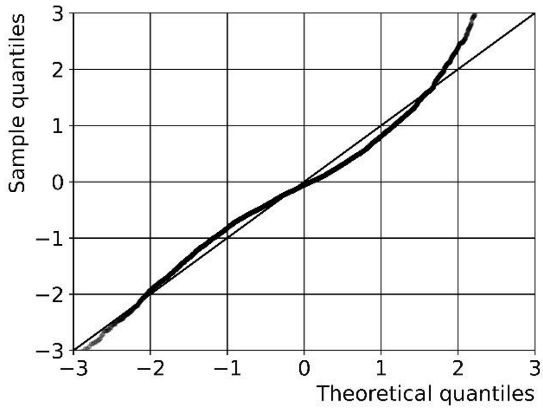


b

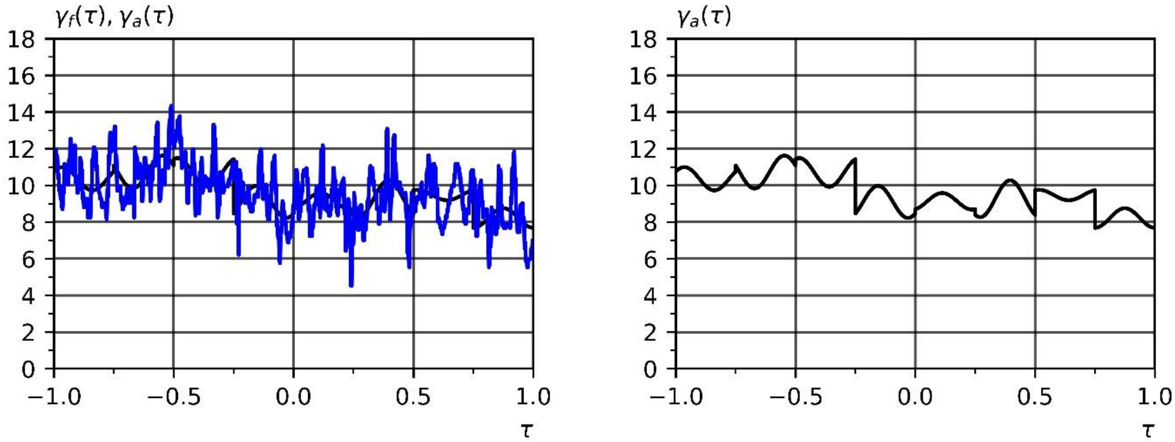
Fig. 4: Approximation error $\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau)$ for the realization of dimensionless material flow $\gamma_f(\tau)$: a – histogram of the distribution of values $\varepsilon(\tau)$; b – Q-Q plots (Quantile-to-Quantile) of values $\varepsilon(\tau)$

Fig. 5 shows the experimental realization of the dimensionless material flow $\gamma_f(\tau)$, with visualization of the process of dividing the experimental realization into eight separate time intervals (Fig. 5, a). This division allows for a fixed number of terms of the canonical expansion (24) to analyze the material flow dynamics in more detail and accurately. Each interval represents a separate sample of experimental values of the material flow, which facilitates a more accurate calculation of statistical characteristics.

To simplify the analysis and to demonstrate the method of smoothing the experimental flow of material within each interval, a canonical expansion was used, which assumes the presence of the first two terms of the expansion (Fig. 5, b).

This approach allows for the effective smoothing of the experimental material flow. In most cases, the first two terms of the canonical expansion often provide a fairly good qualitative approximation to the form of the experimental implementation of the input material flow, allowing for the identification of key process characteristics. Increasing the number of intervals improves the quality of the approximation, providing a more detailed picture of random fluctuations in the material flow.

To achieve high accuracy of results in practical applications, the number of intervals is determined in accordance with formula (30), ensuring an optimal ratio between the volume of data and the accuracy of calculations. The value of the mathematical expectation and the standard deviation for the approximation containing a different number of intervals of partitioning a single realization of the input material flow is presented in Table 1.



a b

Fig. 5: Approximation of the experimental implementation of the input material flow:
a – comparative analysis of the experimental implementation $\gamma_f(\tau)$ and the approximated implementation of the input material flow for eight intervals; b – approximated implementation of the input material flow $\gamma_a(\tau)$

Table 1 – **Comparative analysis of experimental and approximation implementation of the input material flow**

Parameter	**Number of separation intervals of experimental implementation**					
	Experimental implementation	**8**	**16**	**32**	**64**	**128**
Mathematical expectation	8.51	8.51	8.51	8.51	8.51	8.51
Standard deviation	1.37	1.20	1.18	1.16	1.10	1.04

With an increase in the number of partition intervals, the value of the standard deviation characterizing the approximation realization of the input material flow tends to the steady-state value of the standard deviation for the experimental realization of the material flow. Dividing the flow into intervals helps to improve the accuracy of estimating statistical characteristics such as the mathematical expectation and standard deviation.

Conclusion

This paper considers the problem of constructing a generator of values of a stochastic input material flow for modeling a branched conveyor-type transport system. The main attention is paid to transport systems for which the input material flow is approximated by a spectral decomposition of a stationary stochastic input material flow.

The stationary stochastic input flow of material is represented by a canonical expansion as a sum of harmonic oscillations with random amplitudes at various non-random frequencies. The coefficients of the canonical expansion are related to the coefficients of the expansion of the correlation function of the stationary stochastic input flow of material.

The developed method for generating realizations of a stationary stochastic input flow of material allows one to approximate experimental realizations of the input flow of material with a given accuracy.

A two-stage approach is proposed for forming realizations of the input material flow. At the first stage, using the canonical expansion in given coordinate functions, the experimental realization of the input material flow for a given interval is approximated. At the second stage, statistical characteristics of the implementations of the input material flow are calculated.

These characteristics are used in constructing a random value generator for the input material flow of the transport conveyor.

The generator of stochastic input material flow, constructed on the basis of experimental data, plays an important role in modeling conveyor-type transport systems.

It allows simulating various implementations of input material flows, which can be used to study the regularities of the dynamics of the material flow of the transport system. Implementations of the input material flow constructed in this way act as input parameters for the analytical model of the conveyor when designing effective systems for controlling the flow parameters of the transport conveyor.

The conducted analysis showed that the application of the method of smoothing the realizations of the material flow, based on the canonical decomposition of the realizations of the input material flow, ensures a sufficiently accurate reproduction of the statistical characteristics of such a flow, which is important when designing effective systems for managing the flow parameters of a transport system.

Approximation of the material flow based on the first ten harmonics of the decomposition allowed us to achieve satisfactory accuracy in reproducing the dynamics of the input material flow. To design efficient algorithms for controlling the flow parameters of a transport system, it is proposed to use a smoothed material flow that takes into account only the first few terms of the decomposition. The number of the first terms of the decomposition is significantly less than the total number of terms of the decomposition for approximated implementations. Particular attention is paid to the estimation of approximation errors. According to the analysis results, the distribution of the approximation error is close to normal, which confirms the stability of the model. Analysis of Q-Q graphs confirms a sufficiently high degree of correspondence between the theoretical and experimental density distributions of errors.

Thus, the developed method of forming the input flow of material based on statistical characteristics can be successfully used for modeling and designing control systems for transport conveyors. The methods of generating input flows based on experimental data proposed in the paper allow increasing the accuracy of modeling and control of conveyor systems, which in the long term can lead to a decrease in operating costs and an increase in the productivity of conveyor-type transport systems.

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Моделювання стаціонарного стохастичного вхідного потоку розгалужених конвеєрних систем

О. М. Пігнастий, В. В. Усик, А. Бурдук

Анотація. Об'єкт дослідження – стохастичний стаціонарний вхідний потік матеріалу транспортної системи конвеєрного типу. **Предмет дослідження** - метод генерації реалізацій стаціонарного стохастичного вхідного потоку матеріалу на основі експериментальних даних. **Мета дослідження** - розробка 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**. Стаціонарний стохастичний вхідний потік матеріалу представлений канонічним розкладанням як сума гармонійних коливань з випадковими амплітудами на різних невипадкових частотах. Запропоновано двоетапний підхід до формування реалізацій вхідного матеріального потоку. На першому етапі за допомогою канонічного розкладання по заданих координатних функціях апроксимується експериментальна реалізація потоку вхідного матеріалу для заданого інтервалу. На другому етапі розраховуються статистичні характеристики реалізацій вхідного матеріального потоку. Проведений аналіз показав, що застосування методу згладжування реалізацій матеріального потоку, заснованого на канонічній декомпозиції реалізацій вхідного матеріального потоку, забезпечує достатньо точне відтворення статистичних характеристик такого потоку, що важливо при проектуванні ефективних систем управління потоковими параметрами транспортної системи. Проведено порівняльний аналіз кореляційних функцій для експериментальної, апроксимованої та згенерованої реалізацій вхідного матеріального потоку. Обґрунтовано тривалість інтервалу часу, необхідного для проведення експериментальних змін потоку вхідного матеріалу. **Висновок**. Запропоновані в роботі методи генерації вхідних потоків на основі експериментальних даних дозволяють підвищити точність моделювання та керування конвеєрними системами, що в перспективі може призвести до зниження експлуатаційних витрат та підвищення продуктивності транспортних конвеєрних систем.

Ключові слова: матеріальний потік; випадковий процес; генератор випадкової величини; помилка апроксимації.