Leveraging Packet Aggregation to Optimise QoS and Energy Trade-offs in 5G/6G Optical Fronthaul Networks

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***Abstract*—The growing demands of 5G and emerging 6G mobile networks—driven by the proliferation of IoT devices, immersive applications, and high-throughput services—necessitate more efficient and scalable fronthaul solutions. Open Radio Access Networks and cloud-RAN architectures offer promising frameworks by decoupling hardware and software and enabling centralised processing. However, the fronthaul segment still faces challenges related to bandwidth inefficiency, signalling overhead, and relatively high energy consumption, particularly due to the transmission of vast numbers of small packets. Packet aggregation emerges as a viable strategy to mitigate these challenges by grouping multiple small packets into larger payloads, thereby reducing protocol overhead, improving throughput efficiency, and lowering energy consumption in the network as a whole. This paper investigates the impact of packet aggregation on both quality of service (QoS) and energy efficiency in the fronthaul of 5G/6G mobile networks. While prior studies have examined its effects on throughput and latency, the implications for energy consumption remain underexplored. We evaluate how aggregation design parameters—such as time thresholds, size thresholds, and traffic intensity—influence performance metrics such as throughput and latency. We also propose ways to achieve an optimal trade-off between QoS and energy efficiency. Our findings offer insights into the design of energy-aware, delay-sensitive packet aggregation schemes tailored for next-generation mobile network architectures.**

***Index Terms*—5G / 6G optical fronthaul networks, Open Radio Access Network (O-RAN), Quality of Service (QoS), Energy Efficiency, Packet aggregation.**

I. Introduction

The fifth generation (5G) of mobile networks is currently being deployed worldwide, promising unprecedented speed, low latency, and massive connectivity, and the sixth generation (6G) is envisioned to enhance these capabilities further to meet the growing demands of applications like the Internet of Everything (IoE), virtual reality, and 8K video streaming [1]. To support these advancements, the cloud radio access network (C-RAN) in which baseband processing is centralised in a cloud processing data centre has emerged as a promising architecture, requiring efficient connections between radio units (RU) and distributed units (DU), known as the fronthaul [2]. Improving the quality of service (QoS) and reducing the energy consumption at the fronthaul of 5G/6G networks is one of the key concerns for mobile network operators.

Complementing the C-RAN architecture is the Open Radio Access Network (O-RAN) paradigm (see Fig. 1), which introduces *standardized, open interfaces* to enable greater flexibility, modularity, and vendor interoperability [3], [4]. O-RAN decouples hardware and software components, allowing operators to mix and match solutions from multiple vendors while fostering innovation and cost efficiency.

The transmission of massive volumes of small packets—originating from Internet of Things (IoT) devices, multimedia applications, and data services within 5G and emerging 6G radio access networks—poses several challenges when these packets traverse high-speed Internet core networks to reach other access networks or cloud data centers. These challenges include bandwidth inefficiency, increased signaling overhead, underutilization of available network resources, and significant energy inefficiency in the core network [5] resulting from signaling overhead, processing of massive amounts of packets, and the reception and transmission of packets. It is, therefore, essential to develop effective strategies to manage the vast volumes of traffic generated by mobile access networks, particularly those arising from the Internet of Things (IoT), which continues to expand rapidly in scale and scope [6].

One effective strategy to mitigate these issues is the aggregation of small packets into larger payloads at the ingress node of the network. This technique involves grouping mul-

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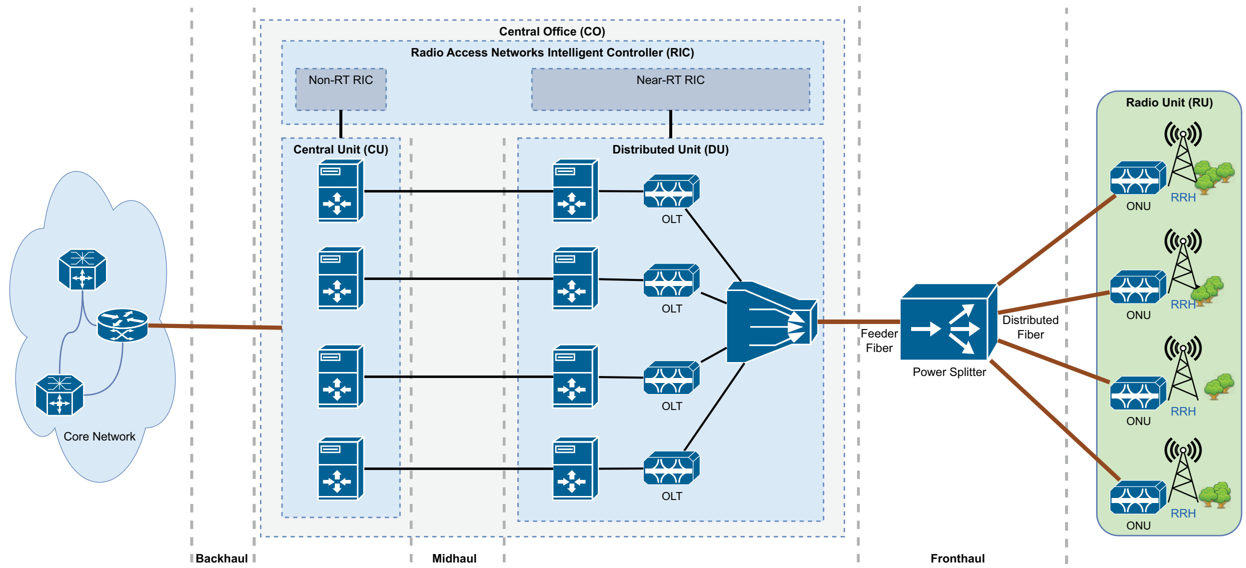

Fig. 1. O-RAN architecture emphasizing open interfaces and intelligent control

tiple packets that share common transmission characteristics under a single header. As a result, the protocol overhead is significantly reduced, throughput is improved, and network resource utilization becomes more efficient. Moreover, energy consumption is reduced due to fewer packet processing and transmission operations. Once these aggregated packets reach the egress node, they are disassembled and forwarded individually to their respective destinations. The main drawback is that the packet aggregation process introduces aggregation delays [7] which increases the latency which is a critical performance metric in 5G/6G networks especially those handling traffic that belong to real-time applications [8].

Packet aggregation can be implemented at the fronthaul interface. Given the proliferation of IoT and mobile devices, networks must handle a high volume of small data packets. Aggregating these packets—either at the RRH or an intermediate node such as an Optical Network Unit (ONU), Optical Line Terminal (OLT), multiplexer, or edge processing server—can significantly reduce protocol overhead. This process improves bandwidth efficiency, reduces energy consumption, and alleviates congestion on the optical fronthaul. Once the aggregated packets reach the BBU pool, disaggregation occurs to enable appropriate processing and routing. This is particularly beneficial in dense urban environments and massive machine-type communication (mMTC) scenarios (e.g., IoT applications), where high-volume, low-payload traffic demands efficient handling to maintain system performance.

In [9], the authors investigated the challenges of multiplexing and aggregating fronthaul and backhaul traffic over C-RAN optical Ethernet links. A related approach to improve transport-layer throughput efficiency in 5G cloud radio access networks (C-RAN) was proposed in [10], focusing on the aggregation of fronthaul packet frames. However, the impact of such aggregation on packet delay—particularly within the context of 5G C-RAN architectures—has received limited attention. Addressing this gap requires a detailed analytical model of the packet aggregation process that accounts for the unique characteristics of 5G traffic patterns and packet size distributions. While prior studies have extensively examined packet aggregation in terms of QoS metrics such as throughput and latency, its influence on energy consumption in fronthaul networks remains largely unexplored.

In this paper, we present an analytical framework for modelling and optimising packet aggregation processes in the fronthaul of O-RAN between the RU and the DU, using a diffusion-based approach grounded in the Fokker–Planck equation. We analyse the influence of key aggregation parameters, including time thresholds, size thresholds, and traffic intensity, on system performance. In addition, we explore strategies to strike an optimal balance between QoS and energy efficiency, offering practical insights for designing energy-sensitive packet aggregation schemes tailored to next-generation mobile fronthaul networks.

The remainder of this paper is structured as follows. Section II presents the diffusion-based model of the packet aggregation mechanism, while Section III evaluates its performance. Section IV analyses the impact of packet aggregation on energy consumption, and Section V concludes the paper.

II. Diffusion-based model of the packet aggregation process

This section presents a mathematical framework for modelling the dynamic behaviour of packet aggregation buffers in network switches. Using a diffusion approximation, we derive analytical expressions for the probability distributions of aggregated buffer content and the distribution of the interdeparture times of aggregated buffer contents under both time-based and size-based aggregation policies. These models enable the evaluation of key performance metrics, including aggregated packet size distributions and the latency associated with each triggering mechanism.

The dynamic evolution of the buffer content in an aggregation switch can be effectively modelled using a diffusion approximation. This is described by the Fokker–Planck equation, a partial differential equation that characterises the time evolution of the probability density function $f(x, t; x_0)$ of the buffer content x, given an initial state x_0. The governing equation is [11]:

$$\frac{\partial f(x,t;x_0)}{\partial t} = \frac{\alpha}{2}\frac{\partial^2 f(x,t;x_0)}{\partial x^2} - \beta\frac{\partial f(x,t;x_0)}{\partial x} \tag{1}$$

In this expression, β denotes the mean rate of change of the buffer content, while α represents the variance in the rate of change. Specifically, these parameters are defined as:

$$\beta = \lim_{\Delta t \to 0} \frac{E[X(t+\Delta t) - X(t)]}{\Delta t}, \qquad \alpha = \lim_{\Delta t \to 0} \frac{\mathrm{Var}[X(t+\Delta t) - X(t)]}{\Delta t} \tag{2}$$

Here, $X(t)$ denotes the total number of bytes accumulated in the buffer at time t. The term β captures the average growth rate of the buffer due to packet arrivals, whereas α reflects the stochastic fluctuations around this average, resulting from variability in packet size and arrival rates.

Packets are accumulated in input buffers until one of two conditions is met. First, in low-traffic scenarios, a maximum time threshold is reached, prompting the dispatch of the content of the buffer to the appropriate output queue for transmission, regardless of its volume. Second, under high-traffic conditions, a maximum size threshold is triggered when the buffer content reaches the defined maximum size threshold, leading to the dispatch of the content of the aggregation buffer to the appropriate output queue.

To model this process, we define $X(t)$ as the buffer content (i.e., number of bytes accumulated) at time t, with the process starting at $x = 0$ (assuming the content of the packet aggregation buffer is cleared before the next aggregation accumulation process is started). The evolution of $X(t)$ continues until it either hits the size threshold $x = B$ or the time threshold $t = T$.

The probability density function (PDF) of the buffer content at the timeout instant (when the time threshold is reached) T is derived from a solution of the diffusion approximation model in 1 and is given by:

$$f(x,T;0) = \frac{1}{\sqrt{2\pi\alpha T}}\left\{\exp\left(-\frac{(x-\beta T)^2}{2\alpha T}\right) - \exp\left(\frac{2\beta B}{\alpha} - \frac{(x-2B-\beta T)^2}{2\alpha T}\right)\right\} \tag{3}$$

This expression captures the likelihood of observing a certain number of accumulated bytes at the end of a fixed

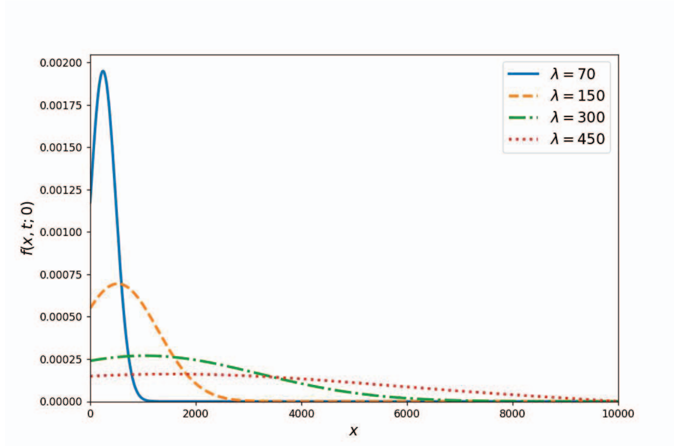

Fig. 2. The PDF of the sizes of aggregated packets (x in bytes), $f(x, t; 0)$ for various values of λ: time-based aggregation algorithm, $t = T = 0.005$

the aggregation period when the time threshold is reached, considering both the mean rate of incoming traffic intensity $\beta = \lambda m$ in bytes per second and its variance $\alpha = \lambda^3\sigma_A^2\sigma_m^2 + \lambda^3\sigma_A^2 m^2 + \sigma_m^2\lambda^2$. This PDF provides information about the distribution of the aggregated packet sizes in the time-based packet aggregation algorithm. The corresponding latency is the value of the time threshold as the aggregation packets are dispatched when the threshold is reached.

Similarly, when modelling the case in which the aggregation buffer fills up before the timeout occurs, the first-passage time distribution gives the density of interdeparture times. That is, the time from when the first passage time occurs to when the size threshold is reached and the content of the aggregation buffer is dispatched to the appropriate output queue. This is described by:

$$\gamma_{0\to B}(t) = \frac{B}{\sqrt{2\pi\alpha t^3}}\exp\left(-\frac{(B-\beta t)^2}{2\alpha t}\right) \tag{4}$$

This function represents the probability density of the time it takes for the buffer to first reach the size threshold B, which directly influences packet departure times under heavy traffic. This PDF corresponds to the latency introduced by the size-based packet aggregation mechanism. These analytical models help in understanding and optimising the trade-offs between throughput and latency in packet aggregation systems, especially under varying network conditions.

III. Performance Evaluation of the Packet Aggregation Algorithms

When considering packet aggregation algorithms, understanding how parameters such as arrival rate and threshold settings influence performance is critical. The probability density functions (PDF) of aggregated packet sizes and interdeparture times under various traffic intensities and aggregation policies provide valuable insight into throughput and delay characteristics.

Fig. 2 presents the PDF $f(x, t; 0)$ of aggregated packet sizes for a time-based packet aggregation algorithm with time

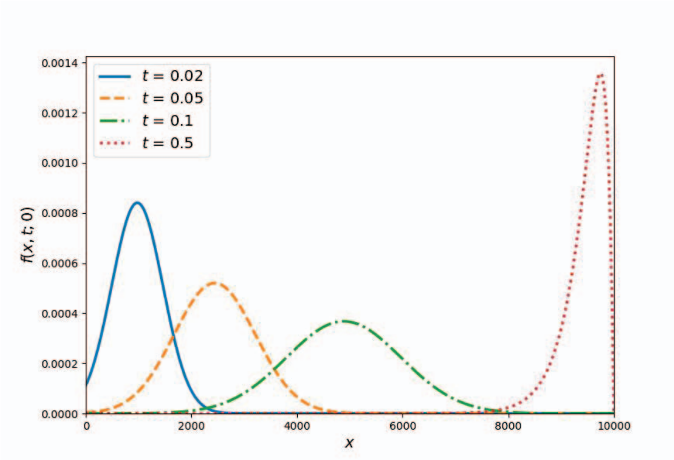

Fig. 3. The PDF of the sizes of aggregated packets (x in bytes), $f(x, t; 0)$ for various values of $t = T$: time-based aggregation algorithm, $\lambda = 70$

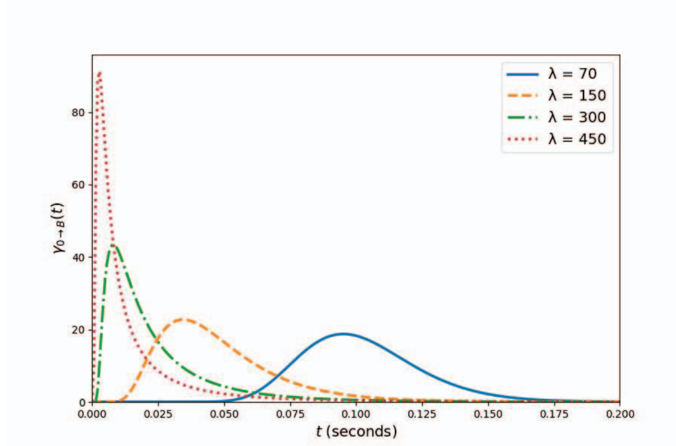

Fig. 4. The PDF of the interdeparture times of aggregated packets from the aggregation buffer, $\gamma_{0\to B}(t)$ for various values of λ: size-based aggregation algorithm, $B = 5000$

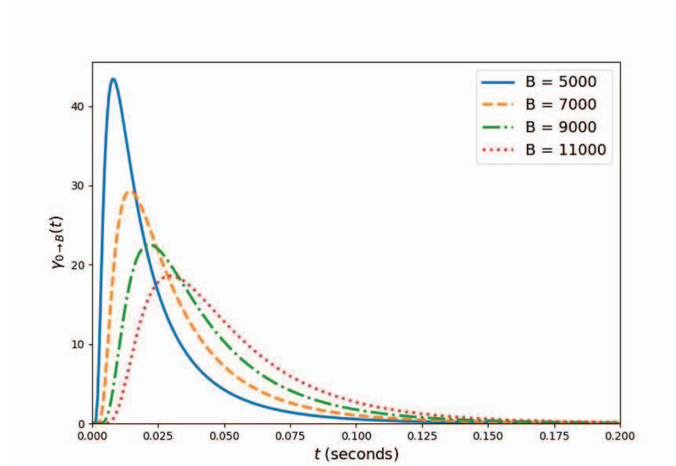

Fig. 5. The PDF of the interdeparture times of aggregated packets from the aggregation buffer, $\gamma_{0\to B}(t)$ for various values of λ: size-based aggregation algorithm, $\lambda = 300$

threshold $T = 0.005$, for varying packet arrival rates λ. As expected, the aggregated packet size increases with higher values of λ. This is because more packets arrive during the fixed time window before the time threshold is reached, leading to a higher accumulation of smaller packets in the packet aggregation buffer and hence larger sizes of the aggregated packets. The result is an increase in throughput. However, this can also cause greater variability in aggregated packet sizes, which must be considered when designing for quality of service (QoS).

Fig. 3 shows how varying the aggregation time threshold T affects the PDF of packet sizes, assuming a constant arrival rate $\lambda = 70$. A larger aggregation window (time threshold) naturally allows more packets to accumulate in the buffer, producing larger aggregated packets. While this improves bandwidth efficiency and throughput, it also increases packet delay—an important trade-off in latency-sensitive applications. Therefore, time thresholds must be chosen carefully based on application requirements.

Fig. 4 depicts the PDF $\gamma_{0\to B}(t)$ of interdeparture times under a size-based aggregation policy with a fixed size threshold $B = 5000$ bytes. When the packet arrival rate λ increases, the buffer fills more quickly, resulting in shorter interdeparture times. This implies that under high-traffic conditions, size-based aggregation offers reduced latency, which is beneficial for maintaining flow responsiveness. However, it also requires careful management to avoid overwhelming the output buffers, as it may result in buffer overflow and packet losses.

Fig. 5 examines the effect of varying size thresholds B on the interdeparture time PDF $\gamma_{0\to B}(t)$, given a constant arrival rate $\lambda = 300$ packets per second. Larger threshold values require more data to accumulate before the content of the aggregation buffer is aggregated and dispatched, leading to increased delays. This highlights the importance of adaptive threshold selection: lower thresholds are better suited for real-time or delay-sensitive traffic, while higher thresholds can be used for non-critical traffic to improve throughput efficiency. One potential solution is to deploy multiple aggregation buffers, each configured with different thresholds based on traffic class, to strike a balance between delay and throughput as proposed in [12]. Furthermore, in the context of Open RAN, adaptive packet aggregation could be implemented and dynamically controlled through xApps or rApps in the near-real-time RIC, or integrated into the user plane logic, depending on deployment objectives and control plane architecture [13].

IV. Impact of Packet Aggregation on Energy Consumption in the Fronthaul Network

The energy consumption of the fronthaul network over a given time interval T is quantified as the integral of the power consumed by various components. Specifically, the total fronthaul energy E_{FH} is given by:

$$E_{\text{FH}} = \int_0^T \left[P_{\text{RU}}(t)+P_{\text{fiber}}(t)+P_{\text{ONU}}(t)+P_{\text{OLT}}(t)+P_{\text{switch}}(t)\right] dt \tag{5}$$

Here, each term represents the time-varying power consumption of the respective fronthaul elements. This model provides the foundation for evaluating energy optimisation strategies in next-generation optical access networks.

The per-port power consumption of each network node is essential for understanding node-level energy dynamics. For the n^{th} line card of a given node, the power budget P_n can be modeled as [14]:

$$P_n = PE_n + R_{i,n}(E_{rx,n} + E_{rs,n}) + \lambda_{p,n}E_p + R_{o,n}(E_{ts,n} + E_{tx,n}) \tag{6}$$

In this equation, PE_n denotes the baseline idle power of the port; $R_{i,n}$ and $R_{o,n}$ represent the ingress and egress traffic rates in bytes per second; $E_{rx,n}, E_{rs,n}, E_{ts,n}, E_{tx,n}$ capture the per-byte energy costs of receiving, processing, storing, and transmitting data; $\lambda_{p,n}$ indicates the packet processing rate; and E_p is the energy required to parse and forward a single packet.

This formulation reflects both static and dynamic energy components, making it suitable for evaluating the impact of traffic variations and packet-level behaviour on the total power consumption of network nodes [14]–[17].

To refine the power model, mean packet sizes at the ingress port ($m_{i,n}$) and egress port ($m_{o,n}$) are introduced. Packet arrival rates are thus expressed as:

$$\lambda_{i,n} = \frac{R_{i,n}}{m_{i,n}}, \quad \lambda_{o,n} = \frac{R_{o,n}}{m_{o,n}}$$

Substituting these expressions into the original model yields:

$$P_n = PE_n + m_{i,n}\lambda_{i,n}(E_{rx,n} + E_{rs,n}) + \lambda_{p,n}E_p + m_{o,n}\lambda_{o,n}(E_{ts,n} + E_{tx,n}) \tag{7}$$

This version highlights the linear dependence of power consumption on packet sizes and traffic intensities. The partial derivatives offer valuable insights into energy contributions per packet component:

$$\frac{\partial P_n}{\partial \lambda_{i,n}} = m_{i,n}(E_{rx,n} + E_{rs,n}), \quad \frac{\partial P_n}{\partial \lambda_{p,n}} = E_p, \quad \frac{\partial P_n}{\partial \lambda_{o,n}} = m_{o,n}(E_{ts,n} + E_{tx,n}) \tag{8}$$

The total energy consumed to process a packet at port n is summarised as:

$$E_{n,p} = m_{i,n}(E_{rx,n} + E_{rs,n}) + E_p + m_{o,n}(E_{ts,n} + E_{tx,n})$$

Assuming symmetric packet sizes at ingress and egress ports ($m_{i,n} = m_{o,n} = m_n$), this simplifies to:

$$E_{n,p} = m_n E_{rst} + E_p, \tag{9}$$

where, $E_{rst} = E_{rx,n} + E_{rs,n} + E_{ts,n} + E_{tx,n}$.
Energy per packet increases linearly with packet size as demonstrated in [14]–[16]. Aggregating smaller packets improves throughput and reduces the per-packet processing cost, but increases the energy cost for transmission and reception. Thus, an optimal balance between traffic rate and packet size is critical for energy efficiency.

At the network node level, total power consumption P is given by:

$$P = P_B + \sum_{n=1}^{K_i} PE_n + \sum_{n=1}^{K_a} \Big[PE_n + m_{i,n}\lambda_{i,n}(E_{rx,n} + E_{rs,n}) + \lambda_{p,n}E_p + m_{o,n}\lambda_{o,n}(E_{ts,n} + E_{tx,n}) \Big] \tag{10}$$

Here, P_B denotes base station-level static power, and K_i, K_a represent inactive and active ports, respectively. This formula integrates idle, dynamic, and per-packet energy components for comprehensive node-level energy analysis.

In the numerical examples presented, the baseline power consumption of the network infrastructure, denoted as P_B, is set to 100 watts, representing the constant power required to maintain system operations regardless of traffic load. The energy consumed per byte of data transmission and reception, E_{rst}, is assigned a value of 0.1 microjoules per byte, capturing the cumulative energy required for receiving, processing, and transmitting a byte of data. Additionally, the fixed energy cost per packet, E_p, is set to 11.5 microjoules, accounting for the overhead involved in handling each individual packet, such as header processing, queuing, and protocol-related tasks. The rest of the parameters are indicated in the various figures.

Fig. 6 shows the power consumption trend as a function of traffic volume for packet sizes $m = \{64, 512, 1500\}$ bytes. It can be observed that smaller packets lead to higher power consumption at equivalent traffic loads due to increased per-packet processing costs. Conversely, larger packets significantly reduce dynamic energy usage, especially at high traffic rates, by amortising processing overhead across more data. This underscores the importance of packet aggregation mechanisms in energy-efficient network design. This benefit is more significant in the entire network, as the traffic arriving at intermediate nodes is significantly reduced due to packet aggregation at the ingress nodes of the network.

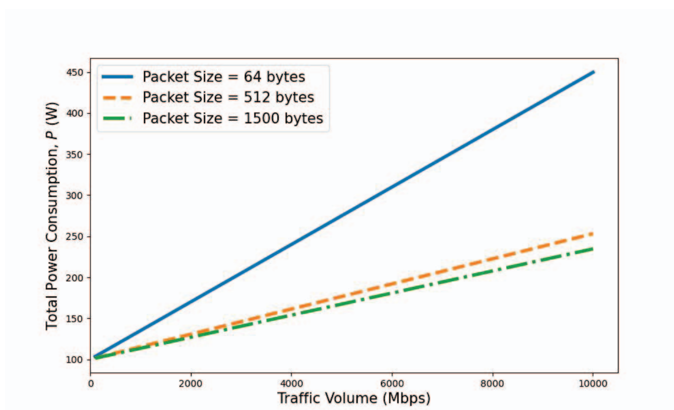

Fig. 6. Power consumption vs. traffic volume for different packet sizes

To better visualise the joint influence of packet size and traffic volume on energy usage, a 3D plot is presented in Fig. 7.

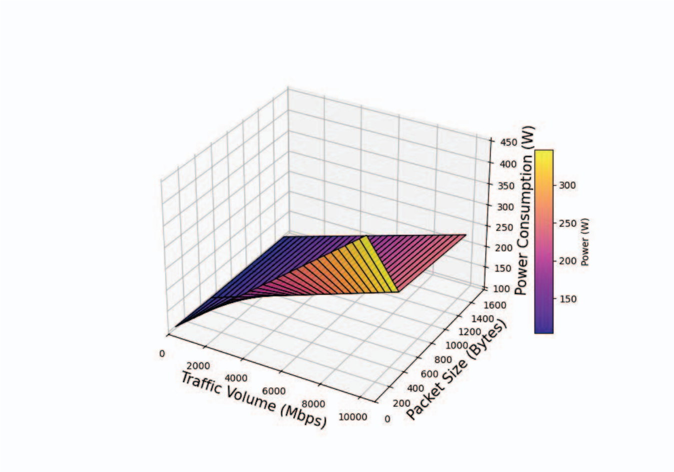

Fig. 7. 3D plot of power consumption as a function of packet size and traffic volume at an intermediate node.

This figure reveals a multidimensional energy landscape where power consumption increases with traffic volume but decreases as packet size grows. The shape of the surface highlights a region of optimal operation—where packet sizes are large enough to minimise per-packet overhead while maintaining acceptable traffic throughput.

This 3D visualisation offers key insights for network operators and designers. It suggests that careful tuning of packet aggregation strategies can significantly reduce energy consumption, particularly under heavy traffic conditions. The analysis also reinforces the importance of traffic shaping and packet aggregation mechanisms in energy-aware network design.

V. Conclusion

This paper has explored the role of packet aggregation on QoS and energy consumption in the fronthaul segment of 5G and emerging 6G mobile networks. With the increasing volume of small packets generated by IoT devices and data-intensive applications, efficient handling of traffic in the fronthaul is essential for maintaining both quality of service (QoS) and energy efficiency. Through an in-depth review and analysis of existing aggregation strategies, we highlighted the potential of packet aggregation to reduce protocol overhead, improve throughput, and minimise energy consumption.

We examined key design parameters of packet aggregation algorithms, including time and size thresholds, and analysed their impact on performance metrics such as latency and throughput. Our findings suggest that although packet aggregation can lead to significant energy savings, improper configuration can result in increased latency, particularly affecting real-time IoT traffic. Therefore, achieving a balance between QoS requirements and energy efficiency is crucial.

Future work will focus on developing adaptive aggregation mechanisms that dynamically adjust parameters based on real-time traffic conditions and application requirements. In addition, integrating machine learning models to predict traffic patterns and optimise aggregation decisions holds promise for further enhancing fronthaul efficiency in next-generation mobile networks.

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