Optical Network Automation, Programmability, and AI: the Path to 6G Readiness

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***Abstract*—The 6G vision predicts a massive increase in connected devices and a greater use of local and distributed intelligence. To support this shift, networks, particularly optical ones, must become more dynamic and flexible. Introducing packet-optical programmable devices will require redesigning control and management functions to leverage artificial intelligence & machine learning (AI/ML) capabilities. This paper explores how network automation and programmability in the optical segment are essential to meet 6G requirements, the latest developments, and the key challenges ahead.**

***Index Terms*—6G, Artificial Intelligence, Machine Learning, Software-Defined Networking.**

I. Introduction

As the fifth generation of mobile networks (5G) is being deployed, the discussions regarding the sixth generation of mobile networks (6G) intensify. The ITU Radiocommunication Sector published the IMT-2030 Framework [1], defining the usage scenarios envisioned for 6G and the key requirements for the radio interface of 6G networks. According to the shared vision, 6G networks will focus on three areas. Firstly, the capabilities of the three main 5G scenarios will be expanded: enhanced mobile broadband (eMBB), massive machine type communication (mMTC), and ultra-reliable and low-latency communication (URLLC). Secondly, three new usage scenarios are defined: integrated sensing, integrated compute & AI/ML, and ubiquitous connectivity. Finally, 6G networks will work towards meeting United Nations (UN) sustainable development goals (SDGs).

Meanwhile, we expect optical networks to remain the key transport technology moving from 5G to 6G. To achieve this goal, in addition to also working towards the UN SDGs, optical networks need to improve their automation and programmability features with the help of AI/ML. This will enable optical networks to support the data rates envisioned for 6G, support low-latency services with even stricter requirements, and provide the higher reliability and dynamicity needed by 6G mobile networks.

This paper aims to highlight the 6G usage scenarios and services that can meet their targets with the help of optical networks. To do so, we first analyze the 6G usage scenarios defined by IMT-2030 [1] and the requirements expected for services taking advantage of 6G networks defined by 3GPP [2]. Then, we discuss critical advances from optical networks that can assist 6G networks in achieving the designated targets, highlighting the contributions and challenges of applying AI/ML in each case. To illustrate concrete results, we present a performance assessment of two selected use cases showcasing recent advancements in optical network automation and programmability. Finally, we discuss three open future challenges identified as crucial for fully realizing the 6G vision.

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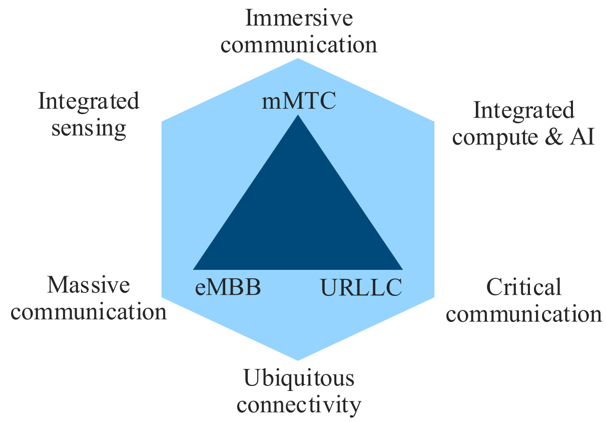

Fig. 1. 6G usage scenarios (adapted from [1]).

II. 6G Use Cases and Requirements

Given the critical role that optical networks played in realizing 5G [3], we expect that optical networks will also be crucial for 6G [4]. In this direction, the optical network community needs to closely monitor the requirements and defined use cases and propose suitable solutions that meet these requirements. This section provides an overview of the recently defined use cases and requirements, focusing on those that require optical network support.

Fig. 1 illustrates the six usage scenarios envisioned for 6G. Three of the 5G scenarios, i.e., mMTC, eMBB, and URLLC, are expected to be extended towards 6G as immersive communication, massive communication, and critical communication, respectively. Three new usage scenarios are introduced in 6G, i.e., integrated sensing, integrated compute & AI, and ubiquitous connectivity. All the usage scenarios just listed

TABLE I
REQUIREMENT EVOLUTION FOR THE AIR INTERFACE FROM IMT-2020 TO IMT-2030 RELEVANT FOR OPTICAL NETWORKS [1].

Requirement	Unit	IMT-2020	IMT-2030
Peak data rate	Gbps	20	50-200
User data rate	Mbps	100	300-500
Area traffic capacity	Mbps/m^2	10	30-50
Density	devices/km^2	10^6	10^8
Latency	ms	1-4	0.1-1
Reliability	-	10^{-5}	10^{-7}
Mobility	km/h	500	1,000

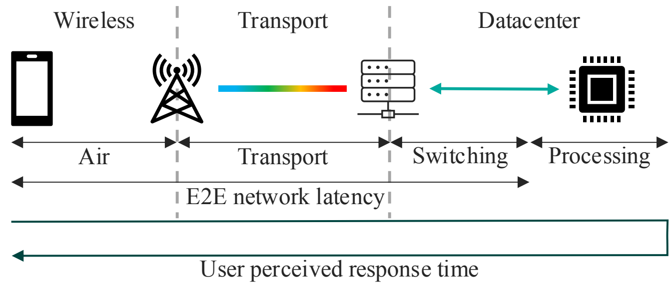

Fig. 2. Latency contributions to the end-to-end (E2E) perceived response time.

guide the development of 6G and are used to define concrete requirements for the upcoming research and standardization efforts.

The IMT-2030 Framework [1] defines 15 capabilities for the 6G technology, 9 of which are enhancements of existing 5G capabilities. Table I summarizes a selection of the enumerated requirements for the air interface, compared to the targets established for 5G. At the time of writing, 6G standardization has not officially started yet, and the values provided in Table I are initial estimates. In the following, we focus on the requirements with concrete target values relevant to optical networks.

A. Data Rate

The first four requirements mentioned in Table I will impact the data rate requirements of the transport network segment, which is usually supported by optical network infrastructure. The peak data rate is the maximum achievable data rate per device under ideal conditions. For 6G, the 50-200 Gbps range is provided as an example. This means that compared to what is expected from 5G (20 Gbps), in areas where these peak data rates need to be supported, the transport segment should expect an increased demand for capacity of 2.5 to 10 times.

The following three requirements pertain to more ubiquitous scenarios. These requirements pose more significant challenges for the optical network infrastructure, as they must be met throughout the 6G deployment. The user data rate refers to the value achievable ubiquitously, and rates of 300 to 500 Mbps are given as examples. The area traffic capacity is expected to increase in the same magnitude as the user data rate, i.e., three to five times compared to what was expected in 5G scenarios. Meanwhile, the density of devices is expected to increase by up to two orders of magnitude. In summary, ordinary 6G deployments may require from 60 ($3 \cdot 3 \cdot 10$) to 2,500 ($5 \cdot 5 \cdot 10^2$) times higher data rates than current 5G deployments, considering the minimum and maximum increase magnitude of user data rate, area traffic capacity, and density, respectively.

B. Latency

The discussion of latency requires us to analyze three different components. First, we must understand the main contributors to the service end-to-end (E2E) latency. Second, we analyze the latency requirements over the air interface, mentioned in Table I. Finally, we can explore the service requirements defined by 3GPP [2] and derive requirements for the transport network.

Fig. 2 shows a simplified view of the network segments and their contribution to the E2E latency. For simplicity, we omit the details of a possible distributed radio access network (RAN) deployment. We also assume that the transport segment is implemented using optical networks. The latency requirements mentioned in Table I refer to the air interface latency. However, 3GPP establishes a maximum E2E latency for several services in their service requirement definition. Therefore, the transport network is left with a given latency budget based on the maximum allowed latency for a given application and the air interface latency. In our case, as shown in Table I, the 6G air interface should impose a latency of 0.1 to 1 ms.

3GPP has initiated the definition of several services expected to take advantage of 6G [2]. One of the services is *immersive gaming*, which requires an E2E latency of 5-20 ms for the compute flows. In this service, other flows for game state and streaming can have more relaxed latency, i.e., 50-100 ms and 200-300 ms, respectively. In the worst-case scenario, the transport network would have a budget of 4 ms, ignoring all the necessary electronic switching. This would give a maximum distance between the antenna and the data center of 8 km. Considering more favorable limits, the distance could reach up to 38 km.

Another service where latency is critical is *seamless immersive reality in education*. In this use case, split rendering enables the rendering workload to be offloaded to the cloud. However, this must be done with a maximum latency of 10 ms. In this case, the maximum distance between the antenna and the data center is 18 km. Considering the necessary electronic switching involved, this distance can be even shorter.

C. Reliability

Regarding reliability, the IMT-2030 Framework [1] defines the air interface as the one that needs to provide a reliability performance between 10^{-5} and 10^{-7}, representing up to two orders of magnitude higher reliability than the 5G case. In turn, 3GPP defines the *ubiquitous and resilient network* use case for 6G [2], which defines a reliability requirement between 10^{-1} and 10^{-4}. This means that the transport and data center segments combined have stringent reliability targets ranging from 10^{-1} to 10^{-6}.

D. Mobility

Finally, 6G is expected to support high-mobility scenarios, going from 500 km/h in 5G to 1,000 km/h [1]. At these speeds, users expect to have ubiquitous connectivity. For the wireless segment, this requires seamless transfer between radio nodes, which can belong to different technologies. For the transport segment, the network needs to adapt much more quickly to changing traffic patterns.

III. AI/ML-Based Optical Network Automation and Programmability for 6G: Use Cases

This section analyzes how new advances in optical network automation and programmability can help achieve the 6G targets. At the end of each section, we provide a contextualized summary of AI/ML use cases and challenges. Due to the strong interest of industry and academia in the topics mentioned in this section and the vast literature produced, we do not aim to make an exhaustive review of the literature. We highlight only a few references that represent examples of recent research efforts.

A. Coherent Multi-Band Multi-Core Optical Networks

As mentioned in Sec. II-A, 6G networks are expected to support up to 2,500 times higher data rates than current 5G networks. These data rates are directly supported by the transport network, which also needs to upgrade its capacity by equal margins. Increasing the supported data rates in optical networks can be achieved through several means, but none can provide such increases independently.

One approach to increasing the data rate is introducing new transmission techniques that improve the spectral efficiency of optical networks. This can be achieved by introducing new transceivers and more efficient modulation formats, such as those using coherent transmission and probabilistic constellation shaping [5]. However, this approach is not sufficient to provide the needed capacity. Further improvement of the capacity among nodes is necessary to achieve the required data rates.

To this end, multi-band and multi-core optical networks have long been investigated, but interest has intensified over the past few years. In multi-band optical networks, the traditional C-band transmission is expanded to use other bands. In multi-core optical networks, optical fibers are fabricated with multiple cores, enabling the parallel transmission of multiple signals through a single fiber cable. However, this scenario poses several challenges.

One refers to the signal impairments that degrade the quality of transmission (QoT) of optical signals. To make multi-band and multi-core technologies viable, we must address the detrimental effects of linear and non-linear interferences in the former and cross-talk among fiber cores in the latter [6]. Moreover, provisioning connectivity services over these multi-core, multi-band optical networks requires revisiting resource assignment problems [7].

AI/ML-based automation is crucial in enabling optical networks to take full advantage of the mentioned technologies. For instance, AI/ML models can be used to improve the efficiency of probabilistic shaping transmission. Another example is the QoT estimation in multi-band and multi-core, which requires complex computations, and AI/ML models can replace analytical models. Finally, the multiple resource dimensions in multi-band multi-core networks make the resource assignment problems quite complex, and deep reinforcement learning (DRL) methods can be used to improve resource efficiency.

B. End-to-End Optical Channels Spanning Edge-to-Core

6G services will pose very stringent latency requirements, as discussed in Sec. II-B. On the cloud computing side, this will require densification in terms of the number of nodes enhanced with computing capabilities. On the optical network side, this will require careful consideration of the routes adopted and reduced electronic switching allowed along the connectivity path. Transparent optical channels from the base station site to the data center nodes will be needed. This means that transport networks, usually segmented between access, metro, and core, will need to support more transparent communication, reducing the impact of these segments on the end-to-end network latency.

To realize this vision, new architectures must be developed, minimizing or removing hard borders between network segments. Moreover, given the higher mobility goals of 6G (discussed in Sec. II-D), transport networks need to be highly reconfigurable and take advantage of multiple technologies [8].

AI/ML techniques are an essential enabler of these technologies due to the need to compute resource assignment considering many parameters from all network segments and technologies involved. Tasks such as traffic prediction can help anticipate capacity needs. Estimating impairment for the various technologies can be crucial for quickly assessing the viability of a given resource assignment solution. Finally, DRL can be used to learn efficient resource assignment solutions.

C. Distributed Decisions at Line Speed

The reliability requirements of 6G applications are strict, leaving the transport network with a tiny margin, as discussed in Sec. II-C. Traditionally, high reliability in optical networks was achieved by providing backup resources that remained idle until a failure was experienced. This leads to low resource efficiency and high cost. Network operators function under constrained profit margins, necessitating cost-efficient strategies for sustainable operations. This includes alternatives to provide high reliability at low cost. This is challenging to achieve using the current logically centralized network control and automation architecture due to long round-trip times between devices and the controller.

New algorithms that take decisions locally need to be developed. These algorithms must run in a distributed fashion, i.e., each instance has the autonomy to reconfigure its local devices without the approval of a centralized controller.

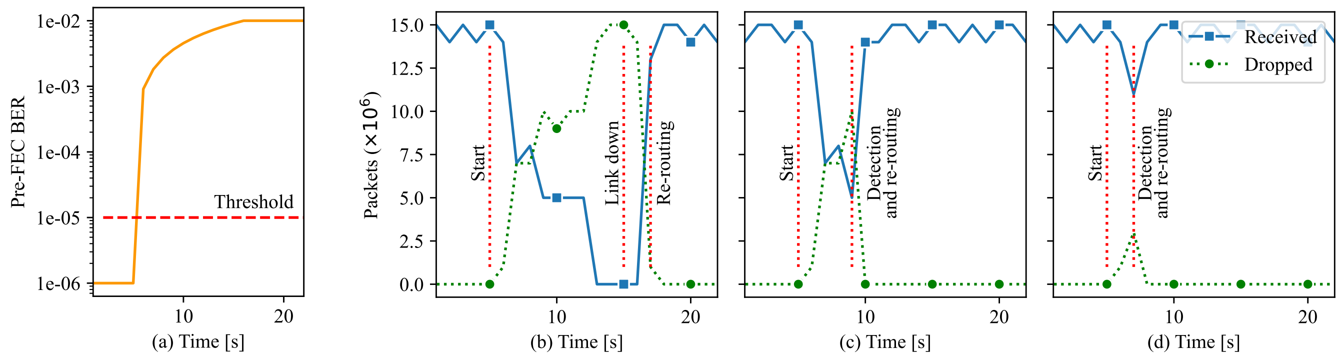

Fig. 3. Simulation results of the on-device re-routing decision: (a) Pre-forward error correction (FEC) bit error rate (BER); packets received/dropped at N1 with (b) proposed framework, (c) telemetry-based centralized decision; and (d) centralized-based hard failure detection (adapted from [9]).

Moreover, these algorithms must run at line speed to allow fast and seamless reconfigurations. Programmable devices (e.g., pluggable transceivers) have been introduced, enabling the deployment of algorithms that run at line speed. Several use cases for programmable devices have been investigated, such as failure recovery [9] and security [10].

In this context, AI/ML models can be essential to assist in local decisions. The distributed decisions need to be quickly computed based on an analysis of many variables. AI/ML models are good in these scenarios where numerous variables are considered. Moreover, AI/ML models can be trained to work collaboratively, potentially preventing conflicting decisions among network elements.

IV. Selected Results

This section presents a few selected results related to the use cases discussed in the previous section.

A. Distributed Decisions at Line Speed

In this use case, we explored how decisions made locally and autonomously by a packet-optical programmable device (i.e., a P4 switch) can enhance the failure recovery process by reducing packet losses. The intuition is that a programmable switch can autonomously use alternative channels to transmit user data when it experiences a soft or hard failure. Firstly, we implemented a proof-of-concept of an algorithm in a real-world P4 Tofino switch. Then, we parameterized an NS-3 simulation to measure the impact of the on-device decision on the packet losses. We assumed three scenarios. The first scenario uses our proposed framework that decides on re-routing at the device. The second scenario assumes a telemetry-based centralized control and monitoring platform. The third scenario assumes a centralized control platform with decisions based on hard failures. In all scenarios, we assume a round-trip time between the switching device and the controller of 1 second. We refer the reader to [9] for a more complete description.

Fig. 3 shows the simulation results. Fig. 3(a) shows the assumed failure scenario, where the pre-FEC BER increases over time, characterizing a soft failure that evolves to a hard failure once the BER violates the FEC limit. Fig. 3(b) shows the packet loss over time for a scenario in which the re-routing is only triggered after a centralized controller receives the *link-down* notification. This notification occurs when transmission is no longer possible between two nodes, i.e., a hard failure. It is possible to observe severe packet losses during an extended period.

Fig. 3(c) shows the results of the scenario where the centralized controller receives telemetry periodically. In this case, it is possible to detect the soft failure. However, we still need to account for the time to receive the telemetry data and send a re-routing command to the switching device.

Fig. 3(d) shows the results of the proposed framework. In this case, the programmable device can analyze the telemetry data locally. Once a soft failure is detected, the device has the autonomy to temporarily switch the traffic to a different route, reducing packet losses substantially. It is important to note that we consider this a temporary solution for soft failures that will develop into hard failures. The benefit is that it gives the network enough time to compute a more permanent solution to the failure while supporting user traffic.

B. AI/ML-as-a-Service

In this use case, we explore the ability of an AI/ML-as-a-Service engine to automatically create, train, evaluate, and deploy an AI/ML model based on a formal description, e.g., through a YAML-based descriptor. The framework takes advantage of meta-learning approaches that the AI/ML community has developed and automates the model lifecycle. We applied the AI/ML-as-a-Service concept to showcase its benefits to the QoT estimation task. Upon receiving the details of an unestablished lightpath, the AI/ML model estimates the generalized signal-to-noise ratio (GSNR) to be expected upon establishment. We used the data openly available from [11] comprising four different datasets characterized by different network topologies and traffic characteristics. We refer the reader to [12] for a more complete work description.

Fig. 4 shows the performance results of the proposed AI/ML-as-a-Service framework with a manually tuned ANN in terms of MAE and MSE. Regarding MAE, the model created by our AI/ML-as-a-Service framework either matches or outperforms the manually tuned ANN. Regarding MSE,

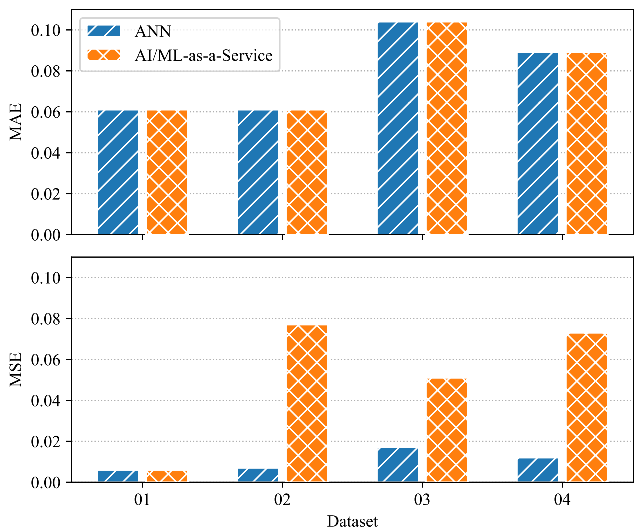

Fig. 4. Regression performance using a testing dataset extracted from [11] for a manually tuned artificial neural network (ANN) and AI/ML-as-a-Service in terms of mean absolute error (MAE) and mean squared error (MSE) (adapted from [12]).

the model created by the AI/ML-as-a-Service framework The comparable performance means that AI/ML-as-a-Service can potentially reduce or even eliminate human intervention from building AI/ML models to support optical network automation tasks.

V. Future Challenges

This section addresses three key challenges in AI/ML-based automation and programmability that academia and industry must overcome to advance optical networks to support the 6G goals. The first two relate to the need to provide high-reliability services supported by optical networks. This will require synergies between network programmability (in the form of on-device local decisions at line speed) and automation (in the form of logically centralized orchestration). AI/ML models will play a key role in both cases.

The first open challenge addresses the development of distributed control algorithms. These algorithms must enable the quick mitigation of anomalies or traffic bottlenecks without the intervention of a central controller. More importantly, they must do so while running locally, on-device, and at line speed. Many decisions can be made locally, but re-routing due to soft/hard failures and security-related tasks has demonstrated the highest benefits in the literature. Academia and industry have developed critical enablers for this. One example was presented in the previous section, where preliminary results of the benefits of on-device distributed decisions at line speed were illustrated. However, only a single optical channel was being monitored [9]. This is also true for many of the works exploring on-device algorithms [10]. These distributed algorithms need to be carefully designed to scale to network-wide deployments. This requires developing design strategies that can pre-compute alternative solutions for many foreseen conditions to be mitigated. Moreover, due to these algorithms' distributed nature, conflict resolution schemes need to be developed to ensure that the network remains consistent even when distributed decisions are made. In this context, AI/ML models must be considered for two tasks. First, the efficiency of AI/ML models must be improved to provide inference at line speed, e.g., through specialized hardware (accelerators). This enables local decisions assisted by traffic prediction, traffic classification, etc. AI/ML models can also replace traditional heuristic algorithms completely. For instance, DRL agents can be trained offline and deployed locally to guide the on-device distributed decisions. Therefore, developing (AI/ML-based) distributed control algorithms for optical networks is crucial for these networks to meet the 6G reliability and dynamicity requirements.

The second open challenge concerns the evolution of entities involved in the centralized control of optical networks, such as network controllers and orchestrators. In the context of this section, these entities are called *controllers* for simplicity. Controllers implement the so-called *automation loops*, responsible for collecting and analyzing data and (re)configuring the network accordingly. Note that as distributed control algorithms are introduced, controllers will remain to provide functionalities requiring coordination of many network elements. However, the frequency/periodicity at which automation loops run needs to be increased drastically to meet the 6G expectations for reliability and dynamicity. In practice, controllers will need to collect, transfer, and analyze monitoring data much more frequently. The efficient transport of monitoring data has been investigated, with telemetry approaches addressing several of the shortcomings [13]. Works in the literature have also focused on reducing the amount of data needed to detect soft or hard failures [14]. Finally, a few studies have also analyzed how to process the received data in a scalable fashion [15]. However, all these works assume monitoring periods ranging from a few to several minutes. The periodicity must increase to every few seconds or multiple times every second. This will increase the monitoring overhead on optical supervisory channels used to transport monitoring/telemetry data and the computing and software used to process this data. Therefore, developing efficient telemetry technology combined with efficient and accurate AI/ML models for analyzing this data is crucial for optical networks meeting 6G reliability and dynamicity requirements.

Finally, a critical challenge is defining and autonomously analyzing optical-network-focused key performance indicators for AI/ML models. In the literature, several studies focused on their explainability and interoperability. In particular, supervised learning [16], unsupervised learning [17], and reinforcement learning [16] have been investigated. A few works also focused on the issues of data imbalance [18] and its impact on trained AI/ML models [19]. However, there are still shortcomings in how AI/ML models are benchmarked. Traditional metrics from the AI/ML community, such as accuracy and MAE, cannot fully characterize models' behavior once deployed in the network. It is also essential to assess the impact of inaccuracies on the overall network performance. For instance, in the case of QoT estimation, evaluating the spectral efficiency and request blocking performance is essential. Moreover, the representativeness of training sets needs to be further analyzed. Therefore, developing a framework that can perform a multi-faceted analysis of AI/ML models towards assessing their trustworthiness in real-world scenarios is crucial for fully exploiting AI/ML capabilities.

VI. Conclusion

In this paper, we analyzed the requirements defined by the IMT-2030 Framework for 6G networks and the ongoing definition of end-user service requirements by 3GPP. Then, we discussed areas where optical networks, through programmability and automation, can help meet the 6G requirements. The AI/ML use cases and challenges were discussed for each area. Two use cases with selected results were presented to illustrate initiatives that address the discussed areas. Finally, we introduced three open future challenges that can be used to guide further research and development in the area of AI/ML-based optical network programmability and automation.

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