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# Self-adaptive Differential Evolution based Optimized MIMO Beamforming 5G Networks

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**Abstract**

The industrial factory is one of the challenging environments for future wireless communication systems, where the goal is to produce products with low cost in short time. This high level of network performance is achieved by distributing massive MIMO that provides indoor networks with joint beamforming that enhances 5G network capacity and user experience as well. Judging from the importance of this topic, this study introduces a new optimization problem concerning the investigation of multi-beam antenna (MBA) coverage possibilities in 5G network for indoor environments, named Base-station Beams Distribution Problem (BBDP). This problem has an extensive number of parameters and constrains including user's location, required data rate and number of antenna elements. Thus, BBDP can be considered as NP-hard problem, where complexity increases exponentially as its dimension increases. Therefore, it requires a special computing method that can handle it in a reasonable amount of time. In this study, several differential evolution (DE) variants have been suggested to solve the BBDP problem. The results show that among all DE variants the self-adaptive DE (jDE) can find feasible solutions and outperform the classical ones in all BBDP scenarios with coverage rate of 85% and beam diameter of 500 m.

**Keywords:** 5G, multiple-input multiple-output MIMO, multi-beams antenna MBA, differential algorithm DE, jDE.

# خوارزمية التطور التفاضلي ذاتية التكيف لأمثلية بث الشعاع الموجه في شبكات الجيل الخامس

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**الخلاصة**

تعتبر بيئة المصانع من البيئات الصعبة لأنظمة الاتصالات اللاسلكية المستقبلية، حيث يتمثل الهدف في إنتاج منتجات بتكلفة منخفضة وفي وقت قصير. يتم تحقيق هذا المستوى العالي من أداء الشبكة من خلال توزيع MIMO الهائل الذي يزود الشبكات الداخلية بتشكيل الحزمة المشتركة الذي يعزز قدرة شبكة الجيل الخامس وتجربة المستخدم أيضًا. انطلاقا من أهمية هذا الموضوع المحموم، تقدم هذه الدراسة مشكلة تحسين جديدة تتعلق بالتحقيق في إمكانيات تغطية الهوائي متعدد الحزم (MBA) في شبكة الجيل الخامس للبيئات الداخلية، المسماة مشكلة توزيع حزم المحطة الأساسية (BBDP). تحتوي هذه المشكلة على عدد كبير من

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المعلمات والقيود بما في ذلك موقع المستخدم ومعدل البيانات المطلوب وعدد عناصر الهوائي. وبالتالي، يمكن اعتبار BBDP مشكلةNP-hard ، ويزداد تعقيدها بشكل كبير مع زيادة أبعادها. لذلك، تتطلب هذه المشكلة طريقة حسابية خاصة يمكنها التعامل معها في فترة زمنية معقولة. في هذه الدراسة، تم اقتراح العديد من متغيرات التطور التفاضلي (DE) لحل مشكلة BBDP. تظهر النتائج أنه من بين جميع متغيرات DE ، يمكن لـ DE التكيف الذاتي (jDE) أن يجد حلولًا مجدية ويتفوق على الحلول الكلاسيكية في جميع سيناريوهات BBDPمع معدل تغطية يبلغ 85 ٪ وقطر الشعاع يبلغ 500 متر.

## 1. Introduction

The recent advent of the new era of 5G network was inevitable due to exponential acceleration of wireless communication networks usage in both business operations and social functions [1]. The Global System for Mobile Communications (GSMA) prediction states that by 2025 there will be 1.2 billion 5G connections and 40% of the population will be covered by 5G [2]. This is what is being witnessed today, the arise of the 4$^{th}$ industrial revolution or as it is called industry 4.0. On the other hand, the expected requirements of 5G are highly challenging and it is difficult to have one core technology to fit all these requirements. Thus, innovated radio access technologies and new core network have been introduced to make the requirements achievable. Massive MIMO and the use of millimetre-waves (mmW) in wireless mobile communication will bring new capabilities as it is known higher frequency means higher data rate. Yet, higher path loss can be involved and in response it contributes to degrading the signal-to-interference-noise ratio (SINR) [3]. To deal with this deficiency, high-gain antenna with multi-directional beams, also referred to as the multi-beam antenna (MBA), can be a good solution since it improves the SINR and enhances the data security [4]. MBA is characterized with independent narrow directed beams with high gain value to cover a predefined angular range. MBAs will serve as the key hardware for enabling massive MIMO as an alternative of the traditional MIMO technology [5].

In literature, several suggestions were provided to improve the performance of Massive MIMO beamforming by applying evolutionary algorithms (EAs). For instance, in [6] and [7] the focus was on expanding the transmission distance and improve the energy efficiency. In [6] the authors used an improved non-dominated sorting genetic algorithm-II, while in [7] proposed an improved biogeography-based optimization. On the other hand, [8] investigated reducing the power consumption by applying a hybrid DE algorithm called Jaya-jDE. In [9], self-adaptive dynamic DE is proposed to minimize the bit error rate for multi-user MIMO. Meanwhile, [10] focused on improving the performance of beamforming by optimizing amplitude weight and time modulation pulse width based on DE algorithm. Finally, [11] attempted to maximize three-dimensional transmitting antenna arrays by applying hybrid method asynchronous particle swarm optimization (PSO) and dynamic DE. However, according to our observation, there is no specific defined problem in the literature which describes the difficulties of optimizing the beams' direction of massive MIMO in a way that satisfies the users' demands for high data-rate in more efficient manner, as we believe a "better" distribution of the beams will increase the throughput significantly.

Thus, in this research paper we introduce a new optimization problem concerned the investigation of the 5G beamforming coverage possibilities for an indoor environment where the data rate can be on a high demand by different users. The beamforming coverage can change adaptively based on the users' locations and the requested data rate. In this optimization problem, the task is to find the solution that produces at least near-optimal plan of beamforming and distribution of the beams while satisfying the problem constraint such as coverage; for this reason, this problem is formulated as constraint optimization problem, hence as NP-hard problem. Thus, it requires special algorithms that should handle it in a reasonable amount of time such as EAs. To achieve this, an efficient BBDP solving approach (model) has been suggested based on classical and adaptive DE algorithms. This also includes constructing several equality measures (models) to evaluate the quality of the solution. Then, to build sufficient simulations of the service area with multiple scenarios and locate several metrics to evaluate and compare the performance of DEs in solving BBDP.

This article is organized as follows: Section 2 presents the definition of the optimization problem and the metrics used to measure the performance of the algorithm. Section 3 explains in detail the implementation of the suggested algorithm on the defined problem including an illustration of the encoded chromosome. Section 4 explains the suggested modified approach to handle the constrained optimization problem. Section 5 is dedicated to demonstrating the conducted experiments and analysis of the results to illustrate the performance of the suggested algorithm on multiple cases. Finally, conclusion of our research is provided in Section 6.

## 2. Base-station Beams Distribution Problem: New definition

To satisfy the users high demands of data rate and to increase the quality-of-service (QoS) with limited resources in massive MIMO, the distribution of the beams of the base-stations (BSs) must be optimized. In this paper, we named this optimization problem as BS beams distribution problem (BBDP). Following is the formal definition and description of BBDP.

Assume an area $A$ of $W \times L$ dimension, contains a set $U = \{u_1, \dots, u_i, \dots, u_M\}$ of users where $u_i \in A$, and each $u_i$ demands a certain data rate. The users' data rate is represented by the following set: $DR^U = \{dr_1^u, \dots, dr_i^u, \dots, dr_{|U|}^u\}$, where $dr_i^u \leq 7.34\ Gbps$. Additionally, $A$ contains a set $BS = \{bs_1, \dots, bs_i, \dots, bs_N\}$ of base-stations where $bs_i \in A$. Each $bs_i$ transmits 16 beams $B_i = \{b_{1,i}, \dots, b_{j,i}, \dots, b_{16,i}\}$ where $b_{j,i} \in A \mid i \in [1, |BS|]$ and $j \in [1, |B_i|]$. Each $b_{j,i}$ covers a certain circular area $a_{j,i} \in A$ within a certain range. In the target area $A$, $BS$ and $U$ are deployed in different locations $L^{BS}$ and $L^U$, in which a set $L^{BS} = \{l_1^{bs}, \dots, l_i^{bs}, \dots, l_{|BS|}^{bs}\}$ of three-dimensional Cartesian coordinate points represent $BS$ locations, where $l_i^{BS} \in A$, and it is $bs_i$'s location. The same for $U$, in which a set $L^U = \{l_1^u, \dots, l_i^u, \dots, l_{|U|}^u\}$ of two-dimensional Cartesian coordinate points represents $U$ locations, where $l_i^u \in A$, and it is $u_i$'s location (uniformly randomly distributed). These notations have been visually depicted in Figure 1.

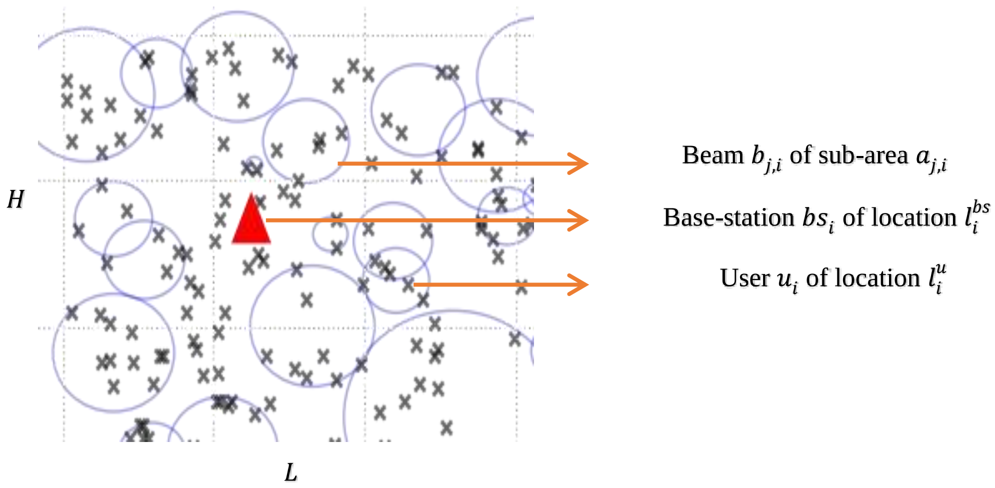



**Figure 1-** A footage of $W \times L$ area $A$, that contains: one base-station, which is set in certain location, several beams distributed with certain locations and ranges, and a number of users with different locations.

When the beams are distributed among the users, certain concerns must be considered: (1) the beams must satisfy the users demands of data-rate as possible (2) The interference between the beams must be reduced as possible. These concerns are translated into the following equality measures:

**a. Beam Width**

The beam diameter or beam width can be defined as: each beam $b$ has a certain circular area $a \in A$ to cover. Thus, each beam has a particular diameter $\emptyset$, which determines the number of users to be covered and the number of array elements required to form this beam. The following formula is used to calculate the diameter average $\Phi$ of the beams in area $A$:

$$\Phi = \frac{\sum_{i=1}^{|BS|}\sum_{j=1}^{|B_i|}\emptyset_{j,i}}{NUM\_BEAMS} \quad (1)$$

where $NUM\_BEAMS$ is the total number of the available beams in $A$. $\emptyset_{j,i}$ is the diameter of the $j^{th}$ beam of the $i^{th}$ base-station.

**b. Coverage Ratio**

Each beam $b_{j,i}$ covers a certain circular area $a_{j,i} \in A$, the users inside $a_{j,i}$ are submitted to $b_{j,i}$. The summation of the data rates that have been assigned to the users inside those beams is denoted as $\psi$, i.e., $\psi$ is the coverage amount of $b_{j,i}$s in terms of data rate. Equation (2) is dedicated to calculating the total coverage ratio of the BSs deployed in area $A$:

$$\Psi = \frac{\sum_{i=1}^{|BS|}\sum_{j=1}^{|B_i|}\psi_{j,i}}{\sum_{i}^{|U|} dr_i} \quad (2)$$

where $\psi_{j,i}$ is the coverage rate of the $j^{th}$ beam of the $i^{th}$ base-station. For making the optimization problem as minimization, the shortage ratio is considered and calculated by subtracting $\Psi$ from one as in the following equation.

$$\grave{\Psi} = 1 - \Psi \quad (3)$$

**3. Differential Evolution for BBDP**

Investigating a rigorous distribution strategy for the base-stations' beams in 5G network in a reasonable amount of time is a challenging problem because of the many parameters and constraints related to BBDP. It can be considered as Np-hard problem as the complexity of BBDP increases exponentially with its higher dimensionality. In this research paper, we suggest employing EA for BBDP, more precisely, classical DE algorithms [12] and its self-adaptive variant jDE (as described in Algorithm 1) [13].

Firstly, in any EA, initialization is implemented at the beginning with a pool of candidate solutions. Suppose the population *P* consists of *PN* candidate solutions – individuals – and each solution carries *D* of sub-solutions – genes – the genes represent the beams; thus, the dimensionality of the problem *D* is the number of the available beams *NB* in the target area $A$. To encode BBDP into evolutionary computing environment, the individual must be represented properly. The next formula represents the individual structure:

$$I_i = [g_{1,i}, \ldots, g_{j,i}, \ldots, g_{NB,i}] \quad (4)$$

Where $g_{j,i}$ is the gene of the $i^{th}$ individual and it represents the $j^{th}$ beam. It is worth mentioning that $g_{j,i}$ holds three attributes: the location of the beam (*x*, *y*) to indicate where the beam will be deployed, and HPBW of the beam, as shown in Figure 2. The beams are part of the evolution process since the individual holds the beams' attributes. Thus, in this first manifestation of the beams, which is related to the initialization of the population, the individual is randomly initialized with the consideration of $x$, $y$, and HPBW boundaries. Afterword, the life cycle of the evolution search launches where the population will endure several phases: variant operation, evaluation, and selection, till the termination criteria is met. This means that the evolution search came to its end and the final "good" solution is delivered.

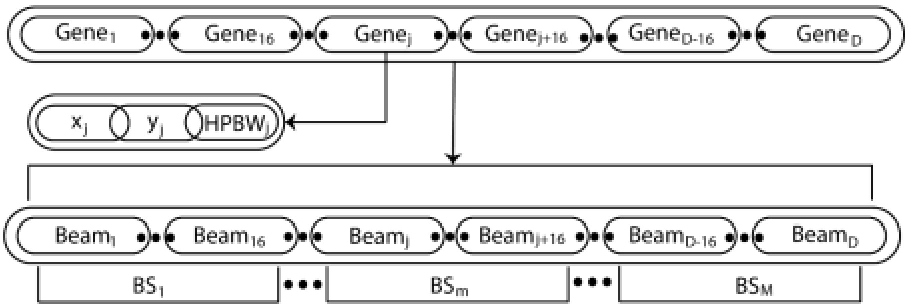



**Figure 2-**Individual architecture for BBDP

Next, to produce new individuals, the mutation operator in DE is applied for every individual. In this study, several mutation operations have been used. It is important to mention that the mutation operator is applied on the gene level, and since in our case study the gene consisted of three parameters, accordingly, the mutation operator is applied for each gene components three times for x-coordinate, y-coordinate, and HPBW.

To generate fully new individuals, the donor vector, which is the production of mutation operator, must undergo crossover phase, DE algorithms are submitted to the same crossover strategy, that is, binomial crossover. In the crossover operator, the whole gene, which includes the beam coordinate point $(x, y)$ and HPBW, is transferred to the new vector – trial vector – as one block only if, the crossover probability $CR$ is less than the random integer $randj \in [1, NB]$.

After the birth of the new beams' attributes, the new solution –individual– must be evaluated. The evaluation is performed based on model 1 or 2. Table 1 describes the two models in terms of the evaluation (fitness) function and problem constraint to be satisfied.

**Table 1-**The models that have been proposed to solve BBDP

| Model | Fitness function | Constraint |
|---|---|---|
| 1 | The shortage ratio $\dot{\Psi}$ in Eq. (3) | The beam diameter Φ in Eq. (1) |
| 2 | The beam diameter Φ in Eq. (1) | The shortage ratio $\dot{\Psi}$ in Eq. (3) |

After the evaluation process of the trial and the target individual, a decision must be made to determine which solution is superior and qualified to be upgraded to the next population. In this paper, a modified feasibility rule approach was used for that purpose, which is discussed in the next section.

Algorithm 1 depicts jDE algorithm. In this algorithm, $F$ and $CR$ are adjusted according to probability of $T_1$ *and* $T_2$, and both assigned to value 0.1. The generated $F_{i,g+1} \in [0.1, 1.0]$, therefore $F_u = 0.9$ and $F_l = 0.1$, because it is rarely that $F$ exceeds 1. In case of $F = 0$, the generated offspring is a product of crossover operator with no mutation.

## 4. Modified Feasibility Rules Approach for Constrained DE

Usually, real-world problems are constrained**.** According to [14], the problem can be classified into two features: constraints and fitness function. Corresponding to the two features, four categories can be made: Constraint Optimization Problem (COP), Constraint Satisfaction Problem (CSP), Free Optimisation Problem (FOP), and no problem in case there are neither constraint nor a fitness function. In this research, we are concerned with COP as our problem required both fitness function and constraints. A general concept regarding multi-constrained nonlinear problems, that is the search space divided into two or more disjoint regions: feasible region/s (F) including solutions that meet the given constraints, and infeasible region/s (U) containing candidate solutions that violate the required constraints. The candidate solution is feasible if it subjects to the expression: $\forall\, j \in [1, M] : g_j(\vec{X}_i) \leq 0 \mid i \in [1, PN]$, where $g_j(\quad)$ presents the constraint function.

**Algorithm 1.** jDE algorithm

| | |
|---|---|
| input $G$, $PN$, $D$, $\vec{X}^{low,high}$; | //defined by the user |
| Set $T_1 = 0.1$; $T_2 = 0.1$; $F_l = 0.1$; $F_u = 0.9$; | //Initialization phase |
| Initialize all values of $F_{i,0}, \mid i \in [1, PN]$ in the first generation to 0.5; | |
| Initialize all values of $CR_{i,0} \mid i \in [1, PN]$ in the first generation to 0.9; | |
| Initialize the first population randomly $P_0 = [\vec{X}_{1,g}, \ldots, \vec{X}_{i,g}, \ldots, \vec{X}_{PN,g}]$ ; | |
| For $g$ = 1 to $G$ | //Main loop |
|   For $i$ = 1 to $PN$ | |
|     Randomly choose $\vec{X}_{r_0^i,g}$, $\vec{X}_{r_1^i,g}$, $\vec{X}_{r_2^i,g}$ from $P$ where $\vec{X}_{r_0^i,g} \neq \vec{X}_{r_1^i,g} \neq \vec{X}_{r_2^i,g} \neq \vec{X}_{i,g}$ | //Mutation phase |
|     Generate donor vector $\vec{V}_{i,g} = \vec{X}_{r_0^i,g} + F_i \cdot \left(\vec{X}_{r_1^i,g} - \vec{X}_{r_2^i,g}\right)$; | |
|     Randomly choose $randj$ from [1, $D$] | |
|     For $j$ = 1 to $D$ | //Crossover phase |
|       If $rand_{i,j}[0, 1] \leq CR \; or \; RandJ = j$ | |
|         $u_{j,i,g} = v_{j,i,g}$; | |
|       else | |
|         $u_{j,i,g} = x_{j,i,g}$; | |
|     If $f(\vec{U}_{i,g}) < f(\vec{X}_{i,g})$ | //Selection phase |
|       $\vec{X}_{i,g+1} = \vec{U}_{i,g}$; | |
|     else | |
|       $\vec{X}_{i,g+1} = \vec{X}_{i,g}$; | |
|     If $rand_2[0, 1] < T_1$ | //Control parameters adaptation mechanism |
|       $F_{i,g+1} = F_l + rand_1[0, 1] * F_u$; | |
|     Else | |
|       $F_{i,g+1} = F_{i,g}$; | |
|     If $rand_4[0, 1] < T_2$ | |
|       $CR_{i,g+1} = rand_3[0, 1]$; | |
|     Else | |
|       $CR_{i,g+1} = CR_{i,g}$; | |
| $\vec{X}_{best}$ = Evaluate the population; | |

The feasibility rules approach in [15] has been used in this research since this approach is a competitive approach. Moreover, it does not require an additional control parameter, instead it modifies the selection operator in the standard DE, as in Eq. 5. According to this equation, the trial vector is superior to the target vector if it satisfies one of the three conditions:

1- If both the target and trial vectors are feasible and the trial vector has better objective function value.
2- If the trial vector is feasible and the target vector is not feasible.
3- If both the target vector and the trial are not feasible, but the trial vector has lower or equal amount of constraints violation.

$$\vec{X}_{i,g+1} = \begin{cases} \vec{U}_{i,g}, & if \begin{cases} \left(\forall j \in [1,M]: g_j(\vec{U}_{i,g}) \le 0 \land g_j(\vec{X}_{i,g}) \le 0\right) \land \left(f(\vec{U}_{i,g}) \le f(\vec{X}_{i,g})\right) \\ \lor \\ \left(\forall j \in [1,M]: g_j(\vec{U}_{i,g}) \le 0\right) \land \left(\exists j \in [1,M]: g_j(\vec{X}_{i,g}) > 0\right) \\ \lor \\ \left(\exists j \in [1,M]: g_j(\vec{U}_{i,g}) > 0\right) \land \left(\forall j \in [1,M]: \grave{g}_i(\vec{U}_{i,g}) \le \grave{g}_i(\vec{X}_{i,g})\right) \end{cases} \\ \vec{X}_{i,g}, & otherwise \end{cases} \quad (5)$$

where $g'(\quad) = max(g_j(\quad), 0)$. In the feasibility rules approach, we find the third rule, where the trial vector is selected only if it provides lower or equal amount of constraints violation, cause many candidate solutions to have the same constraints violation number; thus, it contributes to decelerate the learning process of DE as there are undistinguished values. For instance, if a particular problem has two constraints, then the possibility of obtaining one of the two values {1, 2} (number of constraints violation) is 50%. Therefore, we calculated the sum of the positive constraint functions' values of the candidate solution (How close is the candidate solution to the feasible region). The vector with the smaller amount is selected, and this simple modification made this search convergence faster. The next formula demonstrates the adjustment, where $g'(\quad)$ in Eq. (5) is replaced by $\hat{g}(\quad)$.

$$\hat{g}(\quad) = \sum_{j=1}^{M} num_j = \begin{cases} g_j(\quad), & g_j(\quad) > 0 \\ 0 \quad , & g_j(\quad) \le 0 \end{cases} \quad (6)$$

where $g_j(\quad) | j \in [1, M]$ is the constraint function. It is important to note that the constraint functions must be in $[0, 1]$ interval.

As mentioned in the previous section, two models have been proposed to measure the quality of the candidate solutions through defining the fitness function and their constrains. Due to these models being the building blocks of the whole selection process defined in Eq. (5), a short summary regarding these models is provided. The first model is set to have the shortage ratio $\dot{\Psi}$ as fitness function and the mean of the beams' diameter $\Phi$ as constraint since a wide beam is not reasonable since the purpose of the beams is to divide the target area into covered sub-areas and located as needed. Additionally, the wide beam might interfere with other beams. Thus, the beam diameter range was limited by a predefined value. In model 2, the roles of model 1 were reversed where the fitness function is the mean of the beams' diameter $\Phi$ and the constraint is the shortage ratio $\dot{\Psi}$. However, limiting the beam diameter into certain value, it might cause a limitation on the performance since there are a chance of getting a smaller value by setting the average of diameter as a fitness function instead of a constraint.

Algorithm 2 demonstrates the general outline of DE algorithm for BBDP using different models.

**Algorithm 2.** Outline of DE algorithm employed on several models for BBDP

```
1   Initialize the first population randomly P
2   For i = 1 to M                      //Iteration of the models
3   |   For j = 1 to N                  //Iteration of the variants of DE
4   |   |   Initialize the parameters of DE_n
5   |   |   While the termination condition is false
6   |   |   |   P_fitness = Evaluation(P) based on Model_m
7   |   |   |   Donors = Mutation(P) based on DE_n
8   |   |   |   Trials = Crossover(Donors)
9   |   |   |   Trials_fitness = Evaluation(Trials) based on Model_m
10  |   |   |   Next P = Selection(P_fitness, Trials_fitness)
11  |   |   Output of DE_n of Model_m
```

## 5. Simulation Study

the study simulated a factory environment of size $0.5 \times 0.5\ km^2$, which contained several BSs deployed as a source of the transmitted 16 beams and UEs each associated with their required data rate. The locations of the UEs were uniformly randomly generated, while the locations of BSs were set in an organized pattern. With respect to this factory environment, three scenarios were considered and described in Table 2.

**Table 2**-Enumeration of the cases with setting details

| Case | Target area Size in $km^2$ | No. of UE | No. of BS |
|---|---|---|---|
| C1 | | 200 | |
| C2 | $0.5 \times 0.5$ | 400 | 4 |
| C3 | | 600 | |

Each case in Table 2 was tested using DE algorithms with the two proposed models. The parameters tuning of these DE algorithms were as recommended by the authors of classical DE and jDE, and they are listed in Table 3.

**Table 3-** Parameters tuning of DE algorithms

| DE variant | Parameter | Parameter value |
|---|---|---|
| DE/rand/1/bin | $F$ | 0.5 |
| DE/best/1/bin<br>DE/current-to-best/1/bin | $CR$ | 0.9 |
| | $T_1$ | 0.1 |
| jDE | $T_2$ | 0.1 |
| | $F_l$ | 0.1 |
| | $F_u$ | 0.9 |

**System Specifications:** These experiments were conducted on a PC with system specifications: intel core i5 as processor, CPU at 2.40GHz–2.50GHz, 8 GB of RAM and 64-bit windows as operating system. The simulation was built in Python version 3.9.

The results of the conducted experiments for model 1 and 2 regarding C1, C2, and C3 are demonstrated in Table 4. There are two criteria, in which the comparison is based on: the diameter of the beam Φ, and the shortage $\grave{\Psi}$.

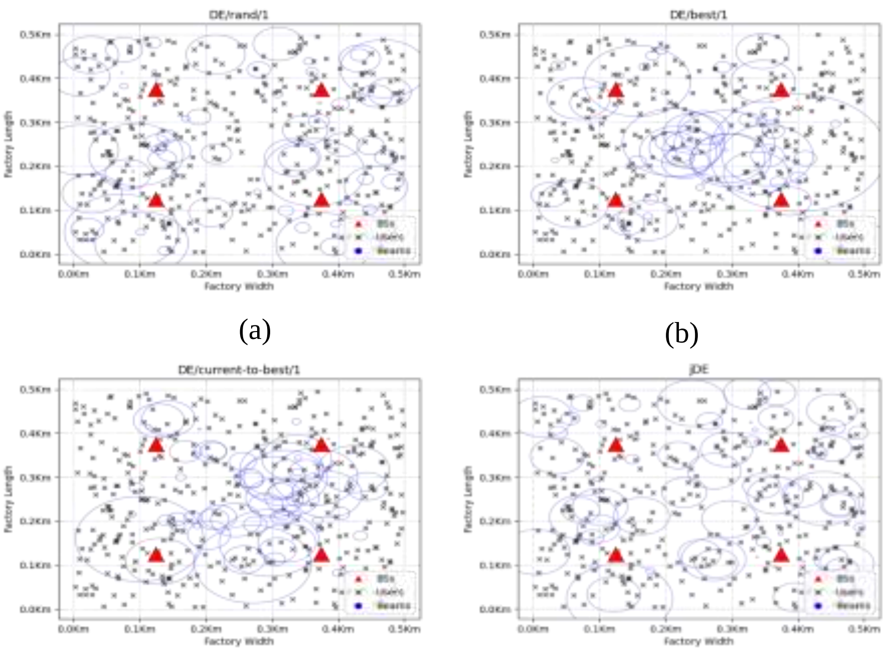
The first experiment sought to minimize the shortage and to keep the diameter of the beams within a range of 0.05 km. This is an attempt to reduce the signal interference while satisfying the coverage (demanded data rate within the predefined limit 85%). As can be seen in Table 4, all DE algorithms could find feasible solutions; however, the self-adaptive DE variant (jDE) outperformed the classical DE.

In the second experiment the aim was to minimize the diameter of the beam and to keep the shortage within 15%. Table 4 shows that the classical DE was not able to find feasible solutions as in this model it appears to be more difficult than the first model for the classical DEs to find a minimum fitness value that satisfies the constraint. This is because the exploration strategy in these algorithms depends highly on the tuned values of the parameters *F*, and *CR*. Unlike self-adaptive DE (jDE), the exploration and exploitation are balanced on-the-fly during the evolution process using its adaptive strategy. It can also be observed that jDE has outperformed the classical DEs in both model 1 and 2 with better performance. This can be justified as jDE uses adaptive parameter control scheme for $F$ and $CR$ based on two constraints: $T_1$ $and$ $T_2$ (as presented in Algorithm 1). Additionally, the survivor individual is a result of the better parameter values, which leads to propagate these better values $F$ and $CR$ to the next generations. Thus, jDE has proven its effectiveness to solve BBDP more than the standard DEs. Finally, Figures 3 and 4 illustrate the results of model 1 for C2 and C3, respectively. Whereas Figures 5 and 6 illustrate the results of model 2 for C2 and C3, in that order.

**Table 4-**The test results of model 1 and model 2. The constraint is Φ (km) and the fitness function is $\grave{\Psi}$ in model 1. The constraint is $\grave{\Psi}$ and the fitness function is Φ (km) in model 2

| | | **Model 2** | | | **Model 1** | | |
|---|---|---|---|---|---|---|---|
| **DE variant** | **Case** | **Constraint $\leq 0.05$** | **Fitness Function** | **Feasibility of the plan** | **Constraint $\leq 0.15$** | **Fitness Function** | **Feasibility of the plan** |
| DE/rand/1 | C1 | 0.048 | 0.571 | Feasible | 0.444 | 0.204 | Infeasible |
| | C2 | 0.049 | 0.579 | Feasible | 0.517 | 0.242 | Infeasible |
| | C3 | 0.048 | 0.6 | Feasible | 0.488 | 0.25 | Infeasible |
| DE/best/1 | C1 | 0.05 | 0.881 | Feasible | 0.39 | 0.291 | Infeasible |
| | C2 | 0.05 | 0.88 | Feasible | 0.429 | 0.309 | Infeasible |
| | C3 | 0.05 | 0.824 | Feasible | 0.351 | 0.239 | Infeasible |
| DE/current-to-best/1 | C1 | 0.049 | 0.847 | Feasible | 0.283 | 0.368 | Infeasible |
| | C2 | 0.05 | 0.919 | Feasible | 0.229 | 0.503 | Infeasible |
| | C3 | 0.049 | 0.806 | Feasible | 0.156 | 0.539 | Feasible |
| jDE | C1 | 0.05 | 0.349 | Feasible | 0.148 | 0.134 | Feasible |
| | C2 | 0.05 | 0.391 | Feasible | 0.149 | 0.157 | Feasible |
| | C3 | 0.05 | 0.417 | Feasible | 0.149 | 0.176 | Feasible |

These figures clearly show the beams, the BSs and the UEs involved in the BBDP problem. They are compatible and support what has already been presented in Table 4 of results. As it can be seen from these figures, the overlap among the beams increases with increasing the number of users specially in model 2 since there is no constraint on the beam diameter. However, jDE in comparison with the standard DEs, shows competitive results, since it managed to reduce the interference among the beams while maintaining the coverage rate up to 85%.




(a) (b)

(c) (d)

**Figure 3-** The illustration of applying DE algorithms on case 2 of model 1: (a) DE/rand/1/bin. (b) DE/best/1/bin. (c) DE/current-to-best/1/bin. (d) jDE.

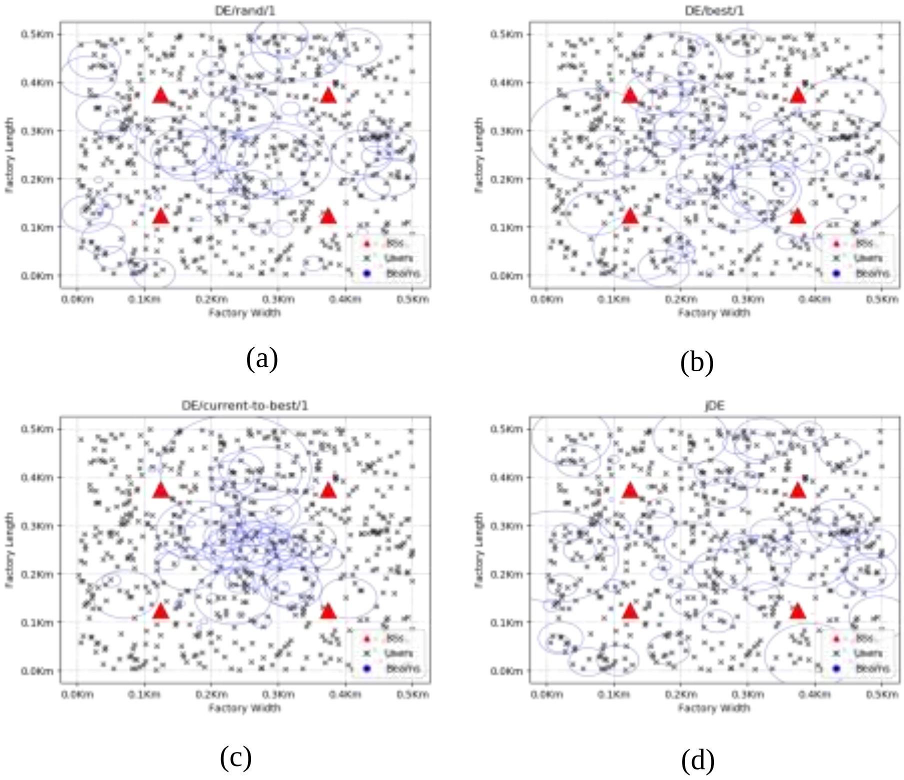



**Figure 4-** The illustration of applying DE algorithms on case 3 of model 1: (a) DE/rand/1/bin. (b) DE/best/1/bin. (c) DE/current-to-best/1/bin. (d) jDE.

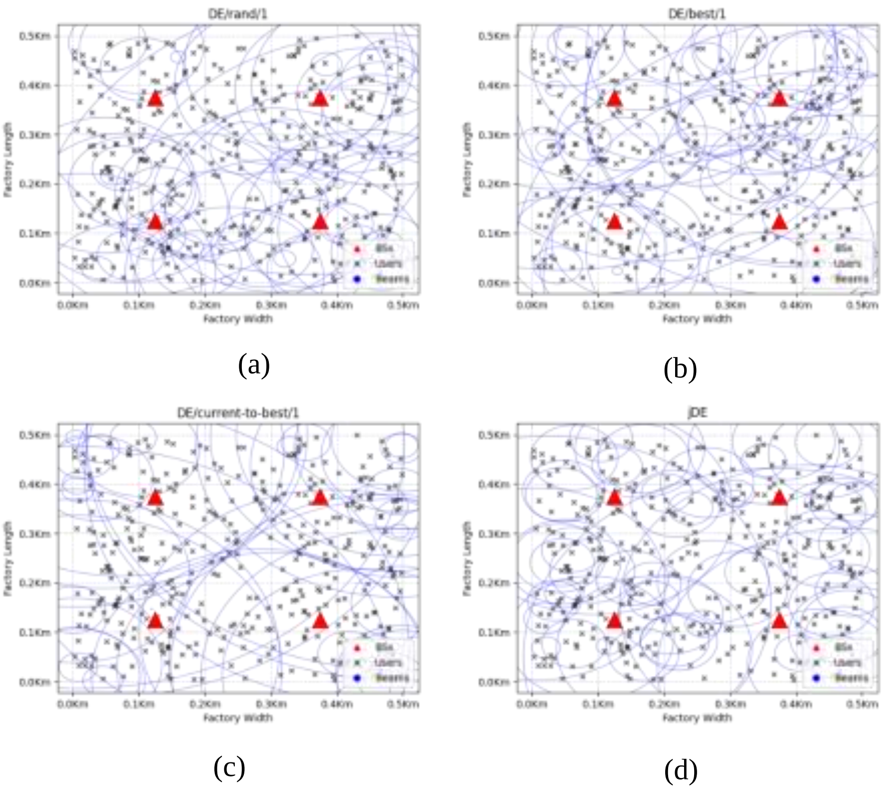



**Figure 5-** The illustration of applying DE algorithms on case 2 of model 2: (a) DE/rand/1/bin. (b) DE/best/1/bin. (c) DE/current-to-best/1/bin. (d) jDE.

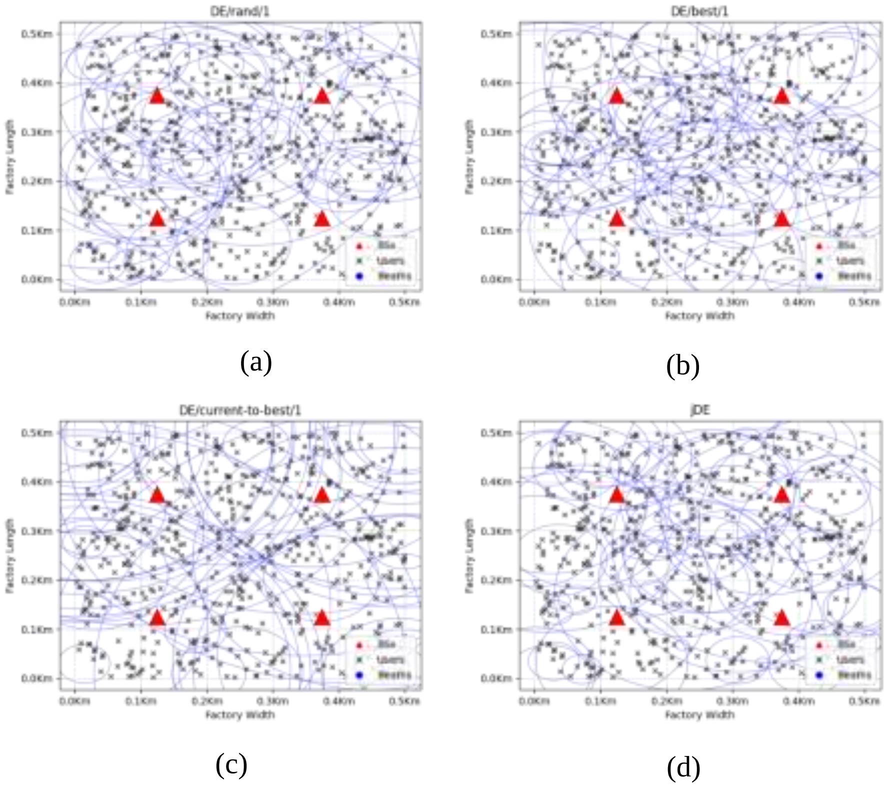



**Figure 6-**The illustration of applying DE algorithms on case 3 of model 2: (a) DE/rand/1/bin. (b) DE/best/1/bin. (c) DE/current-to-best/1/bin. (d) jDE.

## 6. Conclusion

Beamforming and massive MIMO in 5G networks are two critical techniques for providing reliable coverage, while increasing the spectral efficiency and cost-effectiveness as well. In this paper, new optimization problem that defines these new techniques in 5G networks has been formulated and named as BSs Beam Distribution Problem (BBDP). This definition has been stated with two solution models-based beam dimeter and shortage.

Since this problem is realized to be Np-hard problem, four DE algorithm variants have been employed as optimizers for BBDP. These variants are DE/rand/1, DE/best/1, DE/current-to-best/1 and the self-adaptive variant jDE. The latter variant has proven it effectiveness in solving the BBDP using the two models and has managed to find the feasible plans of forming and distributing the beams with 85% coverage and 500 m as beamwidth, which helps to reduce overlapping among the beams. These results show the significance of the adaptive scheme associated with the jDE algorithm and has shown that the behaviour of DE/rand/1 strategy has improved via the dynamic alteration of $F$ and $CR$.

As a future work proposal, DE variants have been rapidly improving; thus, using more powerful DE variants like JADE and SHADE to solve BBDP can be predicted to give better results. Also, BBDP includes many parameters for instance, the number of antenna elements where the beam needs to be formed and the overlapping between the beams is another consideration. Therefore, applying a more coherent model to include multi constraints and multi objectives can be recommended. However, a limitation can also be mentioned which is that the coding of the problem solution must be changed every time new problem parameters are considered and/or changed.

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