Recent Advances in Digital Twin for Optical Communications

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Abstract Digital twin for optical communications with detailed discussion on mirror modelling, data collection and analysis, and intelligent control is reviewed. Recent advances with focus on data-physics hybrid-driven techniques are presented.

Introduction

Digital twin (DT) is gaining popularity in optical network to ensure high-reliability operation and high-efficiency management, which is the key enabling technology for network automation. The DT can help bridge the gap between the ideal physical layer that is commonly assumed in optical communications and physical layer behaviour in deployed networks. The roles of DT in optical communications haves been performed in physical layer mirror modelling, fault management, automatic optimization, measurement uncertainty estimation, topology abstraction, network planning and control, and margin reduction.

The framework of DT in optical network can be composed of three parts: mirror modelling, data collection and analysis, and intelligent control, as illustrated in Fig. 1. First, the establishment of DT relies on precise and dynamic mirror modelling techniques, which necessitate accurate physical layer parameters. Thus, real-time data collection and analysis from the physical layer are essential to ensure the DT can comprehensively characterize the behaviour of physical layer. Once established, the DT can be utilized for network operation and management through intelligent control.

from conventional Different theoretical simulations, the mirror modelling techniques of DT require high-fidelity mapping and real-time updating, creating a virtual replica of the practical physical object rather than a theoretical model [1]. In this context, the primary challenge lies in accurately and efficiently describing the complex impairments and uncertainties along the transmission link, introduced by transceivers, fibre channels, amplifiers, and various crossdevices. Although connection significant theoretical foundations have been established, the primary issue is the high computational complexity. Furthermore, the dynamics of the developing optical networks results in insufficient accuracy of some of the existing modelling techniques, expecting the prospective methods

for DT modelling.

Real-time and accurate mirror modelling techniques require accurate physical layer parameters, which can be achieved by capturing timely data and abstracting useful information from the physical layer. This process is facilitated through telemetry, which involves collecting data from network devices in real time. In contrast to traditional raw data collection from the physical layer, more detailed and insightful information are required by the DT. Consequently, a data analysis unit is required to further analyse the collected raw data. This process enables the ondemand and real-time transmission parameters detection for DT modelling and comprehensive analysis for seamless control.

Without DT, classical operation controllers can only perform basic management tasks based on pre-set functions and metrics. However, by harnessing its modelling capabilities and realtime interfacing with the physical layer, DT can effectively predict performance bottlenecks, automatically provide optimization strategies, and proactively identify potential risks. The capability to simulate, monitor, and manage the physical layer in a holistic manner will allow network operators to gain valuable insights into the behaviour and performance of the network in real-time, contributing to the enhanced efficiency and reliability.

In this paper, we reviewed the recent advances in DT for optical communications, as summarized in Fig. 2. With mirror modelling techniques and real-time data collection and analysis, DT will empower optical network to evolve toward digitalization and automation.

Mirror Modelling for Physical Layer

The ultimate goal of mirror modelling is to accurately describe the various impairments encountered by signals propagating along the link, including both the electrical and optical domains. Among all the component in the transmission link, fibre channel modelling gains most attention as it introduces linear and complex



Fig. 1: Schematic of the digital twin for optical communications. The data is collected from physical layer in real-time and analyzed for mirror modelling, then intelligent control is pushed to the physical layer.

nonlinear impairments during the propagation of optical signals [2]. The baseline method is solving the NLSE by numerical methods, such as the SSFM. To reduce the calculation complexity, perturbation-based methods for the calculation of nonlinear interference (NLI) has been proposed, including the Gaussian noise (GN) model [3], which has been extensively validated with various versions [4,5], and the inter-symbol interference (ISI) model [6]. Such methods act a suitable quality of transmission (QoT) estimation tool, while sacrifice most information of signal sequences for fast calculation speed.

The deep learning (DL) techniques have also been explored. Within the context of fibre channel modelling, data-driven neural networks with diverse structures, including Bidirectional Long Short-Term Memory (BiLSTM) [7], Generative Adversarial Networks (GANs) [8], and transformers [9], have been studied. DL techniques have also been explored for other component, such as amplifiers and crossconnection devices [10,11]. However, datadriven DL methods always suffer from a critical issue of unexplainability, which limits their reliability and generalization ability.

То address this challenge, recent advancements have introduced physics-informed neural networks (PINNs) [12]. These approaches incorporate physical laws, such as partial differential equations (PDEs), into the loss function of neural networks, which requires less and even no labelled collection data. PINN methods have shown promise in the fields of nonlinear optics [13] and optical fibre communications [14], where they have

demonstrated their ability to capture the underlying physics, improve the flexibility, and relieve the data dependence. Furthermore, neural operators, which incorporate the principles of the universal approximation theorem for operators, have also been employed for channel modelling [15]. The utilization of both data and prior physics is expected to be a key technique in mirror modelling to ensure reliability and efficiency and boost the implementation of DT.

Data Collection and Analysis through Telemetry

To achieve the high-accuracy and dynamic DT modelling for optical layer, the real-time data collection and comprehensive information extraction are necessary, which can be achieved by telemetry [16]. For an efficient and unified data pulling, a considerable amount of effort has been paid into creating standardized interfaces and data models [17].

Once the raw data are collected, some of them require further analysis to extract useful information for the DT. For coherent transmission system, sufficient information can be obtained through DSP module. In this context, DL techniques have been employed to analyse the information provided by DSP-based monitoring algorithms and system margin analysis [18,19]. Recently, DSP-based longitudinal monitoring methods attract much attention and have been proved for spatially power profile estimation (PPE) [20], and amplifier gain estimation [21]. Anomaly losses in the link small to 0.77dB can be identified [22]. These methods can be roughly classified to correlation method (CM) and minimum mean



Fig. 2: Recent advances in digital twin for optical communications.

square error (MMSE) method.

Thanks to the incorporation of physical laws, PINN-related methods are also well-suited for parameter identification within PDEs. This can be achieved by updating the inaccurate physical parameters along with the weight and bias parameters of PINN, which is also constrained by physical laws and only minimum measured data are required. PINN has been demonstrated for the identification of fibre parameters [23]. Moreover, the frequency-dependent attenuation and Raman spectrum in wideband can be refined with PINN leveraging monitored channel powers [24].

Intelligent control: efficient management for physical layer

Based on the real-time data collection and accurate mirror modelling of physical layer, the DT can implement the intelligent control and automatic optimization in network layer. With the goal of achieving better performance and lower margin, various GSNR optimization methods have been proposed, including **EDFA** configuration schemes using searching methods [25], gradient descent methods [26], and approximated closed-form optimization, transceiver configuration using autoencoder [27], WSS configuration using neural networks. The efficacy of the DT has been verified through comprehensive simulations and experiments, such as a thorough margin exploration for a large network, BER reduction of the most critical services, and automatic failure recovery [28]. In addition, the DT can also help network operators to visualize and control the physical device in an intuitive manner. In this connection, some interesting applications utilizing virtual/argument reality (V/AR) have also emerged [29].

Data & physics hybrid-driven techniques also plays a role in this context. There is a valuable prior knowledge gain from GN model that the strength of nonlinearity is approximately two times of linear noise when the transmission is close to its optimal performance (3dB principle). This principle can be used to enhance the generalization of neural networks for QoT estimation and performance optimization [30]. This physical insight has also been demonstrated to enable efficient channel power optimization in S+C+L-band transmission systems.

Conclusions

In this paper, recent advances in DT for optical communications from the aspect of mirror modelling, data collection and analysis, and intelligent control were reviewed, as summarized in Fig. 2. It can be envisioned with optimism that DT will play an important role in the development of future optical networks.

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