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On the Management of TSN Networks in 6G: A Network Digital Twin Approach

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***Abstract*—Emerging latency-sensitive applications (e.g. factory automation control, industrial metaverse, digital twin-enabled smart manufacturing) require that the networks ensure data delivery with a guaranteed low and bounded latency. Time-Sensitive Networking (TSN) mechanisms have been developed to enable deterministic features in standard Ethernet. 5G and 6G networks are looking forward to integrate TSN and benefit from its ability to ensure determinism. Accommodating the complexity of TSN networks in 6G is not straightforward. In particular, conventional rule-based heuristic algorithms are not optimized for such environments. Therefore, the TSN network management framework should be equipped with the right tools allowing to compute at runtime new TSN configuration for each event (e.g. change in topology, new application, new device, etc.). To address this problem, recent standardization initiatives (IETF and ITU-T) have investigated the opportunities to use Network Digital Twin (NDT) paradigm for these use cases of 6G networks.**

This paper proposes a framework that puts together the key enablers to support NDT deployment for TSN-based public or private 6G network and to cope with the relevant challenges. In particular, we define a modular and self-learner NDT framework. To construct the DT model, the framework can rely on open source simulators/emulators with predefined models, or in other cases, it may learn the DT model from real infrastructure using Artificial Intelligence (AI)/Machine Learning (ML) techniques trained over collected data. The paper also showcases how NDT, Software-Defined Network (SDN) and deterministic networks (TSN and DetNet) are key enablers for 6G network architecture.

***Index Terms*—6G core network, Network Digital Twin, Time-Sensitive Networking**

I. INTRODUCTION

The rapid deployment of 5G mobile communication networks has led to the emergence of new generations of Internet of Things (IoT)-oriented network applications, such as smart factories and industrial metaverse. These applications are designed to take advantage of the various performance characteristics offered by the 5G standard, including ultra-high bandwidth, ultra-high reliability, and ultra-low latency.

However, managing such increasingly complex communication networks is particularly challenging. Indeed, in such inherently-complex networks, the network nodes may be unpredictably overloaded with intensive processing tasks/operations (e.g., traffic routing, data analysis, video encoding/decoding, and data encryption/decryption, etc.), whereas the network bandwidth may follow unpredictable/chaotic patterns due to event-driven applications (e.g., alarms, context-aware applications and services, etc.) as well as high bandwidth-consuming applications and services (e.g., Virtual/Augmented/Extended Reality, which can be used in immersive environments like smart manufacturing, industrial metaverse, etc.). This complexity presents a significant challenge when it comes to ensuring deterministic throughput while meeting low and bounded latency requirements.

To address this problem, the 3GPP organization has adopted conventional wired time-sensitive networking protocols developed by the IEEE 802.1 TSN Working Group in the 16th release of the 3GPP standard. The integration of TSN into 5G involved deploying TSN translators at the edges of the 5G network to provide TSN bridge functionality. However, this integration alone is not sufficient for future end-to-end time-critical applications. In the future, time synchronization and deterministic communication over a wide area will be considered to support machine-to-machine communications and industrial control. This will also contribute to the creation of new services full of reality that use tactile senses and multiple senses (i.e., multimodal, holographic communications, Tactile Internet) as new communication quality.

6G core network is envisioned to converge with its Radio Access Network (RAN), creating a RAN-core serviced-based mesh architecture [1] [2]. For simplicity, hereafter this RAN-core converged architecture is referred to as 6G core. A native support of IEEE TSN (Layer 2) in 6G core network infrastructure is expected to improve the relevant control and data plane processes [3]–[6] and to provide predictable performances [7], [8]. However, still many challenges are to be met and further research is needed regarding flow scheduling for large scale networks, queue management, resource allocation and scalability to achieve end-to-end ultra-reliable deterministic 6G networks. In particular, TSN management framework should be equipped with engineering tools allowing to accommodate highly-dynamic topology and applications demanding high network throughputs and bounded latency like immersive environments.

Today, the current TSN configuration rely on exact methods, heuristics algorithms or simulation tools for computing TSN configuration. Such approaches lack flexibility and fail to accommodate a highly-dynamic environment such as 6G networks. In addition, the performances obtained through these tools are often far from the performances obtained from real experimentation or measures over a real network [9]. Recent research work have started to investigate the opportunities that the digital twin could bring to future networks in the light of futuristic applications and use cases. The Telecommunication standardization sector of International Telecommunication Union (ITU-T) considers the Network Digital Twin (NDT) as the key technology to build closed-loop network automation [10].

In our work, we believe that NDT is of paramount importance. In fact, the network management tool may rely on the NDT to validate the newly generated TSN configuration before applying it to the physical network. Moreover, in the case the TSN reconfiguration algorithms are based on reinforcement learning (RL) agents [11], the NDT can be used to continuously train these agents even during exploitation [12].

This paper proposes a framework that puts together the key enablers to support NDT deployment for TSN-based 6G network and to cope with the relevant challenges. In particular, this paper contributes to the state-of-the-art in the following ways:

1) It defines a modular and self-learner NDT framework. To construct the DT model, the framework may rely on open source simulators/emulators with predefined models, or in other cases, it may learn the DT model from real infrastructure using to AI/ML techniques trained over collected data.
2) It showcases how NDT, Software-Defined Network (SDN) and deterministic networks (TSN and DetNet) are key enablers for 6G network architecture.

The remainder of this paper is structured as follows. First, the related work is reviewed in Section II. Then, section III highlights various challenges of managing TSN networks in 6G. Section IV presents the existing reference architectures, and Section V introduces the proposed instantiation of the NDT architecture for TSN-based core networks. Section VI provides general insights into the challenges faced when designing an NDT. Finally, Section VII concludes the paper and gives perspectives of this work.

II. RELATED WORK

There are several studies that propose NDT for various types of network. Dong et al. [13] introduced an NDT for Mobile Edge Computing (MEC) system to train a centralised deep learning algorithm. The main inputs of the NDT are network topology, channel and queuing models. For each user association scheme, that algorithm allows making decisions about resource allocation and MEC offloading probability. In [14], the authors presented an NDT for Wide Area Network (WAN) that provides SLA-driven network optimization using Graph Neural Network (GNN). The GNN model takes as inputs the network topology, traffic, scheduling and routing policy, then provides what-if analysis and estimates end-to-end delay. In [15], the authors proposed a scalable NDT for network slicing. This NDT allows to monitor the relationships among slices and manage the end-to-end performance of slices.

There are several other studies that provide vision about digital twin-enabled 6G, as showed in the survey [16]. In this survey, the authors also presented the key design requirements and architecture of digital twin for 6G. According to the paper, digital twin is important for 6G because Internet of Everything in 6G has diverse requirements in terms of quality of service (QoS), therefore we need a framework that can efficiently manage and optimize 6G.

As 6G is not yet standardized, there are few studies that propose design and implementation of NDT for 6G. Instead, there are some studies whose main objective is not to build NDT for 6G, but to improve network performances for digital twin-enabled 6G, for example, to improve edge-computing offloading latency ([17], [18], [19]). In those studies, the objective is obtained with the support of NDT. In [17], the objective is to make decision about edge-computing offloading. The authors proposed a Digital Twin Edge Networks to support this decision. The digital twin of edge servers can analyse its physical counterpart and provide training data for deep learning-based offloading decision. Similarly, the objective in [18] is to minimise offloading latency of digital twin-aided edge networks for Unmanned Aerial Vehicle (UAV). As edge-computing is an important aspect in 6G, the objective of [19] is also to reduce the cost of twin placement and migration for edge association in 6G.

About the research that proposes design and implementation of NDT for 6G, Giovanni et al. [20] presented a simulation-based NDT prototype for 5G and Beyond 5G (B5G) mobile networks. However, even though this study targets also B5G, the paper did not address architectural aspects of B5G or 6G networks. In [21], the authors proposed digital twin in wireless 6G networks, to support the edge association decision. Digital twin in edge server are mapped to IoT physical devices, allowing it to interact and synchronize with physical counterpart through real-time data collection and analytics.

In the studies that provided implementations for NDT, most of the implementations appeared to be enhanced versions of network simulation, and can be viewed as prototype. For instance, Giovanni et al. [20] proposed to use network simulator OMNET++ and its network module SIMU5G to build an NDT for 5G/B5G mobile networks. Kherbache et al. [22] developed a NDT prototype for industrial IoT based on Cooja Simulator, with the support of SDN controller.

Differing from other works in the literature, this paper provides an architecture of NDT for TSN-based 6G network. To the best of our knowledge, this is the first research that addresses the management of TSN in 6G though NDT. A modular and self-learner NDT framework is proposed to facilitate the management of TSN in 6G. We highlight the significance of TSN, NDT, and SDN in 6G deterministic communication. This framework also leverages the use of AI and ML for automating the configuration of TSN.

III. WHY DO WE NEED NDT FOR MANAGING TSN ASPECTS IN 6G NETWORKS

Ensuring various QoS levels will require a more advanced in-fine QoS management support in 6G network infrastructure such as the mechanisms provided by IEEE 802.1 TSN networks. A native integration of TSN in the 6G data plane will

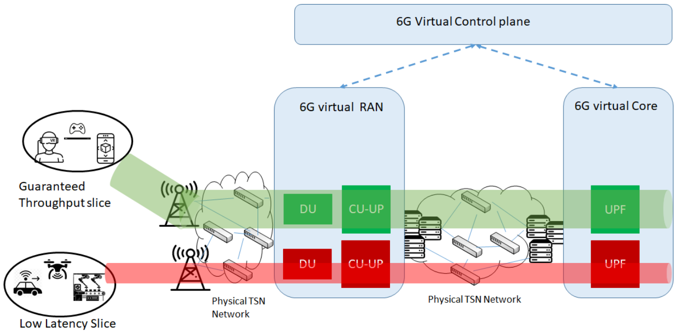

Fig. 1. Network Slicing with native support of TSN in 6G

allow to achieve converged end-to-end deterministic communications. However, this integration raises three mains challenges : (i) the configuration of TSN aspects in an open and dynamic environments, (ii) the presence of wireless links that are well known to be subject to severe communication channel distortions, and (iii) the end-to-end TSN network management. We believe that NDT can address these challenges and facilitate TSN native integration in 6G networks.

A. *Open and dynamic environments*

Besides dynamics caused by user mobility, network slicing introduces another degree of dynamics in 5G/6G networks. The network slicing is a key technology for 5/6G networks where its main advantage is to provide the ability to instantiate and deploy on the fly radio and core networks. For instance, in Fig. 1, through the same infrastructure, the network operator can deploy a low latency slice dedicated for autonomous cars, UAVs or production lines in factory and guaranteed throughput slice for AR/VR and gaming uses cases.

TSN standards offer a flexible and modular framework where TSN mechanisms in data plane are activated and configured depending on flows requirement and network status. Indeed, the configuration of these standards depends on many parameters (e.g. network topology, flows requirements, routing strategy, etc.) making the configuration task cumbersome. In addition,the introduction of network slicing technology introduces another level of dynamics in 6G networks. The network functions associated to one slice can be instantiated, deployed, migrated and destroyed on the fly. As a consequence, the flows associated with the slice will appear/disappear upon creation/destruction of the slice. Hence, the slice is migrated, new paths shall be defined for the associated flows and a reconfiguration of TSN aspects need to take place.

An automated reasoning algorithms for TSN network management is required to adapt to the high dynamics of the slices. These algorithms shall consider slice, applications characteristics and requirements. Nonetheless, accommodating the complexity of this kind of networks is not straightforward. In particular, conventional rule-based heuristic algorithms are not optimized for such environments, because arbitrary parameter assignments based on experiences and rule-based decisions often result in a non-optimal decision-making algorithm [23].Therefore, the TSN network management framework shall be equipped with autonomic runtime reconfiguration algorithms to compute new TSN configurations upon each event [24].

Deploying an NDT capable to reproduce TSN aspects in high fidelity will help meeting this challenge. Recently, Wang et al. [11] proposed to use Deep Reinforcement Learning (DRL) for flow scheduling in TSN networks. The solution allowed scheduling flows in a reasonable time. However deploying the solution in a real infrastructure is not straightforward. Indeed, the DRL agent has been trained over simulation tools that are disconnected from real infrastructure. Therefore, training the DRL agent over the NDT of the 6G network will accelerate the agent deployment in real infrastructure. In addition, the NDT can be used for a continuous training of DRL agents to increase its efficiency. Moreover, for safety reasons, the configurations generated by the DRL agent shall be validated before being pushed to real equipment. The NDT provides a good framework where the agent can test and evaluate the TSN configuration.

B. *Wireless links*

Despite the efforts of 3GPP to improve the RAN by introducing Ultra-Reliable Low Latency Communications (URLLC) mechanisms to ensure the deterministic communication modes, 5G networks are still subject to sources of randomness due to their wireless nature. In fact, wireless networks remain subject to stochastic influences due to channel effects.

C. *End-to-end TSN network management*

The IEEE 802.1 TSN Working Group (WG) proposed the amendment IEEE 802.1Qcc [25] where three network management models are specified: fully distributed, centralized network/distributed user, and fully centralized. In term of managing traffic schedules, paths for data, redundant paths and time synchronization, the standard recommended the centralized configuration approach. The fully centralized configuration model is depicted in Figure 2. It is composed of Centralized User Configuration (CUC) entity and a Centralized Network Configuration (CNC). While the CUC is responsible for building up the applications' requirements, computing the configuration setting and enforcing it (e.g. setting up gates schedules, reserving resources, etc.) in Bridges are done consistently by CNC. Therefore, CNC will be in charge of configuring TSN features namely credit-based shaper, frame preemption, scheduled traffic, per-stream filtering and policing, and frame replication and elimination for reliability.

In the following, we will consider only the fully centralized configuration model.

IV. NDT REFERENCE ARCHITECTURE

The IETF draft [26] proposes a reference architecture for the Digital Twin Network (DTN) along with issues and open research challenges related to its implementation. The Telecommunication standardization sector of International Telecommunication Union (ITU-T) elaborated a recommendation document Y.3090 [10] where the requirements and architecture

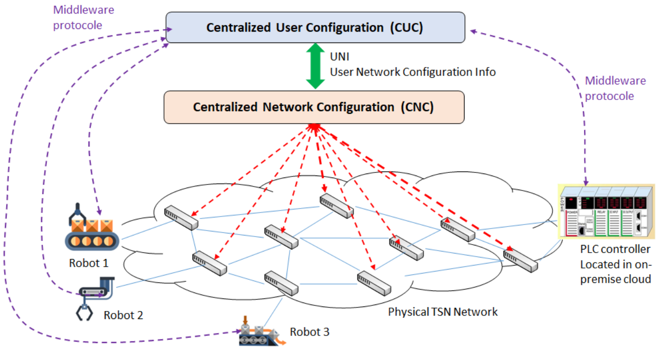

Fig. 2. Fully centralized network model of IEEE 802.1Qcc

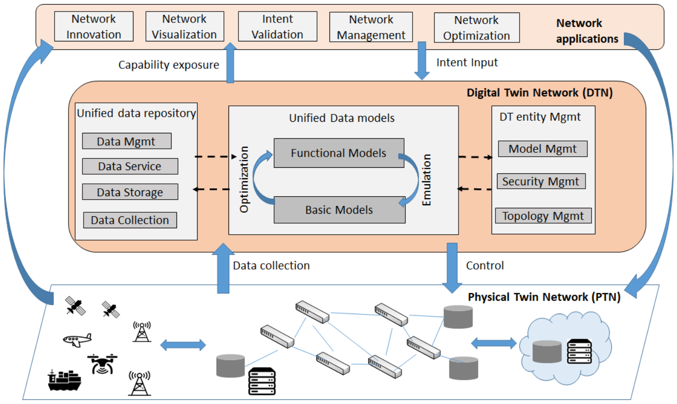

Fig. 3. NDT reference architecture according to IETF and ITU-T.

of a digital twin network are described. ITU-T considers the DTN as an expansion platform of network simulation and sees in it as the key technology to build closed-loop network automation. IETF [26] and ITU-T [10] elaborated a reference architecture of a network digital twin as depicted in Fig. 3. It is composed of three layers:

- **Physical network layer:** All network elements present in the physical networks exchange massive network data and control with a network digital twin via southbound interfaces.
- **NDT layer:** It includes three key subsystems: unified data repository, unified data models and digital twin entity management. The data repository is responsible for collecting and updating the real-time operational data of various network entities through the southbound interface. It contains four key modules: data collection, data storage, data service and data management. The unified data models is in charge of providing model instances for various network applications. It includes basic and functional models. The basic model refer to the network element model and network topology model enriched with information allowing the real-time accurate description of the physical network. The functional model refers to data models which are established by making full use of the network data in the unified data repository for specific application scenarios (i.e. diagnosis, prediction, network analysis, etc.). The digital twin entity management records the life-cycle of the entity, visualize and controls various elements of the network digital twin including topology management, model management and security management.
- **Network application layer:** It inputs the requirements to the network digital twin layer through the northbound interfaces and deploy services through the modelling instances. For example, network operation-maintenance and optimization can provide new routing policy to DTN. This latter will verify the performances obtained with the new routing policy before sending the control updates to physical network twin.

V. NDT FOR TSN-BASED 6G CORE NETWORK

The integration of DetNet/TSN technology in 6G core network will allow to ensure a more advanced QoS management. TSN technology represents a good candidate able to offer an in-fine QoS management. Indeed, TSN offers a flexible framework including a number of activable and configurable mechanisms allowing to ensure the various QoS level.

In future use cases imagined for 6G networks, network flows have various requirements, e.g., critical closed loop control related automation systems use case requires hard transmission deadlines and high reliability while video flows related entertainment use case require high bandwidths. Each flow shall have its requirement met while on the other hand energy efficiency should be maintained as a requirement imposed by the network operator. These varying requirements can be satisfied using a NDT that models the TSN-based 6G core network continuously and keeps an updated view of the network through its entire life-cycle.

A. *Architecture overview*

The architecture of the proposed NDT is depicted in Fig. 4. The physical network interacts with the CNC to share: (1) nodes information (e.g., identity such as UUID or node name, the supported interfaces including associated IP and MAC addresses, TSN capabilities and the list of direct neighbors, current TSN configuration), and (2) nodes states (e.g., links quality, link delay, number of sent/received packets, packet loss, percentage of CPU usage, time synchronization offset).

Thanks to all these information, CNC will be able to construct the global topology of the controlled network. Then, this topology together with nodes states are stored in the CNC database. Having all these information, the CNC is a good candidate to provide data about physical network for the NDT. In case the additional data are required to improve model accuracy and these data do not exist in CNC database, the NDT may request from the CNC to collect these data. To make this possible, the CNC should include a module that allows to dynamically deploy probes in the physical network and the requested data. In some cases, the NDT may request from the CNC to collect a specific data that is required

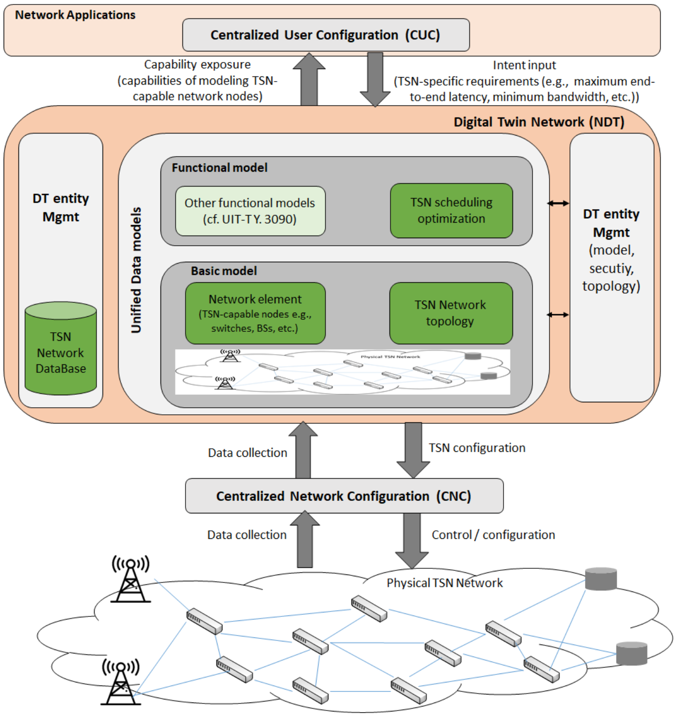

Fig. 4. DT architecture instantiation for TSN networks (based IUT-T Y.3090)

for constructing new models. For example, AI techniques that model the behavior of a specific flow or classify traffic models will need a dataset combining different metrics (e.g. periodicity of the packets, the latency between two successive packets, etc.) related to that traffic.

In addition, the CUC provides to CNC stream join/leave requests in which flows requirements as well as end stations capabilities are given. The CNC stores the flow's information in its database as well.

In our vision, simulation, emulation and AI prediction models are complementary. While AI model may allow to give a prediction within a limited time, simulation will allow to run what-if scenarios. Emulation allows to reproduce at higher fidelity the physical network and therefore to examine a very specific problem such as using logs to reproduce a given node behavior before a failure takes place. In addition, simulators and emulators are part of the NDT analysis toolbox used for knowledge extraction as well. In fact, in some cases, some performances metrics cannot be collected from physical networks. For example, it is hard to collect data related to end-to-end delay metric between a sender and a receiver not hosting probes. In such situation, simulation powered with some real data collected from the physical network allows to provide an evaluation of the end-to-end delay metric.

The simulation & emulation engine in NDT may host several simulation frameworks (OMNET++, NS3, GNS3, CORE, Mininet, etc.). Depending on the context, the NDT can select the adequate framework to be used.

VI. CHALLENGES OF DESIGNING NDT FOR A TSN-ENABLED 6G NETWORK

A. Network complexity

The first challenge of building NDT for 6G is the heterogeneity of communication technologies and protocols. In a TSN-enabled 6G network, there might be multiple domains, e.g., Ethernet TSN domain, cloud-native core network domain with Packet Data Unit (PDU)-session, and wireless domain. An interesting avenue is to develop NDT solutions that take into consideration the heterogeneity of the underlying network infrastructure. This is particularly challenging as network equipment are heterogeneous in terms of technologies, interfaces, performance and may have different capabilities that should be taken into account during constructing NDT models. Among the research question is how to get a uniform representation of exchanged data between Physical Twin (PNT) and NDT and how to design the high fidelity models.

In addition, the dynamic network states (channel states, computation resources, device mobility, available bandwidth, etc.) may hinder the NDT from improving the instant application performance. The NDT will require the ability to detect, understand even slight fluctuations and degradation of QoS levels at the flow level or at the packet level. Simply understanding what is precisely happening to a given packet and how its QoS level are being influenced is becoming even complex with the rise of virtualization. Processing of the Packet may cross multiple virtualization boundaries. VNF instances migration and reconfiguration of the Service Function Chain (SFC) may introduce unintended variations in latency for a number of packets belonging to the same time-sensitive flow.

B. Network infrastructure and connectivity

Providing connectivity between a NDT and its PNT system is another challenge, especially in a large-scale network with time-sensitive applications. These applications require that the network devices be monitored and controlled in real-time manner. For example, AI-based algorithm that configures TSN scheduling 802.1Qbv needs to have real-time monitoring and to send out timely new configurations. Since network equipments feed data into AI algorithms, missing data from some devices or network equipment due to connectivity failure or lack of bandwidth could affect the accuracy of those algorithms and then the performance of the network. In addition, the network overhead (in terms of CPU and bandwidth consumption) related to the communication and synchronization between the PNT and NDT is another challenge to take into account.

Regarding the synchronization between NDT and PNT, there are two possible options: (i) deploying separate special network from to current PNT that is dedicated for monitoring and control (i.e. out-band monitoring), and (ii) the data collection is done through the PNT (in-band monitoring). While the first option allows to avoid congesting the system and therefore impacting the data collection, it generates additional costs for network operator. The second option seems more cost-efficient. However, the PNT should not impact the quality of collected data. Deploying a 6G core network supporting TSN will allow to ensure deterministic communication between NDT and PNT and, therefore, the data accuracy is not impacted.

Moreover, the deployment of NDT will require high performance information technology infrastructure able to operate, manage and execute intensive and computation hungry machine and deep learning algorithms.

C. Data collection

Data collection is an important but challenging task for building unified data repository in NDT, especially with large-scale network. Private 6G can be a small- or mid-scale network, such as a smart factory network. However, public 6G might be a large-scale and highly dense network with user dynamics. This dynamics can come from the mobility of users (e.g., mobile robots, automated guided vehicles), and/or from the migrating/offloading of network functions. Whenever building NDT basic or functional model, the required data should be made available in the data repository. A complete and accurate data in the unified data repository contributes in building rich and accurate data models. However, collecting data from heterogeneous data sources is challenging. An NDT should be able to mirror the state of the physical network.

The NDT of the TSN-based 6G core network shall be aware of the input data for the 6G network:

- Packets sent by the User Equipment (UE) via the uplink channels
- Packets received by the UE, at the IP layer, at the entrance of the network

It requires information about network equipments and their TSN capabilities.

In addition, NDT requires a knowledge about applications requirements and constraints.

The synchronization between the NDT and PNT will produce a high number of network probes, which will consequently increase network overhead. Regarding this aspect, it is important to develop monitoring algorithms that have minimal footprint, without trading off accuracy. One promising research direction is to reduce sampling rate of data collection, then use ML-based algorithms to interpolate missing data.

Respecting user communications, the problem of privacy should be studied thoroughly. Since NDT requires mining into network traffic, the problem of user privacy should be studied thoroughly. The challenge, then, is to develop NDT solution that ensures privacy while at the same time letting network operator address operational concerns.

VII. CONCLUSIONS

This paper presents technical aspects of NDT for TSN-based 6G network, and proposes a framework to build this NDT. The framework addresses the serviced-based mesh architecture of 6G which can be supported by a TSN-native network. This framework provides the relationship among NDT components, especially TSN-specific components. The NDT interacts closely with CUC and CNC (i.e., TSN standard 802.1Qcc) to monitor and control the PNT using AI/ML techniques. The paper also discusses the key challenges when building this NDT, including the challenges related to the characteristics of TSN. These challenges pose a number of problems but also open up several new promising research topics for NDT in 6G. For future works, one desired direction is to experiment and evaluate the proposed NDT for TSN in a proof-of-concept 6G setup. Before that, a detailed data model of NDT for TSN needs be derived. This data model should be highly unified and inter-operational because it is used by several components such as CNC, NDT manager, and ML model. Moreover, this evaluation has to reflect the new cloud-based architecture of 6G, which significantly differ from 5G.

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