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A Novel Design Approach for 5G Massive MIMO and NB-IoT Green Networks Using a Hybrid Jaya-Differential Evolution Algorithm

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ABSTRACT Our main objective is to reduce power consumption by responding to the instantaneous bit rate demand by the user for 4th Generation (4G) and 5th Generation (5G) Massive MIMO network configurations. Moreover, we present and address the problem of designing green LTE networks with the Internet of Things (IoT) nodes. We consider the new NarrowBand-IoT (NB-IoT) wireless technology that will emerge in current and future access networks. In this context, we apply emerging evolutionary algorithms in the context of green network design. We investigate three different cases to show the performance of the new proposed algorithm, namely the 4G, 5G Massive MIMO, and the NB-IoT technologies. More specifically, we investigate the Teaching-Learning-Optimization (TLBO), the Jaya algorithm, the self-adaptive differential evolution jDE algorithm, and other hybrid algorithms. We introduce a new hybrid algorithm named Jaya-jDE that uses concepts from both Jaya and jDE algorithms in an effective way. The results show that 5G Massive MIMO networks require about 50% less power consumption than the 4G ones, and the NB-IoT in-band deployment requires about 10% less power than guard-band deployment. Moreover, Jaya-jDE emerges as the best algorithm based on the results.

INDEX TERMS Massive MIMO, 4G, 5G, NB-IoT, network planning, network design, hybrid networks, power consumption, green networks, evolutionary algorithms.

I. INTRODUCTION

The fifth generation (5G) of cellular networks is expected to offer extremely wide spectrum and multi-Gigabit-per-second (Gbps) data rates for mobile users. Massive multiple-input multiple-output (MIMO) [1], [2] is one of the primary technologies to be incorporated into the fifth generation (5G) framework of cellular systems. In Massive MIMO systems each base station (BS) is equipped with several active antenna elements that communicate with user equipment that have single or multi antenna over the same time and frequency band. Moreover, future wireless access networks will require green networking as essential part for they deployment [3]–[6]. It is expected that the power consumption will increase in the 5G access networks as these will need to expand and become denser. However, Massive MIMO BSs will have a lower power consumption than conventional 4G BSs [7].

Moreover, 3GPP released the first recommendation of the NarrowBand-IoT (NB-IoT) [8]–[10] in 2016. NB-IoT is an emerging new wireless access technology, which will exist together with the other current cellular networks like Global System for Mobile communications (GSM), Universal Mobile Telecommunications System (UMTS) and Long-Term Evolution (LTE). The basic idea from 3GPP standards is the integration of NB-IoT to current mobile 4G networks. NB-IoT devices are low cost and allow massive deployments with reduced data rates [11]. The subcarrier

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bandwidth is 180kHz in case of co-existence with current LTE networks. According to a prediction from Ericsson the number of IoT connected devices will reach 1.5 billion by 2022 [12]. Thus, the massive NB-IoT deployment will generate new optimization problems from the access network point of view. That of optimal coverage and power consumption.

At the same time, machine learning techniques play an important role towards future wireless networks and services [13]. Among others, evolutionary algorithms (EAs) belong to the core of machine learning paradigms. Additionally, the application of EAs to LTE network optimization is also addressed in previous works [14]–[18]. In this work, we consider 4G networks, and 5G-Massive MIMO networks with a minimal power consumption. The optimization framework requires first the selection of the suitable BS locations from a set of given locations, and second the fine tuning of each BS antenna's input power, in order to obtain an energy-efficient network. Moreover, we also consider LTE networks with massive deployment of NB-IoT devices. We also optimize the LTE NB-IoT network towards both optimal coverage and power consumption.

The above-described combinatorial optimization problem can be addressed using suitable EAs. Our goal is to design a wireless network optimized towards power consumption, while preserving QoS (Quality of Service). A capacity-based heuristic, meaning that it will respond to the instantaneous bit rate demand of the user in order to develop an energy-efficient network, was introduced in [6]. Herein, we will use a modified algorithm that combines an EA optimization algorithm with concepts taken from the capacity tool. The application area of all the algorithms is Ghent, Belgium. We compare the obtained results in terms of both the energy and the network performance of all algorithms. We examine six different algorithms in order to compare performance of 4G networks, Massive MIMO future 5G networks and emerging NB-IoT networks. We will use state-of-the-art algorithms that have been recently applied to a wireless sensor network (WSN) optimization problem [19]. Namely, we consider the Teaching-Learning Based Optimization (TLBO) [20], the Jaya algorithm, [21] and the recently proposed hybrid TLBO-Jaya [19]. Moreover, we also apply a self-adaptive differential evolution algorithm (jDE) and a hybrid TLBO-DE algorithm resulting in the improved TLBO (ITLBO) [22]. Additionally, we introduce a new hybrid algorithm that combines Jaya and the jDE algorithms, which we call Jaya-jDE. The main characteristic of all these algorithms is the fact that they are low complexity algorithms. All of them they do not have any control parameters, and the only user selection is the population size and iteration number. It must be pointed out that in [19] the TLBO, Jaya, and TLBO-Jaya algorithms were applied in real-valued optimization problems, while in our case they are applied in a discrete-valued problem. We expect them to perform well regardless of the problem type.

The novelty in our work lies in the fact that (i) we perform such a comparison regarding power consumption in 4G, and 5G/Massive MIMO and NB-IoT networks and (ii) we introduce a novel hybrid algorithm the Jaya-jDE algorithm. Additionally, (iii) the whole optimization framework is modified from the previous heuristic algorithm using a novel meta-heuristic approach and performance is compared for six different algorithms.

The rest of this paper is organized as follows. Section II provides a brief description of related work. The problem description is provided in Section III. We describe the algorithms details in Section IV. Section V, presents the numerical results. Finally, we give the conclusion in Section VI.

II. RELATED WORK

The authors in [23] present an architecture vision for 5G mobile networks. Their proposal uses a two-layer architecture having a radio network and a network cloud. Additionally, [24] uses cooperative distributed radio resource management algorithms for carrier selection, power control and time synchronization. The network planning applies to hyper-dense small cell networks for 5G communications.

The problem of energy efficiency (EE) maximization for 5G mobile networks is addressed in [25]. The authors perform an review of state-of-the-art EE-maximization techniques for hybrid Massive MIMO systems and identify the open research problems.

The authors in [26] propose a novel method for the cell planning problem for LTE networks using metaheuristic algorithms. The authors try to satisfy both cell coverage and capacity constraints simultaneously by formulating an optimization problem that captures practical planning aspects.

In the same context, in [27] the optimization problem is to choose a subset of sites from a candidate list to deploy macro or small cells in order to minimize the total cost of ownership (TCO) or the energy consumption subject to practical constraints. For this reason the authors introduce approximation algorithms to solve two different cell planning cases which are NP-hard.

Moreover, the authors in [28] study advanced energy-efficient wireless systems in orthogonal frequency-division multiple access (OFDMA) downlink networks using coordinated multipoint (CoMP) transmissions between the base stations (BSs) in a heterogeneous network (HetNet). The optimization problem addressed by the authors is transformed into a convex optimization problem and it's solved using an efficient iterative resource allocation algorithm.

The problem of ultra-dense small cell planning using cognitive radio network is studied in [29]. The authors provide an overview of reconfigurable radio and small cell technologies and introduce the tentative network architecture for 5G. They consider two different planning approaches; genetic-based and graphbased. The main purpose is to improve user throughput by eliminating communication interference.

The topic of green cell planning for small cell networks in smart cities is discussed in [30]. The authors model various traffic patterns using a stochastic geometry approach and propose an energy-efficient scheme for small cell planning and deployment in accordance with the selected traffic pattern.

Additionally, the authors in [31] use a genetic algorithm combined with a location intelligence method for energy optimization in 5G Wireless Networks. The authors in [32] propose a new Bioinspired Self-Organizing Solution for automated and efficient Physical Cell Identifier (PCID) configuration in 5G ultra dense networks.

Finally, a review paper that studies the problem of planning future cellular networks is given in [33]. The authors briefly give a tutorial on the cell planning process and they review the more important findings from recent works in the literature that have attempted to address the challenges in planning emerging networks.

III. PROBLEM FORMULATION

Two types of optimization problems are considered in this work: the maximum area coverage problem and the maximum user coverage problem. The details of these problems are presented below. We assume that we have a mobile network that consists of K BSs and N users. The sets of BSs and users are $\mathcal{K} = \{1, 2, \cdots, K\}$ and $\mathcal{N} = \{1, 2, \cdots, N\}$, respectively. Moreover, we define the set of power values of each BS. This is denoted with $\mathcal{P} = \{p_1, p_2, \cdots, p_K\}$. We consider the binary variable, x_{kn} that describes the association of the k-th BS with the n-th user and can be formulated as

$$x_{kn} = \begin{cases} 1, & \text{if } n\text{-th user is associated with the } k\text{-th BS} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Moreover, we define the binary variable y_k that describes the operation or not of the k-th BS and can be formulated as

$$y_k = \begin{cases} 1, & \text{if BS k is turned on} \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Additionally, we can define the discrete variable, p_k that describes the transmission power value of the k-th BS as $p_k \in \{0, 1, 2, \cdots, p_t\}, \forall k \in \mathcal{K}$. where p_t is maximum allowable transmission power for a BS according to 3GPP recommendations. Thus, we define the solution vector to an integer vector that contains both the active or not BSs and the operating power in dBm. All the chosen EAs generate this vector.

A. GREEN NETWORK PLANNING FOR MAXIMUM AREA COVERAGE

The first case is a network optimization problem without taking into account users. Our objective is to derive an optimized network that has the smallest possible number of BSs, while maximizing the coverage area, and having a minimal BS transmission power. Therefore, there are two optimization objectives: the power consumption minimization and the coverage area maximization. We can formulae the first objective as [3, Section 5]:

$$\begin{aligned} P1a : F^p = \min_{\{\boldsymbol{y},\boldsymbol{p}\}} \ & 100\left(1 - \frac{\sum_{k\in\mathcal{K}} P_{\text{calc}}\left(y_k p_k\right)}{P_{\max}}\right) \\ \text{s.t. } & C_1 : y_k \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \\ & C_2 : p_k \in \{0, 1, 2, \cdots, p_t\}, \quad \forall k \in \mathcal{K} \end{aligned}$$

where $P_{\text{calc}}()$ is the calculated power consumption in Watts for a given solution vector, $P_{\max} = K \times P_{\text{calc}}(p_t)$ is the maximum power consumption of the network, i.e. when all BSs operate and their input power is set to the maximum allowable value. The constraint C_1, denotes the operation or not of the k-th BS. Similarly, the constraint C_2 denotes the transmission power level of k-th BS. More details for this power consumption expression are given in [3]. Moreover, we can define the second optimization objective as the maximum coverage area percentage. This is the percentage of the desired area that the network can cover ny using fewer BS with less power. In case of a Massive MIMO (MaMi) BS it has been found that this is approximately it is [7]

$$P_{\text{calc}}^{\text{MaMi}} = \frac{P_{\text{calc}}^{4\text{G}}}{7} \quad (3)$$

where $P_{\text{calc}}^{\text{MaMi}}$, $P_{\text{calc}}^{4\text{G}}$ is the power consumed by a Massive MIMO and an 4G BS, respectively. The coverage function F^c is specified by:

$$\begin{aligned} P1b : F^c = \min_{\{\boldsymbol{y},\boldsymbol{p}\}} \ & 100\frac{A_{\text{target}} \bigcap \sum_{k\in\mathcal{K}} A_{\text{calc}}\left(y_k p_k\right)}{A_{\text{target}}} \\ \text{s.t. } & C_1 : y_k \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \\ & C_2 : p_k \in \{0, 1, 2, \cdots, p_t\}, \quad \forall k \in \mathcal{K} \end{aligned}$$

where A_{target} is the target area to be covered (in km^2), and $A_{\text{calc}}\left(y_k p_k\right)$ is the area covered by the k-BS station (in km^2). The calculation of the $A_{\text{calc}}\left(y_k p_k\right)$ requires first the calculation of the maximum allowable path loss, PL_{max} (in dB), for each operating BS. This is accomplished using the link budget parameters for the 4G and Massive MIMO network of Table 2. We can find the maximum range R (in meters) covered by each BS [3]. Thus, we may define the total area covered by a given solution vector as the union of all BSs coverage areas, which are derived by each maximum range R. From the above we can formulate the complete optimization problem as [3, Section 5]:

$$\begin{aligned} P1c : F_1 = \min_{\{\boldsymbol{y},\boldsymbol{p}\}} \ & \left(F^c + \alpha F^p\right), \\ \text{s.t. } & C_1 : y_k \in \{0, 1\}, \quad \forall k \in \mathcal{K}, \\ & C_2 : p_k \in \{0, 1, 2, \cdots, p_t\}, \quad \forall k \in \mathcal{K}, \end{aligned}$$

where

$$\alpha = \begin{cases} 0 & \textit{if } F^c < 90 \\ \dfrac{(F^c - 90)^2}{5} & \textit{if } 90 \leq F^c \geq 95 \\ 5 & \textit{otherwise} \end{cases} \quad (4)$$

The above objective problem has a minimum value of -600 that is obtained when both F^c and F^p are equal to 100.

B. GREEN NETWORK PLANNING FOR MAXIMUM USER COVERAGE

We present a modified meta-heuristic approach to find the list of BSs covering a given set of users and reduce the total network power consumption [3]. This approach is based on a fitness function and uses concepts from the capacity tool. In this way a global optimizer can be set using any EA.

The solution vector is the input to another algorithm that calculates an objective function based on the number of covered users and the power consumption of the current solution.

In this case, we formulate this objective function as

$$\begin{aligned} P2: F_2 = \min_{\{\boldsymbol{y},\boldsymbol{x},\boldsymbol{p}\}} & \frac{\sum_{k\in\mathcal{K}} P_{\text{calc}}\left(y_k p_k\right)}{P_{\max}} \\ & + \Xi \cdot \left(1 - \frac{\sum_{k\in\mathcal{K},n\in\mathcal{N}} x_{kn} y_k}{N}\right), \\ \text{s.t. } & C_1 : y_k \in \{0,1\}, \quad \forall k \in \mathcal{K}, \\ & C_2 : p_k \in \{0,1,2,\cdots,p_t\}, \quad \forall k \in \mathcal{K}, \\ & C_3 : x_{kn} \in \{0,1\}, \quad \forall n \in \mathcal{N},\ \forall k \in \mathcal{K}, \\ & C_4 : \sum\nolimits_{k=1}^{K} x_{kn} = 1, \quad \forall n \in \mathcal{N} \end{aligned}$$

where Ξ is a very large number. The constraint C_3, denotes the association or not between user n and BS k. Moreover, the constraint C_4 expresses the unique association between one user n with BS k at the same time. Thus, if a possible solution vector is used as input, the algorithm first finds the number of users covered by this solution, and then it calculates the objective function value.

IV. ALGORITHM DESCRIPTION

In this section, we present the details of the algorithms.

A. JAYA ALGORITHM

The Jaya algorithm was created by Rao in [21]. It is a population based stochastic algorithm. The basic idea in Jaya is for each member of the population or possible solution $\mathbf{y_i}$ to be modified using the information of the best solution and moving away from the worst solution found at each iteration. The name Jaya means victory in Sanskrit. Jaya does not have any control parameters. The user has to set only the population size and the maximum number of iterations. The Jaya concept is expressed mathematically by

$$\mathbf{y_i^{new}} = \mathbf{y_i^{old}} + rnd_1\left(\mathbf{y_{best}} - \mathbf{y_i^{old}}\right) - rnd_2\left(\mathbf{y_{worst}} - \mathbf{y_i^{old}}\right) \tag{5}$$

where rnd_1 and rnd_2 are uniformly distributed random numbers within the range $[0, 1]$. In Jaya the new found child vector replaces the old one only in case that the new one obtains a better objective function value than the old.

B. JDE ALGORITHM

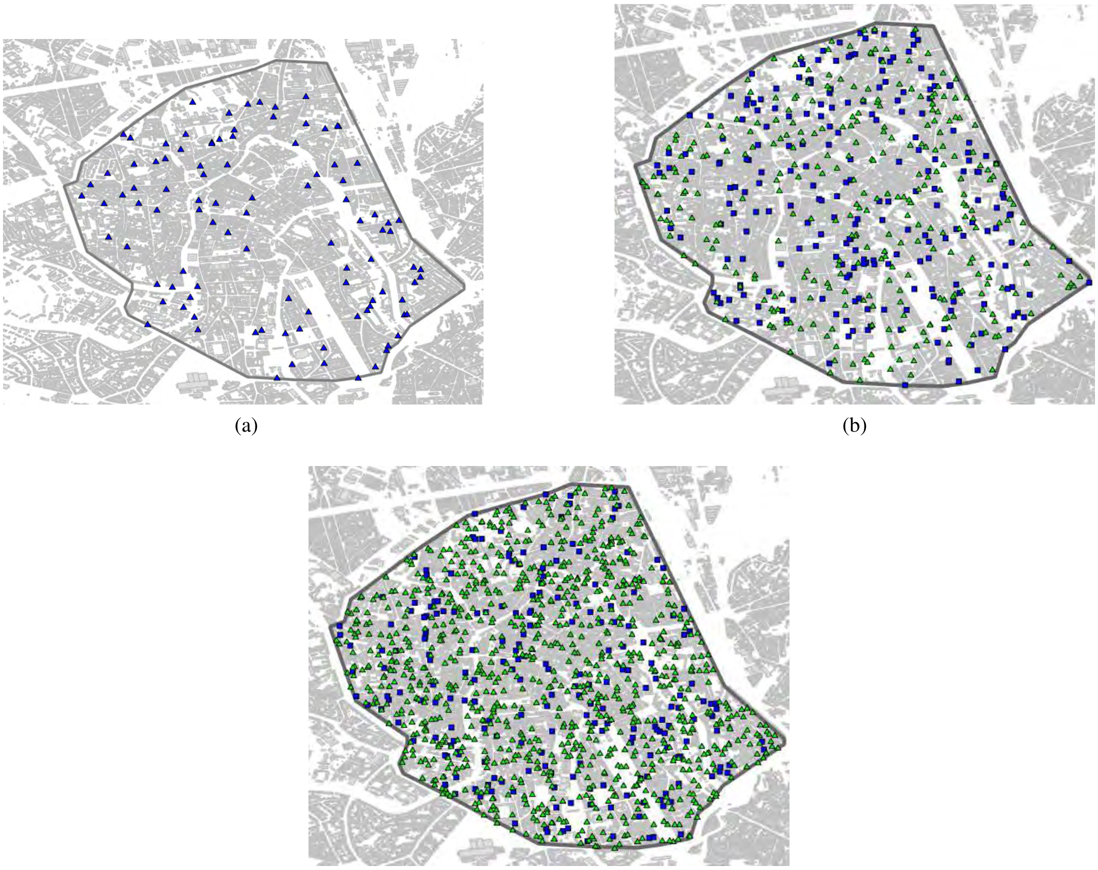
Storn suggested in [34] to select the differential evolution (DE) control parameters M and C^r from the intervals [0.5,1] and [0.8,1], respectively, and to set population size $N_p = 10D$, where D is the problem dimension. The parameter M is the mutation control parameter that is used for mutant vector generation, while C_r is the crossover control parameter that is applied for trial vector generation [34]. The proper selection of the control parameter values is, usually problem-dependent. Thus, additional running is required for finding the optimal control parameter values. In this context, in [35] a self-adaptive DE algorithm is proposed, which they call jDE. In this algorithm the same mutation operator as in DE/rand/1/bin is applied. In jDE each member of the population has its own M and C^r parameters. Thus, each vector is extended with two additional variables. These parameters evolve with the population and the new generated vectors use these values of the control parameters. Then the algorithm selects the vectors with the improved M and C^r values, which are more likely to survive and to generate new child vectors for the next generation. Thus, the newly found vectors use the obtained M and C^r values to the next generation. The way the algorithm self-adjusts the M and C^r parameters is given by the following expressions:

$$\begin{aligned} M_{G+1,i} &= \begin{cases} M_l + rand_{1[0,1]} \times M_u & \text{if } rand_{2[0,1]} < p_1 \\ M_{G,i}, & \text{otherwise} \end{cases} \\ {C^r}_{G+1,i} &= \begin{cases} rand_{3[0,1]} & \text{if } rand_{4[0,1]} < p_2 \\ {C^r}_{G,i}, & \text{, otherwise} \end{cases} \end{aligned} \tag{6}$$

where $rand_{i[0,1]}$, $i = 1, 2, 3, 4$ are uniform random numbers $\in [0, 1]$, M_l, M_u are the lower and the upper limits of M set to 0.1 and 0.9, respectively, and p_1 and p_2 the probabilities of adjusting the control parameters. In [35] it is recommended to use the value 0.1 for these probabilities. As it is reported in [35] when we use the jDE strategy, the time complexity does not increase. In fact, the time complexity of the *jDE* algorithm at each iteration is $\mathcal{O}(N_pD + N_pF)$ [36], where F is the time complexity of the objective function. This is the same as the original DE.

C. HYBRID JAYA-jDE ALGORITHM

Algorithm 1 describes the hybrid Jaya-jDE algorithm. The new hybrid algorithm presented here combines concepts from both Jaya and jDE algorithms. The basic idea is to probabilistically select the way to generate a new vector using the Jaya or the jDE algorithms. The probability of selection p_{sel} is initially set to 0.5, thus both algorithms have equal probabilities. At each iteration the algorithm loops in the entire population and selects to use the Jaya or the jDE algorithms based on the previous successful vector replacements. Thus, the best algorithm for a given optimization problem is more probable to be selected. Additionally, a stagnation avoidance mechanism has been integrated into the new algorithm. In case of stagnation, the algorithm selects with equal



(a) (b) (c)

FIGURE 1. Distribution of users for a) 100 Voice/Data users at 1Mpbs-10Mbps b) 224 Voice/Data users+300 IoT Nodes at 10kbps c) 224 Voice/Data users+ 1000 IoT Nodes at 25kbps. The green triangles denote the IoT nodes, while the blue ones represent the Voice/Data users.

probabilities the way to generate new vectors using the Jaya or the jDE algorithms. Also, it must be pointed out that the new algorithm is control parameter free and requires only the setting of the population size N_p and the maximum number of iterations $G_{\max}$.

For this case, we have introduced a new variable to the original Jaya algorithm, this is denoted as cnt_{jaya} in algorithm 1. This parameter is increased by one if the newly found vector is better than the old one. Thus, this parameter represents the number of successful vector replacements in the Jaya algorithm. Moreover, just like in the Jaya algorithm, the new variable cnt_{jDE} represents the number of successful old vector replacements by the new one when the jDE is executed. The time complexity of the proposed Jaya-jDE algorithm at each iteration is the same as that of the original *jDE* algorithm. Table 1 lists the complexity of each algorithm and computation time for calculating the Sphere function at 30 dimensions for 100,000 function evaluations. The simulations results are for a PC with $i5-3470$ CPU at 3.2GHz with 8GB RAM and Windows 7 operating system.

V. NUMERICAL RESULTS

We address the network planning optimization for all network types given 75 possible BS locations in the city of Ghent, Belgium. The total area to cover is about 6.85 km^2 (Fig. 1). The BS can be either active (binary one) or not (binary zero). For active base stations the range of the input power of the BS antenna is between 0 to 43 dBm for the 4G cases, and between 0 to 46 dBm for the 5G, NB-IoT cases. In all cases the power step is 1dB. In case of a Massive MIMO BS, the input power is divided over all the antennas of the BSs. We consider macrocell BSs for all cases here. The total number of unknowns is 2×75. We apply six different algorithms in each case and compare the results. These are the TLBO, Jaya, TLBO-Jaya, jDE, Jaya-jDE and the ITLBO. The TLBO-Jaya and the

TABLE 1. Comparison of algorithms in terms of complexity and computation ime for the Sphere function.

Algorithm	Complexity	Time (msec)
TLBO	$\mathcal{O}(N_pD + N_pF)$	346
TLBO-Jaya	$\mathcal{O}(N_pD + N_pF)$	276
jDE	$\mathcal{O}(N_pD + N_pF)$	216
Jaya	$\mathcal{O}(N_pD + N_pF)$	199
Jaya-jDE	$\mathcal{O}(N_pD + N_pF)$	224
ITLBO	$\mathcal{O}(N_pD + N_pF)$	207

Algorithm 1 Hybrid Jaya-jDE Algorithm

```
Set Jaya-jDE initial parameters, population size N_p, maximum iterations G_max and cnt_jaya = 0, cnt_jDE = 0, p_sel = 0.5, stagnation = false
Generate a uniformly distributed random population of size N_p, set G = 1
while G ≤ G_max do
    if not (cnt_jaya = 0 or cnt_jDE = 0) then
        if cnt_jDE > cnt_jaya then
            p_sel = cnt_jaya / cnt_jDE
        else
            p_sel = cnt_jDE / cnt_jaya
        end if
        p_sel = p_sel / 2
    end if
    for i = 1 to N_p do
        if not stagnation then
            if cnt_jDE > cnt_jaya then
                if rand < p_sel then
                    generate new vector according to Jaya algorithm
                else
                    generate new vector according to jDE algorithm
                end if
            else
                if rand < p_sel then
                    generate new vector according to jDE algorithm
                else
                    generate new vector according to Jaya algorithm
                end if
            end if
        else
            if rand < 0.5 then
                in case of stagnation give equal selection probability
                generate new vector according to Jaya or jDE algorithm with equal probability
            end if
        end if
    end for
    if best vector does not improve in current generation then
        stagnation = true
    else
        stagnation = false
    end if
    G = G + 1
end while
```

ITLBO are hybrid algorithms, as well as the new Jaya-jDE. We run all algorithms for 20 times [6]. In all cases, except for the Massive MIMO extended set, we select the population size to be 20 and the maximum number of generations is also 20. Therefore, the total number of objective function evaluations is 400.

TABLE 2. Link budget parameters for the 4G/LTE and the 5G Massive MIMO network.

Parameter	4G BS	Massive MIMO BS
Frequency	2.6 GHz	3.7 GHz
Maximum input power BS antenna	43 dBm	46 dBm
Antenna gain of BS	18 dBi	9 dBi
Antenna gain of receiver	0 dBi	0 dBi
Feeder loss BS	2 dB	2 dB
Feeder loss receiver	0 dB	0 dB
Fade margin	10 dB	10 dB
Yearly availability	100.00%	100.00%
Interference margin	2 dB	2 dB
Noise figure of receiver	8 dB	8 dB
Implementation loss of receiver	0 dB	0 dB
MIMO	1x1	128x8
Receiver SNR	1/3 QPSK = -1.5 dB 1/2 QPSK = 3 dB 2/3 QPSK = 10.5 dB 1/2 16-QAM = 14 dB 2/3 16-QAM = 19 dB 1/2 64-QAM = 23 dB 2/3 64-QAM = 29.4 dB	1/3 QPSK = -1.5 dB 1/2 QPSK = 3 dB 2/3 QPSK = 10.5 dB 1/2 16-QAM = 14 dB 2/3 16-QAM = 19 dB 1/2 64-QAM = 23 dB 2/3 64-QAM = 29.4 dB
Bandwidth	5 MHz	5 MHz
Soft handover gain receiver	0 dB	0 dB
Building penetration loss	0 dB (only outdoor coverage considered)	0 dB (only outdoor coverage considered)
Height mobile station	1.5 m	1.5 m

A. LTE AND 5G MASSIVE MIMO CASE

Several papers and reported testbeds use cm-Wave frequencies for Massive MIMO. The authors in [37]–[39] present a Massive MIMO testbed designed for a carrier frequency of 3.7 GHz. Moreover, the authors in a recent study [2] claim that the research on Massive MIMO has been focused on cellular frequencies below 6 GHz, where the transceiver hardware is very mature. Taking the above into account, we assume a carrier frequency of 3.7 GHz for all the simulations using Massive MIMO. Table 2 lists the link budget parameters for the 4G and the Massive MIMO network. We use the Walfisch-Ikegami propagation model for all path loss calculations in the 4G/LTE network, while we apply the propagation model suggested in [7] for Massive MIMO. Fig. 2 compares the range for 4G and Massive MIMO BS for 1Mbps (receiver SNR -1.5dB) and 10Mbps (receiver SNR 19dB) date rates, respectively. The BS is placed on a building with 27.2 m height and the antenna height is considered to be 1.5m. The results are for non-Line-Of-Sight (nLOS) propagation and have been obtained using the above-mentioned propagation models. We notice that as expected the Massive MIMO BS has a significantly lower range, thus more BS are required in this case. We consider different optimization cases.

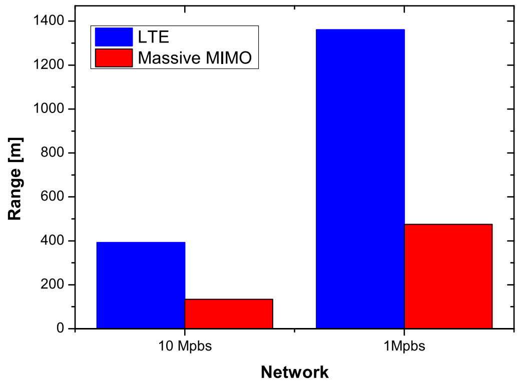


FIGURE 2. Comparison of BS range for 4G and Massive MIMO networks.

TABLE 3. Maximum area coverage case. Algorithms comparative results for all cases in terms of objective function value. The smallest values are in bold font.

4G LTE case				
Algorithm	**Best**	**Worst**	**Mean**	**Standard Deviation**
TLBO	-427.56	-373.81	-400.49	14.86
TLBO-Jaya	-435.03	-361.42	-402.36	20.78
jDE	**-483.90**	-466.59	-474.89	5.48
Jaya	-475.03	-438.59	-452.44	10.74
Jaya-jDE	-483.26	**-476.08**	**-480.59**	**2.02**
ITLBO	-381.63	-139.93	-314.81	69.58
5G Massive MIMO case				
Algorithm	**Best**	**Worst**	**Mean**	**Standard Deviation**
TLBO	-67.61	-66.47	-67.14	0.37
TLBO-Jaya	**-67.84**	-65.32	-66.96	0.68
jDE	-67.10	-66.12	-66.45	0.27
Jaya	**-67.84**	-66.18	-67.24	0.57
Jaya-jDE	**-67.84**	**-67.84**	**-67.84**	**0.00**
ITLBO	-66.14	-59.74	-63.49	1.86

1) CASE 1: MAXIMUM AREA COVERAGE CASE

First, we consider the maximum area coverage case, without taking into account users for both 4G/LTE and 5G Massive MIMO cases. Before we can actually start designing the network, inputs are required: the considered area, which is the city of Ghent as described earlier and the list of possible base station locations. The input to the optimization algorithm is the list of all BSs in the city of Ghent. Additionally, we consider an imaginary extended BS set that consists of 2450 BS distributed all over the city center. Thus, in order to obtain full coverage in case of a 5G network, we run also all algorithms for this extended BS set. The total number of unknowns is 4900 for this case and the problem becomes high dimensional. In order to test the algorithm's performance we set the population size to 100 and the number of generations to 500 for this case.

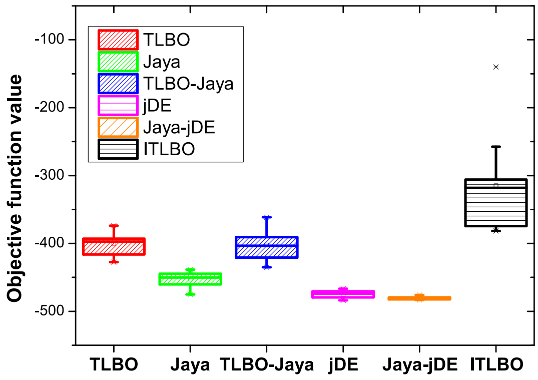
TABLE 4. Maximum area coverage case.Best-obtained results comparison using different algorithms. The best values are in bold font.

4G LTE case			
Algorithm	**LTE BS No**	**Coverage (%)**	**Power Consump. (kW)**
TLBO	26	95	37.13
TLBO-Jaya	28	95	39.61
jDE	**18**	95	27.91
Jaya	20	95	29.71
Jaya-jDE	**18**	95	**27.63**
ITLBO	39	95	52.83
5G Massive MIMO case			
Algorithm	**5G BS No**	**Coverage (%)**	**Power Consump. (kW)**
TLBO	64	67.6	13.79
TLBO-Jaya	60	**67.83**	13.52
jDE	**50**	67.09	**12.12**
Jaya	65	**67.83**	14.13
Jaya-jDE	55	**67.83**	13.34
ITLBO	57	66.14	12.20
5G Massive MIMO case with extended BS set			
Algorithm	**5G BS No**	**Coverage (%)**	**Power Consump. (kW)**
TLBO	**965**	83.3	**206.01**
TLBO-Jaya	1242	78.14	241.03
jDE	1321	79.32	242.01
Jaya	1210	82.32	236.17
Jaya-jDE	1740	**94.24**	332.26
ITLBO	1217	92.53	232.58

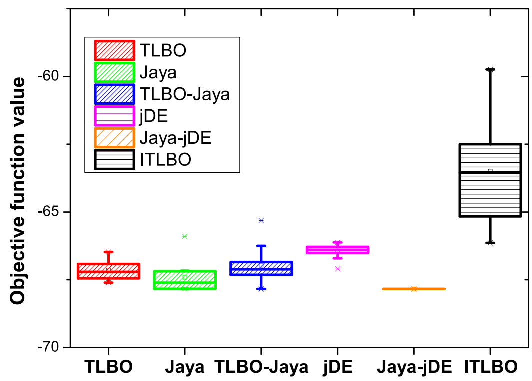
TABLE 5. Power consumption reduction using optimization.

Network	**Total Power Consumption(kW)**	**Power Consumption optimized (kW)**	**Percentage reduction (%)**
4G LTE	123.78	52.83	57.32
5G Massive MIMO	22.60	14.13	37.48
5G Massive MIMO extended	748.32	332.26	55.60

Table 3 holds the algorithms comparative results in terms of objective function values. We notice that for both 4G and 5G networks Jaya-jDE is the superior algorithm in terms of



(a)



(b)

FIGURE 3. Case 1: Maximum area coverage case. Box plots of the algorithms results. a) 4G b) 5G Massive MIMO.

mean, worst and standard deviation of the objective function objective function. For the 4G case the jDE results is the best, while for the 5G case Jaya-jDE obtains the best result. Table 4 reports the comparative results for each technology case. In Table 4 the ''BS No'' column denotes the number of active BS required for the solution. We notice that the 75 BSs are not enough to cover the whole area with Massive MIMO technology and a lower coverage percentage of about 67% is obtained. This can be expected as the 5G network operates at a higher frequency than 4G. An indication that more BS are required using Massive MIMO technology is also evident by viewing the more than double number of BSs required for the Massive MIMO network. In the 4G LTE case, all algorithms succeed in obtaining 95% coverage. However, the results regarding power consumption and the number of required BSs vary. For the Massive MIMO case the number of required BSs increases compared with 4G, which creates the need for a new extended BS set.

Moreover, it is also evident that for the 5G extended BS set case Jaya-jDE obtains the best result with 1740 BS that achieves coverage close to 95%. ITLBO obtains a result with fewer BS (1210) but with smaller coverage percentage (92%). The other algorithms could not find a solution with coverage percentage close to 90%. As it can be expected the power consumption is very high for this case due to the large BS number. Thus, Jaya-jDE is capable of producing a solution for high-dimensional problems with a small population size. It must be also noted that the first 5G implementations will co-exist with current 4G networks, thus it will be heterogeneous networks. Thus 5G coverage will not be provided for the whole city but for specific parts. The 5G network will provide coverage first at points with large concentration of people like stadiums, shopping centers e.t.c.

The benefit of controlling the BS locations as well as the BS power to achieve energy efficiency is proven from the data listed in Table 5. We notice that the percentage of power reduction using an optimization algorithm and by using the worst obtained results ranges from about 37% to 57%. Moreover, Figs. 3a-3b show the boxplots of the algorithms results. It is clear that Jaya-jDE obtained the results with the smaller distribution of values in both case cases.

TABLE 6. Best-obtained results by the capacity tool.

Network	BS No.	Users (%)	Power Consump. (kW)	Capacity (Mbps)
LTE	14	100	20.46	190.39
5G Massive MIMO	26	93	6.72	45260.8

2) CASE 2: MAXIMUM USER COVERAGE CASE

As mentioned previously, next we consider a capacity-based heuristic, which will respond to the instantaneous bit rate demand of the users in the considered area. More details about the capacity tool can be found in [6].

The input to the optimization algorithm for this case is the list of all BSs in the city of Ghent and the list of different types of users (voice/data).

For the LTE and the 5G Massive MIMO networks we consider a randomly generated list of 100 users with their required bit rate: this list contains the location of all the users active in the considered area together with the bit rate they require. The users are uniformly distributed over the considered area i.e., each location in the area has the same chance to be chosen as a user location. Four bit rates are considered: 1 Mbps (66 users), 2 Mbps (20 users), 4 Mbps (11 users) and 10 Mbps (3 users). Fig. 1a shows a randomly generated user distribution in the city of Ghent for the LTE and 5G-Massive MIMO cases.

We apply first the capacity based heuristic. The results are listed in Table 6. The capacity column refers to the total capacity in Mbps offered by each network configuration regardless of user coverage. We notice that although the Mas-

TABLE 7. Maximum user coverage case. Best-obtained results comparison using different algorithms. The best values are in bold font.

Algorithm	BS No	Served Users (%)	Power Consump. (kW)	Capacity (Mbps)
4G LTE case				
TLBO	13	100	15.88	176.79
TLBO-Jaya	**12**	100	**14.69**	**163.19**
jDE	**12**	100	15.02	**163.19**
Jaya	**12**	100	14.86	**163.19**
Jaya-jDE	13	100	16.12	176.79
ITLBO	14	100	17.10	190.399
5G Massive MIMO case				
Algorithm	**BS No**	**Served Users (%)**	**Power Consump. (kW)**	**Capacity (Mbps)**
TLBO	**20**	85	**4.85**	**34815.99**
TLBO-Jaya	21	89	5.15	36556.79
jDE	25	89	5.79	43520.00
Jaya	21	89	4.95	36556.79
Jaya-jDE	24	**93**	6.33	41779.21
ITLBO	23	82	5.36	40038.42

sive MIMO BS number is higher than the 4G one, the 26 BSs cannot cover all the users but 93% of them due to shorter range. We notice that when the goal is user coverage and not area coverage the 5G network has the ability to cover the users with small increase in BS number due to the higher capacity rates offered. The capacity in Mbps offered by both networks is also quite different with Massive MIMO network offering about two orders of a magnitude more. This means that more users that will be close to the BS will be covered. The power consumption of the 4G network is about three times higher than that of the Massive MIMO network.

Next, we optimize both networks using the meta-heuristic approach to address the same problem. We apply again all algorithms. Table 7 shows the best obtained results. For 4G/LTE all algorithms obtained solutions that cover 100% of the users. We notice that for the 4G case the smallest number of 12 BSs is obtained by three algorithms: TLBO-Jaya, Jaya, and jDE. However TLBO-Jaya obtained the best results in terms of power consumption. Thus, the meta-heuristic approach obtained results that require about 14% lower number of BS and about 28% less power consumption for the 4G/LTE case. For the 5G Massive MIMO case the BS number is 8% lower and the power consumption about 6% less than the results obtained by the capacity tool for the same user coverage percentage. The capacity based heuristic obtained results with higher input power and smaller dispersion of values, while the hybrid algorithm obtained results with smaller average input power at about 14 dB.

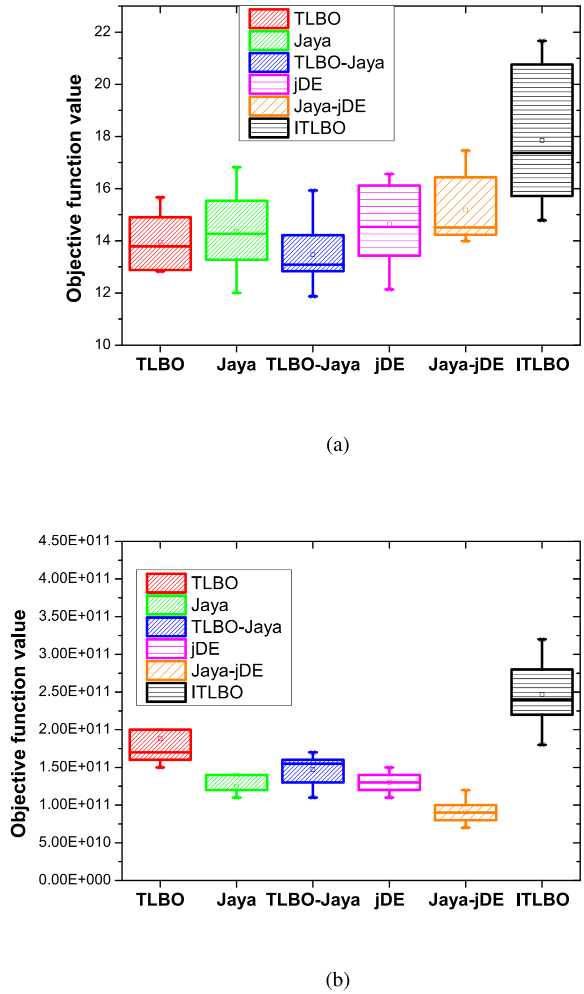


FIGURE 4. Case 2: Maximum user coverage case. Box plots of the algorithms results for a) 4G b) 5G Massive MIMO.

Figs. 4a-4b show the box plots of the algorithms results for both network cases. We notice that for the 4G network, the TLBO-Jaya obtained the smallest dispersion of values, namely the standard deviation is about 1.2. For the Massive MIMO case Jaya-jDE obtained the best result. Jaya obtained the best result in terms of value dispersion.

The presented results show that future 5G networks using the Massive MIMO technology will need to be more denser than current 4G networks, even if they operate in the cm-Wave frequencies. The main advantage of such 5G networks will be the significantly lower power consumption and the higher bit rates offered. To reduce further the power consumption heuristic or meta-heuristic approaches can be applied. The heuristic approach is generally faster. The meta-heuristic approach could require more time, but it is considered to be a global optimizer.

B. NB-IoT CASE

Finally, we address the network planning optimization problem for 4G NB-IoT networks. We consider a carrier frequency

TABLE 8. Link budget parameters for the NB-IoT network.

Parameter	Macrocell BS
Frequency	2.1 GHz
Maximum input power base station antenna	46 dBm
Maximum Tx power for NB-IoT in-band	35 dBm (6 dB PSD boosting)
Maximum Tx power for NB-IoT guard-band	34.9 dBm (6 dB PSD boosting)
Antenna gain of base station	18 dBi
Antenna gain of receiver	0 dBi
Feeder loss base station	2 dB
Feeder loss receiver	0 dB
Fade margin	10 dB
Interference margin	2 dB
Noise figure of receiver	5 dB
Implementation loss of receiver	0 dB
MIMO	2x2
Receiver SNR	10.5dB for Voice/Data 3.7dB for IoT nodes
Bandwidth	10 MHz
Soft handover gain receiver	0 dB
Building penetration loss	0 dB (only outdoor coverage considered)
Height mobile station	1.5 m

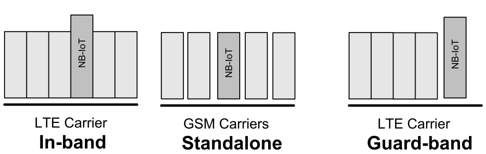


FIGURE 5. NB-IoT modes of operation.

TABLE 9. NB-IoT 300 nodes case. Best-obtained results comparison using different algorithms. The best values are in bold font.

In-band				
Algorithm	**BS No**	**Served Users (%)**	**Power Consump. (kW)**	**Capacity (Mbps)**
TLBO	14	100	24.86	190.39
TLBO-Jaya	15	100	25.90	203.99
jDE	**16**	100	26.89	217.59
Jaya	13	100	22.30	**163.19**
Jaya-jDE	**12**	100	**21.31**	163.20
ITLBO	13	100	22.08	176.79
Guard-band				
Algorithm	**BS No**	**Served Users (%)**	**Power Consump. (kW)**	**Capacity (Mbps)**
TLBO	16	100	27.99	217.60
TLBO-Jaya	16	100	26.96	217.60
jDE	17	100	29.50	231.20
Jaya	16	100	25.97	217.60
Jaya-jDE	**13**	**100**	**21.80**	**176.80**
ITLBO	15	100	26.20	203.99

TABLE 10. Best obtained solutions for different IoT nodes number.

In-band				
IoT Nodes	**BS No**	**Served Users (%)**	**Power Consump. (kW)**	**Capacity (Mbps)**
1000	17	100	27.14	231.19
3000	20	100	35.10	272.00
5000	25	100	41.27	340.00
10000	51	99.45	85.53	693.60
Guard-band				
IoT Nodes	**BS No**	**Served Users (%)**	**Power Consump. (kW)**	**Capacity (Mbps)**
1000	19	100.00	32.45	258.39
3000	24	100.00	40.49	326.40
5000	28	100.00	49.96	380.80
10000	42	99.58	54.64	571.20

of 2.1 GHz for all the simulations, which is one of the possible frequency bands for NB-IoT (Table 8) operation [8]. There are three possible ways of deploying NB-IoT [40], [41]. These are the stand-alone as a dedicated carrier, in-band within the occupied bandwidth of a wideband LTE carrier, and within the guardband of an existing LTE carrier (see Fig. 5). In stand-alone deployment NB-IoT uses one GSM channel of 200kHz, while for in-band and guard-band operation, it uses 180kHz. The latter is equal to bandwidth used by LTE for each physical resource block (PRB). The number of PRBs in an LTE network depends on the total LTE bandwidth, for 10 MHz bandwidth there are 50 PRBs. In guard-band operation the NB-IoT occupies one LTE guard-band, thus the total number of PRBs increases by one. In all NB-IoT simulations we assume the maximum BS transmitted power to be equal to 46dBm and 2×2 MIMO operation for the

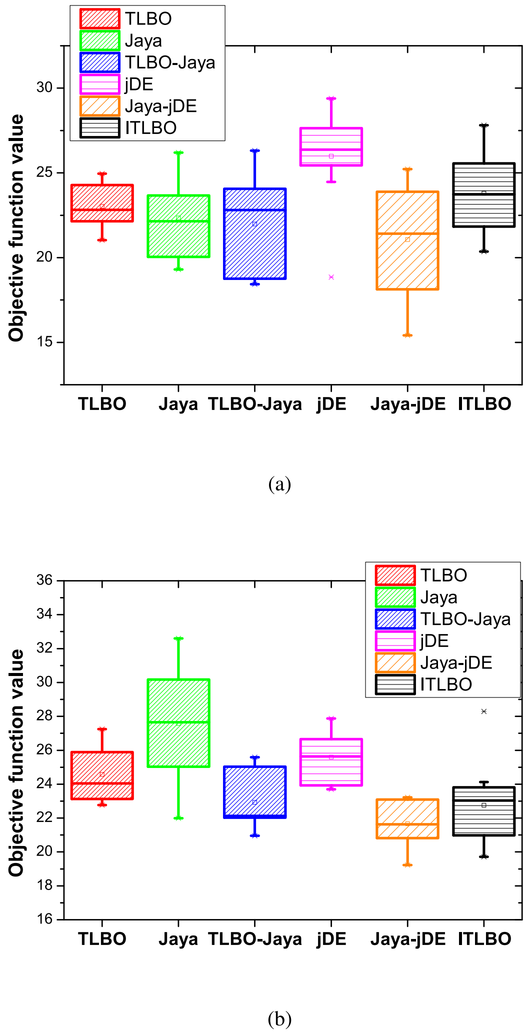


FIGURE 6. **NB-IoT case. Box plots of the algorithms results. For 224 Voice/Data users and 300 IoT Nodes at 25 kbps a) in-band b) guard band.**

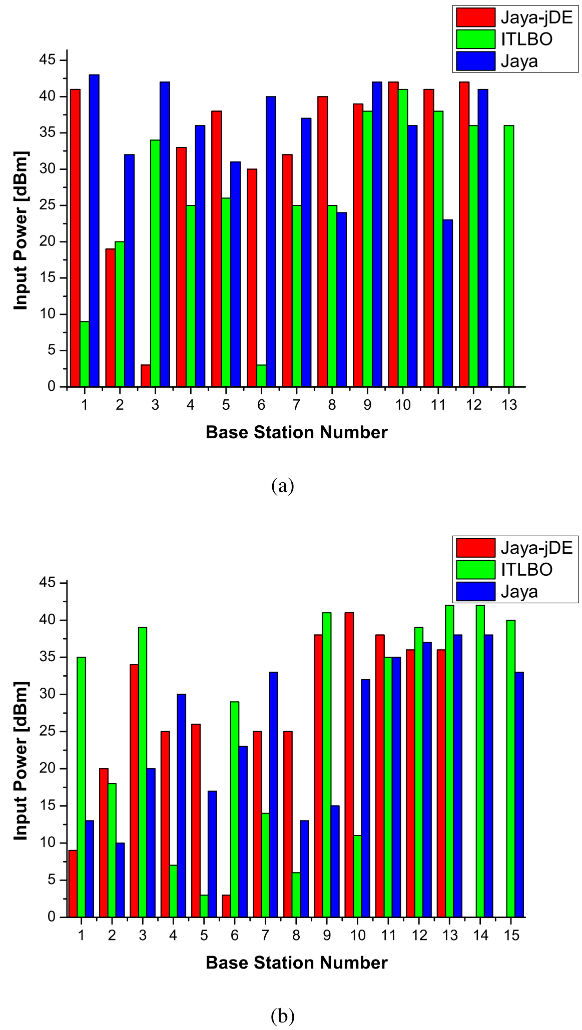


FIGURE 7. **NB-IoT case. Distribution of BS input power of the best obtained solutions. For 224 Voice/Data users and 300 IoT Nodes at 25 kbps a) in-band b) guard band.**

BS. We consider also as described by 3GPP that the NB-IoT band is boosted by 6dB. Thus, the maximum BS transmit power for NB-IoT is 35dBm and 34.9dBm for in-band and guard-band operation respectively.

The input to the optimization algorithm for this case is the list of all BSs in the city of Ghent as well as the list of different types of users (voice/data/IoT nodes). As a result of the reduced bandwidth NB-IoT nodes use low data rates. We set the maximum data rate to 25kbps. The link budget parameters for the LTE NB-IoT network are listed in Table 8. Additionally, as in previous cases, the propagation model used is the Walfisch-Ikegami.

Moreover, different user distribution cases for the NB-IoT network are considered. The number of total users is a constant number of regular voice/data users plus a larger number of low rate IoT nodes. Here, we have 224 voice/data users with rates of 64kbps/1Mbps respectively [3]. In each case, there is also a large number of NB-IoT nodes spread in the city center. The IoT nodes is a specific data user type with low bit rate and low power requirements. The first case is that of 300 IoT nodes having a low bit rate of 25kbps. This is in agrement with a typical number of nodes for smart city applications as it is considered by the authors in [42]. We consider both in-band and guard-band cases. Different network sizes are also considered starting from 1000 IoT nodes to 10000 IoT nodes. Figs 1b-1c depict the user distribution in the city of Ghent for 300 and 1000 IoT nodes. The IoT nodes are depicted by the green triangles, while the voice/data users are presented by the blue squares.

Table 9 lists the best obtained values for network configurations having 300 IoT nodes. One may notice that for the in-band case Jaya-jDE obtained a solution with 12 BS, while the other algorithms obtained best solutions with more BSs (13-16). Moreover, it is evident that a large difference in the power consumption among the algorithms (21.31-26.89kW) exists, where Jaya-jDE obtained the lowest power consumption. In general, as expected, the guard-band operation requires more BSs than in-band since it uses an extra PRB with 12 more subcarriers. For the guard-band case again Jaya-jDE finds a solution with fewer active BSs than

TABLE 11. Average rankings achieved by friedman test.

Algorithm	Average Rank	Normalized values	Rank
TLBO	3.71	2.37	3
TLBO-Jaya	3.86	2.46	4
jDE	4.29	2.73	5
Jaya	3.29	2.09	**2**
Jaya-jDE	**1.57**	**1.00**	**1**
ITLBO	4.29	2.73	5

the other algorithms (2-4 less BSs than the others). In both cases ITLBO is the second best algorithm.

Figs. 6a-6b show the box plots of all the algorithms runs. In the in-band case, we notice that the TLBO results have the narrower distribution of values, however the smaller values are obtained by Jaya-jDE. For the guard band case Jaya-jDE obtained the best results, while Jaya obtained the larger distribution of values. The distribution of BS input power of the best obtained solution by the three best algorithms is shown in Figs. 7a-7b. We notice that there is a variation of the BS input power, which differs in most of the cases from the maximum power.

Finally, we compute the network configuration using only Jaya-jDE with an increasing number of IoT nodes for both modes of operations. Again, in each case there are also 224 voice/data users as in previous example. We notice that the network can support up to 10000 IoT nodes with covering about 99% of the users. As it can be expected power consumption increases as the number of IoT nodes increases. It is interesting to notice that for the in-band case the number of BS increases from 17 to 51, while the power consumption increases from 27.14 to 85.53 kW. Moreover, for the guard band case the BS number rises from 19 to 42, while the power consumption increases from 32.45 to 54.65 kW.

C. NON-PARAMETRIC STATISTICAL TESTS

Moreover, in order to validate the algorithms performance we have conducted a non-parametric statistical test. Namely, the Friedman test, which has been used as a metric for the performance evaluation of EAs [43]–[45]. We used the data from the obtained results. Table 11 lists the ranking results. We can see that Jaya-jDE algorithm ranks first and outperforms the other algorithms.

VI. CONCLUSION

In this paper, we have presented and addressed the problem of designing emerging cellular networks like Massive MIMO and LTE NB-IoT for the best possible coverage and optimal power consumption. We have compared results for different networks using different heuristic and metaheuristic approaches. The results show that the Massive MIMO access networks will be denser than current 4G technology and will offer a greater capacity. Moreover, in-band operation in NB-IoT requires less power than guard-band operation (about 10% less in average). We have also proposed a novel algorithm that combines both an EA and heuristic concepts to address the network design problem. Moreover, we have applied and introduced a new and simple algorithm to this problem, the Jaya-jDE algorithm. Jaya-jDE is a hybrid Jaya and differential evolution algorithm that combines concepts from both algorithms and includes a probabilistic selection mechanism and a stagnation avoidance mechanism. The proposed algorithm was compared with others in different cellular network design cases. The results indicate that in most cases it obtained a better performance than other emerging algorithms and achieved the best result in the Friedman test. The Jaya-jDE algorithm allows to achieve a good trade-off even when it does not have the best performance. Future work can consist of the analysis of distributed Massive MIMO networks.

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