

Original Research

Enhancing IoT Connectivity through Advanced Scheduling at 142 GHz Sub-THz in 5G and Beyond Networks

Mohammed Mahfoudi^{1,*} , Ismail Angri² , Abdellah Najid² ,
Mohammed Fattah³ , Moulhime El Bekkali⁴ 

¹Engineering Laboratory for Intelligent Technologies and Transformation, EST, Abdelmalek Essaadi University, Tetuan, Morocco

²Telecommunication Systems, Networks and Services (STRS) Laboratory, National Institute of Posts and Telecommunications (INPT), Rabat, Morocco

³EST, Sidi Mohamed Ben Abdellah University, Fez, Morocco

⁴Artificial Intelligence, Data Science & Emerging Systems Laboratory, Sidi Mohamed Ben Abdellah University, Fez, Morocco

*Corresponding author: m.mahfoudi@uae.ac.ma

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Abstract:

5G technology promises to revolutionize how we engage with the digital realm. 5G networks are developed in such a way to answer to the growing needs of various applications, ranging from Enhanced Mobile Broadband applications, through Massive Machine Type Communications, and ending at Ultra-reliable and Low Latency applications. One crucial element of 5G is its capability to interconnect massive Internet of Things equipment, although in this paper we focus on the Massive Machine Type Communications. However, the exponential growth of IoT (Internet of Things) devices has hamstrung existing network infrastructures with a dearth of connectivity links, necessitating innovative approaches to optimize and to manage the increasing demand of high quality connectivity. To tackle these issues, literature research has been undertaken the promise of advanced scheduling techniques that can be adopted by IoT connectivity within 5G networks. To ensure efficient optimization of the existing spectrum resources, the Radio Resource Management (RRM) function, responsible for managing and allocating radio resources like frequency, time, and power to ensure effective optimization of the existing spectrum, through an optimal scheduling algorithm can prioritize resource allocation based on specific requirements for IoT applications, such as latency, reliability, and throughput. Many scheduling algorithms are available with different focuses on performance goals such as delay sensitivity plus reliability or throughput. In this paper, we will introduce the latest developments in scheduling algorithms for 5G-IoT networks and their impact. Next, we propose a new scheduling algorithm aligned with IoT applications need.

Keywords: Internet of things; Fifth generation mobile networks; Sixth generation mobile networks; Massive machine type communications; Enhanced mobile broadband; Ultra reliable and low latency communications; Radio resource management

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1. Introduction

1.1 Background and motivation

The fifth generation (5G) of wireless and mobile communication systems aims to support various new and

traditional services provided by different vertical industries through the very dense deployment of the base stations, called small cells or femtocells, to extend network capacity and offer higher data rate services. The

future vision of 5G is that the convergence of the cellular networks and the Internet of Things (IoT) seems to offer numerous opportunities. To achieve this vision, two similar designs exist, extended range (ER) and cell-free massive Multiple-Input–Multiple-Output (CF-MIMO) [1]. For the hotspot scenarios, targeting coverage extension, data rate enhancement, power save, and reduced interference, together with Quality of Experience (QoE) and energy efficiency are an open issues, especially in the context of Low Power Wide Area (LPWA) and Massive Machine Type Communication (mMTC) [2].

The ecosystem of IoT projects a very positive outlook in terms of spectrum requirements as shown in recent research work both for the usage of sub-GHz frequencies for vehicle-to-vehicle and the higher bands around 5 GHz, 28 GHz, and 60 GHz for the infrastructure-to-vehicle and vehicle-to-everything, respectively. Additionally, the 142 GHz band, part of the Sub-THz-Wave spectrum, offers promising potential for IoT applications that require extremely high data rates and low latency [2], particularly in dense urban environments. While its shorter range and line-of-sight requirements may limit its applicability in broader IoT deployments, the 142 GHz band is well-suited for advanced, high-capacity IoT use cases, such as autonomous driving, real-time high-definition mapping, and smart city infrastructure [3].

Despite these advances, there are still open issues to address like how to cope with advanced scheduling of the traffic in these networks. The proposed system leverages the C-RAN architecture to bring optimal control of the network by addressing cohesively radio and network operations using advanced and predefined scheduling techniques.

1.2 Importance of IoT in 5G networks

The importance of Massive Machine-Type Communication (mMTC) in 5G networks arises from the ambition to not only evolve the news and data services, that people use every day via their smartphones, but also potentially transform human lives and the way people, business products, and services are connected. All that is through the integration of billions of MTC devices, such as sensors and switches in automated systems, across all economic sectors [4]. Retail and wholesale fill inventories based on point of sales of goods, farmers can manage the welfare of the cattle and the environment in which the animals are located, municipalities monitor the air quality in cities, factories and machine maintenance systems are able to optimize machines [5]. The need for such technologies will accelerate the data transfer of many small messages in a dense area. Providing the scalability and variable delay characteristics required for the different combinations of Ultra Reliable Low Latency Communications (URLLC) and mMTC links [6].

5G networks are engineered to provide the high-speed, low-latency, and reliable connectivity that IoT applications demand [7]. The seamless integration of IoT within the 5G framework enables new use cases and enhances existing ones by improving data throughput,

reducing latency, and ensuring consistent connectivity. This integration not only boosts the performance of IoT applications but also drives innovation across various industries, leading to smarter, more efficient systems and processes [8].

1.3 Objectives and scope of the paper

This exploratory research seeks to build an understanding of the fundamental scheduling challenges faced by 5G networks. In particular, the impact caused by massive machine-type communication (mMTC) transmissions in the scheduled connection establishment [9], comprising moderate rate communications between the gNodeBs (gNBs) and the terminals is analyzed. Given the ultra-dense deployment required by mMTC, increasing the overhead on the connection establishment for these pre-crash avoidance accesses [10]. We will design specific scheduling policies minimizing the access procedure overhead on gNB control in terms of control channel resources, attribute channel resource design, and complexity in the transmission access grant implementation by the gNB. Clearly, the proposed solutions are dependent on the channel model and on the random variable, extraction methods of the mMTC traffic that make our fundamental study a proof of concept.

The resource allocation complexity is expected to be the second major challenge for such a system, mainly due to the expected thousands of mMTC devices within the coverage area of each gNB. Only very simple signal processing schemes are envisioned, with minimal signaling. The resource allocation is part of the design of the overall wireless network, but it should also take into account the control-plane signaling overhead that is required to facilitate access for both Massive User Deployment (MUD) device and Dynamic Interference Coordination (DIC) device behaviors [11]. Additionally, it is expected that some user devices will have Quality Of Service (QoS) requirements that are time sensitive and possibly include mobility. In this case, retransmissions may be needed to maintain the required link reliability. The uncertainty in the decision process of serving such devices with the limited resources will result in retransmissions for enabling adaptive modulation, coding, or both [12].

The primary objective of this paper is to investigate the latest advancements in scheduling algorithms for optimizing IoT connectivity in 5G networks. Specifically, the paper aims to Review existing scheduling algorithms, propose a novel-scheduling algorithm, evaluate the proposed algorithm and discuss the implications.

In this paper, we realized deep analysis of the more known scheduling algorithms within 5G-IoT networks context [13]. It includes a review of existing literature, newly developed algorithm that is evaluated through specific simulations and compared with the well know algorithms, this work is concluded by realistic discussion about the practical implications of the findings. This developed approach aims to contribute to the enhancement of IoT connectivity, as well as improving that 5G net-

works can effectively support the ongoing development of the ecosystem of connected IoT devices.

2. Literature review

2.1 Overview of 5G network capabilities

The fifth generation of mobile network technology (5G), compared to the previous generations, designed to offer significantly higher data rates, ultra-low latency, and improved connectivity. In this context, IoT plays a crucial role in the 5G ecosystem as it provides a wide array of applications that rely on real-time data processing and communication. The capabilities of 5G networks are designed to answer diverse needs of IoT devices. This may include as mentioned in recent review work combining IoT with generator control and supervision systems IoT-enabled monitoring of synchronous generators that allows real-time health diagnostics and predictive maintenance [14], we can talk also about applications in smart cities environment [15], healthcare centers, automated industry, and beyond [16]. To be able to connect billions of devices with various requirements, an implementation of a robust and flexible network infrastructure, where IoT devices can operate efficiently without compromising on performance or reliability is a necessity. The primary capabilities that 5G networks offer as we can see in Fig. 1:

Enhanced Mobile Broadband (eMBB): Delivers high-speed internet access, enabling applications such as High Definition video streaming, augmented and virtual reality [17].

Ultra-Reliable Low Latency Communications

(URLLC): Concerns delay-critical applications that require minimal latency and good reliability, like autonomous driving, remote surgery, and automated industry [17].

Massive Machine-Type Communications (mMTC): Makes the connection easier for a big number of IoT devices, ranging from smart meters to environmental sensors, with efficient resource utilization [17].

Large-scale deployment of IoT devices is expected in a wide range of vertical domains. This enormous growth of IoT devices is foreseen to be realized through advances in cellular IoT technology. In the 3rd Generation Partnership Project (3GPP), LTE has already been enhanced to efficiently support massive IoT deployments. Low-cost MTC and eMTC techniques are widely used for IoT services. eMTC is designed for delay-sensitive applications and devices. However, LTE technologies are fundamentally limited in some features. Particularly, these technologies cannot provide long-term battery life for IoT devices [18]. One of the key features of the 5G network is the use of flexible radio interface for different service types and optimized to support a wide range of capabilities.

2.2 Overview of existing scheduling algorithms for IoT in 5G

In this section, we present a critical review of different scheduling strategies specifically tailored for the efficient deployment of IoT network services in a 5G environment [19]. To thoroughly investigate the most interesting studies related to our work, we initially consider recent

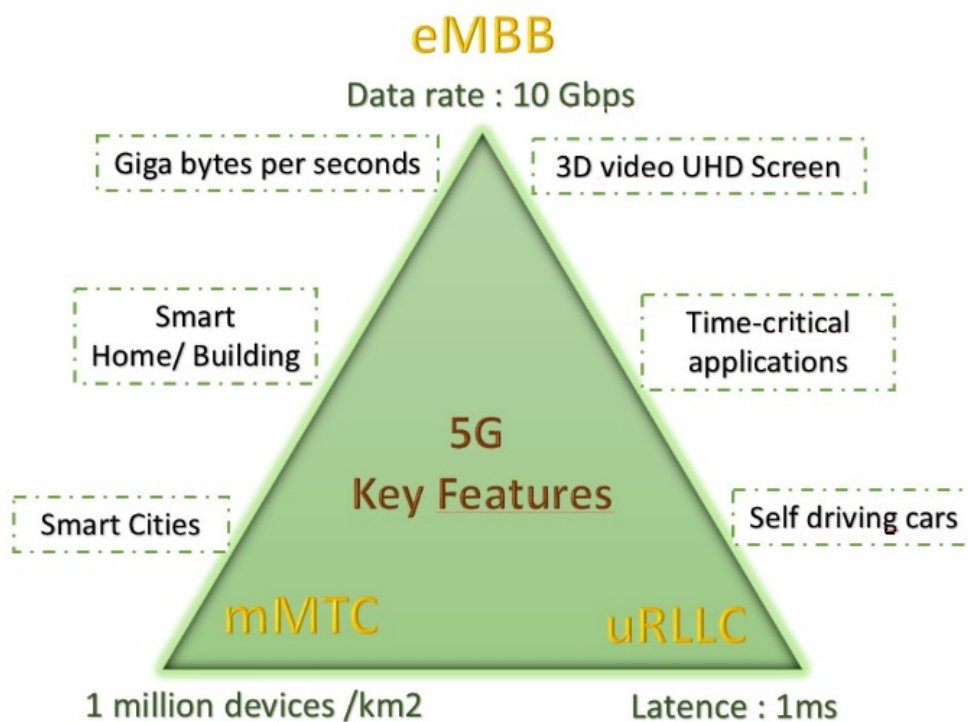


Figure 1. 5G key features

conference and journal articles, focusing in particular on 5G network management, including IoT applications within the Information and Communication Technology (ICT) domain [20]. Most of these studies address the scheduling problem considering the orthogonal frequency division multiple access (OFDMA) structure of the LTE radio interface, which stands for the long-term evolution in mobile networks. Nonetheless, official releases of the 3GPP since Release 10 are already specifying novel IoT-oriented features in the upcoming wireless system, i.e., 5G NB-IoT, such as the narrower radio bearers and the resource-saving capabilities for reduced device cost and prolonged battery life. These proposals aim to guarantee connectivity for the user equipment with reliable IoT communications, which satisfy quality-of-service (QoS) requirements such as coverage, spectral, and energy efficiency in the network [20].

It is extremely important to stress that, in the 5G IoT scenario, the key challenge lies in the implementation of QoS-aware scheduling strategies [21]. Any 5G scheduling policy jointly takes into consideration different key performance indicators, such as energy consumption, latency, reliability, frequency, computational resources, clock synchronization, and data [22]. Recent studies propose smart home scheduling systems that leverage distributed strategies to significantly reduce electricity bills and peak loads, achieving reductions of up to 95.25% in energy costs and 70.8% in peak demand under optimized scenarios [23]. The solution to the scheduling problem adopted in the design of the Internet of Things prefers simple control services, not causing resource blocks to be lost because of the lower data rate of IoT devices that access the network. Furthermore, it considers the unequal distribution of traffic loads among devices in IoT applications.

In 5G networks, various scheduling algorithms has been developed to improve Internet of Things (IoT) devices connectivity, the unique challenges posed in increasing user demands and various traffic types needs. From the well-known existing algorithms in literature, we found, the EXP-MLWDF, Proportional Fairness (PF), MAX-RATE and MAW-WEIGHT schedulers. These scheduling algorithms has been proposed and implemented, each focusing on different performance objectives [24]. Each one of these algorithms has been designed to answer to a specific aspect of network performance, such as throughput, SINR (Signal-to-Interference-plus-Noise Ratio) and delay, key scheduling algorithms include:

EXP-MLWDF (Exponential-Modified Largest Weighted Delay First): This algorithm prioritizes users based on their packet delays and the exponential function of the delay. It ensures that delay-sensitive applications receive timely resource allocation. The weight of each packet is determined by both its delay and a priority factor, which can adjust dynamically based on network conditions.

PF (Proportional Fair): The Proportional Fair algorithm balances between maximizing total network

throughput and ensuring fairness among users. It assigns resources based on a proportional fair metric, which considers both the current data rate and the average historical data rate of each user. This approach helps maintain a balance between users with good channel conditions and those with poorer conditions.

Max-rate: The Maximum Rate algorithm focuses on maximizing the overall network throughput by allocating resources to users with the highest instantaneous channel quality. This algorithm tends to favor users with better channel conditions, potentially leading to higher overall throughput but less fairness among users.

Max-weight: is a scheduling strategy that seeks to balance network throughput with fairness by taking into account both the channel conditions and the queue lengths (or the amount of data waiting to be transmitted) of different users.

The integration of these scheduling algorithms within Massive MIMO frameworks further enhances IoT connectivity by addressing key issues such as pilot contamination and interference management. In other side, techniques such as user clustering for pilot allocation not only mitigate interference but also significantly improve spectral efficiency, which is paramount in a densely populated IoT environment. By implementing these advanced scheduling strategies, network can achieve not only higher throughput and reduced latency but also a scalable infrastructure capable of accommodating a growing number of IoT devices. Together, these algorithms represent a crucial step in enhancing network performance and user experience within 5G networks.

2.3 Challenges in IoT connectivity

To enhance network efficiency and adaptability towards better resource management in large-scale IoT networks, emerging technologies such as Machine Learning (ML) and Software-Defined Networking (SDN) are integrated. Also for optimizing resource allocation with better QoS for heterogeneous IoT devices based on types and locations, Deep reinforcement learning techniques are used in the control plane. Although, newly published studies have also proven that the reinforcement learning-based algorithms have improved the network performance in terms of QoS parameters of delay and throughput against Random and Round Robin scheduling. Compared to other alternatives advanced techniques, such as fuzzy-logic-based and predictive models [25]. Reinforcement-learning approaches have enhanced resource allocation equally or sometimes even better. The integration of IoT devices into 5G networks introduces several challenges:

Scalability: Managing a vast number of connected devices requires scalable solutions that can efficiently handle resource allocation and connectivity management.

Heterogeneity: IoT devices have diverse requirements in terms of data rate, latency, and reliability, necessitating flexible and adaptable scheduling algorithms.

Energy Efficiency: Many IoT devices are battery-powered, making energy-efficient communication crucial to prolong device lifespans.

Security and Privacy: Ensuring secure communication and protecting sensitive data from breaches is vital in IoT networks, requiring robust encryption and authentication mechanisms [26].

The realization of IoT with its various applications has been looked at as something inseparable from the way modern technology carries on, however, the place and constraints on IoT devices increase vulnerability of the network since many of them are open. Security forms an important part of IoT applications because their pervasive nature affects many aspects of daily life. One challenge is that traditional security mechanisms do not work since the limited computational capability of IoT devices and sheer number of connected nodes make device-to-device communication complicated. However, one promising method is to use Intrusion Detection Systems (IDSs) for distinguishing malicious from benign traffic. Lightweight IDS solutions are needed for better accuracy and efficiencies. Even fog computing has been explored in recent studies that bring services much closer to the electronic devices to optimize IDS performance [27].

Addressing these challenges involves developing advanced scheduling algorithms that can dynamically adapt to the varying needs of IoT devices while optimizing network performance in terms of throughput and SINR.

3. Methodology

3.1 Parameters and used metrics

The simulation was done respecting specific parameters to reflect a realistic 5G-IoT environment. The primary performance metrics used in the evaluation are Throughput, Signal-to-Interference-plus-Noise Ratio (SINR) and Delay, The key parameters are presented in Table 1.

3.2 Description of our new scheduling algorithm

The study compares our novel algorithm with four well-known scheduling algorithms in literature, already dis-

cussed in section 2.2, each with different approaches to resource allocation.

Our new proposed scheduling algorithm called DUWF (Delay Urgent Weighted Fair Scheduling) is specifically designed to address the needs of IoT applications in 5G networks and beyond, particularly for densely connected environments like smart classrooms, smart schools or smart industry (IIoT). As shown in Table 2, The key innovation in DUWF is its ability to dynamically adjust resource allocation based on real-time network conditions and the specific requirements of different IoT applications. This ensures a more balanced performance across various metrics, aiming to enhance throughput, delay and SINR.

What makes our DUWF algorithm more suited for next-generation IoT deployments is that it is built on four fundamental principles that make it unique:

Delay Sensitivity: DUWF recognizes both packet delays and deadlines, and prioritizes time-sensitive applications and interactive learning scenarios that depend upon real-time response.

Urgency-Aware Traffic Prioritization: The DUWF algorithm utilizes exponential urgency metrics to flexibly adjust traffic priorities. Accordingly, applications with deadlines that are approaching receive timely attention, even during heavy load periods.

Weighted Decision Logic: DUWF incorporates resources availability and application emergency into its decision logic, allowing it to find practical compromises between network efficiency in general, and the specific performance requirements of each of the applications.

Fairness: The DUWF algorithm maintains fairness and equity among many devices and applications with equally high demand for the same resources, especially in dense areas; it prevents domination by one node from taking the bandwidth all for itself.

Taking into consideration $r_{i,j}$ (the available rate of the i -th stream on the j -th subchannel for UE and R_i (the average throughput), DUWF ensures that each device

Table 1. Simulation parameters.

Parameter Value	Parameter Value
Number Of Gnb	1
Number Of Iot Devices	50 (Dense Area)
Simulation Time	5 Seconds
Inter-Packet Interval	100 Ms
Flow Types	Ngbr, Voice & Video
UE Speed	3 km/h
UE Mobility Model	Randomdirection2d
UE Channel State	LOS And NLOS
Symbols Per Subframe	24
Min Distance (Gnb-UE)	10 m
Max Distance (Gnb-UE)	200 m
HARQ Enabled (Harqenabled)	True
RLC AM Enabled	True

Table 2. NEW Algorithm Working Steps (MAX-Weight Based).

NEW Algorithm working steps (MAX-Weight Based) :
1- Define the flows 'lflow' and 'rflow' (l for left and r for right);
2- Define ($r_{i,j}$) (the available rate of the i-th stream on the j-th subchannel for UE) and (R_i) (the average throughput);
3- Define (LargestDelayIt) as the lflow delay threshold value: <ul style="list-style-type: none"> • $lLargestDelayIt = \max_element(lflow \rightarrow m_txPacketDelays.begin(), lflow \rightarrow m_txPacketDelays.end());$
4- Define (rLargestDelayIt) as the rflow delay threshold value: <ul style="list-style-type: none"> • $rLargestDelayIt = \max_element(rflow \rightarrow m_txPacketDelays.begin(), rflow \rightarrow m_txPacketDelays.end());$
5- Define the (lRelDeadlinei) as the lflow HOL packet delay: <ul style="list-style-type: none"> • $lRelDeadlinei = lflow \rightarrow m_deadlineUsi - lflow \rightarrow m_txQueueHolDelayi;$
6- Define the (rRelDeadlinei) as the rflow HOL packet delay: <ul style="list-style-type: none"> • $rRelDeadlinei = rflow \rightarrow m_deadlineUsi - rflow \rightarrow m_txQueueHolDelayi;$
7- Compute the urgency factor for left flow: <ul style="list-style-type: none"> • $lUrgencyFactor = \exp \frac{lLargestDelayIt}{lLargestDelayIt - lRelDeadlinei}$
8- Compute the urgency factor for right flow: <ul style="list-style-type: none"> • $rUrgencyFactor = \exp \frac{rLargestDelayIt}{rLargestDelayIt - rRelDeadlinei}$
9- Compute the weight for left flow: <ul style="list-style-type: none"> • $W_{(i,j)_{NEW-left}} = \frac{lflow \rightarrow r_{i,j}}{R_i} \times lUrgencyFactor$
10- Compute the weight for right flow: <ul style="list-style-type: none"> • $W_{(i,j)_{NEW-right}} = \frac{rflow \rightarrow r_{i,j}}{R_i} \times rUrgencyFactor$
11- Return ($W_{(i,j)_{NEW-left}} > W_{(i,j)_{NEW-right}}$)
12- Schedule the flow with the greatest weight.

receives appropriate network resources based on both its technical requirements and educational priority.

4. Simulation environment and setup

In this study, the simulation environment was performed with NS-3 network simulator [28], this simulation environment has been widely acknowledged by its fidelity in modeling communication networks behaviors. The simulation is performed to emulate a 5G network with IoT based devices in it, as there are multiple network element and network parameters that needs to be check, quite obviously that it should be made realistic.

To assess in this study the proposed scheduling algorithm performances, we built new simulation environment representing 5G-IoT architecture, in which our devices are operating in the Terahertz band. However, to represent future capabilities of 6G IoT, simulation parameters are chosen carefully.

The simulation scenario presented in Fig. 2 shows an Ultra Dense Network Environment, where a large volume of interconnected IoT devices operate in real time, such as high-resolution cameras, AR/VR headsets, smart boards, sensors, and users terminals (UEs). This scenario simulates next-generation data and latency sensitive applications.

To simulate realistic results, the simulation setup

includes the most relevant and required network components. The simulation environment models: base stations, user equipment (UEs), motion models, mobility models, and traffic generators. The devices are distributed within an Ultra Dense Area topology, and are generating heterogeneous traffic patterns for many different sources of data, including video traffic, sensor traffic, and control messages. Since the scheduling and the resource allocation algorithms were modeled under dynamic traffic loads, the algorithms can sufficiently adapt, based upon the results of this study.

The simulation-environment Key features include:

Network Topology: A single base station (gNodeB) serving a high density of IoT devices, with a coverage area supporting 50 IoT devices. Device Distribution: With distances ranging from 10 to 200 meters from the base station, IoT devices are randomly distributed within the network coverage area, simulating as well as possible a realistic spatial distribution in Ultra Dense Network.

Traffic Generation: To emulate real-world applications scenarios, IoT devices, generate divers set of traffic types, including video streaming, sensor updates and control signaling.

Performance Evaluation: In order to maintain some consistency and statistical validity, various simulations will be run several times. The averages of all performance metrics will be calculated across runs to account for

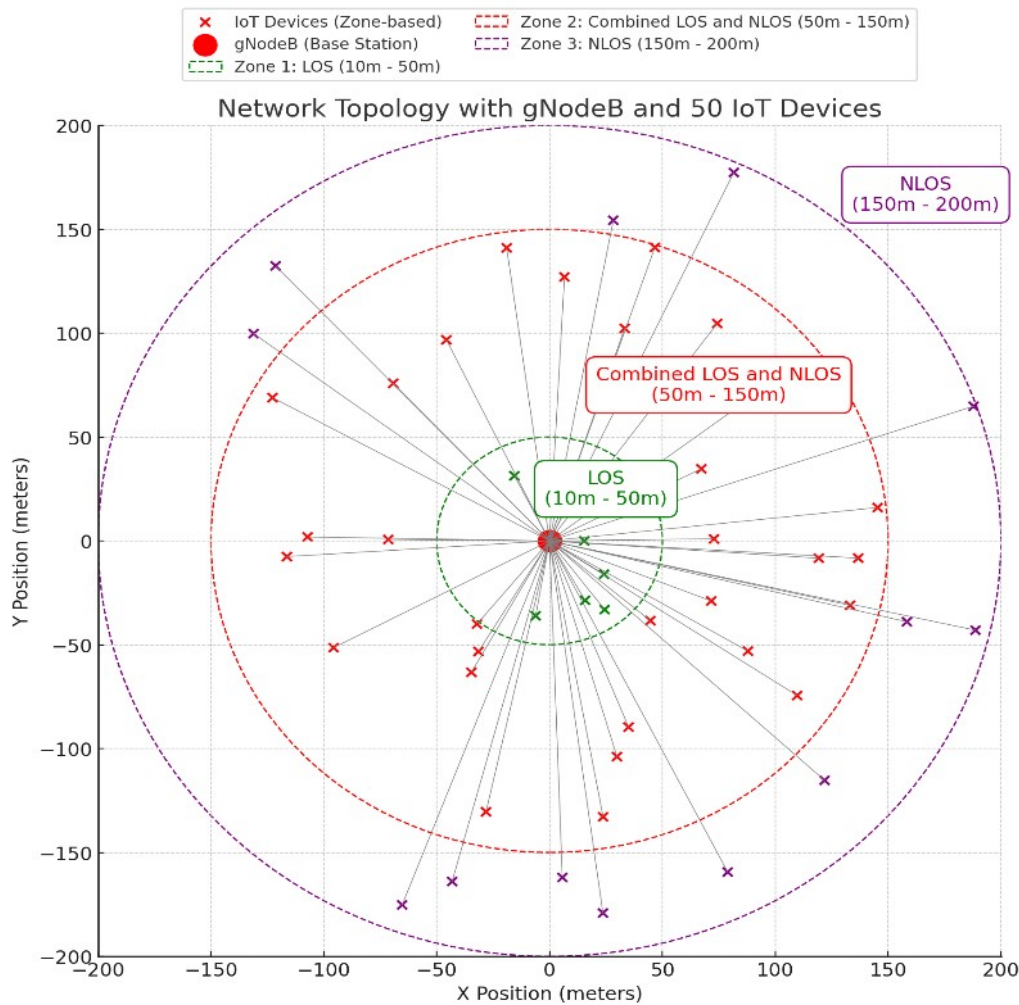


Figure 2. Network Topology

variability and obtain samples that will produce stronger results.

Channel Models: Advanced channel models are incorporated within the simulations to include realistic wireless propagation effects and account for the impacts of path loss, shadowing, and fast fading, which align with Terahertz communication environments characteristics.

Traffic Models: Several traffic patterns are implemented to reflect the heterogeneous nature of IoT applications, particularly in use cases that are heavily interactive and delay sensitive, such as Ultra Dense Networks.

Performance Metrics: Detailed key performance indicators was collected throughout the simulations to analyze the efficacy of the suggested scheduling algorithm, this performance metrics of interest included throughput, delay, and SINR.

5. Results and discussion

In the following section, we present detailed discussion about simulation results considering different traffic types as well as NGBR (Non-Guaranteed Bit Rate), video and VoIP (Voice over IP) traffic types. We further evaluate performances of these traffic classes using various important metrics such as Throughput Analysis, SINR,

and Delay. Based on these metrics, we aim to evaluate the behavior of the proposed DUWF scheduling under different traffic conditions, as well as its performance compared to other scheduling schemes, and its influence on the network performances.

5.1 VoIP flow analysis

In this scenario, we consider the Voice over Internet Protocol (VoIP) traffic flows, which are highly relevant for IoT applications that require real-time communication, like Ultra Dense Networks and telehealth centers. In this environment, VoIP flows require low-latency, high-reliability to ensure clear and continuous voice communications. The performance evaluation metrics considered in this problem are the average throughput, SINR and Delay per 50 IoT devices.

5.2 Throughput analysis

The throughput study in 5G networks, especially for improving lot connectivity, is essential due to the growing number of lot devices and the increasing volume of data traffic they produced. Conventional mobile network standards such as LTE-A are being challenged to support this increasing traffic more efficiently. They often suffer

from spectrum access limitation that affects directly the efficiency of throughput for IoT applications. The integration of 5G technology become a necessity, it represents the more effective solution, thanks to its advanced capabilities to accommodate large data streams.

Moreover, while previous radio mobile generation such as LTE-A standard may not be able to provide good and optimal solution, 5G architecture with the increase in its available bandwidth and lower latencies becomes a promising alternative for future IoT traffic. With this transition, it becomes feasible to better accommodate the high data demands expected from IoT devices. The continuous development of algorithms that leverage such intermediate aggregation techniques will be pivotal in refining overall throughput and ensuring that 5G and beyond networks can effectively meet the anticipated increase in IoT-related data traffic. In short, throughput analysis not only reveals current network limitations but also highlights potential pathways to optimize IoT connectivity in the evolving 5G landscape. Elsewise, this metric is important to evaluate the performance of scheduling algorithms in terms of their capacity of allocating resources effectively and maintaining high throughput.

Figure 3 demonstrates that our DUWF algorithm significantly outperforms the other algorithms in terms of throughput, providing the highest average Throughput for VoIP traffic across 50 IoT devices, demonstrating its superior ability to efficiently allocate resources for real-time application like Customer service and call Center Solutions. This makes the DUWF algorithm particularly well-suited for environment where maintaining low latency and high throughput is critical for seamless communication.

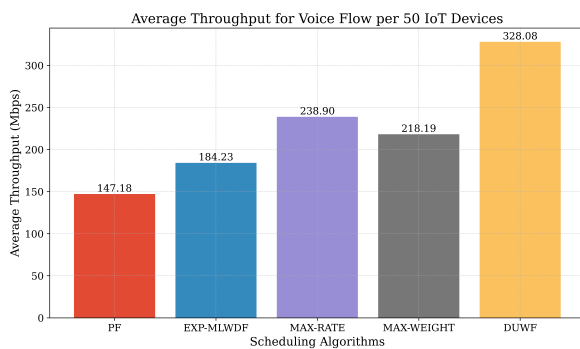


Figure 3. Average throughput for VoIP flow per 50 IoT objects.

5.2.1 SINR analysis

Signal to Interference plus Noise Ratio (SINR) is a fundamental metric to evaluate the performance of wireless networks, and it is relevant to enhance Internet of Things (IoT) connectivity within 5G networks. SINR is a measure of the ratio of the desired signal power under the impact of noise and interference, so it directly impact the quality of service (QoS) experienced by users. A higher SINR reflects better communication quality, which facilitates more efficient resource allocation and scheduling

strategies. In IoT environments, where a large number of IoT devices communicate simultaneously, attempting optimal SINR levels is essential for reducing latency and guarantying reliable data transmission.

Moreover, the dependence between SINR and radio resource allocation in 5G networks and beyond has pointed out the importance of continuous monitoring and dynamic regulation, particularly under the various conditions presented by multiple IoT device connections. Accurate SINR analysis not only facilitates a deeper understanding of the propagation environment but also enhances the strategic deployment of network resources, ensuring robust connectivity and performance across increasingly dense IoT ecosystems. As 5G technology evolves, it becomes imperative to further refine SINR-related algorithms to support efficiency and maximize connectivity potential for all user equipment.

For VOIP, Fig. 4 demonstrates that our DUWF algorithm not only achieves the highest throughput but also delivers a competitive SINR even if it's not the best but it provides nearly similar SINR Value. This indicates that the algorithm is capable of maintaining strong signal quality while optimizing performance, making it highly effective in supporting VOIP applications, which rely on both high throughput and excellent signal integrity for seamless communication.

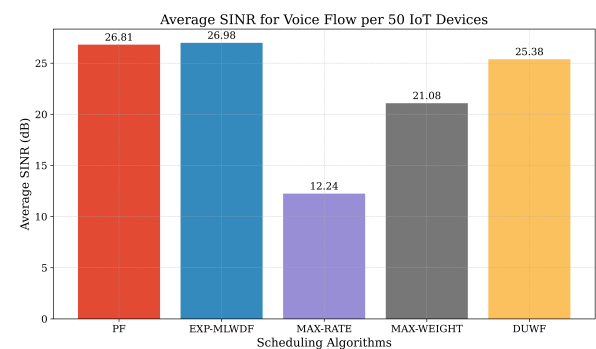


Figure 4. Average SINR for VoIP flow per 50 IoT objects.

5.2.2 Delay analysis

In the context of fifth-generation (5G) networks, delay analysis is crucial for optimizing Network performances, particularly for applications requiring strict latency specifications. For instance, the tactile Internet requires an end-to-end delay of less than 1 millisecond. Delay analysis in such ultra-dense networks would pose great challenges, because it's not just an aggregate of individual delays but also a convoluted function imparted by several factors such as network load, MAC (Medium Access Control) protocols, and path loss characteristics. Normally, these contributions to delay can be classified into processing, queuing, transmission, and propagation delays.

Capturing complex interactions between multiple queuing systems is a major factor in 5G networks for delay analysis. Traditional queueing models, almost based on simple scenarios would probably not cater

for due to the large number of servers and queues that would typically present in ultra-dense networks. The complexity is even more pronounced in systems where the condition upon which the service rate of one queue depends on the states of other queues making effective delay computation more difficult.

An important takeaway from recent studies indicates that scheduling methods, such as RR (Round Robin) scheduling, exhibit better delay performance than first in first out (FIFO) strategies under heavy traffic loads which is particularly important as these patterns become more complex within a 5G context. Thus, developing a new model that accounts for both, the queuing processes and the resultant delays, is beneficial for the design and implementation of 5G. Ensuring as well as it can be, that they meet the rigorous latency requirements, especially in time-sensitive applications like VoIP, video streaming, and IoT communications where low delay is essential for proving good quality of service (QoS).

As shown in Fig. 5, our new algorithm gives better performance results by reducing delay, making it particularly very suited for real-time communication applications like VoIP, where low latency is essential for ensuring smooth and uninterrupted interactions which affect directly the provide Quality of Service.

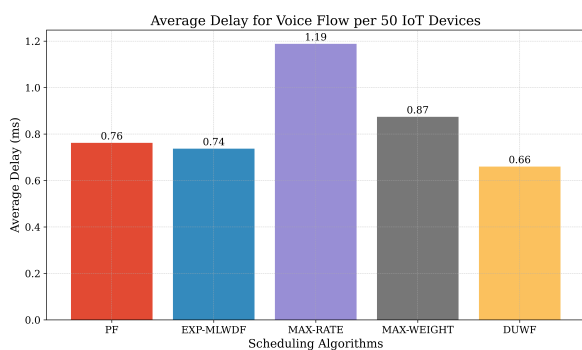


Figure 5. Average delay for VoIP flow per 50 IoT objects.

5.3 Video flow analysis

Video flows are very important for IoT applications especially thus related to video streaming and surveillance such as security cameras, video doorbells, and remote monitoring systems belonging to this category. Therefore, the scenario of video flow covers the requirement for streaming video content where high data rates plus low latency plays a vital role for ensuring smooth playback as well as good quality of video streaming. Video flows are sensitive to latency as well as jitter, which may affect the watching experience. The simulation scenario defined in this paper aims to assess how well the proposed DUWF scheduling algorithm performs compared to some other algorithms under conditions that can be described as having intensive videos.

5.3.1 Throughput analysis

For video flows, Fig. 6 shows the average throughput obtained for the tested algorithms, It appears clearly

that the DUWF scheduling algorithm proposed in this study outperforms all other algorithms and delivers the highest throughput. Thus, it is well appropriate for video streaming applications that operate at high bandwidth levels. This performance gain is due to the fact that the algorithm is designed to handle video traffic prioritization and dynamic resource allocation based on the flow level which contribute to the improvement of the smooth delivery as well as on the enhancement of the Quality of Experience in real-time settings.

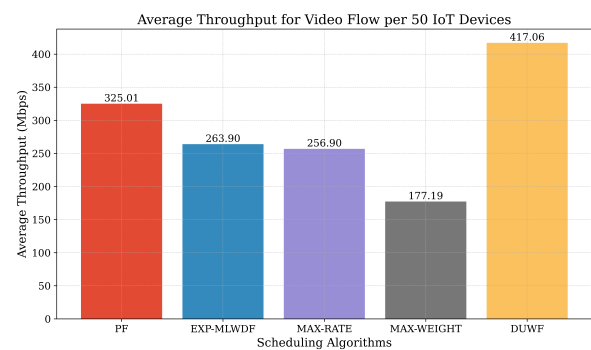


Figure 6. Average throughput for video flow per 50 IoT objects.

5.3.2 SINR analysis

Always for the case of video flows, as illustrated in Fig. 7, the SINR results corroborate the fact that the DUWF scheduling algorithm outperforms all other comparable methods in achieving the maximum allowed SINR value. As stated before, maintaining acceptable levels of interference is critical and equally important for maintaining strong signal quality and enhancing network performances. The best SINR results were noted with the newly proposed algorithm, which can be explained by the ability of this implement to allocate resource assigning to high-SINR links for video delay-sensitive traffic and ensure consistent quality and less range for intense bandwidth demands.

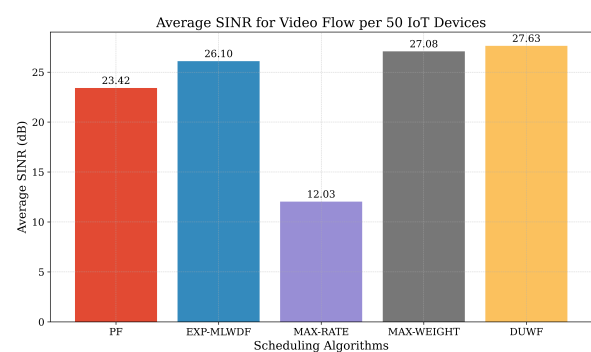


Figure 7. Average SINR for video flow per 50 IoT objects.

5.3.3 Delay analysis

As seen in Fig. 8, the “DUWF” algorithm provides a competitive delay even if it is not the least one. This happens because of its priority mechanism, which sometimes priorities higher SINR or throughput flows over delay

sensitive ones, the additional layers of decision making in the scheduling logic do slightly increase smoothly time but make for better overall efficiency. For video applications that need both stability and responsiveness, this trade-off is acceptable.

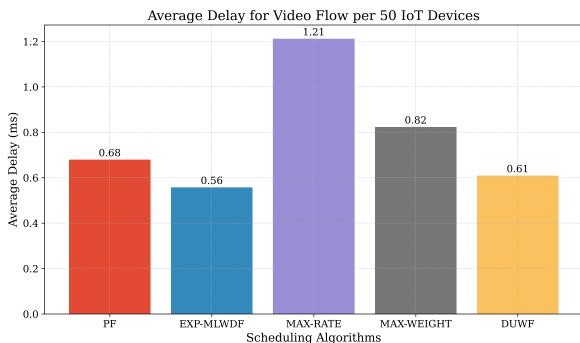


Figure 8. Average delay for video flow per 50 IoT objects.

5.4 NGBR flow analysis

This scenario focuses on Non-Guaranteed Bit Rate (NGBR) flows. For a wide range of IoT applications, this traffic type is relevant especially for applications that involve background data transfers, such as sensor data collection, firmware updates and batch processing tasks. It is true that these flows do not have strict latency requirements, making them more flexible but still important for overall network performance. For example in Smart Class environment, NGBR traffic supports various operations such as remote device synchronization, periodic content updates, and learning analytics aggregation, ensuring as well seamless digital infrastructure with continuous real-time educational activities.

5.4.1 Throughput analysis

As illustrated in Fig. 9, and similar to its previous results, our DUWF algorithm continue to outperform all other approaches for NGBR flows in terms of average throughput. This given performance reflects the algorithm's ability to allocate efficiently unused or underutilized resources to traffic with less priority without compromising the performance of delay-sensitive flows. By smartly adjusting to traffic conditions and optimizing scheduling choices, the algorithm maximize the use of overall resources, proving it very useful for background IoT tasks in urgent situations like smart education systems and the hall Ultra Dense Networks environments in general.

5.4.2 SINR analysis

Consider we are in charge of a smart IoT network where 50 devices such as thermostats, health sensors, coffee makers, and even smart doorbells, are all trying to get your attention at the same time. It's like hosting a dinner party where everyone wants to relate their account at once. Some voices may be lost in the noise, while others may take over the discussion to share their story at once. Some voices, that's where DUWF steps in, like the perfect host who makes sure everyone gets a fair chance

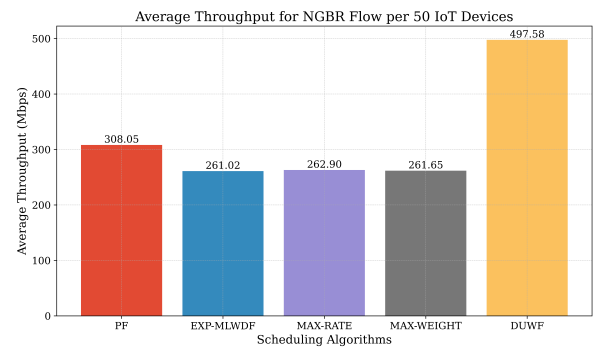


Figure 9. Average throughput for NGBR flow per 50 IoT objects.

to speak and ensures as well as possible that each voice is loud and clear.

DUWF algorithm continue to outperform all the tested algorithms, delivering the higher SINR (Fig. 10), which means fewer dropped messages and better overall data quality that is absolutely crucial for things like health sensors, where even a single missed message could have real-world consequences.

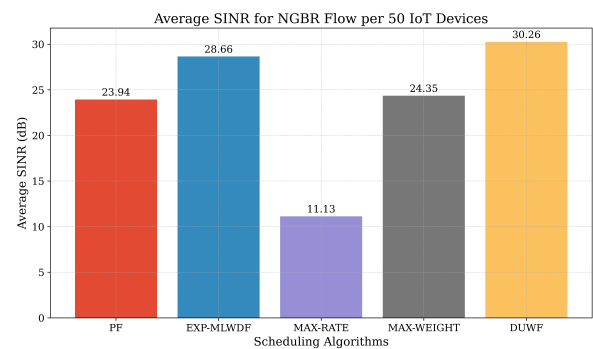


Figure 10. Average SINR for NGBR flow per 50 IoT objects.

5.4.3 Delay analysis

From Fig. 11, we found that the "DUWF" algorithm excels in delay minimization by offering a better delay performance compared to MAX-WEIGHT, PF and MAX-RATE. With an average 0.57 ms delay, it ensures that even the most time-sensitive messages like health sensor alerts get through almost instantly. This ultra-low delay is particularly critical for IoT applications since a little lag can mean so much in terms of performance or even safety. EXP-MLWDF is slightly faster on average, clocking in at 0.52 ms.

6. Conclusion

In this study, we evaluated the performance of various schedulers to optimize IoT connectivity within 5G networks. Using the NS-3 simulator [28], we analyzed the throughput, delay and SINR performance, for EXP-MLWDF, PF, MAX-RATE, MAX-WEIGHT and our proposed algorithm (DUWF), considering various IoT traffic flows: VoIP, Video, and NGBR. Results prove that our algorithm performs better in all metrics measured making it a strong candidate for environments requiring

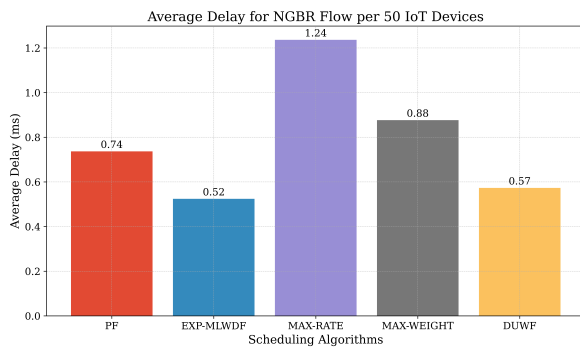


Figure 11. Average delay for NGBR flow per 50 IoT objects.

high throughput, good signal quality, and low latency.

Crucially, the introduction of the Terahertz (THz) bands for 6G imposes important benefits. With their ultra-broadband and ultra-low latency capabilities, they are best choice for bandwidth-hungry, time-delay requiring applications. Our results demonstrates that the DUWF algorithm exploits the THz spectrum to the most, and evidently ensure efficient use of spectrum resources while maintaining QoS for both real-time and background traffic.

These findings place our approach as an optimistic scheduling scheme for the forthcoming ultra-dense capacity 6G IoT deployments in Ultra Dense Networks (UDN) and beyond. Deep learning models have recently shown high accuracy in classifying digital modulation types for 6G systems, even under challenging conditions like CFO, PN, and low SNR [29].

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Authors contributions

All authors contributed equally to the conception, design, execution, and writing of this work. All authors read and approved the final manuscript.

Availability of data and materials

The authors declare that the data supporting the findings of this study are available within the paper.

Conflict of interests

The authors assert that they do not have any identifiable conflicting financial interests or personal relationships that might be perceived to influence the work presented in this paper.

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