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The Role of Optical Transport Networks in 6G and Beyond: A Vision and Call to Action

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Abstract: As next-generation networks begin to take shape, the necessity of Optical Transport Networks (OTNs) in helping achieve the performance requirements of future networks is evident. Future networks are characterized as being data-centric and are expected to have ubiquitous artificial intelligence integration and deployment. To this end, the efficient and timely transportation of fresh data from producer to consumer is critical. The work presented in this paper outlines the role of OTNs in future networking generations. Furthermore, key emerging OTN technologies are discussed. Additionally, the role intelligence will play in the Management and Orchestration (MANO) of next-generation OTNs is discussed. Moreover, a set of challenges and opportunities for innovation to guide the development of future OTNs is considered. Finally, a use case illustrating the impact of network dynamicity and demand uncertainty on OTN MANO decisions is presented.

Keywords: 6G; optical networks; next-generation networks; robust optimization; model drift; distributed intelligence; 5G and beyond; management and orchestration

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1. Introduction

The recent advances in 5G networking technologies have led industry, academia, and standardization agencies alike to look toward the next generation of networking, 6G. Such 6G networks are characterized by ubiquitous connectivity, higher speeds, and stricter performance requirements compared to 5G and previous generations. Furthermore, 6G networks are envisioned to have a much more profound integration of Artificial Intelligence (AI) and Machine Learning (ML) to aid in Management and Orchestration (MANO) decision making. To this end, it is important to understand the various factors affecting network requirements, such as changing user behavior and the introduction of new and advanced use cases when looking toward the development of future networks.

Regarding performance requirements, 6G pushes the limits of 5G networks with an enhanced user experience and service delivery [1]. In 5G, data rates of 20 GB/s are achievable, whereas, in 6G, TB/s data rates are envisioned. Furthermore, due to the rapid advancements in the Internet of Things (IoT), connection densities of 10^7 users/km^2 are being considered in 6G, thereby exceeding 5G's connection density by an order of magnitude. Regarding latency, 5G boasts delays as low as 1 ms; however, 6G networks will further reduce this to 10–100 µs. Finally, 6G networks will be more reliable than 5G networks, with 99.9999% end-to-end reliability.

The aforementioned performance requirements consider a direct comparison between 5G and 6G networks; however, additional requirements will be introduced that are not currently supported in 5G networks. One such requirement is the intelligence level metric, essentially defining the level of ML/AI integration in the system. To this end, a set of novel Key Performance Indicators (KPIs) will be developed to gauge the network's ability to meet the new system requirements. Given the push for ML/AI adoption, one of the prevalent 6G KPIs is known as the Age of Information (AoI), which considers the time between information generation and information consumption. The AoI KPI significantly impacts ML/AI model performance, as the freshness of the data impacts the quality and usefulness of a model's predictive capabilities.

In 5G networks, key use cases, including Ultra-Reliable Low-Latency Communications (uRLLC), Massive Machine-Type Communication (mMTC), and Enhanced Mobile Broadband (eMBB), are proposed. The implementation of 6G advances each of these use cases through the introduction of Extremely Reliable Low-Latency Communications (eRLLC), Ultra-Massive Machine-Type Communication (umMTC), and Further Enhanced Mobile Broadband (feMBB). Additionally, 6G introduces additional use cases, such as Extremely Low Power Communications (eLPC) and Long-Distance and High-Mobility Communications (LDHMC) [1]. The proposed 6G use cases enable the emergence of a plethora of next-generation networking applications.

One of the major applications considered for 6G networks is seamless Augmented and Virtual Reality (A/VR). In 5G, such applications are projected to require a bandwidth capacity of 20 GB/s; however, in 6G, these applications are expected to reach 1 TB/s [2]. Another emerging application is the idea of holograms enabling telepresence. It is estimated that an uncompressed hologram requires 4.32 Tb/s data rates with sub-millisecond latency, something which is currently not possible with 5G networks. The widespread emergence of telehealth and e-health services is expected to continue into the 6G networking era. Regarding these applications, eRLLC is required to deliver <100 μs latency and 7 9's (99.99999%) reliability. Finally, maturing alongside the height of the Industry 4.0 revolution puts 6G networks in a prime position to enable massive deployments of the IoT and Industrial IoT through eLPC and umMTC.

As discussed throughout this section, 6G networking is expected to push the boundaries and test the limits of our network capabilities. The increased number of users, evolving use cases, and increasingly stringent performance requirements suggest that 5G networks will not be able to support the future demand. Additionally, due to its data-centric nature, the amount of data generated, transported, and consumed will be unprecedented. As previously mentioned, the AoI is a critical metric in terms of 6G and beyond networks reliant on intelligence and automation. To this end, the factors contributing to this metric, including the delay in environment sensing, information processing, information generation, information transfer, and information consumption, must be considered. The majority of the mentioned contributors of the AoI metric relate to node computing resources and algorithmic efficiency; however, when considering the delay in information transfer, the conditions and efficiency of the transport network are critical to minimize this delay.

The rise of Optical Transport Networks (OTN) and technologies such as Dense Wavelength Division Multiplexing (DWDM) has revolutionized the state of our backbone transport networks. These technologies, and their subsequent evolution, will be critical in enabling future networking generations by addressing the data transfer needs across all network regions. The advancements in the physical technology of these networks are not the only consideration that must be made; the way in which OTNs are managed and orchestrated and their levels of intelligence and resilience will play a critical role in their ability to meet the growing demand.

Several works have begun outlining the requirements of 6G and how to get there. Liu et al. [3] outline the vision and requirements for the network architecture of 6G and beyond mobile networks focusing on digital twin integration, new application scenarios, performance requirements, and network features. David and Berndt [4] discuss the 6G vision and requirements for 6G, focusing on the transition between networking generations and the requirements of 6G from the user and regulator perspectives. Finally, Liu [5] presents an overview of enabling optical network technologies for 5G and beyond with a focus on communication requirements and technologies. While each of the aforementioned works discusses various aspects and requirements of future networks, they do not conclusively address the challenges regarding the MANO of these networks as seen by the network operators. Furthermore, many of the existing resources are highly technical and not targeted at a diverse and mixed audience. Additionally, to the best of our knowledge, there exists no comprehensive resource that specifically considers the vision, technologies, challenges, and opportunities of the OTN and the role that it will play in enabling 6G and beyond networks.To this end, the contributions of this paper can be summarized as follows:

- A vision of the role of optical networks and what they will look like in future networking generations;
- A discussion as to how intelligence and automation can be leveraged and integrated into OTN MANO;
- An overview of some of the key enabling optical technologies for future networks;
- A discussion of the challenges and opportunities for innovation in the paradigm-shifting transition between networking generations;
- A case study highlighting the impact of network dynamicity and demand uncertainty on management and orchestration decisions.

The remainder of this work is structured as follows. Section 2 outlines the role of optical in 6G networks and key technologies being considered for integration into future networks. Section 3 analyzes the effect of increasing intelligence on network operators. Section 4 discusses open challenges and opportunities for innovation. Section 5 presents a case study regarding dynamic networks and their effect on MANO decisions. Finally, Section 6 concludes the paper.

2. Optical and 6G

Given the increasing performance requirements associated with 6G networks, the role of OTNs is critical in realizing next-generation networking systems. As network complexity and the amount of data the network generates increases, transport network operators must adapt and enhance their networks and technologies to cope with the increasingly stringent requirements. To this end, this section will discuss some of the key features and qualities of OTNs in 6G and beyond networks that are not currently considered in 5G networks and list some of the critical enabling technologies considered to realize 6G and beyond networks.

2.1. Features and Qualities of Next-Generation OTNs

The essential qualities of next-generation OTNs in 6G and beyond networks are high-capacity fronthaul and backhaul networks, long-distance remote connectivity, and deep-rooted AI/ML integration. As networks shift from being traditionally analytical model-based to data-based, a significantly increased amount of network-generated data traffic needs to be transported quickly and efficiently throughout the network. Concurrent with the OpenRAN convention, the backhaul network is the connectivity between the Central Unit (CU) and the Core Network (CN). In contrast, the fronthaul network is the connectivity between the Distributed Unit (DU) and the Radio Unit (RU). The main contributing factor to the required increase in the backhaul network's capacity is the exponential increase in network data generation and consumption rates. Conversely, in the fronthaul networks, the increase in cell towers, user density, and the emergence of small cells is the motivating factor for increasing capacity [6,7]. Figure 1 illustrates the current Radio Access Network leveraging OpenRAN architecture, Transport Network, and Core Network configuration, along with some expected types of User Equipment (UE) in 5G and beyond networks.

One of the main advancements of 6G networks over 5G networks is their ubiquitous coverage. Currently, 6G is envisioned to provide network connectivity to highly remote areas where optical fiber backhaul networks are sometimes not feasible. Additionally, 6G coverage will extend far beyond any conceivable bound of past networking generations through the development of underwater and outer space networks. To this end, Free-Space Optical (FSO) networks have been proposed as an alternative to traditional fiber-based OTNs [6]. Some advantages of FSO networks include ease of installation, maintenance, and reconfiguration; increased mobility; and comparable transmission speeds. Regarding disadvantages, FSO is less secure as it is susceptible to interception.

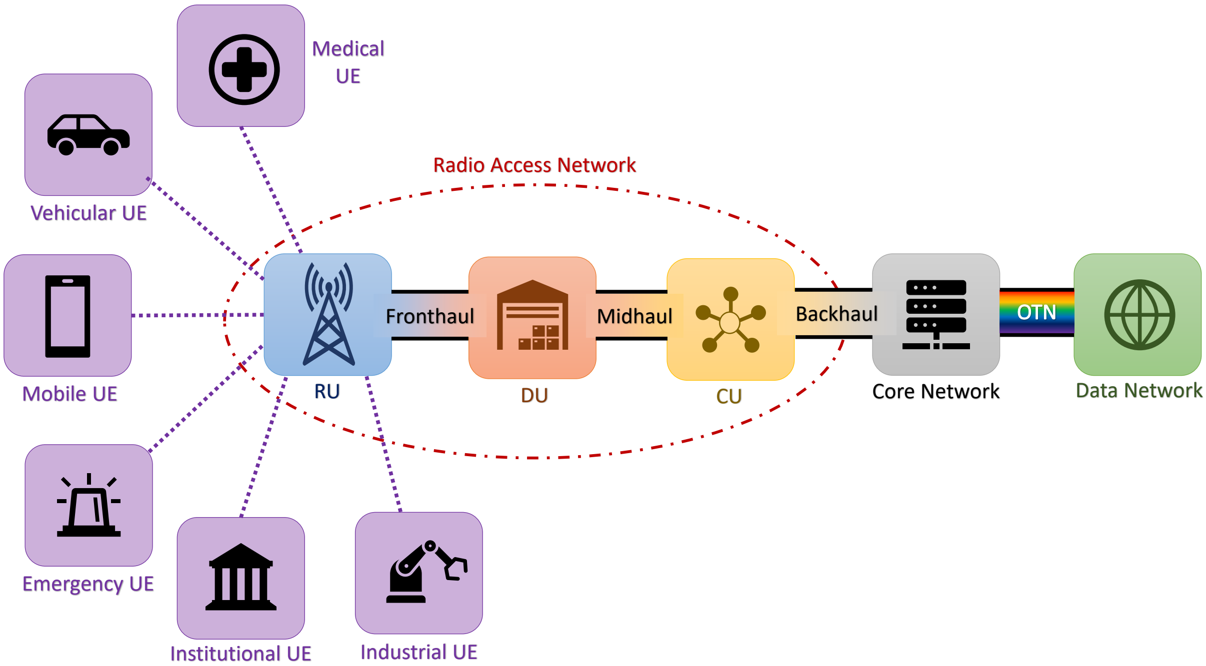

Figure 1. Current State-of-the-Art Network Architecture highlighting UE types; the OpenRAN architecture; the identification of the front-, mid-, and backhaul networks; the core and data networks; as well as a depiction of the connectivity between all network elements and regions.

The final quality of next-generation OTNs is the deep-rooted AI/ML integration into all levels of the network. Some initial plans for AI applications in 6G include traffic classification, demand prediction, and topology design [8]. Additionally, AI is required to attain zero-touch network service management to improve MANO activities through self-optimization, self-configuration, and self-healing.

2.2. Emerging Technologies for Next-Generation OTNs

2.2.1. Software-Defined Optical Networks

Software-Defined Networking (SDN) is a paradigm-shifting approach that separates the control- and data- planes of the network. Due to this separation, an SDN controller is introduced as a centralized entity responsible for network control. The application of SDN to optical networks yields the Software-Defined Optical Network (SDON) to control the intricacies of optical networks characterized by high transmission rates and extensive switching capabilities. Regarding SDONs, significant research has been conducted at all levels of the network, as summarized in [9]. The use cases for SDONs include infrastructure control, such as transceivers and Reconfigurable Optical Add-Drop Multiplexers (ROADMs), performance monitoring at the infrastructure layer through cognitive equipment and the application layer in terms of Quality of Service (QoS), as well as the virtualization of access, metro, and core networks.

2.2.2. Passive Optical Networks

Passive Optical Networks (PONs) have been used extensively to deliver Fiber-to-the-Home (FTTH) service [10]. In contrast to active optical networks, PONs leverage optical beam splitters to split a single input signal into multiple output signals. These beam splitters are described as being passive, as they are not powered devices. PONs are being actively considered in 6G and beyond networks as a solution to the fronthaul capacity requirement stemming from the increased user and cell density. Combined with Wavelength Division

Multiplexing (WDM) or Time Division Multiplexing (TDM) technologies, the PON optical beam splitter can serve as a powerful demand aggregator for this increased user base. Additionally, using nonpowered devices' positions, PONs as energy efficient compared to traditional optical networks.

2.2.3. Elastic Optical Networks

Elastic Optical Networks (EONs) have been suggested as a candidate technology to address the rigidity of traditional WDM-based systems [11]. The flexibility of EONs stems from their ability to adjust essential network resources and parameters, such as channel spacing and modulation format, based on the requested demand. This dynamic allocation of network resources can lead to increased efficiency and better optical spectrum utilization while ensuring that user QoS requirements are met. Another critical advantage of EONs is the ability to provide adaptive data rates that can be scaled based on user behavior and requirements.

2.2.4. Spectrum-Sliced Elastic Optical Path

Spectrum-sliced Elastic Optical Path (SLICE) networks are characterized by their use of Orthogonal Frequency Division Multiplexing (OFDM) and their fine grooming granularity capability [12]. By using OFDM, SLICE networks leverage clusters of sub-carrier frequencies to meet a demand. Since the granularity of these sub-carrier frequencies is much finer than the granularity of wavelengths in WDM-based systems, SLICE networks are better equipped to handle many smaller demands. Consideration must be taken in SLICE networks regarding the spectral continuity and consecutive sub-carrier constraints, which ensure the availability of sub-carriers from source to destination and the spectral adjacency of selected sub-carriers, respectively.

3. Intelligence and Automation

Improved network performance and AI/ML capabilities are two topics that form a symbiotic relationship in the realm of future networks [13]. In order to realize the full potential of future AI applications, the network must be able to quickly and efficiently transfer data to reduce the AoI metric and ensure the AI model has access to the freshest data and information. Conversely, AI is necessary to optimize network MANO activities to achieve future network performance. Fundamentally, future networks must have both elements to ensure the required performance targets are met.

A distinct path to achieve AI integration into the core network has been defined, starting in 5G with the introduction of the Network Data Analytics Function (NWDAF) into the core network architecture [14]. The NWDAF is the first standardized induction of AI/ML into the core network operating practices and is designed to support policy and decision-making practices in 5G networks. Looking towards future networking generations, the role of AI/ML will be significantly more profound than a single core network function, with widespread and ubiquitous intelligence expected at all levels of the network. Additionally, as future networks take shape, the need for advanced methods of intelligence that address the increasing complexity, scalability requirements, and privacy and ethics concerns must be considered [15]. Finally, given the massive amounts of network-generated data, unsupervised learning techniques are expected to be an integral part of the data-processing pipeline, specifically for data labeling purposes.

While the role of AI/ML in the core network is becoming increasingly well-defined and more precise, a focus must be put on ensuring the same for next-generation OTNs. Specifically, regarding OTNs, AI has been highlighted as providing benefits such as improving network device operation and optimizing network performance. The extensive list of AI applications for next-generation OTNs can be classified into network-level and equipment-level applications.

Regarding network-level applications, resource prediction, management, and allocation are at the forefront of consideration [16]. By being able to predict future resource requirements and autonomously manage their allocation lifecycle, network operators can ensure the higher efficiency and utilization of said network resources. Another critical application considering the increased QoS requirements and SLA guarantees in 5G and beyond networks is the ability to vary SLAs dynamically [13]. Regarding network security, intrusion detection systems coupled with traffic classification have been a significant area of research for AI, with numerous advancements in recent years. These advancements will continue into future networking generations and integrate new security technologies such as quantum security [6,17]. In terms of network performance, one of the main applications of AI is traffic forecasting as a means of load prediction and peak detection. Finally, end-to-end QoS, application-based Quality of Experience (QoE), and physical network Quality of Transmission (QoT) forecasting can be used to predict unfavorable network conditions and proactively work towards mitigating them before they materialize.

In terms of equipment-level AI applications, predictive maintenance is a critical use case being considered across many fields. Through predictive equipment maintenance, the failure of a specific piece of equipment can be predicted such that planned maintenance can be conducted instead of reactive maintenance. Economically, planned maintenance is much more cost-efficient than reactive maintenance, and practically, planned maintenance allows the operator to ensure service continuity without experiencing a fault scenario. Additionally, through AI, fault detection and localization can be conducted more accurately and efficiently. Regarding the management of equipment and devices, AI can be leveraged to optimize their configurations and active management, similar to resource management in network-level applications [17]. Finally, fiber-related issues such as fiber nonlinearities can be detected and mitigated.

As demonstrated throughout this section, the impact of AI applications in future transport networks is profound. Realizing this incredible potential through the cycle of continuous network performance improvement and enhanced AI capabilities is a critical step toward shaping the future of OTNs.

4. Challenges and Opportunities for Innovation

The following section will outline the challenges and opportunities of next-generation optical networks.

4.1. Challenge: Demand Uncertainty

Given the increasing number of users and emerging applications with each networking generation, demand uncertainty significantly affects network MANO decisions. The effects of demand uncertainty on a network capacity planning problem can be detrimental to the final network performance, more specifically, the survivability of the network. Traditionally, MANO decisions are made using snapshots of network conditions along with deterministic solution methods. Considering the highly dynamic nature of next-generation networks, this approach is exceptionally naïve, as it assumes network conditions will not vary over time. To this end, solutions leveraging robust optimization are better suited to address the demand uncertainty in future networks [18].

4.2. Opportunity: Robust Optimization and Learning Methods

Robust optimization methods consider the effect of parameter deviation when determining a solution. They are flexible in the conservativeness of the solution they return through tunable parameters determining the number of system parameters that can deviate from their nominal value and the percentage of their nominal value by which they deviate. Due to their mechanics, robust optimization solutions may be sub-optimal at the time of solving compared to a deterministic optimization solution; however, given parameter uncertainty, the solution will be protected, and the constraints will not be violated in the presence of uncertainty [19]. Leveraging robust optimization techniques enables the network operator to plan for the future condition of the network and proactively ensure its survivability and reliability.

Despite its benefits, robust optimization has seen limited use in network MANO problems. One of the reasons for this is that it introduces additional variables in the formulation, making it more complex to solve than deterministic optimization problems. Given the increasing size and complexity of next-generation networks, optimization problem formulations, in general, are becoming more and more infeasible, given the processing and time requirements to achieve a solution. To this end, a critical avenue for future work is the development of robust learning methods that can emulate the performance of robust optimization formulations with reduced time complexity. An essential technique for achieving this will be deep reinforcement learning, given its ability to learn policy decisions and adapt to various environments.

Another criticism of robust optimization in OTNs is the level of overprovisioning in the network due to reserve capacity, a common concern with optical path recovery schemes as well, despite the ability to directly configure the required level of overprovisioning in the parameterized formulation. To this end, the results of a study conducted by the Fibre to The Home Council of Europe are particularly interesting [7]. In their study, the council explored using spare fiber capacity to handle demand uncertainty. Their study found that reserving spare fiber capacity to address demand uncertainty had minimal additional initial cost with incredible reactive cost reduction. The results of this study are promising for developing the appropriate practices to ensure that the intricacies of future networks, including demand uncertainty and variable QoS and QoE requirements in services and applications, are considered throughout the entire MANO lifecycle.

Figure 2 compares solutions to a resource allocation problem which use deterministic and robust methods. As seen in Figure 2, the deterministic method produces an allocation that uses the entirety of the initial capacity. In contrast, the robust allocation has some unused capacity—the effects of demand uncertainty cause parameter deviation, which lead to a demand increase. Since the robust method has some unused capacity, it can deal with the increase in demand. In contrast, an overcapacity event is observed since the deterministic allocation did not consider the possibility of parameter deviation. This theme will be further explored in the case study of this paper.

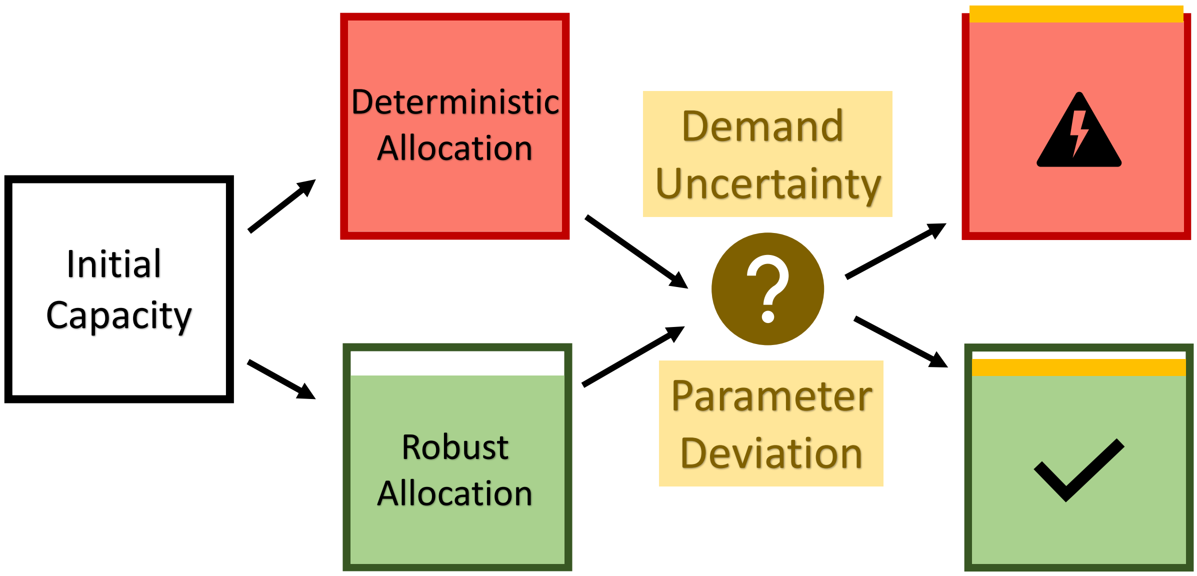

Figure 2. Robust vs. Deterministic Capacity Allocation under Demand Uncertainty and Parameter Deviation. When using robust allocation methods, some spare capacity is provisioned to ensure the solution's feasibility under parameter deviation. The increase in demand (yellow) during uncertainty is handled by the robust allocation but exceeds the capacity in the deterministic allocation.

4.3. Challenge: Machine Learning Model Drift

All machine learning applications are subject to model drift; however, given the expected dynamicity, the use of AI/ML in future networks is severely prone to the effects of model drift [20,21]. Model drift can be defined as degradation in the performance of a trained ML model due to a change in its deployment environment. ML model training is highly dependent on the training data or training environment it learns from; if the environment in which a model was trained is not representative of the environment in which it is deployed, the effects of model drift will be felt. There are various types of model drift, including data drift, in which a change in the statistical distribution of the data changes, and concept drift, where the underlying relationship changes. In order to ensure the safety and reliability of ML-based decisions in future networks, care must be taken to ensure model drift events are detected and mitigated before they can negatively impact network MANO decisions.

4.4. Opportunity: Drift-Resistant Architectures and Frameworks

Detection, mitigation, and prevention are the main aspects of addressing model drift [22]. In terms of detection, methods that monitor the performance of a model or the statistics of the environment data observed can be used to detect the presence of model drift. Once detected, drift adaptation techniques that continue model training or that train a new model can restore performance to a pre-drift state. In terms of prevention, drift-resistant architectures such as federated and reinforcement learning can be used to survive a drift without performance degradation.

In terms of innovation, the continual development, improvement, and deployment of drift detection and mitigation frameworks, as well as drift-resistant model architectures that conform to the requirements of future networks, is critical. Given the detrimental impact model drift can have on a network coupled with the widespread use of AI/ML in future networks, the prompt detection and mitigation of drift are paramount. To this end, reducing the detection time of drift is a first step towards this end goal; however, a forecasting framework capable of predicting drift events before they occur is ideal, as it would give the operators enough time to take steps towards drift mitigation before the drift materializes.

Figure 3 illustrates an ML system drift detection and mitigation framework. As seen in Figure 3, when an observation is passed to an ML model, the preferable architecture is to consult with a drift detection framework based on the model's prediction. If a drift is detected, the drift mitigation framework activates to remedy the situation. The result of these added components to the ML lifecycle is the performance recovery stage. Conversely, when no mechanisms are in place to detect and adapt to a drift, the model experiences performance degradation.

4.5. Challenge: Distributed Network Data and Information

Given the vast expansion of future networks, OTN management data are expected to be distributed throughout the network [23]. To this end, relaying all data to a centralized location is inefficient in terms of communication resources but also in terms of privacy and security. This data distribution poses a challenge for MANO activities, as centralized intelligence methods would not reach their full performance potential with fragmented and oftentimes incomplete representations of the network through partial data availability. Furthermore, the relationships observed at various network regions may differ, leading to model drift if not handled accordingly. To this end, various strategies for distributed learning must be explored, adapted, and implemented for use in next-generation OTN networks.

4.6. Opportunity: Distributed Intelligence Techniques

The most prevalent form of distributed intelligence, which was alluded to earlier in this section, is federated learning. Since its development, federated learning has gained significant traction due to its ability to preserve privacy while leveraging insights from various data sources. In federated learning, all collected data are stored and processed locally without being transferred to a central location. An entity known as an aggregation agent distributes a global model to each federated node, which is then trained locally using the node's available data. The node then sends a model update to the aggregation agent, who aggregates all the node updates and distributes the revised global model. This training process continues perpetually or until a termination criterion is met [24,25].

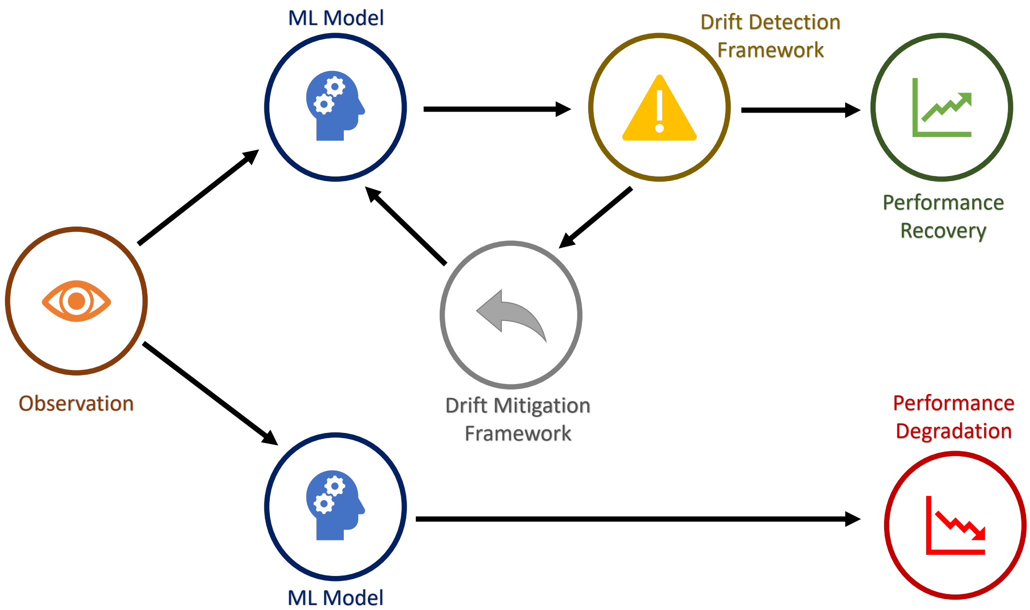

Figure 3. A high-level comparison of the ML system performance with and without a drift detection and mitigation framework. Without a framework in place, a noticeable performance degradation is observed. Conversely, when a framework is in place, corrective actions are taken to recover and restore system performance to pre-drift levels.

While federated learning is an important distributed intelligence technique, it is not the only one and is not suitable for every situation. Additional ML frameworks and architectures, such as gossip learning, which removes the aggregation agent and employs a more peer-to-peer approach, have recently gained attention [26]. Furthermore, moving beyond the model architecture and framework, the concept of digital twins will play a significant role in future networks. Digital twins can be described as a virtual replica of a physical process that exists in parallel to the process. To this end, using distributed learning techniques in digital twin architecture is a logical next step and has already been coined as federated digital twin architecture [27]. The continual development of distributed learning techniques, their inclusion in digital twin architectures, and the role of digital twins in next-generation OTNs is a critical avenue of future work in the field.

Figure 4 compares a centralized intelligence scheme against a distributed one. As discussed above, the premise of this comparison is that network data and acquisition will occur over a distributed area. In the case of centralized intelligence schemes, all collected data must be sent to a centralized intelligence entity responsible for model training and prediction. This is highly inefficient in terms of communication resources and model inference time and leads to a single point of failure in the system. In contrast, each data collection point in the distributed intelligence framework has its own intelligent agent, and no mass data sending occurs.

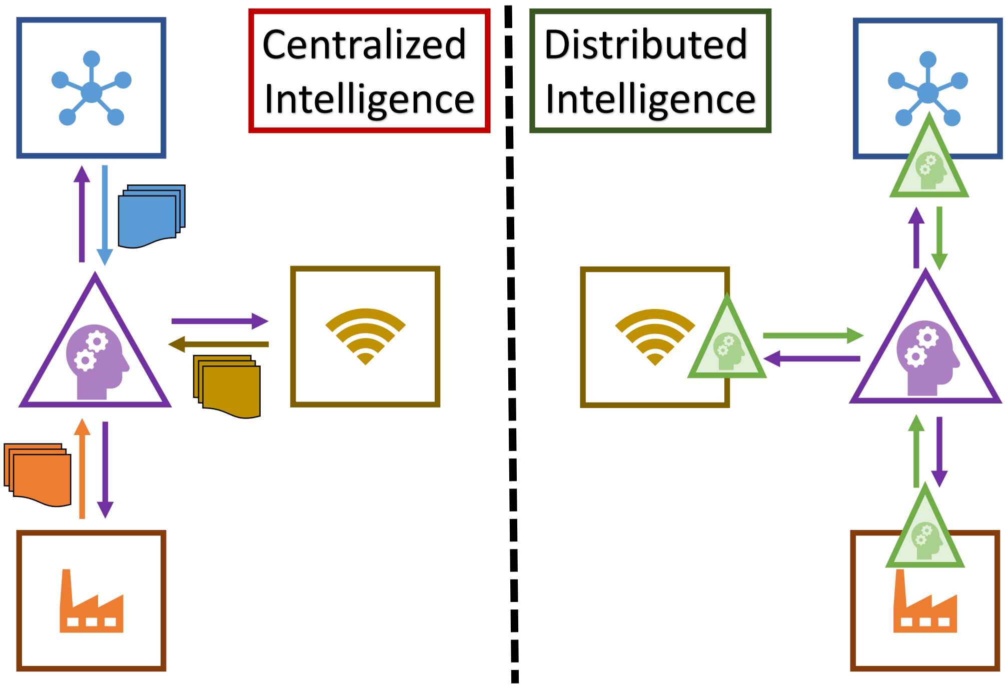

Figure 4. A comparison between a centralized intelligence scheme and distributed intelligence scheme (federated learning). In the centralized scheme, all entities send their data to a centralized agent that is responsible for processing and insight generation. Conversely, in the distributed scheme, all entities have an intelligence agent that exchanges model parameters and insights with the aggregation agent without the transfer of entity data.

5. Case Study: Network Dynamicity—Demand Uncertainty

This section compares robust and deterministic optimization applied to the OTN traffic grooming and infrastructure placement problem. This case study is meant to be illustrative and highlight the benefits of robust optimization. A full mathematical formulation and extensive analysis of the results is available in [28]. The premise of this illustrative use case is that a network planning engineer is required to plan the OTN infrastructure required to groom a set of demands. The inputs to this optimization problem are the physical network topology and the set of demands. This optimization problem aims to minimize the cost-weighted number of optical channels created and OTN switches deployed in the network. Given this objective, the optimization problem determines the optimal grooming and required OTN infrastructure. The capacity constraints pertain to both the optical channel capacity constraint (i.e., the sum of demands using an optical channel cannot exceed its capacity) and the wavelength capacity constraint (i.e., the number of optical channels created using a physical link cannot exceed the available wavelengths on said link). The demands are allowed to be fractional flows in this formulation to refine the level of grooming.

The National Science Foundation Network (NSFNET) topology is used for the experiment, with 80 wavelengths on each physical link. Optical channel capacities are determined based on the standard modulation formats corresponding to physical distances traversed. A set of 250 demands with requested bandwidth uniformly distributed along the range from 10 to 50 GB/s is considered. Multiple robust solutions are determined while varying the number of demands subject to uncertainty and the maximum percentage by which each demand can deviate from its nominal value. It should be noted that when conducting robust optimization, the worst-case demand deviation is considered and protected against in the solution. Additionally, the deterministic solution is used as a basis for comparison, as all deterministic solutions, including near-optimal heuristic solutions, will behave similarly. Furthermore, performance-wise, the set of deterministic solutions can perform as good as but not better than the optimal solution. The optimization models were run on an Intel® Xenon® Gold 6348 CPU@2.6 GHz 512 GB RAM industrial-grade server.

Figure 5 presents the first set of results, where the robust and deterministic solutions' objective values are considered. It should be noted that the case where 0% of the demands are allowed to deviate (denoted by the red bars) corresponds to the deterministic solution and hence is consistent across all deviation percentages. The x-axis denotes the maximum percent deviation a demand can assume. In contrast, the bar's color determines the percentage of demands allowed to deviate when determining the robust solution. Both these parameters control the conservativeness of the solution and, by extension, the level of overprovisioning in the system. As seen through these results, as the number of demands allowed to deviate increases, so does the objective value due to overprovisioning through reserve capacity. Additionally, as the percentage of deviation increases, so does the objective value. Comparatively, the increase in percentage deviation yields a higher jump in the objective value compared to the increase in the number of demands that can deviate.

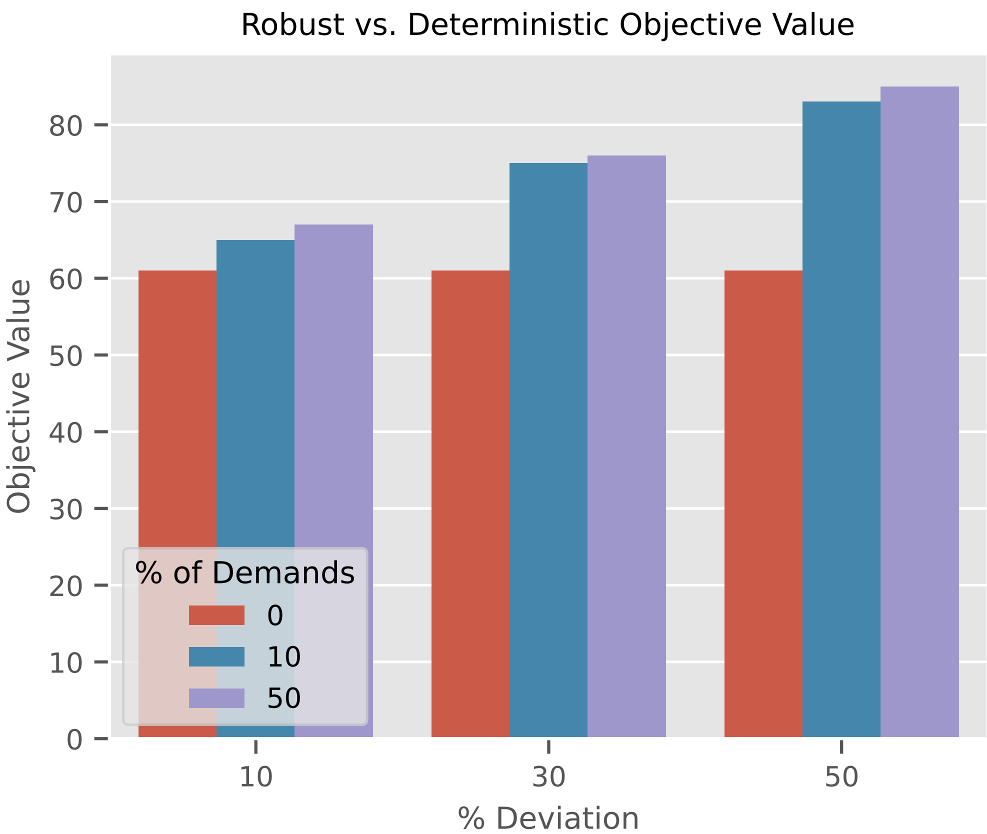

Figure 5. A comparison of the objective value between the deterministic (red) and robust (blue, purple) optimization model across various levels of solution conservativeness.

Figure 6 presents the second set of results where the percentage of capacity violations resulting from simulated demand uncertainty is compared. In order to simulate demand uncertainty, each demand is allowed to vary along a range defined by the nominal value and the percent deviation. For example, if a demand has a nominal value of 10 and a deviation percentage of 10%, its value during the demand uncertainty is along the range between 9 and 11. Similarly, if the same demand has a deviation percentage of 50%, its value during the demand uncertainty is along the range from 5 to 15. In order to assess the performance of the models across a range of uncertainty scenarios, these simulated demand uncertainty trials are conducted 10,000 times. The results in Figure 6 present the number of optical channels that experience an overcapacity event stemming from the aggregate statistics of the 10,000 trials. As seen through these results, in all cases, the robust optimization led to a solution that protected against demand uncertainty in every scenario.

The same cannot be said for the deterministic solution, in which 50–100% of the optical channels in use experienced an overcapacity event at some point during the demand uncertainty simulation trials.

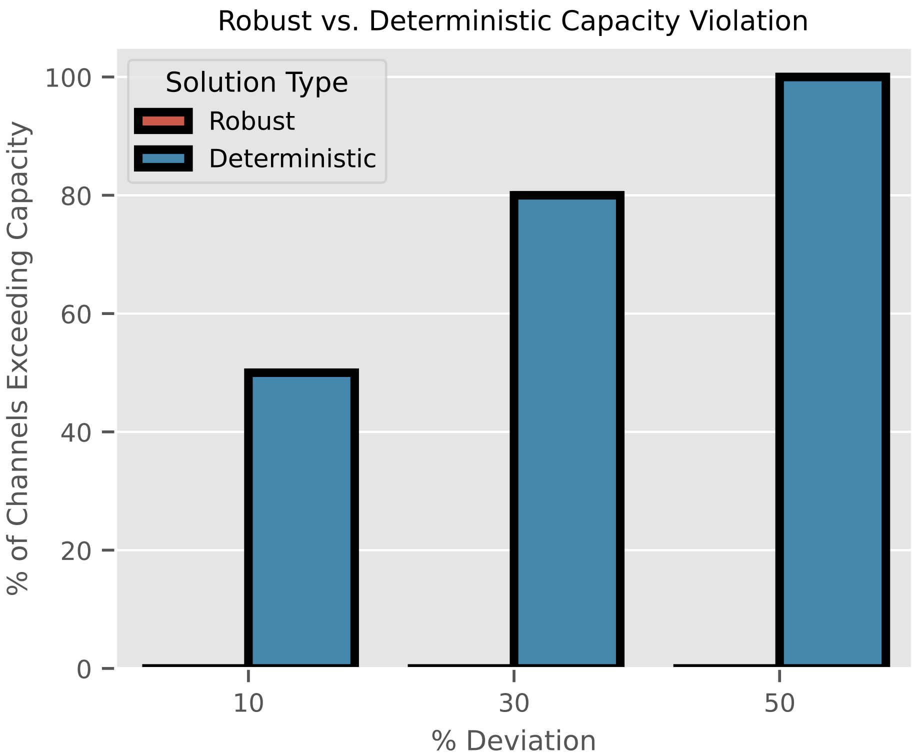

Figure 6. A comparison between the solution of the deterministic and robust optimization models under varying levels of demand uncertainty and parameter deviation. The robust method was able to cope with the demand uncertainty and protect the solution, exhibiting no overcapacity events. Conversely, the deterministic solution was unable to cope with the demand uncertainty and exhibited an increasing percentage of overcapacity.

These overcapacity events suggest that the grooming solution and deployed infrastructure cannot cope with demand uncertainty and the change in load exhibited. Practically speaking, this would lead to blocked requests, incomplete services, and network disruptions requiring reactive maintenance and reconfiguration. As previously mentioned, the initial cost of reserve capacity to deal with demand uncertainty is minor compared to the costs associated with reactive network maintenance. This use case illustrates the detrimental effect demand uncertainty can have on a deterministic solution using a snapshot of the demand matrix and a given point in time.

6. Conclusions

In conclusion, this paper presents a comprehensive resource for all audiences discussing the role OTNs will have in enabling the next-generation and future networks, the technologies being considered to achieve the anticipated performance requirements, the challenges faced by network operators, various opportunities for innovation to address these challenges, as well as a case study demonstrating the effect of demand uncertainty on OTN resource allocation tasks. The work presented in this paper demonstrates the integral role of optical transport networks in next-generation networking systems. Integrating technologies such as Software-Defined Optical Networks, Passive Optical Networks, Elastic Optical Networks, Spectrum-sliced Elastic Optical Path Networks, and Free-Space Optical Networks will help realize the vision and performance requirements of 6G and beyond networking generations. As discussed, machine learning and artificial intelligence will have a significant role to play in next-generation optical network management and orchestration. Finally, challenges such as demand uncertainty, model drift, and distributed network data give rise to incredible opportunities for innovation regarding next-generation optical network development.

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Abbreviations

The following abbreviations are used in this manuscript:

OTN	Optical Transport Network
MANO	Management and Orchestration
AI	Artificial Intelligence
ML	Machine Learning
KPI	Key Performance Indicator
AoI	Age of Information
uRLLC	Ultra-Reliable Low-Latency Communications
mMTC	Massive Machine-Type Communication
eMBB	Enhanced Mobile Broadband
eRLLC	Extremely Reliable Low-Latency Communications
umMTC	Ultra-Massive Machine-Type Communication
feMBB	Further Enhanced Mobile Broadband
eLPC	Extremely Low Power Communications
LDHMC	Long-Distance and High-Mobility Communications
AR	Augmented Reality
VR	Virtual Reality
DWDM	Dense Wavelength Division Multiplexing
CU	Central Unit
CN	Core Network
DN	Distributed Unit
RU	Radio Unit
UE	User Equipment
FSO	Free-Space Optical
SDN	Software-Defined Networking
SDON	Software-Defined Optical Networking
ROADM	Reconfigurable Optical Add-Drop Multiplexer
QoS	Quality of Service
PON	Passive Optical Network
FTTH	Fiber-to-the-Home
WDM	Wavelength Division Multiplexing
TDM	Time Division Multiplexing
EON	Elastic Optical Network
SLICE	Spectrum-sliced Elastic Optical Path
OFDM	Orthogonal Frequency Division Multiplexing
NWDAF	Network Data Analytics Function
QoE	Quality of Experience
QoT	Quality of Transmission
NSFNET	National Science Foundation Network

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