# Network Digital Twin for the Industrial Internet of Things


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***Abstract*—Digital Twins are starting to revolutionize many industries in the last decade providing a plethora of benefits to optimize the performance of industrial systems. They aim to create a continuously synchronized model of the physical system which enables rapid adaptation to dynamics, mainly unpredicted and undesirable changes. A wide range of industrial fields have already benefited from digital twins technology such as aerospace, manufacturing, healthcare, city management and maritime and shipping. Furthermore, recent research works are starting to study the integration of digital twins for computer networks to allow more innovation and intelligent management. One of the basic building blocks of digital twins technology is the Internet of Things where wireless sensors and actuators are deployed to ensure the interaction between the physical and digital worlds. This type of network is complex to manage due to its severe constraints especially when it controls critical industrial applications, resulting in the Industrial Internet of Things (IIoT). We believe that the optimization of the IIoT will lead to efficient integration of Digital Twins in Industry 4.0. In this paper, we design a Network Digital Twin for the IIoT where sensors, actuators and communication infrastructure are replicated in the digital twin to enable intelligent real-time management of such networks. This way, new networking services such as predictive maintenance, network diagnosis, resource allocation, energy optimization with other intelligent services can be efficiently integrated and exploited in the network life-cycle. We validate the proposed architecture by providing a promising prototype implementation that should unleash the full potential of the network digital twin.**



***Index Terms*—Digital Twin, Internet of Things, Industy 4.0**


## I. Introduction

The Internet of Things (IoT) market is growing rapidly as a consequence of developing smart buildings, smart industries, intelligent transportation, among others. It is expected to grow by 26% during the period of 2017-2022 [13]. The IoT is seen as a key technology in enabling the fourth industrial revolution with the advent of Industrial Internet of Things (IIoT) enabling a broad range of industrial applications to profit from full automation and high productivity.

IIoT are known to be complex and hard-to-manage systems since they control constrained industrial applications where various requirements need to be satisfied. Reliability, strict real-time constraints and energy requirements are the most crucial ones among others. To meet these diverse growing requirements, novel technologies are needed to assist these wireless systems. Digital Twins (DT) is one promising candidate technology to this purpose. In fact, a DT is particularly promising for building a continuously updated model of a physical system to allow rapid adaptation to changing dynamics [9]. Moreover, it provides a powerful simulation framework and can enable cognitive capabilities for the replicated system [2].

DT technology is classified as one of the top ten most promising technological trends for the next decade by Gartner [5]. Moreover, it is expected to grow at a Compound Annual Growth Rate (CAGR) of 58% during the period 2020-2026 [14]. The digital replication of the physical system enables intelligent monitoring, innovation and various augmented functionalities. Various fields are already taking advantage of this fast growing technology such as manufacturing [12], healthcare [4], aerospace [15], smart city [16], among others.

Recent research work have started to investigate the opportunities that DT could bring to computer networks. The IETF draft [21] proposes a reference architecture for the Digital Twin Network (DTN) along with issues and open research perspectives related to its implementation. More detailed architectures are proposed in [1, 10] and their implementation is discussed across various aspects such as DTN model construction using machine learning algorithms, procedures to enable new networking functionalities (what-if analysis, troubleshooting, network planning, etc.) along with enabling technologies for efficiently implementing the DTN. Moreover, data collection for the DTN is further addressed in [22] and knowledge graphs are leveraged to concretely construct the DTN. With an application-level viewpoint, the DTN is leveraged to predict the global QoS (Quality of Service) by using Graph Neural Networks in [7] while an application-driven DTN middleware is proposed in [3].

While DTN-related research are gaining a progressive interest recently, there is still a gap in providing a detailed architecture of a network digital twin for the IIoT given its constrained nature and complex characteristics that should be taken into consideration. We recently proposed in [11], a holistic DT-based architecture that should enable closed-loop IIoT network management and that enables augmented functionalities for the design and during the service of the IIoT. The current paper is a completion and a more in-depth architecture of the

Network Digital Twin for the IIoT taking advantage of the SDN (Software Defined Networking) paradigm and enabling intelligent networking services such as predictive maintenance, network diagnosis, energy optimization, resource allocation, sustainability, among others. It is designed with a terre-à-terre vision that should allow its efficient implementation.

The remainder of the paper is organized as follows. Section II covers related work on the DTN. In Section III, the architecture of the NDT for IIoT is presented while Section IV an implementation of a prototype providing basic functionalities of the NDT is introduced. Section V concludes the paper.

## II. Related work

Several research work are studying the DTN concept, proposing different architectures, modeling aspects and methods along with the proposition of various networking services to enable the real potential of digital twins in the networking context. The IETF group is currently engaged in standardizing the DTN concept. Their latest draft [21] outlines the basic concepts and a reference architecture as well as the main challenges and issues for building a DTN.

An ML-based DTN is introduced in [1] as a key enabler of efficient control and management of modern real-world networks. The adoption of DTN allows network operators to efficiently design network optimization solutions, perform troubleshooting, what-if analysis and network planning. The authors argue that Deep Learning techniques can be leveraged to model the DTN of a network taking as input some parameters such as traffic, topology, routing, scheduling policies, etc. Then producing as output some network-related performance metrics (utilization, delay, packet drops, etc). By adopting a feedback-based iterative approach between the DT and a network optimizer, this latter can find the best network configuration that satisfies the requirements set by a network operator.

Another work in [10] presents a high-level architecture for digital twin of wireless systems in a three layers fashion: Physical interaction layer, Twin layer and Services layer. Two aspects are considered to discuss different details concerning digital twins of wireless systems. Twins for wireless deals with the role of the digital twin in enabling wireless systems. On the other hand, wireless for twins deals with the efficient utilization of wireless resources for enabling effective twin signaling over a wireless link.

With a particular focus on DTN modeling and addressing the problem of data collection for the DTN, [22] proposes a four-layer architecture for the DTN consisting of a Physical network layer, Data lake layer, DT layer and Network application layer. The data lake layer collects, stores and preprocesses the collected data to provide knowledge and relation extraction to the DT layer for DTN model construction. The DT layer consists of : i) physical entity modeling that completes the modeling of the different networking components, ii) requirements modeling that is used to develop a multitude of scenario models such as network resource prediction, anomaly detection, automatic operation through AI algorithms, iii) Twin management & control center which orchestrates the DT layer to satisfy the intended requirements. A sketch based data collection algorithm is proposed for efficiently collecting data in the data lake layer and knowledge graphs are used to construct the DTN. The relationship between different network characteristics (topology, routing, queue scheduling, and input traffic) is modeled in [7] using a digital twin that exploit Graph Neural Networks (GNNs) to predict the global QoS (predict the mean per-flow delay). It includes an optimizer that finds the best routing and/or scheduling policies fulfilling complex Service Level Agreements (SLAs). The particularity of the proposed model is its generalization capability as it performs well in network scenarios unseen in the training set.

An Application-driven Digital Twin Networking (ADTN) middleware is proposed in [3] to facilitate the interaction with heterogeneous distributed industrial devices and the dynamic management of network resources by adopting an application-level approach. This architecture is based on an SDN cross-layer approach to dynamically manage the industrial environment as well as considering the quality of service requirements and the network configuration adaptation abilities.

In the context of mobile networks, [6] presents an algorithmic framework combining digital twin technology, reinforcement learning and expert knowledge to enable self-optimization in mobile networks. First, a digital twin network is constructed to predict the future state of the network based on its current state. After that, reinforcement learning and expert knowledge extract the predicted state to make optimization decisions and send them back to the digital twin which evaluates these decisions and applies the best one in the physical network. This latter sends the new network state back to the digital twin after applying these decisions after an evaluation time duration and thus allowing a closed-loop self-optimization of the physical network. A 5G Digital Twin is provided in [17] to assist the development and deployment of complex 5G networks and permit cost-effective access to 5G, given that the deployment of 5G networks is too expensive.

In the context of vehicular networks, The Software Defined Vehicular Network (SDVN) based on an intelligent digital twin in [20] was developed to enable intelligent and adaptive routing in vehicular networks. Another work in [19] designed a digital twin network to model an edge service aggregation scheme of vehicular networks. Potential edge service matching among massive vehicle pairs are revealed by the DTN. This latter divides the complex vehicular network into multiple parts according to potential service associations which reduces considerably the edge service scheduling complexity.

In order to enable flow emulation in the DTN, [18] proposes a complete flow emulation framework for digital twin network to keep physical network traffic in consistency with that in digital twin network. The authors demonstrate through a case study how the proposed framework can enable accurate delay measurement capabilities without affecting the physical network.

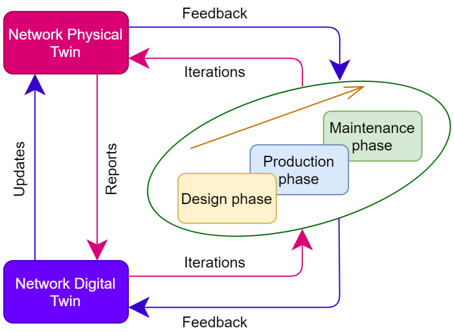


Fig. 1. NDT throughout the network lifecycle [11]

## III. Network Digital Twin for IIoT

The IIoT is enabling the fourth industrial revolution through the integration of sensors and actuators in industrial systems. These devices are of a constrained nature in terms of energy since they only use batteries as a source of power supply. In addition, in terms of reliability since the communication between nodes is ensured with a wireless shared medium. Several research efforts are made to enable energy saving while ensuring a sufficient reliability in IIoT. Also, in time-sensitive industrial systems the communication between nodes should respect strict deadlines. The required information should reach its destination in time while on the other hand energy efficiency should be maintained to increase the network's lifetime.

These varying requirements can be satisfied using a Network Digital Twin (NDT) that models the IIoT network continuously and keeps an updated view of the network through its entire life-cycle. In other words, from the design to the service phase including production and maintenance as shown in Figure 1. The physical network sends reports to the NDT which in turn analyzes them for potential enhancements of the networking performance. From another angle, the NDT iterates continuously through the network development process (design, production and maintenance phases) while getting feedback in return from the physical network. This iterative process enables a cycle of continuous improvement and innovation through the coupling of modeling and analysis with execution [11].

The NDT enables multiple intelligent features thanks to the data collected continuously from the physical network. This data can be translated to knowledge by intelligent algorithms and simulation capabilities integrated in the NDT. In other words, the NDT allows predictive maintenance, network diagnosis, efficient energy optimization, security management, optimized resource allocation and real-time network monitoring. Furthermore, interoperability between different networking devices can be ensured since their corresponding components in the digital world are platform independent and they can be managed following common mechanisms without worrying about the technicalities of the different devices. To enable such intelligent services, the NDT should be carefully crafted to take into consideration how data is collected and stored, how it is processed to model the network in the digital world and how services are implemented and requested to satisfy the applications requirements. That is why a detailed architecture of the NDT is proposed in Figure 2.

The physical network interacts with the SDN-Controller to share relevant data such as nodes general information (e.g., address, radio interference range, the list of direct neighbors, etc.) or data representing the node's state (e.g., energy level, link quality, number of sent packets, number of received packets, etc.) among others.

The SDN-Controller interpretes the received node's general information data to construct a global topology and stores the node's state information as well as the constructed topology in the data lake. Also, the SDN-Controller acts as an interface between the NDT and the physical counterpart in a way that it can interpret service requests from the real network and translate them so that the NDT can understand them and provide the requested service. In addition, the SDN-Controller is responsible for applying the network decisions made by the NDT in the real network. The SDN paradigm is adopted because it allows Network Function Virtualization (NFV) and network slicing. NFV makes it possible to run multiple applications on the same network infrastructure while network slicing can divide the network into virtual slices independent from each other and each tailored to satisfy the requirements of a specific application. The capabilities brought by these technologies play an essential role in unlocking the full potential of the NDT.

The data lake is part of the NDT and it is considered as a database where different data structures are stored and retrieved. Logical models of the network can be built based on the data provided by the data lake. They can either be basic models representing the network components or they can be more advanced models including more features for functional purposes such as anomaly detection, communication scheduling, security management, among others.

Digital Twin Entity Orchestrator (DTEO) is the management entity of the whole NDT system. Requesting models to assess the network performance by executing different what-if scenarios and learning continuously the best network parameters. Setting simulation parameters into a simulation/emulation asset and getting back performance metrics that should help in improving the network operation. This orchestrator leverages intelligent networking services to satisfy the applications requirements.

Real-time network monitoring is implemented in the NDT by interacting with the DTEO and also requesting the intelligent networking services when needed. It can be seen as the human-machine interface of the NDT system since it includes a visualization tool where the network engineer can intervene when needed to better assist the network.

The NDT exposes the networking capabilities to the applications which in return send their QoS/QoE (Quality of Service/Quality of Experience) requirements. An interface between the NDT and the applications is provided to translate the networking capabilities to the applications and also

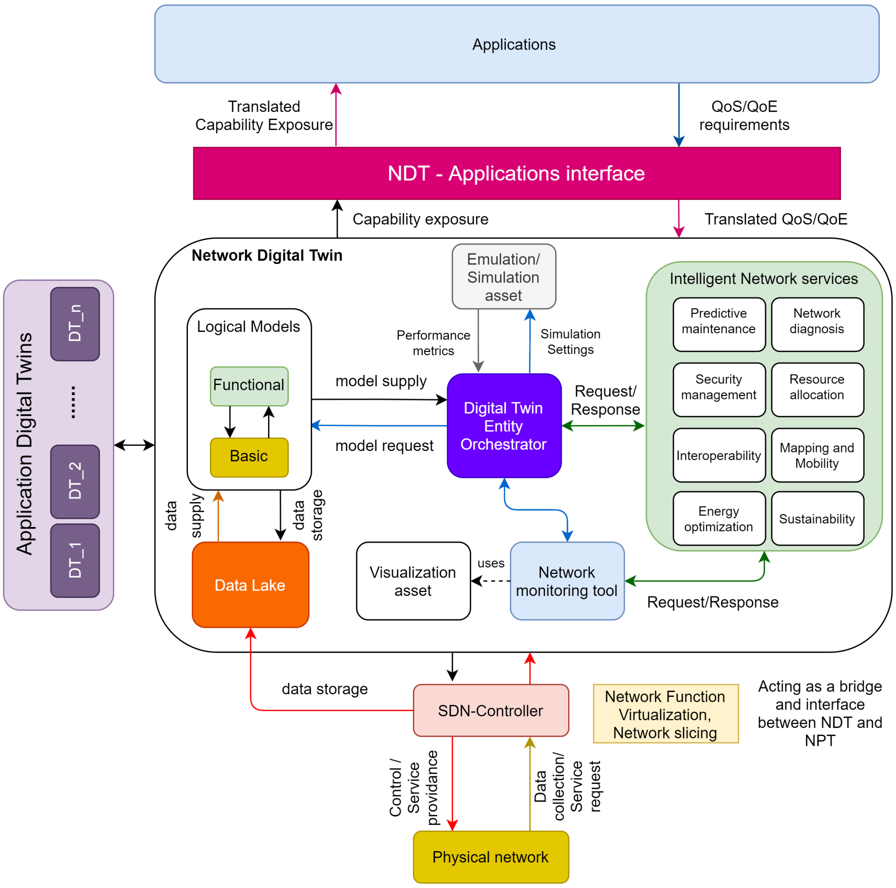


Fig. 2. Network Digital Twin architecture for the IIoT.

the QoS/QoE requirements to the NDT. Based on the sent applications requirements, the NDT finds the best networking configuration that should satisfy these needs.

Intelligent networking services are implemented in a modular fashion and can be requested anytime by the DTEO or the network monitoring tool :

*a) Predictive maintenance:* the objective of this service is to predict network failures in advance, AI algorithms could be leveraged for this purpose based on data related to the networking operation. In addition to the historical data collected from the physical network, possible what-if scenarios could be simulated to get more insights and further enrich the dataset used for predictive maintenance.

*b) Network diagnosis:* through this service, the network behavior is observed continuously and possible breakdowns such as node failures, link failures, network misconfigurations, security attacks, etc. can be detected. Comparing the NDT behavior with the real network's behavior continuously and whenever an unexpected behavior in the physical network occurs, an anomaly is arised. This service outputs diagnosis reports that can be visualized in the network monitoring tool giving the network engineer insights on the networking operation. Based on these reports, accommodation of the current network policies is performed or in more severe cases the network is reconfigured to overcome the detected anomalies.

*c) Security management:* this service enables testing security attacks safely in the NDT in order to detect possible security breaches and reinforce the network's security.

*d) Resource Allocation:* this service allows efficient resource allocation for scheduling the communication between the wireless network nodes. Reinforcement Learning (RL) is a potential algorithm for this purpose since it can provide a general policy that can give the best communication scheduling valid for various scenarios. Taking advantage of the NDT, the learning phase will be executed in a replicated version of the real network and continuous enhancements of communications scheduling can be ensured. During training, the actions chosen in each episode can be simulated and evaluated in the NDT. This latter returns the reward to the RL agent based on the simulation performance and the training agent iterates in this way until converging to an optimal policy.

*e) Interoperability:* this service is responsible for ensuring the interoperability between the different application digital twins and breaking the software silos between their various closed platforms or interfaces. It includes formatting capabilities allowing the translation of multiple closed platforms/interfaces specificities to a common format understood by the NDT.

*f) Mapping and Mobility:* this service aims at tracking the network nodes and can provide their location coordinates or even estimate them in case of the unavailability of such information. It plays an essential role in the sustainability service, e.g., giving the location of a node that should be removed or replaced for environmental purposes.

*g) Energy Optimization:* this service has the objective of increasing the network's lifetime by providing mechanisms that should reduce the energy consumption of the network. It can be requested for example when a node's energy level has reached a certain threshold in order to reduce its usage by adapting the deployed network policies according to that.

*h) Sustainability:* dedicated sustainability features provide a global view of the environmental footprint of the IIoT infrastructure. They take into account issues related to energy, battery management to change and recycle batteries, management of wireless nodes that will have to be replaced and removed to avoid contaminating nature in the case of environmental monitoring applications, monitoring the impact of radio waves, etc. Node obsolescence models integrated in the digital twin coupled with real system information allow to anticipate maintenance and recycling phases. This module leverages the *Mapping and Mobility* service providing the location of the wireless nodes when an intervention should be carried out on them (e.g., replacement, removal). This sustainability aspect is essential, given that in 2025, the number of connected objects is estimated at more than 75 billion.

## IV. Prototype Implementation

In this section, a functional prototype of the NDT is presented as depicted in Figure 3. It is based on an existing SDN solution for WSNs (Wireless Sensor Networks) called SDN-WISE [8]. Data collection from the IIoT network is ensured via an SDN controller that receives packets containing nodes general information and decrypts them to construct a graph describing the network topology. These packets are called *reports* and they are sent periodically to make sure that the network topology is always updated in the SDN controller. This latter shares the constructed topology with the NDT.

The NDT has two implemented services in our case which can be requested by the DTEO :

*a) Communication scheduling:* allows an efficient resource allocation by scheduling the communication between the nodes. In our case, the WSN uses TSCH (Time Slotted Channel Hopping) as a MAC (Medium Access Control) protocol and TASA (Traffic Aware Scheduling Algorithm) algorithm is executed to perform timeslots/channels allocation. This service produces TSS (TSCH Scheduling Specification) packets containing scheduling information for each node and shares them with the DTEO that ensures their forwarding to the physical network via the SDN controller.

*b) Routing management:* ensures the routing function for the WSN. It executes the SPF (Shortest Path First) Dijkstra algorithm on the topology graph to get the shortest path from each node to the sink in a tree form. OpenPath packets are constructed from the resulting SPF tree and shared with the DTEO as a response to a routing request. The DTEO forwards such packets to the physical network. The DTEO interacts with Cooja simulator which takes as input an XML (Extensible Markup Language) file describing the simulation scenario to be executed. Cooja outputs simulation log files that are processed by the DTEO to get insights on the networking performance.

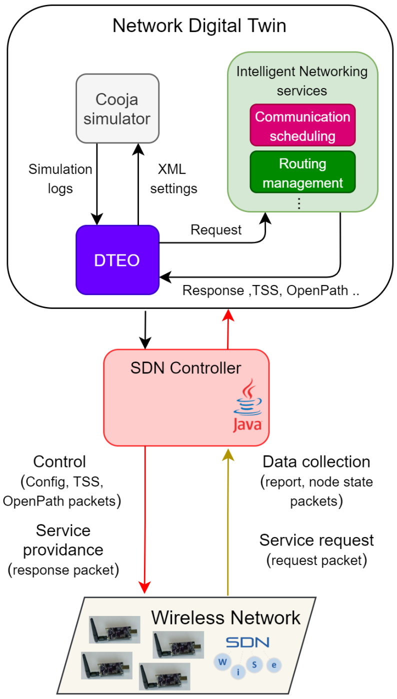

Fig. 3. Implementation of the NDT prototype.

We believe that this first prototype can be enhanced with more functionalities and more services. For example, we can integrate more scheduling algorithms in the communication scheduling service and more routing algorithms in the routing management service. These various algorithms can be simulated and evaluated thanks to the DTEO and Cooja simulator interaction. After that, the algorithms giving the best performance are chosen to be deployed in the physical network.

The SDN-WISE data plane also includes a *request* packet, that is sent to the controller when a node doesn't know a route for a packet. This is a service request for routing and a response is sent from the controller giving the node instructions on how to route the packet. The request packet can be generalized for other service requests that can be demanded from the WSN to the NDT, e.g., requesting energy optimization when the node's energy level is low, requesting resource allocation accommodation when a node is overcharged with high traffic flows, etc.

Furthermore, the current implementation allows sending a *Config* packet from the controller to the WSN to read or write some parameters. This packet can be enhanced to enable more configuration capabilities for the NDT to update the network configuration for better performance.

## V. Conclusion

In this article we presented an NDT for the IIoT by taking into consideration the complexity of such constrained networks. The core of the NDT is investigated and developed to enable a set of intelligent network services such as predictive maintenance, network diagnosis, security management, interoperability, sustainability, etc. Each service is carefully defined to meet the requirements of the IIoT. Finally, a prototype implementation of the proposed architecture based on SDN-WISE is presented.

In the future, we plan to further develop the proposed prototype with a particular focus on a resource allocation case study using reinforcement learning for scheduling the communication between the network nodes.

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