Coordination of Radio Access and Optical Transport

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***Abstract*—New 5G and beyond applications demand strict delay requirements. In this paper, we propose coordination between radio access and optical transport to guarantee such delay while optimizing optical capacity allocation. Illustrative results show near real-time autonomous capacity adaptation benefits based on radio access delay requirements.**

Keywords—Network Segment Coordination; Multidomain networks

I. INTRODUCTION

The support of 5G and beyond use cases requires bringing the optical network to the very edge of the network not only to increase capacity, but also to guarantee end-to-end (e2e) quality of service (QoS), e.g., delay. Such e2e QoS requires that both 5G radio access network (RAN) and optical transport operate under strict QoS constraints [1]. However, establishing fixed capacity optical connections to connect RAN to 5G core entails large capacity overprovisioning, increasing thus the total cost of ownership to network operators. An option is to implement digital subcarrier multiplexing (DSCM) optical systems, which allows to activate/deactivate each subcarrier (SC) independently in near real-time to provide just the needed capacity and meet the maximum delay requirement [2]. Near real-time operation needs to be implemented as close as possible to the data plane, to liberate the software-defined networking (SDN) controller from those tasks. In our previous work in [2], we proposed a solution based on Reinforcement Learning (RL), which showed its ability to learn the optimal policy based on the specified operational objectives.

Even though the use of DSCM systems can reduce costs, there is still a large amount of overprovisioning in the optical network just because of the lack of coordination between radio and optical segments. In this paper, we propose coordination between both network segments, so the e2e delay is ensured and optical capacity overprovisioning is decreased. To this end, we adopt the deep RL (DRL) solution from [3] that used pre-trained models for specific operational parameters, e.g., delay. With such solution, the maximum delay allowed for the optical network can be changed based on the requirements from the RAN and adapt the optical capacity accordingly; this will bring capacity overprovisioning to a minimum.

II. AUTONOMOUS OPERATION

Fig. 1a shows the analyzed e2e scenario, where user equipment (UE) request virtualized 5G services placed in a remote location in the fixed network, e.g., a metro/core site. Without loss of generality, we assume that UEs and the 5G core are the endpoints of e2e traffic and that some *maximum e2e delay* needs to be ensured. Hence, the e2e traffic flow consists of two components for the RAN and the optical network.

The component of such e2e traffic flow that traverses the RAN is represented by a blue thick arrow. We consider that a RAN cell consists of a single macro base station (i.e., a next-Generation Node B - gNB) that covers the whole cell area. The configuration of the gNB, e.g., numerology, bandwidth, power, etc., can be configured to support capacity and latency requirements. This configuration has a direct impact on the actual QoS. As an example, the inset graphs in Fig. 1a show the behavior of the RAN delay component as a function of gNB load, assuming a typical 5G configuration. We observe that, in order to achieve low delay, the *RAN controller* needs to operate the gNB up to some percentage of its capacity (e.g., 60%); otherwise, the RAN delay component would increase up to the point that the committed e2e delay requirement (e.g., 2 ms) cannot be achieved. Even when the RAN works in that low to moderate load regime, delay fluctuations can be observed since traffic typically varies throughout the day, making load also variable in time. In the example, the RAN delay component oscillates between 1 and 1.5 ms in a day, which entails a stringent delay budget for the optical network delay component that such network has to guarantee.

Let us assume that a *cell site gateway* (CSG) is the boundary between the RAN and the fixed optical transport network. For the sake of simplicity, we assume that traffic flow at the fixed network (green thick arrow) transparently traverses single or multiple optical domains inside a single e2e lightpath. The capacity of such lightpath can be properly dimensioned by dynamically activating/deactivating SCs to provide the required QoS. In line with [2], autonomous optical capacity management with QoS guarantees can be realized in the fixed transport network segment by means of the control architecture sketched in Fig. 1a, where different entities are considered (from bottom to top): *i*) the *transponder* (TP) *agent* that is in charge of collating telemetry data, e.g., traffic and measured delay from the TPs, as well as to manage SCs to ensure the committed QoS; *ii*) the *capacity manager* that uses telemetry to run policies, models, and rules to find the required capacity that better satisfies the target QoS; *iii*) the *SDN controller* that is in charge of the initial lightpath setup and of communicating the capacity manager key parameters, such as the required QoS.

It is worth noting that both RAN and optical network

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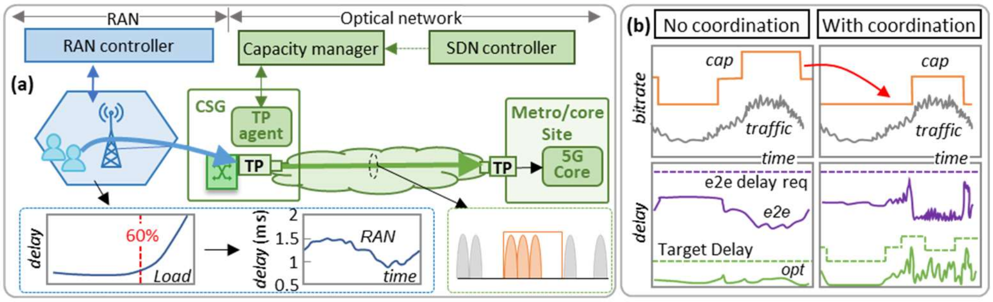

Fig. 1 Reference e2e scenario, b) autonomous capacity management performance

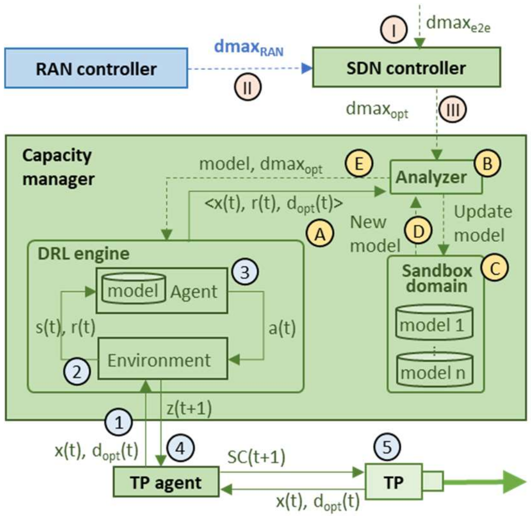

Fig. 2 Coordinated RL-based operation

domains operate without any coordination among them, which entails overprovisioning capacity in the lightpath to meet a fixed target optical network delay component that absorbs delay variations introduced by the RAN. This is illustrated in Fig. 1b (left), where the optical capacity is dynamically adjusted to keep the optical network delay component under control. In our example, if the RAN can introduce up to 1.5 ms of delay, the target optical network delay needs to be setup at 0.5 ms to guarantee that the maximum 2 ms of e2e delay is met. Although this uncoordinated strategy can guarantee e2e QoS and provide some dynamic capacity adaption, it results in large overprovisioning if the RAN delay is far from the maximum.

In view of the above, we propose coordinating RAN and optical network operation to dynamically adjust the target optical network delay component to the current traffic conditions. We claim that overprovisioning can be greatly reduced while guaranteeing e2e delay (Fig. 1b right). Next section presents a coordinated RL-based solution for optical capacity management with QoS guarantees.

III. AUTONOMOUS CAPACITY MANAGEMENT BASED ON DRL

Fig. 2 details the proposed architecture for RL-based capacity management with QoS guarantees. We adapted the architecture for packet flow management in single network domains in [2] to deal with: *i*) coordination between RAN and optical network domains; *ii*) QoS assurance; and *iii*) DSCM-based optical capacity management.

At the core of the system, the capacity manager implements a *DRL engine*. The engine finds, at every time interval t, the minimum optical capacity $z(t)$ to ensure that the optical network delay component $d_{opt}(t)$ does not exceed a given target $dmax_{opt}$. Thus, at every time t, telemetry traffic $x(t)$ and delay $d_{opt}(t)$ are retrieved from the TP agent and fed into the DRL *environment* (1 in Fig. 2), which is in charge of computing the current state $s(t)$ and reward $r(t)$ (2). In particular:

$$s(t) = z(t) - x(t) \tag{1}$$

$$r(t) = r_l(t) + r_d(t) + r_z(t), \tag{2}$$

where reward penalizes traffic loss (r_l), target delay violation (r_d), and capacity overprovisioning (r_z).

Eqs. (3)-(5) present detailed expressions for all reward components, where Ω and β are constants ($\Omega > \beta > 1$). Then, the DRL *agent* processes $s(t)$ and $r(t)$ for both learning and decision-making (3). Action $a(t)$ is translated into the required capacity for the next time interval $z(t+1)$ (4), which is processed by the TP agent to activate/deactivate SCs (5).

$$r_l(t) = \begin{cases} -\Omega - \dfrac{x(t)}{z(t)}, & x(t) > z(t) \\ 0, & x(t) \le z(t) \end{cases} \tag{3}$$

$$r_d(t) = \begin{cases} -\beta - \dfrac{d_{opt}(t)}{dmax_{opt}}, & d_{opt}(t) > dmax_{opt} \\ 0, & d_{opt}(t) \le dmax_{opt} \end{cases} \tag{4}$$

$$r_z(t) = -z(t)/x(t) \tag{5}$$

To better adapt to large variations in $d_{opt}(t)$ or changes in $dmax_{opt}$, the *analyzer* block receives relevant inputs from DRL engine (labeled A in Fig. 2), evaluates the performance of the current DRL model (B) and, if needed, requests the *sandbox domain* entity to provide the pre-trained model that better fits the current scenario (C). Upon request, the sandbox provides a new model (D) that is fed into the DRL engine (E).

Finally, coordination between domains is implemented to satisfy the e2e delay requirement. Let us assume that, upon provisioning of the e2e service, the optical network controller receives the required e2e delay $dmax_{e2e}$ (labeled I in Fig. 2). Once operation starts, the RAN controller is able to asynchronously notify its maximum delay $dmax_{RAN}$ to the optical network controller (II). The optical network controller computes the requirement for the optical segment as $dmax_{opt} = dmax_{e2e} - dmax_{RAN}$, and pushes this value to the capacity manager (III). At this point, the DRL engine will work to guarantee such updated $dmax_{opt}$ requirement.

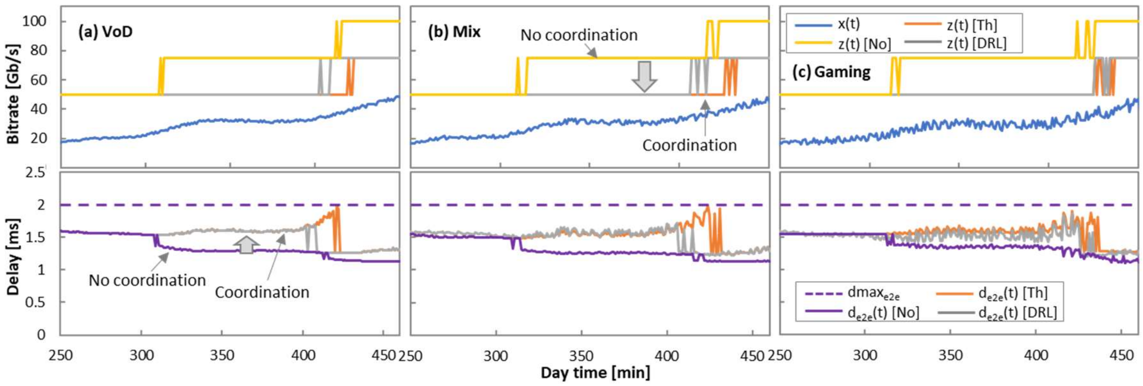

Fig. 3 Capacity management and e2e delay assurance for scenarios: VoD only (1), VoD + Gaming (2), and Gaming only (3).

Table 1. Allocated capacity and SC changes per day

Approach	Capacity [Tb/s]			SC changes		
	VoD	Mix	Gaming	VoD	Mix	Gaming
No	109.9	109.7	10.9.1	19	17	25
Th	87.9	87.7	87.2	12	18	30
DRL	**87.3**	**87**	**86.3**	**10**	**8**	**12**

IV. Results and Concluding Remarks

For numerical evaluation, we developed a simulation environment combining different tools for RAN and optical network emulation. Regarding RAN simulation, we adopted the open-source discrete-event ns-3 network simulator with the 5G-LENA module extension [4] to simulate the 5G New Radio (NR) technology. In particular, we simulated a scenario with a gNB (one omnidirectional antenna, single bandwidth part at a central frequency of 28GHz and 400MHz of bandwidth) and several UEs sending uplink UDP traffic. Traffic from video on demand (VoD) and online gaming services were generated according to the characterization in [5]; we assume a typical daily profile to create variable gNB load in a time not exceeding 60%. For the sake of simplicity, we considered interference-free radio links with line-of-sight between the gNB and the UEs. The *proportional fair* scheduler was considered. UDP traffic was scaled up to emulate a dense area with 40 gNBs with the same input traffic and delay behavior.

The UDP traffic and maximum delay obtained with the RAN simulator were then aggregated with granularity of 1 minute and injected as $x(t)$ and $dmax_{RAN}$ in a Python-based optical simulation environment. This tool, built upon those ones in [2] and [3], implements all the blocks and procedures shown in Fig. 2. The DRL engine was implemented using Twin Delayed Deep Deterministic Policy Gradients (TD3), an off-policy DRL algorithm that uses a pair of critic networks and an actor-network that is updated with some periodicity. A set of TD3-based models, trained with traffic with similar characteristics to that of VoD and gaming for different operational ranges for $dmax_{opt}$, were loaded in the sandbox domain before starting simulations. Finally, a DSCM-based lightpath was emulated, assuming a 100 Gb/s optical TP equipped with 4×25 Gb/s SCs.

The proposed DRL-based coordination method described in Section III (hereafter, referred to as *DRL*) has been numerically evaluated and compared against two benchmarking approaches. Aiming at evaluating the benefits of coordination, the first method (labeled *No*) assumes no coordination and hence, $dmax_{opt}$ is fixed to a restrictive value to ensure $dmax_{e2e}$. Then, aiming at evaluating the performance of the proposed DRL-based engine, the second method (labeled *Th*) implements coordination but it implements a threshold-based method to adjust capacity with *perfect knowledge* of the actual future delay, which is unfeasible to implement in a real network.

Fig. 3 shows the allocated optical capacity (top row) and e2e delay (bottom row) for part of a day with increasing traffic; results for the evaluated approaches and different traffic scenarios (only VoD, mix of VoD and gaming, and only gaming) and $dmax_{e2e}$ = 2ms are plot. Table 1 complements Fig. 3 with the optical capacity allocated in a day and the total number of SC activation/deactivations per day. We observe that coordination allows remarkable reduction of overprovisioned capacity in all evaluated scenarios without violating $dmax_{e2e}$. Interestingly, low loads produced slightly higher $dmax_{RAN}$ (and consequently, stringent $dmax_{opt}$ requirement), which is due to signaling overhead [6]. We observe that the proposed DRL-based method is able to improve the unrealistic threshold-based method with *a priori* perfect knowledge of $d_{opt}(t)$. Such improvement is small in terms of allocated capacity but significant in terms of the number of SC changes. Note that our DRL approach requires less changes, which indicates that its operation is able to anticipate increments or decrements of optical capacity, thus reducing unnecessary capacity fluctuations as well as overall management complexity.

The benefits of coordination between RAN access and optical transport for e2e QoS assurance have been demonstrated thought simulation and the proposed DRL-based operation showed optimal and smooth optical capacity allocation.

[1] A. Bernal *et al.*, “Near real-time estimation of end-to-end performance in converged fixed-mobile networks,” Comp. Comm., 2020.

[2] L. Velasco *et al.*, “Autonomous and Energy Efficient Lightpath Operation based on Digital Subcarrier Multiplexing,” IEEE JSAC, 2021.

[3] S. Barzegar *et al.*, “Packet Flow Capacity Autonomous Operation based on Reinforcement Learning,” Sensors, 2021.

[4] N. Patriciello *et al.*, “An E2E Simulator for 5G NR Networks,” Elsevier Simulation Modelling Practice and Theory, 2019.

[5] M. Ruiz *et al.*, “CURSA-SQ: A Methodology for Service-Centric Traffic Flow Analysis,” IEEE/OSA JOCN, 2018.

[6] N. Patriciello *et al.*, “5G new radio numerologies and their impact on the end-to-end latency,” in proc. IEEE CAMAD, 2018.