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Modeling and Stabilization of Conveyor Transport Systems with Intelligent Control

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Abstract—This paper deals with a generalized mathematical model of a controlled belt conveyor with a variable angle between the horizontal and belt planes. The model is defined using a system of four nonlinear differential equations with switching. It includes the linear movement of the conveyor belt, changes in the system momentum, axial and linear friction, the damping of the horizontal position of the conveyor, and the factors of smooth loading and instant unloading of cargo. Stabilization conditions are established for this model considering simulation components related to the nature of loading and unloading modes of the conveyor belt. A PID controller, a neuro-PID controller, and neural network controllers of recurrent and non-recurrent types are designed to control the angular position of the conveyor. Linear velocity control is implemented by introducing a sliding mode. Computational experiments are carried out and given an interpretation. The performance of the controllers mentioned above is comparatively analyzed.

Keywords: mathematical modeling, differential equations with switching, conveyor systems, intelligent control, stabilization, neural network controller, PID controller, neuro-PID controller, machine learning

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1. INTRODUCTION

The design, automation, and monitoring of conveyor systems are topical lines of research [1–11]. The range of important problems includes, e.g., stabilization of conveyor traction, monitoring of dynamic load of conveyor belts, optimization of conveyor control parameters, design of intelligent conveyor systems, and creation of multifunctional continuous transport systems. The solution of these problems requires using methods of control theory, optimization theory, and artificial intelligence tools.

The mathematical modeling of controlled technical systems, including conveyor transport systems, involves such artificial intelligence tools as fuzzy control, artificial neural networks, and machine learning [4, 12–20]. For example, the construction of a fuzzy tracking system for the state of a conveyor belt was discussed in [16]. Several aspects of conveyor control optimization using artificial neural networks were studied in [17]. The issues of applying machine learning models for the high-precision classification of rubber conveyor belt loads were considered in [18].

As is known, conveyor systems are characterized by the switching mode of operation. When describing and studying dynamic models of conveyor transport, it seems reasonable to use the concepts and methods of the theory of switched systems [21–23] and design methods of different controllers, including PID controllers [24, 25]. The behavior of switched systems in some important cases is studied by introducing sliding modes [26]. The development of computer models of switched systems was considered, e.g., in [23]. An important problem is to analyze the stability of switched systems [27–29]. Numerical optimization algorithms related to nature-inspired methods can be used to investigate switched systems; note differential evolution as a popular method of this class [30, 31]. Reinforcement learning [32] finds application in the design of controlled systems with switching. The computer modeling of switched systems is supported by high-level languages; among them, we mention Python and Julia [33, 34] with appropriate mathematical libraries.

The control of dynamic systems based on the PID controller is widely known and has been considered in many publications, particularly in [35]. There exist various optimal tuning algorithms for the PID controller [25, 36, 37]. A new approach to tuning and optimizing PID controller parameters was proposed in [25] based on reducing the original problem to an optimization problem. Within this approach, the performance of the controller is evaluated by a quadratic criterion of the system output. The PID controller is tuned against uncertainty in the initial conditions to make the system output uniformly small while additionally ensuring a given degree of stability of the closed-loop system. The performance of PI and PID controllers in the integral saturation mode was analyzed in [38]. (This mode arises when imposing constraints on the controller output.) The forms of PID controllers, as well as algorithms of their automatic tuning and adaptive control, were surveyed in [24]. The issues of tuning the parameters of the PID controller of a belt conveyor for coal transportation were studied in [39] using a neural network; more precisely, a neural network model of torque control was constructed therein.

It is interesting to compare the performance of the PID controller and the neural network controller under the same conditions [40]. The differential evolution method from the Scipy mathematical library has shown quite effective results for tuning the PID controller coefficients. Methods for investigating a belt conveyor model based on the design of PID controllers and neural network controllers were proposed in [40]. The authors considered a simplified belt conveyor model without axial drag and damping as well as without smooth cargo loading and unloading.

The modified mathematical model of the belt conveyor developed in [41] includes the axial drag and dynamic change of the angle between the horizontal and conveyor belt planes. The neural network controller and PID controller were designed for the model, and optimal control problems were solved using these controllers. The results of computer experiments with trajectory dynamics were presented. Control laws for stabilizing the elevation angle of the conveyor belt were designed under the variable weight of cargo and the change in the center of gravity of the conveyor. The adaptability of neural network control and PID control to a linear increase in axial drag was studied.

A neural network controller for a belt conveyor model with a dynamic change of the angle between the horizontal and conveyor belt planes, the factors of smooth loading and instantaneous unloading of cargoes, and without axial drag was designed in [42]. The results of computer experiments of this model were compared with those of the model considered in [41].

The models described in [40–42] can be refined in the direction of analyzing the effect of various factors; among them, we note the impact of transients on system dynamics when changing the modes and nature of loading of the conveyor. Other directions to improve the models include the analysis of various dissipative effects and conveyor position regulation based on damping subsystems.

This paper consists of seven sections. Section 2 describes and analyzes the generalized model of a controlled belt conveyor. An optimal control problem is formulated for belt movement and the angular position of the conveyor; in addition, stabilization conditions are established for the model. In Section 3, we design a PID controller, a neuro-PID controller, and neural network controllers of recurrent and nonrecurrent types. Linear velocity control is implemented by introducing a sliding mode. Section 4 summarizes the results of computational experiments and provides an interpretation of the trajectory dynamics based on different types of controllers. In Section 5, we compare the performance of the designed controllers and present the corresponding measurement results. The results of this paper, as well as the qualitative effects of the application of intelligent control, are discussed in Section 6.

2. DESCRIPTION AND ANALYSIS OF THE GENERALIZED CONTROLLED BELT CONVEYOR MODEL

Consider the problem of designing a control system for a belt conveyor with a dynamically varying elevation angle of the belt. The state space of the system model is formed by the following coordinates: the linear movement of the belt, the system momentum, and the elevation angle above the plane. Objects of different weights are loaded to and unloaded from the moving conveyor at random time instants, which can affect its motion characteristics. We neglect the belt stretching and also suppose negligibly small the influence of the momentum on the change of the angular velocity. It is required to ensure the stationary mode while maintaining the linear velocity and a constant elevation angle in the process of conveyor operation. In view of these conditions, the mathematical model of the belt conveyor control system can be represented as the system of differential equations

$$
\begin{gathered}
\dot{x} = \frac{p}{m}, \\
\dot{p} = u_p(t) - k\frac{p}{m} - (m - m_0)g\sin(\alpha), \\
\dot{\alpha} = \omega, \\
\dot{\omega} = \frac{u_\alpha(t) - l\omega}{mc\varepsilon^2} - \frac{g\cos(\alpha)}{\varepsilon} + \frac{1}{(\alpha + \frac{\varepsilon_0}{g}\frac{1}{\tau})^\tau}, \\
u_p, \quad u_\alpha \in U, \quad \varepsilon \in E, \quad m \in M,
\end{gathered}
\tag{1}
$$

with the following notations: x is the movement of the conveyor belt; p is the momentum of the system; α is the elevation angle of the conveyor relative to the zero position; ω is the angular velocity of the conveyor; g is the gravitational acceleration; m_0 is the weight of the conveyor belt; m is the total weight of the system; $u_p(t)$ is the conveyor traction control function; $u_\alpha(t)$ is the belt elevation angle control function; ε is the position of the conveyor's center of gravity relative to the bottom roller; c is the coefficient determining the conveyor's moment of inertia; k is the rolling friction coefficient; l is the axial drag coefficient; ε_0 is the averaged position of the center of gravity; finally, τ is the damping stiffness coefficient. The sets M, E, and U include the values of the weights of cargo, the center of gravity, and the controls, respectively. Operation modes in model (1) are changed at the instants of choosing the corresponding values $m_1 = m - m_0$ and ε in accordance with a definite rule that specifies the switching scheme.

A switching scheme was developed to choose the values of ε and m_1. This scheme implements simulation modeling of cargo loading and unloading at arbitrary time instants. We propose to calculate particular values of the vectors (ε, m_1) based on a simulation algorithm. The change of cargo weights on the belt is determined by weight-switching algorithms of two types, namely, 1) instantaneous loading with instantaneous unloading and 2) smooth loading with instantaneous unloading. The physical meaning of smooth loading consists in the gradual transfer of kinetic energy from the belt to the load. In the case of instantaneous loading, this effect is not considered. The loading and unloading modes were described in [42].

Definition 1. The controlled system (1) that models the conveyor belt motion with switching is said to be locally stabilizable if, for $t \in (t_1, \infty)$, any trajectory of (1) lies inside some tube in the multidimensional state space.

Definition 2. The system state is the vector $\theta = (\dot{x}, \alpha, \omega)$ of the state parameters of system (1).

Definition 3. The *target state* λ of system (1) is an equilibrium $\lambda = (\bar{s}, \bar{\alpha}, 0)$ that system (1) must reach in the control process.

Here we consider a stabilization problem for system (1) in which it is required: a) to ensure the transition from an initial state λ_0 to the target state λ in the minimum time; b) to maintain the system state in a small neighborhood ε of the target state λ as $t \to \infty$.

As a measure of stabilizability, we can choose the norm of the difference between the target state vector λ and the partial state vector of system (1). With this measure of stabilizability, under some condition that can be interpreted as error boundedness on an infinite time interval, it is not difficult to formulate a sufficient condition for the local stabilizability of system (1). To justify this sufficient condition, we use the definitions of local stabilization and the target state as well as the properties of the state variables of system (1) that are significant for the dynamics of the belt conveyor model with a variable elevation angle (namely, the variables $\dot{x}$, α, and ω).

Further, let the error in system (1) be $\sigma = \lambda - \theta$. In view of this error, we assume the existence of feedback control functionals u_1, u_2, ζ_1, and ζ_2 such that

$$u_p(t) = u_1(\zeta_1(\sigma(t))), \quad u_\alpha(t) = u_2(\zeta_2(\sigma(t))). \tag{2}$$

Theorem 1. *Let $t \in [t_1, \infty)$. If, under the control functions* (2),

$$\forall \theta(t) : t \in [t_1, \infty) \ \exists \delta : \|\sigma\| \in [0, \delta), \tag{3}$$

then system (1) *is locally stabilizable.*

Indeed, condition (3) holding for any t defines some δ-neighborhood of the target state in which the representative point of the trajectory can be located. The set of such neighborhoods geometrically forms a tube. Thus, system (1) is locally stabilizable.

The concept of local stabilization corresponds to the cases of "partial" stabilization of the conveyor system when there exist trajectories with non-decaying oscillations or trajectories "parallel" to λ. In these cases, the control problem has only partial solutions.

In the cases of full stabilization, system (1) always gives an adequate response to perturbations, and the rate of stabilization of the system under the perturbations is proportional to the deviation from the center of the tube. From a formal point of view, the derivative of the error is proportional to the magnitude of the error itself in the chosen metric. The above stabilization condition is more stringent, which allows us to conceptualize the global stabilizability of the system.

Definition 4. System (1) is said to be globally stabilizable if, on some time interval $t \in (t_0, t_k)$, the error tends to zero under constant perturbations (i.e., $m_1 = \text{const}$).

Due to the simulation component of this model, the system in which the above conditions hold in the absence of time-isolated perturbations can be considered globally stabilizable. We have the following result.

Theorem 2. *Let system* (1) *with* (2) *satisfy condition* (3)*. If, under the condition* $\frac{dm_1}{dt} = 0$,

$$\forall \theta(t) : t \in [t_1, \infty) \ \exists \delta_1(t) \leqslant \delta : \|\sigma\| \in (0, \delta_1(t)), \quad \dot{\delta}_1(t) < 0, \tag{4}$$

then system (1) *is globally stabilizable.*

Indeed, if conditions (3) and (4) hold under a constant weight of cargo, the trajectory will be isolated in a continuously tapering tube until fulfilling $\sigma = \vec{0}$, which means the absence of an error. To ensure optimal control of system (1), we have to add optimality criteria to the conditions of Theorems 1 and 2.

In the sequel, two optimality criteria will be considered for angular position stabilization, namely, complex and simplified ones. The complex optimality criterion (with respect to the two state variables α, ω) has the form

$$C_1 = \int_{t_1}^{t_2} \|S - (\alpha, \omega)\| dt, \quad S = (\bar{\alpha}, 0). \tag{5}$$

We begin with the problem of minimizing the criterion (5) considering the angular position and angular velocity deviation errors. For the system stabilized in the global sense, the criterion (5) can be reduced to

$$C_2 = \int_{t_1}^{t_2} |\bar{\alpha} - \alpha| dt. \tag{6}$$

Second, we study the problem of minimizing the criterion (6) considering the angular position deviation error. Reduction of the criterion (5) is associated with the proportional dependence of the angular position and angular velocity deviation errors under the conditions of Theorem 2.

3. CONTROLLER DESIGN

The conveyor motion is regulated using controllers for the linear velocity and elevation angle. A sliding mode controller is applied to regulate the linear velocity:

$$\text{If } \dot{x} \geqslant \bar{s}, \text{ then } u_p = -\bar{u}; \text{ otherwise, } u_p = \bar{u}.$$

Here s is a given linear velocity and $\bar{u}$ is a fixed control value.

According to preliminary computational experiments, implementing angular position control by introducing a sliding mode does not stabilize system (1). In this regard, we design and compare the following types of controllers for regulating the angular position of system (1): a PID controller, a neural network controller, a recurrent neural network controller, and a recurrent neuro-PID controller. The PID controller and the neural network controller have the standard structure [40–42]. The structure of the recurrent controllers is presented in Figs. 1 and 2.

Figure 1 shows the diagram of the recurrent neural network controller with the 3-4-1 topology and tangential activation functions in the hidden and output layers. The values of the error, conveyor angular velocity, and neural network output with the unit delay are supplied to the input. Figure 2 shows the diagram of the recurrent neuro-PID controller: a neural network with the 3-4-3 topology is used to tune the PID controller coefficients.

The following notations are adopted in Figs. 1 and 2: e is the value of the angular position error; $\dot{e}$ is the time derivative of the angular position error; $u_\alpha(t)$ is the control value; Δi is the unit delay operator. The output values u have different ranges: $u \in (-1, 1)$ for the neural network controller with the tangent activation function, and $u \in (0, \infty)$ for the neuro-PID controller. Due to this difference, we apply a gain and filtering loop to obtain the value $u_\alpha(t)$. For the recurrent neural network controller, the tangent activation function symmetric about the origin is applied. The recurrent neuro-PID controller implements the DreLU and reLU activation functions in the hidden and output layer, respectively. These activation functions are conventional in neural network modeling [17, 18].

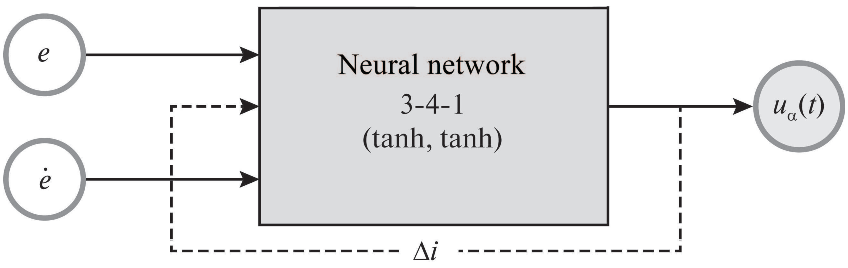

Fig. 1. The diagram of the recurrent neural network controller.

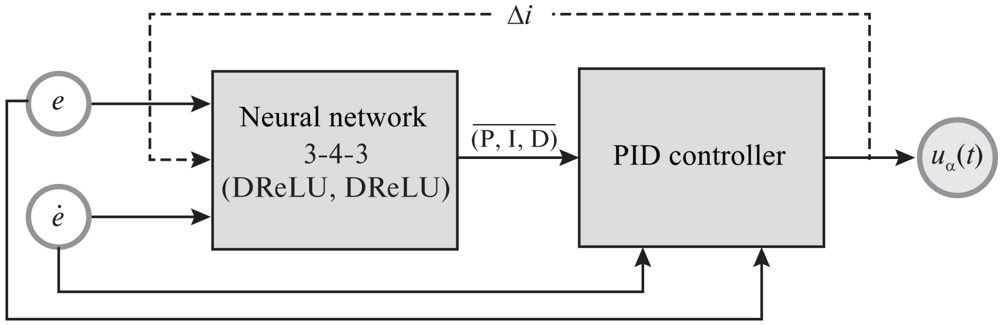

Fig. 2. The diagram of the recurrent neuro-PID controller.

The control period parameter Δt is set in each angular position control algorithm with a particular controller. The trajectory dynamics of system (1) changes depending on Δt. The control period $\Delta t \geqslant 0.05$ is characterized by a decrease in the uniformity of the belt angular position trajectories and a "jagged" plot of the linear velocity.

Note that the angle and linear velocity controllers may operate with different periods. The operation of controllers with different periods is due to the need to minimize the number of switching operations and save equipment life as well as to control implementability in practice. Different control periods are associated with inertia constraints. It is interesting to study a conveyor system model considering the admissible inertia of the conveyor drive.

When the control period decreases and the maximum differentiation step of the ODE solver is reduced accordingly, we observe a more smooth character of the linear velocity trajectory of the conveyor belt due to more switchings in the sliding mode. Note that increasing the control period decreases control robustness with respect to perturbations in system (1). Here robustness means preserving the range of values and control structure under perturbations in the system.

The parameters of all the designed angular position controllers are found using a reinforcement learning procedure based on an evolutionary optimization algorithm (differential evolution). The loss function for model (1) is obtained in the following steps: 1) setting the controller parameters; 2) calculating n trajectories (in the example below, $n = 3$) of the system with a particular controller; 3) calculating the mean value of (6) for the n trajectories. The topologies for the feedforward and recurrent neural networks were selected by computational experiments with limited training time. For the (feedforward and recurrent) neural network controllers, the tangential activation function in the hidden layer shows the best results in terms of the smallest mean value of (6). The control signal for the controllers is amplified and filtered as follows: for neural network controllers, the gain $\nu = 100$ is applied; for the PID controller, all values $u_\alpha \notin (-100, 100)$ are truncated.

A computer program was developed to numerically simulate the dynamics of the controlled model (1) with the designed controllers. The results of the computational experiments are presented below.

4. THE RESULTS OF COMPUTATIONAL EXPERIMENTS

The developed controllers were parametrically optimized using algorithms based on reinforcement learning. The simulation results are shown in Figs. 4–8. First, we consider the results of computational experiments using the PID controller. The initial conditions and initial parameters are $(x; p; \alpha; \omega) = (0;\ 0;\ 0.5;\ 0)$ and $(m_0; m; k; g; c; \varepsilon; \tau) = (0.1;\ 1.5;\ 0.5;\ 9.8;\ 0.5;\ 1;\ 10)$, respectively. The case of the smooth loading and instantaneous unloading of the belt is studied in the computational experiments.

The trajectories in Figs. 3 and 4 correspond to five runs of system (1) with the same parameters but different switching events.

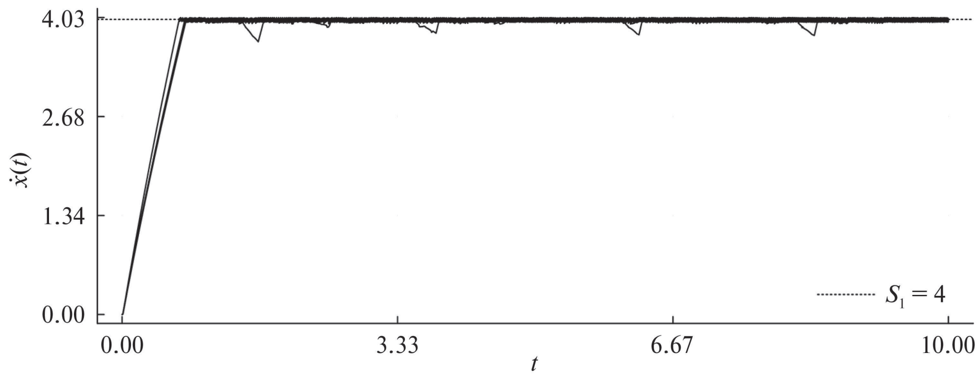

Fig. 3. The linear velocity of the belt for model (1) with the sliding mode controller and PID controller.

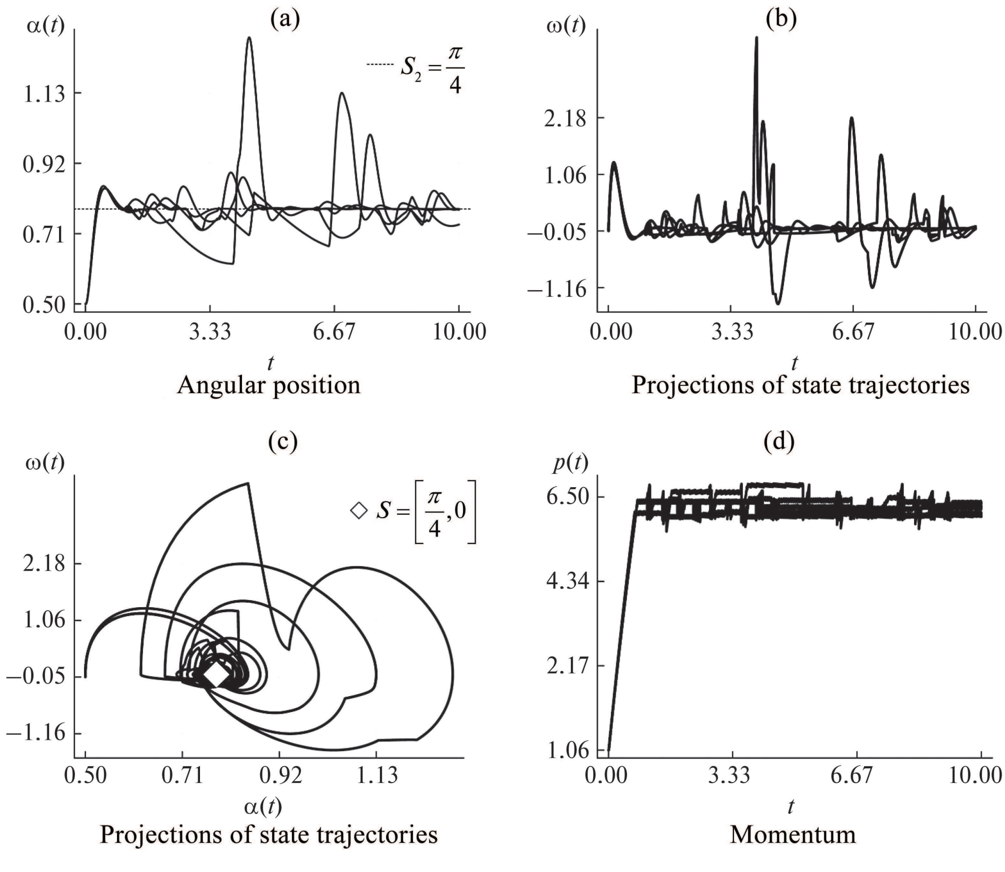

Fig. 4. The set of trajectories of system (1) with the PID controller.

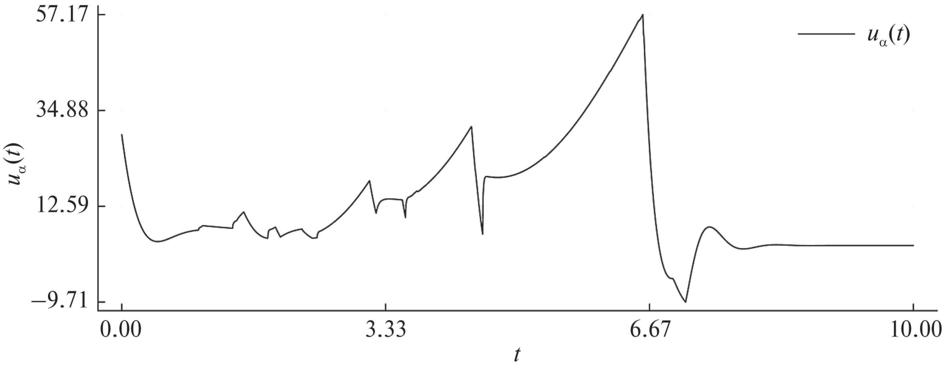

Fig. 5. The control function for the PID controller.

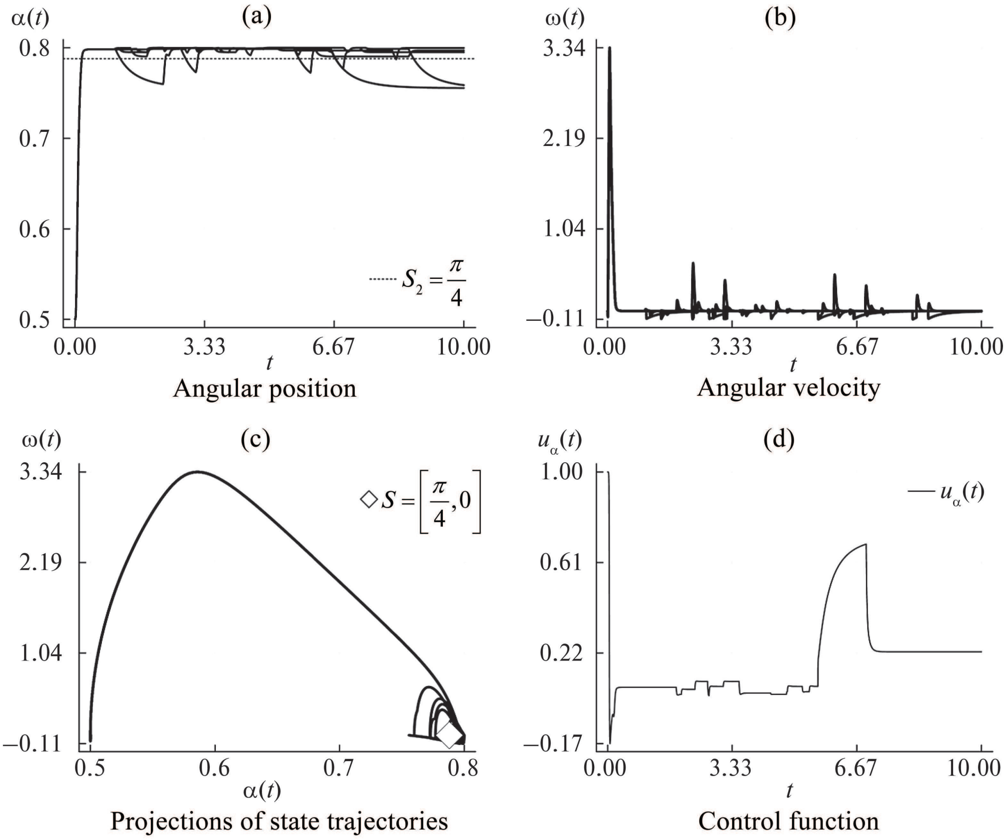

Fig. 6. The set of trajectories and control function for system (1) with the neural network controller.

Figure 3 illustrates linear velocity stabilization with single deviations due to cargo loading and unloading. The set of oscillatory trajectories in Fig. 4a has mean values tending to λ. Next, Fig. 4b presents the plots of the angular velocity of the conveyor belt; the deviations due to cargo loading and unloading can also be observed. According to Fig. 4c, the resulting trajectories have variability with respect to the occurrence of mode-switching events. In Fig. 4d, the reader can see the jump changes due to a one-step change in the momentum of system (1) during unloading.

Note that the conditions of Theorem 1 hold for the PID controller under the chosen factors of the computational experiment, but there is a control deficit with the impossibility of obtaining stable negative feedback in the control loop.

Figure 5 shows the plot of $u_\alpha(t)$ for the PID controller. According to Fig. 5, the control function is located above the abscissa axis, and the points of avoidable discontinuities are tracked.

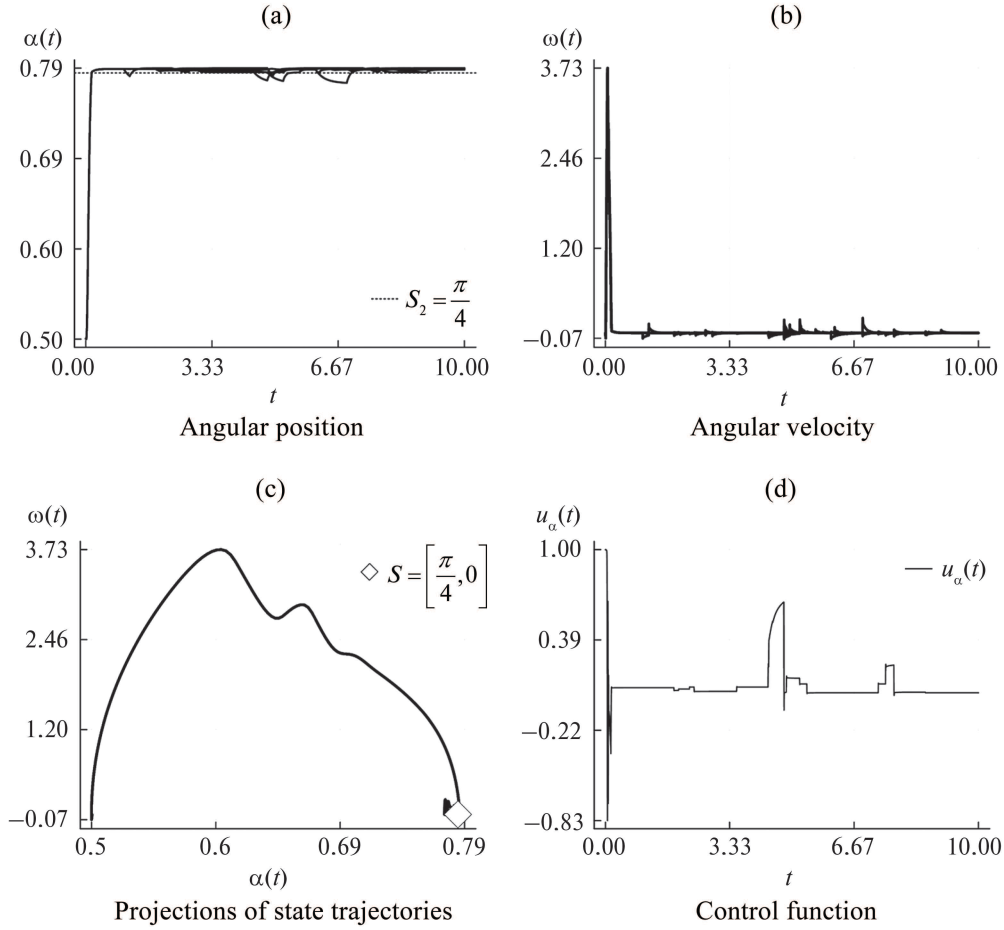

Fig. 7. The set of trajectories and control function for system (1) with the recurrent neural network controller.

Next, we consider simulation results for the dynamics of system (1) with the feedforward neural network controller. Figure 6 provides the results of five runs of system (1) as well as the plot of the control function.

According to the results, the neural network controller exhibits a significantly higher control performance level for model (1) compared to the PID controller. In Figs. 6a and 6b, the deviations from λ during cargo loading and unloading are significantly smaller; however, Fig. 6c shows a repeatable transient pattern regardless of the external conditions for the recurrent neural network controller. The plots of the linear velocity and momentum under the neural network controller are similar in nature to those in Figs. 3 and 4d, respectively. Note that for small negative values of the error, there is a feedback deficit, and the conditions of Theorem 1 also hold for the neural network controller.

The plot of the control function with the neural network controller differs from that with the PID controller by the presence of negative values and segments of constant positive control values, which indicates more pronounced feedback.

The simulation results with the application of the recurrent neural network controller are presented in Fig. 7.

According to Figs. 7a and 7b, the recurrent neural network controller demonstrates the highest control performance level for the angular position of the conveyor system compared to the previously considered controllers. The system dynamics is close to stationary near the expected equilibrium;

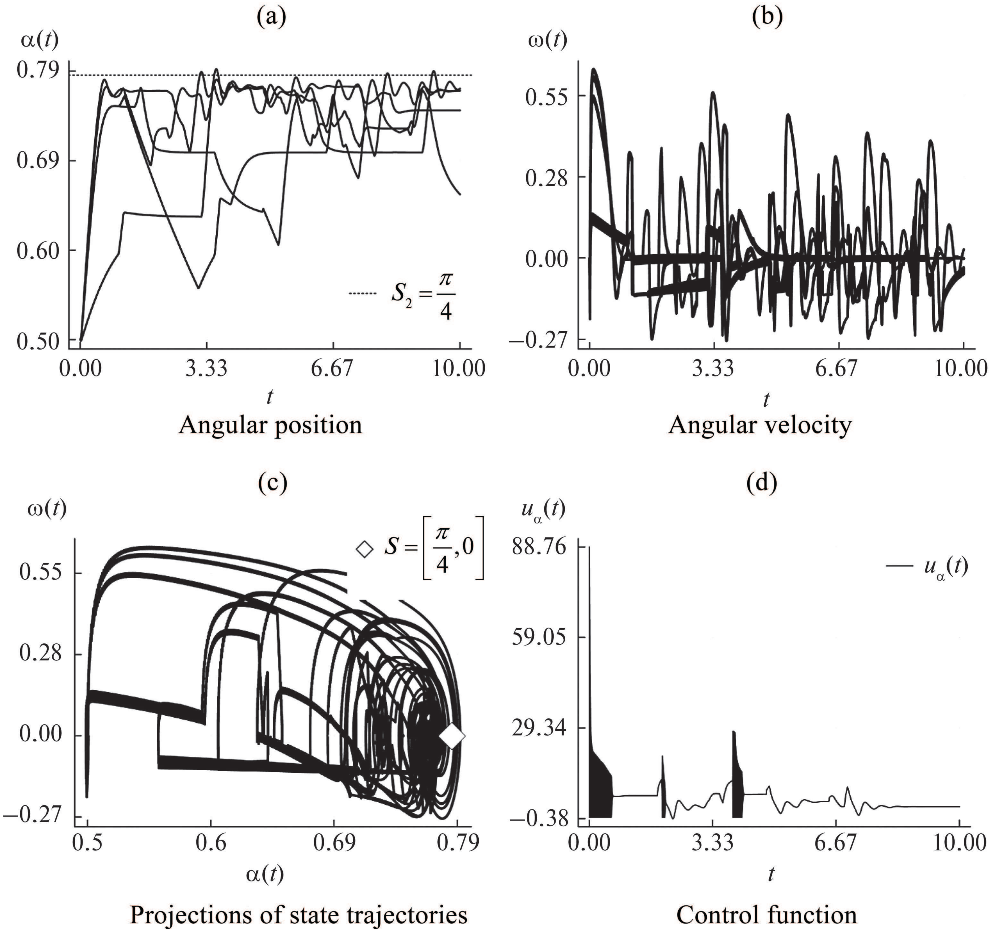

Fig. 8. The set of trajectories and control function for system (1) with the recurrent neuro-PID controller.

see the angular position plot. An insignificant scatter of the trajectories is due to cargo loading and unloading. The plots of the linear velocity and momentum under the recurrent neural network controller are similar in character to those obtained under the PID controller and the feedforward neural network controller. Figure 7c illustrates a slight variability associated with cargo loading and unloading. The plot of the control function with the recurrent neural network controller is provided in Fig. 7d. The transient has high-frequency oscillations, gradually being replaced by stationary modes with dominating small constant control values.

Next, Fig. 8 shows the simulation results for the recurrent neuro-PID controller.

According to Figs. 8a and 8b, the recurrent neuro-PID controller demonstrates a relatively low control performance level compared to the PID, neural network, and recurrent neural network controllers. There is a significant feedback deficit, and the system trajectories move considerably away from λ during cargo loading and unloading. Figure 8c illustrates the variability of the conveyor system trajectories during cargo loading and unloading. The plots of the linear velocity and momentum under the recurrent neuro-PID controller are similar to those obtained under the PID controller.

The long-lasting high-frequency oscillations of the control function in Fig. 8e indicate self-excitation in the feedback loop and a low level of control robustness. Nevertheless, the conditions of Theorem 1 are fulfilled with the application of the recurrent neuro-PID controller.

5. COMPARATIVE ANALYSIS OF THE PERFORMANCE OF DESIGNED CONTROLLERS

The mean values of the optimality criteria and the weighted mean error values are given in the table below. Note that the criterion C_2 can be found for each controller under consideration, but its informativeness will be reduced in the case of no data on the global stabilizability of the system.

Mean values of optimality criteria and mean error for different controllers

Controller	C_1	C_2	Mean$(e(t))$
PID controller	1.7412	0.3654	0.0022
Neural network controller	0.4906	0.1333	−0.0033
Recurrent neural network controller	0.3632	0.0597	−0.0012
Neuro-PID controller	1.2762	0.6517	0.0648

According to this table, the recurrent neural network controller demonstrates the highest performance level (the lowest values of all the three indicators). Also, we emphasize the different maximum performance levels of the controllers when implemented as computer programs. Performance measurements using the BenchmarkTools library are presented in Figs. 9–11. (The PC configuration is CPU AMD Ryzen 5 5600X and RAM 16GB.)

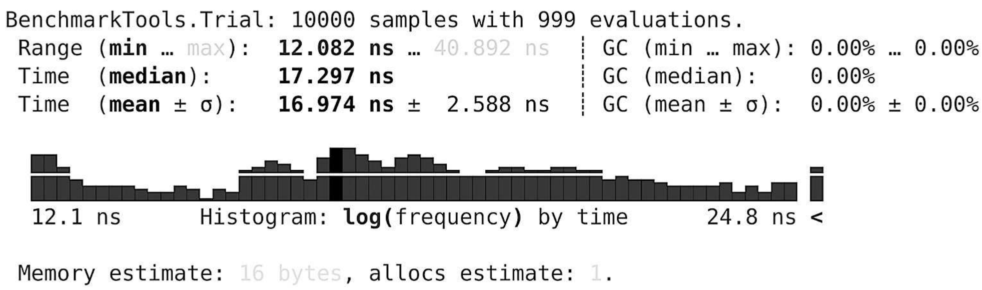

Fig. 9. Performance measurements for the PID controller.

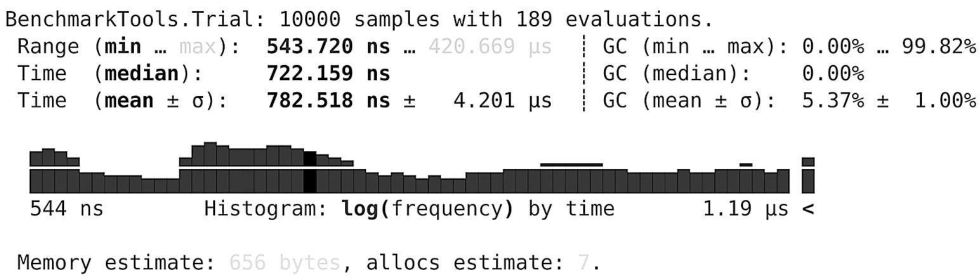

Fig. 10. Performance measurements for the neural network controller.

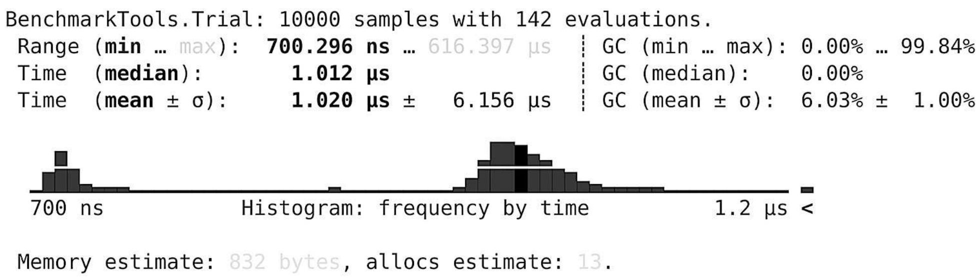

Fig. 11. Performance measurements for the neuro-PID controller.

In Figs. 9–11, “min ... max” and “median” indicate the range of the execution time and the median execution time, respectively; “mean $\pm\sigma$” and GC correspond to the mean time with the standard deviation and the percentage effect on the time when collecting garbage. Obviously, the PID controller exhibits a significantly higher maximum performance level than the neural network and neuro-PID controllers. However, all types of the controllers have a maximum performance level of at least one million counts per second in the PC configuration.

The performance of the designed controllers is essential when implementing them as embedded devices and increasing the efficiency of reinforcement learning algorithms.

6. DISCUSSION OF THE RESULTS

Within this work, we estimated the influence of the integration step and control period on the calculation accuracy and the effectiveness of the designed controllers. Based on the results of preliminary experiments, we chose suitable values for the integration step and control period. With the chosen integration step, some effects were revealed concerning the simulation accuracy of the controlled conveyor system. The control structure for the neural network controller can be visualized by a heat map since this controller has no integral component. The heat map is shown in Fig. 12.

According to Fig. 12, the control values for the neural network controller form two domains with values -1 and 1 separated by a curvilinear boundary with an illegible transition. This boundary forms the admissible values of the control variable (see Fig. 6d), which indicates that the values e and $\dot{e}$ belong to this boundary under effective control.

The results of computational experiments provided in Figs. 3–8 show that the recurrent neural network controller is the most efficient among the designed ones; see the lowest values of C_1 and C_2 in the table. The feedforward neural network controller also demonstrates a quite high performance level compared to the PID and neuro-PID controllers but is characterized by higher values of C_1 and C_2 than the recurrent neural network controller. The PID controller has limited ability to stabilize system (1) since fast loading and unloading events cause a long transient, destabilizing the system dynamics. The neuro-PID controller is insufficiently effective in stabilizing system (1): the mean error has a large positive value of $(\mathrm{mean}(e(t)) = 0.05)$, indicating a control deficit even in the absence of destabilizing events. However, the mean value of C_1 for the neuro-PID controller is lower than that for the PID controller.

The stabilization conditions proposed in Theorems 1 and 2 were used to interpret the operation of the PID controller and the neural network controllers of different types for system (1). These conditions can serve as a methodological support for further research in the development of new algorithms and design of new intelligent controllers.

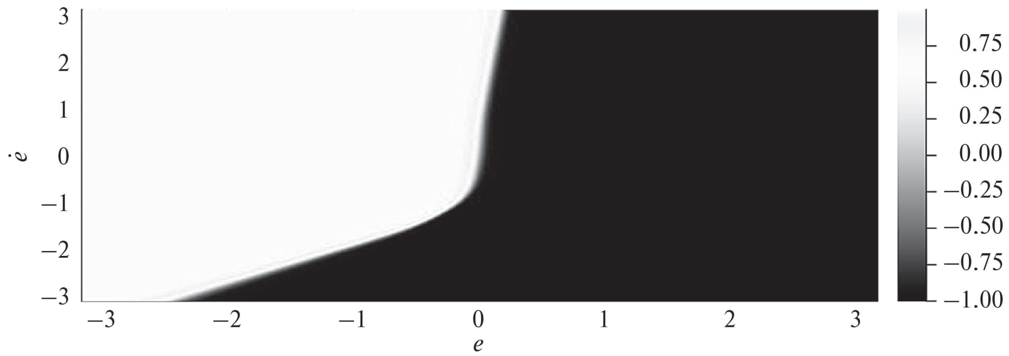

Fig. 12. Heat map of neural network controller values.

The computational experiments were carried out by software on Julia. The software was developed using the DifferentialEquations, Plots, and BlackBoxOptim libraries as well as an original library for neural network calculations.

7. CONCLUSIONS

This paper has developed an approach to modeling and stabilization of conveyor transport systems with intelligent control. The mathematical model of a controlled belt conveyor with a variable elevation angle has been formally described. The problem of optimal control of the belt movement and angular position of the conveyor has been formulated and solved in practically important special cases. The stabilization conditions of this model have been developed considering the simulation components responsible for the logic of conveyor belt loading and unloading. The algorithmic and intelligent controllers have been designed and the conditions for carrying out computational experiments have been chosen to interpret the results and describe new qualitative effects for technical conveyor transport systems.

According to the results of this study, the neural network controllers of different types have significant adaptive control possibilities for the conveyor transport model with switching. In particular, these controllers adapt to the change of the gain in the control loop and to the change of the control period Δt, stabilizing system (1). In addition, an important aspect is that the highest training effectiveness of the neural network is achieved for a sufficiently small gain, and further increasing its value after training improves the control quality. Unlike the PID controller, the neural network of the nonrecurrent type does not contain integral error components but successfully controls system (1).

The results of comparing the performance of the intelligent and algorithmic controllers proposed above can be used in the design and optimization of new conveyor transport systems as well as other types of controlled technical systems. Promising lines of further research in the area include the construction and analysis of models of more complex controlled conveyor systems with dynamic positioning (e.g., models of multilink conveyor systems or conveyor systems with a moving base). In addition, the model can be generalized to expand the simulation part and improve the switching logic; new types of hybrid intelligent controllers can be designed to achieve higher effectiveness and performance.

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