Toward Intelligent Cyber-Physical Systems: Digital Twin Meets Artificial Intelligence

Milan Groshev, Carlos Guimarães, Jorge Martín-Pérez, and Antonio de la Oliva

Industry 4.0 aims to support smarter and autonomous processes while improving agility, cost efficiency, and user experience. To fulfill its promises, properly processing the data of the industrial processes and infrastructures is required. Artificial intelligence (AI) appears as a strong candidate to handle all generated data, and to help in the automation and smartification process. This article overviews the digital twin as a true embodiment of a cyber-physical system (CPS) in Industry 4.0, showing the mission of AI in this concept.

Abstract

Industry 4.0 aims to support smarter and autonomous processes while improving agility, cost efficiency, and user experience. To fulfill its promises, properly processing the data of the industrial processes and infrastructures is required. Artificial intelligence (AI) appears as a strong candidate to handle all generated data, and to help in the automation and smartification process. This article overviews the digital twin as a true embodiment of a cyber-physical system (CPS) in Industry 4.0, showing the mission of AI in this concept. It presents the key enabling technologies of the digital twin such as edge, fog, and 5G, where the physical processes are integrated with the computing and network domains. The role of AI in each technology domain is identified by analyzing a set of AI agents at the application and infrastructure levels. Finally, movement prediction is selected and experimentally validated using real data generated by a digital twin for robotic arms with results showcasing its potential.

Introduction

The rapid advancements in information and communication technology (ICT) are transforming the industrial sector toward a full digitalization and integration concept. This transformation, known as Industry 4.0, enhances industrial systems with the ability to make decentralized and autonomous decisions through the use of cyber-physical systems (CPSs). Consequently, the industrial world can improve the productivity and logistics, and lower production costs [1]. CPSs are the main linchpin for Industry 4.0 to move toward a fully automated industrial infrastructure that relies on real-time capabilities, distributed control systems, virtualization, service orientation, and modularity [2].

Digital twin is defined as "*a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision-making*" [3]. This concept truly embodies the cyber-physical integration within Industry 4.0, combining any industrial process achieved through closed-loop feedback mechanisms. The digital factory includes geometrical and virtual models of tools, machines, operatives, products, and so on, as well as behaviors, rules, physics, and analytic models. The outputs of the digital twin processes are executed on the factory floor to improve the physical object performance [4].

The adaptation of digital twin in Industry 4.0 is inseparable from recent advances in ICT, such as 5G and supporting technologies. 5G networks are architected to simultaneously support different types of service profiles in the shared infrastructure, such as enhanced mobile broadband (eMBB), massive machine type communication (mMTC), and ultra-reliable low-latency communication (URLLC). Together with edge [5] and fog [6] computing, they provide a communication link with low end-to-end (E2E) latency, low jitter, and localization awareness to industrial services. Still, by themselves these technologies cannot efficiently manage automation or compute the best decisions to achieve dynamic adaptation.

In this sense, cyber space mirrored through digital twins arises as the perfect playground for the development of artificial intelligence (AI) agents [7]. Moreover, machine learning (ML) is a strong candidate to implement such agents, as an alternative to heuristic or decision-tree-based solutions, among others. Digital twins provide the tools for transferring the domain expertise of specialized personnel into raw data in cyber space, which can later be used to train and cross-validate different ML algorithms used in AI agents. These agents not only develop expertise in specific tasks, but also extend and optimize them beyond human capability due to the volume of data they can handle to make decisions. Ultimately, smarter and more accurate digital twins can be devised where autonomy is achieved through AI-controlled processes that operate in all types of environments and conditions.

This article overviews the digital twin as a CPS solution, where AI is introduced as the missing piece in its integration with networks and computing. In particular, it focuses on providing an analysis of different AI agents based on ML algorithms, with relevant applicability to improve and enhance digital twins. We introduce the envisioned concept of an Industry 4.0 environment, highlighting specific aspects of a digital twin that can be enhanced with AI capabilities. The identified AI agents, at both the application and infrastructure levels, are discussed later, followed by the experimental validation of a selected AI agent. Finally, conclusions are presented.

Towards Intelligent Integration of Digital Twins with Computing and Networks

This section overviews the digital twin, and its integration with the underlying computing and network infrastructure, emphasizing open challenges to be tackled by AI.

Digital Object Identifier: 10.1109/MCOM.001.2001237

The authors are with Universidad Carlos III de Madrid.

Digital Twin

Digital twin in Industry 4.0 integrates any industrial process achieved through the implementation of closed-loop feedback mechanisms. It creates digital replicas of physical objects in the cyber space, replicating the behaviors of their physical counterparts, and provides feedback mechanisms for control. The control loop starts with the physical object sending sensor information and its current state to the digital replica, which then closes the control loop by sending back commands in real time. In doing so, industrial machines become software-enhanced objects that incorporate self-management capabilities and respond quickly to changes. In this way, cyber-physical integration is achieved, providing a new set of tools to monitor, control, and predict behaviors and to accurately optimize the factory floor.

Digital twins for industrial applications in the areas of design, production, and system health checks demonstrate superiority over the traditional solutions. These allow reinforcement of the collaboration between design and manufacturing, mimicking the real factory environment to ease remote control operations and facilitate the detection of machinery problems, respectively.

Challenge #1: How to effectively use sensors' real-time data streams in digital twins to further improve remote control operations and maintenance.

Computing

In Industry 4.0, physical objects are composed by either low-performance and constrained hardware or hardware tailored to a specific task. Due to the development of virtualization, software components of the physical object are represented as modular virtualized functions whose execution is outsourced into more powerful computing resources.

Cloud-based solutions were initially exploited for implementing such concepts [8], by providing the elastic and powerful computing capabilities required to support the digital twin. However, cloud providers cannot ensure the performance of the network between the physical object and its digital replica, worsening with their network distance and the number of providers in between. As a result, cloud-based digital twins suffer from time-varying network delay, unpredictable jitter, limited bandwidth, and data loss. These drawbacks prevent time-sensitive tasks, including real-time remote control, being fully supported by the cloud computing substrate. To overcome the shortcomings of cloud computing, edge and fog computing emerged as a natural extension. While edge computing provides computing capabilities near the physical objects via static substrates, fog computing also integrates volatile, constrained, or mobile resources (including the physical objects). By exploiting edge and fog computing, the digital twin can offload time-sensitive processing from the physical object, which in turn contributes toward further optimizations of the hardware costs. Additionally, new algorithms for efficient data filtering, envisioning privacy and security improvements [9], can be applied, and the data can be restricted within a trusted private infrastructure. Finally, due to the close proximity, edge-based digital twins can use the available radio network information

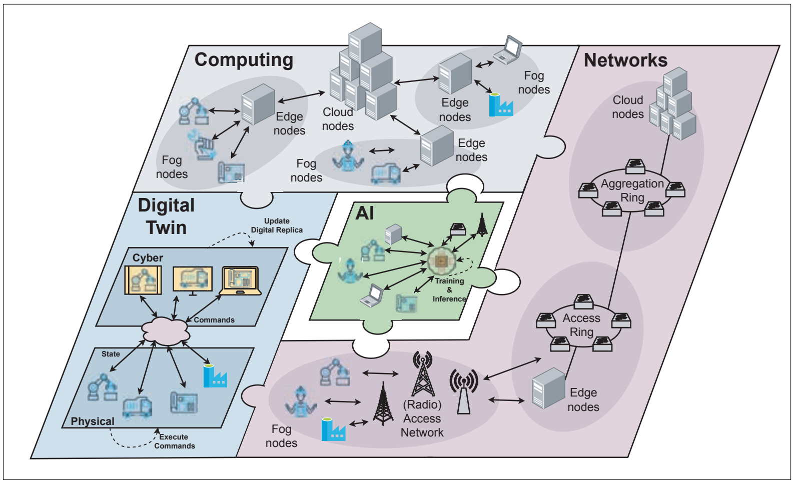

FIGURE 1. General concept for digital twin.

to adapt physical objects' operations or to optimize resource allocation in order to improve the quality of experience (QoE).

Challenge #2: How to optimally allocate computing resources for digital twins in the cloud-to-thing continuum, to satisfy key performance indicators (KPIs) such as latency and security requirements.

Networks

The underlying network infrastructure of the digital twin comprises different dynamic and heterogeneous topologies. It can be divided into three segments, as shown in Fig. 1:

- Aggregation ring
- Access ring
- (Radio) access network ([R]AN)

The aggregation ring resides far from the physical objects, relying on wired connectivity to connect cloud-based digital twins that are suitable for human-scale responsive services and delay-tolerant tasks (e.g., monitoring). The access rings are closer to the physical objects, interconnecting multiple (R)ANs. The access rings are locally present and expose radio network information (e.g., radio channel) to edge-based digital twins, namely for time-sensitive tasks (e.g., remote manipulation). Finally, the (R)AN is in the vicinity of the factory floor, providing connection to the physical objects using both wired and wireless connectivity. Different radio access technologies (RATs) are available (e.g., WiFi, LTE, 5G), differing in their capabilities with respect to latency, range, data rate, power profile, and scalability.

Wired technologies are most suitable for fulfilling the communication requirements of digital twins. Due to their limitations in terms of flexibility, mobility, and high-density connections, wireless technologies are becoming more appealing in the (R)AN. However, the critical processes within industrial environments are sensitive to radio frequency interference, requiring RATs to be interference-free, to work on licensed bands and to provide an extremely controlled environment. Industry 4.0 claims 5G as a key enabler to fulfill the communication requirements set by digital twin [10], not only through radio enhancements but also by employing network slicing and virtualization as core features. At the same time, WiFi

	AI agent	Input data	Outcomes	ML algorithm(s)	Candidate runtime location
Application	Movement prediction	Historic of commands, real-time commands	Predictions on the N next commands	VAR, TCN, GRU, LSTM	Fog, edge
	Task learning	Demonstrations of the task from different knowledge domains (e.g., physical object states)	Generalized task policy	IL, RL	Fog, edge
	Risk reduction	Sensor data, video streams, localization data and machinery states	Identification and forecasting unsafe situations	CNN	Fog, edge
	Predictive maintenance	Machinery and environmental sensor data (e.g., motors status, vibration, temperature)	Failure predictions	ARIMA, LSTM + LR, SVM	Edge, cloud
Infrastructure (computing and networking)	Dynamic scaling	Resource usage, date and time, task, number of instances, application KPIs and SLAs	Scale in/out or up/down suggestions	RL, RT, RF, MLP, BN	Edge, cloud
	Privacy, security, and intrusion detection	Infrastructure and network context information, traffic flows patterns, service and infrastructure KPIs	Security breaches and suspicious flows	PCA, *K*-means, autoencoders	Edge, cloud
	Heterogeneous RAT selection	Radio network information, available resources, mobility patterns, application KPIs and SLAs	RAT and handover candidate selection	RL, ANN, fuzzy logic	Fog, edge

ANN: artificial neural networks; ARIMA: autoregressive integrated moving average; BN: Bayesian network; CNN: convolutional neural network; GRU: gated recurrent unit; IL: limitation learning; LR: logistic regression; LSTM: long short-term memory; MPL: multi-layer perceptron; PCA: principal component analysis; RL: reinforcement learning; RF: Random Forest; RT: Random Tree; SVM: support vector machine; TCN: temporal convolutional networks; VAR: vector autoregressive.

TABLE 1. Summary of AI agents for digital twin.

6E appears as another candidate for Industry 4.0, with trials already showcasing its capability to sustain the presence of interference and noise, and to meet the stringent requirements of most use cases.

Challenge #3: How to build digital twins that benefit from optimal use of heterogeneous RAT resources and overcome radio interference problems,

The aforementioned challenges demand digital twins that satisfy the expected real-time and secure performance. Furthermore, digital twins should also tackle the problems derived from its integration with the network and computing infrastructure. AI agents are strong candidates to handle such challenges, as they can benefit from ML algorithms to exploit existing data sources with context information at both the application and infrastructure levels.

AI Agents for Digital Twins

In order to address the challenges presented in the previous section, exemplary AI agents for digital twins are identified (Table 1), including possible ML algorithms [11] to implement them. The *in-network* or *on-device* deployment strategies are envisioned while leveraging on the pervasiveness of the cloud-to-things continuum (i.e., fog, edge, and cloud). Moreover, AI agents can be trained in the cloud (cloud learning) for computation-intensive training, or in the edge (edge learning) for local training considering enormous real-time and private data generated by the industrial processes.

Application-Related Enhancements

The following AI agents describe different enhancements on top of digital twins, which improve the robustness and reliability of the existing processes and pave the way for novel features and capabilities that rely on highly automated processes.

Movement Prediction: Remotely controlling a physical object over a wireless channel via its digital twin can be prone to unpredictable radio frequency interference that introduces high jitter and packet loss. Consequently, the remote operator experiences lagging behavior that breaks the real-time control of the physical object and creates an unsafe environment.

A solution that recovers from such unpredictable behaviors, keeping the remote control uninterrupted, is required. AI stands out as a strong candidate that can forecast future movements providing extra reliability in case movement commands are lost.

In this context, *movement prediction* uses historic commands to predict future ones using ML time-series algorithms like VAR, TCN, GRU, and LSTM (see bottom of Table 1 for definitions). Whenever the next command is lost or does not arrive on time, movement prediction triggers the forecasting of such a command to keep the remote control uninterrupted (as showcased later).

To prevent packet loss and high latencies, movement prediction has to be deployed in the fog, executing when a failure occurs, or in the edge, piggybacking predictions with every real command.

Task Learning: In industrial scenarios, there are still highly complex and dynamic tasks that require human expertise/presence. Traditional agents based on finite state machines are not suitable for automating such tasks, as they cannot react in unforeseen situations, such as the appearance of unpredictable obstacles. *Task learning* AI agents based on IL and RL algorithms are potential solutions to overcome such situations, as they are designed to learn and afterward interact with a dynamic environment. Task learning is first trained through observations of human-based operations, in a trial and error fashion, through the simulated environment enabled by the digital twin. Then its behavior is validated in the simulated environment, which includes unexpected and random situations. Finally, its runtime deployment is envisioned on the factory floor (i.e., fog or edge) to ensure secure, reliable, and low-latency execution of the task. For example, task learning is able to introduce generalization and adaptability to drive a lift truck for package delivery. Thus, the digital twin can learn how to act robustly upon introduction of obstacles in the path, or changes in the shapes or position of packages.

Risk Reduction: As remote control mechanisms emerge and physical objects become more autonomous, safety plays a critical role in the design of a digital twin. When considering human-machine collaboration scenarios, failures of either humans or machines may pose a safety risk. Factory floors equipped with surveillance cameras could reuse them to perform image segmentation and pattern recognition in order to identify and mitigate dangerous situations. In recent years, it has been proved that AI solutions based on CNN algorithms achieve the best performance on computer-vision-related tasks. Hence, *risk reduction* uses CNN algorithms to identify dangerous situations analyzing a video stream, helping the digital twin to act preventatively, such as blocking the physical object or adapting its operation. Since fast countermeasures are required, its runtime deployment is best fit in the edge or, in scenarios with higher degree of autonomy, in the fog. For example, based on a real-time video stream, risk reduction can detect that a human operator is in dangerous proximity to an operational industrial machine, and use this information to block the machine.

Predictive Maintenance: Industrial physical objects have always been held to a higher reliability and predictability standard than any general-purpose systems. Industrial companies consider unplanned downtime and emergency maintenance caused by failures a major challenge. For preventing eventual failures, the future state of a given component must be forecast and classified in order to verify if it requires maintenance. ML-based solutions provide high accuracy to solve both prediction and classification problems. Thus, a *predictive maintenance* AI agent is a suitable candidate to preemptively detect failures or repair needs by using combinations of algorithms including ARIMA, LSTM, LR, and SVM. Predictive maintenance checks if the available sensor data might lead to failure situations, and if so, it schedules the maintenance of the physical object. Since this AI agent is not performing time-sensitive operations, it can be deployed anywhere from the edge up to the cloud. For example, if historical data reports high vibrations upon the break of a screw, predictive maintenance can forecast future vibrations (e.g., LSTM) and decide if maintenance is required (e.g., SVM).

Infrastructure-Related Enhancements

The following AI agents highlight several enhancements applicable to the computing and network domains, which have the potential to impact and optimize the performance of a digital twin.

Dynamic Scaling: With the recent development of virtualization technologies, smart factories benefit from having digital twins coexisting under the same cloud-to-thing continuum. During the lifetime of a given application, adequate scaling of resources is required so that digital-twin-related KPIs (e.g., latency) are satisfied without deteriorating the performance of others. Such a problem is analyzed in the existing literature as an NP-hard problem, that is, optimal scaling polices cannot be found in feasible runtimes. Consequently, AI solutions based on Markov decision processes can be used to find near optimal scaling policies in feasible times using algorithms based on RL, RT, RF, MLP, and BN. *Dynamic scaling* follows scaling policies learned with the aforementioned algorithms, training with data such as resource consumption, date and time, task, and number of instances and sessions. Dynamic scaling can then compute scaling decisions in order to fulfill KPIs and service level agreements (SLAs). The runtime deployment of this AI agent is most suitable on the network side (i.e., edge or cloud), depending on inference time and network latency toward the orchestrator. For example, whenever a new robotic arm is added on the factory floor, dynamic scaling increases the allocation of vCPUs to the virtual instance in charge of holding its digital replica, allowing its processing delay to stay below a threshold.

Privacy, Security, and Intrusion Detection: By employing digital twins in an industrial environment, huge volumes of network traffic are distributed in the cloud-to-things continuum in order to create the digital factory. This makes the detection and diagnosis of security breaches and intrusions very challenging and complex for the infrastructure operators and their tenants. Performing an exhaustive analysis of all the network traffic would take a vast amount of time, which is infeasible to detect intrusions or security breaches early. ML learning algorithms, like PCA, *K*-means, and autoencoders, are ideal solutions to shrink traffic volume and speed up traffic inspection. *Privacy, security, and intrusion detection* uses these algorithms to detect malicious traffic and consequently block remote control of physical objects through their digital twins. Moreover, federated learning and transfer learning appear as ML approaches that boost collaborative training across different industrial players, which by not centralizing the training data retain the privacy and locality of private data. The edge and cloud are candidate locations to deploy this AI agent, depending on whether on-site security operations are required or not.

By employing digital twins in an industrial environment, huge volumes of network traffic are distributed in the cloud-to-things continuum in order to create the digital factory. This makes the detection and diagnosis of security breaches and intrusions very challenging and complex for the infrastructure operators and their tenants.

Heterogeneous Network (HetNet) Selection: In an industrial environment comprising multiple RATs, the challenge of being always best connected arises, directly affecting the design and performance of digital twins. RAT selection is traditionally solved by applying rules derived from the network infrastructure with prior domain knowledge and experience of experts. However, applying this type of RAT selection to digital twins is often complex to manage on dynamic and heterogeneous industrial environments. A *HetNet selection* AI agent that uses ML algorithms (e.g., RL, ANN, and fuzzy logic) appears as a tool to mitigate the aforementioned challenges. It exploits the locally available radio context information to select the best RAT for each physical object on

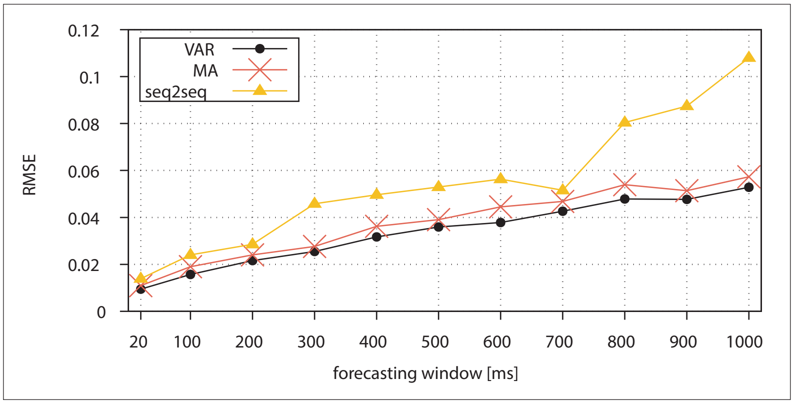

FIGURE 2. RMSE performance for different prediction windows.

the factory floor and, if required, the best handover candidate. The radio context information is defined by European Telecommunications Standards Institute (ETSI) multi-access edge computing (MEC), and provided by different radio information services, such as radio network information service (RNIS) and WLAN access information service (WIS) [12]. Based on such information, HetNet selection detects when, for example, an AGV will be out of coverage and lose the connection to the point of attachment. The digital twin can use this information to preemptively transfer state information to the new point of attachment, and to instruct the AGV to change its RAT in order to seamlessly move around the factory floor. Since this AI agent depends on locally available information, its preferable deployment location is the edge or fog.

Movement Prediction: Experimental Validation

A proof of concept showcasing movement prediction is implemented over a digital twin application for robotic arms (as defined in [10]), extending the baseline service with a newly implemented movement prediction component.

Experimental Setup

The digital twin application consists of:

- *Digital replica* used for remote operation
- *Robotic stack*
- *Robotic drivers*
- *Movement prediction*

The digital replica and robotic stack are deployed in a virtual machine with 1 vCPUs and 2 GB of RAM in an edge server (Dell PowerEdge R430), while the robotic drivers and movement prediction are deployed in a Niryo One robotic arm. The robotic arm is equipped with IEEE 802.11n interface and an edge TPU accelerator for ML inference. Note that the robotic arm is part of the fog computing infrastructure, and thus included in the network service graph. Finally, all components are deployed through Docker containers.

The *movement prediction* continuously stores received commands as Cartesian coordinates (i.e., xyz points), computing the prediction of the subsequent movements. This allows creation of a dataset with the past movements in order to compute the predictions. If the robotic arm does not receive the corresponding movement on each control loop, the *movement prediction* triggers the execution of a predicted movement.

This proof of concept compares two ML-based algorithms:

- Vector autoregressive (VAR) [13]
- Sequence-to-Sequence neural network (seq2seq) [14], which produces a prediction matrix of the three xyz coordinates

A classic moving average (MA) is used as a benchmark. Results are derived using a seq2seq implementation in Tensorflow and a VAR implementation using the statsmodels library. The seq2seq model has a layer of 200 LSTM units [15] with 163,200 parameters, and a repeat vector layer that feeds a dense time-distributed layer of 603 parameters.

A set of four actions is considered for the creation of the dataset. Each action is manually repeated 20 times by an operator making use of the digital replica. Lastly, a new instruction is issued every 20 ms, representing a total of 22,893 instructions. Eighty percent of the dataset is used for training, and the remaining 20 percent for testing the performance of each selected technique.

Prediction Accuracy

Figure 2 depicts the performance of each algorithm with respect to the root mean square error (RMSE), a widely adopted metric for prediction accuracy. As the prediction window increases (i.e., number of movements ahead), seq2seq increases its error faster than the MA and VAR. Even though the loss function converges in 100 episodes for seq2seq, it does not manage to properly train the 163,803 parameters that end up having scenarios of 1 s forecasting windows. VAR beats MA by an order of 10^{-3} units.

Figure 3 showcases how the different forecasting methods differ from the real position given prediction windows of:

- 5 movements (100 ms)
- 50 movements (1000 ms)

The position is represented using the distance from the origin. On the five movements' forecasts, the predicted values overlap the real one, given the short prediction period. However, in the scenario of 50 movements' forecasts, all solutions evidence a delay in the predicted values, unable to anticipate the peaks until the increase/decrease of past values happens. Nevertheless, VAR guesses the different actions (each different action is appreciated by different peak patterns highlighted with dashed circles), despite some perturbations appearing in a sawtooth fashion (Fig. 3b between 3000 ms and 5000 ms). On the other hand, seq2seq presents a delayed stair-step pattern that deviates more than VAR with respect to the real position (Fig. 3b).

Overall, Fig. 3b shows that seq2seq provides worse predictions than VAR, a solution designed to forecast correlated signals. Moreover, it is very likely that seq2seq's underperformance is due to its vast amount of training parameters.

Given the performance of VAR, future work will consider exponential smoothing methods and the vector autoregression moving average (VARMA). The latter method combines the benefits of both MA and VAR to prevent the sawtooth oscillations, and anticipate more quickly the increases/decreases of the time-series. Additionally, the required look-ahead for different RATs (i.e., 5G and WiFi 6E) will be studied, considering that

RATs directly affect the packet arrivals and consecutive packet losses.

Integration with Digital Twin Operation

VAR and seq2seq algorithms are integrated in the developed proof of concept to evaluate the benefits introduced in remote operation of digital twins. The WiFi link between the robotic arm and the edge is configured with a delay of 5 ± 1 ms and with 5 percent probability of packet loss. The purpose is to emulate an unreliable link, causing movement commands to be lost.

Figure 4 compares the remote operation of the robotic arm with and without the assistance of movement prediction against the expected action. When AI is not in place, the loss of movement commands leads to bouncy operation of the robot. Movement prediction fills the gap created by a missing movement, allowing the robotic arm to move smoothly and to make the recovery less abrupt. However, results show that this case is only achieved when movement prediction is implemented using VAR. Its implementation using seq2seq was shown to be faulty and error-prone, with no clear benefits.

Conclusions

This article discusses the role of artificial intelligence in addressing some of the challenges in Industry 4.0, mainly related to the digital twin. AI agents, with the help of ML algorithms, open the range of opportunities to enable optimizations in terms of reliability, robustness, and performance in the digital twin. This article starts by introducing the re-modeled concept for digital twin, where cloud, edge, and fog computing are integrated with emerging networking technologies such as 5G and WiFi 6E, and physical processes. It then identifies and analyzes exemplary AI agents for the digital twin, spanning from the application to the infrastructure level. Experimental validation has been carried out to demonstrate the applicability of the movement prediction AI agent to predict the next movement(s) by using real data from a digital twin for robotic arms. Results indicate that VAR is more accurate than seq2seq and MA in predicting the next movements, with clear benefits when integrated in remote control operations via a digital twin.

Finally, digital twins are expected to grow over 30 percent by 2026 in market size worldwide. Through AI, digital twins are evolving into powerful, dynamic, and automated tools to explore and monitor the whole industrial environment through, for example, an immersive digital world without temporal or spatial constraints. Altogether, there are several challenges to cope with industrial environments, like the creation and validation of virtual models, the need for expertise from different engineering fields (e.g., robotics, networking, software), and real-time access, connection, and synchronization to production data. The latter aspect will be a driving factor for the future 6G networks.

Acknowledgments

This work has been (partially) funded by the H2020 EU/TW joint action 5G-DIVE (Grant #859881) and the H2020 5Growth project (Grant #856709). It has also been funded by the Spanish State Research Agency (TRUE5G project, PID2019-108713RB-C52PID2019-108713RB-C52/AEI/10.13039/501100011033).

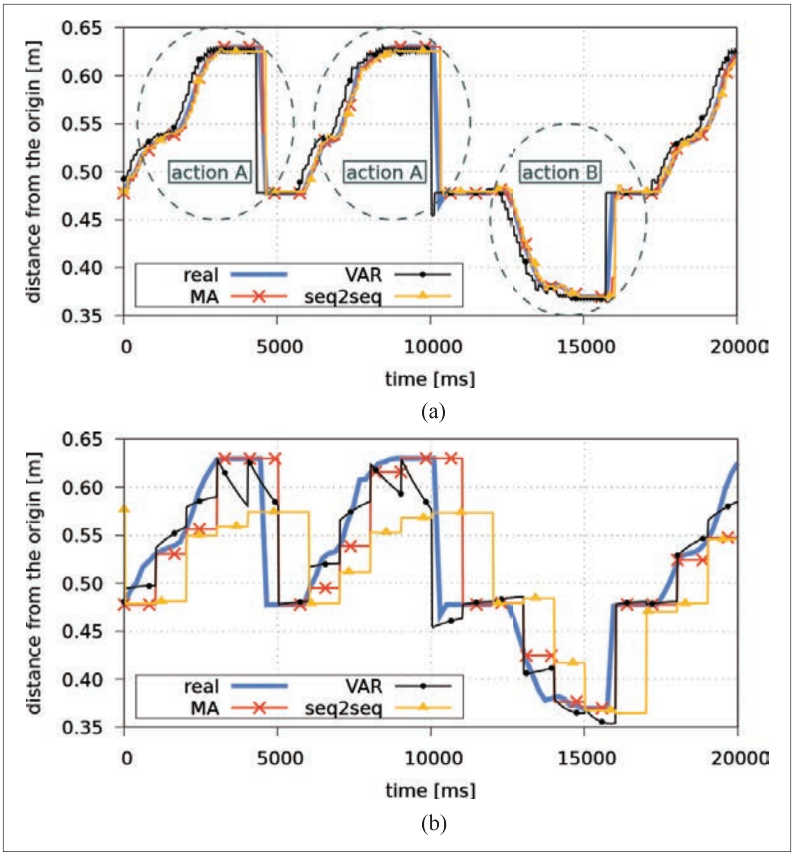

FIGURE 3. Movement predictions.

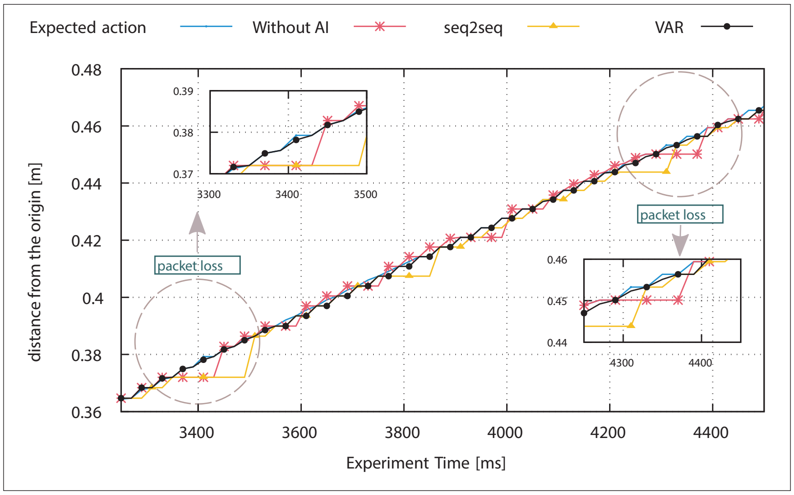

FIGURE 4. Synchronization between robotic arm and digital replica.

References

[1] K. Henning, W. Wolfgang, and H. Johannes, "Securing the Future of German Manufacturing Industry: Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0," final report of Industrie 4.0, Apr 2013.

[2] P. Leitão, A. Colombo, and S. Karnouskos, "Industrial Automation Based on Cyber-Physical Systems Technologies: Prototype Implementations and Challenges," *Computers in Industry*, vol. 81, Sept. 2015.

[3] A. Rasheed, O. San, and T. Kvamsdal, "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective," *IEEE Access*, vol. 8, 2020, pp. 21,980–22,012.

[4] F. Tao *et al.*, "Digital Twin in Industry: State-of-the-Art," *IEEE Trans. Industrial Informatics*, vol. 15, no. 4, 2019, pp. 2405–15.

[5] W. Shi *et al.*, "Edge Computing: Vision and Challenges," *IEEE Internet of Things J.*, vol. 3, no. 5, 2016, pp. 637–46.
[6] C. Mouradian *et al.*, "A Comprehensive Survey on Fog Computing: Stateof- the-Art and Research Challenges," *IEEE Commun. Surveys & Tutorials*, vol. 20, no. 1, 2018, pp. 416–64.
[7] K. Xia *et al.*, "A Digital Twin to Train Deep Reinforcement Learning Agent for Smart Manufacturing Plants: Environment, Interfaces and Intelligence," *J. Manufacturing Systems*, vol. 58, 2021, pp. 210–30.
[8] K. Borodulin *et al.*, "Towards Digital Twins Cloud Platform: Microservices and Computational Workflows to Rule a Smart Factory," *Proc. 10th Int'l. Conf. Utility and Cloud Computing*, New York, NY, 2017.
[9] M. De Donno *et al.*, "Cyber-Storms Come from Clouds: Security of Cloud Computing in the IoT Era," *Future Internet*, vol. 11, no. 6, 2019.
[10] L. Girletti *et al.*, "An Intelligent Edge-Based Digital Twin for Robotics," *IEEE GLOBECOM Wksp. Advanced Tech. for 5G Plus*, Taipei, Taiwan, Dec. 2020.
[11] M. Z. Alom *et al.*, "A State-of-the-Art Survey on Deep Learning Theory and Architectures," *Electronics*, vol. 8, no. 3, 2019.
[12] ETSI, "Mobile Edge Computing (MEC); Framework and Reference Architecture," Group Spec. 003 v2.2.1, Dec 2020.
[13] H. Lütkepohl, *New Introduction to Multiple Time Series Analysis*, Springer Science & Business Media, 2005.
[14] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to Sequence Learning with Neural Networks," *Advances in Neural Info. Processing Systems*, Z. Ghahramani *et al.*, Eds., vol. 27, 2014, pp. 3104–12.
[15] J. Chung *et al.*, "Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling," arXiv preprint arXiv:1412.3555, 2014.

Biographies

Milan Groshev, who received his M.Sc. degree in 2016, is a Ph.D. student at University Carlos III Madrid, Spain.

Carlos Guimarães, who recived his M.Sc.degree in 2011 and his Ph.D. degree in 2019, is a postdoctoral researcher at Universidad Carlos III de Madrid

Jorge Martín-Pérez, who received his M.Sc. degree in 2017, is a Ph.D. student at University Carlos III Madrid.

Antonio de la Oliva, who received his M.Sc.'degree in 2004 and his Ph.D. degree in 2008, is an associate professor at Universidad Carlos III de Madrid.