LTE Coverage Planning Based on Improved Grey Wolf Optimization

Original Scientific Paper

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Abstract *– Automatic planning and dimension optimization of LTE is one of the crucial tasks in the mobile networking community. It is well known that this process is an NP-hard issue that requires huge computing resources. We also noticed that the actual proposed solutions are still inefficient in terms of scalability (handling a large number of eNodeBs) and runtime effectiveness. Moreover, SINR handling and variability of propagation loss models with respect to areas' types further complicate the coverage planning task. In this paper, we propose a swarm intelligence-based method for effectively placing and configuring the eNodeBs of an LTE network. In particular, we propose two variants of grey wolf optimizer (GWO), namely a discrete version of GWO (DGWO) and an improved version of GWO (IGWO) for LTE coverage planning. The improved version consists of an additional local search rule that allows for exploring regions closer to the promising solutions. The approaches are simulated on an urban area with many types of clutter. The IGWO technique had a coverage of 99.0% of 10 dB SINR rate and 95.1% of 12 dB SINR rate. The obtained results show that IGWO is more effective than the discrete one and other existing metaheuristics in terms of cost and coverage rates. More specifically, it ensures a coverage improvement (with respect to 10 dB SINR rate) of 10.6%, 10.5%, and 2.6 % in comparison to DGWO, Tabu search (TS), and discrete particle swarm optimization (DPSO) respectively.*

Keywords*:* *cellular planning, coverage planning, grey wolf optimizer, metaheuristics, LTE*

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1. INTRODUCTION

Cellular radio networks recognize a high evolution speed, which is mainly driven by the user's needs, such as reliable coverage, traffic capacity, and other QoS metrics. To meet these requirements, Long Term Evolution (LTE) networks provide a set of ingredients to ensure reliable communications, user' s throughput satisfaction, low latency (for some specific applications), and better scheduling schemes of radio resources [1, 2]. Regarding the increase in the communication data rate, LTE networks must face the delay spread caused by multipath propagation of the transmitted signal (which increases the duration of the symbol by up to 1-5 micro seconds, causing the interference with the subsequent symbol). Consequently, this delay spread gets translated into frequency-selective fading, which deteriorates the SINR (Signal-to-Interference-plus-Noise Ratio) and hampers the data rate improvement. To palliate this issue, the LTE standard uses multiple subcarriers of lesser bandwidth (typically 15 KHz) which are orthogonal and more resilient to frequency-selective fading channels (this division technique is called orthogonal frequency division multiplexing or OFDM). As a result, the intercarrier interference is significantly reduced, and the total spectrum is efficiently managed. Furthermore, the LTE standard adopts a flexible set of frequency bands with different bandwidths (from 1.4 MHz to 20 MHz) that serve the needs of regions with varying user densities and varying data rate requirements. We mention that the extension of OFDM for serving different users at the same time, also known as orthogonal frequency division multiple access, is used in the downlink stream of LTE; however, the single carrier frequency division multiple access (SC-FDMA) is used in the uplink stream because of the low processing capabilities of the user equipment (UE). It is worth highlighting that the issue of high peak-to-average-power ratio can be palliated with SC-FDMA, and therefore complex operations are not needed in UE. For the same purpose of enhancing the data rates and channel reliability, the use of multiple-input-multiple-output systems (MIMO) allows for reinforcing the diversity (and therefore the enhancement of the overall SINR that is targeted in the coverage planning) and spatial multiplexing (and accordingly an improvement in capacity). Furthermore, the availability of sophisticated computing power in eNodeBs (and sometimes UE) enables the execution of crucial operations such as inverse fast Fourier transforms (IFFT) and matrix processing (such as precoding and beamforming in MIMO settings). In sum, these enabling capabilities (MIMO, OFDMA) allow the fulfillment of a high spectral efficiency of the network, which may reach 15 bits/Hz for the 20 MHz bandwidth.

Planning an LTE network is a complicated task that may involve several potentially conflicting objectives concerning coverage, capacity, cost, power, and eventually other metrics [3, 4]. Further, the lack of an accurate propagation model that completely involves all the geographical details of the studied area (e.g., terrain, vegetation, building height, etc.) will hamper the attainment of a satisfying coverage result. Moreover, the temporal variability of the abovementioned geographical factors further exacerbates the quantification of the shadowing and interference (and this situation will negatively impact the coverage planning issue). It is estimated that cellular radio network operators need to extend the capacity for dozens of billion connections in the future [5]. Moreover, the theoretical complexity of network planning is known to be NP-hard [6, 7], and consequently, manual simulations or ad-hoc planning methods are not adequate for large-scale problems.

According to [8], network planning is the process of estimating, placing, and configuring a set of base stations (BSs[1], or eNodeBs in the LTE context) to ensure the coverage and capacity of a given area. There are three steps in network planning: pre-planning, also called dimensioning; detailed planning; and post-planning or optimization [8, 9]. The dimensioning phase consists of roughly estimating the number of BSs needed to cover an area of interest. This result is considered as an input of the detailed-planning phase. The detailed planning consists of deciding the physical locations of BSs in the target area of interest. Finally, the optimization step is a post-deployment task that consists of rectifying the network performance after having analyzed the ground measurements.

Coverage planning is a crucial phase in the deployment of a cellular network. It involves choosing an adequate propagation model based on the area's terrain, clutter, and population characteristics [10]; in addition, coverage planning is aimed at satisfying the constraint of having a received signal power greater than a predefined threshold in every location of the target area. Sometimes, this coverage constraint is aimed at having a SINR level greater than a predefined threshold at every point of the studied area. As stated before, coverage planning is an NP-complete problem [7, 11], and accordingly, there is no efficient (polynomial) algorithm that can solve it with a perfect optimality rate.

In general, the existing works on cellular planning mainly focus on a reduced set of conflicting objectives (such as cost, coverage, capacity, power consumption, and handover zone management), but there have been few initiatives to tackle the fully automatic placement and configuration of BS [9, 12]. Moreover, there is a lack of approaches that leverage artificial intelligence (AI) and swarm intelligence (SI) in optimizing this task. In fact, numerous works adopt simplistic heuristics or semi-automatic methods for estimating or placing BS [13, 14]. However, totally automatic AI-based methods are still sparsely available in the field of LTE planning. Moreover, the comprehensive analysis of the impact of SI's hyperparameters on the planning quality (e.g. SINR levels) are still insignificant the literature. To handle this gap, we propose in this paper an improved version of a Grey Wolf Optimizer (GWO) [15], termed IGWO, that addresses the automatic placement and configuration of eNodeBs so as to best meet the coverage and cost requirements of an LTE network. It is worth noting that swarm-intelligence-based methods (and specifically GWO variants) can be used to handle larger sizes of search space problems, reduce the time taken to achieve near-optimal planning configurations, and ensure high agility to the changes observed in the coverage or capacity of the studied network. Moreover, the use of a variant based on GWO can spark a significant improvement in the quality of the retained solutions. In fact, the use of a majority voting rule and a set of guiding agents in the search (instead of a single agent, as is the case for other swarm intelligence-based methods), may improve the quality of the retained optimum under some assumptions [16]. Furthermore, adjustment of the perturbation distance can help orient the search for more promising regions and avoid less attracting parts of the cost function landscape. Inspired from the voting theory, we advocate that the more the diversity of guiding agents is high, the better the quality of the retained solutions.

The key contributions of this paper can be summarized as follows:

[1] https://www.forsk. com/atoll-overview

- The optimal eNodeB placement/configuration of an LTE network is implemented using a discretized GWO (DGWO) algorithm that optimizes the deployment cost and coverage; furthermore, the adjustment of the SINR thresholds will directly enhance the network capacity.
- An improved version of the previous GWO, termed IGWO, is designed and applied in the studied area, with the addition of a new operator based on a local search. This latter one replaces the perturbed distance move used in the standard GWO and aims to bring an added value to the search. A detailed comparison among DGWO, IGWO, and other metaheuristics (e.g., TS, PSO) is demonstrated in the evaluation section.
- The impact of different population sizes on the cost of eNodeB deployment, coverage rate, and CPU time is evaluated.
- The remainder of this paper is organized as follows: Section 2 contains a review of the existing works on LTE planning. In Section 3, we formulate the problem as a multi-objective optimization issue with constraints. Section IV presents the GWO and IGWO optimization algorithms. Section V presents the results and the related discussions. Finally, Section 6 specifies the conclusion and future directions.

2. LITERATURE REVIEW

Many works have been proposed recently in the field of cellular radio planning [12, 17- 20]. They mainly differ in terms of the planning algorithm (simple heuristics, exponential methods, metaheuristics), the optimized goals (pertaining to coverage, capacity, cost, handover management, and power consumption), and the leveraged input/output parameters. For instance, some papers specify site locations, traffic models, BS configurations, propagation models, type of base station, and frequency reuse strategy [18-20]. Other works, such as [17], investigate all the alternatives that can be used to enhance the coverage for both Long Term Evolution (LTE) and 5G mobile networks. These alternatives include network deployments, frequency bands, and interference mitigation. Along the same lines, Elsawy et al. [20] propose a rigorous mathematical model based on stochastic geometry [21] for analyzing the coverage of cellular radio networks; specifically, the authors used random networks to approximate the SINR score and accordingly other related metrics such as outage probability and average data rate.

In what follows, we cover the main categories for achieving the best coverage and capacity in the cellular planning.

2.1. SIMPLE HEURISTIC/SIMULATION-BASED METHODS

The works in this category address only a part of the whole problem or exploit properties (or heuristics) to reduce the problem complexity. For example, the work cited in [22] addresses partial aspects (such as azimuth tuning) of the cellular planning using the divide-and-conquer strategy.

In [23], the authors exploit the maximum allowable path loss (MAPL) heuristic to estimate the cell area and accordingly predict the dimensioning of the network. Thereafter, a comprehensive set of simulations is conducted to determine the BS locations.

In [24], the authors addressed both coverage and capacity planning; the final number of estimated BSs is the maximum given by the procedures that resolve each of them. To solve the coverage/capacity planning, the proposition leverages empirical models and statistical formulas to estimate the cell area, number of users, data volume, and user's throughput. The authors do not handle the location of BS sites.

The work presented in [9] addresses LTE dimensioning by leveraging three scenarios: macrocell deployment, small cell deployment, and heterogenous deployment. The BS deployment is deemed acceptable if it meets the requirements of all users (i.e., the satisfaction of both target uplink throughput and target downlink throughput).

The adopted algorithm starts from a superfluous number of initially deployed BSs. Then, it gradually removes the redundant BSs until it arrives at near-optimal set of BSs (from which any site reduction will cause a dramatic deterioration of the throughput metric of the cellular network).

The study presented in [25] leveraged the Cost-Hata propagation model in order to set the locations of LTE BSs. The conducted simulations assessed several planning parameters, such as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), SINR, and throughput.

In the context of 5G-NR planning, the authors in [26] analyzed and compared a plethora of propagation models (such as Knife Edge Diffraction [KED] and Dominant Path model [DPM], 3rd Generation Partnership Project [3GPP] and ASTER) for both the millimeter-wave band (28GHz) and the 3.5 GHz band. The work targeted an urban area (Quito city) in Equador and leveraged multiple configurations of MIMO (2×2 and 4×4, 64×64) streams. More specifically, the planning is performed using the platform of Atoll , and it is evaluated using the metrics of throughput, RSRP, and RSRQ indicators; the analysis also provides consistent insights to choose a suitable propagation model for deploying a 5G-NR network.

To achieve the 5G NR planning, the authors used the C-band/mm-wave bands. More specifically, they considered the maximum allowable path loss (MAPL) heuristic and several propagation models (which are compatible with 5G), namely, Urban Macro model (Uma) and Urban Micro model for both line-of-sight (LOS) and no-line-of-sight (NLOS) cases to derive the cell radius (of the gNodeB). Then, the coverage planning was performed using Atoll environment and the estimated number of gNodeBs; simulations were achieved for two operating frequencies: 3.5 GHz and 28 GHz. The authors derived the levels of RSRP and SNIR and downlink throughputs using the Atoll simulations over the urban area.

To handle the poor coverage issue of eNodeBs, the authors in [27] leveraged the automatic cell planning (ACP) optimization module of Atoll software to improve the LTE network planning in the city of Solok (Indonesia). in particular, the authors enhanced the RSRP and SINR parameters. This optimization method enables deriving the best setting of sectoral antenna parameters (tilting, azimuth, and antenna height) and allows for palliating the coverage holes and the interferences issues.

2.2. APPROXIMATION-BASED METHODS

In such methods, the optimality of the solution is compromised with the efficiency of the search algorithm. Particularly, these approaches prefer approximate (and efficient) methods to get near-optimal solutions. The works presented in [28, 29] exploit the division of global planning problems into local ones using heuristics of locality. Then, the solutions of individual local problems are fused to derive approximate global solutions.

2.3. EXHAUSTIVE/EXPONENTIAL METHODS

These methods exploit exhaustive search or exponential methods coupled with heuristics to alleviate the exploration overhead of BS assignment/configuration. The works presented in [30, 31] detail concrete implementations of exhaustive search methods for cellular planning.

2.4. METAHEURISTIC-BASED METHODS

In this category, the authors leverage higher-level optimization algorithms, such as particle swarm intelligence (PSO) [13], genetic algorithms [5, 12, 32, 33], and bee colony optimization [34], to efficiently solve NP-hard planning problems.

The authors of [12] simultaneously address the objectives of coverage, capacity, and power consumption in LTE planning. The coverage sub-goal is met by satisfying a minimum value of the received signal strength at each position of the target area. Moreover, each eNodeB is characterized by its position, tilt, sector, azimuth, and transmit power.

To ensure efficient eNodeB placement and configuration, the authors used the multi-objective metaheuristic of nondominated sorting genetic algorithm-II (NSGA-II). This algorithm is able to reach the pareto optimal solutions (evaluated in terms of the previous three objective functions) in an adequate time.

A genetic algorithm is proposed in [7] to plan an LTE network with mixed cell structures (including macro cells, micro cells, and relay nodes). The model addresses both coverage and capacity while minimizing the cost of cells.

In [8], the researchers leveraged simulated annealing (SA) to handle the dimensioning and placement of BSs in LTE networks for optimal capacity satisfaction; they handled both macrocell deployment and hybrid macro and microcell deployment.

The SA metaheuristic involves conducting a random search with perturbations on the parameters of the utility function (which consists of the satisfaction of users' throughputs). We also highlight that the algorithm occasionally accepts moves that increase the scores of the objective function with a small probability, p, that is inversely proportional to the temperature hyperparameter of SA.

In [35], the authors proposed a hybrid dragonfly algorithm [36] with differential evolution (DADE) for LTE cell planning in vulnerable areas or post-disaster zones. The proposition takes into account the user coverage, user association, and capacity requirements. Moreover, the emergent dragonfly metaheuristic leverages a set of reflexes such as cohesion, food source attraction, alignment, separation and distraction from enemies to improve the advances in the search space. These five reflexes, in addition to the momentum term, are combined to compute the new position of the agent (i.e., dragonfly); the results indicate a high performance with respect to other metaheuristics such as PSO, differential evolution (DE), whale optimization algorithm (WOA), and GWO.

The authors of [13] tackled both coverage and capacity planning of LTE networks. First, they deduced the approximate number of BSs using MAPL and the estimated cell surface. Then, they applied two metaheuristics to determine the best locations of all BSs that would allow maximizing both coverage and capacity: PSO and GWO. The PSO/GWO simulation was performed on an area of 100 km2 with a carrier frequency of 1.8 GHz and 10 MHz bandwidth. The minimum data rate used in the capacity optimization (for every user) was set to 64 kbps for the uplink channel and 1 Mbps for the downlink channel.

In [33], the authors presented an Adaptive Variable Length Genetic Algorithm (AVLGA) as a novel metaheuristic for optimizing BS positioning in LTE networks. The proposed approach employs a weighted fitness function that combines the coverage and capacity.

The major enhancement of this proposition is the acceptance of length-variable solutions in genetic algorithms (GA). The results show a better management of interferences with respect to the conventional optimization techniques.

In [37], the authors optimized the BS locations in order to plan the coverage and capacity of LTE networks (the objectives were combined with a nonlinear scheme).

They implemented the standard GWO metaheuristic and a GWO variant to handle the optimization of BS locations. The variant leveraged two patterns for varying a hyperparameter that controlled the exploration/exploitation trade-off. The results confirmed the superiority of the GWO variant with respect to the standard one.

In [38], the authors leveraged GA to optimize the coverage probability of LTE networks (which is based on the SINR computation). They used three decision variables (BS location, BS height, and BS transmission power) to tune the deployment of BSs.

The authors of [39] used the Tabu search metaheuristic to plan 3G UMTS networks. More specifically, they aimed at tuning the BS configuration (tilt, azimuth, power allocation) and placement in order to enhance the coverage and capacity objectives.

In [40] the authors addressed the planning of 5G BSs in the urban area of Thapathali (Nepal), using both the frequency carriers of 28 GHz and 3.6 GHz (the first scenario includes the mmWave frequencies). Different metaheuristics were employed to determine the optimal placement of 5G BSs that would maximize the coverage and capacity, minimize the interference, and improve the cost. These alternatives include GA, PSO, SA, and GWO. All these techniques involve exploring the possible BS configurations and locations to derive the best trade-off. Before applying the metaheuristics, the authors estimated the radius using link budget analysis and wireless propagation models that are compatible with 5G.

The obtained results indicate that PSO showed superior performance in all the metrics (including the coverage, capacity, and cost of infrastructure) and for both the 28 GHz and 3.6 GHz operating frequencies; GA also provided a satisfiable performance, ranking second in terms of the overall performance.

The works by [41] is focused on the tuning of resource block (RB) distribution and power allocation in the context of optimizing both the coverage and capacity of LTE networks. To this end, the authors employed two techniques: GA and the water filling algorithm. Both algorithms allow for finding the near-optimal assignment of resource blocks to the sub-cells of the network.

In [42], the authors leveraged genetic algorithms to optimize the antenna positioning problem (APP) and enhance the coverage planning of LTE networks. To meet this objective, the authors implemented seven empirical models for propagation losses (including, Hata and Cost-231-Hata). The results showed that an appropriate empirical model selection is able to derive a satisfying performance of PPA for all area types (urban, suburban, and rural areas).

2.5. MACHINE LEARNING/ HYBRID METHODS

The overwhelming complexity of cellular network planning can be palliated using machine learning [43] or hybrid approaches [44] that may combine heuristics, metaheuristics, and machine learning. Following this line of thought, the authors of [43] leveraged both reinforcement learning (more specifically, the actor-critic method) and Bayesian optimization to select the best parameters for BSs (transmit power and tilt). The two objective functions handled by the authors are the under-coverage (which handles the coverage holes) and the over-coverage (which handles the interferences emanating from other cells). Under-coverage means that the maximum signal power received (such as RSRP in LTE) from the cell sector antenna is larger than a given threshold T1, and over-coverage means that the difference between the maximum received signal power (e.g., RSRP) and the sum of received powers from other cells does not exceed a second threshold T2 (common values for T1 and T2 are -110 dBm and 6 dB).

In this setting, the aim is to identify the set of Pareto optimal solutions that best balance the two objectives. The reinforcement learning model contains two neural networks; the first one is a deep neural network (called actor) that learns the policy using gradient decent and predicts as outputs the configuration parameters of the sector antennas. The second network (called critic) learns the Q-score of each pair (state, action), (which is also seen as the long-term reward).

In [45], the authors addressed the planning and optimization of LTE networks. The coverage planning is accomplished through randomly segmenting the possible locations of BSs into groups; this segmentation is done with respect to the Channel Quality Index (CQI) heuristic. Thereafter, an exhaustive search is executed in each segment to derive the near-optimal solution.

In contrast to the majority of cellular planning works (that are concerned with lowering the number of BSs), the authors of [44] address network planning by modeling it as a power consumption minimization problem with cell coverage rate and cell load constraints. This energy-oriented approach is based on fuzzy c means clustering to choose the BS locations.

In [46], the authors provided a hybrid approach involving three stages. In the first phase, a feasible solution to the issue is calculated using constraint satisfaction strategies embedded with a tailored heuristic search. The second phase consists of conducting a local search to improve the found solution. The third phase entails further enhancing to the solution calculated through the second phase.

In [47], the authors highlighted the lack of accuracy in path loss empirical models, especially in some physical area scenarios (such as flat areas found in plains and other rural areas). To achieve accurate planning of LTE networks, the authors proposed a neural network model combined with the PSO technique to correct the standard propagation model (SPM). This latter adjusted SPM model was applied to palliate the planning problems such as over-coverage, coverage holes, overlapping coverage, and high interference ratios.

Table1 the main approaches designed for network planning. For the sake of conciseness, we denote the cost as co, capacity as ca, coverage as cov, and power consumption as po.

Table 1. Main classes of cellular planning approaches

Approach	Technique Used for BS Placement	Supported Objective Functions	Target Networks
[21]	Heuristics and simulations	co, cov	LTE
[23]		co, cov	
[9]		ca, po, co	
[48]		cov, ca	
[7]	GA	co, ca, cov,	LTE
[33]		cov, ca, co	LTE
[38]		po, cov, co	LTE
[14]		po, ca	5G
[12]		ca, po, cov	LTE
[13]	GWO	ca, cov	LTE
[37]		ca, cov	
[34]	Bee colony optimization	cov, co, po	WIMAX
[39]	TS	co, ca, cov, po	3G UMTS
[13]	PSO	ca, cov	LTE
[40]		ca, cov,co	5G
[8]	SA	ca, co	LTE
[40]		ca, cov, co	5G
[43]	Machine learning	cov (with balancing)	LTE
[44]		ca, co, po	
[45]	Hybrid approach	co, ca, cov	LTE
[46]	Hybrid approach	co, Handover	3G UMTS

3. PROBLEM STATEMENT

As stated earlier, the cellular network planning problem is known to be an NP-complete problem, and in fact, it can be considered as an instance of the set covering problem (SCP) [49]. Before presenting its mathematical expression, we first introduce some necessary concepts that are crucial for the subsequent parts.

The channel gain (in dB scale) between the user equipment UE located at the point k and the BS j over the sub-band (or the subcarrier) i is given by [9]:

$$H_{kij} = (-C - \alpha\, Log_{10}(d_{kij})) - \xi_{kij} + 10\log10\, F_{kij} \quad (1)$$

The first term indicates propagation loss, with C representing the path loss constant, d_{kij} the distance in km from the user's location, k, to BS j, and α the path loss exponent. The second term, $\xi_{k\,i\,j}$ corresponds to log-normal shadowing, with zero mean and a standard deviation σ. The last factor, $F_{k\,i\,j}$, stands for the fast fading power (or small-scale fading). $F_{k\,i\,j}$ follows the Rayleigh distribution. Since cellular network planning is mainly concerned with large-scale fading, we only consider the first and second terms (path propagation loss and shadowing) in the SINR definition (see equations (13) and (16)). This large-scale fading (the combination of propagation loss and shadowing) is denoted as LSF_{kij}.

$$LSF_{kij} = (-C - \alpha\, Log_{10}(d_{kij})) - \xi_{kij} \quad (2)$$

The path propagation loss can be calculated using one of the well-known empirical models, such as Cost231-Hata model. This latter model is focused on the frequency range of 1500 MHz up to 2000 MHz and estimates the loss as follows [50]:

$$PL=L+C_m \quad (3)$$

$$L=46.3 + 33.9 \times log\,(f) - 13.92 log\,(H_{bs}) - a(H_r) + (44.9 - 6.55 \times \log(H_{bs})) \times log(d) \quad (4)$$

$$a(H_r)=(1.1 log\,(f) - 0.7)\, H\_r - (1.56 log(f) - 0.8) \quad (5)$$

Where:

H_{bs}: The BS height (m).

H_r: The receiver antenna height (m).

d : The distance between the BS and MS (m).

f: The carrier frequency (MHz).

C_m: Constant factor (in urban zones, it is 3 dB).

Before defining the objective function of the planning, we introduce the following parameters:

M is the total number of all possible eNodeBs (BS).

N is the total number of possible locations in the studied

$$\text{area: } N = \frac{\text{AreaLength}}{\text{ResolutionStep}} \times \frac{\text{AreaWidth}}{\text{ResolutionStep}} \quad (6)$$

The length, width, and ResolutionStep are defined in Section 5. In the following, we assume that each location point in the studied area is defined by the latitude and longitude coordinates (x, y).

If we denote the locations/configurations (x1, y1, $config$(1)),...,(x_M, y_M, $config(M)$) of the M possible eNodeBs as Sol, then the problem of coverage planning can be defined as follows:

$$Min\ TotalCost(Sol) = \sum_{j=1}^{M} Position_{j,x_j,y_j} * Cost_{eNB}\left(x_j, y_j, config(j)\right) \quad (7)$$

Where,

$$\sum_{all(x,y)\in Area} Position_{j,x_j,y_j} \le 1\ , for\ every\ eNodeB\ j \in \{1, \ldots M\}, \text{ and } Position_{j,x_j,y_j} \in \{0,1\} \quad (8)$$

$$Min\left(Cov^{DL}(Sol), Cov^{UL}(Sol)\right) \ge Thresh1 \quad (9)$$

$Position_{j,\,x_j,\,y_j}$: This variable is equal to 1 if the eNodeB with ID j is installed at the location (x_j, y_j); otherwise, it is equal to 0.

$Cost_{eNB}$ (x_j, y_j, $config(j)$) indicates the installation cost of an eNodeB; it depends on the location (x_j, y_j) and the configuration $config(j)$). For the sake of simplicity, this cost coefficient is set to 1 in our experiments, which means that all eNodeBs have the same cost; $config(j)$) involves the parameters of height, tilt, and transmit power.

The constraint defined in (8) imposes the fact that an eNodeB is at most assigned to a single location.

The constraint defined in (9) means that the coverage rate in the uplink (UL) and downlink (DL) must exceed a given threshold Thresh1 (which can be interpreted as the target coverage rate).

$$Cov^{DL}(Sol) = \frac{1}{N}\sum_{all\ (x,y)\in Area} Pr^{DL}_{coverage}(x,y) \quad (10)$$

$$Cov^{UL}(Sol) = \frac{1}{N}\sum_{all\ (x,y)\in Area} Pr^{UL}_{coverage}(x,y) \quad (11)$$

In Equation (10), we define the DL coverage rate as the average probability of getting a satisfying SINR in the DL direction over all locations (x, y). Likewise, Equation (11) defines the UL coverage rate as the average probability of getting a satisfying SINR in the UL direction over all possible locations (x, y).

For the DL direction, the coverage probability at a given location (x, y) is defined as follows:

$$Pr^{DL}_{coverage}(x,y) = \begin{matrix} 1, if\ SINR(x,y) \geq Thresh2 \\ 0, \qquad elsewhere \end{matrix} \quad (12)$$

According to Equation (12), the coverage probability (in the DL direction) is ensured at the location (x, y) if the SINR level exceeds another threshold, Thresh2 (which is defined in Section 5).

The SINR, as defined in Equation (13), includes all the components of large-scale path loss and the other gains in the numerator part. The denominator defines the interference power, which is caused by the neighboring BS working on the same frequency band, and it is defined in Equation (14), as well as the noise power (see Equation (15)).

The SINR in the DL direction at location (x, y), which belongs to the cell covered by BS j over the subcarrier i, is defined in the linear scale as follows:

$$SINR(x,y) = \frac{P^{DL}_{i,j} G_t G_r LSF_{(x,y),i,j}}{I_{i,x,y} + Noise} \quad (13)$$

The numerator is the received power at the location (x, y) from the j-th BS. More specifically, $P_{i,j}^{DL}$ is the transmitted power by the BS j on the subcarrier i; G_t, G_r are the antenna gains of the transmitter and receiver (respectively). $I(i, x, y)$ is the interference power (over subcarrier i) coming from the neighboring BS of j, and Noise is the noise power over subcarrier i (in case of UL direction, Noise is computed over another UL bandwidth).

$$I_{i,x,y} = \sum_{v\neq j} P^{DL}_{i,v} G_t\ G_r LSF_{(x,y),i,v} \quad (14)$$

$I(i, x, y)$ is the sum of powers transmitted by the neighboring BS of the current j-th BS over the same sub-bandwidth i.

$$Noise = K'TB \quad (15)$$

where K' is the Boltzmann's constant (1.38×10−23 J/K1.38×10−23 J/K), T is the temperature in Kelvin, and B is the bandwidth in Hz (which corresponds to the subcarrier i in DL).

In the LTE context, SINR is not computed using the power of a single subcarrier, but it is computed using RSRP, and RSRP is the average power of all reference signals in all subcarriers of all resource blocks (12*NRB), where NRB is the number of resource blocks; in our experimental study (Section 5), NRB is set to 50. In an ideal case scenario (almost zero interference and noise), and under full load, RSRP (in linear scale) is the Received Signal Strength Indicator (RSSI) divided on (12*NRB). Where, RSSI represents the total received power in the entire bandwidth (12*NRB subcarriers).

The DL SINR in dB scale is defined as

$$SINR_{DB}(x,y) = 10log_{10}\left(P^{DL}_{i,j}\right) + G_t + G_r + LSF_{(x,y),i,j} - 10log_{10}(I + Noise) \quad (16)$$

Similarly, we compute $Pr^{UL}_{coverage}(x, y)$ using the same equation defined in (12), except that the SINR in the UL direction is computed as follows

$$SINR_{UL(dB)}(x,y) = 10log_{10}\left(P^{UL}_{UE}\right) + G_t + G_r + LSF_{(x_j,y_j),UL,(x,y)} - 10log_{10}(I_{UE'\neq UE}) + Noise) \quad (17)$$

We mainly change the target frequency channel to UL spectrum instead of the subcarrier i, the transmit power is set to that of UE (i.e., Pr^{UL}_{UE}), the transmitter height is set to that of UE, the receiver height is set to that of BS j (this permutation is involved in the computation of LSF), the interference power ($I_{UE'\neq UE}$) is related to the other UE' that use the same UL bandwidth, and the UL noise (Noise) is computed using Equation (15) and the UL bandwidth .

4. PROPOSED APPROACH

GWO [15] is an innovative metaheuristic algorithm that simulates the hunting behavior of a pack of grey wolves. A swarm of grey wolves is structured into a social hierarchy that includes α (the leader or the best solution), β (the assistant of α or the second-best solution), δ (the helper of α and β, or the third-best solution), and ω (which represents the rest of the wolves or the remaining solutions). The main idea of the hunting process consists of three steps that are repeated throughout the iterations: encircling, search (exploration), and attack (exploitation). The algorithm leverages a perturbed distance that allows the gradual approach toward the best solution; moreover, GWO uses a hyper-parameter denoted as A so as to control the trade-off between the exploration (searching for new regions) and exploitation (focusing the search on a specific region). Since all the used input variables are discretized, we adopt a discretized version of GWO (termed DGWO) that copes with our setting. The DGWO implementation assumes the following input variables:

- BSLOC: A vector containing the physical locations (x, y) of M eNodeBs. (x, y) represents the latitude and longitude of one eNodeB.
- BSH: A vector containing the heights of M eNodeBs (see Table 3 for the possible values). Each eNodeB is

characterized by three values, since we have three cells.

- BST: A vector containing the tilts of M eNodeBs (see Table 3 for the possible values). Each eNodeB is characterized by three values, since we have three cells.
- NL, NC: The number of lines and columns of the discretized study area (for coverage computation, each row or column of the grid represents around 50 m in the physical area). From these parameters, we infer the quantity N that stands for the total number of possible UE locations in the studied area: $N=NL \times NC$ (see also Equation (6)).
- MaxM: The maximum number of eNodesBs (or BSs), while M is the actual number of BSs.
- BSTP: A vector containing the transmit power of the M eNodesBs (the three sector BS).
- COVT: The percentage that represents the coverage target in the studied area (e.g., 95%).
- SINRTH: The minimum accepted SINR threshold (in dB) in every location (x, y) of the studied area.
- P: The size of the population (Pop) of grey wolves.

We assume that transmit power is the same for all eNodeBs (all BSTP(i) are equal); moreover, we assume that the azimuth values are the same for all eNodeBs. The three sector antennas have the following azimuth values: 0, 120, and 240. Accordingly, the optimization algorithm will tune the parameters of BSLOC, BSH, and BST for each eNodeB to get the best performance.In addition, DGWO uses a local function (see line 4) that computes the (E-UTRA Absolute Radio Frequency Channel Numbers (EARFCNs) of the DL/UL carrier frequencies and applies a (fractional) frequency reuse scheme (FFR) to plan the frequency allocation of cells. For the DGWO outputs, we assume the following quantities:

- Toll: The deployment cost of the best wolf (α).
- COV: The coverage percentage achieved by the best wolf (α).
- W*: The configuration/position of eNodeBs.

The pseudocode of DGWO is given below:

DGWO

Input: **Pop of wolves =** $\{W_1, \ldots W_p\}$
MaxM, NL, NC, COVT, SINRTH, P

Output: ***COST*, *COV***

1. M=28; COV=0;
2. **While** $M \leq MaxM$ **and** $COV < COVT$
3. Pop= $RandomInitialization(P, M)$
4. $FrequencyAllocation(Pop)$
5. α, β, δ=$CoverageRanking(Pop)$; $W^*= \alpha$
6. A=init(); C′=init()
7. **For** t=1, $Tmax$
8. **For** i=1, P
9. $D_{i1}=PDist(C', W_i, \alpha)$;
$D_{i2}=PDist(C', W_i, \beta)$;
$D_{i3}=PDist(C', W_i, \delta)$
10. X_1=Move (A, D_{i1}, α);
X_2=Move (A, D_{i2}, β);
X_3=Move (A, D_{i3}, δ)
11. $W_i=X_1$ (with probability p_1)
12. $W_i=X_2$ (with probability p_2);
$W_i=X_3$ (with probability p_3);
13. **End**
14. $A=update(A)$; $C'=update(C')$
15. $\alpha, \beta, \delta=CovergeRanking(Pop)$;
$W^*=update(W^*, \alpha)$
16. $CovDL=Cov^{DL}(W^*)$
17. $CovUL=Cov^{UL}(W^*)$
18. $COV=Min(CovDL, CovUL)$
19. $TOLL=TotalCost(W^*)$
20. **End**
21. $M=M+1$
22. **End**
23. **Return** $(W^*, COV, TOLL)$

Line 1: Initialize the values of M and COV; the possible values of M are shown in Table 2. $MaxM$ is the highest possible value of M.

Lines 2–22: The while loop first applies the cell frequency planning (using a frequency reuse scheme) to the $\boldsymbol{M}$**×3** cells and then invokes the discrete GWO to ensure the target coverage rate $COVT$; if $DGWO$ fails (in achieving $\boldsymbol{COVT}$), M is incremented (see line 21), and we try another $DGWO$ simulation.

Line 3: We randomly initialize the P wolves; each wolf is a quadruplet $W_i=(BSLOC, VH, VT, BSTP)$; it represents a positioning/configuration of all *eNodeBs*. This step initializes the M *eNodeBs* using the domains shown in Table 3.

Line 4: We assign the frequency channels to the cells (using *EARFCNs* and the frequency reuse scheme).

Line 5: We sort the wolves of Pop (using the coverage metric) and retain the Top 3 solutions. This metric is computed in Line 18, and it is based on Equations (10) and (11) cited in Section 3. In addition, the best solution W^* is initialized (i.e., $W^*= \alpha$).

Line 6: In our discrete version, C' is a binary vector that indicates the wolf' s dimensions (C' and W_i have the same size) that are involved in the distance computation shown in Line 9. Moreover, the trade-off factor A is a vector of the same size as C'; each element $A(i)$ of A belongs to [-1,1] and it is linearly decremented toward 0 (see line 14).

Line 7: It is the principal loop of GWO that controls the wolves' position updates.

Lines 8–13: This loop iterates over all wolves and performs several tasks: (1) the computation of perturbed distance D_{ij} (see Line 9); (2) the computation of the temporary position of W_i according to A, D_{ij}, and the Top_j wolf of the population (see Line 10); and (3) the effective value of W_i that is randomly selected from the three candidate positions calculated in step (2) (see Lines11–12).

The selection probabilities P_1, P_2, and P_3 are tuned during the experiments (see Section 5).

Line 14: The hyperparameter C is randomly updated; the hyperparameter A is linearly decreased toward 0.

Line 15: The Top3 wolves, as well as W^*, are updated.

Lines 16–18: The coverage rate of W^* is computed using the DL and UL orientations.

Line 19: The total cost of W^* is computed.

Line 21: M is updated.

Line 23: The best solution, the total cost, and the coverage rate are returned to the decision-maker.

The improved GWO (termed IGWO) shown in the next pseudocode consists of replacing the update based on the δ wolf by a local search operator. More specifically, in Line 11 of IGWO, we first choose a random wolf from the set $\{\alpha, \beta, \delta\}$, and then we apply a local search on that wolf by choosing two dimensions to update.

If the chosen dimension is the height of a given eNodeB, then the old value $V_k \epsilon \{V_1, V_2, \ldots, V_k\}$ is replaced by V_{k-1} or V_{k+1}.

The same thing can be said for the tilt dimensions. The old value is replaced by one of the two neighboring values in the variable domain. If the chosen dimension is the physical location (x, y) of a given eNodeB, then

$$(xnew, ynew) = (xold, yold) + (\Delta_x, \Delta_y) \tag{18}$$

where
$\Delta_x \epsilon \{-50m, -25m, 0m, 25m, 50m\}$, and
$\Delta y \epsilon \{-50m, -25m, 0m, 25m, 50m\}$.

The adopted resolution step for placing eNodeB is set to 25 m.

The remaining instructions of IGWO are the same as for DGWO. In Section, we evaluate the impact of this new operator on both the cost and coverage rate.

It is worth noting that the SINR formula (see Equations (13) and (16)) is learned using the Adaboost method [51]. In particular, we generated hundreds of pairs of inputs/outputs using the Atoll simulator (version 3.3.2). The input of each pair (or example) contains the 03 vectors BSLOC, BSH, and BST (the eNodeB positioning and configuration), while the output contains an $NL \times NC$ matrix of SINR values generated by the input disposition of eNodeBs. We must mention that Adaboost is based on the KNN regression weak -learner.

IGWO

Input: **Pop of wolves =** $\{\boldsymbol{W_1}, \ldots \boldsymbol{W_p}\}$
MaxM, NL, NC, COVT, SINRTH, P

Output: ***COST, COV***

1. M=28; COV=0;
2. **While** $M \leq MaxM$ **and** $COV < COVT$
3. $Pop = RandomInitialization(P, M)$
4. $FrequencyAllocation(Pop)$
5. $\alpha, \beta, \delta = CoverageRanking(Pop)$; $W^* = \alpha$
6. A=init(); C′=init()
7. **For** t=1, $Tmax$
8. **For** i=1, P
9. $D_{i1} = PDist(C', W_i, \alpha)$;
   $D_{i2} = PDist(C', W_i, \beta)$;
10. X_1=Move (A, D_{i1}, α);
    X_2=Move (A, D_{i2}, β);
11. $Wolf = RandomChoice(\alpha, \beta, \delta)$;
    $X_3 = LocalSearch(Wolf)$
12. $W_i = X_1$ (with probability p_1);
13. $W_i = X_2$ (with probability p_2);
14. **End**
15. $A = update(A)$; $C' = update(C')$
16. $\alpha, \beta, \delta = CovergeRanking(Pop)$;
    $W^* = update(W^*, \alpha)$
17. $CovDL = Cov^{DL}$ (W^*)
18. $CovUL = Cov^{UL}$ (W*)
19. $COV = Min(CovDL, CovUL)$
20. $TOLL = TotalCost(W^*)$
21. **End**
22. $M = M+1$
23. **End**
23. **Return**(W^*, COV, $TOLL$)

To evaluate the time complexity of IGWO, we first give insights about the complexity of the standard GWO, frequency planning, SINR complexity, and local search operator.

We notice that the standard GWO has a complexity of O $(Tmax * P * D_{in})$, where:

D_{in} (dimensionality of the input): it is estimated as $NumberOfCells$ * 4, (4 represents the number of parameters, which are the location (x, y) of BS, height, and tilt).

NumberOfCells: it is the number of eNodeB times 3 (M*3).

$MaxM$: it the maximum number of eNodeBs, in our experiments it is set to 42.

$Tmax$: the number of iterations (see the possible values in Table 2).

P: the size of wolf population (see the possible values in Table 2).

$Dout$ (dimensionality of the output): it is a 2D matrix of N=11464 floats, each element represents the SINR of a square region of 50*50 m^2.

$NumberOfChannels$ (NC): we divided the spectrum of the DL stream of E-UTRA Band3 into NC=6 channels, each channel is assigned to a cell in a way that minimizes the interference.

We also notice that the step 4 of IGWO (frequency planning) has a complexity of $O(NC^{NumberOfCells})$.

The SINR calculation done in lines (17 or 18) is achieved using the adaboost testing phase which has a cost equal to O ($NumberOfweaklearner$ * $TrainingSetSize$ * D_{in} *D_{out}).

$NumberOfWeakLearners$: by default, it is set to 3.

$TrainingSetSize$: by default, it is set to 500 examples (it represents the cardinal of the training set).

The complexity of the local search (line 11 of IGWO) is the product of the SINR complexity with neighborhood size.

We define the neighborhood size (NS) of a solution as NS=$SizeTilts$ * $SizeHeights$ * $SizePositions$. To reduce the computation overhead, we consider only one new position (for $SizePositions$) instead of 5 possible positions. Thus, NS=8*10*1=80. The local search complexity is:

O (NS * $NumberOfweaklearner$ * $TrainingSetSize$ * D_{in} * D_{out}).

The complexity of IGWO (with frequency planning) is:

O ($MaxM$ * (P * $MaxM$ + $NC^{NumberOfCells}$ + (P* $NumberOfweaklearner$ * $TrainingSetSize$ * D_{in} * D_{out})+ $Tmax$ * (P * ($NumberOfCells$ + (NS * $NumberOfweaklearner$ * $TrainingSetSize$ * D_{in} * D_{out}))) + ($NumberOfweaklearner$ * $TrainingSetSize$ * D_{in} * D_{out}))).

5. RESULTS AND DISCUSSIONS

The reported experiments were conducted using a machine with an Intel Core i5-1245U CPU at 1.60 GHz, 16GB memory (RAM), and Windows 12 with a 64-bit operating system. We used Python 3.9 to develop all the algorithms, namely DGWO, DGWO with a single leading agent (AlphaGWO), IGWO, DPSO, and TS [52]. In AlphaGWO, we only use the Alpha agent, the beta and delta agents are eliminated, this variant serves for evaluating the impact of the voting rule on the performance of the search.

We simulated the planning on an urban geographic area (Oran city of Algeria); more specifically, we chose a rectangular area with sides measuring 4 km and 7 km for an area of 28 km^2. To compute the SINRs (Equations (13) and (16)), we used the Cost-231-Hata empirical model. Initially, the eNodeBs were randomly distributed in the area according to the uniform law with a density of 1 eNodeB per km^2; thus, we started the simulation with M = 28 eNodeBs (and consequently we started with 28*3 = 84 cells). This number was gradually increased so as to meet the target coverage rate.

Our experiments adopt the E-UTRA Band 3 - 10MHz band. We defined 6 channels for allocating the spectrum to eNodeBs (in particular, we have 6 DL-EARFCNs).

In the following, we give the frequency plan for DL-EARFCNs. For the DL orientation (1805-1880 MHz), we defined the first and the last EARFCNs as follows:

First DL EARFCN= 1 250, last DL EARFCN = 1 850, the step separating the channels is set to 100.

Table 2 shows the technical parameters of our two algorithms (DGWO and IGWO). Table 3 shows the simulation parameters that concern the deployed eNodeB (e.g., frequency band, channel bandwidth, and antenna gain). Furthermore, we assume that the UE antenna gain is set to 1 in the linear scale (or 0 dBi).

We also suppose that the resolution step in Equation (6) is equal to 50 m for calculating the coverage formula (see Equations (10) and (11)); this variable determines the SINR matrix size); however, it is set to 25 m for placing the eNodeBs (this setting determines the minimum values of (Δx, Δy)).

To initialize the wolves' positions/configurations of DGWO and IGWO, we first generated a hundred random values; thereafter, we selected the first P wolves that had the best coverage score; these P wolves constitute the first generation of the wolves' population.

Table 2. GWO Parameters

Parameter	Values
Population size (P)	20, 30, 40, 50
Max number of iterations ($Tmax$)	20, 30
Number of eNodeBs (M)	28, 32, 36, 38, 40, 42
Probability thresholds P_1, P_2, P_3	40%, 30%, 30%
Target coverage rate ($COVT$)	95%
SINR threshold	10 dB, 12 dB

Table 3. Simulation parameters.

Parameter	Values
Antenna transmit power	43 dBm
Shadowing standard deviation	5 dB
UL and DL channel bandwidth	10 MHz
Frequency band	1800 MHz
MIMO configuration	2_x2 MIMO
eNodeB Antenna gain	17 dBi
eNodeB Tilt	0, 1, 2, 3, 4, 5, 6, 7, 8, 9
eNodeB Height	10, 15, 20, 25, 30, 35, 40, 45
UE Height	1.5

Fig. 1 shows a comparison between IGWO and GWO in terms of coverage (with a minimum SINR of 10 dB), M = 36, and P = 30. The results confirm the superiority of IGWO with respect to DGWO. We observe that both of

them converge around the fifth or sixth iteration. However, we note that IGWO can reach 98.8% of 10 dB SINR satisfaction, while DGWO reaches only 88.2% of satisfaction rate (Thresh2 = 10 dB). Therefore, we conclude from this experiment that the addition of a local search (applied on the Top3 wolves) has a positive impact on the coverage performance. This operator modifies a subset of parameters using the neighborhood values and aims at enhancing the wolf score. In the experiments introduced in Figs. 2–6, we assume that $M = 36$.

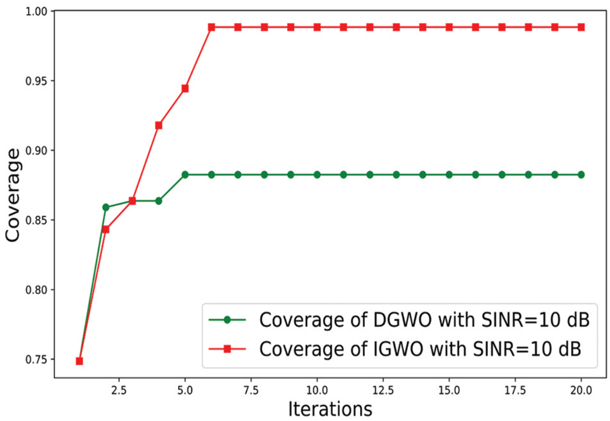

Fig. 1. Coverage rates for both DGWO and IGWO (Thresh2 = 10 dB)

Fig. 2 demonstrates the coverage evolution of IGWO (of the previous execution) for two different SINR thresholds. We first observe that the convergence is ensured after six iterations (with a population of 30 wolves), then we notice that the ensured coverage rate is 98.8% for a threshold of 10 dB; however, it is equal to 76.0% for a SINR threshold of 12 dB. This experiment indicates the necessity of adding more eNodeBs to reach the target coverage for 12 dB SINR.

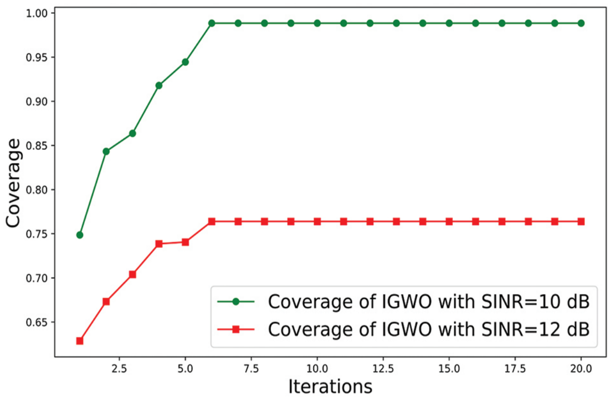

Fig. 2. Coverage rates of IGWO for Thresh2 = 10 dB and Thresh2 = 12 dB

Fig. 3 shows the impact of the population size on the average coverage percentages. It is clearly indicated that a size P greater than or equal to 30 can achieve satisfying results for a threshold of 10 dB, while the average coverage rate is still low for 12 dB (for all P) due to the weak value of M.

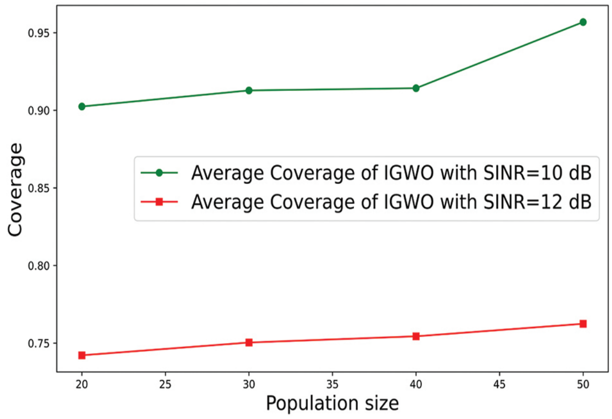

Fig. 3. Average coverage rate vs. Population size

Fig. 4 illustrates the consumed CPU time with respect to the population size of IGWO and the size of the neighborhood of TS; the number of iterations is set to 20 for both methods. We notice a linear increase in time for both techniques; in particular, the CPU time ranges from 400 s up to 1100 s for IGWO, while it ranges from 800 s to 1800 s for TS. Accordingly, we conclude that the perfect population size (of IGWO) ensuring an acceptable delay for the user ranges between 30 and 40.

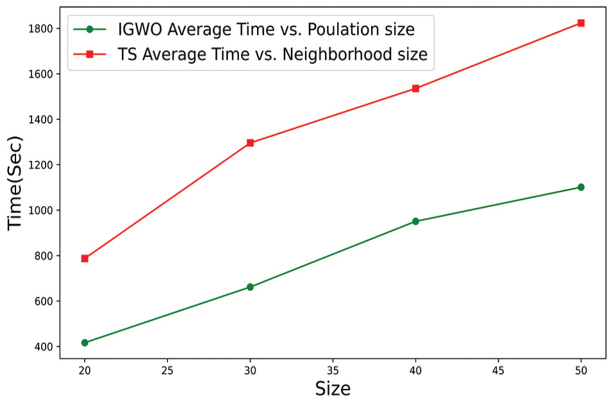

Fig. 4. IGWO execution time vs. Population size

In Fig. 5, we show a comparison between the performance of IGWO, DPSO, AlphaGWO, and TS. We notice that IGWO, DPSO, and AlphaGWO have the same population size which set to 30 (P = 30). Clearly, IGWO outperforms all methods for the same SINR threshold (10 dB). We note that TS was implemented with a neighborhood size of 40 and a Tabu list size of 3. Despite the fact that both algorithms (TS and IGWO) converge before the sixth iteration, we notice that the local search used in TS is not sufficient to optimize the coverage of a moderately sized geographical area (despite using a large neighborhood). The experiment shows that the TS simulation reaches a coverage rate of 88.3% for a SINR threshold of 10 dB. On the other hand, we notice that DPSO is ranked second, and consequently this social-oriented gradient descent confirms its effectiveness in cellular planning (it reaches a coverage rate of 96.2 %). Regarding AlphaGWO, we observe that its coverage rate is slightly lower than that of TS (and even DGWO).

In fact, AlphaGWO reaches a coverage rate of 88.1%, and therefore, we can conclude that the voting rule (which is implemented in DGWO and absent in AlphaGWO) has a powerful impact on the quality of the derived solutions.

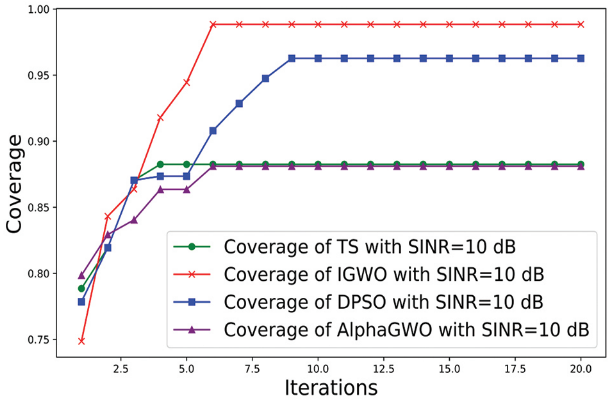

Fig. 5. IGWO performance vs. All methods

In Fig. 6, we present the frontiers of cells (36*3 = 108) and their respective SINR levels in the studied urban area. This result corresponds to the best wolf given by the IGWO experiments illustrated in Figures 1 and 2 (i.e., 98.8% of 10 dB SINR satisfaction or 76.0% of 12 dB SINR satisfaction). The green color represents a SINR of at least 10 dB, and the yellow and red colors represent higher SINRs.

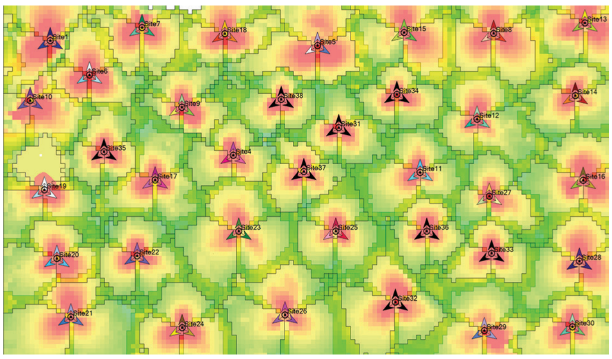

Fig. 6. Cell frontiers for the best wolf given by IGWO with $M = 36$

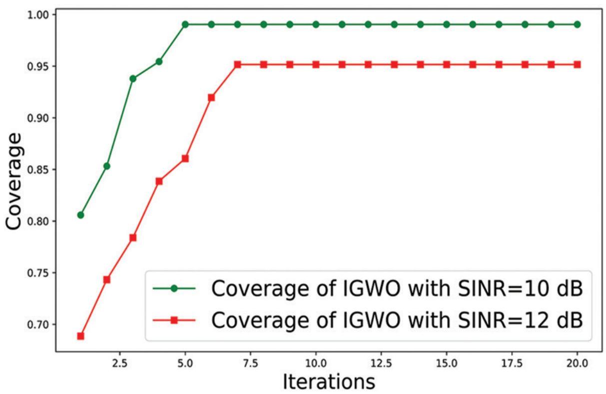

Fig. 7. Coverage rates of IGWO with M=42, Thresh2=10 db, and Thresh2=12 db

In Fig. 7, we present the evolution of IGWO with $M = 42$ and $P = 30$. As clearly indicated, IGWO converges to the final performance of 95.1% after seven iterations (using a SINR threshold of 12 dB). However, it reaches the performance of 99.0% for the 10 dB SINR threshold after five iterations. This experiment supports the efficiency of IGWO in reaching near-optimal solutions of eNodeB deployment.

6. CONCLUSION

We have presented in this paper an automatic approach for planning the coverage of an LTE network while considering compromises in cost and capacity. Our proposition includes the development of both a discrete GWO and an improved GWO for tuning the parameters of eNodeBs. Besides replacing the averaging rule with the probabilistic voting rule, the improved version of the Grey Wolves Optimizer (IGWO) contains an additional local search operator during the exploration phase. This operator modifies a subset of parameters using the neighborhood values and is aimed at enhancing the wolf score. Our algorithm optimizes the eNodeBs positions, their heights, and their tilts and provides a deployment option with the best coverage/cost pair. We also highlight that IGWO is able to outperform the standard GWO, the PSO technique, and the TS metaheuristic in coverage planning based on the SINR threshold of 10 dB.

In future works, we plan to compare our proposition with other effective metaheuristics such as Dragonfly algorithm or spider monkey optimization (SMO). Additionally, we aim to handle other objective functions (e.g., number of users and power consumption) or other constraints. Finally, we also aim to extend our work for planning other emergent networks.

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