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Towards 6G: Machine Learning Driven Resource Allocation in Next Generation Optical Access Networks (Invited)

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Abstract *6G networks will deliver immersive applications that bridge real and digital worlds. The next-generation optical access network is a potential optical transport solution. In view of dynamic network conditions, we propose a machine learning driven solution that rapidly self-adapts to support new 6G applications. ©2022 The Author(s)*

Introduction

Over the last 30 years, optical access networks have continued to evolve to satisfy the ever-increasing bandwidth demand, customer numbers and quality-of-service requirements of fixed business and residential, as well as 4G and 5G mobile network deployments [1]. Specifically, passive optical network (PON) standards are now specifying speeds of up to an aggregate 50 Gbps, e.g. IEEE 802.3ca 25G/50G-EPON standard [2] and the ITU-T G.9804 High Speed PON [3]. With a point-to-multipoint physical topology that harnesses a shared fibre infrastructure, low component count alongside an unpowered optical distribution network (ODN), PON yields substantial cost-savings [4]. The physical topology of the PON also lends itself naturally to statistically multiplexing densely located remote radio units (RU) of the centralised radio access network (RAN) architecture. In this architecture, Central/Distribution Units (CU/DUs) are located at the central office of the PON and are connected directly via the ODN to remote Radio Units (RUs) located at the optical network units (ONUs).

Today, as mobile networks evolve towards 6G with the use of increasingly higher carrier frequencies that necessitates shorter-ranged, smaller-sized and highly-dense cells, the above-mentioned benefits of PON as a mobile fronthaul (MFH) solution, is just as relevant. With fibre installations penetrating deeper towards the end user equipment (UE) and with speeds of 50 Gbps and beyond, PON technology is expected to increase the reach and provide the capacity required by 6G. The business case to consider an optical rather than a radio access network (RAN) becomes even more compelling when spare fibre in already installed optical access networks, e.g. urban cities, is available for use [5].

However, 6G is envisioned to support diverse and immersive applications including mixed reality (XR), holographic communication, human-to-machine/robot communications, Tactile Internet, digital sensing, *etc*. [6]. So even though the deployment of PON technology may meet MFH bandwidth requirements, open challenges pertaining to meeting differing quality-of-service requirements of 6G immersive applications, still exist. That is, not only must the unprecedented demand for high-bandwidth capacities (> 1Tbps) be met, ultra-low latencies (~ microseconds), ultra-high reliability (6 nines), and massive connectivity over 3D coverage areas must also be supported [1].

As such, 6G will need to adopt truly open RANs (O-RANs) with intelligent and interoperable RAN elements and RAN software, alongside machine intelligence to enable real-time network resource and network failure management decisions. In this regard, the O-RAN Alliance supports the functional split of option 7.2 to meet high-capacity and high-reliability requirements [7]-[8]. The ability of enhanced Enhanced Common Public Radio Interface (eCPRI) to run on Ethernet is a significant advantage in urban areas and in indoor environments such as factories and office blocks. At this functional split, baseband processing is partially or wholly executed in the RU, and packetised eCPRI data is transmitted through an Ethernet interface over the PON. Option 7.2 has a strict latency requirement of 250 μs (one way) on the MFH. With the PON serving as the optical fronthaul, the uplink latency performance is highly dependent on how bandwidth is allocated to each RU for uplink transmission seeing that in the upstream direction, bandwidth is shared.

Innovative bandwidth allocation schemes to satisfy the uplink MFH bandwidth and latency requirements have been previously proposed. These rely on the report-grant process typical of TDM-PONs [9], including cooperative-dynamic bandwidth allocation (DBA) schemes that uses fronthaul traffic information through a cooperative transport interface message to improve overall

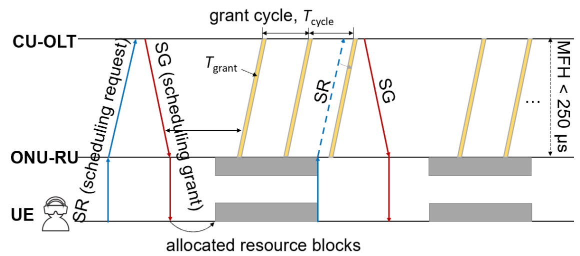

Fig. 1 An illustration of MFH DBA.

latency and bandwidth utilisation, e.g. [10]-[13], priority scheduling DBA based on traffic load [14], bandwidth guaranteed DBA based on network slicing of mobile and other services [15], and self-adjusting DBA that dynamically adjusts fronthaul allocation intervals based on reports [16].

Considering a dynamic network environment that also supports immersive experiences, the MFH of 6G must be able to rapidly adapt to changing traffic patterns and network conditions. In this work, we propose a rapid and self-adaptive Machine Learning (ML) driven DBA that incorporates reinforcement learning (RL) to achieve self-adaptive and optimised bandwidth decision for the MFH, with transfer learning (TL) to reduce the decision learning time. Here, we show an uplink latency of less than 150 µs can be attained in a 16 ONU-RU XGS-PON MFH under different traffic pattern and load scenarios.

Fast Self-Adaptive DBA (FSA-DBA) for MFH

Different to conventional DBAs, and as shown in Fig. 1, existing MFH DBA schemes rely on the synchronization of the PON DBA report-grant process with the MFH bandwidth allocation process through CU-OLT scheduling and the estimation of the bandwidth required by ONU-RUs, i.e., T_{grant}. In existing MFH DBA schemes, T_{grant} estimation depends on knowing ONU-RUs traffic characteristics.

Our proposed FSA-DBA does not depend on prior knowledge of MFH traffic for fast and self-adaptive T_{grant} decision. Through RL, the CU-OLT progressively adjusts T_{grant} based on the rewards received from executing different T_{grant} decisions. To reduce latency, a negative uplink latency from allocating a T_{grant} in MFH is deemed as the reward. The CU-OLT then uses a decision-value function, termed as Q_{target}, to associate a T_{grant} with its long-term average reward. The Q_{target} in turn serves as the metric to adjust T_{grant}. Such an iterative learning and decision adjustment process enables self-adaptive and optimized T_{grant} decision.

As the decision exploration in RL costs time, rapid learning that reduces the number of nonn-optimised T_{grant} decisions is thus critical to reducing uplink latency. We leverage TL to reuse existing decision-value knowledge to expedite

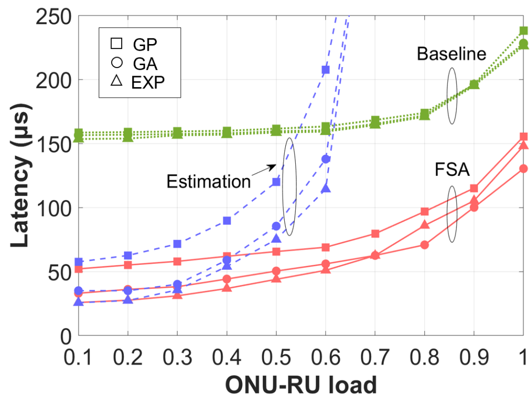

Fig. 2 Latency performance of FSA-DBA with different traffic patterns in simulations.

learning. Referring to a set of source decision-value set $\boldsymbol{Q} = \{Q_{source,n}\}$ pre-acquired either through simulations or past MFH operations, the FSA-DBA identifies the source knowledge, indexed by n^*, that is most related to the learning of the Q_{target} as follows:

$$n^* \leftarrow \mathrm{argmax}_n |Q_{source,n} - Q_{target}| \qquad (1)$$

The distance $|Q_{source,n} - Q_{target}|$ in (2) implies the similarity between the source environment where $Q_{source,n}$ is obtained and the current learning environment [16]. Knowing Q_{source,n^*} guides the decision exploration in a neighbourhood range $D = [T^*_{grant,n^*} - \delta, T^*_{grant,n^*} + \delta]$ to the T^*_{grant,n^*} = argmax Q_{source,n^*}. For fast convergence, the greedy policy is adopted to adjust T_{grant}:

$$T_{grant} \leftarrow \mathrm{argmax}_D Q_{target} \qquad (2)$$

With the source knowledge to guide the decision exploration, learning time can be reduced. In operation, an ONU-RU will report its latency every K cycles. At the CU-OLT, Q_{target} will be updated based on the empirical reward reported by ONU-RUs. Subsequently, T_{grant} is adjusted by referring to the source $\boldsymbol{Q}$ set following (1) and (2).

Performance Evaluation

We perform packet-driven simulations to validate the latency and learning rate of the FSA-DBA. We consider a 10 km-link XGS-PON with 16 ONU-Rus to support a MFH with 500Mbps radio access capacity. We further upstream packet arrivals to be exponentially (EXP) [10]-[11], Generalized Pareto (GP) [17] and Gamma (GA) [17] distributed.

Fig. 2 compares the latency performance of FSA-DBA, cooperative DBA scheme with arrival estimation in [12] and baseline DBA scheme, i.e., IPACT via report-grant process. Unsurprisingly, the baseline scheme incurs the highest latency since each packet needs to be first reported and then granted bandwidth. At minimum, the packets wait for approximately 100 μs, i.e. round-trip between ONU-RU and the CU-OLT. Using cooperative DBA eliminates the report-grant process, and hence the latency is reduced as compared to the baseline DBA scheme. Nonetheless, decisions for T_{grant} arer based on the arrival estimation of fixed-length cycles (50 μs) and its results in Fig. 2, clearly reflect its lack of flexibility towards different traffic patterns and loads. In comparison, FSA-DBA does not encounter such issues due to its ability to self-adaptively adjust bandwidth decisions as well as grant cycles, achieving the lowest uplink latency (150 μs) with optimised decisions via explorative learning.

We also investigated the learning rate and latency of applying FSA-DBA to empirical traffic traces previously collected from an immersive human-to-robot application experiments. [18]. Simulated Q functions in afore-mentioned settings, i.e., EXP, GP, GA distributed traffic and ONU-RU loads between 0.1 to 1, were used as source $\boldsymbol{Q}$ to assist the learning of Q_{target} for our empirical traffic. With K = 10, our results highlight that TL, only a few tens of iterations are needed to explore an optimal decision as compared hundreds of iterations with just RL.

Summary

We proposed an ML-driven DBA that rapidly self-adapts bandwidth allocation decisions to achieve low-latency uplink transmissions in the MFH. Results show uplink latencies of less than 150 μs can be achieved with self-adaptive decisions under different traffic patterns and load scenarios. By using simulated decision-value knowledge to assist empirical decisions, decision learning is further expedited. With PON as a potential optical mobile fronthaul solution, the proposed bandwidth allocation scheme, FSA-DBA, not only satisfies the uplink MFH bandwidth and latency requirements of 6G immersive experiences but also rapidly self-adapts to changing traffic conditions.

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