# Cooperative Scheduler to Enhance Massive Connectivity in 5G and Beyond by Minimizing Interference in OMA and NOMA

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*Abstract*—The fifth-generation (5G) and beyond 5G (B5G) wireless networks introduced massive machine-type communications (mMTC) to cope with the growing demand of massive Internet of things (IoT) applications. However, the heterogeneous characteristics of massive IoT and diverse quality of service (QoS) requirements may lead to severe interference that could degrade the expected QoS of the cellular ecosystem.

Therefore, this paper studies the impact of interference caused by mMTC connections. We theoretically model the inter-cell interference (ICI) minimization problem for the existing orthogonal multiple access (OMA) technique and propose its corresponding solution. Furthermore, we jointly solve the ICI and the co-channel interference minimization problem for the IoT users when the non-orthogonal multiple access (NOMA) technique is used. For the proposed OMA and NOMA schemes, we design a cooperative scheduler to reduce the impact of such interference. The results show that our proposed schemes provide up to 58%, 75%, and 100% more improvements in terms of user's data rates, energy consumption, and connection density, respectively

## *Index Terms*—NB-IoT, OMA, NOMA, ICI, mMTC

## I. INTRODUCTION

Unlike the previous mobile technology generations where the primary focus was to enable human-to-human communications, the fifth-generation (5G) focuses equally on enabling industrial communications by means of service verticals such as massive internet of things (IoT), mission-critical communications, and enhanced mobile broadband (eMBB) communications.

It is predicted that by the end of 2023 the number of connected devices needed for supporting the massive IoT deployment will reach 15 billion [1]. Such growth in connectivity

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will also address the requirements of use cases such as utility monitoring, health-care IoT applications, autonomous vehicles (AVs) controlling, and mission-critical applications [2], [3]. In this regard, this paper focuses on solving the interference challenges that are brought by the dense deployment of wireless IoT devices in order to enhance the IoT connectivity.

Legacy non-cellular commercial technologies such as Wi-Fi, and Bluetooth low-energy (BLE) have limited coverage ranges, which hinders the massive deployment of IoT use cases. This is because these technologies only support short-range wireless access for a few hundred devices [4]. Therefore, to cope with the growing demand for massive connectivity for widearea coverage, the  $3^{rd}$  generation partnership project (3GPP) introduced massive machine-type communications (mMTC).

mMTC is enabled by licensed IoT technologies (e.g., Narrow-Band IoT (NB-IoT) [5], and unlicensed technologies (e.g., LoRa) [6]. Both of these technologies are categorized as low power wide area networks (LPWAN), aiming at servicing devices located in hard-to-reach areas, with minimum human intervention. However, in contrast to unlicensed technologies, licensed technologies reuse the existing cellular infrastructure and are, therefore more economical and advantageous for cellular telecommunication operators.

The current 5G deployments implement orthogonal multiple access (OMA) schemes which provide orthogonality in terms of frequency resources. However, for massive IoT technologies (i.e., NB-IoT and LTE-M), these OMA schemes are not able to reach the capacity demand for supporting 52, 000 devices per cell. Additionally, the 5G broadband and 5G new radio (NR) capabilities bring the possibility of massive connectivity support of up to 1,000,000 devices per square kilometer [7], [8]. In this regard, proactive scheduling and advanced multiple access techniques to support such dense deployment become of great significance.

The non-orthogonal multiple access (NOMA) scheme is considered to be the promising technique to provide capacity enhancement of above 100, 000 devices per cell [9]. Contrary to the OMA approach, the NOMA approach gives the possibility to simultaneously superpose multiple devices in a given available radio resource by allocating different power coefficients or codes to enable the successive interference cancellation (SIC) at the receiver [10]. In this regard, NOMA brings an exponential increase in device support as compared to OMA, but at the cost of increased receiver complexity [11].

Despite the advantages that NOMA brings to 5G and B5G

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networks, it is still unclear if it can be implemented in lowpower IoT devices. This is because NOMA involves superposition coding (SC) and SIC at the transmitter and receiver, respectively, which are highly computationally complex for mMTC applications [12].

Furthermore, for both OMA and NOMA approaches, if the radio resources are not well managed, the massive connectivity will lead to massive interference, which will severely degrade the performance of legacy, 5G, and B5G network systems. That is why our work proposes an interference mitigation framework to enhance the cell performance of the OMA and NOMA schemes in a multi-cell scenario. The main contributions presented in this paper are as follows;

- Firstly, we explicitly formulate the massive interference problem for the OMA and NOMA schemes and propose the corresponding solutions to optimally schedule the radio resources and hence reduce the massive interference.
- Secondly, we propose a cooperative scheduling strategy to minimize massive interference for the OMA and NOMA schemes by sharing the scheduling tables between the base stations to increase the overall network capacity.
- Thirdly, we present the performance enhancements obtained with our proposed approaches and compare the results with existing OMA and NOMA techniques.

To the best of the authors' knowledge, this is the first work that presents a framework to mitigate massive interference caused by massive connectivity of IoT deployment for both OMA and NOMA techniques in 5G and B5G networks.

The rest of the paper is organized as follows: Section II presents the related works. Section III presents the analysis of OMA in mMTC systems. For system modeling, we use the NB-IoT system to represent 5G mMTC technology [13]. Section IV presents the analysis of NOMA in mMTC systems. Section V presents the design of the proposed scheduler to mitigate the impact of inter-cell interference for both OMA and NOMA schemes. Section VI presents the simulation setup, the performance evaluation and achieved enhancements for the OMA and NOMA schemes. The concluding remarks of the paper are given in Section VII.

### II. RELATED WORKS

Several works have studied the OMA / NOMA schemes and their suitability in 5G and B5G systems. For example, in [14], the authors intended to minimize the total energy consumption subject to the computation capacity and execution latency limits. They obtained an optimal transmit power and computation resource allocation based on the Karush-Kuhn Tucker (KKT) conditions. Their results showed that the total energy consumption for both NOMA and OMA schemes increases with the number of NB-IoT user equipment (UEs). However, when compared to OMA, NOMA reduces the total energy consumption by 53.23%. Critically, it should be noted that the authors neglected the impact of inter-cell interference (ICI).

In [15], the authors investigated the downlink performance of NOMA with randomly deployed cellular users. From the

Table I THE SUMMARIZED COMPARISON OF CONTRIBUTIONS BETWEEN THIS WORK AND THE EXISTING LITERATURE.

Article	Covered aspects in the contributions			
[Ref]	OMA NOMA CCI-aware ICI-aware UE Scheduler			
[14]				
[15]				
$[16]$				
$[17]$				
[18]				
This work				

presented analytical formulations, it is shown that the NOMA scheme leads to significant performance gains in terms of ergodic sum-rate. However, the allocated power and the targeted data rate could directly influence the outage performance, i.e., if the allocated power is lower than the required power for successful transmission, the UE will suffer from the outage.

In [16], the authors dealt with the connection density maximization problem in NB-IoT networks by using NOMA. The authors used the bottom-up power filling algorithm and proposed item clustering heuristic approach which allows any number of devices to be multiplexed per sub-carrier. It should be noted that the authors suggested multiplexing any number per sub-carrier without considering the impact of ICI, which is a potential threat to meeting the performance requirements of NB-IoT massive connectivity.

In [17], the authors proposed two cooperative relaying schemes i.e. ON/OFF - full-duplex relaying (ON/OFF - FDR), and ON/OFF - half-duplex relaying (ON/OFF - HDR) schemes. Either of the proposed schemes is applied to the cell center user (with good channel conditions) to help relaying the direct NOMA transmissions on the downlink of cell edge users. In this regard, the ON/OFF relaying decision depends upon the quality of direct and relay links from the base station to the cell edge user. From the results, it is shown that the proposed cooperative scheme significantly improves the outage performance and the sum rate of both cell-center and cell-edge users. However, for mMTC devices such as in the LPWAN category, relaying of information leads to an increase in device complexity and cost, which is the limitation for most massive IoT use-cases.

In [18], the authors proposed a novel resource allocation technique for NOMA, based on cooperative cellular networks. In their proposed framework, the NOMA users with good channel conditions act as group heads, hence can relay information to NOMA users with bad channel conditions. Despite the gains of the proposed scheme for high complexity devices, it should be noted that the reduced complexity of NB-IoT devices, power-saving mode, and extended discontinuous reception (eDRx) make relaying of information (i.e. at the low complexity device) unfeasible.

Additionally, new advancements have been made in order

to realize the goal of massive IoT under cellular technologies. For example, proactive techniques such as intelligent reflecting surfaces, that enhance the IoT links to the corresponding access point (AP) by counteracting the high pathloss, are introduced in [19]; the improved links are then exploited to better optimize the offloading of computations from the AP to the mobile edge computing (MEC) server. Similarly, proactive radio resource scheduling by means of machine learning techniques [20], and modern link-level adaptation by means of novel interference management approaches are being explored [20]. However, these techniques are not in the scope of this paper. Table I presents the comparisons between contributions of this work and the existing literature.

The next section explores the OMA approach and presents the proposed solution to mitigate the massive interference that is caused by the dense deployments of IoT devices in a multicell scenario.

# III. THE ANALYSIS OF OMA IN MMTC SYSTEMS

#### *A. System model and problem formulation for OMA scheme*

For the analysis, we use NB-IoT since it is a long-range promising technique for 5G massive connectivity that currently uses OMA techniques for resource unit scheduling.

Before delving into the details, observe that the notations and abbreviations used in the mathematical analyses throughout the paper are summarized in Appendix A.

We assume that  $z = \{1, 2, \dots, Z\}$  represents the index of the resource units.  $x_c$  represents the cell c's UEs, and C, i.e  $c = \{1, 2, \ldots, C\}$ , represents the number of cells used in simulation. Therefore, the signal to interference plus noise ratio of user  $x_c$  in cell c at unit z is given as:

$$
SINR_{x_c}^z = a_{x_c}^z \left( \frac{|h_{x_c,c}^z|^2 P_{x_c}^z}{\sum_{l \neq c, l \in C} \sum_{q \in Q_l} |h_{q_l,c}^z|^2 P_{q_l}^z a_{q_l}^z + \sigma_N} \right) (1)
$$

where  $|h_{x_c,c}^z|$  is the channel gain of user  $x_c$  at resource z to the base station in cell c,  $P_{x_c}^z$  is the transmission power of user  $x_c$  at resource z. l represent the interfering cells, with the group of users  $Q_l$  and q represents the index of that user.  $|h_{q_l,c}^z|$  represents the channel gain of user  $q_l$  on unit z attached at cell c, and  $P_{q_l}^z$  represents the transmission power of user  $q_l$ at unit z.  $a_{x_c}^z$  represents the channel allocation matrix i.e.,  $a_{x_c}^z = 1$  when the resource is in use, and  $a_{x_c}^z = 0$  otherwise.  $\sigma_N$  denotes the receiver's noise power.

In this regard, we aim to minimize the ICI at user  $k$  in order to improve the detected SINR to satisfy the expected quality of service. Hence, the optimization problem becomes:

$$
\min \sum_{c \in C} \sum_{z \in Z} \sum_{l \neq c, l \in C} \sum_{q \in Q_l} |h_{q_l, c}^z|^2 P_{q_l}^z a_{q_l}^z \tag{2}
$$

subject to:

$$
SINR_{x_c}^z \ge \vartheta_{x_c,lim} \tag{3}
$$

where  $\vartheta_{x_c,lim}$  is the user  $x_c$ 's  $SINR$  threshold to satisfy its QoS,

$$
a_{x_c}^z \left( \frac{|h_{x_c,c}^z|^2 P_{x_c}^z}{\sum_{l \neq c, l \in C} \sum_{q \in Q_l} |h_{q_l,c}^z|^2 P_{q_l}^z a_{q_l}^z + \sigma_N} \right) \ge \vartheta_{x_c,lim}(4)
$$
  

$$
0 \le P_{x_c}^z a_{x_c}^z \le P_{maxm}, \forall c \in C, \forall x_c \in X_c, \forall z \in Z.
$$
 (5)

where  $P_{maxm}$  is the maximum power that a given device can use for its transmission.

$$
\sum_{x_c \in X_c} a_{x_c}^z \le 1, \forall z \in Z, c \in C.
$$
 (6)

#### *B. Proposed solution for the OMA scheme*

From the above analysis, the formulation represents a mixed binary integer non-linear programming (MBINP) problem, with  $a_{x_c}^z$  and  $P_{x_c}^z a_{x_c}^z$  which are very difficult to solve. Therefore, a step-wise algorithm is used as presented in [21], in order to perform the resource unit and power allocation. The proposed algorithm will implement three main steps as follows;

# • First: initializing transmit power

We aim to set the initial transmit power equal to a required power, which is a function of the  $SINR$  threshold to satisfy the required QoS. In this regard, interference level, e.g. average, tolerable, threshold, is already known from the statistics of the channel conditions. Hence, we denote this level as  $In_{x_c}^z$ and compute the initial transmit power as follows;

$$
SINR_{x_c}^z = \frac{|h_{x_c,c}^z|^2 P_{x_c}^z}{In_{x_c}^z} \tag{7}
$$

The transmit power becomes:

$$
P_{x_c}^z = \frac{I n_{x_c}^z SINR_{x_c}^z}{|h_{x_c,c}^z|^2}
$$
 (8)

Considering the SINR threshold, the inequality becomes;

$$
P_{x_c}^z \ge \frac{I n_{x_c}^z \vartheta_{x_c,lim}}{|h_{x_c,c}^z|^2} \tag{9}
$$

Therefore, the lowest acceptable transmit power to satisfy the QoS can be presented as:

$$
P_{x_c}^z = \frac{I n_{x_c}^z \vartheta_{x_c,lim}}{|h_{x_c,c}^z|^2}
$$
 (10)

# • Second: resource allocation

Since the power is already initialized, the optimization problem becomes:

$$
\min \sum_{c \in C} \sum_{z \in Z} \sum_{l \neq c, l \in C} \sum_{q \in Q_l} |h_{q_l, c}^z|^2 P_{q_l}^z a_{q_l}^z \tag{11}
$$

subject to:

$$
SINR_{x_c}^z \ge \vartheta_{x_c,lim} \tag{12}
$$

$$
\sum_{x_c \in X_c} a_{x_c}^z \le 1, \forall z \in Z, c \in C.
$$
\n(13)

Now the equation represent a 0-1 assignment problem, hence, we implement the cooperative scheduling scheme as presented in Section V.

# • Third: power allocation

We ignore the impact of intra-cell interference, thanks to the use of OMA scheduling scheme. However, the intercell interference from adjacent cells' users is experienced at each resource units, therefore we solve the interference problem for each resource unit. In this regard, we assume that, implementing optimal transmit power will reduce unnecessary energy consumption per user.

Therefore, the optimization goal becomes:

$$
\min \sum_{c \in C} \sum_{l \neq c, l \in C} |h_{l,c}|^2 P_l \tag{14}
$$

subject to:

$$
SINR_c = \left(\frac{|h_{c,c}|^2 P_c^t}{\sum_{l \neq c} |h_{l,c}|^2 P_l + \sigma_N}\right) \ge \vartheta_{c,lim} \tag{15}
$$

$$
0 \le P_c^t \le P_{maxm}, \forall c \in C. \tag{16}
$$

where  $|h_{c,c}|^2$  and  $|h_{l,c}|^2$  are the channel gains of transmitting user, and interfering user, respectively.  $P_c^t$  and  $P_l$  are the transmit powers of of transmitting user and interfering user, respectively.

Since constraint (15) is non-linear, we therefore make it linear as follows:

$$
|h_{c,c}|^2 P_c^t \ge \vartheta_{c,lim} \left( \sum_{l \ne c} |h_{l,c}|^2 P_l + \sigma_N \right) \tag{17}
$$

equivalently,

. . .

$$
-|h_{c,c}|^2 P_c^t + \vartheta_{c,lim} \left( \sum_{l \neq c} |h_{l,c}|^2 P_l \right) \leq -\vartheta_{c,lim} \sigma_N \quad (18)
$$

Performing the inequality expansion for  $c = 1, 2, \ldots, C$ :

$$
c = 1 : -|h_{1,1}|^2 p_1 + \vartheta_1 |h_{2,1}|^2 p_2 + \vartheta_1 |h_{3,1}|^2 p_3 + ,
$$
  
\n
$$
\dots, +\vartheta_1 |h_{C,1}|^2 P_c^t \leq \vartheta_1 \sigma_N
$$
  
\n
$$
c = 2 : -|h_{2,2}|^2 p_2 + \vartheta_2 |h_{1,2}|^2 p_1 + \vartheta_2 |h_{3,2}|^2 p_3 + ,
$$
  
\n
$$
\dots, +\vartheta_2 |h_{C,2}|^2 P_c^t \leq \vartheta_2 \sigma_N
$$
  
\n
$$
c = 3 : -|h_{3,3}|^2 p_3 + \vartheta_3 |h_{1,3}|^2 p_1 + \vartheta_3 |h_{2,3}|^2 p_2 + ,
$$
  
\n
$$
\dots, +\vartheta_3 |h_{C,3}|^2 P_c^t \leq \vartheta_3 \sigma_N
$$

The above expansion follows a matrix form which can be shortened as

$$
\tilde{A}\tilde{p} \le \tilde{c} \tag{19}
$$

In this work, Algorithm 1 presents the simulation implementation with additional procedures as discussed in Section V.

Since the OMA approaches employ orthogonality when allocating the available resources, most of the 5G mMTC systems fail to reach the cell capacity target as specified in the standard due to the limited available spectrum.

To overcome this limitation, the NOMA scheme presents significant advantages regarding spectrum efficiency, hence it is a promising technique to accommodate massive IoT applications for beyond 5G networks [22]. A generic architecture presenting the principles of the OMA and NOMA schemes in 5G networks is shown in Fig. 1. As can be seen, the OMA scheme allocates orthogonal physical resource blocks (PRB) to different user equipment (UE) transmitting at a given time slot. The NOMA scheme allocates a given PRB to multiple

# Algorithm 1 Proposed OMA scheme

1: **procedure** USER EQUIPMENT CREATION ⊳ applying Okumura-Hata model

2: 
$$
k \leftarrow |h_{x_c,c}^z|^2
$$
  
3. while  $P^z \neq 0$ 

3: while 
$$
P_{x_c}^{z_c,c_1} \neq 0, j \neq i
$$
 do

4:  $Equation(1)$ 

5: return  $SINR_{x_c}^z$ 

6: procedure SHARE THE SCHEDULING TABLES

- 7: while  $Equation(10)$  do
- 8: compute the best combination of UEs
- 9: return  $x_c$

10: **procedure** OPTIMAL POWER ALLOCATION

11: 
$$
\frac{In_{x_c}^* \vartheta_{x_c,lim}}{|h_{x_c,c}^z|^2} \leftarrow p
$$
  
12: **while** 
$$
\frac{In_{x_c}^* \vartheta_{x_c,lim}}{|h^z - h_{x_c}^z|^2} \leftarrow p
$$

13: **while** 
$$
\frac{|h_{xc,c}^z|^2}{|h_{xc,c}^z|^2} \leftarrow p
$$
 **do**  
13: *calculate\_Rate\_R\_k*

14: **return**  $R_k$ 



Figure 1. Generic architecture representing the OMA and NOMA schemes over 5G networks. In the OMA scheme, every UE is provided with a unique physical resource block at a given time. In the NOMA scheme, multiple UEs are superposed in a given resource block but with different power coefficients or codes to enable the superposition coding and the SIC at the transmitter and receiver, respectively

UEs, with different power coefficients or codes in order to guarantee the successful decoding of data at the receiver.

The next section studies the NOMA approach and proposes the corresponding solution in order to mitigate the co-channel and inter-cell interference in a multi-cell scenario.

# IV. THE ANALYSIS OF NOMA IN MMTC SYSTEMS

## *A. System model and problem formulation for NOMA scheme*

We consider a system of  $x$  transmitting users served by cooperating base stations, and  $x = \{1, 2, ..., X\}$  be its index set of users. We consider  $M$  to be a positive, maximum number of devices that can be supported per sub-carrier.  $z = \{1, 2, \ldots, Z\}$  represents the index of the resource units.  $x_c$  represents the cell c's UEs, and C, i.e  $c = \{1, 2, \ldots, C\},\$ represents the number of cells used in simulation. Therefore, the signal to interference plus noise ratio of the NOMA user  $x_c$  at unit z is given as:

$$
SINR_{x_c,NOMA}^z = a_{x_c}^z \left( \frac{|h_{x_c,c}^z|^2 P_{x_c}^z}{I_c^z + \sigma_N} \right)
$$
 (20)

where  $I_c^z$  is the total interference experienced by user  $x_c$  from the co-allocated interfering users  $i$  and users  $l$  from adjacent cells, which is given as

$$
I_c^z = \sum_{i \neq k, i \in M} |h_{i,c}^z|^2 P_i^z a_{i_c}^z + \sum_{l \neq c, l \in C} \sum_{q \in Q_l} |h_{q_l,c}^z|^2 P_{q_l}^z a_{q_l}^z (21)
$$

As was also the case for OMA, we aim to minimize the ICI at user  $x_c$  from users  $q_l$ , and interference from the NOMA users  $i$  of the same cell assigned to the same resource unit. The objective function can therefore be expressed as:

 $\min$  $\sum$ c∈C  $\sum$  $(\nabla)$  $|h$ z  $z_{i,c}$  $^{2}F$ z  $i^z a$ z  $\frac{z}{i_c}$  +  $\sum$  $\sum$  $|h$ z  $_{q_l,c}^z|$  $^{2}P$ z  $q_l$ a z  $q_l$  $\setminus$ (22)  $SINR_x^z$  $\frac{z}{x_c, NOMA} =$  $\frac{|h|}{\sqrt{2\pi}}$ z  $\frac{z}{x_c,c}$  $^{2}F$ z  $x_c$ j j  $\mathcal{L}$ 

subject to;

$$
a_{x_c}^z \left( \frac{|h_{x_c,c}^z|^2 P_{x_c}^z}{I_c^z + \sigma_N} \right) \ge \vartheta_{x_c,lim} \tag{23}
$$

$$
0 \le P_{x_c}^z a_{x_c}^z \le P_{maxm}, \forall c \in C, \forall x_c \in X, \forall z \in Z. \tag{24}
$$

where  $P_{maxm}$  is the maximum allowed power per device.

$$
\sum_{x_c \in X} a_{x_c}^z \le 1, \forall z \in Z, c \in C.
$$
 (25)

$$
\sum_{x_c \in X} a_{x_c}^z \le M, \forall i \in M \forall z \in Z, c \in C.
$$
 (26)

It can be seen that the objective function is a combinatorial optimization problem and is hence difficult to solve. In this regard, the proposed solution is presented as follows.

### *B. Proposed solution for NOMA scheme in NB-IoT system*

To solve the NOMA problem we follow the same steps as in OMA. Firstly, we set an initial interference power for all the users. Secondly, we perform the scheduling for all the users. Finally, we implement the power allocation to further reduce the interfering powers at the desired receiver. The initial interference power will be allocated as we did for OMA. However, the channel allocation problem in equation 22 will have two assumptions:

- The power is not a variable,
- There are no power constraints.

Therefore, we perform power allocation after the channel assignment. We rewrite the optimization problem in a similar way to that of OMA, i.e. by working per resource unit since there is no interference from adjacent resource units; however, we have to add the NOMA interference users in a given resource unit. Since in the OMA we had one user per resource unit per cell, there was no need to add a subscript for the resource unit. However, because of NOMA, we have more than one user, thus, we define  $M_c$  as the group of NOMA users per cell per resource unit, and  $x_c$  is a user in cell  $c$  that

belongs to  $M_c$ , and we omit the resource unit index. In this regard, the optimization goal becomes:

$$
\min \sum_{c \in C} \sum_{x_c \in M_l} \sum_{l \neq c, l \in \mathcal{Q} \in M} |h_{l,c}^j|^2 P_l^j + \sum_{y \neq x_c, y \in M_c} |h_{c,c}^z|^2 P_c^y) (27)
$$

where  $h_{l,c}^j$  is the channel gain from user j, belonging to cell l and the NOMA group  $M_l$  within the cell, on cell c.  $P_l^j$  is the power of this user. These two terms represent the intercell interference from all the NOMA users of other cells. As for the NOMA part;  $h_{c,c}^z$  is the channel gain of NOMA user y belonging to the same group  $M_c$ .

subject to:

$$
SINR_{x_c,NOMA}^z \ge \vartheta_{c,lim} \tag{28}
$$

$$
0 \le P_{x_c}^z \le P_{maxm}, \forall c \in C. \tag{29}
$$

The  $SINR_{x_c,NOMA}^z$  is then given as:

$$
\sum_{z \in Z} \left( \sum_{i \neq k, i \in M} \left| h_{i,c}^z \right|^2 P_i^z a_{i,c}^z + \sum_{l \neq c, l \in C} \sum_{q \in Q_l} \left| h_{q_l,c}^z \right|^2 P_{q_l}^z a_{q_l}^z \right) (22) \, SINR_{x_c, NOMA}^z = \left( \frac{\left| h_{x_c,c}^z \right|^2 P_{x_c}^z}{\sum_{l \neq c} \sum_{j \in M_l} \left| h_{l,c}^j \right|^2 P_l^j + \sigma_N} \right) (30) \\ + \sum_{y \neq x_c, y \in M_c} \left| h_{c,c}^z \right|^2 P_c^y
$$

which can be solved in the same way as for OMA. However, the number of inequalities will be larger. Moreover, this equation does not take into account the SIC effect on removing interference from other NOMA users within the same cell in the same resource unit. The effect of the SIC can be included in the inequalities by simply putting zero for the NOMA interference users within the same cell as the main user after passing through the SIC. The constraint (28) is not linear; in this regard, we start by substituting equation 30 into eqn. 28, hence linearize as follows;

$$
\left(\frac{|h_{c,c}^{k}|^{2}P_{c}^{k}}{\sum_{l\neq c}\sum_{j\in M_{l}}|h_{l,c}^{j}|^{2}P_{l}^{j} + \sigma_{N}}\right) \geq \vartheta_{c,lim}
$$
\n
$$
+ \sum_{y\neq x_{c}, y\in M_{c}}|h_{c,c}^{j}|^{2}P_{c}^{y}
$$
\n
$$
|h_{c,c}^{k}|^{2}P_{c}^{k} \geq \vartheta_{c,lim} \Big(\sum_{l\neq c}\sum_{j\in M_{l}}|h_{l,c}^{j}|^{2}P_{l}^{j} + \sum_{y\neq x_{c}, y\in M_{c}}|h_{c,c}^{z}|^{2}P_{c}^{y} + \sigma_{N}\Big)(32)
$$
\n
$$
|h_{c,c}^{k}|^{2}P_{c}^{k} - \vartheta_{c,lim}\Big(\sum_{l\neq c}\sum_{j\in M_{l}}|h_{l,c}^{j}|^{2}P_{l}^{j}\Big)
$$
\n
$$
(4)
$$

$$
- \vartheta_{c,lim} \Big( \sum_{y \neq x_c, y \in M_c} |h_{c,c}^z|^2 P_c^y \Big) \geq \vartheta_{c,lim} \sigma_N \qquad (33)
$$

equivalently,

$$
- |h_{c,c}^k|^2 P_c^k + \vartheta_{c,lim} \Big( \sum_{l \neq c} \sum_{j \in M_l} |h_{l,c}^j|^2 P_l^j \Big) + \vartheta_{c,lim} \Big( \sum_{y \neq x_c, y \in M_c} |h_{c,c}^z|^2 P_c^y \Big) \leq \vartheta_{c,lim} \sigma_N \qquad (34)
$$

Substituting  $c = 1, 2, \ldots, C$  equation becomes:

$$
c = 1, k = 1 : -|h_{1,1}^1|^2 p_1^1 + \vartheta_{1,min} \left( |h_{2,1}^1|^2 p_2^1 + |h_{2,1}^2|^2 p_2^2 + \dots + |h_{3,1}^1|^2 p_3^1 + |h_{3,1}^2|^2 p_3^2 + \dots, \dots, +|h_{C,1}^1|^2 p_C^1 + |h_{C,1}^2|^2 p_C^2 + \dots \right) + \vartheta_{1,min} \left( |h_{1,1}^2|^2 p_1^2 + |h_{1,1}^3|^2 p_1^3 + \dots + |h_{1,1}^{M_1}|^2 p_1^{M_1} \right) \leq \vartheta_{1, \lim \sigma_N}
$$

$$
c = 1, k = 2 : -|h_{1,1}^2|^2 p_1^2 + \vartheta_{1,min} (|h_{2,1}^1|^2 p_2^1 + |h_{2,1}^2|^2 p_2^2 + \dots + |h_{3,1}^1|^2 p_3^1 + |h_{3,1}^2|^2 p_3^2 + \dots, \dots, + |h_{C,1}^1|^2 p_C^1 + |h_{C,1}^2|^2 p_C^2 + \dots) + \vartheta_{1,min} (|h_{1,1}^1|^2 p_1^1 + |h_{1,1}^3|^2 p_1^3 + , \dots, + |h_{1,1}^{M_1}|^2 p_1^{M_1}) \le \vartheta_{2,lim} \sigma_N
$$

$$
c = 2, k = 1 : -|h_{2,2}^1|^2 p_2^1 + \vartheta_{2,min} (|h_{1,2}^1|^2 p_1^1 + |h_{1,2}^2|^2 p_1^2 + \dots + |h_{3,2}^1|^2 p_3^1 + |h_{3,2}^2|^2 p_3^2 + \dots, \dots, + |h_{C,2}^1|^2 p_C^1 + |h_{C,2}^2|^2 p_C^2 + \dots) + \vartheta_{2,min} (|h_{2,2}^2|^2 p_2^2 + |h_{2,2}^3|^2 p_2^3 + \dots, + |h_{2,2}^{M_2}|^2 p_2^{M_2}) \le \vartheta_{3,lim} \sigma_N
$$

etc. The above expansion can be shorten as a matrix of the following form:

$$
\tilde{B}\tilde{q} \le \tilde{v} \tag{35}
$$

In this regard, equation 34 can be solved by linear programming solutions in Matlab. Algorithm 2 presents the proposed implementation of the NOMA approach; simulation parameters are presented in Table II, unless specified otherwise.

# *C. Complexity analysis*

. . .

As seen in Algorithm 2, from line 1 to line 5 the algorithm computes the channel parameters for all users attached to the corresponding base stations. This operation has a computation cost of  $O(n)$ . Then from line 6 to line 14, there is the nested while or for-loop such that in the first loop, the interference weight is analyzed, and users (i.e., which have lower interference impact on each other) are superposed at a given subcarrier. In the second loop, the transmit power is allocated to users in order to reduce unnecessary energy consumption. This operation has the computation cost of  $O(n^2)$ . From line 16 to the end of the algorithm, we evaluate the achieved user performance and the computation cost is  $O(n)$ . In this regard, the computation complexity becomes:

$$
O(n + n^2 + n) \tag{36}
$$

Thus, the computational complexity of our proposed algorithm is  $O(n^2)$ , i.e. quadratic complexity.

If we analyze the computation complexity in the single form (i.e., without considering the interference impact), from line 1 to line 5 the algorithm computes the channel parameters for all users attached to the corresponding base stations. The operation still has a computation cost of  $O(n)$ . However, from line 6 to line 14, we will have only one whole or for-loop to allocate different power coefficients to NOMA users to enable the SIC at the receiver. This operation has a computation cost of  $O(n)$ . From line 16 to the end of the algorithm, we evaluate the achieved user performance and the computation cost remains  $O(n)$ . In this regard, if we do not consider interference reduction, then the computation cost becomes  $O(n + n + n) = O(n)$ .

# Algorithm 2 Proposed NOMA scheme



Therefore, the complexity overhead of our proposed scheme  $(O(n^2)$  vs.  $O(n)$ ) is an acceptable trade-off, given the performance enhancements brought by the interference reduction.

In the next section, we present the proposed cooperative scheduler that is used to minimize the previously studied impact of massive interference for both OMA and NOMA schemes.

## V. PROPOSED COOPERATIVE SCHEDULER

We consider cooperation between base stations in order to enhance the interference minimization by sharing the scheduling tables, which contain the channel parameters of UEs to be scheduled. For example, during OMA scheduling, the scheduler computes the interference possibilities for each UE by considering the inter-cell interference that is caused by UEs that are allocated at the same resource at a given time. Furthermore, we assume that the impact of co-channel interference is negligible i.e., by orthogonality, hence the main impact of interference is ICI. To reduce such impact of ICI, we utilize the shared scheduling tables to compute the best combination of UEs that have the minimum impact of interference. From the retrieved best combination, each base station allocates the available resource unit at a given time slot for its corresponding UE. For the NOMA approach, each base station classifies the UEs into three groups based on their channel parameters, i.e., good, moderate, and bad UEs. We assume that we have two main sources of interference i.e., NOMA interference from users that are simultaneously allocated at a given resource unit at a given time slot, and the ICI from other users transmitting at the same resource unit but from adjacent cells. Then the scheduling tables from each base station are shared with the cooperative scheduler. After receiving the tables, the scheduler selects one UE from each



Figure 2. Proposed radio resource management scheme exploiting the NOMA scheme in NB-IoT systems. Each cooperating base station (BS1 to BS3) share their respective scheduling tables for their future transmission. Then ICI is avoided by allocating resources to UEs whose impact in terms of interference is the lowest among the UEs. Then the base stations implement the OMA or NOMA scheme for their corresponding choice of strategy

group of users to be simultaneously superposed at a given resource unit.

In this regard, a maximum number of 3 UEs can simultaneously occupy a given resource unit at a given time slot. The scheduler computes the best combination of UEs for all the available resource units before sharing the respective allocation of slots within a frame to the base stations. Additionally, the scheduler performs the power allocation to reduce the impact of co-channel interference as well as ICI. During power allocation, we assume the power constraints for each group as follows: good channel users  $P_{const} = 14$  dBm, moderate channel users  $P_{const}$  = 20 dBm, and bad channel users  $P_{const} = 23$  dBm. Different power coefficients are assigned to users to successively perform SIC at the receiving base station. We assume that the good channel users are close to their serving base station and hence can be given lower power constraints, and vice-versa is true for bad channel users. An overview of the proposed cooperative strategy for OMA and NOMA is presented in Fig. 2.

In general, unlike the joint processing in coordinated multipoint (CoMP) in LTE systems where a UE at the cell-edge is served by two or more base stations to improve signals quality and increase throughput [23], in our proposed cooperative approach each base station serves its own users. The simulation parameters are similar as presented in [24], with some modifications adapted for the NOMA approach. The overview of the followed scheme is highlighted in Algorithms 1 and 2. We also selected additional scheduling schemes i.e. proportional fair (PF), max-min, and round-robin as benchmarks for comparison purposes. Furthermore, we adapt the Okumura-Hata channel model for small-medium cities as presented in [26]. And we use Jain's fairness index to analyze the fairness

Table II MAIN SIMULATION PARAMETERS FOR THE PROPOSED COOPERATIVE SCHEDULING STRATEGY [25]

<b>Simulation Parameters</b>			
Name	Value		
(a) Transmit power of base station, $\{UE\}$ (dBm)	$46, \{14, 20, 23\}$		
(b) Modulation scheme	<b>BPSK</b>		
(c) Carrier frequency (MHz)	900		
(d) Receiver Thermal Noise density (dBm/Hz)	$-174$		
(e) No. cooperating base station	3		
(f) No. of UE per cell	10		
(g) Interference Margin (dB)	$\Omega$		
(h) Channel model	Okumura Hata		
(i) Effective Noise Power (dBm)	$d + q + f + 10\log(r)$		
(i) Required / calculated SINR (dB)			
(k) Receiver sensitivity	$h + i$		
$(l)$ MCL $(dB)$	a - i		
(m) Modulation scheme	<b>BPSK</b>		
(n) No. of antenna support per UE	1		
(o) Height of base station, UE (m)	100, 1		
(p) Radius of a cell (km)	1		
(q) Noise figure of base station, UE (dB)	9,5		
(r) Occupied System bandwidth (kHz)	180		

of the studied schemes.

It should be noted that, even though the measure of fairness is generally subjective, we assume that if a system reaches fairness, then all the connected devices should achieve individual fairness. In this regard, the Jains' fairness index provides quantitative insight into the overall system fairness; however, it can not identify the UEs that are unfairly treated. Entropy could also be used to categorize the fairness performance among the studied schemes; however, its effectiveness regarding fairness measurements is not clear yet [27].

Furthermore, in an adequate fairness model, especially for low complexity IoT devices such as NB-IoT in massive connectivity scenarios, long-term fairness is more important due to the scarcity of the radio resource. In this regard, throughout this study, the fairness analysis is performed at the end of the allocation life cycle.

For performance evaluation, the parameters used in the simulation are presented in Table II. We consider three cooperating base stations, as shown in Fig. 2. We perform scheduling for each slot in a given total scheduling frame consisting of 10 time-slots, and 12 resource units (sub-carriers). For the OMA approach, only 1 UE can occupy a given resource unit, at a given time slot in a given base station. This yields a capacity limit of 10 UEs per base station for the total scheduling frame. However, for the NOMA approach, up to 3 UEs can occupy a given resource unit at a given time slot in a given base station. This yields a capacity limit of 30 UEs per sub-carrier within a total scheduling frame. It should be noted that with increased system bandwidth the number of connected devices exponentially increases.



Figure 3. Comparison of UE energy consumption between OMA and NOMA schemes

#### VI. PERFORMANCE EVALUATION

We perform the analysis for 1000 iterations; for each iteration, the UEs are randomly distributed across each cell in order to calculate the channel parameters at different positions. We select a set of transmitting UEs from all base stations and another set of interfering UEs from adjacent cells at a given time slot. For the OMA scheme, we consider the set of interfering UEs as the UEs having the same time slot but from adjacent cells. For NOMA, however, we consider the interfering set as the UEs from adjacent cells transmitting at the same time slot, and UEs transmitting at the same time slot but from the same cell. We compute different performance metrics and the results are as presented in the next section.

Some of the simulation parameters may impact the results significantly. For example, increasing the number of users per cell increases the number of interfering users and hence can lower the actual performance as compared to the expected one. In this regard, it is advisable to set the expected quality of service requirement for the serving base station and for the served users. Similarly, as the radius of the cell increases, the experienced path-loss at the user increases; in this regard, it is advisable to follow the base station settings from the telecommunication operator as the benchmark for the scenario under study.

Figure 3 presents the UE energy consumption for OMA and NOMA with the proposed scheme against the benchmark schemes. It can be noted that the OMA scheme experiences relatively lower energy consumption as compared to the NOMA scheme. For example, 50% of UEs under the proposed OMA experience about 40% and 75% lower energy consumption than MaxMin and Round Robin, respectively. Similarly, for NOMA, our proposed scheme achieves lower energy consumption as compared to the traditional power domain NOMA (PD NOMA). The energy consumption enhancements are enabled by the reduced impact of inter-cell interference



Figure 4. Comparison of UE achieved data rates for OMA and NOMA schemes

and the optimal power allocation that reduces the excessive transmission power while guaranteeing the expected QoS at the transmitting users. Furthermore, the reduced interference impact maximizes the SINR, hence relatively reduces the number of repetitions at the transmitting UEs.

For example, the MaxMin scheme maximizes the minimum achieved QoS by allocating more resources to cell-edge users, this approach causes UEs to use maximum transmit power which yields more energy consumption. On the other hand, Round Robin implements a first-come first-saved strategy while allocating resources to UEs; while doing so, cell edge UEs suffer from uncontrolled massive interference from adjacent cells hence increases the transmit power to counteract the ICI.

On the other hand, traditional PD NOMA simultaneously allocates the same available resources to a given number of UEs, when the ICI is not well managed these UEs suffer from both the co-channel interference as well as interference from adjacent cell UEs. In this regard, the impact of interference at a given sub-carrier is more significant, hence the UEs are forced to use the maximum allowed power to transmit which leads to excessive energy consumption.

Our proposed NOMA scheme takes into account both the co-channel interference and ICI; in this regard, UEs are better scheduled and their transmit power is optimized. In doing so, the overall energy consumption is reduced.

Figure 4 presents the achieved UE data rates. From the analysis of the results, our proposed scheme outperforms both the Round Robin and Maxmin schemes. Contrary to the MaxMin scheme that favors the UEs under bad channel conditions, and Round Robin that operates under a first-comefirst-served strategy, our proposed scheme considers the UEs in both good and bad channel conditions by allocating different power coefficients to avoid interference. By doing so, the UEs under our proposed scheme, especially under the OMA approach achieve relatively higher throughput. It should be





Figure 5. Comparison of the total number of devices that can be connected in a given scheduling frame for OMA and NOMA schemes

Figure 6. Comparison of the degree of fairness for OMA and NOMA schemes

noted that the OMA approach has fewer UEs per resource unit, therefore experience a low impact of interference which leads to higher achieved throughput.

It is observed that, with our proposed approach, more than 50% of the UEs achieve above 120 kbps, however, Round Robin and the MaxMin scheduling schemes achieve only 70 kbps and 105 kbps, respectively. On the other hand, the UEs under the proposed NOMA scheme achieve an average of 40 kbps higher than the UEs under traditional PD NOMA. The enhancements are due to the controlled ICI impact, as well as limiting the number of UEs that can be superposed at a given sub-carrier.

Figure 5 presents the number of connected devices for OMA and NOMA schemes, at the cell center and the cell edge. It can be noticed, our proposed NOMA scheme outperforms the OMA schemes by more than double for both cell-center users as well as for cell-edge users. Similarly, our proposed NOMA scheme outperforms the traditional NOMA scheme in terms of connected UEs by up to 21%. These enhancements are achieved thanks to the minimized ICI impact, enhanced by the cooperative scheduling between the adjacent base stations. Contrary to the OMA schemes, the overall connectivity enhancements for the NOMA schemes are due to the possibility of superposing multiple UEs in the same tone. For example, in the OMA scheme, only one UE can occupy one or multiple tones at a given uplink scheduling frame.

Figure 6 presents the UE fairness when our proposed scheme is compared to other scheduling schemes from literature. During the fairness analysis, the simulated SINR range was based on real-time SINR values from IoT sensors; the SINR values range from  $-5$  dB (i.e., lowest SINR) to 35 dB (highest SINR). Since most of the schedulers consider the channel parameters before attributing the radio resources to UEs, the higher SINR values trigger the increase in scheduling fairness. Our proposed NOMA scheme outper-

forms the traditional PD scheme and OMA schemes hence is more suitable for massive connectivity in dense networks. With proactive scheduling (avoiding ICI) and optimal power allocation, the same available resources can be used for devices at the cell edge and devices at the cell center.

On the other hand, the Round Robin scheme outperforms the benchmark OMA schemes by allocating resources to UEs regardless of their channel condition. For example, our proposed OMA scheme lags behind both Round Robin and MaxMin schemes; this is due to its selection process which incurs prioritization, and as a consequence, results in lower fairness. If these schemes are implemented in practical systems, the fairness measurements shown above can help to compensate the devices that are treated unfairly (low fairness index) in the previous allocation step and improve the targeted QoS in the current allocation step.

The potential drawback of our proposed strategy is that as the number of cooperating base stations increase, the backhaul delay increases. Similarly, with the increased number of devices per cell, the sharing of scheduling tables may generate potential delays. Additionally, our proposed approach necessitates high synchronization between cooperating base stations in order to ensure real-time end-to-end performance. In this regard, it may increase the computational complexity at the base stations. In this regard, it is necessary to implement strong computing machines with real-time synchronization clocks at the base stations and utilize high-speed links between the base stations in order to ensure the feasibility of our proposed schemes in real systems.

## VII. CONCLUSION

In this work, we analyzed the impact of massive interference due to massive connectivity in 5G and B5G networks. We proposed the corresponding solutions for the OMA and NOMA approaches to enhance the users' and cell performance. To assess our proposed approach, we compared it with benchmark schemes from the literature. The simulation results show that the proposed NOMA scheme is more spectrum efficient than OMA as it supports more than twice the number of connected devices for the same number of available resources. Furthermore, other network performance metrics such as throughput, user's energy consumption, and fairness are analyzed, discussed, and compared for both the OMA and NOMA schemes. In general, the reduced impact of interference and the proposed power allocation techniques reduce the average energy consumption per device hence are more suitable for massive IoT deployments as it enhances the device's battery life longevity. Our future outlook involves analyzing the complexity trade-off that our proposed scheme will influence at the base station. Similarly, we aim to study the flexible duplexing technique in order to efficiently use the available spectrum to further enhance the massive connectivity of IoT devices for 5G and beyond networks.

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#### APPENDIX

#### **NOMENCLATURE**

Mathematical symbols

ql z

 $\frac{P^z_{q_l}}{P^z_{r_l}}$ 

- $\sigma_N$  is the receiver's noise power
- 
- $\vartheta_{c,lim}$  is the SINR threshold to satisfy the QoS for the UE in cell c<br> $\vartheta_{x_c,lim}$  is the SINR threshold for user  $k_c$  to satisfy its QoS is the  $SINR$  threshold for user  $k_c$  to satisfy its QoS
- $a_{i,c}^{\overline{z}}$ is the allocation matrix of user  $i$  at cell  $c$  occupying sub-carrier  $z$
- $a_{q_l}^{z^-} \ a_{x_c}^{q}$ is the channel occupancy matrix of user  $q_l$  at sub-carrier z
- allocation matrix of user  $x_c$  at sub-carrier z  $h_i^j$
- is the channel gain from user  $j$ , belonging to cell  $l$  and the NOMA group  $M_l$  within the cell, on cell  $c$ .  $h_i^j$ 
	- is the channel gain from user  $j$ , belonging to cell  $l$  and the NOMA group  $M_l$  within the cell, on cell  $c$
- $h_c^y$ is the channel gain of NOMA user y belonging to the same group  $M_c$
- $h_i^{\bar{z}}$ is the channel gain of the co-allocated interfering user  $i$  at cell  $c$  on subcarrier z
- $h_{q_l}^z$ channel gain of user  $q_l$  at cell  $c$ 
	- is the channel gain of user  $q_l$  to the base station c at sub-carrier  $z$
- $\frac{\hbar_{x_c,c}^{z^*}}{\hbar_{c,c}}$ is the channel gain of the transmitting user  $c$  at base station  $c$
- $h_{q_l}$ is the channel gain user  $q_l$  at cell  $c$  $I_c^z \overline{P^j_l} \overline{P^z_i} \overline{P^z_s} \overline{P^z_a}$ 
	- interference on resource unit  $z$  in cell  $c$
	- is the power of the NOMA user  $y$  belonging to the same group  $M_c$ is the power of the co-allocated interfering user  $i$  at sub-channel  $z$
	- is the interference power caused by user  $q_l$  at sub-carrier z
	- is the transmission power of the interfering user  $q_l$  at resource unit z
	- is the transmission power of user  $k_c$ 's at resource unit z
- $\frac{F_{x_c}}{P_{maxm}}$ is the maximum power that can be used by the user for its transmissions





- $SIC$  Successive interference cancellation<br> $UE$  User equipment
- User equipment



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