Resource Allocation in Satellite Networks – From Physical to Virtualized Network Functions

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Abstract *– The integration of satellite communications (SatCom) and networking into fifth generation wireless networks (5G) and their foreseen role in the forthcoming 6th generation (6G) has been gaining relevance, especially with the advent of nano-satellites. However, full SatCom integration into 5G and beyond requires carefully revisiting radio resource allocation techniques that have been developed and successfully applied in the satellite context to fit in the highly virtualized environment that characterizes these networks. This entails adaptation of both architectural and algorithmic aspects, in order to maintain end-to-end performance requirements in a highly heterogeneous networking framework. We consider in particular bandwidth allocation schemes and suggest modeling and architectural paradigms that appear as more promising in this respect.*

1. Introduction

Fifth generation (5G) mobile networks (and beyond) will allow a much higher data rate per user with respect to the current one, a greater number of connected devices implying much higher traffic volume, a significantly reduced latency allowing a huge number of new services. The requirements of 5G networks will translate in Key Performance Indicators (KPIs), such as: bandwidth, spectrum efficiency, data rate, latency, device density, area traffic capacity, reliability, availability, energy efficiency, coverage, mobility, positioning accuracy, security metrics, among others. 5G scenarios allow envisaging applications belonging to science fiction up to few years ago, in particular in the context of Smart Cities, Smart Industries, and Smart Farms, where a huge amount of “things” connected over a high-speed network will allow: to access medical devices remotely, to control ambulances, to have municipal command and control services, smart grids, home energy management, hospital optimization, transport optimization, automated car systems, but also factory process control and optimized agriculture. The pervasiveness of the smart devices together with a ubiquitous coverage will be employed to monitor both metropolitan and hazardous isolated areas by sensors, microphones, and videos.

Special attention may be deserved to protect critical infrastructures which are complex systems and assets that provide services considered vital for the society as an integrated entity: Chemical, Commercial Facilities, Communications, Critical Manufacturing, Dams, Defense Industrial Base, Emergency Services, Energy, Financial Services, Food and Agriculture, Government Facilities, Healthcare and Public Health, Information Technology, Nuclear Reactors, Materials and Waste, Transportation Systems, Water and Wastewater Systems.

So, if, on one hand, 5G can make concrete the intuition of Mark Weiser [1] and the paradigm of pervasive computing depicting a world where a wide set of physical quantities (vibrations, heat, light, pressure, magnetic fields, ...) are acquired through sensors and transmitted through suitable seamless communication networks for information, decision, and control aim [2], on the other hand the introduction of new components, the increased data exchange and interaction, the presence of services that, in the past, were operated over separated networks unconnected to public communication infrastructures, but now have turned to exploit the services and data provided by telecommunications networks, increase the need of managing and understanding this huge amount of data. In this challenging environment the importance of Quality of Service (QoS, identified in 5G through the concept of KPIs) is evident and each application requires a specific level of assurance from the network that is characterized by a great heterogeneity: portions managed by different Service Providers; different transmission means such as cables, satellites, and radios; different implemented solutions from the protocol viewpoint, as well as different users who can require different services and may have different availability and willingness to pay for them. In practice, we can bring out again the old concept of “network of networks” originally used for the Internet.

In this challenging environment satellites can play multiple roles as portions of a heterogeneous end-to-end network thanks to their intrinsic ubiquity and broadcasting capabilities. They can act as a main single backhaul segment for rural areas, aircraft, vessels, and trains, as additional backhauls to provide enhanced connectivity and, to improve service continuity, as pure transport networks. They can be applied in the edge computing scenario to exploit the unicast/multicast/broadcast geographical distribution of video, audio, and application software binaries simultaneously. Associated immediate outcomes are in the field of Smart Cities, Smart Industries, and Smart Farms.

The problem of end-to-end QoS has been deeply discussed in [3]: essentially QoS requests should traverse the overall network from the source to the destination through portions that implement different technologies and different protocols; QoS requests should be received and understood by each specific portion where QoS may have different meaning and interpretation, which depend on used protocols and network features; QoS requests should be managed by control mechanisms suited for the aim; each single QoS solution is composed of layered architectures and each layer must have a specific role in QoS provision. The overall problem of QoS interworking may be structured into two different actions: Vertical and Horizontal QoS Mapping. The former is based on the idea that a telecommunication network is composed of functional layers and that each single layer must have a role for end-to-end QoS provision. Consequently, it is necessary to define an interface between adjacent layers through which to offer a specific QoS service. The latter, even if much linked to the previous concept when implemented in the field, is represented by the need to transfer QoS requirements among network portions implementing their own technologies and protocols. Special tools called QoS gateways can take charge of that, by isolating specific network portions that deserve special attention and control actions such as traffic shaping, scheduling schemes, call admission control (CAC), QoS routing, and Resource Reservation, often declined as Bandwidth Reservation.

In this context, this contribution will focus on QoS Gateways that “open the door to satellite portions”, as sketched in Figure 1, from the point of view of bandwidth allocation, by analyzing the evolution in these last years. The problem is mainly linked to the concept of Vertical QoS

Mapping and service provision between adjacent layers, clarified in the next Section, in particular between higher layers (IP and upper layers) and lower layers (data link and physical ones) implemented on satellite network cards. At the same time, we will also consider the integration of the satellite segment in the upcoming 5G and Beyond 5G (B5G) scenario, and the evolution of the architectural solutions that were developed for vertical QoS mapping toward the virtualized networking environment that is a fundamental characteristic of this scenario.

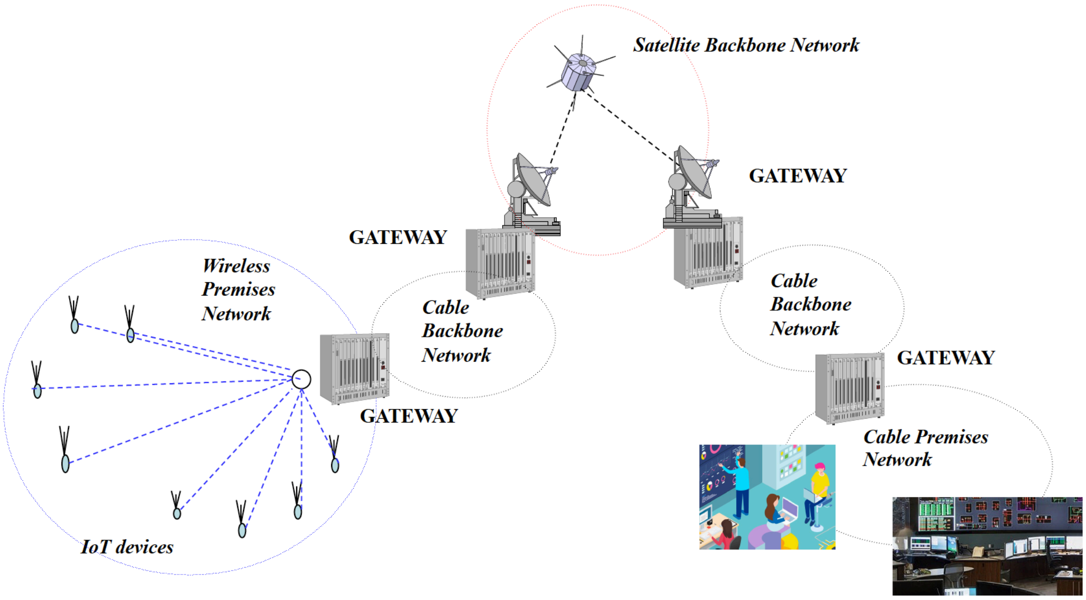

Figure 1. End-to-end QoS service through satellite backhaul.

2. Vertical QoS Mapping

An example of formal relation among layers and a clear example of vertical QoS mapping is represented by the protocol architecture proposed by ETSI [4] for the access points to a Broadband Satellite Multimedia (BSM) network portion. The architecture is reported in Figure 2. The reference stack for the upper layers is the TCP/IP suite: application layer and transport layer implemented through either TCP or UDP or other protocols adapted for satellite communications and acting, for example, within TCP PEPs (Performance Enhancing Proxies). Either IPv4 or IPv6 act at the network layer and represent the Satellite Independent (SI) layers, i.e., those whose action is totally independent of the implementation details of the lower layers acting over the satellite link, even if IPv4/IPv6 must receive a QoS-service from the lower layers. Satellite physical and data link layers strictly dependent on the satellite features and on the specific data link (structured into Satellite MAC and Link Control sublayers, strictly satellite dependent – SD) are isolated from the rest by a Satellite Independent Service Access Point (SI-SAP), which should offer specific QoS services to the upper layers. The SD layers receive a service request from the SI layers through the SI-SAP. Satellite Dependent Layers are decoupled from Satellite Independent Layers by the SI-SAP interface. In the following, we will also use the more general terms Technology Independent (TI) and Technology Dependent (TD) to identify our vertical partitioning, when not referring explicitly to the satellite context.

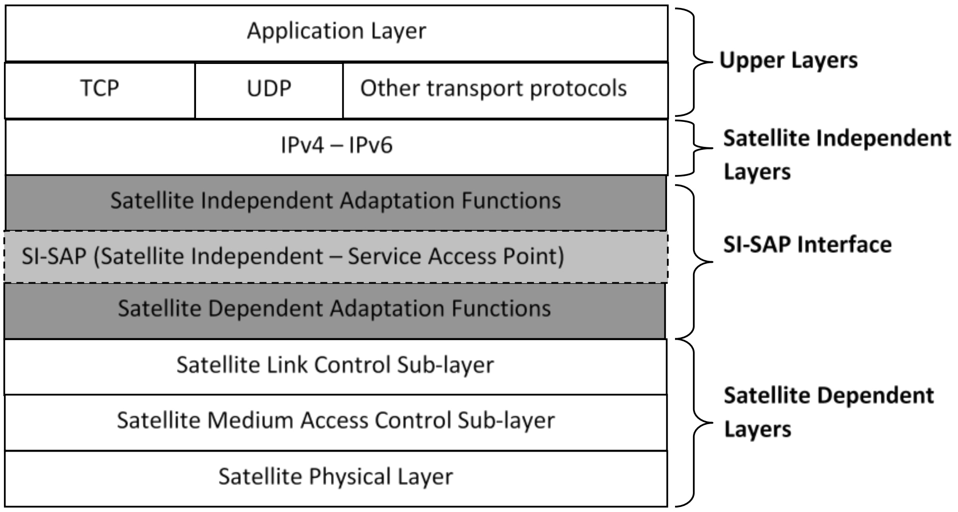

Figure 2. ETSI BSM Protocol Architecture.

Figure 3 identifies exactly the SI-SAP action point within satellite QoS Gateways, here corresponding to Satellite Terminals (STs) that give access to the satellite portion. IPv4/IPv6 has been used as relay layer because SI-SAP (even if it has a general meaning) has been formally defined only for IP-based networks, as shown in Figure 3.

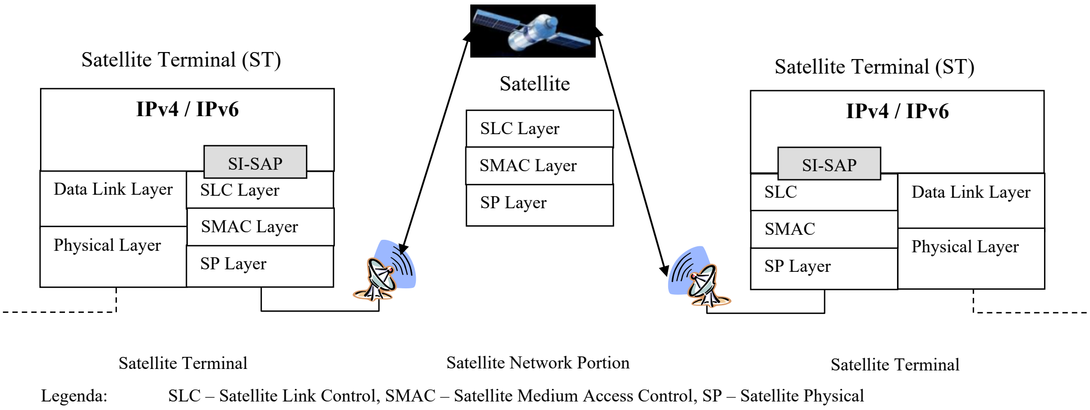

Figure 3. SI-SAP location within a satellite network portion.

The ETSI definition implies the involvement of management, control and user planes within the framework of QoS Gateways. As said, a key point, in particular in satellite communications, is represented by resource allocation schemes. A set of queues is used to define QoS mapping operations performed at the SI-SAP interface, as similarly used in reference [5] and [6] (for DVB at the SD layer).

Along the lines drawn in [7] and [8], the control plane is composed of the following control blocks.

- The TI layer Resource Management Entity making resources available for the IP layer.
- The TD layer Resource Management Entity, which physically manages the necessary resources at the lower layers and should have feedback information from the physical state of the links. It may act together with a Network Control Centre (NCC), widely used in the case of radio and satellite networks where the bandwidth to be allocated is shared among

different stations. The bandwidth to be allocated to each single station to match vertical QoS requirements may overcome the maximum limit capacity of the shared network.

- The QoS Mapping Management Entity (QoS Mapping Manager) that receives the resource allocation requests from the TI Resource Management Entity. A request may concern resource reservation, release, and modification. The communication between QoS Mapping Management and Resource Management Entity should be established through a proper interface. A proposal specific for satellite interfaces (SI-SAPs) comes from [7]. It refers to the composition of a set of primitives to establish the mentioned communication and is based on the creation of a set of abstract queues. Figure 4 contains the mentioned control modules and shows the decoupling between user and control plane, as well as the presence of the mentioned NCC.

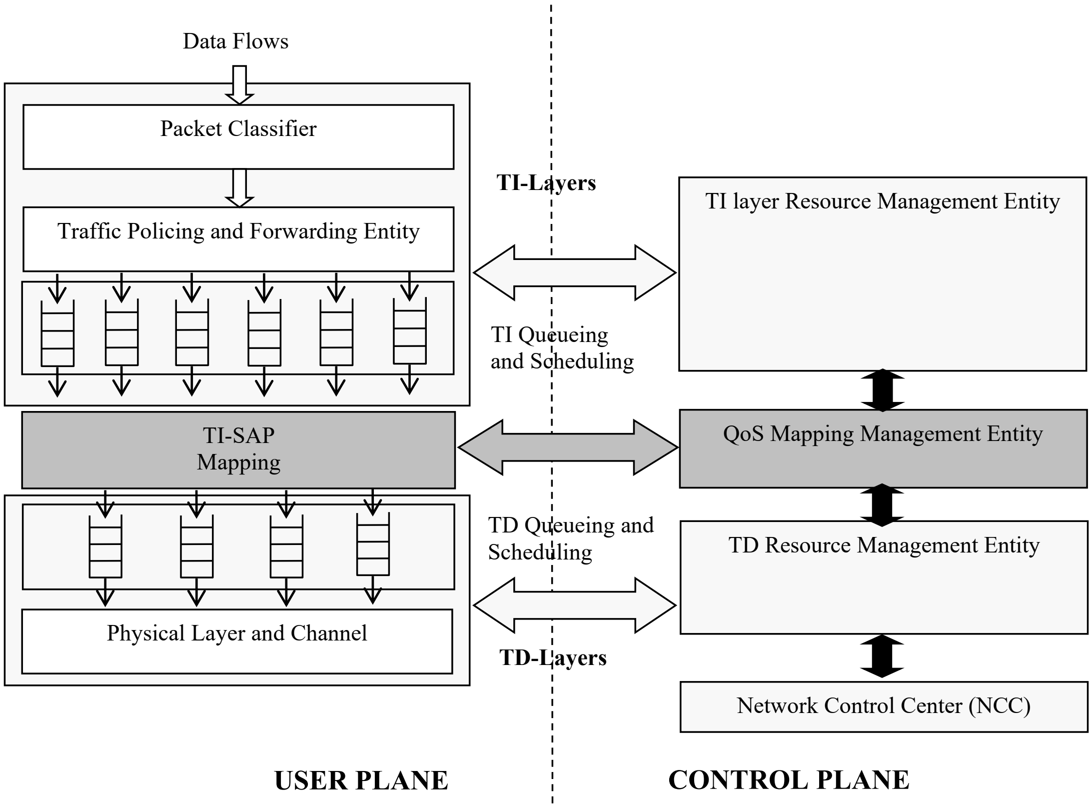

Figure 4. Vertical QoS mapping: information forwarding and control module interaction.

There are three problems arising from the action of two layers in cascade. The first two may be generically applied: change of information unit and aggregation of heterogeneous traffic. The last one is related to time varying channels. In the authors' experience it is related to satellite and radio communications. Concerning the change of information unit, at each layer, the information coming from the upper layer is encapsulated within a new frame composed of header and, possibly, trailer. It means that the TI layer packet accesses the TD queue after being encapsulated in a new frame. It is intuitive that the service rate at the TD layer must consider the additional bits of the header/trailer to keep a fixed level of service. As regards the aggregation of heterogenous traffic and referring to the satellite environment, as outlined in [9] concerning BSM systems, "it is accepted in the BSM industry that at the IP level (above the SI-SAP interface) between 4 and 16 queues are manageable for different IP classes. Below the SI-SAP these classes can further be mapped into the satellite dependent priorities within the BSM which can be from 2 to 4 generally". The due association of IP QoS classes to Satellite Dependent (SD) transfer capabilities is also limited by hardware implementation constraints.

The bandwidth assigned to the queues acting at the lower layer must assure the QoS requirements to the TI queues, even if the traffic has been aggregated in a lower number of queues. It is important to note that bandwidth allocation at TD layer may be hardly standardized to avoid the violation of implementers' freedom, but it is still a very interesting technological and scientific problem that this chapter would like to treat, at least giving some examples and theoretical indications. Finally, yet importantly, many transmission environments, such as satellite links, need to tackle time varying channel conditions due to fading. The overall model is reported in Figure 5, by showing a set of queues identified by an index, let us say k, and served by a given bandwidth R_k^{TI}[1]. Traffic aggregation, together with the overhead imposed by encapsulation and framing, will require a specific bandwidth at TD layer R^{TD}. From the mathematical viewpoint, the fading effect, of extreme importance for our purpose, may be modelled as a reduction of the bandwidth actually "seen" by the SD buffer, at least in satellite communications [10]. The reduction is represented by a stochastic process $\varphi(t) \in [0,1]$. At time t, the "real" service rate $R_{real}^{TD}(t)$ (available for data transfer) is $R_{real}^{TD}(t) = R^{TD} \cdot \varphi(t)$, where time dependency is explicitly indicated to enforce the concept of varying channel conditions, as well as to consider traffic fluctuations.

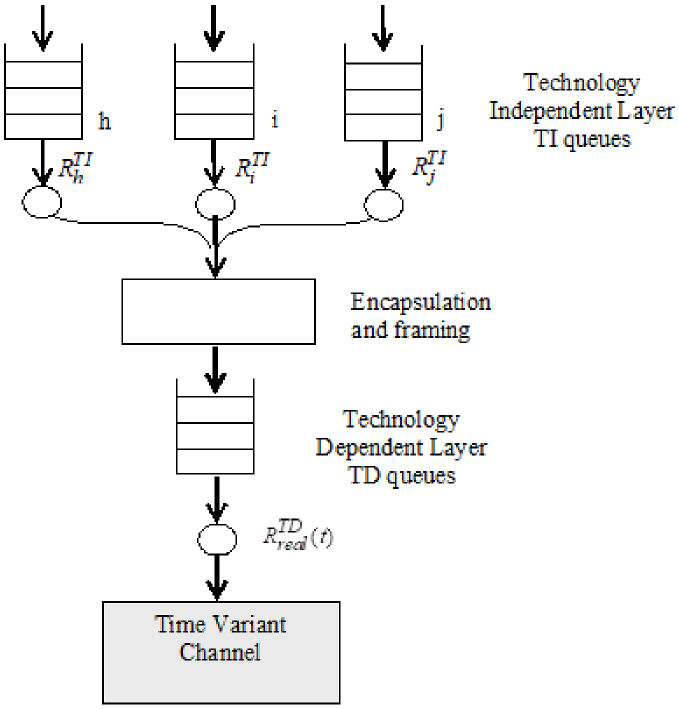

Figure 5. Joint model of vertical QoS mapping.

It is obvious that also other solutions based on off-line measures and on a reasonable overprovision can give good results. The problem is stimulating from the scientific viewpoint. A possible idea to solve the mentioned problems, limiting the information exchange between adjacent layers and without using off-line information will be presented in the next Section.

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[1] As is sometimes done in networking, we may refer to "bandwidth" either in terms of Hz or of bit rate. Obviously, these are not identical quantities; however, once fixed the channel characteristics, the type of modulation and the signal-to-noise ratio, a one-to-one correspondence can be established between the two, which also provides the spectral efficiency of the method in use [bits/s/Hz].

3. QoS Gateways for Satellite and Radio Communication

We will now focus the entire attention on a satellite network portion (to fix ideas, and without loss of generality, we consider a geostationary (GEO) satellite). The creation of the bandwidth pipe derives, in particular, from the action of bandwidth allocation, developed by the block identified as Network Control Centre (NCC). The problem is now how to allocate bandwidth to the satellite portion of the network and, in more detail, to the different earth stations. The reference general architecture is shown in Figure 6.

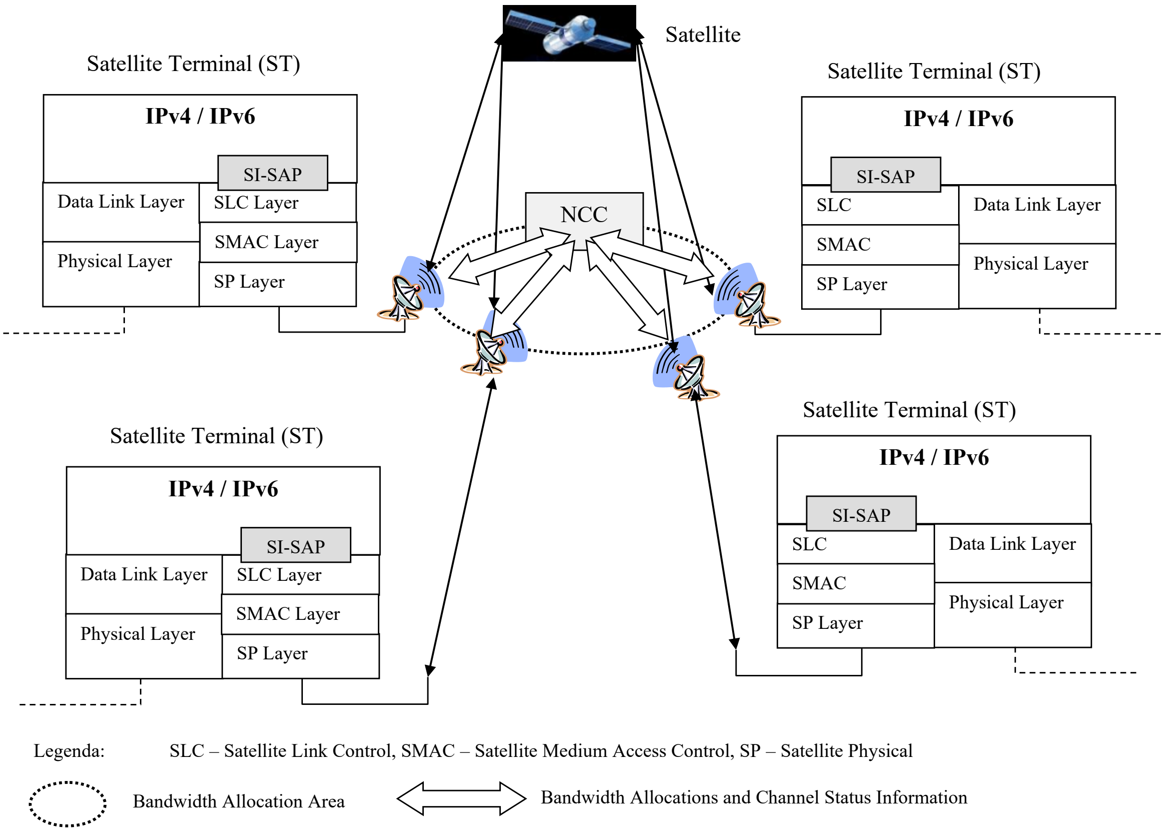

Figure 6. Satellite portion bandwidth allocation.

To formally introduce the problem of bandwidth allocation, it is important to establish models to describe the satellite network portion, the bandwidth allocation scheme, and the channel behavior.

3.1. Network Topology and Bandwidth Allocation Scheme

The network portion considered is composed of Z Satellite Terminals (STs) ($Z=4$, in Figure 6), modelled as nodes gathering traffic from the sources and connected through a satellite connection. The control architecture is centralized: the NCC manages the resources and provides the Satellite Terminals with portions C_Z of the overall bandwidth C_{tot} (TDMA slots, for example, or any other kind of resource units), which provide the maximum service rate of the satellite link. The NCC may be a single physical device or a virtual function, envisaging application in the 5G environment. The practical aim of the allocation is the guarantee of specific QoS requirements (the Service Level Specification – SLS – offered by SD to SI layer) if the overall available bandwidth allows it.

The general scheme of bandwidth allocation is shown in Figure 7.

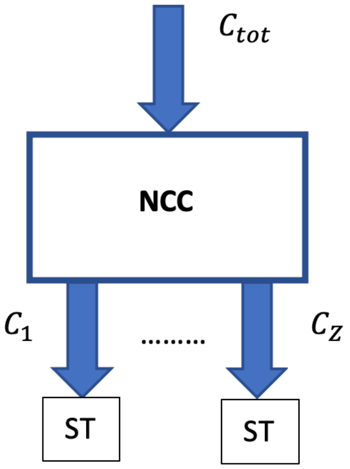

Figure 7. Action of the Bandwidth Allocation.

3.2. A Simple Channel Model

In satellite systems the degradation of the channel quality represents the cause of detriment of communications services. In practice, satellite channels are affected by the same problems of typical terrestrial wireless channels, but additionally they are also significantly corrupted, if the transmission frequencies are high, by meteorological precipitations. In other words, satellite channels are typically affected by rain fading, which is predominant at higher frequencies, especially above 10 GHz. It has a negative impact on QoS. The meteorological state over an ST determines the real availability of the channel bandwidth for transmissions. Fading effects may be compensated (besides power allocation or diversity techniques) by a range of Forward Error Correction (FEC) coding schemes, useful at providing efficient broadband services working under different attenuation conditions. Depending on the fading conditions, the number of bits dedicated to FEC may be increased (or decreased), so improving (or not) the protection power against channel errors. In consequence of the change of the quantity of bits dedicated to protection (or of those dedicated to user information) per channel use, the size of the transported information changes. In dependence on meteorological conditions, Satellite Terminals may provide low-rate services involving powerful FEC coding schemes, when fading is severe, up to high-rate services when channel conditions are good.

So, the problem related to the usage of powerful coding schemes is the bandwidth reduction that determines the effective bandwidth availability. Due to the redundancy bits introduced at the physical layer, the capacity really "seen" by higher layers of the network is reduced, so creating possible bottlenecks. This condition may affect significantly the overall performance. The bandwidth allocation is used to compensate the reduction and to obtain simultaneously physical channel reliability.

The bandwidth reduction due to FEC may be modelled as a multiplicative factor of the overall bandwidth assigned to STs, coherently with reference [10]. The model has been presented in the previous section and it is reported again here by slightly changing the notation, so as to adapt it to bandwidth allocation and to the introduced network topology. The stress is now on the assignment of bandwidth and not on buffer service rate, even if, from the operative viewpoint, there is no difference at all: the assigned bandwidth is just the service rate "given" to the corresponding ST at a given time instant *t*. Mathematically, it means that the real bandwidth $C_z^{real}(t)$ available for the *z-th* ST is its nominal bandwidth $C_z(t)$ reduced by a factor $\varphi_z(t)$, which is, in general, a variable parameter contained in the real numbers interval [0, 1]:

$$C_z^{real}(t) = C_z(t) \cdot \varphi_z(t), \varphi_z(t) \in [0,1] \subset \mathbb{R}, z = 1, \dots, Z \tag{1}$$

A specific value $\varphi_z(t)$ corresponds to a fixed attenuation level "seen" by the *z-th* ST at the instant *t*. The channel model maps the link layer corruption problem to a congestion problem. In this view, the capacity reduction has been considered through the factor $\varphi_z(t)$ and the consequent assumption is that all the packet losses happening during communication may be supposed due to congestion events. On the other hand, in the conditions described, with the use of FEC, the loss due to link layer corruption may be supposed tending to zero and the simple proposed channel model seems to be a reasonable approximation of the satellite radio channel behavior. A numerical example of the mapping between the Carrier Power to One-Sided Noise Spectral Density Ratio P^C/N_0, $\varphi_z(t)$, and used FEC is contained in Table 1 [10, 11], where the overall bit rate available for a carrier is fixed to 8.192 [Mbps]. The values reported in the table allow limiting the bit error probability below 10^{-7}.

P^C/N_0 [dB]	$\varphi_z(t)$	Code Rate and bit rate per carrier
> 77.13	1	4/5, 8.192
74.63 – 77.13	0.8333	2/3, 8.192
72.63 – 74.63	0.625	1/2, 8.192
69.63 – 72.63	0.3125	1/2, 4.096
66.63 – 69.63	0.15625	1/2, 2048
< 66.63	–	outage

Table 1. Signal to Noise ratio and related $\varphi_z(t)$ level at a fixed instant *t*.

In the scenario we consider, each fading level is supposed to happen with an associated probability and associated with a particular FEC. The interpretation of the reduction factor allows making important assumptions:

- in satellite environments, the most common type of link corruption due to noise occurs in the above fashion and packet loss is due mainly to it;
- nevertheless, if FEC schemes are used, the link corruption may be considered as a congestion event.

In practice, increasing FEC bits, the errors due to a faded link may be neglected but, at the same time, the available bandwidth for information is reduced, so creating possible bottlenecks and consequent loss. The considered simple model actually neglects the instantaneous dynamics of fading and, in this view, it should be substituted with a more precise channel model. Nevertheless, within the described framework, the assumption is not too severe and seems a reasonable approximation of the satellite channel behavior, at least concerning bandwidth control algorithms [10 – 12].

3.3. Bandwidth Allocation Algorithms

The computation of individual $C_z(t)$ allocations at instant *t* depends on the total amount of resources $C_{tot}(t)$ available at the NCC and on the amounts requested by the STs at the specific decision time. The latter may stem from the vertical mapping mechanism that has to decide how to translate the service rates $R_k^{TI}, k = 1, \dots, K,$ for the Technology Independent service queues (determined by the Service Level Agreement (SLA) negotiated with the specific traffic flow each one is serving) into the aggregate service rate $R_{real}^{TD}(t)$ (considering, without loss of generality, mapping to a single TD queue), which takes also into account the channel conditions, in order to maintain the performance requirements (e.g., in terms of packet loss rate and average delay per packet) as close as possible to the values required by the SLAs.

Before providing a hint to a specific technique to perform this operation, whose treatment is reported in [3] and [13], it is worth making a general remark pertaining to this setting. Indeed, the specific architecture we have described lends itself almost naturally to a hierarchical control structure, where local decisions are taken at the earth stations or at the satellite gateways, in correspondence of a certain bandwidth assignment, and a global optimization is performed by the NCC, which plays the role of a coordinator in deciding the bandwidth allocation, which may be periodically updated if channel or traffic conditions change significantly. This vision has been followed by many papers that appeared in the first decade of the years 2000; some of them are surveyed, among others, in [14] and [15]. Regarding the local optimization, two alternative possible approaches are the aforementioned vertical QoS mapping (a different formulation of which has been also considered in [16, 17]), where differentiated queues are present for QoS categories, or a rougher division among real-time and best-effort traffic, as taken for instance in [11, 10, 18].

Whereas the approaches taken in the above-mentioned references are based on analytical queueing models, the mechanism adopted in [3] and [13] is based on Infinitesimal Perturbation Analysis (IPA), in the mathematical framework of Stochastic Fluid Models [19, 20]. Under a fluid dynamic representation of the queueing system in terms of inflow and outflow rates, suitable cost functions to be minimized are defined for the SD layer. They reflect the quadratic deviation of loss and workload, at the SD layer, from the same quantities measured at the SI layer, used as thresholds, in order to try to follow (chase) the performance at the SI layer. Following IPA, estimations of the gradient of the cost functions are obtained in real time on the basis of traffic samples acquired during the system evolution and descent steps are taken along a realization of the underlying stochastic processes.

Regarding instead the centralized NCC problem in the presence of analytical traffic and system models, it can be solved either through ordinary numerical minimization, by considering the bandwidth portions to be assigned as continuous variables, or through discrete optimization, by applying a computationally efficient dynamic programming algorithm [18], or even by posing it as a multi-objective optimization problem [12]. However, fluid models and IPA can be applied also in this setting, with the advantage of not requiring an analytical model or knowledge of the underlying stochastic processes [21, 22]. In this perspective, we outline a discussion in the next section that will lead us to consider Machine Learning (ML) implementations, which, as we will see later on, fit with the current architectural evolution towards network virtualization and with the increasing complexity of the problems at hand, caused by the growth in the number of devices, users and user-generated traffic volumes.

4. From Analytical Modeling to ML Techniques

As we have seen in the bandwidth allocation problems above, traditional approaches to network management and control often rely on analytical models. These entail some knowledge of the physical phenomenon under study, which may happen in a Cyber-Physical System (CPS) or in the elements of the network itself, like buffers, links, gateways, routers and switches, network processors, etc., along with a characterization of the traffic flows through such elements, possibly with different granularities (typically, flow- or packet-level).

Typical (stochastic) dynamic models in these settings may be in the form of Markov processes or also non-Markovian queueing systems. Depending on the time scales of the phenomenon of interest, it may be necessary to represent a non-stationary or stationary behavior (i.e., where the probability distributions do not change in time, at least over a certain time horizon). Then, if one wants to formulate an optimal control problem for the system under consideration, different performance (or cost) functions can be constructed that reflect a property or KPI of interest (often in the form of expected values). In the dynamic non-stationary case, the control law (i.e., the function mapping the system state or observations thereof to control actions) will be influenced by the system dynamics. Typically, this will be the case of Markov Decision Processes (MDPs) and, depending on the complexity of the problem, the form of the control law may be left general and unknown (giving rise to a *functional* optimization problem that may be solved analytically in very few cases), or it may be fixed a priori, limiting the optimization to control strategies of a specific form (e.g., an on-off – also called “bang-bang” – control law, a threshold function, a linear or affine one, …), which may be represented by a finite number of parameters, transforming the optimization problem into a *parametric* one to be solved by numerical methods. Most of the analytical approaches to bandwidth allocation we mentioned in the previous section fall under this category. In all these cases, where the performance indexes may be expressed by averages computed over a finite or infinite time horizon, various techniques are available to decompose or simplify the problem (Dynamic Programming, Open-Loop-Feedback or “Receding Horizon” controls, etc.; see e.g. [23]). A situation of parametric optimization is found also in the presence of stationary queueing models, if the control can be expressed in terms of parameters (representing, e.g., load balancing coefficients, bandwidth partitions, processors’ energy states, …), as in some of the works we have cited above.

Somehow intermediate to the two approaches described (MDP with functional optimization or parametric optimization), are other ones that employ different techniques that, though possibly still based on models, require less knowledge on the stochastic phenomena underlying the system dynamics. One of these is that of Neely [24], based on Lyapunov optimization, which has actually been applied in a Low Earth Orbit (LEO) satellite context, where energy efficiency was accounted for as one of the KPIs [25] (see, e.g., [26, 27] for energy efficiency / performance trade-offs in satellite communications and networking). A concept that somehow captures “… a summary of the statistical characteristics of sources over different time and space scales” [28] (even in the case of poorly characterized traffic, as noted by the author) is that of effective (or equivalent) bandwidth. Though not in the satellite environment, another analytical approach to rate control that does not require a statistical characterization of traffic is that of [29].

Such analytical approaches have been at the basis of numerous successful achievements in network management and control, under the general context of *Teletraffic Theory*. However, the network softwarization phenomenon and the ensuing introduction of virtualization concepts in networking, along with new traffic characteristics, have rendered the complexity of network management and control problems much higher than it used to be in legacy networks with special-purpose hardware. Networks have become much more akin to computer systems, and the boundary between computation and communication tasks has turned out to be less well-defined. On the other hand, while tasks in computer systems are under the control of a central unit, the nature of computational processes occurring in networks is much more distributed. A chain of virtual network functions performing a network service is composed of multiple virtual elements that may be physically separated and, moreover, reside on shared hardware, where access to the resources is mediated by a hypervisor; performance requirements and QoS are often expressed and measured in end-to-end terms. For instance, regarding energy consumption KPIs, it becomes much less straightforward to attribute part of the energy consumed by the hardware to a specific virtual entity, in order to trade-off energy with performance indicators on the basis of clear analytical models. Moreover, with the growing complexity and distribution of network functions and services, the need arises for autonomous mechanisms that can perform network management and control operations autonomically and with minimal human intervention.

As was noted in [22], among others, quite a few optimization problems for resource allocation in networking have a discrete stochastic programming nature. Without consideration of the system's dynamics, which may add further complexity, a general characterization of these problems is in terms of a vector $\boldsymbol{\theta}$ of decision variables, often in the form of nonnegative integers, which must be modified along time as outputs of the control policies, in order to optimize the system performance (e.g., our previously considered bandwidth allocation variables). In very broad terms, one looks for the vector $\boldsymbol{\theta}^*$ such that

$$\boldsymbol{\theta}^* = \operatorname*{argmin}_{\boldsymbol{\theta}\in\Theta} \underset{\boldsymbol{\omega}}{E}\{L(\boldsymbol{\theta},\boldsymbol{\omega})\} \tag{2}$$

where $\boldsymbol{\omega}$ represents a vector of stochastic variables, E denotes statistical expectation (over all possible realizations of the stochastic variables), $L(\cdot,\cdot)$ is a function representing a metric of interest (e.g., average delay per packet, packet loss probability, or, in the case of flows, blocking probability) and Θ is a constraint set. Still in many cases, the random variables may have a poor statistical characterization, the cost function may not be expressed analytically or, even if it is, the expectation may be very difficult to compute, requiring the use of gradient approximation techniques (with suitable relaxations of the problem in the case of integer decision variables), where a descent step is performed along a *realization* of the stochastic variables. Note that, in general, the vector $\boldsymbol{\theta}$ may represent a set of parameters, but also the output of decision strategies mapping observations to control actions (which would render the problem one of *functional* optimization). Another drawback in such problems, in the presence of system dynamics, may be the difficulty of obtaining closed-form functional costs that can lead to closed-loop control strategies, limiting the search to parameter-adaptive *certainty equivalent* control [23].

We have seen that in this context, IPA provides sensitivity algorithms that allow estimation of the gradient of the cost function, on the basis of observations of the sample paths followed by the underlying stochastic process. In the case of discrete variables, suitable relaxations can be constructed (*online surrogate optimization methodologies*) that allow the use of such gradient descent techniques [30, 31]. However, such pure gradient descent optimization techniques may perform well in parametric optimization problems under a stationary behavior of the stochastic processes but may be less efficient in facing control problems where the decision variables are functions of information acquired in successive instants and the system evolution is described by dynamic equations. In [22] the IPA-based online surrogate optimization problem in a satellite environment has been compared to a solution obtained by using neural networks, whereas the first technique has been adopted in a similar setting in [21].

Though the above-mentioned IPA techniques are not ordinarily classified as ML mechanisms, nevertheless they are representative of control approaches that deal with difficulties in obtaining an analytic system and cost representation. ML approaches represent a class of more powerful techniques, and also have the advantage of not necessarily requiring an underlying model, as they are by definition based on numerical approximations. In many cases, what is required is the parametric approximation of an unknown function depending on multiple variables, by means of linear combinations of *Fixed Structure Parametrized* (FSP) [32] functions (often represented by nonlinear functions containing parameters to be tuned inside such basis functions). Among them, Neural Networks (NNs) and, more recently, Deep Neural Networks [33, 34] have become the most popular ML mechanisms based on FSP functions. Two recent works that survey this field in relation to wireless networks are [35] and [36].

Regarding NN-based ML architectures, however, a clear distinction and a thorough analysis is performed in [32] between the use of FSP functions to approximate a function of several variables (which may be known only pointwise), with a certain approximation error with respect to a given norm (which is one of the most common applications of NNs, e.g., in the recognition of features or objects), and the use of FSP functions in the approximation of multi-variable functions that constitute the solution to an Infinite Dimensional Optimization (IDO) problem, like the *functional* optimization problems arising in closed-loop optimal control. The *Extended Ritz Method* (ERIM) introduced in [32] reveals to be in many cases a powerful mechanism for this type of problems, many of which appear also in networking. Basically, by means of ERIM, the (functional) solution of many complex control and decision problems can be approximated by families of FSP functions, by expressing the approximation as a linear combination of fixed structure FSP basis functions, where parameters also appear within the basis functions themselves (e.g., One Hidden Layer (OHL) or Multi Hidden Layer (MHL) neural networks). A potential advantage here is that in quite a few cases of IDO control problems, a family of approximating functions can be found that allows avoiding the so-called "curse of dimensionality": namely, the growth in the dimension of the parametrization with increasing number of variables the function to be approximated depends on. It is worth noting that the nonlinear optimization problems stemming from this approach to the solution of IDO control problems can be solved "off-line", either at the edge itself in micro-datacenters or in the datacenter of a remote cloud. However, once computed the parameters of the approximating functions (if the iterations of the nonlinear program converge within the limits of a fixed approximation error), the approximated control law is available and, for each realization of variables upon which it performs its mapping, the calculation of the corresponding control actions is straightforward. As in all parametrized problems, decision strategies implemented in this way can be applied as long as the underlying system structure or the statistics of the random variables characterizing the input traffic do not change significantly (within certain tolerance margins: a significant change in these quantities would imply the necessity of recalculating the parameters of the approximating functions). Another potential power of the method is that it can be applied also in informationally decentralized control problems with multiple decision makers (DMs), which are usually very difficult to solve analytically, especially in the team theory context and in the presence of constraints, where the DMs have a common goal but different online information.

Still in the control setting, other widely adopted uses of neural FSP functions are in *Neuro-Dynamic Programming* [37] (which has similarities with *Reinforcement Learning* – a name mostly used in the Artificial Intelligence (AI) literature, and *Q-learning*; see [38] for a survey), and *Approximate Dynamic Programming* for optimal control problems over finite or infinite time horizons [32]. Though differing in various respects, all these techniques construct an approximation of the *cost-to-go* of Dynamic Programming (DP). A brief description may be in order here (to fix ideas, we refer to the minimization of a cost function). In a DP decomposition, the basic step is to decompose an optimization problem into stages, and perform a minimization at each stage, by accounting for the effect of the control strategy so computed on the future stages of the problem. If the application of the control at a current state value and the state itself are associated a cost that depends only on them and the total cost is a sum of such terms, the decomposition can be applied by proceeding backwards, and by minimizing at each step t the sum of the stage cost and of the optimal cost corresponding to all forward stages from the current one, which is a function of the state value at stage $t + 1$. This second term in the minimization is exactly what is termed *cost-to-go*. In different ways, all the techniques we have mentioned in this last paragraph of the Section construct functional approximations of this term, which may be very difficult, if not impossible, to compute analytically in the presence of nonlinearities in the state equations, non-quadratic cost and non-Gaussian noise, besides the possible discretization of the state variables when their components range over a subset of the reals. Depending on the technique adopted, the system dynamics may be known or even partially or completely unknown.

5. Toward a Functional Architecture for 5G-Integrated Satellite Networking

The evolution in algorithms and techniques that we have outlined in the previous Section is in line with the architectural paradigms that accompanied the development of 5G and the growing integration between the mobile wireless and fixed network segments, and that have been spreading at a fast pace. Network Functions Virtualization (NFV) [39], Software Defined Networking (SDN) [40] and Mobile Edge Computing (MEC) [41] are among the main concepts behind such paradigms, which have spread from the cloud to embrace the networking domain and have brought forth the abstraction of network slices [42]. In this framework, as we noticed in [43], "*[t]he business/operational support systems (BSSs/OSSs) of upcoming 5G network platforms are meant to expose "customized" and isolated virtual projections of the mobile network (i.e., network slices) to vertical industries and OTT players, so as to enable them to run their applications and services on top of these network slices. To this end, a network slice is composed of a number of logical subnetworks that can have different roles and configurations. Such subnetworks can be instantiated as "private" network projections inside the slice, or shared among multiple slices (e.g., to attach multiple slices to the same radio access network).*"

The flexible and programmable networking environment stemming from this scenario lends itself, on one hand, to the full integration of the satellite segment and, on the other, to the adoption of the novel ML techniques for resource allocation that we have mentioned. With regard to the first aspect, quite a few works, besides [43], have addressed the issue (see, e.g., [44 – 46]). However, in the evolutionary perspective we have undertaken, it is worth outlining here the conceptual connection between the BSM architectural view we have started from and the novel architectural concepts that allow the service orchestration and logical separation (at both application and network levels) at the basis of the new paradigms.

Orchestration is needed to handle the complexity of application services that are designed and created as chains of micro-services at the application level and as chains of Virtual Network Functions (VNFs) at the network level (where a relevant framework is provided in particular by ETSI MANO – Management and Orchestration [47]). An important aspect, however, not always properly evidenced, is that of the separation of concerns between applications' and network functions' orchestrators, which has been stressed specifically by the recently concluded H2020 5G PPP European Project MATILDA [48, 49]. More specifically, the domain of vertical cloud-native applications [50], empowered with the service mesh concept [51, 52] and with suitable *sidecar proxies* [53] that allow the application developer to extend the micro-services capabilities with the specification of their communications needs, should be the concern of a Vertical Application Orchestrator (VAO). The VAO should allow application providers and application developers to operate with the mechanisms of the cloud environment they are used to; however, at the same time, it should enable them to fully exploit the advanced communication capabilities offered by 5G, by abstracting the physical network with the slice concept, transparently with respect to the heterogeneous underlying physical infrastructure (including the satellite segment) and providing the means to convey their communication needs and constraints to the Telecommunication Service Provider (TSP), and to constantly maintain this interaction during the lifecycle of their applications. Through the mediation of the OSS the TSP can receive the specifications that characterize a particular vertical application via a *slice intent*, and has the task to configure, deploy and manage the needed resources for the creation of the slice (by means of the Virtual Network Functions Orchestrator – NFVO – provided in the MANO framework), which is then exposed to the VAO through a well-defined Northbound interface, and can be monitored and reconfigured, if necessary, to maintain QoS requirements.

We advocate that a similar separation concept is intrinsic to the BSM architecture we have briefly described in Section 2, entailing a clear separation between SI and SD (or, more generally, TI and TD) layers, with the interaction granted through the SI-SAP (or, more generally, TI-SAP). As such, this architectural perspective can play a similar role within the network, by separating what is closer to the physical infrastructure, where functionalities may be implemented by means of a mix of VNFs and Physical Network Functions (PNFs), orchestrated by a Satellite Dependent Orchestrator (SDO), from what pertains to the VNFs in the Technology-Independent layer. We believe that this separation concept could greatly foster the integration of the satellite segment within 5G and beyond, along the lines we have sketched in [43].

An additional remark is in order here to stress the relevance of a specific type of satellite communications in this integration. So far, to fix ideas, we have almost implicitly referred to GEO satellites. However, the growing importance of LEO small- and nano-scale satellite constellations [54] is hard denying. They are part of what is termed the “Internet of Space Things” in [55] and will constitute an essential complement to the terrestrial wireless part. In that framework, characterized by the presence of multiple constellations, intermittent connectivity, intersatellite links and, in general, more distributed data and control plane functionalities, the SI-SD separation acquires even more momentum.

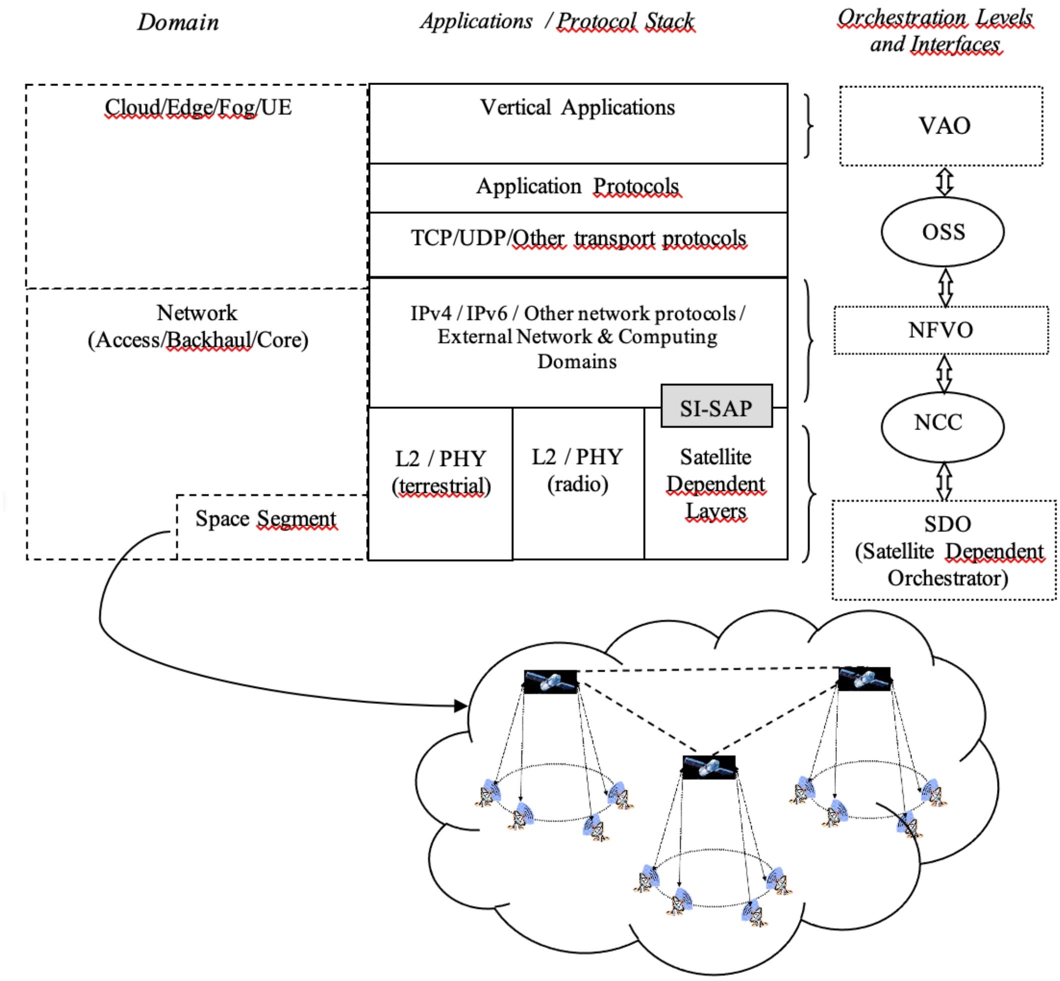

Figure 8. Architectural layout with the inclusion of the satellite segment and its orchestration.

We report in Fig. 8 an abstract view of the architectural layout we have described, referring to a satellite constellation with the presence of inter-satellite links, and highlighting the domains spanned and the presence of the various orchestration levels, along with the mediation points between them (OSS and NCC, as regards the VAO-NFVO and NFVO-SDO interactions, respectively). The creation of a slice in this case would start from the request of the VAO, passed along to the NFVO through the slice intent; in the case that satellite resources were needed, the NFVO would request the appropriate configuration to the SDO via the NCC.

Finally, we have already mentioned some of the reasons that would push towards the adoption of the ML techniques that were briefly surveyed in Section 4 in flexible and programmable networks. There is actually a mutual influence between the "softwarized" networking and application environment that was described above and the adoption of optimization techniques for resource allocation, management and control based on powerful functional approximation methodologies, especially in the Edge, where computational intelligence is being moved. In this respect, reference [36] contains an interesting discussion about ML for Communications (MLC) and Communications for ML (CML), and the vision presented in [56, Ch. 4], where "AI-as-a-Service" (AIaaS) is envisaged, is in line with it.

6. Conclusions

We have attempted in this chapter to merge the vision of flexible and programmable networks that already permeates the networking scenario in the evolution toward the Next Generation Internet, which entails a growing integration between the mobile wireless and the fixed network (as already happens in 5G and is bound to strengthen in 6G), and the satellite segment. In doing so, we have taken a historical perspective and we have mixed architectural and algorithmic considerations.

Starting from the ETSI BSM vision of the early 2000s, we have outlined its relevance in the analytical and numerical approaches that marked the development of resource allocation (mainly, in terms of bandwidth) prior to the advent of network softwarization. We have then examined some of the reasons behind the adoption of ML techniques to perform the same operations in a more powerful fashion and, finally, we have tried to match these techniques to the new architectural paradigms stemming from network softwarization.

We believe that there are plenty of opportunities for research in this field to revisit some of the problems that were posed in the earlier context and to devise the new solutions and approaches that are made possible by the joint action of architectural and computational advances.

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