Programmable Computing in 6G

Zubair Md Fadlullah and Mostafa M. Fouda

Abstract There is a sharp rise in communication and computing needs. The iterative generations (xG) of communication networks typically improve capacity and quality of service (QoS) parameters by an order of magnitude. In the emerging 5G+ and 6G networks, there is a call for embedded intelligence which can bring a revolutionary change in the network fronthaul as well as backhaul. Programmable computing is aligned with the computational concepts from the original inspiration of the Software-Defined Networks (SDNs). However, the essence of the SDN concept has been lost throughout the years due to rapid industry-absorption of the architecture-specific details whereas the programmable computing part has been widely overlooked. In this chapter, we describe a programmable computing architecture in the 6G network system. Then we demonstrate the key enablers that can support this programmable computing architecture. We provide a simple case study to illustrate how programmable computing can be leveraged in the emerging 6G use-cases.

1 Introduction

Communication networks are all around us. As the name suggests, communication networks are typically used for communication, whether this is cellphones for making

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a voice call, video streaming, controlling your IoT (Internet of Things) devices for smart home applications, or drone-based surveillance and monitoring systems [1]. Even the smart, wireless TVs in your living room are part of the massive, wireless communication ecosystem as they serve on-demand high-definition contents which typically require high-speed Internet connection through the home access point or router. These wide examples of communication networks are rolled out every few years in terms of a new generation (xG). The evolution of wireless communication networks from 2 to 5G has already been astounding and associated with a sharp increase in the number of supported users along with much-improved capacity and service performance guarantees. The better the service performance, the more satisfied the users are. As the 5G networks are being rolled out, both academia and industry are drafting the next generation of wireless and mobile networks, which are referred to as the 6G networks [2, 3]. Is 6G just hype? Or does it bring a new flavor of communication? Is it just a business model to sell new networking equipment to your favorite mobile broadband provider and cellular network operators so that they can impose a heftier monthly subscription charge? Or does it really provide something additional to what we already have in 4G (LTE, WiMAX) and 5G networks [4]?

To answer this question, we need to understand what 4G and 5G were designed to deliver to mobile users. A key difference between 4 and 5G is the adoption of millimeter-wave (mmWave) bands (for higher capacity and supporting more users) and much lower delay requirements. There are many small and densified cells in 5G networks that use beamforming and other technologies to deliver 1–30 Gbps (gigabits per second) of speed compared to the speed in the order of hundreds of MBps (megabits per second) in the predecessor 4G networks. On the other hand, the 6G networks are different from 5G networks in terms of providing 100 Gbps to 1 Tbps (1 terabit per second) speed. This is an ambitious requirement drafted, inspired by some of the laboratory experiments conducted recently with Terahertz (THz) frequency and VLC (visual light communication) technology. However, in 6G networks, to accommodate this very high-speed communication, the nodes need to be within even smaller areas than those in 5G networks, referred to as tiny cells. Imagine so many tiny cells in your city, which are dynamically formed on a need basis, then dissolved, and then formed again to cater to a different service need. This dynamism will be much more dominant in 6G networks because of the integrated aerial-terrestrial-satellite networks. In 4G and 5G networks, typically terrestrial network base stations are used to serve the users. However, in 6G networks, drone cells, terrestrial base stations, nanosatellites, etc. will all be connected [5, 6]; and it is very difficult to satisfy the capacity and delay requirements to combat the ultra-high level of dynamism in such a complex mesh of networks. As a consequence, flexible architecture is required to compute the resource allocation, security provisioning, service quality assurance, and so forth. In this chapter, we talk about the softwarized or programmable computing for 6G networks, which can be considered as the key manager of tiny cells of 6G networks.

The softwarized network programming is inspired by the fusion of AI (artificial intelligence)-based computing [7] and the software-defined networks, commonly referred to as SDNs [8, 9]. The reason for this conception is two-fold. 6G networks, in contrast to earlier generations of communication systems, are being designed for embedded intelligence, particularly in the network edge [10]. Therefore, the coordination of 6G should be done in such a way that considers AI natively. You must have read about AI, or watched science fiction movies that talk a lot about intelligent robots! Although we haven't reached that level of intelligence yet, communication networks are a leading area where intelligence may have great success. By intelligence, we refer to the basic pattern recognition algorithms and mainly data-driven models. In popular lingo, we refer to this as machine learning or deep learning models which are built on observing various trends and patterns in the communication networks. These are also known as predictive techniques. If your network operator can predict that there will be 100 cellphone users in your shopping mall area in the suburbs during the next half an hour, it can switch on the tiny cell base stations to serve those users and the other time it doesn't have to keep those base stations active, thereby saving energy. Energy-efficient technology, although appearing to have a negligible impact on the carbon footprint at a tiny cell level, can lead to much reduced emissions on a collective level across a town or city. This is just but one example of the awesome features predictive technologies can provide to communication network users. They can proactively assign network resources (called channels) [11, 12], they can forecast what type of content (movie, music, etc.) the users may want to watch [13], how the users will interact with one another, etc. If such intelligence can be embedded into smartphones and other devices in the edge of the network, they can transform those small user-devices into powerful edge computing devices which can take part in distributed learning to figure out interesting computing problems, for example, contact tracing, pandemic modeling in a distributed environment in real-time, and so forth. We hope that you could get the big picture of the usefulness of embedded AI in 6G systems.

On the other hand, the SDN architecture needs to be fused with the embedded AI in 6G networks also. Typically SDN architecture was coined from a computer science perspective, to make the best use of object inheritance and code reusability [14]. What do we mean by this? If you are familiar with object-oriented programming such as C++, C#, Java, etc., you will definitely be familiar with abstractions such as classes, objects, encapsulation, inheritance, polymorphism. Clever computer scientists thought about using this concept to extend to network entities. On the top level, a network router may have some basic class of operations, and the next level of the router may have further abstraction with some added features. All we have to do is: define the objects, and extend the classes, and map them to the hardware implementation of network routers and other network equipment. This is an abstract but powerful concept, which unfortunately became lost in "translation" from the computer science perspective to network engineering practice. Practitioners of 4G and 5G networks overlooked and forgot the inherent significance of the original concept of SDN, and simply implemented the central coordinator/controller-based management of network nodes and routers. By referring to such implementations as SDN, the programmability feature was entirely missed. If we can bring the programmable computing from the original SDN concept and infuse AI with it, it can do wonders for the embedded AI as a key enabler for emerging 6G network systems.

We hope that we understand the big picture of programmable computing in 6G by now. Let us embark on the journey into the chapter where we will be able to tell you about the machine/deep learning-based AI models that can help the 6G systems to do on-demand model building and deployment. We will first provide some related work regarding programmable computing, inspired by SDNs. Then we will provide preliminary on machine learning and deep learning models. Next we will present the 6G programmable computing architecture with AI as well optimization model incorporation. A use-case will be then provided so that readers can have a high-level understanding of how such programmable computing can provide high service performance in 6G systems. Future challenges and directions for programmable computing in 6G networks will then be briefly discussed.

2 6G Network Requirements

Readers should take note of the fact that at the time of writing this chapter, 6G is still at the conceptualization phase. Even though 6G networks do not exist yet, theoretical and experimental work are encouraging researchers and telecommunication engineers to learn from the limitations of the current generations of networks (4G, 5G, etc.) to help make a completely different generation of networks with several key requirements. The connectivity between devices (not just cell phones and smart devices but also billions of IoT devices) will be complex yet fluid in an integrated aerial-terrestrial-satellite network. Each component of such a complex network system has its own physical specifications and requirements. For example, aerial networks can be formed much faster in remote/rural areas with ease compared to the conventional terrestrial base stations. However, their achilles heel is the battery (energy constraint)! Readers are familiar with drones that can take aerial photography but can be in flight for not more than half an hour (take for example an off-the-shelf DJI Phantom drone). When you use such drones for communication to form a mesh network, they can do wonders for remote sensing to detect fire in the forest bed, or connect rural villages or Indigenous communities that cannot be accessed with hard-to-deploy and much more expensive terrestrial links using fiber optics. Drones can use 2.4 GHz (gigahertz) links which are similar to what you typically have at a home wireless access point, and other high-frequency links for collecting and forwarding packets to the Internet. But their mobility, energy constraint, capacity, wireless channel quality, blocking, and path loss models are quite different when compared to terrestrial base stations and users. Now imagine if you use these two radio access technologies with various inherent requirements together! Now imagine you throw the nanosatellites and low earth orbit satellites into the mix. The 6G network will be so difficult to manage in such a complex co-presence of the different radio access technologies. What is the 6G network management for? There are several requirements of 6G systems considered by researchers

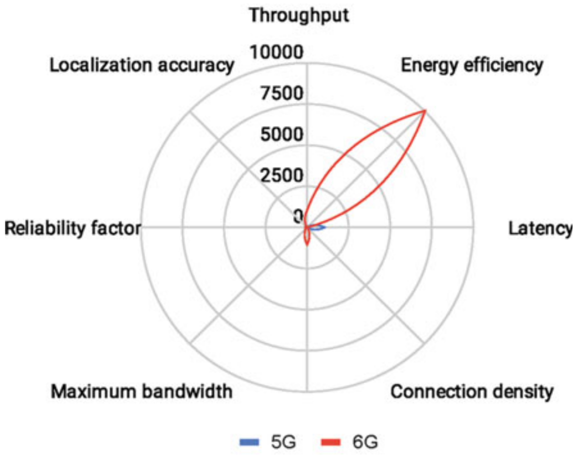

Fig. 1 6G network requirements compared with those considered in 5G settings

which include: up to 1 Tbps capacity, 1 ms or below delay, embedded intelligence for native support for edge computing, and so forth. Now why these requirements? These requirements of 6G systems are needed to support the killer applications of the future that include: tactile internet, remote surgery, haptic connections, immersive infotainment (e.g., using virtual/augmented reality), autonomous cars, etc. These applications typically require a huge amount of bandwidth which justifies the high capacity of 6G networks. Such applications also need a very low communication delay in the order of a few milliseconds, and typically require local computer vision and natural language processing tasks that in turn heavily rely on AI models. Readers can refer to a simple comparative illustration of 6G network requirements compared to the predecessor 5G network settings in Fig. 1. Next we will derive inspiration from the existing work to be able to sketch a programmable computing infrastructure for 6G network systems that can adequately support the aforementioned requirements and applications.

3 Background and Motivation

Software-Defined Networks, commonly referred to as SDNs, have been widely studied and considered in various network technologies from 4G/5G core networks to IoT systems. From SDNs we derive the motivation because it is the focal point of computer science theory for reusable coding for programming/reprogramming network elements and current telecommunication engineering practice. So let us take a closer look at SDNs first and try to understand what is actually missing that makes it not readily scalable to 6G networks with the required embedded intelligence.

Refer to Fig. 2 which describes the operation of the SDN controller. It typically separates (decouples) the control and data plane when packets are

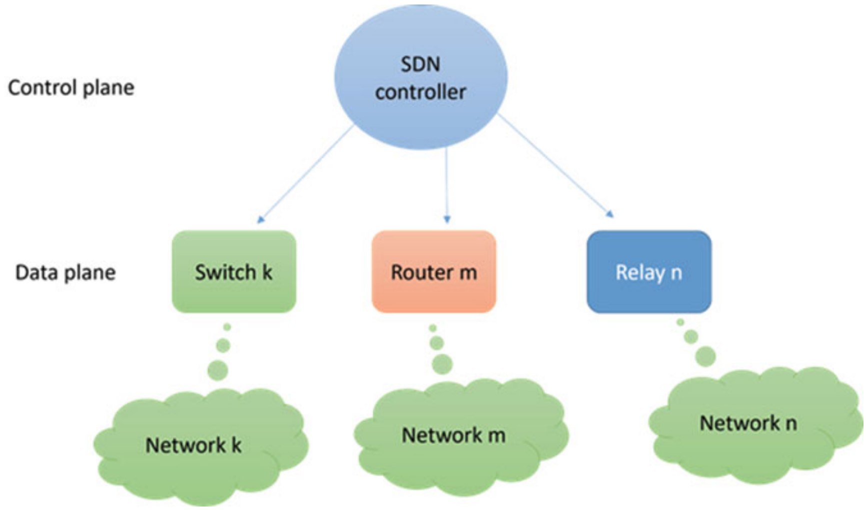

Fig. 2 SDN controller decoupling the control plane from the data plane

forwarded over networks. Traditional routers perform a dual role, they process both control (computing) and data (packet forwarding) planes. But this puts a lot of processing/computing burden on these network nodes, such as bridges, routers, access points, etc. Why do we want to separate these planes? Let us consider a simple example. You are a distribution manager and a distributor at the same time at the pickup corner of a large shopping outlet. As the distribution manager, you receive various calls, emails, etc. for customer orders, and then also need to distribute them to the customers for curbside pickup, home delivery, etc. This is a very complicated job. If you could separate this between you and your colleague, life could be much easier, right? In this simple example, the distribution manager is the example of a control plane while the distribution tasks are analogous to the packet forwarding operations on the data plane of the SDN.

While the control functionality is placed on the SDN controller (or several SDN controllers) to coordinate the entire network which could be your university campus network or the power grid cyber-physical system network, today's SDNs miss the object-oriented design concept. This could strengthen the SDNs to be systematically built and scaled. However, the network engineering practitioners, probably out of the excitement, absorbed the architectural essence of SDN and forgot the programmability part. This is where the motivation for a programmable network starts for us. What does the programmability imply? Think about a network node; which has simple or basic functionality such as packet forwarding. The packet forwarding could be a class and all the simple packet forwarding elements could then be instances of that class. An extended class could be a router with firewall functionality that can forward packets and also have the ability to act as firewalls. The key takeaway of this idea is code reusability. First, we have a basic abstract network element class, and all the instances of this class will be simple network forwarding entities. By simple code reusability and extension, we can have a firewall class to make many other instances of routers with firewall capability. There could be many more extensions with such programmability.

Such a programmable computing-powered SDN controller can simply make new classes and instances and deliver those instances to the off-the-shelf, "empty" routers. In other words, the network controller could decide, for switch k, to add more new rules when the traffic load variation significantly changes in Fig. 1. An even more dramatic example of the programmable computing-aided scenario could be a drone which can act as a "transformer" by changing its role from a flying access point, energy harvesting static access point, a home router in a rural area, or a relay node, or even a surveillance node. How can the node change its modus operandi on the go? To build such a versatile drone (or a versatile network functionality box) will mean there should be lots of hardware resources and multiple software packages on a self-contained system. This raises the cost and practicality of such systems in a significant way.

This brings the next question: how can the controllers have the capability to make the best models and decisions fast enough so that these models could be deployed down onto the network switches, routers, relay nodes, drones, and so on. The answer is: by either a rule-based or data-driven approach. Rule-based approaches include optimization techniques, heuristics, etc.; while the data-driven approaches typically consist of supervised learning, unsupervised learning, and reinforcement learning. Next, we provide the preliminaries of these rule-based data-driven approaches that are the building blocks of the softwarized, programmable computing in 6G networks for performing a diverse set of network and service functions.

4 Preliminaries of Rule-Based and Data-Driven Approaches

As mentioned earlier, there are rule-based techniques which are the traditional techniques. On the other hand, there are data-driven approaches to train a model that can be readily deployed to the network nodes.

4.1 Rule-Based Techniques

There are various approaches to optimize network performance based on the network traffic load dynamics and other variables in the 6G radio access side or the fronthaul. For formulating resource allocation and scheduling problems in various 6G tiny cells, optimization models based on linear programming, convex optimization, Lyapunov optimization, stochastic optimization, and matching algorithms are widely used.

While such techniques are well suited for obtaining closed-form solutions to the optimization problem, collecting all the information typically is a time-intensive process particularly when the search space for finding the solution is large. On the other hand, when optimization techniques do not provide an optimal solution, an acceptable solution is still required. This is when heuristics, such as greedy approaches, are designed. Let us consider a simple example. Suppose there is an array of intelligent reflective surfaces in a 6G network. How to find the optimal angle of the reflecting surface elements with respect to the different frequency bands used in the network? Since there is no unified channel model for multi-band frequencies, it is difficult to obtain a closed-form solution for this problem. So the next best solution is to approximate a solution using trial-and-error-based approaches or heuristics, or greedy algorithms that can provide at least some reasonable or acceptable throughput and delay performances. Typically these algorithms need to be designed manually. Human operators need to observe the various network variables, formulate an objective function subject to various constraints, and then figure out whether the conventional optimization algorithms are computationally hard or not. If this is the case, the problem is typically broken down into simplified problem(s) or subproblems that can be easily solved; and heuristics are developed to opportunistically solve the simplified problem or the subproblems. While for known network configurations, the optimization techniques typically provide optimal or near-optimal solutions, their execution time and the single-shot solution (once at a time) warrant a different method, namely the data-driven approach.

4.2 Data-Driven Approach: Machine Learning and Deep Learning

The data-driven approaches typically build an experiential learning model by discovering various patterns in the network activities. While they do not provide closed-form solutions, they are known to perform very well given large data sizes. The experience culminated by big data originating from the IoT system or a cellular network can allow the network coordinator to predict how much resources need to be allocated in the several next minutes, which frequency bands and channels are likely to be occupied, which contents will be in high-demand, and so on. There are statistical approaches that typically provide descriptive analytics and are widely used for constructing anomaly detection in network intrusion detection systems. There are machine learning-based approaches such as support vector machines and random forest (based on decision trees) to mainly train AI models for deciding various regression and classification tasks. These can provide fast, embedded intelligence for the resource-constrained nodes (e.g., IoT devices and drones) in 6G networks. On the other hand, for complex and large data processing which involves non-linearity and cannot be handled with conventional rule-based approaches, the deep learning methods using various neural networks are gaining popularity. For instance, artificial neural networks (ANNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) are used for various types of classification tasks involving non-linear pattern identification in complex networks data. When these models are trained over a long period of time, for similar networks the pre-trained models can be quickly deployed by the network coordinator to the network entities to reprogram their functionality and optimally handle the prevailing network dynamics. This is the power of these AI models, in conjunction with the network manager/coordinators, to provide an on-demand reconfiguration of network nodes.

5 6G Programmable Computing with Optimization and AI Models

With the above preliminary, we are now ready to describe the 6G programmable computing architecture with optimization and AI models. We will use Fig. 3 to describe this architecture.

As shown in Fig. 3, there are three layers in the proposed programmable computing architecture with optimization and AI models: the application plane, hardware plane, and data plane. For detailed description of the inspiring architecture, please refer to the authors' inspiring work in this area in [15]. Let us start from the bottom up, with the data plane. The data plane consists of various base stations (BSs) ranging from terrestrial to drone-managed networks. Satellite networks in the integrated 6G networks could also be shown, but for simplicity, we decided not to make the illustration more complex than it already is. The base stations could be static or mobile cellular base stations managing 6G tiny cells or macrocells. There could be user devices acting as device-to-device (D2D) nodes or hotspots acting as relay entities for packet forwarding where the traditional base stations cannot reach. There could be drones or aerial base stations also to cover areas where the conventional base stations access is not available or they are overwhelmed due to network traffic congestion. These various networks generate a lot of traffic competing for 6G base station resources, and under highly dynamic channel conditions, blocking models, and ultra-high mobility; the serving base stations need to be reprogrammed to deliver the best service and minimize the possibility of a service outage.

Based on the traffic demand, user movement pattern, channel conditions, and other network dynamics, the 6G network manager, located at the 6G network home office (HO) where hardware virtualization is performed to facilitate the control plane and to provide service/application plane functionalities including QoS and security provisioning in terms of network slicing, virtual network function (vNF), signal processing, remote radio resource allocation, mobility control, sleep scheduling of base stations, etc.

The base stations placed on the data planes consist of terrestrial and aerial (drone) base stations, mobile user equipment (UEs), wireless local area network access points

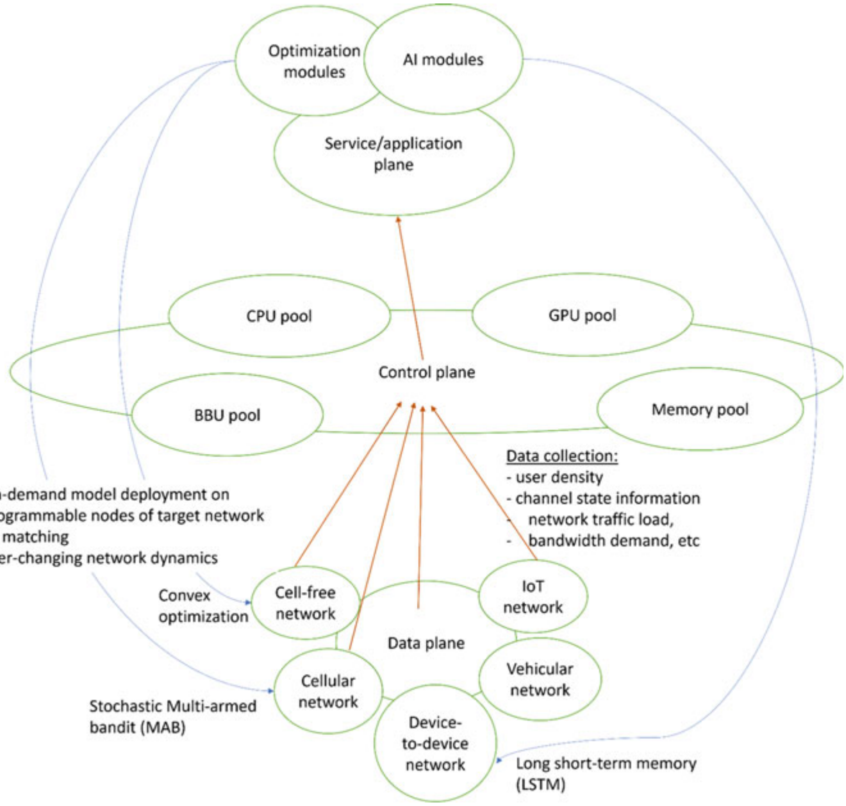

Fig. 3 Programmable computing architecture with optimization and AI models in 6G networks [15]

(WLAN-APs), visible light communication (VLC) base stations, vehicle-to-other (V2x) nodes, IoT devices, etc. The 6G network manager, which could be a centralized or a distributed/virtualized platform, is responsible for deriving and on-demand distribution of optimal and intelligent models and/or policies to these various base stations, access points, and wireless equipment to optimally forward the data packets for satisfying the 6G communication requirement. On the data plane, the wireless nodes, based on the derived optimal and/or intelligent model/policy, observe the current traffic demand, channel conditions, and so forth and then decide which models are ideal for the current situation. Therefore, by matching the network dynamics, they proactively download the optimal/intelligent network policy as shown in Fig. 2. For example, the stochastic multi-armed bandit (MAB) model [16], belonging to the reinforcement learning family, is deployed for stationary D2D nodes while the adversarial MAB model is downloaded by the mobile UEs [17]. Thus, the proposed system model benefits from the reusability of the MAB schemes for new programmable network nodes. Specifically, the application plane has to define a few primary instances of optimization and AI model types. Upon current network topology and dynamics, network devices can simply be reprogrammed to accommodate an appropriate model to combat the prevalent conditions by merely creating an instance or a program based on the base definition that it procures from the repository of optimization/AI modules in the application plane.

As mentioned earlier, the classical optimization techniques are not scalable with the highly varying network dynamics. As a result, it is often challenging to provide closed-form expression on the existence and guarantee of an optimal solution for a well-defined, complex problem. Many of the constraints and conditions are often relaxed upon the utilized algorithm design to find suboptimal solutions. Furthermore, such optimization techniques are typically a one-shot process as they require centralized, oracle-like knowledge to ingest the whole dataset to give the optimal benchmark decision. On the other hand, a supervised learning model is typically trained before decision-making since inference is known to be much faster than the training time. However, such supervised learning models require extensive and versatile training datasets. The lack of an adequate dataset, which is critical to train the existing machine/deep learning models, will be a crucial barrier to maximizing their predictive performance. Moreover, the performances of such supervised learning-based models are typically sub-optimal, and a lack of interpretation as to why they provide such performance still raises a lot of concerns among researchers for mass deployment on networking devices in contrast with the traditional straight-forward, feedback-based decision making. Therefore, ultra-fast online learning techniques are essential to be deployed to the 6G users (e.g., BSs, home APs, mobile UEs, and so forth) for localized, distributed decision making. The type of MAB can also be changed on-demand to cater to the sudden change in the network dynamics experienced by the 6G users. Furthermore, the recent advances in regret analysis for the variants of MAB algorithms can be leveraged to demonstrate their tightly bounded performance guarantee. Thus, MAB emerges as the most viable candidate compared to the classical optimization and supervised learning counterparts.

6 Conclusion: Future Directions and Caveats

Intelligent decision-making is anticipated to be a key embedded feature in the upcoming 6G networks that will realize innovative future applications. Since these services have ultra-reliable requirements easily impacted by varying network dynamics, on-demand ultra-fast learning techniques emerge as a formidable research challenge. In this chapter, we addressed this challenge and proposed a softwarized network consisting of an on-demand policy selector that considers the ongoing network dynamics and accordingly chooses the best intelligence module for deploying to the nodes for that particular network.

Unlike the classical optimization and supervised learning methods, online/sequential learning techniques such as MAB algorithms with different policies can be focused on viable online, sequential learning techniques for 6G node deployment by the proposed on-demand selector.

As a caveat, it is worth noting that for deploying the models on-demand, there could be some connectivity issues causing the AI models not to be timely updated that may cause the target routers/network nodes to be rendered dysfunctional. To combat such a corner case, we may assume a default, basic functionality of programmable routers to cope with such scenarios. How to optimally generalize such a default functionality is left open as future work for 6G softwarized networks and programmable routers.

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