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Towards Intelligent Cyber-Physical Systems: Digital Twin meets Artificial Intelligence

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Abstract—**Industry 4.0 aims at supporting 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 such concept. It presents the key enabling technologies of the Digital Twin such as Edge, Fog and 5G, where the physical processes are integrated with 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 level. Finally, movement prediction is selected and experimentally validated using real data generated by a Digital Twin for robotic arms with results showcasing its potential.**

Index Terms—**Cyber-Physical System, Digital Twin, Artificial Intelligence, Industry 4.0**

I. Introduction

The rapid advancements in Information and Communication Technology (ICT) are transforming the industrial sector towards 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, logistic and lower production costs [1]. CPSs are the main linchpin for Industry 4.0 to move towards 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, etc., as well as behaviors, rules, physics and analytic models. The outputs of the Digital Twin processes are executed in 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 the 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 best decisions to achieve dynamic adaptation.

In this sense, the 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 personal into raw data in the cyber space, which can be later 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 it beyond the 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. Section II introduces the envisioned concept of an Industry 4.0 environment, highlighting specific aspects related of a Digital Twin that can be enhanced with AI capabilities. The identified AI agents, both at application and infrastructure level, are discussed in Section III, followed by the experimental validation of a selected AI agent in Section IV. Finally, conclusions are presented in Section V.

II. 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 still open challenges to be tackled by AI.

A. Digital Twin

Digital Twin in Industry 4.0 integrates any industrial process achieved through the implementation of closed-loop feedback

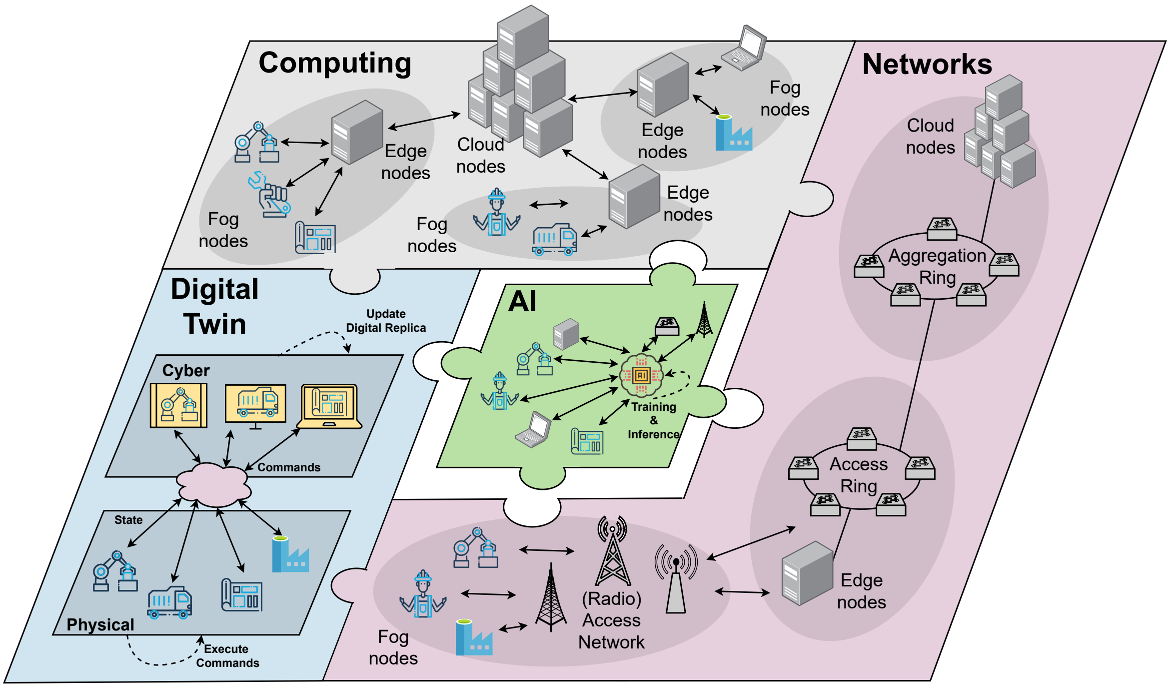


Fig. 1: General Concept for Digital Twin

mechanisms. It creates digital replicas of physical objects in the cyber space, replicating the behaviors of their physical counterparts, and provide 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 machinery 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 to reinforce 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?

B. Computing

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

Cloud-based solutions have been initially exploited for implementing such concepts [8], by providing 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, or data loss. These drawbacks prevent time-sensitive tasks, including real-time remote control, to be fully supported by the Cloud computing substrate. To overcome the shortcomings of Cloud computing, Edge and Fog 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 towards 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 to adapt the 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) as latency, and security requirements?

C. Networks

The underlying network infrastructure of the Digital Twin comprises of different dynamic and heterogeneous topologies. It can be divided in three segments, as shown in Figure 1:

(i) Aggregation Ring; *(ii)* Access Ring; and *(iii)* (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 go 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 on their capabilities with respect to latency, range, data rate, power profile, and scalability.

Wired technologies are most suitable for fulfilling the communication requirements of a 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 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 an 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. On top, 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 level.

III. AI Agents For Digital Twin

In order to address the challenges presented in the previous section, exemplary AI agents for Digital Twins are identified (Table I), 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.

A. 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.

1) Movement Prediction: Remotely control a physical object over a wireless channel via its Digital Twin can be prone to unpredictable radio-frequency interference that introduce high jitter and packet loss. Consequently, the remote operator experience lagged 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 strong candidate that can forecast future movements providing extra reliability in case movement commands are lost. In this context, *Movement Prediction* uses the historic of commands to predict future ones using ML time-series algorithms like VAR, TCN, GRU or LSTM (see bottom of Table I for description). Whenever the next command is lost, or do not arrive on time, the *Movement Prediction* triggers the forecasting of such command to keep the remote control uninterrupted (as showcase in Section IV). To prevent from packet loss and high latencies, the *Movement Prediction* has to be deployed in the Fog, executing when a failure occurs, or in the Edge, piggybacking predictions with every real command.

2) 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 under unforeseen situations, such as 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, afterwards, interact with a dynamic environment. The *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 in the factory floor (i.e., Fog or Edge) to ensure secure, reliable, and low-latency execution of the task. For example, the *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.

3) 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 suppose a risk for the safety. Factory floors equipped with surveillance cameras could reuse them to perform image segmentation, and pattern recognition in order to identify and mitigate dangerous situations. Over the recent years, it has been proved that AI solutions based on CNN algorithms achieve the best performance on computer vision related tasks. Hence, the *Risk Reduction* uses CNN

TABLE I: Summary of AI agents For Digital Twin

	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 Networks; GRU: Gated Recurrent Unit; IL: Imitation 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 Machines; TCN: Temporal Convolutional Networks; VAR: Vector Autoregressive.

algorithms to identify dangerous situations analyzing a video-stream, helping the Digital Twin to act preventively, such as blocking the physical object or adapting its operation. Since fast counter-measures 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, the *Risk Reduction* can detect that a human-operator is in a dangerous proximity of an operational industrial machine, and use this information to block the machine.

4) 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 from eventual failures, the future state of a given component must be forecasted and classified in order to verify if it requires maintenance. ML-based solutions provide high accuracy to solve both prediction and classification problems. Thus, *Predictive Maintenance* AI-agent is a suitable candidate to preemptively detect failures or repair needs by using a combinations of algorithms as ARIMA, LSTM, LR or SVM. The *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 a time-sensitive operations, it can be deployed anywhere from the Edge up to the Cloud. For example, if historical data reported high vibrations upon the break of a screw, the *Predictive Maintenance* can forecast future vibrations (e.g., LSTM), and decide if maintenance is required (e.g., SVM).

B. 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.

1) 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, an 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 a NP-hard problem, that is, optimal scaling polices cannot be found in feasible run-times. 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. The *Dynamic Scaling* follows scaling policies learned with the aforementioned algorithms, training with data such as resource consumption, date and time, task, number of instances and sessions. The *Dynamic Scaling* can then compute scaling decisions in order to fulfill KPIs and Service Layer 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 towards the orchestrator. For example, whenever a new robotic arm is added in the factory floor, the *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.

2) 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 unfeasible to early detect intrusions, or security breaches. ML learning algorithms, like PCA, K-means or autoencoders, are ideal solutions to shrink traffic volume and speed up the traffic inspection. The *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 a 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.

3) 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 by 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 in the factory floor and, if required, the best handover candidate. The radio context information is defined by 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, the *HetNet Selection* detects when e.g., 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 seamless move within the factory floor. Since this AI agent depends on the locally available information, its preferable deployment location is the Edge or Fog.

IV. MOVEMENT PREDICTION: EXPERIMENTAL VALIDATION

A proof-of-concept showcasing the *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.

A. Experimental setup

The Digital Twin application consists of: *(i) Digital Replica* used for remote operation; *(ii) Robotic Stack*; *(iii) Robotic Drivers*; and *(iv) Movement Prediction*. The *Digital Replica* and the *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 the *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 inferring. Note that the robotic arm is part of the Fog computing infrastructure, therefore 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 for 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: (*i*) Vector Autoregressive (VAR) [13]; and a (*ii*) Sequence-to-Sequence Neural Network (seq2seq) [14] that produces a prediction matrix of the three xyz coordinates. A classic Moving Average (MA) is used as 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 163200 parameters, and a repeat vector layer that feeds a dense time-distributed layer of 603 parameters.

A set of 4 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 20ms, representing a total of 22893 instructions. 80% of the dataset is used for training, while the remaining 20% for testing the performance of each selected technique.

B. Prediction Accuracy

Figure 2 depicts the performance of each algorithm with respect to the Root Mean Square Error (RMSE), a widely adopted metric for predictions' accuracy. As the prediction window increases (i.e., number of movements ahead), seq2seq increases its error faster than the Moving Average and the VAR. Even though the loss function converges in 100 episodes for seq2seq, it does not manage to train properly the 163803 parameters that ended up having with scenarios of 1sec forecasting windows. Whereas VAR beats the 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 (a) 5 movements (100ms), and (b) 50 movements (1000ms). The position is represented using the distance from the origin. On the 5 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 of some perturbations appearing in a saw teeth fashion (Figure 3b between milliseconds 3000 and 5000). On the other hand, the seq2seq presents a delayed stair-step pattern, that deviates more than VAR with respect to the real position (Figure 3b).

Overall, Figure 3b evidences that seq2seq provided worse predictions than VAR, a solution designed to forecast correlated signals. Moreover, it is very likely that seq2seq underperformance is due to its bast amount of training parameters.

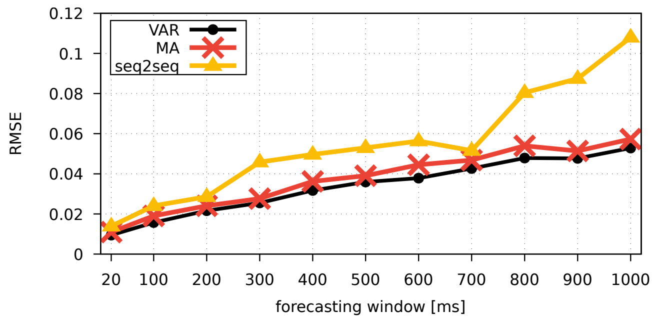


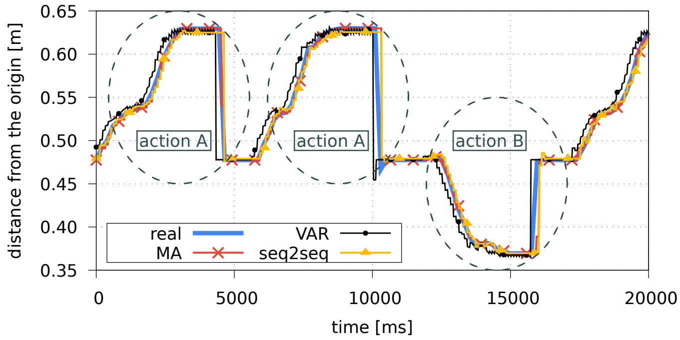
Fig. 2: RMSE Performance for Different Prediction Windows

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 saw-teeth oscillations, and anticipate faster 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.

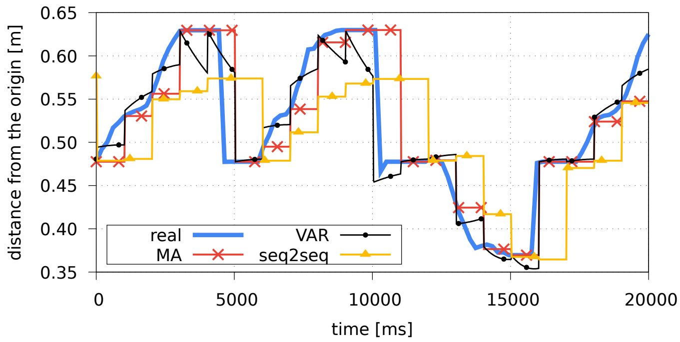
C. Integration with Digital Twin Operation

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$\pm$1ms and with 5% probability of occurring a 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 the *Movement Prediction* against the expected action. When AI is not in place, the loss of movement commands leads to a bouncy operation of the robot. The *Movement Prediction* fills the gap created by a missing movement, allowing the robotic arm to move smoothly and to make the recover less abruptly. However, results show that such case is only achieved when the *Movement Prediction* is implemented using VAR. Its implementation using seq2seq showed to be faulty and error prone, with no clear benefits.



(a) 5 movements ahead



(b) 50 movements ahead

Fig. 3: Movements Predictions

V. 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 expecting to growth over 30% by 2026 in the market size worldwide. Through AI, Digital Twins are evolving into powerful, dynamic and automated tools to explore and monitor the whole industrial environment through e.g. 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 en-

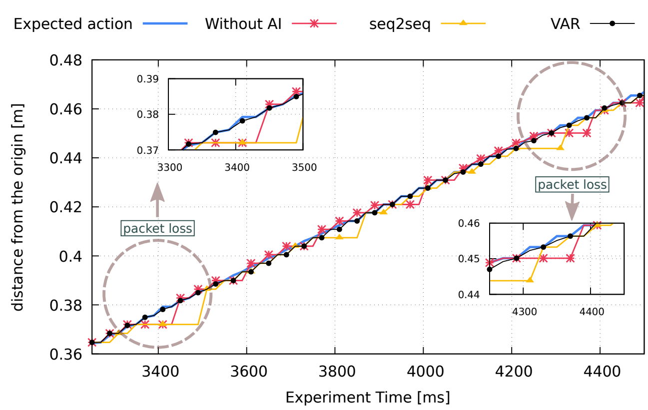


Fig. 4: Synchronization between Robotic Arm and Digital Replica

gineering fields (e.g., robotics, networking, software), and the real-time access, connection and synchronization to production data. The latter aspect will be a driving factor for the future 6G networks.

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