When Digital Twins Meet Optical Networks Operations

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Abstract: We discuss the potential of deploying a network digital twin to support future data-driven optical networks implementing advanced telemetry. Use cases of intent-based connection allocation and soft-failure localization are addressed.

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1. Introduction

The concept of building a twin for troubleshooting dates back to the Apollo Mission in the 70s, where accurate replicas of space vehicles were used to reproduce on the ground eventual adverse conditions encountered in space [1]. The notion of a digital twin emerged as an evolutionary step in computer simulation and modeling with very accurate outputs, enabling systems to operate and self-repair autonomously. Until recently, simulators were restricted to R&D departments with a limited set of users [1]. The concept of digital twins aims at expanding this scope of application, bringing accurate simulation and modeling to system planning and autonomous operation. The idea of a digital twin can mean different things in different industries. An interesting classification presented in [2, 3], describes a digital twin as composed of a physical object, a virtual object, and communications channels from physical to virtual and from virtual to physical. A relevant aspect of this classification is that it calls a digital twin the entire system, composed of these four elements, and not only the virtual object as found in many texts. More than a simulator, according to this view, the digital twin is a dynamic environment for accurate modeling and a key enabler for decision-making in autonomous systems.

The use of digital twins in communication networks has been accelerated by software-defined networking (SDN) and intent-based networking (IBN) approaches leveraging streaming-type telemetry services for real-time data extraction without overloading traditional management and control plane systems. The architecture of a network digital twin (NDT) is being discussed within the Internet Engineering Task Force (IETF) in the draft entitled "Digital Twin Network: Concepts and Reference Architecture" [4]. The proposed architecture contains three layers: the physical network, the NDT, and an application layer that uses the NDT instance. Unlike [2,3] that denotes the entire system as an NDT, [4] denotes only the virtual object as an NDT. The physical network exposes telemetry data to the NDT, which returns control messages, resulting in a closed-loop control system. The NDT instance contains a data repository, a digital twin management entity, and service mapping models.

Narrowing the discussion down to optical networks, the NDT literature has increased significantly in the last few years [5–11]. Reference [7] experimentally deploys and operates an NDT composed of a data collector, data repository, service mapping models (SMM), and digital twin entity manager (DTEM). In [8], a dual domain NDT is proposed to better characterize the optical layer in both time and frequency domains. In [9], the optical route planning library, called Gaussian noise simulation in Python (GNPy) [12], is used as an NDT of the physical layer for open and disaggregated optical networking. In [10], the NDT consists of topology, lightpath, and telemetry twins to mimic the optical network in failure scenarios. The NDT generates synthetic failure scenarios to train an artificial neural network able to localize soft-failure events. In [11], using artificial neural networks, a deep-learning-based NDT is proposed to model optical links and nodes.

The IETF also addresses NDTs for optical networks in the draft entitled "Performance-Oriented Digital Twins for Packet and Optical Networks" [5] that presents a so-called Optical Performance Digital Twin (OPDT), which generates transmission performance estimates considering the physical topology, the optical service topology, and network equipment particularities. The OPDT focuses on quality of transmission (QoT) estimation, although use cases related to optical network survivability and planning are also discussed. The OPDT architecture is illustrated in Fig. 1. A physical network exchanges information with an NDT instance through a management plane. The management plane reads measurements through the measurement interface and configures the network using the configuration interface. The exchange of information between the management plane and the NDT is carried out by the NDT interface. The management plane also appears as a hub for exchanging information with external

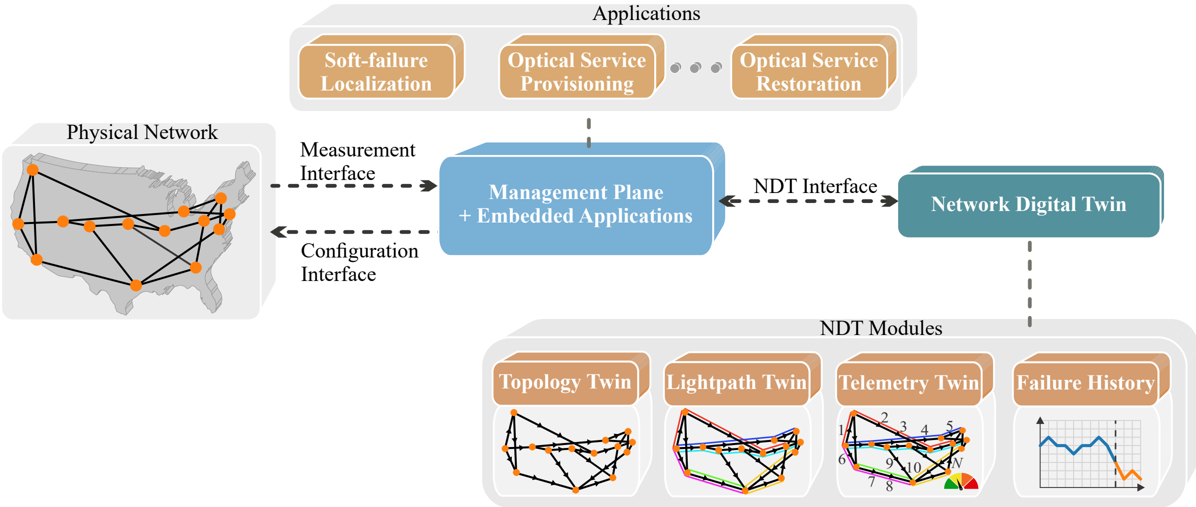

Fig. 1. Architecture of an optical performance digital twin [5] with example applications. The management plane works as a hub for exchanging information between the physical network and the NDT. Possible applications include soft-failure localization, service provisioning, and service restoration. An NDT can consist of a topology twin, a lightpath twin, a telemetry twin, and a failure history module used for survivability intents.

applications or embedded applications. In Fig. 1, we also suggest possible NDT applications, such as optical service provisioning, optical service restoration, and soft-failure localization.

2. Optical network digital twin elements

The main idea of an NDT is to yield a digital mirror of the network that is updated online according to the network telemetry. With this purpose, in [10] we designed a digital twin consisting of three main elements: a topology twin, a lightpath twin, and a telemetry twin, as shown in Fig. 1. The topology twin records the physical network topology, including the available fiber links and network nodes consisting of fixed or reconfigurable optical add-drop multiplexers. The lightpath twin registers the routes and spectral properties of all lightpaths established within the network. Finally, the telemetry twin attempts to mimic the network telemetry based on component parameters (e.g., amplifier gain and noise figure) and the physical and lightpath topologies. As an example, the telemetry twin implemented in [13] records the input and output powers of transponders and amplifiers. To generate an accurate telemetry twin, the lightpath twin should track the per-lightpath power of the signal, amplified spontaneous emission noise, and nonlinear interference. Naturally, the telemetry twin will differ from the real telemetry, triggering the process of adjusting the component parameters in an attempt to minimize the difference between real telemetry and digital twin telemetry. Adapting the NDT figures to real telemetry is an active field of research. Possible alternatives in this field involve iterative algorithms that tweak the network parameters or black-box machine learning (ML) algorithms.

Another aspect that can be managed in NDTs is optical network survivability. Registering a history of network failures and repairs allows the network operator to derive reliability measures and improve automated decision-making in intent-based networking. So far, protection allocation based on availability metrics calculated from repair and failure rates has relied on static figures derived from long-term statistics. Adapting reliability metrics from the element failure history may help operators to fulfill service-level agreements and improve the relationship with customers. For example, premium connections may avoid underground fiber links in highly dense metropolitan areas to avoid disconnections and increase connection availability. In a scenario of closed-loop intent-based networking with survivability intents, such failure history can be the basis for automatically deciding about connection protection or the utilization of shared-backup path protection.

3. Use cases

There are several practical use cases for NDTs in optical networks, some of them mentioned in [5]. In the following paragraphs, we list some of the most promising applications.

Network planning. Optical network planning is currently based on analytical formulas and the application of margins. Expansions of network segments can rely on extended NDTs to perform planning, leveraging the knowledge provided by existing connections. This approach would approximate the planning team from the operation, using the NDT as a common interface.

Service provisioning. NDTs can be used to estimate the QoT of new lightpaths before they are actually established [9, 14–18]. QoT estimation can rely on analytical or machine-learning-based NDTs. Analytical NDTs are advantageous in terms of explainability since each power, noise, and interference parameter is well-described by analytical equations involving, e.g., the Gaussian noise (GN) model for modeling nonlinear interference [19]. On the other hand, ML-based NDTs have high flexibility and are very successful in automatically learning complex input-output relationships. Combining the best of both worlds, analytical and ML-based NDTs can be jointly implemented to improve the overall QoT estimation accuracy. In addition to QoT figures, the network failure history can also be used to satisfy user survivability intents [20].

Service restoration. Service restoration refers to the reactive allocation of network resources after a failure has occurred in the primary path. Unlike protection, which precomputes the survivability resources *offline*, restoration is an *online* process. Again, the NDT (using analytic expressions of ML-based) can evaluate the QoT of the alternate path before the connection is actually established.

Soft-failure localization. Soft failures are those that have an impact on the network telemetry without disrupting the service or generating alarms. Eventually, soft failures can evolve into hard failures if the (soft)-faulty device is not subject to preventive maintenance. Soft-failure localization can be eventually implemented by if-else rules applied to equipment telemetry. An alternate approach relies on ML-based techniques applied to network-wide telemetry [21]. Compared with the use of if-else rules, ML algorithms have interesting advantages, such as providing a probabilistic approach and tolerating missing information on the recorded telemetry. An important challenge in supervised ML techniques is the training phase. In particular, for failure localization, a set of failures has to be generated to train the localization algorithm, which is unfeasible in real networks where failures are relatively rare events. Alternatively, in [13] we use an NDT (called in this work *network mirror*) to generate synthetic soft failures and train the ML algorithm. In [21], we demonstrate that the ML-based scheme can localize soft and hard failures with full and partial telemetry. In [10, 22], we successfully localize single and double failures in a small-scale lab setup using an NDT to create a failure dataset.

4. Conclusions

The deployment of NDTs is a natural trend in contexts with abundant telemetry and increasing levels of automation. NDTs become even more relevant for intent-based networking with automated closed-loop operation. Optical NDT use cases include applications of network planning, service provisioning, service restoration, and soft-failure localization. NDTs have already been successfully demonstrated for QoT estimation and soft-failure localization in small-scale lab experiments. As common to several promising data analytics techniques developed for optical networks, the lack of field data from large-scale networks is still a challenge to bridging academic results and practical applications in the wild.

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