



ISSN: 0067-2904

A Comparative Study on Meta-Heuristic Algorithms For Solving the RNP Problem

Abeer Sufyan Khalil, Rawaa Dawoud Al-Dabbagh

Department of Computer Science, College of Science, University of Baghdad, Baghdad, Iraq

Abstract

The continuous increases in the size of current telecommunication infrastructures have led to the many challenges that existing algorithms face in underlying optimization. The unrealistic assumptions and low efficiency of the traditional algorithms make them unable to solve large real-life problems at reasonable times. The use of approximate optimization techniques, such as adaptive metaheuristic algorithms, has become more prevalent in a diverse research area. In this paper, we proposed the use of a self-adaptive differential evolution (jDE) algorithm to solve the radio network planning (RNP) problem in the context of the upcoming generation 5G. The experimental results prove the jDE with best vector mutation surpassed the other metaheuristic variants, such as DE/rand/1 and classical GA, in term of deployment cost, coverage rate and quality of service (QoS).

Keywords: differential evolution, self-adaptive, radio network planning.

دراسة مقارنة على خوارزميات الموجه العام لحل مشكلة تخطيط الشبكات الراديوية

عبير سفيان خليل ، رواء داود الدباغ

قسم علوم الحاسوب، كلية العلوم، جامعة بغداد، بغداد، العراق

الخلاصة

أدى التوسع المستمر في حجم البنية التحتية للاتصالات الحالية إلى أن الخوارزميات الحالية واجهت العديد من التحديات فيما يتعلق بمشكلات التحسين الأساسية. لهذا السبب ، فإن الافتراضات غير الواقعية والكفاءة المنخفضة للخوارزميات التقليدية تجعلها غير قادرة على حل مشاكل الحياة الواقعية التي يكون حجمها كبيراً في وقت معقول. أصبحت تقنيات التحسين التقريبية مثل خوارزميات الموجه العام التكييفية نشطة إلى حد كبير في مجال البحث المتنوع. في هذا البحث ، اقترحنا استخدام خوارزمية التطور التفاضلي الذاتي التكيف (jDE) لحل مشكلة تخطيط الشبكة الراديوية (RNP) في سياق الجيل القادم 5G. تثبت النتائج التجريبية أن jDE مع أفضل طفرة متجهة قد تجاوز المتغيرات الأخرى لطرق الموجه العام مثل DE / rand / 1 و GA الكلاسيكية فيما يتعلق بتكلفة النشر ومعدل التغطية وجودة الخدمة (QoS).

1. Introduction

Over the last decades, cellular networks, network infrastructures, and Internet services have developed quickly. This development has resulted in a higher demand for data communications. Recently, much attention has been placed on telecommunication and technology represented by frequency assignment to cellular phones, optimal allocation of base stations (BSs), antenna design and structural design problems associated with routing information by the network [1]. One such important problem is the cellular network configuration or cells deployment because, at present, wireless

*Email: abeersufyan1978@gmail.com

networks are consuming large power as the number of worldwide subscribers has reached 5 billion; therefore, cellular network operators should consider energy issues. This problem has also been defined as radio network planning (RNP) in which the least number of BSs needs to be planned and satisfy the network requirements. Thus, the modern trend in [2] was to propose a heuristic approach to reduce total power exhaustion in long term evolution (LTE) radio networks of the fourth generation (4G). The proposed heuristic has led to energy savings by turning on and off chosen BSs based on different traffic scenarios. By contrast, the authors in [3] focused on the BS itself because it consumes high power that reaches 58% of the total power used by cellular networks. Therefore, they developed a genetic algorithm (GA) to determine the closest optimal solution for RNP problem not only by considering the location of BS but also by its height. Then, the concern was towards the new generation of cellular networks (5G); thus, the authors of [4] modified the approach in [2] and applied it to 5G networks. They used the millimeter wave (mmW) carrier frequencies with heterogeneous networks to achieve users' requirements, especially in dense areas involved in the area of interest. The authors in [5] presented a novel view to the RNP problem and defined it as a hyperdense deployment problem (HDDP) of wireless communication for the requirements of 5G. Their perspective suggested and illustrated how multi-objective GA can be adopted to solve the HDDP efficiently. The self-adaptive differential evolution (jDE) and Barebones DE (BDE) have been integrated into the Barebones Self-adaptive Differential Evolution (BSADE), which has been used to maximize the coverage and minimize the power consumption in 4G networks [6]. The work in [7] formulated the capacity and coverage problem in the context of 4G as a multi-objective optimization problem and used MOGA to solve it. The main focus was on optimizing the transmitted sector and antenna pattern with respect to its pointing direction. Finally, the mechanisms of artificial intelligence (AI) have been increasingly investigated to solve different cellular networks problems in the context of 5G, especially in planning and operation processes; as such, [8] has been written to determine how these AI techniques revisited those problems to find proper understanding and solutions.

The main contribution of this paper is answering the problem of RNP in the context of 5G using self-adaptive differential evolution algorithms (i.e. jDE/rand/1 and jDE/best/1) to find a near-optimal deployment plan for different network scenarios. In the literature, this problem has already been formulated as a constraint optimization problem in [9]; in which, the objective function is to minimize the deployment cost of a number of candidate BSs while maintaining the converge rate within a pre-specified threshold as the only constraint in the system [10].

This paper is organized as follows: Section 2 introduces the preliminary concepts and problem formulation of the adopted 5G system model. In Section 3, four different meta-heuristic algorithms have been presented and described upon their implementation to solve the RNP problem. The results and discussions are presented in section 5. Finally, conclusions and future suggestions are given in section 6.

2. 5G System Model and Problem Formulation

At present, advanced LTE and incoming 5G technologies are considered the heart of the upcoming advanced telecommunications. The speed of data transmission and reliability will be increased, whereas transmission delay will be decreased to its minimum. All these advantages and more can be realized with respect to the utilization of the mmWave carrier frequency and the deployment of small cells (in this study, **macro** and **micro** cells have been considered) [11]. Radio network planning (RNP) is an essential step in deploying wireless networks in which the plan should meet the deployment cost, quality of service, specific coverage and capacity [2]. Several 5G models are available in the literature because the final system configuration has yet to be settled. In this study, the 5G model in [4] was adopted because it involves a detailed description to constitute a reliable and complete 5G model. The main part of this model is the value of the received power of each mobile station k (MS). This value determines whether this MS is under coverage with respect to the signal power standards (i.e. $P_k \geq P_{thr}$). The power of the received signal can be formulated as

$$P_{k,j}(dB) = 10 \log_{10} \left(\frac{P_{BS}}{K_{BS}} \right) - PL_{k,j} \quad (1)$$

where P_{BS} is the transmitting power of BS j depending on its type, K_{BS} is the maximum number of users that can be connected to BS j and $PL_{k,j}$ is the resulting pathloss between MS k and BS j . Equation 1, indicates that this value is affected considerably by the value of the pathloss PL because

the larger the value of pathloss, the lesser the received power that can be gained from BS j . In this study, the adopted pathloss model is formulated as

$$PL_{k,j}(dB) = 92.4 + 20 \log_{10}(d_{k,j}) + 20 \log_{10}(f) + \alpha(d_{k,j}) + h_{k,j} \quad (2)$$

where f is the carrier frequency which is set to 28 GHz, α is the atmospheric attenuation which is almost ignored in 5G, $h_{k,j}$ is a random number generated in the range $[0, 1]$ to represent the channel loss and $d_{k,j}$ is the Euclidean distance between the Cartesian coordinate of MS k (x_i, y_i) and BS j (x_j, y_j) as follows,

$$d_{k,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (3)$$

The quality of service (QoS) of each MS k is measured by the value of signal to interference and noise ratio (SINR) as

$$SINR_k = \frac{P_{k,BS(k)}}{\sigma^2 + In_k} \quad (4)$$

Where $P_{k,BS(k)}$ is the power of the received signal by MS k from BS(k), σ^2 is the power of the thermal noise and In_k is the amount of intercell interference affected MS k by its neighboring BSs (NeB) and can be formulated as follows,

$$In_k = \sum_{j=1, j \neq BS(k)}^{NeB} P_{k,j} \quad (5)$$

In order to satisfy good QoS for each MS k , the below inequality must hold,

$$SINR_k \geq SINR_{thr} \quad (6)$$

Finally, the main objective of this system model is to minimize the deployment cost of initially deployed BSs and the formula proposed in [9] has been adopted as follows:

$$\min \sum_{i=1}^{NoB} c_i \cdot cost_i \quad (7)$$

where NoB is the total number of initially deployed BSs, c_i is a flag to indicate whether BS i is deployed and $cost_i$ is the deployment cost of BS i depending on its type.

3. Metaheuristic algorithms based 5G RNP Problem

Metaheuristics are advanced search mechanisms such as evolutionary algorithms (EAs). They are based on the rules of natural evolution, namely adaptation and survival of the fittest and consist of a set of individuals (solutions) called population P . The quality value of each individual is assigned to a function, namely, fitness function. In the beginning, the population is created randomly by the meta-algorithm. Then, at each step, new individuals are created by means of selection and variation operators (mutation, recombination). These steps are repeated until a maximum number of generations $MAXG$ or any other stopping criterion is fulfilled [12]. In this study, four well-known meta-algorithm variants, including two self-adaptive differential evolution algorithms are adopted: DE/rand/1, jDE/rand/1, jDE/best/1 and classical GA [13, 14]. In the following subsections, a complete description of the implementation of these four algorithms to the 5G RNP problem is presented in which some of these details have already been discussed in [9].

3.1 Individual representation and population initialization

This step is a common one in all meta-algorithms because it is how the individual is represented to better fit the problem and the way the initial population is first created accordingly. For the RNP problem, each individual (or target vector) I is represented as a vector of D genes, and each gene consists of the location as a Cartesian coordinate (x_{BS}, y_{BS}) of a candidate BS as, $I = \{(x_1, y_1), (x_2, y_2), \dots, (x_D, y_D)\}$. As such, the new population P consists of PN solutions as

$$P = \{I^1, I^2, \dots, I^{PN}\}$$

The values of these individuals are initialized using a uniformly distributed random number generator in the interval $[I^L, I^U]$ as follows:

$$I_{0,j}^i = rand[0,1] \cdot (I_j^U - I_j^L) + I_j^L \tag{8}$$

Equation 8 is used to generate an individual of length $D \times 2$ because each gene occupies two values with respect to the x- and y-coordinates of each BS.

3.2 Mutation Operator

This step differs for different meta-algorithms, but they share the same concept in that this step is responsible for maintaining the genetic diversity of the individuals from one generation to another.

In DE, the mutation operator is the first step to be implemented in the meta-algorithm; every target vector is passed through this stage to produce the donor vector. In the literature, DE has many mutation variants based on the vector to be perturbed and the number of difference vectors considered for perturbation [15], for example:

DE/best/1

$$V_{G+1} = I_{best,G} + F \cdot (I_{r1,G} - I_{r2,G}) \tag{9}$$

DE/rand/1

$$V_{G+1} = I_{r1,G} + F \cdot (I_{r2,G} - I_{r3,G}) \tag{10}$$

DE/current-to-best/1

$$V_{G+1} = I_{i,G} + F \cdot (I_{best,G} - I_{i,G}) + F \cdot (I_{r1,G} - I_{r2,G}) \tag{11}$$

where $i, r1, r2, r3 \in NP$ and they are distinct and $X_{best,G}$ is the current best vector. The strategy DE/rand/1/bin appears to be the most successful and the most widely used strategy. It requires four distinct members from NP to produce a new vector; thus, NP must be four at the minimum.

The control parameter $F \in [0,1]$ is used to control the amplification of any difference vectors in DE strategies. In practical terms, finding the right value of F takes an unacceptably long time and may differ because the problems may differ. jDE algorithm has been suggested to apply a self-adaptive rule to update the value of F of each individual dynamically during evolution (Eq. 12). This rule is simple and flexible, and can be applied to any DE strategy.

$$F_{i,G+1} = \begin{cases} F_l + rand_1 \cdot F_u, & \text{if } rand_2 < T_1 \\ F_{i,G} & \text{otherwise} \end{cases} \tag{12}$$

where $rand_j, j \in \{1,2\}$ are uniform random values $\in [0,1]$. $T_1 = 0.1$ is the probability of updating the F factor, $F_l = 0.1, F_u = 0.9$. The new F takes a random value from $[0.1, 1.0]$.

In GA, the mutation operator plays an essential role in the genetic search that assists in exploring the entire search space and preventing the population from stagnating at any local optima. The mutation operator performs a random modification to one or more gene values and somewhat modifies the genetic information of the offspring. Unlike DE, this operator follows the selection and crossover operators in GA. Many types of mutations are available in GA, but based on the RNP problem, the best method would be to modify the gene value using Eq. 8 with respect to a predefined mutation probability p_m .

$$I'_j = \begin{cases} rand[0,1] \cdot (I_j^U - I_j^L) + I_j^L & \text{if } rand_i[0,1] \leq p_m \\ I_j & \text{otherwise} \end{cases} \tag{13}$$

In this work, the mutation operators mentioned in Eqs. 9-10 and Eq. 13 are applied to an individual of length $D \times 2$.

3.3 Crossover Operator

In all meta-algorithms, the aim of the recombination or crossover operator is to create a mixture(s) of the genetic information of two or more individuals. This operator is used to explore the search space in which one or two offsprings are produced from two or more parents. In DE, this operator follows the mutation operator in which the target vector I with the donor vector V are recombined with respect to the following rule, the so-called binomial crossover (or bin), for producing the trial vector U .

$$U_{j,G+1}^i = \begin{cases} V_{j,G}^i & \text{if } rand(j) \leq CR \text{ or } j = Ir(i) \\ I_{j,G}^i & \text{if } rand(j) > CR \text{ or } j \neq Ir(i) \end{cases} \quad (14)$$

where $CR \in [0.8, 1]$ is the crossover rate and a randomly generated $Ir(i) \in \{1, 2, \dots, D\}$. This condition ensures that at least one element from the donor vector is passed to the next generation. The control parameter CR is used to determine the probability of the number of genes inherited from the donor vector and $(1 - CR)$ probability from the target vector. In the jDE algorithm, the value of CR is also updated dynamically during evolution using the same self-adaptive rule in Eq. 12 as follows:

$$CR_{i,G+1} = \begin{cases} rand_3, & \text{if } rand_4 < T_2 \\ CR_{i,G} & \text{otherwise} \end{cases} \quad (15)$$

where $rand_j, j \in \{3, 4\}$ are uniform random values $\in [0, 1]$ and $T_2 = 0.1$ is the probability of updating the CR factor. The new value of CR is given within the range $[0, 1]$ during evolution. In GA, a crossover follows the selection strategy and its main idea is to generate an offspring ch that combines the characteristics of the selected two or more I^1 and I^2 parents with respect to a predefined crossover probability $P_c \in [0, 1]$. In literature, the most powerful crossover operator is the uniform crossover because it permits the offspring to search all opportunities of recombination of unlike genes in parents as follows:

$$ch_j = \begin{cases} I_j^1 & \text{if } rand \leq 0.5 \\ I_j^2 & \text{otherwise} \end{cases} \quad (16)$$

where $rand$ is a uniform random number generator within the range $[0, 1]$.

In the RNP system, the crossover operators in Eqs. 14 and 16 are applied in the same way except for the value of index j , in which, it will be increased by 2 (i.e. $j = 1, 3, \dots, D$) as the values of x -coordinate and y -coordinate for one BS are considered one single problem parameter (gene).

3.4 Selection Operator

In metaheuristics, this operation is responsible for selecting the best individuals to survive to the next generation. Given that RNP is a minimization problem, the resultant vector of this operation is the vector with the lowest fitness function in which it indicates the plan with the minimum deployment cost f described in Eq. 7. However, minimizing the cost is normally associated with maximizing the coverage rate (Eq. 17) as its main constraint to obtain a near-optimal deployment plan [9]. DE with constraint handling selection named as *feasibility rules* has been adopted to satisfy both objectives. In this selection strategy, the deployment cost is considered to be the objective of the RNP system, whereas the coverage rate is treated as a constraint to guide the search towards feasible solutions, as follows:

$$I_{G+1}^i = \begin{cases} U_G^i & \left(out_{U_G^i} \leq \beta \text{ and } out_{I_G^i} \leq \beta \right) \text{ and } (f(U_G^i) \leq f(I_G^i)) \text{ or } (out_{U_G^i} \leq out_{I_G^i}) \\ I_G^i & \text{otherwise} \end{cases} \quad (17)$$

where

$$out = \frac{\text{no.of unconnected users } (P_k < P_{thr})}{U} \quad (18)$$

In Eq. 17, β refers to the outage rate threshold to indicate whether the deployment plan is feasible. In Eq. 18, U refers to the total number of users distributed in an area of interest. Notably, that minimizing the number of deployed BSs of RNP needs to satisfy the following coverage constraints:

1. A user k can receive power signal from BS_j if and only if the $c_j = 1$ of BS_j which means BS_j is deployed (see Eq. 7).
2. Only one BS can serve a user k as maximum.
3. BS_j can serve a specific number of users depending on the available subcarriers and its type (i.e. macro or micro).

In GA, the selection operator is usually the first strategy to be implemented in the entire evolution process. In this strategy, individuals are selected from the population for reproduction to the next generation based on their fitness value. Many exciting types of selection methods can be found in GAs, including rank-based fitness assignment, roulette wheel selection, and tournament selection. Tournament selection, the one adopted in this study, is the most frequently used as a selection scheme. The basic idea is as follows. A random selection is made to a set of randomly selected individuals from the current population. The best individual among these individuals is then selected to survive for breeding using the aforementioned crossover operator (Eq. 16). In the RNP system based GA, the selection criteria of feasibility rules in Eq. 17 is used to decide which solution is superior to its alternatives in the tournament set.

4. Experimental Results and Discussion

In this section, four different metaheuristic algorithms (DE/rand/1, jDE/rand/1, jDE/best/1 and GA) have been implemented to tackle the RNP problem in the context of the 5G network. Tables-(1, 2) provide the settings related to the problem in hand and the meta-algorithms adopted. Three different user scenarios (850, 1000 and 1200 MS) have been used. These scenarios are distributed uniformly randomly in an area of interest $5 \text{ km} \times 5 \text{ km}$. Two outage rate values (0.15 and 0.13) were considered to assess the efficacy of the meta-algorithms in terms of imposing confront constraints to the search process. For all experiments conducted, five macrocells have been deployed randomly in the area of interest assuming that those fixed BSs belong to the former generation, i.e. 4G/IMT.

The performances of these four meta-algorithms were compared with respect to multiple metrics. The most important metric is the deployment cost of the best plan achieved by the algorithms after five independent runs. However, this best plan would not be considered if its associated outage rate does not fall within the pre-specified outage threshold β ; otherwise, this plan is considered unfeasible. The two other metrics are the average received power and the average SINR for all users. Tables-(3, 4) present the results obtained from the four meta-algorithms in which the best deployment plans are shown in bold and the second best plans are shown in italics font.

Table 1-5G RNP system parameters

Parameter description	Value	Parameter description	Value
No. of Macrocell	50	No. of Microcell	150
$P_{BSmacro}$	40 W	$P_{BSmicro}$	10 W
$K_{BSmacro}$	22 MS	$K_{BSmicro}$	8 MS
$K_{thrmacro}$	8 MS	$K_{thrmicro}$	3 MS
$SINR_{thr}$	-9 dB	σ^2	$5.97 \times 10^{-15} \text{ W}$
P_{thr}	-80 dBm	β	0.15 and 0.13
Deployment cost of Macrocell	\$150	Deployment cost of Microcell	\$50
No. of fixed Macrocell	5	D or NB	200 (150 macro+ 50 micro)
f (frequency of newly deployed Macro)	28	f (frequency of fixed Macro)	3.5

Table 2- Metaheuristics parameters

Parameter description	Value
NP	100
F	0.5
CR	0.9
MAX_G	1500
P_m	0.1
P_c	0.9

Table-3 shows the results obtained for the four algorithms when the outage rate was set to a high value (i.e. 0.15). This table shows all meta-algorithms have successfully achieved the feasibility of the plans, but jDE/best/1 was managed to compete with the other three algorithms with lower cost and minimum outage. In this algorithm, the values of F and CR were encapsulated with each individual and updated dynamically during evolution. The effects of these two self-adaptive parameters together with the greediness tendency of jDE/best/1 successfully created the desired balance point between exploration and exploitation to find a near-optimal plan. Table-4 also shows jDE/best/1 competed with the other three algorithms with respect to the deployment cost and outage rate even when the outage threshold has been set to a low value (i.e. 0.13), in which finding feasible solutions became more challenging. This behavior of jDE/best/1 can be explained by the RNP problem with constraints requiring a focus on good solutions, thereby indicating that the algorithm with the exploitation capability can perform better than the algorithms with high exploration capability, such as jDE/rand/1. The balance that jDE/best/1 has created can be attributed to the adaptive rule that causes the algorithm to perform effectively and satisfy the two contradictory search objectives. The second algorithm performance is of jDE/rand/1 and GA. These algorithms have almost the same randomness tendency, although jDE/rand/1 has self-adaptive merits that update the values of F and CR during evolution.

Experiments show the values of the average received power and SINR rate have always been within the required threshold. Thus, and to the make the comparison fair, we included these two values in the tables but not as a constraint in the main objective.

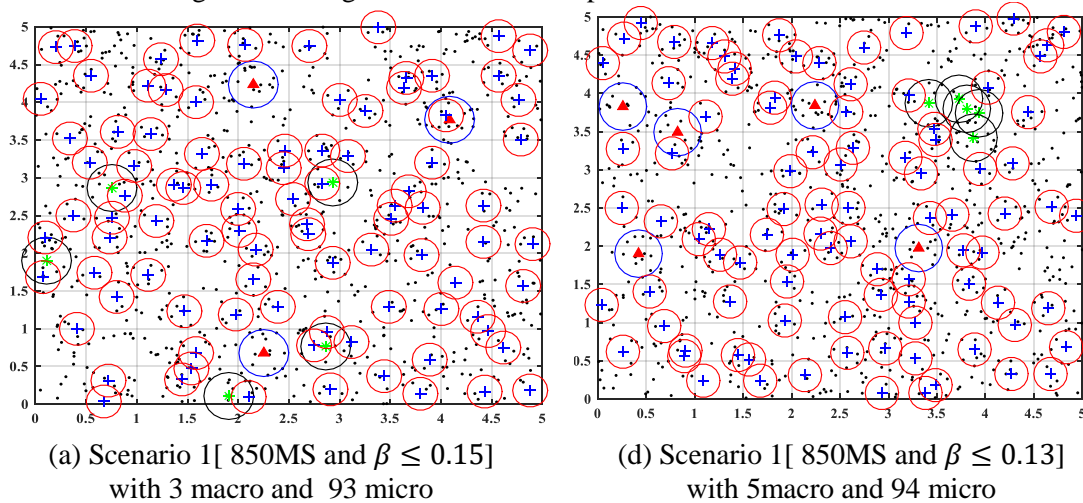
Table 3-Performance comparison of the four metaheuristics after 5-independent runs in terms of the deployment cost and outage rate ≤ 0.15 in which feasibility of the plan is to be attained

Meta-algorithm	No. of MSs	Avg. received power (dbm)	Avg. SINR	Outage rate ≤ 0.15	Deployment Cost	No. of Macro	No. of Micro
DE/rand/1	850	-73.4111	0.2180	0.147	5300	6	88
	1000	-74.0638	0.1941	0.145	6250	10	95
	1200	-72.5709	0.2333	0.145	7300	11	113
jDE/rand/1	850	-72.9735	0.2243	0.1494	5150	3	93
	1000	-72.5582	0.2294	0.143	6050	6	103
	1200	-73.2761	0.3716	0.1441	7300	11	113
jDE/Best/1	850	-73.0448	0.2728	0.1447	5150	3	93
	1000	-72.4030	0.2394	0.136	5950	6	101
	1200	-72.3229	0.2284	0.1483	7150	10	113
GA	850	-72.4923	0.2647	0.147	5250	5	90
	1000	-72.6004	0.2303	0.143	5950	5	104
	1200	-72.7951	0.2580	0.1491	7150	12	107

Table 4-Performance comparison of the four metaheuristics after 5-independent runs in terms of the deployment cost and outage rate ≤ 0.13 in which feasibility of the plan is to be attained

Meta-algorithm	No. of MSs	Avg. received power (dbm)	Avg. SINR	Outage rate ≤ 0.13	Deployment Cost	No. of Macro	No. of Micro
DE/rand/1	850	-73.3266	0.3258	0.1235	5700	7	93
	1000	-72.8762	0.2590	0.13	6550	8	107
	1200	-73.1492	0.2666	0.1275	7650	12	117
jDE/rand/1	850	-72.6376	0.2263	0.1270	5450	5	94
	1000	-72.5029	0.2215	0.124	6350	8	103
	1200	-72.8042	0.2093	0.13	7450	13	110
jDE/Best/1	850	-72.4638	0.2726	0.1258	5450	5	94
	1000	-72.7572	0.2107	0.129	6300	11	93
	1200	-72.5148	0.2665	0.1266	7300	11	113
GA	850	-72.2324	0.2875	0.1282	5450	6	91
	1000	-72.9425	0.2642	0.123	6350	8	103
	1200	-72.9009	0.2229	0.13	7550	12	115

Figure-1 depicts the results of the six deployment plans achieved by jDE/best/1 algorithm by visualizing the Cartesian coordinates of the deployed macro and micro cells of three users scenarios (850, 1000 and 1200) distributed uniformly randomly in an area of interest, and two outage rates (0.15 and 0.13). This figure clearly shows that some of the deployment plans have deficiencies in providing coverage for some regions such as the plans depicted in Figures-1 (b) and (c). In these plans, many users are still in outage even though these are the best plans obtained to date on these scenarios.



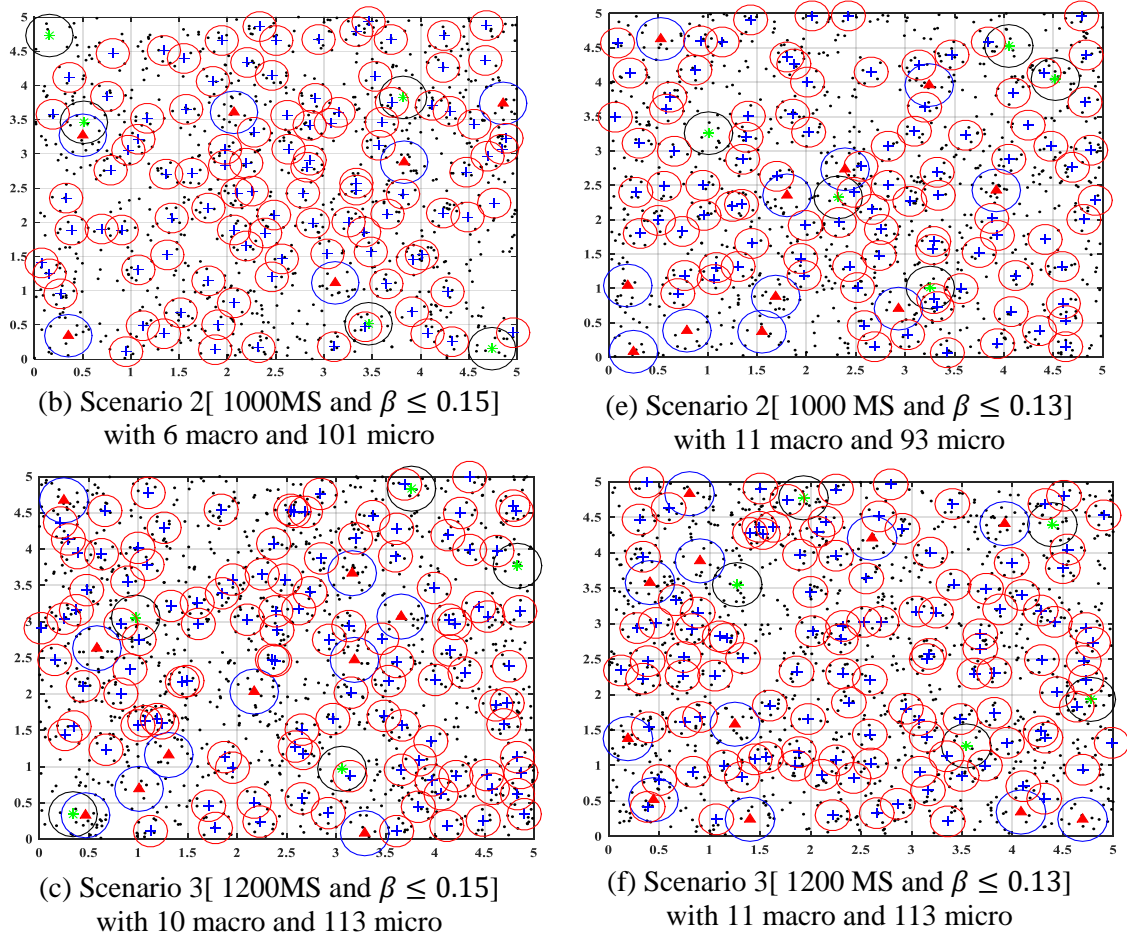


Figure 1-The best deployment plans achieved by jDE/best/1 algorithm in which the outage rate is set to 0.15 and 0.13 of three users scenarios (850, 1000 and 1200). The (.) represents a user, a circle with (▲) represents a newly deployed macro cell, a circle with (+) represents a newly deployed micro cell and a circle with (*) represents a fixed location macro cell.

5. Conclusion

The problem of radio network planning has been investigated in this paper by utilizing four metaheuristic variants that attempt to find a near-optimal deployment plan. From the results presented, we can infer that the four meta-algorithms (DE/rand/1, jDE/rand/1, jDE/best/1 and GA) have successfully achieved feasible plans with respect to two outage rates (0.15 and 0.13) as problem constraints. The main comparison criterion is the deployment cost of these plans in which the algorithm jDE/best/1 could manage to obtain the best plan among the other algorithms in all problem scenarios (850, 1000 and 1200 MSs). We can conclude that the self-adaptive rule of updating F and CR has helped to guide the greedy algorithm towards promising search regions by acting as a local search for the DE/best/1 strategy. Moreover, to affirm the good performance of these self-adaptive algorithms, the 5G model adopted can be extended to include rain attenuation and foliage noise as a future work suggestion.

References

1. Alba, E. and Chicano, F. **2006**. "Evolutionary Algorithms in Telecommunications," presented at the 13th IEEE Mediterranean Electrotechnical Conference (MELECON 2006), Malaga, Spain.
2. El-Beaino, W., El-Hajj, A.M. and Dawy, Z. **2012**. "A Proactive Approach for LTE Radio Network Planning With Green Considerations," presented at the 19th International Conference on Telecommunications (ICT), Jounieh, Lebanon.

3. Al-Samawi, A., Sali, A., Noordin, N.K., Othman, M. and Hashim, F. **2013**. "Base Station Location Optimisation in LTE using Genetic Algorithm," presented at the International Conference on Information and Communication Technology Convergence (ICTC '13), Jeju, Republic of Korea.
4. El-Beaino, W., El-Hajj, A.M. and Dawy, Z. **2015**. "On Radio network planning for next generation 5G networks: A case study," presented at the 2015 International Conference on Communications, Signal Processing, and their Applications (ICCSPA).
5. Tsai, C.W., Cho, H.H., Shih, T.K., Pan, J.S. and Rodrigues, J.J.P.C. **2015**. "Metaheuristics for the deployment of 5G," *IEEE Wireless Communications*, **22**: 40 - 46, 31.
6. Goudos, S.K., Deruyck, M., Plets, D., Martens, L. and Joseph, W. **2017**. "Optimization of Power Consumption in 4G LTE Networks Using a Novel Barebones Self-adaptive Differential Evolution Algorithm," *Telecommunication Systems*, **66**: 109–120, 2017.
7. Tsoulos, G.V., Athanasiadou, G.E., Valavanis, I.K. and Zarbouti, D.A. **2017**. "Green 4g radio network planning," presented at the 2017 11th European Conference on Antennas and Propagation (EUCAP), Paris, France.
8. Pérez-Romero, J., Sallent, O., Ferrús, R. and Agustí, R. **2015**. "Artificial Intelligence-based 5G network capacity planning and operation," presented at the 2015 International Symposium on Wireless Communication Systems (ISWCS), Brussels, Belgium.
9. Al-Dabbagh, R.D. and Jabur, A. J. **2017**. "Constrained Differential Evolution for Cost and Energy Efficiency Optimization in 5G Wireless Networks," presented at the Simulated Evolution and Learning. SEAL 2017. Lecture Notes in Computer Science, Shenzhen, China.
10. Luna, F., Durillo, J.J., Nebro, A. J. and Alba, E. **2010**. "Evolutionary algorithms for solving the automatic cell planning problem: a survey," *Engineering Optimization*, **42**: 671-690 08.
11. Akyildiz, I.F., Nie, S., Lin, S.C. and Chandrasekaran, M. **2016**. "5G roadmap: 10 key enabling technologies," *Computer Networks*, **106**: 17-48, 14.
12. Boussaïd, I., Lepagnot, J. and Siarry, P. **2013**. "A survey on optimization metaheuristics," *Information Sciences*, **237**: 82-117, 10.
13. Holland, J.H. **1992**. "Genetic Algorithms," *Scientific American*, **267**: 66-72.
14. Brest, J., Greiner, S., Boskovic, B., Mernik, M. and Zumer, V. **2006**. "Self-adapting control parameters in differential evolution: A comparative study on numerical benchmark problems," *Ieee Transactions on Evolutionary Computation*, **10**: 646-657.
15. Storn, R. and Price, K. **1997**. "Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces," *Journal of global optimization*, **11**: 341-359.