Modeling of the belt conveyor control system using artificial intelligence methods

O V Druzhinina\textsuperscript{1}, O N Masina\textsuperscript{2} and A A Petrov\textsuperscript{2}

\textsuperscript{1} Federal Research Center “Computer Science and Control” of Russian Academy of Sciences\textsuperscript{‘}, 44, building 2, Vavilov str., Moscow, 119333, Russian Federation
\textsuperscript{2} Bunin Yelets State University, 28, Kommunarov str., Yelets, 399770, Russian Federation

E-mail: ovdruzh@mail.ru

Abstract. The paper is devoted to the development of instrumental and methodological support for the study of conveyor transport systems with intelligent control mathematical models. An optimal control model is constructed for a belt conveyor with a dynamic change in the angle between the horizontal plane and the belt plane. Methods for studying the belt conveyor model based on the design of PID controllers and neural network controllers are proposed. The results of computational experiments using the training of a feedforward neural network and the use of reinforcement learning are presented. A comparative analysis of computational experiments with the use of control based on the synthesis of a fuzzy controller, control using artificial neural networks, and control based on a PID controller is performed. The obtained results can be used in neural network modeling of complex systems and in solving problems of automation of technological and production processes.

1. Introduction

The production organization problems require of modern technological and production processes automation. The main means of these processes automation include continuous transport machines and corresponding control systems. The use of these continuous machines, in particular conveyors, can significantly increase the level of automation and create a single integrated production technology [1]. Questions of conveyor transport systems design and application are considered, for example, in [2].

For the development of conveyor transport control systems, computer modeling methods of nonlinear, non-stationary and inhomogeneous processes with the use of artificial intelligence methods can be successfully used. Artificial intelligence methods include artificial neural network methods, fuzzy logic, and machine learning [3–5]. Among the theoretical and applied problems of production process control, there are such problems, the solution of which requires the use of artificial intelligence methods. Such problems include the synthesis of new intelligent models of conveyor transport, as well as the analysis of control under conditions of uncertainty and abrupt changes in load [6–8]. In the problems of designing large transport and technological systems involving the presence of various types of vehicles the use of intelligent control methods is particularly relevant.

The aim of the paper is to synthesize a controlled mathematical model of a belt conveyor with a dynamically changing angle between the horizontal plane and the belt plane, as well as to analyze this model using intelligent control.
In section 2, a model of a controlled belt conveyor is constructed, a quality criterion is formulated, and control algorithms are proposed. Section 3 describes the results of computational experiments on control by belt conveyor model. Section 4 provides a brief comparative analysis of the results of the PID controller implementation and the control based on the neural network controller.

2. Models and methods

We study a generalized model of a single-drive belt conveyor with a dynamically variable lifting angle. We will assume that the conveyor belt is inextensible, the loads on the belt have a significant effect on the momentum and angular momentum of the conveyor; the friction force of the loads on the conveyor belt is decided to neglect. In this case, the differential equations of the model can be represented as:

\[
\begin{align*}
\dot{x}_0 &= x_1, \\
\dot{x}_1 &= \frac{u_1 - kx_1 - m_0 g \sin(\alpha_0)}{m_1 + m_0}, \\
\dot{\alpha}_0 &= \alpha_1, \\
\dot{\alpha}_1 &= \frac{u_2 + l \alpha_1}{s \varepsilon^2 (m_0 + m_1)} - \frac{g \cos(\alpha_0)}{\varepsilon}, \\
(u_1, u_2) &\in U, \quad m_0 \in M,
\end{align*}
\]

where \(x_0\) is the movement of the conveyor belt, \(m_0\) is the mass of the conveyor belt, \(\alpha_0\) is the angle of lifting of the conveyor, \(\alpha_1\) is the angular speed of the conveyor lifting, \(m_1\) is the total mass of loads on the conveyor, \(s\) is the coefficient of the conveyor inertia, \(\varepsilon\) is the position of the gravity center of the conveyor, \(k\) is the coefficient of rolling friction, \(l\) is the coefficient of axial friction, \(u_1\) is the linear force of translational motion of the conveyor, \(u_2\) is the torque value for controlling the lifting angle of the conveyor, \(U\) is the set of control vectors, \(M\) is the set of loads masses.

Various types of optimal system control problems (1) are of theoretical and applied interest. We will consider such a statement of the problem in which the optimal control is the one that stabilizes the system (1) over an infinite time interval. The following conditions are considered necessary and sufficient for the stabilization of the system (1):

\[
X(0) \in E_i, X(t_u) \in E_2, \forall t_u \in (t_1, \infty),
\]

where \(X = (x_1, \alpha_0, \alpha_1)\) is the partial phase vector of the system (1), \(t_1\) is the time taken to stabilize the system (1), \(t_u\) is the boundary of the time interval under consideration, \(E_i \cap E_2\) are some subspaces of the phase space of solutions, and \(E_2 \subset E_1\).

Further we will formulate a control quality criterion based on conditions (2). Let \(E_\varepsilon\) be a certain neighborhood of the target point \(e\) of the phase space. Then the quality criterion aimed at limiting the trajectories of system (1) close to \(e\) can be written as:

\[
\lim_{t_n \to \infty} \frac{1}{t_n} \int_0^{t_n} \| X - e \| \ dt \to \min,
\]

where the incoming values are explained after formulas (1), (2).

We consider the problem of finding such controls \(u_1, u_2\) that satisfy (2), (3). To control the model (1), we propose a combined scheme. Computational experiments show that to control the linear speed of the conveyor, a sliding mode with the scheme...
\begin{align*}
    u_t(t) &= s + d \quad \text{if} \quad x < \hat{x}, \\
    u_t(t) &= s - d \quad \text{if} \quad x > \hat{x}
\end{align*}

(4)

is sufficient. In this scheme \(s\) is the coefficient that characterizes the deviation of the system (1) from the singular point (taking into account the equality \(x_1(t) = 0\)), \(d\) is the constant value of the control thrust, \(\hat{x}\) is the required state of equilibrium. The described scheme functions at \(t \in (t_1, t_2, \ldots, t_k)\), where \(k\) is the number of switches.

The synthesis of angular speed control for the model (1) is carried out on the basis of a fuzzy controller, on the basis of a neural network controller, and also on the basis of a PID controller. Thus, we consider three types of control.

For the first type of control, the Mamdani algorithm is used with a base of 7 rules. More detailed results and a description of the controller operation are given in [9].

The second type of control uses a feedforward neural network with 8 neurons in 1 hidden layer. The inputs of the neural network \(i_1, i_2\) are fed the values of the mismatch error and its derivative (the conveyor lifting speed). The hidden layer and the output layer are represented by neurons with a tangential activation function. Also in the topology of the neural network there is an additional gain layer, which linearly increases the value of the control signal by multiplying by a constant factor. The control carried out in a switchable mode at fixed time intervals, i.e. that is the condition

\[ \forall t \in (t_1, t_2, \ldots, t_n): u_{t_1}(t) = N(\sigma, \sigma) + s \]

(5)

is satisfied, where \(t_1, t_2, \ldots, t_n\) are the switching moments, \(N\) is the neural network functional, \(\sigma\) is the mismatch error, and the value of \(s\) is explained above.

The neural network is trained using the reinforcement learning algorithm, which consists of the following steps:

1. To initialize a neural network with random weight coefficients.
2. To find the trajectory of the model (1) with neural network control.
3. To calculate the quality criterion (3) for the resulting trajectory.
4. To adjust the weight coefficients of the neural network.
5. If the stop condition is reached, terminate the algorithm. Otherwise go to step 2.

Besides, for a comparative analysis of efficiency we consider PID-based control. The dynamic systems analysis problems based on the PID controller is considered in many papers (see, for example, [10]). In our paper we use the following model of the PID controller:

\[ u = P\left(\sigma(t) + I\int_0^t \sigma(t)dt + D\frac{d\sigma(t)}{dt}\right), \]

(6)

where \(P, I, D\) are the proportional, integral, and differential coefficients of the PID controller, \(\sigma(t)\) is the mismatch error. The tuning problem of the PID controller is to find such coefficients that best meet the quality criterion.

The setting up procedure for the coefficients consists of the following steps:

1. To set random values of \(P, I, D\).
2. To find the trajectory of the model (1) with control based on the PID controller.
3. To calculate the quality criterion (3) for the resulting trajectory.
4. To adjust the values of \(P, I, D\) using the optimization algorithm.
5. If the stop condition is reached, terminate the algorithm. Otherwise go to step 2.
Various algorithms for finding the optimal values of the PID controller are known [11]. In this paper, we use the differential evolution algorithm from the Scipy mathematical library [12].

3. Results
To conduct computational experiments, a team of authors developed a computer program in Python 3. The following conditions are considered. The conveyor length is assumed to be 2 m. Relative to the belt, loads are loaded or unloaded at random moments, i.e. \( \Delta m \in (-0.25, 0.25) \). The position of the conveyor mass center changes arbitrarily in the range from 0.8 m to 1.2 m.

The control goal is to stabilize the model in a given motion mode close to \( x_1 = 2 \) m/s. We choose \( \alpha_0 = \frac{\pi}{10}, \alpha_1 = 0, t_n = 250 \). Let us assume the following initial conditions for the model (1):

\[
x(0) = 0, \dot{x}(0) = 0, \alpha(0) = 0.5, \dot{\alpha}(0) = 0.
\]  

Figure 1 shows the phase curve, the nature of this curve indicates the orbital stability of the system (1). It can be noted that this indicator is close to the specified mode of motion. Figure 2 shows the value of the control signal. The specified signal is a continuously increasing value with fluctuations occurring at the moments of loading/unloading. The oscillation amplitude of \( u_2 \) is limited by the gain of \( y_1 \). The value of the optimality criterion (3) for neural network control at \( t = 250 \) is 158.507.

Further we consider control with a PID controller under conditions similar to those for control with a neural network controller. To adjust the coefficients of the PID controller, we use the method of differential evolution from the Scipy mathematical library. The results of the computational experiments (PID control) are shown in figure 3.

**Figure 1.** Phase curve of the system (1) under neural network modeling.

**Figure 2.** Control of the lifting angle in the system (1) under neural network modeling.
The phase trajectory in figure 3 is similar to the phase trajectory shown in figure 1 (neural network control). However, the amplitude of the deviation from the specified angle value $\frac{\pi}{10}$ significantly exceeds the amplitude of the deviation in figure 1.

The value of the quality criterion for control with a PID controller at $t = 250$ is 362.488. This value significantly exceeds the value of the quality criterion for neural control. Thus it can be noted that control with a PID controller for this problem is less effective than control based on an artificial neural network.

4. Discussion
In this paper, a dynamic model (1) of a belt conveyor is synthesized and a number of computational experiments are performed under given conditions. In this paper, a belt conveyor model is synthesized, given by a system of differential equations (1), and a number of computational experiments are carried out under given conditions. The obtained results demonstrate a number of neural network control advantages in comparison with control based on the PID controller. In particular, this is evidenced by the structure of the phase trajectories in figure 1 (using the neural network controller) and figure 3 (using the PID controller). At the same time, the structure of the PID controller is simpler than the structure of the neural network controller.

It is important to note that further development of research on mathematical modeling of conveyor transport systems can lead to effective results with the use of both neural network and other types of control in the model (1). First of all, we note the prospects for the possibility of complicating the experimental conditions. The proposed approach to modeling allows us to take into account the influence of abrupt changes in the parameters on the dynamics of the system (1). More complex experimental conditions imply the introduction of errors in the estimation of the model parameters.

The software developed in the framework of this paper is used as a basis for the developing of modules of a software package for modeling continuous transport systems with intelligent control. This software package allows to study new controlled mathematical models of belt conveyors using artificial intelligence methods.

5. Conclusion
The synthesized controlled model and the proposed algorithms for the implementation of regulators can serve as a basis for the instrumental and methodological support of conveyor transport systems with intelligent control. The developed approach to modeling allows us to perform a comparative analysis of control based on the synthesis of the PID controller and control using artificial neural
networks. In addition, this approach allows us to solve problems of conveyor models optimal control using various types of quality criteria. The obtained results can be used in the design and construction of continuous machines with the use of artificial intelligence.

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