Predictive analysis of the interval material flow rates in transport conveyors based on experimental data

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Abstract

This study examines a method for constructing a generator of random values of the input flow of material to form a training data set in highly efficient transport conveyor models based on a neural network. Dimensionless parameters are introduced that make it possible to represent the model of the input material flow of a transport conveyor in a dimensionless form. Coordinate functions are determined to approximate the experimental realization of the input material flow. A canonical decomposition of the experimental realization of the input material flow in terms of coordinate functions based on the use of fixed intervals is presented. For the selected canonical decomposition of the experimental realization of the input material flow, a theoretical correlation function is determined. It is shown that as the number of intervals increases, the correlation function of the experimental realization tends to the theoretical correlation function. The stages of constructing a random value generator for the input material flow are presented in detail. A comparative analysis of the experimental, approximated and generated realization for the input material flow is presented and estimates of the statistical characteristics of the realizations of the input material flow are given. The correlation functions constructed for the experimental, approximated and generated realizations of the input material flow are analyzed. An estimate is given of the length of the time interval required to carry out experimental changes in the input material flow.

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 use of conveyor belts is widespread in mining industries due to their ability to efficiently transport large quantities of materials [1]. The conveyor systems are integral to the operation of mining processes, providing a continuous and reliable means of moving raw materials from extraction points to processing facilities [2]. The efficiency and effectiveness of the conveyor belt systems were made them a standard in the industry, with applications ranging from ore transport to handling waste materials. Their versatility and reliability make them indispensable for ensuring smooth and continuous operations in mining environments, where downtime can be particularly costly [3]. To increase the economic efficiency of the functioning of transport systems, models and systems for controlling the flow parameters of the conveyor are developed [4, 5]. These models aim to optimize the operation of conveyor systems by improving throughput, reducing energy consumption, minimizing wear and tear on equipment, and ensuring the safety of operations [6]. By precisely controlling the flow parameters, it is possible to enhance the overall productivity of mining operations and extend the lifespan of conveyor components. Traditional models often rely on deterministic approaches, which assume that the flow of incoming material is determined to a given accuracy. These deterministic models provide a simplified view of conveyor operations, making it easier to apply mathematical and computational techniques for optimization [7]. However, they do not account for the inherent variability in material flow that can result from

ICST-2024: Information Control Systems & Technologies, September 23-25, 2023, Odesa, Ukraine.
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fluctuations in mining operations, variations in material properties, equipment performance, and other stochastic factors [8]. A further development of traditional deterministic models for describing the flow parameters of a conveyor system [9] is the development of models that assume that the input material flow is a stochastic material flow [10]. Stochastic models incorporate the randomness and unpredictability of real-world conditions, providing a more realistic representation of the dynamic conveyor system. These models take into account the probabilistic nature of material flow, allowing for better handling of uncertainties and variances in the system. By incorporating stochastic elements, it is possible to develop more adaptive and resilient control strategies that can maintain optimal performance under varying conditions [11, 12]. The use of realizations of the input material flow, formed on the basis of experimental data, enhances the accuracy and applicability of these stochastic models [13]. Experimental data provides a foundation for understanding the statistical characteristics of the stochastic input material flow, such as mean, variance, correlation function and distribution patterns. This data-driven approach enables the determination of the law of distribution of the values of the input material flow, facilitating more precise control and optimization of conveyor systems [14]. By analyzing extensive experimental datasets, it is possible to capture the true behavior of material flow in different scenarios, leading to more robust and effective modeling [15, 16]. In addition to improving control strategies, the application of stochastic models based on experimental data in conveyor systems has broader implications for the mining industry. It supports predictive maintenance by identifying patterns that may indicate potential failures, enhances resource allocation by optimizing material flow schedules, and contributes to reducing energy consumption by transporting material.

Overall, the integration of stochastic modeling and experimental data represents a significant advancement in the management of material transport in mining industries. It enables more accurate forecasting, better risk management, and increased operational efficiency, ultimately contributing to the economic and environmental sustainability of mining operations. By leveraging experimental data and statistical analysis, these models offer improved performance and higher economic efficiency. This approach not only optimizes the current operational parameters but also provides a framework for continuous improvement and adaptation in the face of changing operational conditions and technological advancements.

2. Literature review

The calculation of the statistical characteristics of the input material flow is presented in [17, 18]. For several transport conveyors, the mathematical expectation and standard deviation of the value of the input cargo flow are calculated, and the distribution function of the value of the input material flow is analyzed. The paper [18] presents an assessment of the correlation function of the input material flow. The paper [19] presents methods for calculating the mathematical expectation, standard deviation and correlation function of the values of the input material flow, based on a small number of realizations of the stochastic input material flow, as well as an analysis of the distribution law of a random variable. Statistical characteristics provide the opportunity to build a generator of random values of the input flow of material to form a training data set in highly efficient transport conveyor models based on a neural network [20, 21, 22]. The difficulty in developing generators of random values of the input material flow lies in the formation of a material flow with a given distribution function of a random variable and a correlation function for the values of the input material flow, which correspond to the statistical characteristics of the experimental realization of the input material flow. The correlation function provides relationships between successive input material flow values when generating stochastic material flow values.

One of the methods for solving this problem is to typify the input material flows. It is assumed that the type of stochastic material flow is determined on the basis of two aggregated factors directly related to the type of distribution function of the values of the input material flow and the correlation function of the input material flow. Due to the fact that the distribution function and correlation function of the values of the input material flow can be represented by a superposition of functions, each of which depends on several parameters, then determining the type of input material flow comes down to assessing multi-parameter criteria for determining the type of distribution function and correlation function [23]. These circumstances significantly complicate the solution of the problem of typing the input flow of material. An additional error arises due to the finite length of the implementation interval for the input material flow. An approximate method for solving the typing problem is demonstrated in [24]. For the values of the input material flow, a distribution function is proposed with the values of the mathematical expectation and standard deviation obtained as a result of experimental studies based on theoretical assumptions about the distribution law of a random variable. The experimental realization of the input material flow is divided into time intervals equal to one minute. The average value of the material flow over a minute time interval is considered as a random variable. Using the initial data, the input material flow of the transport conveyor is modeled. The process of modeling the input material flow is represented by the following subsequent steps: a) determining the statistical characteristics (mathematical expectation and standard deviation) of the input material flow based on the experimental implementation; b) selection of the distribution function for the values of the input material flow based on theoretical justification; c) constructing a generator of input material flow values based on the first two steps a) and b).

The purpose of this article is to develop a method for constructing a generator of random values of the input flow of material to generate a training data set in transport conveyor models based on a neural network. The random input material flow generator based on this method can be used to form a data set for training neural networks in transport conveyor models and to improve the quality of dynamic models of the transport system. This generator aims to replicate the statistical properties of real-world input flows. Integration of stochastic characteristics into real dynamic models of transport conveyor will improve the quality of modeling of flow parameters of the transport system.

3. Problem statement

A class of stochastic flows of material in a transport system is consider, for which it is possible, on a time interval $t \in [t_{\min}, t_{\max}]$, to approximate the experimental implementation of a random process by an realization separated by Z fixed-length intervals, $\Delta t = (t_{\max} - t_{\min})/Z$. At each of the intervals $t \in [(z-1)\Delta t, z\Delta t]$, $z = 1..Z$, the input material flow takes random values, regardless of the previous and subsequent values of the input material flow. A representative of this class is the stochastic input flow of material of a transport conveyor with minute measurements of the volume of incoming material (a fixed-length time interval is equal to one minute). The realization of a random process, presented as an approximation of the experimental implementation of a random process, with a mathematical expectation value equal to the value of the input material flow for the experimental implementation.

To model and analyze the input material flow, dimensionless parameters are introduced:

$$\gamma(\tau) = \frac{\lambda(t) - m_\lambda}{\sigma_\lambda}, \quad \gamma_f(\tau) = \frac{\lambda(t)}{\sigma_\lambda}, \quad m_f = \frac{m_\lambda}{\sigma_\lambda}, \quad \tau = 2\frac{t - t_{\min}}{t_{\max} - t_{\min}} - 1, \quad \vartheta = \frac{2\eta}{t_{\max} - t_{\min}}, \ \tau \in [-1, 1], \quad (1)$$

$$m = M\left[\frac{\lambda(t) - m_\lambda}{\sigma_\lambda}\right] = M[\gamma(\tau)] = 0, \ \ \sigma^2 = M\left[\frac{\lambda(t) - m_\lambda}{\sigma_\lambda}\right] = M\left[\gamma^2(\tau)\right] = 1, \ \ k(\vartheta) = M[\gamma(\tau)\gamma(\tau - \vartheta)], \quad (2)$$

where m_λ, σ_λ are mathematical expectation and standard deviation of the values of the stochastic material flow $\lambda(t)$. The dimensionless centered stochastic input flow is a centered stationary random process with mathematical expectation $m = 0$ and standard deviation $\sigma = 1$. When a set of sample data is specified by the realization of a centered stationary random process, time averaging for the stochastic process $\gamma(\tau)$ is replaced by averaging over the population:

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

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

The choice of interval $\tau\in[-1{,}1]$ is determined by the integration conditions to determine the correlation function $k(\vartheta)$. In the general case, the limits of the interval can be selected from the conditions for solving the problem. Marginal equality is

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

a sufficient condition for the fulfillment of equalities (3), (4). An approximation of the experimental realization of a centered stationary random process $\gamma(\tau)$ is a realization that represents a sequence of random values of material flow, constant over time intervals T_z fixed in length:

$$\gamma(\tau)=\sum_{z=1}^{Z}\Theta_z\rho_z(\tau),\ \ T_z=T=2/Z,\quad z=1..Z, \tag{6}$$

$$\rho_z(\tau)=H(zT-\tau-1)-H((z-1)T-\tau-1),\quad H(S)=\begin{cases}0, & S<0,\\ 1, & S\ge 0,\end{cases} \tag{7}$$

where Θ_z are independent random variables whose distribution function is characterized by mathematical expectation m_Θ and standard deviation σ_Θ; $H(x)$ is Heaviside function. The functions $\rho_z(\tau)$ are orthogonal functions on the interval $\tau\in[-1{,}1]$

$$\frac{Z}{2}\int_{-1}^{1}\rho_z(\tau)\rho_k(\tau)d\tau=\begin{cases}1 & \text{if } z=k,\\ 0 & \text{if } z\ne k.\end{cases} \tag{8}$$

A centered stationary random process $\gamma(\tau)$ takes on random values Θ_z on a time interval $\tau\in\left[\frac{2(z-1)}{Z}-1,\frac{2z}{Z}-1\right]$, $z=1..Z$ when the next event occurs. For the presented approximation of a random process $\gamma(\tau)$ it is necessary to build a generator that generates a random flow that has statistical characteristics (3)–(5), defining a centered stationary random process $\gamma(\tau)$. The length $T=2/Z,$ of the interval can be chosen as one of the criteria for the similarity of realization of the stochastic material flows.

4. Method for constructing a generator of input material flow values based on experimental implementation

When $Z>>1$ the approximation realization of the random process (6) will quite accurately repeat the experimental implementation for the input flow. Accordingly, the value of the standard deviation calculated for the approximation realization of the random process (6) will tend to the value of the standard deviation of the experimental realization.

Let us define the correlation function of the approximation implementation of the random process (6), which has statistical characteristics

$$m_a=m=0,\quad \sigma_a\approx\sigma=1. \tag{9}$$

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

$$M[\gamma(\tau)]=M\left[\sum_{z=1}^{Z}\Theta_z\rho_z(\tau)\right]=\sum_{z=1}^{Z}M[\Theta_z\rho_z(\tau)]=\sum_{z=1}^{Z}\rho_z(\tau)M[\Theta_z]=m=0, \tag{10}$$

$$D[\gamma(\tau)] = M\left[\left(\sum_{z=1}^{Z}\Theta_z\rho_z(\tau)\right)^2\right] = \sum_{z=1}^{Z}\rho_z^2(\tau)M\left[\Theta_z^2\right] = \sum_{z=1}^{\infty}\rho_z^2(\tau)\sigma_a^2 = \sigma_a^2 \approx \sigma^2 = 1. \quad (11)$$

Let us define the correlation function to implement the random process (6). Let's choose an arbitrary point τ belonging to the interval $\tau \in \left[\frac{2(z-1)}{Z} - 1, \frac{2z}{Z} - 1\right]$. Then the quantity $x = \left(\frac{2z}{Z} - 1 - \tau\right)$ is a random variable, uniformly distributed over the interval $x \in \left[0, \frac{2}{Z}\right]$, for which the equalities are written:

$$\begin{cases} k(\vartheta) = \sigma_a^2 & \text{if } \vartheta \le x, \\ k(\vartheta) = 0 & \text{if } \vartheta > x, \end{cases} \quad x = \left(\frac{2z}{Z} - 1 - \tau\right), \quad \tau \in \left[\frac{2(z-1)}{Z} - 1, \frac{2z}{Z} - 1\right], \quad x \in \left[0, \frac{2}{Z}\right], \quad \vartheta \ge 0. \quad (12)$$

Taking this into account, the correlation function for the implementation of the random process (6) is defined as follows

$$k(\vartheta) = \sigma_a^2 P(x \ge \vartheta) + 0 \cdot P(x < \vartheta) = \begin{cases} k(\vartheta) = \sigma_a^2(1 - |\vartheta|) & \text{if } |\vartheta| \le \frac{2}{Z}, \\ k(\vartheta) = 0 & \text{if } |\vartheta| > \frac{2}{Z}. \end{cases} \quad (13)$$

The correlation function $k(\vartheta)$ for flow $\gamma(\tau)$ (6) satisfies limit equality (5). The sufficient condition for the fulfillment of equalities (3) and (4) used to calculate the statistical characteristics of the approximated random process $\gamma(\tau)$ is fulfilled. An important result is the fact that the correlation function for the realization of the random process (6) does not depend on the distribution law of the random variable Θ, that determines the material flow values. This approach makes it possible to determine the law of distribution of a random variable of the input material flow based on experimental data, which significantly simplifies the process of constructing a generator of input material flow values. This process comes down to creating a generator of random values of random material according to a given distribution function of experimental values without taking into account the type of correlation function. With an increase in the number of partitions Z of the experimental realization, the approximation accuracy increases, which affects the quality of the generated generator of random values of the input material flow.

5. Analysis of results

Paper [9] presents the results of studies of the input stochastic flow of material (Figure1), carried out for a brown coal quarry (Bełchatów, Poland).

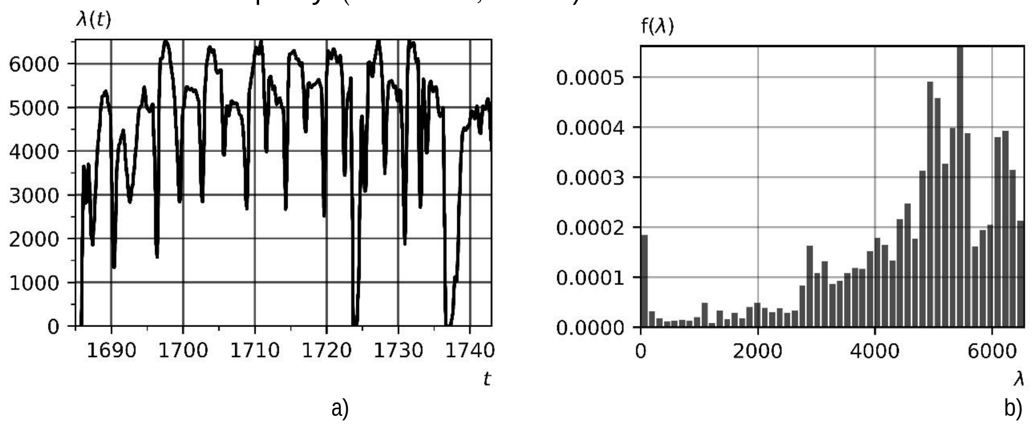


Figure 1: Experimental measurements of the input material flow for a brown coal mine (Bełchatów, Poland) [9]: a) realization of input material flow; b) histogram of distribution of input material flow values.

The results of experimental measurements of the volumetric productivity of an excavator SRs 2000 are given. Experimental realization of the input material flow demonstrates a fairly high unevenness of the material flow due to production conditions.

With a quasi-constant period of oscillation, the amplitude of the oscillation is one third of the maximum value of the material flow. Particular attention is paid to the problem of energy recovery for inclined conveyors.

The realization obtained as a result of measuring the values of the input material flow is presented, Figure1. Statistical characteristics of the input material flow are not used in the proposed energy recovery model.

This is due to objective difficulties in determining statistical characteristics based on available experimental data and is a separate study. An option to overcome these difficulties may be the use of techniques that determine both the type of input material flow and its statistical characteristics.

Taking into account the dimensionless parameters (1), (2), let us reduce the input material flow $\lambda(t)$ to the dimensionless form $\gamma_f(\tau)$, Figure2. Let us approximate the dimensionless realization of the input material flow $\gamma_f(\tau)$ by implementation (6).

When constructing the experimental realization N =57950 consecutive values of the input material flow were used. To approximate, the number $Z = 100$ of intervals is used each of which contains ~580 material flow values.

The material flow value at each interval is calculated as the mathematical expectation of the material flow values belonging to the interval.

Increasing the number of intervals leads to an increase in the accuracy of approximation of the experimental realization.

The result of the approximation for the realization of a dimensionless material flow $\gamma_f(\tau)$ is presented in Figure 3.

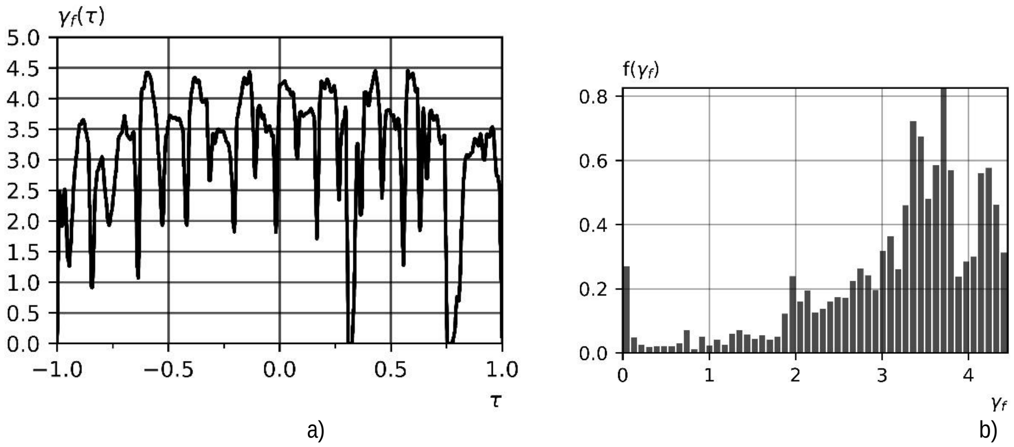


Figure 2: Dimensionless input material flow (experimental): a) realization $\gamma_f(\tau)$ of material flow; b) histogram of distribution of random values γ_f of material flow.

The approximation error $\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau)$ of the experimental realization $\gamma_f(\tau)$ of dimensionless material flow is demonstrated in Figure 4. The approximation error value ε distribution law is quite close to the normal distribution law (Figure 4a). The presence of tails on the Q-Q plot (Quantile-to-Quantile) (Figure 4b) and, as a consequence, the presence of deviations from the normal distribution law is explained by restrictions on the upper and lower values of the input material flow.

The statistical characteristics of the approximation realization $\gamma_a(\tau)$ are used to construct a generator of random values of the input material flow. To ensure a given law of distribution of a random variable that determines the value of the input material flow, the inverse function method is used.

The distribution of the random variable γ_a of material flow is used as the base distribution, the distribution histogram of which is presented in Figure 3b. An realization of the generated dimensionless input material flow and a histogram of the distribution of input material flow values for the interval $\tau \in [-1,1]$ are shown in Figure 5.

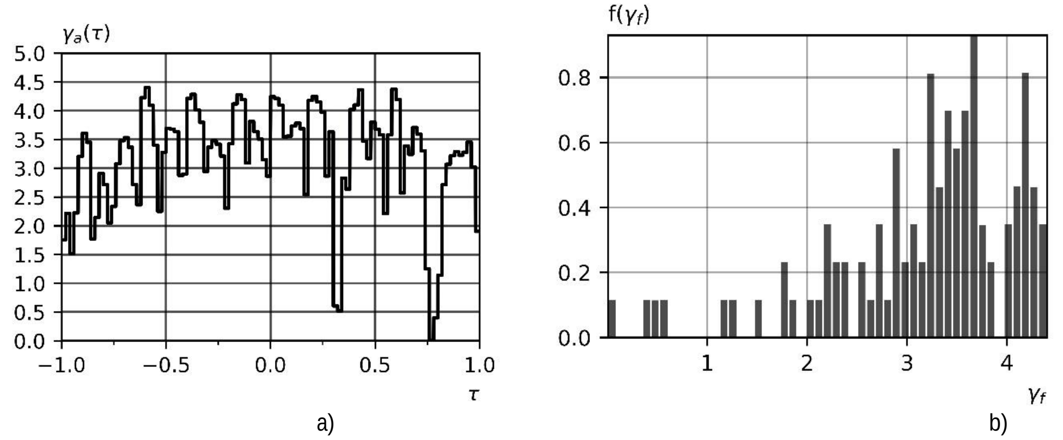


Figure 3: Dimensionless input material flow (approximation): a) realization $\gamma_a(\tau)$ of material flow; b) histogram of distribution of random values γ_a of material flow.

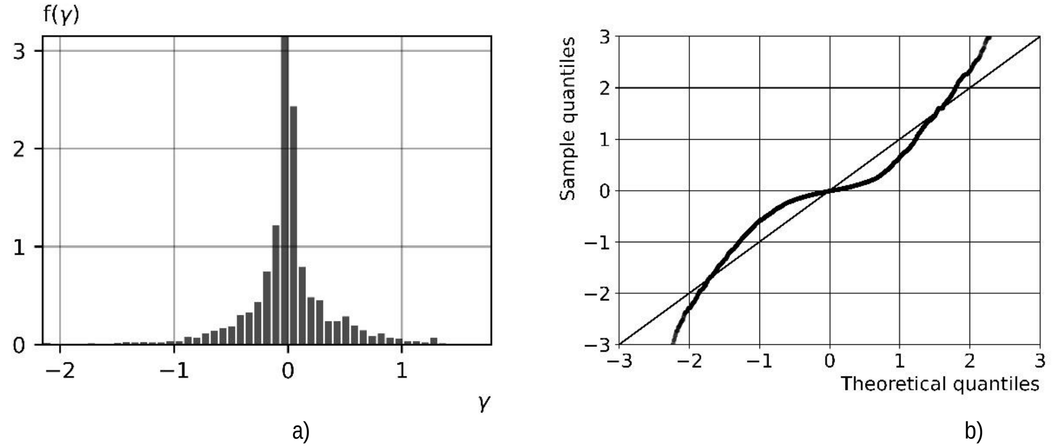
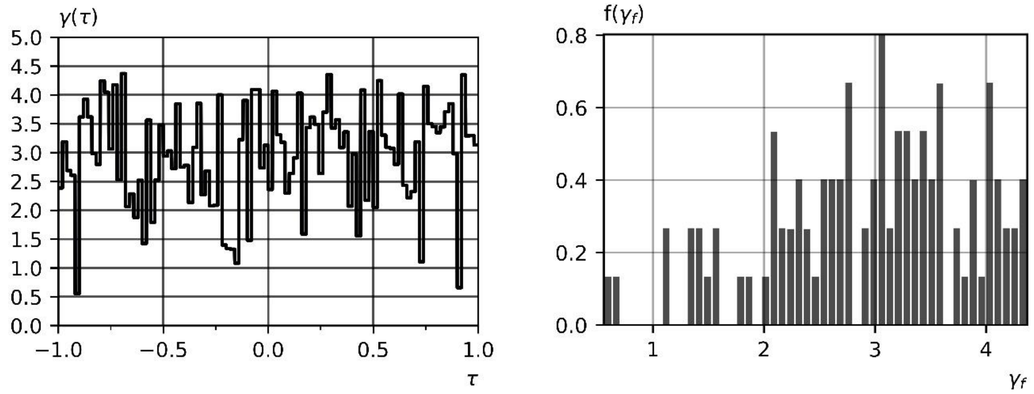


Figure 4: Approximation error for experimental realization of dimensionless material flow $\gamma_f(\tau)$: a) error value distribution histogram $\varepsilon(\tau) = \gamma_f(\tau) - \gamma_a(\tau)$; b) Q-Q ε error plot to demonstrate the quality of the approximation.

As the next step of the study, the comparative analysis of the correlation functions for the experimental, approximated and generated implementations of the input material flow is performed (Figure 6).

The correlation function for the approximated realization $\gamma_a(\tau)$ (Figure 6b) repeats the correlation function for the experimental realization $\gamma_f(\tau)$ (Figure 6a) with a sufficient degree of accuracy.

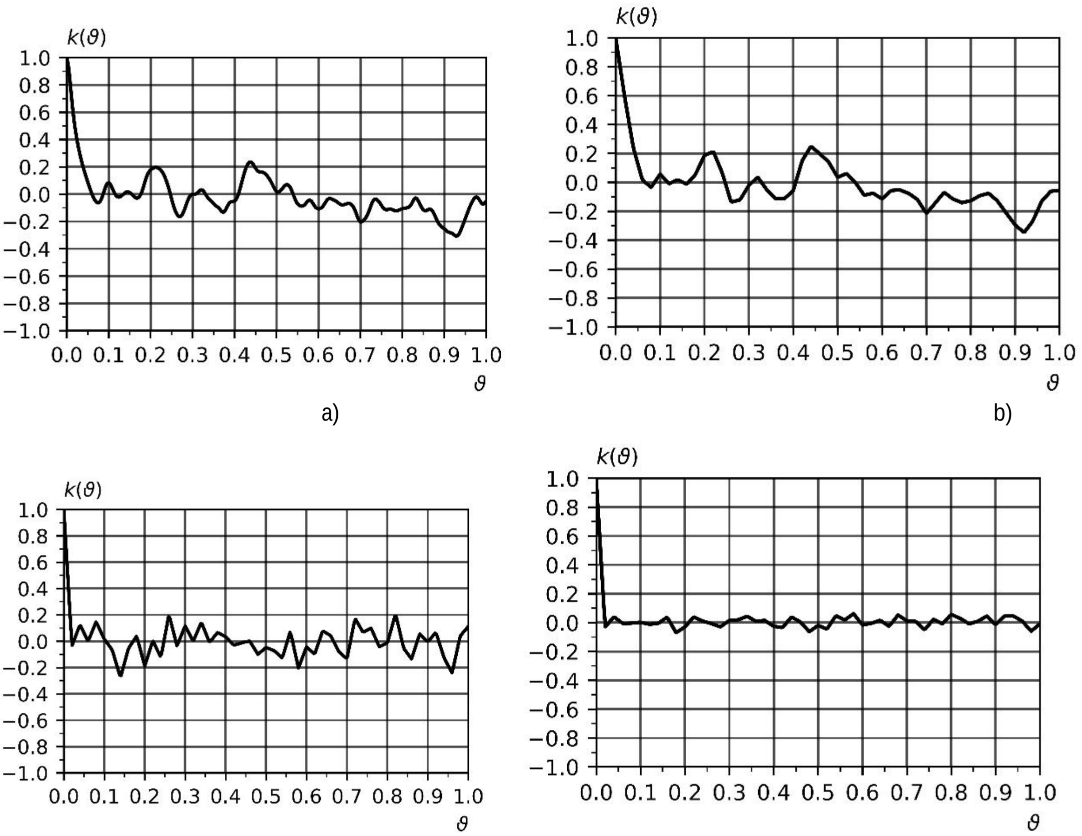
The correlation time is commensurate with the length of the interval chosen as the unit interval for approximation $\vartheta_{cor} \sim 2/Z = 0.02$. As discussed above, the length of a fixed interval $2/Z$, and accordingly the correlation time ϑ_{cor} of a stochastic process, is a similarity criterion in the model of the input material flow.



a) b)

Figure 5: Generated dimensionless input material flow: a) realization of input material flow; b) histogram of distribution of input material flow values.

The correlation function for the generated realization of the input material flow with the total length of generation time $\tau \in [-1,7]$ $(Z = 400)$ and $\tau \in [-1,31]$ $(Z = 1600)$ are presented in Figure 6c and Figure 6d, respectively. As the length of the interval increases, the correlation function takes on a pronounced form corresponding to the theoretical formula (13). The amplitude of oscillations relative to the zero value decreases with increasing number of approximation intervals.



c) d)

Figure 6: Correlation function $k(\vartheta)$ for realization the input material flow: a) experimental realization of the input material flow; b) approximation realization of the input material flow on the interval; c) realization of the input material flow generated on the interval $\tau \in [-1,7]$; d) realization of the input material flow generated on the interval $\tau \in [-1,31]$

The correlation function for the approximated realization $\gamma_a(\tau)$ (Figure 6b), constructed for a small number of intervals ($Z = 100$), acts as a zero approximation of the theoretical correlation function. A set of material flow values for fixed intervals of the approximation realization is used to determine the statistical characteristics of the material flow, which are used in the input material flow generator model. A comparative analysis of the statistical characteristics of the material flow represented by the experimental, approximated and generated realizations for the time interval $\tau \in [-1,1]$ ($Z = 100$) is given in Table 1.

The mathematical expectation and standard deviation for the experimental, approximated and generated realization of the input material flow have fairly close values, which is a criterion for assessing the accuracy of the experimental realization approximation process along with the Q-Q error plot (Figure 4) and comparative analysis of the correlation function for the generated realization of the material flow (Figure 6). Analysis of the experimental and generated realizations allows us to estimate the minimum number of fixed intervals for the approximation process.

Table 1
Characteristics of the realization of the input material flow

Parameter	experimental realization	approximated realization	generated realization
mathematical expectation	3.1729453	3.1729453	2.9460778
Standard deviation	1.0	0.9254287	0.8862863
Maximum value	4.4515155	4.4010264	4.3697888
Minimum value	0.0	0.0076316	0.5580695

For a generated realization of the input material flow that satisfies the condition of the minimum permissible number of fixed intervals for $\tau \in [-1,31]$, the correlation function for the implementation of 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.

6. Conclusions

This work solves the current problem of constructing realizations of the input material flow for training a neural network in models of a transport system containing a large number of interacting conveyors. A class of transport systems has been defined for which implementations of the input material flow allow approximations in the form of fixed intervals with random values of the input material flow. The approximation of the material flow is presented in the form of averaging of the material flow values at each fixed interval.

When approximating the experimental realization, it is assumed that the values of the material flow for each fixed interval of values are random, independent of previous and subsequent values, described by the same law of distribution of a random variable for the values of the input material flow, which allows us to assume the stationarity and ergodicity of the random process, characterizing the input flow of material of the transport system.

To build a generator of random values of the input flow of material of a transport system, a method is developed, consisting of successive steps. The first step is to represent the realization of the input flow in dimensionless form on the interval $\tau \in [-1,1]$. The second step is the choice of coordinate functions for the canonical expansion, allowing the approximation of the experimental realization by fixed intervals of a given length. In practice, minute intervals for the input material flow are considered to describe the input material flow. The third step is the canonical decomposition of the experimental realization of the input material flow into coordinate functions. The averaged material flow values for each fixed interval are random, independent of previous and subsequent values. This expansion corresponds to a theoretical correlation function, for which the limit equality is valid $\lim_{\vartheta \to \infty} k(\vartheta) \to 0$. The results of this canonical decomposition show a strong correlation with theoretical models, indicating the robustness of the approach. This allows us to use a single experimental realization of the input material flow to determine the statistical characteristics of the input material flow. The fourth step is to determine the statistical characteristics of the input material flow based on the experimental realization. The form of the correlation function does not depend on the form of the distribution law of the random variable for a fixed approximation interval. In other words, the same correlation function, determined by the canonical expansion of the experimental realization in coordinate functions, corresponds to many variants of the laws of distribution of a random variable of the input material flow for a fixed interval. The fifth step is based on the fact that, given the canonical expansion of the experimental realization in coordinate functions, the form of the correlation function does not depend on the distribution law of the random variable for a fixed approximation interval. This developing highlights the versatility of the proposed method in dealing with different distribution laws without compromising accuracy. This simplifies the solution to the problem of constructing a generator for values of the input material flow distributed according to a given distribution law of a random variable and a given correlation function. As a given distribution law of a random variable, a set of values of the input material flow for fixed intervals of the approximated realization is used. The form of the correlation function is uniquely determined by the choice of the canonical expansion of the experimental realization in terms of the coordinate functions proposed in this paper. 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. When generating random values that form the realization of the input material flow, the statistical characteristics of the generated realization correspond to the statistical characteristics of the experimental realization. The length of the time interval of the experimental realization has a significant impact on the statistical characteristics of the realization of the input material flow. A comparative analysis of correlation functions constructed for time intervals of different lengths is given. The accuracy of approximation of the correlation function constructed on experimental data taking into account the given type of approximation to the theoretical analogue can be used as a criterion determining the minimum permissible length of the time interval of experimental measurements. This will ensure the required quality of the random value generator of the input material flow. The results show that longer time intervals yield more accurate statistical characteristics, which is critical for the quality of the data used in building high-performance transport conveyor models. This study clearly demonstrates that with a small amount of partitioning into fixed intervals, the statistical characteristics of the experimental realization 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. Future work will focus on refining the methodology to further minimize deviations and enhance the accuracy of the generated data.

The prospect of further research is the development of methods for estimating the minimum acceptable length of the time interval for performing experimental measurements, as well as the analysis of the dependence of the quality of the random value generator on the number of experimental realizations.

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