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End-to-End Data Flows Management in the Decentralized 5G/6G Mobile Networks

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ABSTRACT The evolution of 5G and the anticipated emergence of 6G networks demand significant enhancements in optical backhaul infrastructure to support higher bandwidth, low latency, and increased reliability. Considering a wide range of feasible applications with different quality requirements, the key challenge for the underlying backhaul and optical transport network is in the high load variance in the optical switching nodes and complicated data flows management. In this paper, a novel approach is proposed for end-to-end data flows management in decentralized 5G/6G mobile networks, which are interconnected by the optical burst switching transport infrastructure. The key idea is to train a deep recurrent neural network over a real network statistic obtain at the different network segments and service slices. Then, predictions made by deep neural network are used for predictive resource allocation in each node of the optical burst switching network to ensure a target quality of service for each end-to-end data flow. The experimental results show that proposed approach provides 90% accuracy of predictions and allows to effectively utilize the resources of optical network.

KEYWORDS optical burst switching; 5G/6G backhaul; deep learning; traffic prediction; end-to-end data flows management.

I. INTRODUCTION

THE global proliferation of mobile communication technologies has fundamentally transformed various sectors, including business, healthcare, education, and entertainment. The advent of 5G technology represents a significant leap in the evolution of mobile networks, promising enhanced data rates, reduced latency, and the capacity to support a vast number of connected devices [1]. However, the transition from 4G to 5G and the anticipated progression towards 6G pose substantial challenges in terms of network infrastructure and integration. The essence of 5G technology lies in its ability to facilitate ultra-reliable, low-latency communications (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) [2]. These capabilities are essential for supporting emerging applications such as autonomous vehicles, smart cities, remote healthcare, and immersive augmented and virtual reality experiences. However, realizing these capabilities requires a robust and scalable transport infrastructure that can handle exponentially increasing data traffic with minimal latency and high reliability [3]. A critical aspect of 5G and future 6G networks is the utilization of high-frequency millimeter waves, which offer significantly broader bandwidths compared to traditional frequency bands. However, the propagation characteristics of these waves necessitate a much denser deployment of base stations to ensure comprehensive coverage [4, 5]. This increased density presents a substantial challenge in terms of infrastructure investment and deployment. Decentralized mobile networks have emerged as a promising solution to address the limitations of traditional centralized network architectures. In the context of network architecture, the hierarchical structure of 5G networks, which involves distributed units (DUs) and centralized units (CUs), plays a crucial role in managing network functions. DUs handle resource scheduling and are sensitive to delay, while CUs manage less time-critical functions. By distributing network functions across multiple nodes, decentralized networks can enhance scalability, flexibility, and resilience [6, 7]. However, the integration of these decentralized networks with existing optical transport networks poses several technical and operational challenges. The existing optical transport infrastructure, designed primarily for traditional communication paradigms, must evolve to support the unique requirements of decentralized mobile networks. This evolution involves enhancing the transport network's capacity, flexibility, and intelligence to manage the dynamic and heterogeneous traffic patterns associated with 5G and future 6G applications. One of the primary challenges in integrating decentralized mobile networks with optical transport infrastructure is ensuring consistent quality of service (QoS) across diverse application domains. The diverse service requirements of eMBB, mMTC, and URLLC necessitate sophisticated traffic management strategies to maintain high performance and reliability. Mapping QoS Class Identifiers (QCI) from mobile networks to Differentiated Services Code Point (DSCP) in optical transport networks is crucial for achieving this objective [8].

To address these challenges, this paper proposes the use of advanced machine learning techniques, specifically long short-term memory (LSTM) deep neural networks, for intelligent traffic prediction and resource allocation in optical transport networks [9, 10]. Proposed end-to-end data flows management can accurately predict traffic patterns and dynamically allocate resources in optical aggregation and switching nodes, thereby optimizing network performance and ensuring better service quality.

II. RELATED WORK

A. ADVANCEMENTS IN OPTICAL TRANSPORT NETWORKS

Optical networks, pivotal for high-speed data transmission, have evolved from traditional circuit switching to more sophisticated switching techniques to optimize network performance and capacity [11]. Circuit-switched optical networks establish direct, continuous channels between nodes by assigning different wavelengths to different channels [12]. This method ensures robust throughput during active transmission sessions [13]. However, the utilization of optical channels drops significantly when traffic intensity is low, leading to underutilization and diminished network capacity [14].

To address these inefficiencies, packet-switched optical transport networks (POTNs) have been developed, leveraging Multi-Protocol Label Switching (MPLS) to enhance channel utilization and overall network performance [15]. MPLS improves throughput efficiency by dynamically allocating resources based on real-time traffic demands. However, POTNs face challenges under high traffic conditions, as the overhead from signaling data necessary for managing individual packet transmissions can become substantial, potentially impacting network efficiency [16].

Optical Burst Switching (OBS) networks present a hybrid approach, combining the benefits of both circuit and packet switching while mitigating their respective drawbacks. In OBS networks, IP packets are aggregated into logical units called bursts, which are then transmitted as single entities [17]. These bursts consist of homogeneous IP packets that share the same destination and Quality of Service (QoS) requirements, optimizing traffic management and ensuring efficient use of network resources [18]. The creation of bursts allows for the segregation of traffic based on throughput needs and destination addresses, enhancing network performance and scalability [19].

To coordinate burst transmissions, a Burst Header Packet (BHP) is generated for each burst. The BHP contains crucial information, including source and destination node addresses, QoS requirements, and additional control data essential for burst scheduling and switching. The signaling schemes utilized in OBS networks can vary, impacting how BHPs manage and optimize burst transmissions [18].

OBS networks typically employ a mesh topology, wherein each node is interconnected with multiple neighboring nodes, facilitating robust and flexible network architecture. Each optical switch in an OBS network comprises two functional components: edge nodes and core nodes. Edge nodes are responsible for aggregating traffic from various access networks, forming IP packet bursts, and generating corresponding BHPs. Core nodes handle burst routing and switching based on the information encoded in the BHPs, utilizing all-optical switching technologies to maintain high-speed, transparent data transmission [17].

The all-optical switching employed in OBS networks ensures that data remains in the optical domain throughout transmission, avoiding the need for electrical conversion. This technique significantly reduces latency and enhances transmission efficiency. The BHP is transmitted ahead of the burst, creating a transparent virtual channel to the destination node. This preemptive scheduling ensures that bursts traverse the network with minimal delays, as the optical switching time is comparable to the signal propagation time through the optical fiber. Consequently, burst transmission between two edge nodes can be logically perceived as a direct connection, despite the bursts potentially traversing multiple intermediate hops [19].

Recent advancements in OBS networks continue to refine these processes, integrating more intelligent routing algorithms and adaptive QoS management to cater to the diverse needs of modern applications. Moreover, research into the integration of OBS with emerging technologies, such as quantum communications and software-defined networking (SDN), promises to further enhance the flexibility, security, and efficiency of optical networks, paving the way for the next generation of high-performance communication infrastructures [19-21].

B. 5G/6G OPTICAL BACKHAUL CHALLENGES

The deployment and enhancement of 5G networks, as well as the anticipated transition to 6G, have spurred a plethora of research focused on addressing the backhaul infrastructure's challenges [22]. Optical backhaul, with its high capacity and low latency, remains a central focus in this domain.

Recent studies have demonstrated that optical backhaul can effectively support the high bandwidth and low latency requirements of 5G networks. For instance, the integration of dense wavelength division multiplexing (DWDM) in optical networks can provide the necessary capacity for 5G backhaul, significantly enhancing the performance and scalability of the network [23]. DWDM allows multiple data streams to be transmitted simultaneously on different wavelengths, maximizing the utilization of the fiber optic medium.

Additionally, advancements in passive optical networks (PONs) have shown promise for 5G backhaul applications. Next-generation PONs (NG-PON2) can deliver the necessary bandwidth and flexibility for 5G backhaul, leveraging technologies such as time and wavelength division multiplexing (TWDM) [24]. Despite these advancements, several challenges remain in the deployment of optical backhaul for 5G networks. One major challenge is the cost and complexity of fiber deployment, particularly in urban areas where infrastructure is dense and in rural areas where distances are vast. The capital expenditure (CAPEX) and operational expenditure (OPEX) associated with laying new fiber can be prohibitive, necessitating innovative solutions such as fiber leasing or the use of existing infrastructure [25].

Another significant challenge is the integration of optical backhaul with existing heterogeneous network architectures. 5G networks are expected to operate alongside legacy 3G and 4G networks, requiring seamless interoperability between different backhaul technologies. Effective integration requires advanced orchestration and management solutions capable of handling diverse network requirements and ensuring optimal resource allocation [26]. The application of artificial intelligence (AI) and machine learning (ML) in managing optical backhaul networks is gaining traction. AI/ML algorithms can predict network traffic patterns and dynamically allocate resources, thereby optimizing network performance and reducing latency [27]. These intelligent systems can significantly enhance the efficiency and reliability of optical backhaul networks.

As sustainability becomes a key concern in network design, some research is focused on enhancing the energy efficiency of optical backhaul networks. There is a need for energy-efficient optical components and network designs that minimize power consumption while maintaining high performance [28, 29]. This is particularly important as network traffic continues to grow.

Future networks are likely to see a convergence of access and backhaul technologies, enabling more seamless and efficient data transport. An integrated architecture where optical backhaul and access networks are managed as a single entity can leverage shared infrastructure and resources to improve overall network performance and reduce costs [30].

C. CLASSIFICATION OF QOS PARAMETERS FOR END-TO-END DATA FLOWS MANAGEMENT

5G mobile networks face the challenge of meeting diverse network parameter requirements due to the significant heterogeneity of their applications. While eMBB services require high bandwidth to support multimedia services, virtual and augmented reality, and other applications with high data rate demands, they typically involve a relatively small number of devices that are connected simultaneously. On the other hand, mMTC services are used for connecting various Internet of Things (IoT) devices. These services are characterized by low data rate requirements and moderate latency demand but require simultaneous operation of thousand end devices within small neighborhood. Finally, URLLC services are essential for critical infrastructure applications such as nuclear power plants, gas supply systems, and traffic control systems [31].

In the context of end-to-end quality of service (QoS) management for mobile network subscribers, it is crucial to harmonize QoS parameters between mobile and transport network domains. Historically, mobile networks have used a different QoS nomenclature than fixed networks, reflecting key differences in service quality assurance methods between fixed and mobile networks [31]. Consequently, a table of correspondence between QCI (QoS Class Identifier) for mobile networks and DSCP (Differentiated Services Code Point) for transport networks is used to align traffic handling policies between 5G base stations and optical transport network edge nodes, as defined by 3GPP standards and IETF recommendations (Tables 1 - 3) [32-36].

Thus, the existing concept of optical transport network construction must be transformed accordingly to ensure automated end-to-end logical separation of network resources for specific service types in 5G and future networks [37, 38].

Table 1. Classification and Correspondence of 5QI and DSCP Identifiers for Guaranteed Bit Rate (GBR) Services

5QI	Type	Priority	Service Example	DSCP
1	GBR	2	Real-time voice	44
2		4	Real-time video	35
3		3	Real-time games, V2X messages, power grid control, industrial process automation	19
4		5	Non-real-time video	37
65		0.7	Critical voice services (PTT) (Push To Talk)	42
66		2	Non-critical voice services (PTT)	43
67		1.5	Critical video services	33
75		2.5	V2X messages	17
71		5.6	Upstream streaming multimedia	35
72				
73				
74				
76				

Table 2. Classification and Correspondence of 5QI and DSCP Identifiers for Delay Critical Guaranteed Bit Rate (DC-GBR) Services

5QI	Type	Priority	Service Example	DSCP
82	DC-GBR	1.9	Discrete automation (small packets)	25
83		2.2	Discrete automation (large packets)	27
84		2.4	Intelligent transport systems	31
85		2.1	High-voltage power systems	23
86		1.8	Intelligent transport systems	29

Table 3. Classification and Correspondence of 5QI and DSCP Identifiers for Non-Guaranteed Bit Rate (Non-GBR) Services

5QI	Type	Priority	Service Example	DSCP
5	Non-GBR	1	IMS signaling	40
6		6	Non-real-time video, TCP services (www, email, chat, ftp, p2p)	10
7		7	Real-time voice and video, interactive games	38
8		8	Non-real-time video, TCP services (www, email, chat, ftp, p2p)	12
9		9		14
69		0.5	Critical signaling (MC-PTT signaling, MC video signaling)	41
70		5.5	Critical non-real-time video services and TCP services (www, email, chat, ftp, p2p)	20
79		6.5	V2X messages	21
80		6.8	Ultra-broadband low-latency services (TCP/UDP), virtual and augmented reality	32

III. MATERIAL AND METHODS

A. END-TO-END INFRASTRUCTURE OF 5G MOBILE NETWORKS BACKHAUL

5G networks use a hierarchical principle in building network infrastructure. Given the high density of 5G base stations, the use of classic radio access network principles is significantly complicated from both the wireless access segments and optical network infrastructure perspectives [39, 40]. Therefore, in 5G networks, most of the base station functions are transferred to distributed units (DUs) and centralized units (CUs). The resource scheduling functions, which are sensitive to delay, are transferred to the distributed units (DUs), while more general management functions, which are less sensitive to delay, are transferred to the centralized units (CUs) [41].

The overall architecture of the passive optical access network, which integrates the hierarchical model of mobile network construction, is presented in Figure 1. The architecture presented in Figure 1 divides three types of transport communication channels with different requirements for bandwidth and delay.

The first type includes Backhaul (BH) channels, which provide the backbone transport infrastructure for connecting CU nodes. These channels are characterized by flexible bandwidth and delay requirements.

The second type includes Midhaul (MH) channels, which facilitate the interaction of CU nodes with their corresponding DU nodes. MH channels require higher bandwidth and allow delays up to 8 ms. The third type includes Fronthaul (FH) channels between DU nodes and the end radio transmitters (RUs). The FH channels have high requirements for both bandwidth and delay because all signal processing functions at the L1/L2 levels are performed directly in the DU node. Thus, the complete signal constructs are transmitted via FH channels to the corresponding RU nodes, which then transmit them to the subscribers via the radio channel.

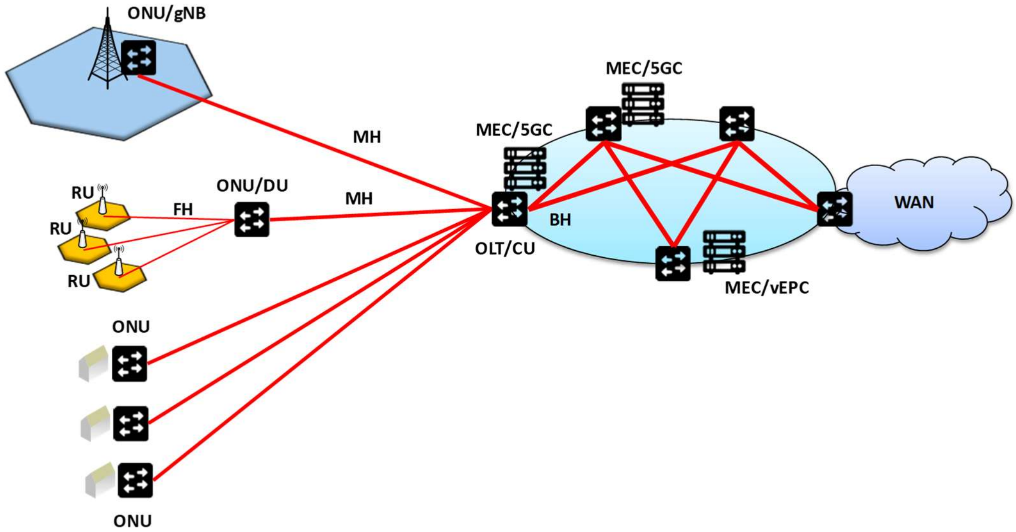

Figure 1. The general architecture of the passive optical access network with the integration of decentralized mobile networks.

Considering the peculiarities of converting radio signals for their transmission in fiber-optic communication lines, FH channels must provide bandwidths ranging from 10 to 25 Gbps, depending on the total bandwidth of the cells, ensuring a delay of no more than 100 µs, allowing the DU-RU pair to function as a single logical base station [37].

The architecture of OBS consists of two types of functional elements. The first type is Edge Nodes (EN), which are designed for aggregating/de-aggregating information flows (Ethernet, 4G/5G) and forming BHP headers [8, 17, 18]. In the proposed flow management model, the edge node is combined with the OLT node of the WDM-PON network and the CU node of the 5G network. The second type is Core Nodes (CN), which are intended for end-to-end optical switching of bursts based on the information contained in the BHP headers (Fig. 2) [14, 17, 18].

The CN plays a crucial role in the OBS network, acting as an intermediary between transport and access networks. This node aggregates IP traffic from various access networks, including PON, enterprise networks, cellular networks, and cloud data center networks. Consequently, the incoming traffic at the edge node is highly heterogeneous, as each access network imposes different quality of service (QoS) requirements, such as throughput, latency, and packet loss probability (Fig. 3).

For instance, packets from cellular networks often have stringent latency requirements due to the delays already incurred within the cellular network system. In contrast, packets from optical access networks with similar service demands can afford longer delays at the edge node while still delivering the same user experience. Conversely, non-real-time packets with high throughput demands, such as those from online video-on-demand services, can tolerate longer delays but require higher throughput for transmission. Additionally, the OBS network must support both IPv6 and IPv4 traffic, which introduces compatibility challenges due to differences in packet structure, compounding the existing QoS requirements issue.

Figure 3 illustrates the burst aggregation process within the edge node of an OBS network [17, 18]. Initially, incoming streams of IP packets from different access network segments are multiplexed into a single stream based on their arrival times. Next, a packet classifier distributes packets into their respective bursts and communicates the burst status to the scheduler. Concurrently, the scheduler assigns the appropriate output fiber and wavelength for each burst and informs the BHP generator. The BHP generator then creates BHP packets based on the scheduler's data. Finally, the scheduler transmits the BHP and, after a predefined delay known as offset time, sends the corresponding burst.

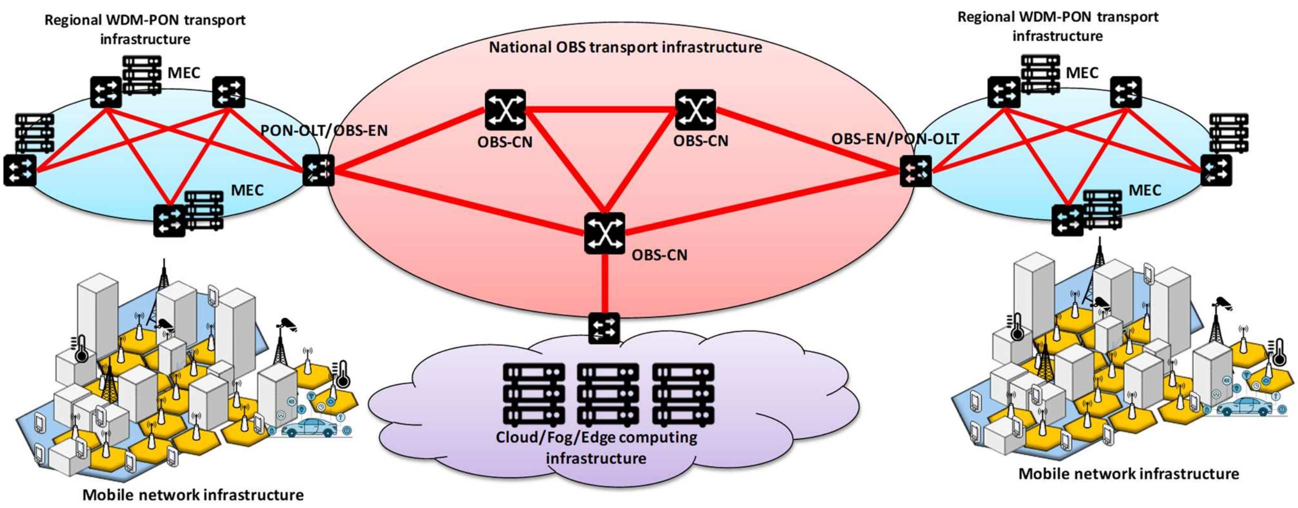

Figure 2. The architecture of the optical transport infrastructure based on burst switching networks.

The offset time is predetermined for each route to ensure that the BHP is processed at the destination node before the corresponding burst arrives. As the burst traverses the network without processing in core nodes, a "chasing" effect occurs, where the distance between the BHP and the burst decreases after each intermediate core node. This ensures that the virtual channel remains active precisely for the duration of burst transmission, maximizing throughput efficiency [17-19].

Determining the optimal size for each burst is a critical aspect of the burst aggregation process. The burst size refers to the total size of all IP packets aggregated into one burst. Given the offset time between the BHP and the burst, larger bursts generally provide better throughput utilization compared to smaller bursts, as fewer bursts are needed to transmit the same amount of data. However, the maximum burst size is constrained because, at low traffic intensities, the transmission deadline of the first packet in a burst might be reached before the burst is fully assembled. Therefore, using a size threshold is not optimal for burst transmission. Another approach is to create a time threshold for burst transmission based on the first packet's deadline. However, this can lead to buffer overload when traffic intensity increases, as bursts may become too large before the deadline occurs. An adaptive algorithm proposed in [19] offers a compromise by adjusting the delay time and burst size based on traffic intensity.

The core node in OBS facilitates all-optical switching of each incoming burst, directing it to the target destination node. The core node is composed of two parallel systems: an all-optical switching system and a BHP processing system [17, 18]. The BHP processing system examines incoming BHPs to extract information about the burst's destination node, QoS requirements, burst size, and arrival time. Based on this information, the BHP processor executes complex routing by considering all incoming bursts within the same time interval, thus enabling the distribution of available channel resources in accordance with QoS requirements [19].

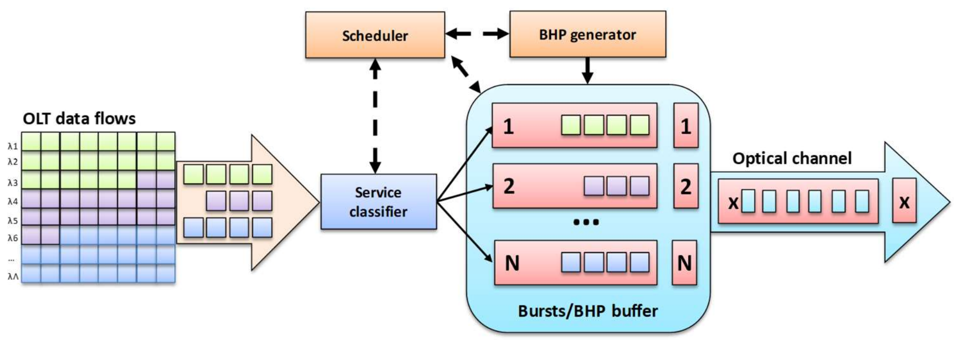

Figure 3. Traffic aggregation in the OBS-EN.

The all-optical switching system handles the burst switching process without converting optical signals to electrical signals and back, using the switching matrix provided by the BHP processing system. This all-optical switch can employ various optical switching technologies, such as micro-electro-mechanical systems (MEMS) switching, electro-optical switching, acousto-optical switching, or liquid crystal switching [42].

B. INTELLIGENT DATA FLOWS MANAGEMENT IN OPTICAL TRANSPORT AND BACKHAUL INFRASTRUCTURE OF 5G MOBILE NETWORKS

For consistent differentiation of information flows coming from decentralized mobile networks, it is important to consider additional aspects that were not previously accounted for in centralized networks. Using the general mathematical model of information flows from decentralized mobile networks, we can represent the total aggregated flow at the OBS-EN node as:

$$F^{(OBS-EN)} = \sum_i \sum_j \sum_k \sum_l f_{i,j,k,l},\ f_{i,j,k,l} \in \mathbb{R}^{I\times J\times K\times L}, \quad (1)$$

where $\mathbb{R}^{I\times J\times K\times L}$ – combined space of users $i=\{1,2,\ldots I\}$, services $j=\{1,2,\ldots J\}$, operators $k=\{1,2,\ldots K\}$ and base stations $l=\{1,2,\ldots L\}$; $f_{i,j,k,l}$ – the smallest fraction of the data flow of i-th user, j-th service, through l-th, base station and k-th operator.

The partial data flows of decentralized mobile networks are calculated as following:

$$\begin{cases} F_i^{(UE)} = \sum_j \sum_k \sum_l f_{i,j,k,l} \text{ - for user i;} \\ F_j^{(S)} = \sum_i \sum_k \sum_l f_{i,j,k,l} \text{ - for service j;} \\ F_k^{(O)} = \sum_i \sum_j \sum_l f_{i,j,k,l} \text{ - for operator k;} \\ F_l^{(gNB)} = \sum_j \sum_j \sum_k f_{i,j,k,l} \text{ - for base station l.} \\ F^{(OBS-EN)} = \sum_i F_i^{(UE)} = \sum_j F_j^{(S)} = \sum_k F_k^{(O)} = \sum_l F_l^{(gNB)} \end{cases} \quad (2)$$

From expression (2), it is easy to see that the $\mathbb{R}^{I\times J\times K\times L}$ implies traffic prediction at the node of the mobile network. Based on the predicted values of the total information flows, corresponding decisions are made regarding traffic management at the nodes of the transport network infrastructure.

For example, $F^{(O)}$ is used for resource reservation by the operator at the PON channel level between its own base stations and the virtualized core in the edge computing infrastructure; $F^{(gNB)}$ is used to determine the interdependence of traffic between neighboring cells and the multiplexing of information flows during handover; $F^{(UE)}$ is used for service management and content caching at the subscriber device level; $F^{(S)}$ is used for network slicing management and end-to-end quality assurance of information flow transmission.

When aggregating data flows from mobile networks in the transport network, the 5QI service classes are transformed into DSCP classes (5) [28, 29]:

$$\underline{\mathbf{F}}(i,j,k,l) \xleftrightarrow{5QI\leftrightarrow DSCP} \underline{\mathbf{F}}(i,j',k,l), \quad (3)$$

where $j'=\{1,2,\ldots J'\}$ is the set of DSCP identifier values. After this, the formation of aggregated flows $\underline{\mathbf{F}}(:,j',:,:)$ and the prediction of total traffic volumes $F_{j'}^{(S)}$ are carried out using recurrent neural networks.

Considering the additional parameters of operators and independent subscribers, as well as the presence of new types of services in 5G/6G networks, the classical approach to block prioritization and quality of service assurance based on DSCP (Table 4) is insufficient for effective end-to-end flow management.

By comparing the parameters in Tables 1-3 with the parameters in Table 4, it can be concluded that the existing flow management methods in OBS networks are inadequate for such critical services as tactile internet, which requires URLLC. Furthermore, the tables show that services that have different priorities from the perspective of mobile networks correspond to a single block priority in the OBS network.

Table 4. Classification of DSCP Identifiers and Corresponding Block Priorities in OBS Networks

Class	DSCP		Burst priority	
	Binary	Decimal	Individual	Aggregated
CS0	000 000	0	7	5
CS1	001 000	8	6	4
CS2	010 000	16	5	
CS3	011 000	24	4	3
CS4	100 000	32	3	
CS5	101 000	40	2	2
EF	101 110	46	1	1
CS6	110 000	48	0	0
CS7	111 000	56		

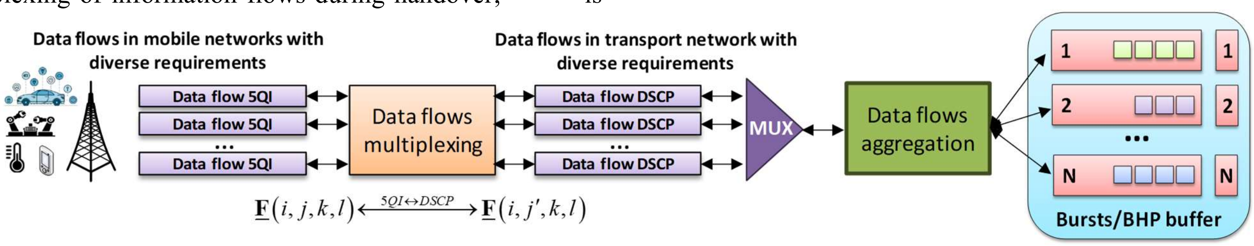

Figure 4. Process of data flow aggregation in an OBS network.

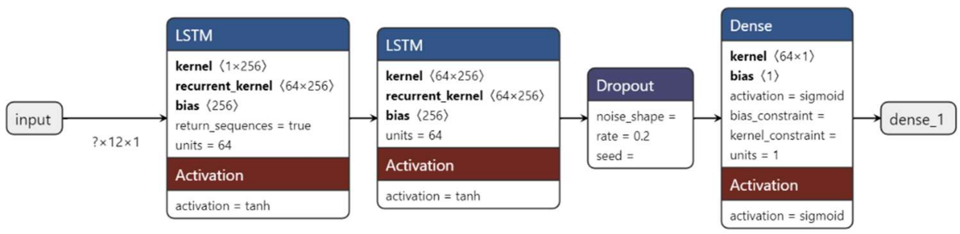

Figure 5. Combined architecture of the logical information flow separation system in the OBS-EN node based on deep neural networks.

IV. EXPERIMENTAL RESULTS

The proposed method involves using a combined architecture of deep neural networks, which includes a service classifier that ensures logical separation of information flows among block priorities and a set of independent LSTM recurrent neural networks, each responsible for traffic prediction for its respective block priority (Figure 5).

According to the results of experimental studies (Figure 6), the proposed method achieves 90% accuracy based on the calculation of the mean-squared error (MSE) metric. This, in turn, allows the scheduler to adaptively redistribute the resources of optical transport networks for individual slices, ensuring consistent differentiation of information flows between mobile networks and the optical transport infrastructure.

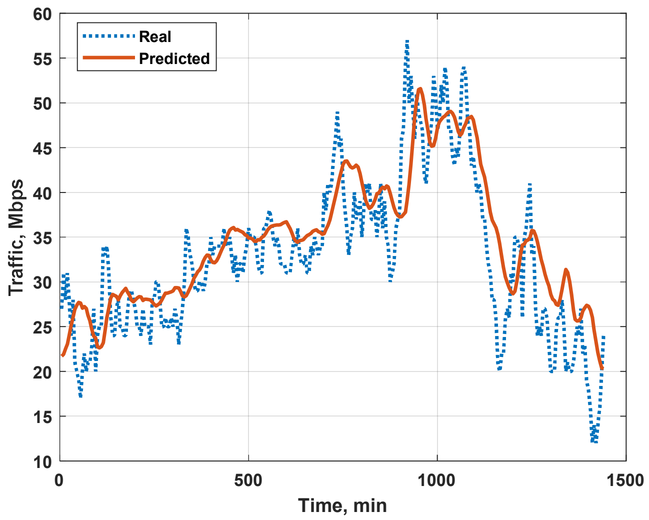

Figure 6. Traffic prediction results for one type of burst using the intelligent information flow management method.

Furthermore, by forecasting not only at the service level but also at the destination address level, the proposed method allows for the advance reservation of necessary resources, such as optical fibers, wavelengths, and switching links at OBS-CN nodes.

Three types of network slices were selected for modeling: eMBB, URLLC, and mMTC. The dataset used for training the intelligent management model contains information flows from all three slices, randomly mixed in time. The structure of the dataset is provided in the appendix.

Initially, the neural network is trained to classify service slices. After classification, traffic time series are formed for each individual slice, based on which separate models of recurrent neural networks are trained. The recurrent blocks utilize LSTM technology, which employs internal context state cells that provide both long-term and short-term memory properties [9, 10]. This capability allows for the prediction of long-term traffic dependencies, considering the relevant historical context for each logical network slice or for each destination address. The results of resource allocation at the OBS-EN node among different types of services are presented in Figures 7-8.

The combination of the methods for managing information flows developed in this paper at the PON and OBS network levels allows for the integration of decentralized mobile communication systems into a unified network infrastructure. This integration ensures end-to-end quality management of information flow transmission for various operators and types of services (Figure 9).

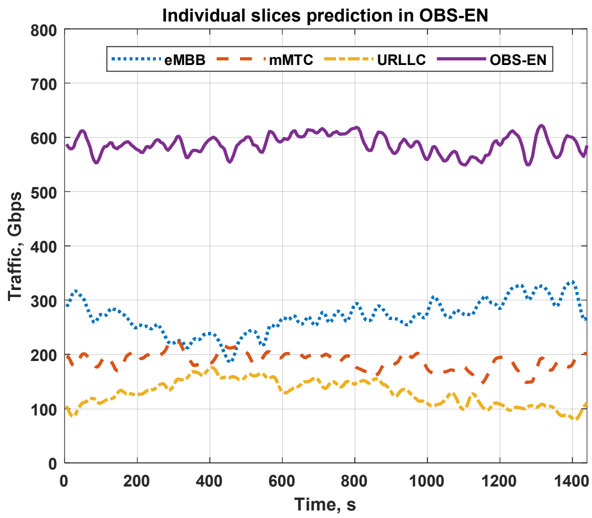

Figure 7. Example of total traffic prediction in the OBS-EN node for individual slices eMBB, mMTC, and URLLC.

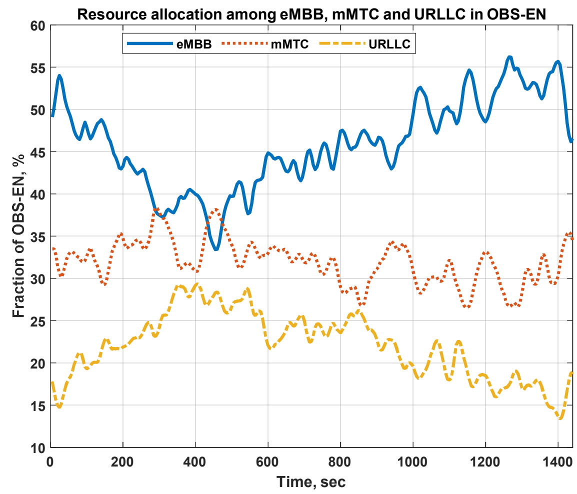

Figure 8. Resource utilization shares of the OBS-EN node by eMBB, mMTC, and URLLC services

VI. CONCLUSIONS

This paper proposed a new solution for the end-to-end data flows management in decentralized 5G/6G mobile networks. The hybrid network architecture based on OBS transport infrastructure and WDM-PON backhaul is considered, with integrated 5G/6G distributed radio access network. The data flows management process is based on the traffic prediction of the key switching nodes by deep recurrent neural network. The neural network has been trained over real network statistic obtained at the different network segments and service slices. Proposed solution allows to allocate resources in advance for each node of the optical burst switching network to guarantee the end-to-end quality of service for each data flow. Simulation results show that proposed approach provides 90% accuracy of resource allocation for each slice of the 5G mobile network. Future research may be focused on enhancing the intelligence, efficiency, and security of 5G and 6G backhaul networks through innovations in AI and quantum computing.

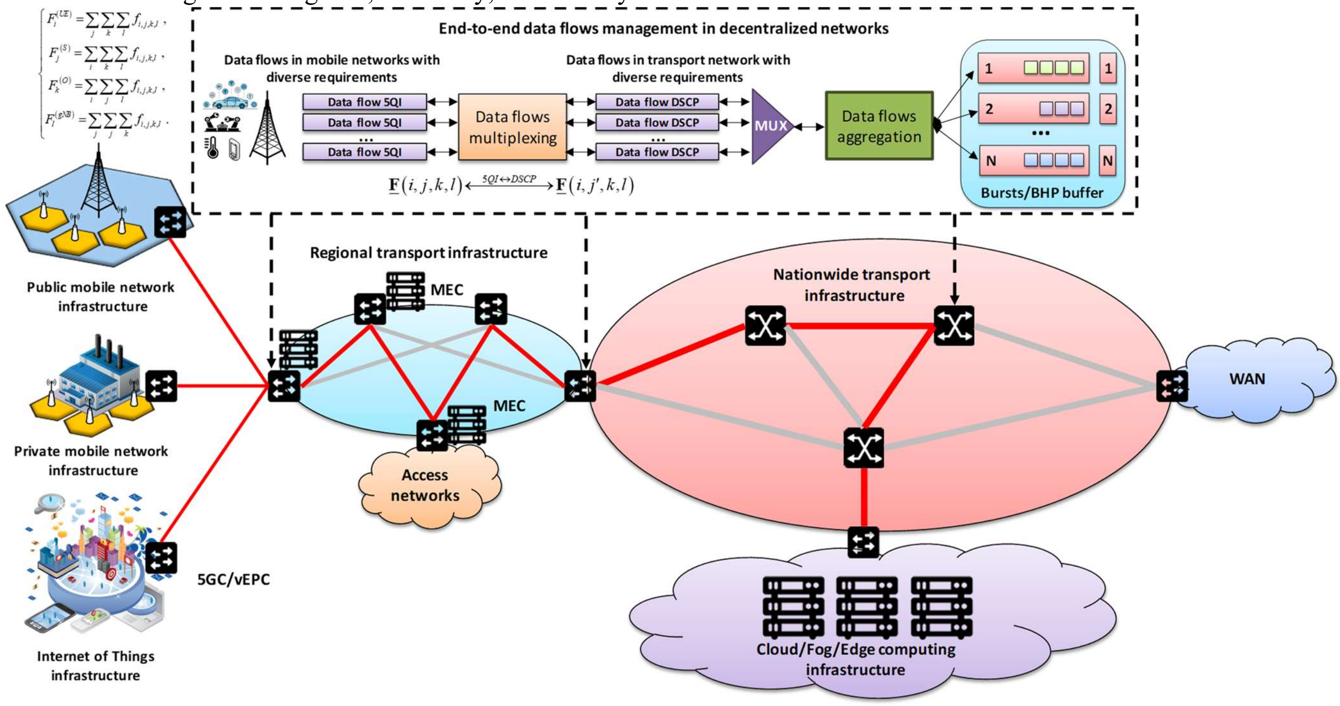

Figure 9. Global infrastructure of optical transport networks with end-to-end information flow management for decentralized mobile communication systems.

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