Dynamic-Adaptive AI Solutions for Network Slicing Management in Satellite-Integrated B5G Systems

Lei Lei, Yaxiong Yuan, Thang X. Vu, Symeon Chatzinotas, Mario Minardi, and Jesus Fabian Mendoza Montoya

***Abstract*—The integrated terrestrial and non-terrestrial networks in 5G and beyond 5G are envisioned to support dynamic, seamless, and differentiated services for emerging use cases with stringent requirements. Such service heterogeneity and rapid growth in network complexity pose difficulties to network management and resource orchestration. Network slicing paves the way for delivering highly customized services and enabling service-oriented resource allocation. In this context, artificial intelligence (AI) becomes a key enabler for network slicing management. However, AI-based approaches encounter critical challenges in adapting to dynamic and complex wireless environments. In this article, firstly, we aim at providing a comprehensive understanding of these challenges, open issues, and future research opportunities. Secondly, we highlight the investigations on dynamic-adaptive AI solutions for dealing with the effect of concept drift. Thirdly, we identify typical dynamic scenarios in case studies and provide numerical results to illustrate the effectiveness of the discussed AI solutions.**

***Index Terms*—Machine learning, network slicing, satellite-5G network, resource management, dynamic wireless network.**

I. Introduction

With the deployment of 5G commercial networks, academic and industrial communities have started to envision 6G communications towards 2030. This early stage of 6G is defined as beyond 5G (B5G) or 5G+ [1]. The path from 5G to B5G is foreseen to be evolutionary and enhanced by potential key technologies, e.g., non-terrestrial network (NTN) integration, artificial intelligence (AI), and network slicing [1]–[3]. The evolution towards B5G and 6G is expected to overcome the drawbacks in 5G terrestrial networks such as high deployment cost in remote areas and incapabilities of serving air-ocean scenarios [2]. Towards the wide coverage, seamless connectivity, and cost-efficient data services in B5G, the NTN, e.g., non-geostationary orbit (NGSO) satellites or NGSO constellations, is studied in the third generation partnership project (3GPP) [3].

In B5G, this wave of multi-tier and heterogeneous networks can exponentially increase the degrees of freedom and complexity in network optimization and management. In an attempt to streamline the multi-tier network management, both the research and industry stakeholders have been progressively adopting network virtualization and softwarization technologies [1]. Network slicing, as a form of programmable and virtual network architecture, relies on software defined networking (SDN) and network function virtualization (NFV), where the former separates the control plane from the data plane, while the latter decouples hardware infrastructures and software via running virtual network functions (VNFs) on virtual machines [4]. By slicing common physical infrastructures into multiple virtual logical networks, network slicing creates multiple end-to-end slice instances. Each slice becomes an independent virtual network that guarantees multiple service level agreements (SLAs) and provides complete network functionalities. In B5G network slicing, multiple tenants (slice owners), e.g., over-the-top operators or mobile virtual network operators, need to rent multi-dimensional resources, e.g., radio, computing, storage resources, from multiple infrastructure providers (InPs), e.g., ground or satellite telecom infrastructures, to support diversified and customized services. In this context, efficient and intelligent solutions become a must for network slicing management [5].

This predominant trend offers an opportunity to depart from the conventional paradigm of model-based iterative optimization [1], [6]. Towards online network slicing and resource management, this type of approach may soon reach its limits in meeting strict real-time requirements. Artificial intelligence (AI), e.g., deep learning (DL), has been introduced to overcome shortcomings and has become an important problem-solving method in the network-slicing toolbox over the past few years. Reliable and advanced AI solutions are expected to be integrated into the future B5G or 6G system [1], [5], [6], mainly relying on the capabilities of sophisticated learning, knowledge exploitation, and efficient decision making.

An illustrative architecture of AI-assisted satellite-B5G network slicing is shown in Fig. 1, where the satellite network is integrated into the 3GPP-based 5G architecture as a transport network (TN) [4], to provide backhauling services to the 5G next-generation base stations (gNBs), offer broadcasting services, or relay signals from massive IoT devices to the core network (CN) in three network slice instances (NSI). According to the 3GPP definitions [5], a set of network slice subnet instances (NSSI) form an NSI. An NSSI consists of a group of network functions from radio access network (RAN), CN, or TN parts, including physical network functions (PNF) or VNF, along with their corresponding resources. The satellite-based TN part can be connected to 5G RAN/CN by using the N2 and N3 interfaces [5], where N2 connects the TN user-plane functions (UPF) with the 5G RAN/CN control-plane functions (CPF), while the N3 interface establishes links between the UPF or data-plane functions of TN and the UPF of 5G RAN/CN [4]. In the management and orchestration

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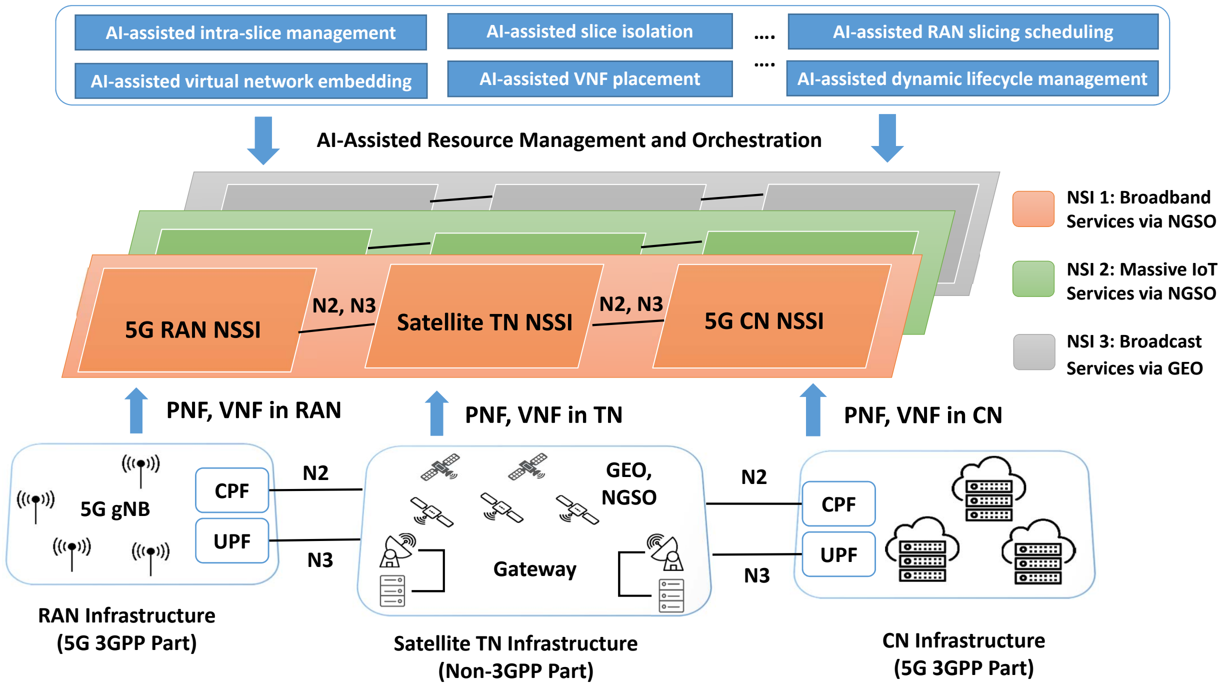

Figure 1. An illustrative example: Satellite-integrated B5G network slicing with AI-assisted resource management, where the satellite network, as a TN part, is integrated into the 5G 3GPP-based RAN and CN architecture.

(MANO) part, efficient solutions assisted by AI are expected to address various challenging optimization problems, such as resource allocation among slices, virtual network embedding (VNE), VNFs placement, or intra-slice resource management [7]. Based on the architecture of Fig. 1, we mainly focus on two emerging issues in network slicing management:

- When one applies AI to resource management in B5G network slicing, what are the potential issues and candidate solutions in adapting to dynamic environments?
- When NTN is integrated into B5G systems, what are the impacts and challenges for resource management in network slicing?

A. Motivation

The major motivation of this work stems from a common and practical issue in developing AI-based solutions for many resource management problems in B5G network slicing. That is, the classical AI techniques, e.g., deep neural network (DNN), deep reinforcement learning (DRL), usually fail to deal with non-ideal cases with unforeseen variations in network slicing management. This issue becomes even severe when an additional tier, i.e., NGSO satellites with very high mobility, is integrated into the B5G system. The reason is that, on the one hand, the performance of a conventional AI model closely depends on the adopted training or observed data sets, and its generalization capability is typically limited [8]. On the other hand, the realistic wireless environment is highly complex and dynamic. These facts together cause the issue of *concept drift* in machine learning [9]. The new inputs can become no longer relevant to the statistical properties of historical data, which may result in unforeseeable changes in the underlying input-out relationship. As a consequence, the trained AI model may become invalid for the new environment, leading to a deep degradation of the learning performance, e.g., loss, accuracy, convergence. To remedy, one has to recollect the up-to-date data sets and retrain the model, which can be time-consuming. This is considered as one of the main obstacles for applying AI in practical B5G systems [9], and thus motivates our investigation to avoid re-training from scratch and achieve a fast response against dynamic environments towards practical AI deployment.

B. Objective and Contribution

To enable intelligent MANO, significant efforts in developing novel AI algorithms and enhancing the solution effectiveness in dynamic scenarios, are essential for the future B5G network slicing. To this end, the main objective of this work aims at:

- Outlining fundamental and critical challenges of applying AI to dynamic network slicing management.
- Characterizing the impact of integrated NGSO on AI-enabled network slicing.
- Identifying promising dynamic-adaptive AI solutions for a wide range of optimization problems in network slicing management.

As a distinctive contribution compared to previous works [1], [6], we focus on AI solution development for non-ideal network environments and generalization enhancement of AI in adapting to dynamic B5G network slicing. It is worth noting that the considered dynamic-adaptive AI solutions can be extended and applied to support two classes of problems, i.e., complex resource management problems and simple machine-learning tasks in network slicing management. The former can include a wide range of resource management tasks, e.g., VNF placement, or VNE. The latter can be classification-like or regression-like predictions during network slicing operations, e.g., forecasting aggregated data, user preference, traffic load, or determining the necessity of performing resource reconfiguration or migration among slices.

II. AI for Satellite-B5G Network Slicing: State-of-the-Art and Challenges

A. State-of-the-Art

Advanced solutions for implementing B5G-satellite network slicing have been investigated in recent works, e.g., hierarchical resource-orchestration frameworks [1], integrated terrestrial-satellite architectures [2], [4]. A variety of practical implementation issues are widely considered, such as how to create, activate, maintain, and deactivate slices in an efficient way and how to accurately abstract and isolate virtualized network resources [7], [10]. In another line of studies, the core issues of resource management, i.e., inter-slice and intra-slice management, have been widely investigated in [6], [7], [10]. For the former, the InPs are responsible to provide multi-dimensional resources to slice tenants and to ensure the different slices well coordinated. Once new slice requests arrive, the network controller will need to determine how to embed virtual network requests (VNRs) onto the physical network efficiently. This virtual-to-physical mapping corresponds to combinatorial optimization problems, e.g., the classical VNE problem [7]. In intra-slice optimization, once an end-to-end slice has been instantiated, it becomes a specific collection of network functions and resource-allocation modules isolated from other slices. The slice tenant can manage the provisioned resources individually [10]. Subsequently, service-specific resource optimization is required for each module.

A majority of the previous works focus on static and deterministic algorithm design for network slicing problems, e.g., VNE, slices configuration, isolation [7]. Namely, the deterministic optimization problem is solved on a static network snapshot without considering spatio-temporal variations. However, B5G systems are highly heterogeneous and dynamic, and require efficient online solutions. To this end, AI techniques, e.g., DNN, RL, DRL, have triggered considerable research attention in network slicing [1], [5]–[7]. Beyond the state-of-the-art of deterministic optimization and AI solutions, the main challenges are outlined by the following two aspects.

B. Challenges of Applying AI to B5G Dynamic Network Slicing

Despite the promise of new paradigms, the AI-based B5G-NGSO network slicing in meeting heterogeneous services and operational requirements is challenging. In practice, AI-enabled methods may require large amounts of data in training or re-training if supervised learning applies. With the growing network scale and service-oriented requirements, AI approaches could be difficult to achieve satisfactory performance in realistic operations. In general, many open challenges are emerging, such as how large-amount of labeled data can be collected and processed, which features can be learned, and how the features can be extracted from raw data.

Moreover, one major shortcoming in existing AI algorithms is the lack of resilient capabilities in adapting to dynamic environments. An AI model approximates the input-output mapping based on the historically observed/trained data and provides the best prediction in the inference phase. In most cases, this mapping is presumed to be static, which means that the statistical property of data and the underlying relationship may not be changed over time in an unforeseen way [9]. In general, satisfactory performance in a dynamic environment can be likely achieved if the inputs are structured or follow certain probability distributions, e.g., Rician distribution for satellite-channel fading or Poisson distribution for traffic requests [11]. However, in realistic scenarios, the input data can be dramatically changed due to, e.g., topology variations in physical networks, bursty traffic demands in some slices, frequent user departure/arrival, an explosion of slices' access requests, and dramatic fluctuation in channel conditions. Dealing with such unforeseen changes in the context of online network-slice management is an essential challenge.

The fast-response and resilient capabilities of an AI model are of importance. In practice, an AI model, e.g., DNN or an agent in DRL, may require a long time to converge [12], which can result in long-term degraded performance. This is because the dynamic scenarios can lead to fast parameter variations over time, e.g., delay, capacity, link failure probability. Such time-varying nature could make the AI model vulnerable to the upcoming unknown data if the adopted AI model is not continuously optimized and adjusted in new circumstances. Confronted with the varying environments, AI performance can deteriorate and need a considerable amount of time to adjust due to lacking up-to-date knowledge.

C. Challenges of the Integrated NGSO for B5G Network Slicing

Apart from the intrinsic limitations of AI itself and the inherently dynamic nature of wireless environments, we also outline the distinctive impacts and challenges of the integrated NGSO for network slicing management and AI applications.

Frequent typology variations and handovers: During the life cycle of a slice, the very high mobility of NGSO satellites can result in several issues, e.g., frequent variations in network typologies and handovers [11]. Some terminals in a slice may periodically lose the visibility of their serving satellite and have to switch to other satellites. To avoid service interruption, timely optimization or computations for updating the flow-forwarding tables in the SDN data plane is needed and can be a challenging task in real-time network slicing. Moreover, in multi-orbit satellite systems, terminals within a satellite slice are able to connect to multiple orbits at the same time by relying on their advanced beamforming capabilities [11], which results in another type of highly dynamic issue for the RAN part in network slicing. In addition, how to meet strict energy requirements in some massive-IoT slices is an issue. This is because longer round-trip time in satellite communications and frequent switches of IoT-satellite links can lead to a longer wake-up period and thus more energy consumption for IoT devices to perform access procedures and data transmission.

Availability, isolation, and reconfiguration of virtual resources: With the NGSO motion, the originally allocated virtual resources for a slice may become unavailable. This might fail to satisfy the slice's quality of service (QoS) or quality of experience (QoE) requirements. The slice's isolation requirement may become hard to meet due to the shortage in resource preservation [10]. Thus, the network controller has to react, namely, measuring the impact first to see if the current network-slicing solution is immune to the variation or a reconfiguration process is needed, and how high the reconfiguring cost will be. In addition, with the satellite movement, when a new link is established, the antenna alignment needs to consume a certain amount of time and energy to adjust the angle [11]. All of these additional issues typically mean solving a set of optimization problems that can be computationally heavy. This also renders a difficult learning task for AI models.

Onboard limitations: The characteristics of satellites and limited onboard resources, e.g., energy, bandwidth, computation, and storage, can introduce new dimensions in resource orchestration and AI solution development [11]. These limitations could force the constraints in resource management to be more tight and sensitive, which may pose great obstacles in developing QoS-guaranteed AI solutions. In addition, in a dynamic environment, there is a need to collect and monitor the network status, e.g., topology, link parameters, resource demand, and the usage of NGSO's residual energy and storage, for slice resource management. The detection and reporting of slice status information are real-time for conventional terrestrial-based network slicing, whereas the relatively long propagation delay between a satellite and ground nodes may limit the timely interaction between the data and control planes.

III. Proposed Solutions for Dynamic Network Slicing

Herein, we divide the dynamic network variations into two general categories, i.e., predictable and unpredictable. Then we consider tailored solutions for each of them.

A. Predictable Network Variations

Thanks to the periodic movement of NGSO satellites, this type of variation is time-varying but predictable, e.g., satellite position over time, network topology, and transmission delay [4], [5], [11]. To cope with this case, we apply the concept of time-expanded graph (TEG) to facilitate a direct application of existing AI solutions. To illustrate, we present TEG for solving a VNE problem in Fig. 2 as an example, where in the substrate (or physical) network, the NGSO nodes, saying node 2, are time-varying and predictable, and the ground nodes are stationary during a life cycle of VNRs. In TEG, the substrate network topologies in multiple time intervals can be represented by a single time-varying graph, consisting of a series of static snapshots of each time interval, and expanded by replicated nodes across time. Each node has store-and-forward capabilities in transmission, e.g., node 2 can receive the data from node 1 at time 1 and store it for certain time

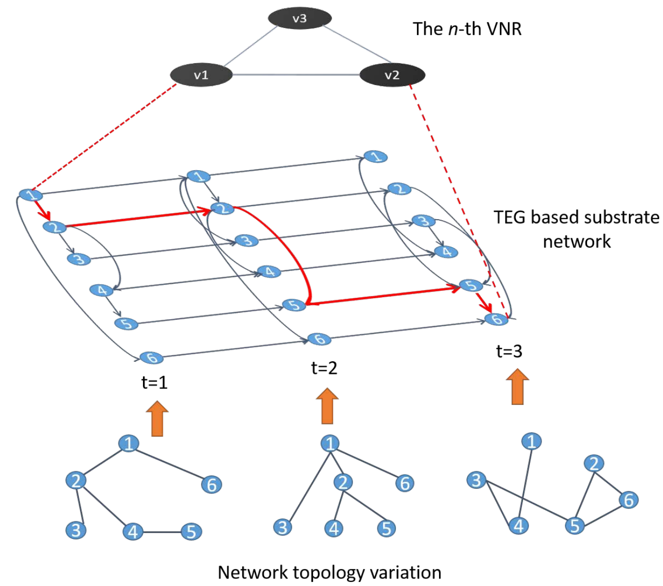

Figure 2. An illustrative example of TEG based VNE: representing time-varying topologies by a static expanded graph to facilitate AI applications.

intervals, then forwards it to another node later on when a lower-cost path is established [13]. As a result, the VNE problem is solved only once based on TEG rather than making multi-round decisions at each time interval. By foreseeing the upcoming topologies in TEG, the solution has a global view to achieve better performance. For example, virtual nodes $v1$ and $v2$ are embedded to physical nodes 1 and 6, respectively. A better path, e.g., the red-solid path in Fig. 2 with a lower cost than the path from node 1 to 6, can be obtained. By employing TEG, the existing AI solutions for static VNE problems, e.g., AI-based node-link embedding solutions for max-flow or min-cost flow, can be simply extended to adapt to this type of dynamic scenario.

B. Unpredictable Network Variations

In this type of variation, the statistical properties of input data can be changed significantly. For example, an obstacle can largely affect line-of-sight channels, or a device may switch from voice to high-definition video services with the surged amount of data. The structured data that was previously trained or observed may become unstructured or noisy. This is considered as the main cause of AI performance degradation. In general, there are two schemes, i.e., passive and active, to address the effect of concept drift [9]. The former periodically updates the AI model by re-training the model on the most recently observed data sets, no matter if the update is needed or not, whereas the latter assesses the necessity first by relying on a concept-drift trigger mechanism to re-train the model.

In the passive solution, the granularity for periodical re-training needs to be carefully designed. In the active solution, the key issue is the drift detection [9]. This can be implemented by monitoring the online error rate (or loss) in AI operations. The detection mechanism sets two thresholds for error rate. One is the warning level and the other is the drift level. When

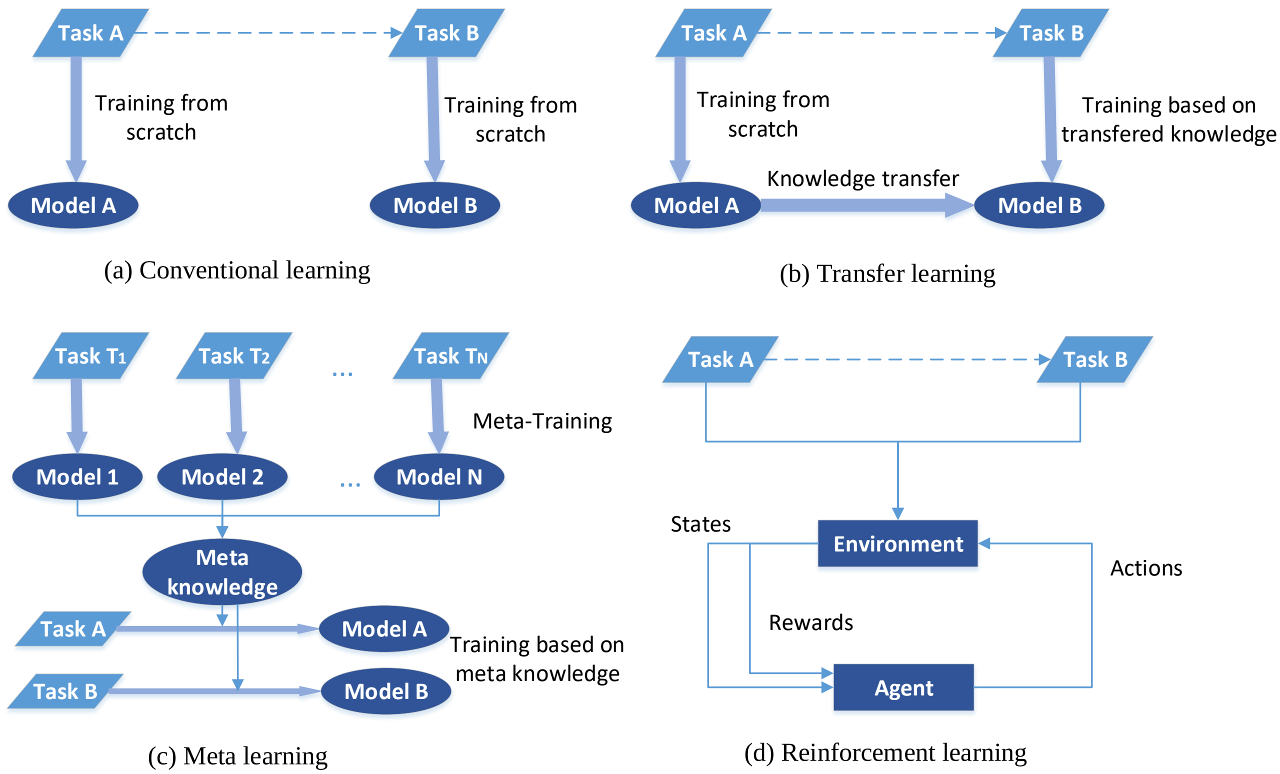

Figure 3. Summary of the considered AI models shifting from solving a source task to a new task.

the error rate reaches the warning level at the n-th sample, this warns the control plane that the statistical properties of the input data may have been changed. If the error rate falls back later on, it means a false warning. Otherwise, the re-training decision can be made if the error rate continuously increases to the drift level.

It is worth noting that both passive and active strategies impose a re-fitting procedure, which includes new data collection and re-training the AI model. Next, we provide candidate AI solutions, i.e., transfer learning (TL), meta learning (ML), and combined with RL, in order to achieve a fast response and collect fewer samples. The general frameworks of the considered AI solutions are illustrated in Fig. 3, with the following main characteristics:

The conventional supervised learning, e.g., DNN, in Fig. 3(a) is treated as a baseline scheme that re-trains the AI model from scratch in the target task (Task B) without utilizing any knowledge from the source task (Task A). Taking an intra-slice resource allocation problem [7] as an example, task A can be the problem under common mathematically-tractable assumptions, e.g., Poisson-arrival based traffic requests within a slice, uniform user distribution, Rician-fading channels, or exponential service time. Task B can be considered as any non-ideal case that the above assumptions may no longer be applicable when dramatic variations occur. When the trained AI model A, e.g., DNN, is adopted to make predictions for task B, the performance can significantly degrade, thus the DNN model has to be re-trained to re-fit task B, referred to as “Model B” in Fig. 3(a).

Transfer learning focuses on how to transfer the knowledge acquired from task A to task B. The parameters learned from the source task can be shared with the target task to speed up the re-training process. With the acquired parameters, training the target task can avoid starting from scratch, and may not need a large amount of training data. The difficulty lies in the definition of the degree of correlations between the target and source tasks [14].

Meta learning aims at training meta knowledge based on a variety of learning tasks. With the meta knowledge, the learning model can solve new learning tasks with fewer amounts of training data (for supervised learning). In general, ML resembles TL. It uses previous knowledge and experience to guide the learning of new tasks. The difference is that ML does not transfer the knowledge of a certain model to assist in training a new task but to train a model capable of well adapting to new tasks that have never been encountered previously. In general, the difficulty is to collect different classes of tasks as training data to learn the generalized initialization in meta optimization [15].

Combining with reinforcement learning enables an agent to learn from the prior experience without the need for training data sets [8]. The agent interacts with the underlying/surrounding environment, comprising of states, actions, state transition functions, and an immediate reward. The concept of ML or TL can be implemented based on an RL framework, which can accelerate the convergence in re-training and enhance the overall re-fitting capability. For example, in meta-critic methods [15], a meta critic is added in the agent to guide the critic to better supervise the actors’ behaviors, which enables strong generalization abilities to adapt to different tasks. With a well-trained meta critic, the agent can efficiently train an actor by consuming fewer learning episodes and saving the re-fitting time.

IV. Case study and numerical results

In this section, we demonstrate the effectiveness of the considered AI solutions in dealing with dynamic network environments. As an example, we consider a typical RAN slicing problem [10] under two typical dynamic scenarios, i.e., bursty traffic and devices' arrival/departure in slices. The objective is to minimize the overall cost of slices, defined as a composited utility function consisting of weighted energy and bandwidth consumption in NGSO and ground segments, while satisfying users' QoS and inter-slice isolation requirements. The key issue is to appropriately determine which users to simultaneously access the same radio resources, e.g., bandwidth, on each time slot. We then use AI models to learn and mimic the scheduling behaviors, e.g., optimized user groups. In simulations, we consider 3 slices and 3-10 associated users per slice, where the physical NGSO-ground infrastructures are logically mapped to the virtual networks (slices), and the spectrum resources are aggregated to form a resource pool [10]. Each individual slice may own the RAN resources from terrestrial base stations, NGSO satellites, or both.

In the first case study, Fig. 4 shows the evolution of loss and cost (or objective) values in reacting to an event of bursty demand among five AI schemes, where a convolutional neural network (CNN) is adopted for conventional supervised learning; TL and ML are implemented based on a CNN framework; DRL is implemented without re-fitting process or combined with ML in DRL-ML. The bursty traffic occurs at the 250-th time slot, which makes the upcoming inputs irrelevant to the statistical properties of the historical data. As a result, the loss values in CNN, TL, and ML schemes deteriorate significantly and trigger the drift-level warning, then start remedying by the subsequent re-collecting and re-training procedure. After convergence, the loss value returns to previous levels by consuming around 100, 70, 40 elapsed time slots, which suggests the faster recovery capabilities in TL and ML than the baseline CNN scheme. Note that this consumed time in re-fitting can increase rapidly with the problem's scale growth. In contrast, the loss value in DRL moderately increases, but consistently undergoes higher loss and cost, which is undesirable for long-term operations. The combined DRL-ML scheme shows promising trade-off performance, e.g., less sensitive to the variation than three NN-based solutions, and lower loss value than DRL. This combined approach can be enhanced to further reduce the loss and cost values.

In Fig. 5, we conduct the second case study to evaluate the capability of adapting dynamic and frequent slice-user entry/leave. The comparisons are among CNN, ML, and an optimal solution which can be obtained offline as a benchmark. From the 250-th time slot, we assume random entry/leave events happening every 100 time slots which is also the deadline for completing a re-fitting procedure in CNN and ML. From the results, ML is able to converge in re-training

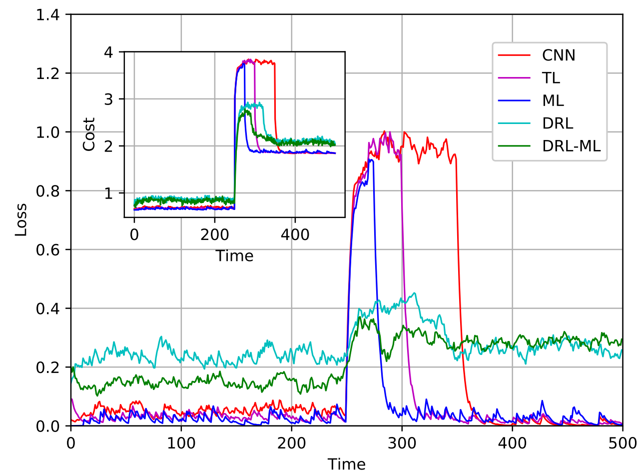

Figure 4. Effectiveness of AI solutions in adapting bursty demands.

within roughly 60 slots before the deadline. In contrast, CNN leads to an undesirable case. That is, the re-trained model is not able to converge to react to the first event but the second has arrived. As a result, CNN is not able to re-fit timely, and the cost performance fluctuates dramatically with the dynamic user mobility.

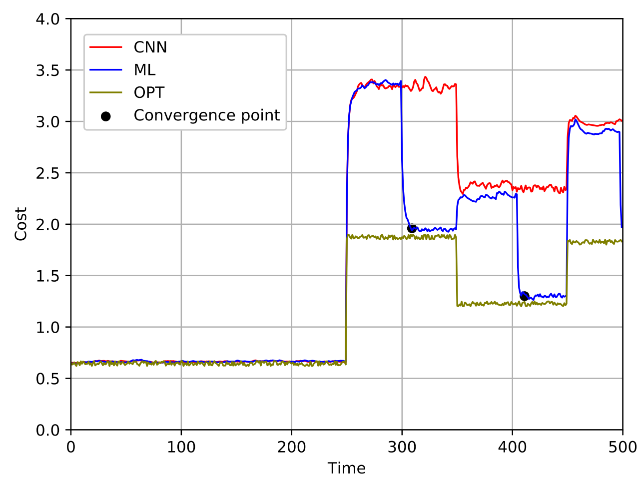

Figure 5. Performance of AI solutions in dealing with periodic slice-user arrival/departure.

V. Open issues and future directions

While the B5G network slicing has been widely studied, the development of AI-enabled solutions is in its infancy. Towards maturity, plenty of open issues need further investigations. Some of them are summarized below.

Firstly, the conventional AI solution has proven its effectiveness in relatively simple decision-making tasks, e.g., traffic prediction, but it typically has limitations in tackling complicated and constrained optimization problems which are, however, the major type of many network slicing problems, e.g., VNE, RAN slicing scheduling, or VNFs replacement with numerous practical constraints. In this context, any inaccurate prediction at the inference phase may sensitively violate some constraints and result in an overall infeasible solution. For example, the reward function in DRL can be designed to meet simple constraints but might not have a feasibility guarantee for a large number of constraints. Thus, current AI solutions have not lived up to their potentials for guaranteeing QoS or QoE in B5G networks.

Secondly, in AI-enable B5G network slicing, there are many trade-off issues that should be carefully investigated and evaluated. Due to the "no free lunch theorem", no single AI solution can outperform any other algorithms on all aspects. Thus, the trade-off analysis between AI performance and cost is of importance in selecting an appropriate AI model for solving a specific problem. In addition, trade-offs among multi-dimensional resources, e.g., flexible resource configuration by exchanging storage and computation capabilities, and the trade-offs between AI cost and other costs in network slicing, e.g., using clouds to increase available computation resources for AI but at the expense of raising the overall budget and security concerns, are also needed to be considered.

Last but not least, the services supported by different slices in this work might be more suited for latency-tolerant communications, e.g., eMBB or mMTC services, due to relatively long propagation delay in satellite data transmission. In addition, the inherent limitations of AI at this early stage pose obstacles in extending to safety-sensitive communications, e.g., autonomous driving, and mission-critical communications, e.g., remote health care. In such challenging scenarios, high prediction accuracy in AI models, proper representation of problems, and error-tolerant frameworks are needed for further investigations.

VI. Conclusion

In this article, we have focused on how to make AI solutions adapting to dynamic NGSO-B5G network slicing. Beyond state-of-the-art, we have pointed out the major issue of applying AI and integrating NGSO to network slicing management. We have provided tailored solutions to two categories of dynamic scenarios, i.e., with predictable or unpredictable variations. A set of dynamic-adaptive AI solutions and their potentials, benefits, and limitations have been discussed. The considered AI solutions have been evaluated in two dynamic scenarios to validate their effectiveness. Numerical studies suggest promising AI solutions, e.g., combining DRL with ML or TL, for future B5G network slicing management.

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