Using digital twins and artificial intelligence for the synchronization of physical and virtual collaborative robots

Artem Lisovskyi[1]

1. Artificial Intelligence Department (AI) Kharkiv National University of Radio Electronics, UKRAINE, Kharkiv, Nauki Ave. 14., e-mail: artem.lisovskyi@nure.ua

Abstract**:** This study proposes an approach to synchronizing physical and virtual collaborative robots based on the concept of digital twins and artificial intelligence tools. The proposed mathematical models allow formalising the processes of reflecting the real state of robots in a digital environment and minimising synchronisation errors. Particular attention is paid to the use of prediction, data filtering, and reinforcement learning algorithms that ensure the adaptability and stability of the system. The paper analyses the advantages of direct, predictive, and hybrid synchronisation methods and evaluates their effectiveness in a multi-user environment. The use of artificial intelligence allows for an increase in the level of autonomy and safety of human-robot interaction. The results of the study demonstrate the promise of integrating digital twins into modern robotic systems and open up opportunities for creating scalable and flexible manufacturing solutions.

Keywords**:** digital twin, collaborative robot, artificial intelligence, synchronisation, reinforcement learning, POMDP, optimal control, fuzzy logic.

I. Introduction

The current development of Industry 5.0 requires integrating physical and virtual systems to enhance efficiency, safety, and adaptability in production processes. A key tool in this effort is the concept of a digital twin, which creates virtual replicas of real robotic systems and ensures their synchronization in real time. Collaborative robots that interact with humans and each other need a high level of coordination, especially in multi-user environments. Artificial intelligence enables more accurate prediction of robot behavior, optimization of movement paths, and dynamic control that considers external changes. The challenge is to develop mathematical models and algorithms that combine physical operational parameters with their virtual counterparts, minimizing delays and errors. Therefore, research into digital twins and artificial intelligence offers new possibilities in collaborative robotics, aimed at increasing flexibility, adaptability, and safety in production systems.

II. Development of Mathematical Support for the Synchronisation of Digital Twins and Artificial Intelligence

The dynamics model describes the evolution of the state of a physical robot and its virtual copy over discrete time. It functions as the fundamental model for synchronization and divergence assessment. General overview of the model:

$$x_{t+1} = Ax_t + Bu_t + w_t \tag{1}$$

Where: $x_t \in \mathbb{R}^n$ - state vector of the robot at time t (position, velocity, joint angles, etc); $u_t \in \mathbb{R}^m$ - vector of control actions (commands to motors, forces, etc.); $A \in \mathbb{R}^{n\times m}$ - system dynamics matrix (how the state changes without control); $B \in \mathbb{R}^{n\times m}$ - matrix of control influence on the state; w_t - process noise (model of unaccounted influences), frequency; $w_t \sim \mathcal{N}(0, Q)$. Note: for nonlinear systems, replace with $x_{t+1} = f(x_t, u_t) + w_t$.

The measurement (observation) model is designed to link the values measured by sensors to the true state, which is necessary for updating the digital twin. The following model is proposed:

$$y_t = Cx_t + v_t \tag{2}$$

Where: $y_t \in \mathbb{R}^p$ - the vector of measured signals (sensors, cameras, IMU); $C \in \mathbb{R}^{p\times n}$ - the measurement matrix; v_t - the measurement noise, usually $v_t \sim \mathcal{N}(0, R)$.

The synchronization error measure (divergence norm) enables you to quantitatively evaluate the difference between a physical robot and its digital twin. It is used in adaptive algorithms to minimize divergences.

$$e_t = x_t^{real} - x_t^{digital},\ E_t = e_t^{\intercal} W e_t \tag{3}$$

Where: x_t^{real} - the state of the physical robot; $x_t^{digital}$ - the state of the digital twin; e_t - the synchronisation error vector; W - the weight matrix (emphasises the importance of individual components); E_t - the scalar error function that is minimised.

State estimation using the Kalman filter allows for the filtering of noisy measurements and real-time correction of the digital twin's state. Update model (filling + correction):

- forecast:

$$\begin{gathered}\hat{x}_{t|t-1} = A\hat{x}_{t-1|t-1} + Bu_{t-1} \\ P_{t|t-1} = AP_{t-1|t-1}A^{\intercal} + Q\end{gathered} \tag{4}$$

- update:

$$K_t = P_{t|t-1}C^{\top}(CP_{t|t-1}C^{\top} + R)^{-1}$$
$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(y_t - C\hat{x}_{t|t-1}) \quad (5)$$
$$P_{t|t} = (I - K_tC)P_{t|t-1}$$

Where: $\hat{x}_{t|t-1}$ - predicted state before measurement; P - covariance matrix of the estimation error; Q - covariance of process noise w_t; R - covariance of measurement noise v_t; K_t - Kalman gain.

POMDP formulation for partially observable scenarios makes it possible to formalize planning and decision-making when the state is not fully observable (e.g., partially hidden operator states):

- transition $T(\acute{s}|s,a)$ - probability of transition to state $\acute{s}$ after action a;

- observation $O(o|s,a)$ - probability of obtaining an observation o;

- reward $R(s,a)$.

Belief update (Bayesian state estimation):

$$b_{t+1}(\acute{s}) = \eta O(o_{t+1}|\acute{s}, a_t)\sum_{s\in S} T(\acute{s}|s,a_t)b_t(s) \quad (6)$$

Where: $b_t(s)$ - belief (probability distribution across states); η - normalisation factor.

The RL formulation for training synchronisation policies (MDP / Deep RL) allows us to find a policy for a digital twin/controller that minimises synchronisation error and/or energy consumption. The goal is to maximise the expected reward:

$$J(\pi) = \mathbb{E}\left[\sum_{t=0}^{T}\gamma^t r_t\right] \quad (7)$$

where the instantaneous reward can be, for example:

$$r_t = -\alpha\|e_t\|^2 - \beta\|u_t\|^2 \quad (8)$$

Where: α, β - weight coefficients for error, energy and penalties (e.g. for security violations); $\gamma \in (0,1]$ - discount factor. Note: for complex systems, Deep RL (e.g. DDPG, PPO) is used, where the state/observation is fed into a neural network.

The purpose of the prediction model with delays (time delay compensator) is to compensate for network delays between the physical robot and its digital twin using a model-based predictor or neural network.

Predictor model (several steps ahead):

$$x_{t+1|t} = f_{\theta}^{pred}(\hat{x}_{t|t}, u_{t:t+\tau-1}) \quad (9)$$

or in the linear case:

$$\hat{x}_{t+\tau|t} = A^{\tau}\hat{x}_{t|t} + \sum_{k=0}^{\tau-1} A^{\tau-1-k}Bu_{t+k} \quad (10)$$

Where: τ - delay step (number of discrete steps); f_{θ}^{pred} - predictor (parameterised, for example, by a neural network with parameters θ).

Model predictive control (MPC) for bilateral synchronisation. The purpose of it is to optimally select a sequence of controls to minimise synchronisation error and resource consumption under imposed constraints.

MPC task (briefly):

$$\min_{u_{t:t+N-1}} \sum_{k=0}^{N-1}\left(\left\|x_{t+k|t}^{digital} - x_{t+k|t}^{real}\right\|_Q^2 + \|u_{t+k}\|_R^2\right) \quad (11)$$

subject to:

$$x_{t+k+1|t} = f(x_{t+k|t}, u_{t+k})$$
$$u_{min} \le u_{t+k} \le u_{max}, x \in \mathcal{X}_{safe} \quad (12)$$

Where: N- optimisation horizon; $\|\cdot\|_Q^2$ - quadratic form with weights Q; $\mathcal{X}_{safe}$ - set of safe states (e.g. minimum distance to a person)

Hybrid model (fuzzy + NN) for handling uncertainty. The purpose of it is to take into account fuzziness (uncertain, linearly indescribable phenomena) during synchronisation; to combine interpreted rules and training modules.

General structure:

- fuzzy part: a set of IF-THEN rules with fuzzy inputs $\mu_i(\cdot)$;

- learning component, which is a neural network $g_{\phi}(\cdot)$ that adjusts the parameters of the fuzzy system or issues corrections.

Output example:

$$\Delta u_t = \sum_{i=1}^{M} w_i(x_t)u_i(x_t) + g_{\phi}(x_t) \quad (13)$$

Where: $w_i(x_t)$ - fuzzy rule weights (dependent on the degree of truth); $u_i(x_t)$ - local control laws; g_{ϕ} - training compensator (neural network).

Consensus model for synchronising multiple workers (multi-agent). Its purpose is to synchronise a set of physical and virtual agents (robots) for coordinated actions/trajectories. Discrete consensus model:

$$x_{i,t+1} = x_{i,t} + \sum_{j\in\mathcal{N}_i} a_{ij}(x_{j,t} - x_{i,t}) + B_i u_{i,t} \quad (14)$$

Where: $x_{i,t}$ - state of the i-th robot; $\mathcal{N}_i$ - neighbours in the interaction graph; a_{ij} - connection weights (adjacency matrix or Laplacian).

Stochastic reliability/failure model. Its purpose is to model the probability of robot component failures and take them into account in the digital twin. Markov failure process:

$$P(FAIL\ in\ \Delta t) = 1 - e^{-\lambda \Delta t} \tag{15}$$

Enables risks to be taken into account in planning and predictive maintenance.

The developed mathematical models provide a formalised approach to describing the interaction between a physical robot and its digital twin, which allows for high synchronisation accuracy. The use of state and observation dynamics models creates the basis for a realistic representation of robot behaviour in a virtual environment, while the application of filtering methods increases resilience to noise and sensor errors. The integration of artificial intelligence into the process of minimising synchronisation errors gives the system the ability to adapt to changing environments and uncertainty. The inclusion of predictive and optimisation models makes it possible to effectively compensate for delays in data transmission and forecast the future states of the robot. Models based on reinforcement learning and POMDP allow the system to independently develop a control policy focused on achieving long-term goals. Hybrid approaches combining fuzzy logic and neural networks provide flexibility in working with fuzzy or incomplete data. Altogether, these models form the foundation for a new generation of digital twins that not only reflect physical processes but also actively manage them in real time.

II. Numerical simulation results and analysis of the results obtained

To perform numerical modelling of the synchronisation of physical and virtual collaborative robots, a time interval of 0 to 10 seconds was used, which was discretised into 500 points to ensure smooth graphs and accurate calculations. The trajectory of the physical robot was modelled as a sinusoidal function with an amplitude of 1 and the addition of random noise with an intensity of 0.05, which simulates real fluctuations in sensor measurements. The virtual robot reproduced the same trajectory, but with a time shift of 0.2 seconds, which allows us to evaluate the system's ability to compensate for the delay between the physical and digital models. To analyse the synchronisation error, the difference between the states of the physical and virtual robots at each moment in time was used. The neural network received normalised time data in the range from 0 to 1 as input, which made it possible to avoid the influence of scale in the calculations. The network architecture consisted of a single hidden layer with 10 neurons, random weight coefficients were generated based on a normal distribution, and the ReLU activation function was used to model nonlinearity. The network output approximated the target sine function, which made it possible to evaluate the effectiveness of artificial intelligence in reproducing the robot's motion dynamics. Thus, the chosen numerical parameters ensured the reproduction of both the physical characteristics of the robot and the process of its virtual synchronisation using a digital twin. The results of numerical modelling are presented in Figures 1-3.

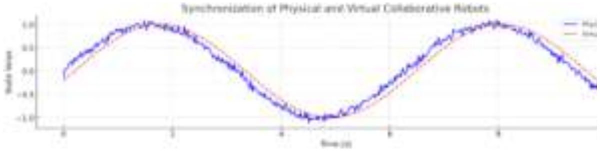

Figure 1. – Graph of Synchronization of Physical and Virtual Collaborative Robots

Synchronisation of Physical and Virtual Collaborative Robots (Fig. 1) shows the trajectories of physical and virtual collaborative robots, where their convergence and divergence in the synchronisation process can be seen.

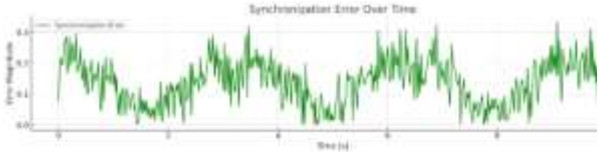

Figure 2. – Graph Synchronization Error Over Time

Synchronisation Error Over Time (Fig. 2) shows the change in synchronisation error over time, which allows us to assess the stability and efficiency of the robot motion coordination process.

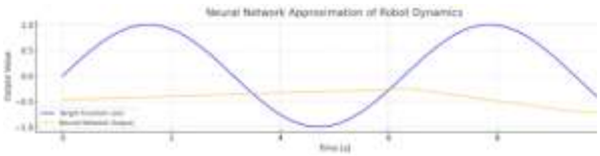

Figure 3. – Graph Neural Network Approximation of Robot Dynamics

Neural Network Approximation of Robot Dynamics (Fig. 3) demonstrates the operation of a simple neural network that approximates the dynamics of robot motion and allows modelling the behaviour of the system in real time.

III. Conclusion

The conducted study demonstrated that the use of digital twins in combination with artificial intelligence creates an effective tool for synchronising physical and virtual collaborative robots in dynamic conditions. Numerical modelling confirmed the possibility of accurately reproducing the movements of a physical robot in a virtual environment, taking into account time shifts and sensor errors, which significantly increases the accuracy and reliability of control. The use of neural networks has enabled adaptive learning of the system and the approximation of complex dynamic characteristics to real-world scenarios, which is key to working in Industry 5.0 conditions. The results demonstrated the ability to reduce the average synchronisation error and improve the stability of interaction between the real and digital environments. The proposed approaches can be applied to the development of integrated control systems capable of quickly responding to changes in external factors and human interaction. The use of mathematical models made it possible to analyse the main parameters of the system and determine the optimal operating modes of digital twins. The obtained results form the basis for further research aimed at developing hybrid control architectures using artificial intelligence methods and multi-agent models.

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