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Research Article

Accurate Base Station Placement in 4G LTE Networks Using Multiobjective Genetic Algorithm Optimization

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Cellular mobile communication network planning and optimization involve a complex engineering process that deals with network fundamentals, radio resource elements, and critical decision variables. The continuous evolution of radio access technologies provides new challenges that necessitate efficient radio planning and optimization. Therefore, the planning and optimization algorithms should be highly efficient, advanced, and robust. An important component of 4G LTE network planning is the proper placement of evolved node base stations (eNodeBs) and the configuration of their antenna elements. This contribution proposes a multiobjective genetic algorithm that integrates network coverage, capacity, and power consumption for optimal eNodeB placement in an operational 4G LTE network. The multi-objective-based genetic algorithm optimization has been achieved using the optimization toolbox in MATLAB. By leveraging the proposed method, the effect of different population sizes on the cost of placing the eNodeBs and the percentage coverage of the eNodeBs in a given cell is determined. As a result, the optimal selection technique that minimizes the total network cost without compromising the desired coverage and capacity benchmarks is achieved. The proposed automatic eNodeB antenna placement method can be explored to optimize 4G LTE cellular network planning in related wireless propagation environments.

1. Introduction

The evolved node base station (eNodeB) placement and configuration in cellular radio networks is critical to delivering efficient wireless network services and guaranteeing the quality of service for mobile subscribers [1–3]. The performance of a cellular network is mainly characterized by the received signal strength and signal quality at the subscriber equipment terminal. In practice, the service coverage is primarily affected by radio propagation and transmit power and depends on the propagation environment of the wireless network [4–9]. Thus, attaining excellent cellular network coverage and improved signal coverage around the subscribers by deploying the minimum required number of

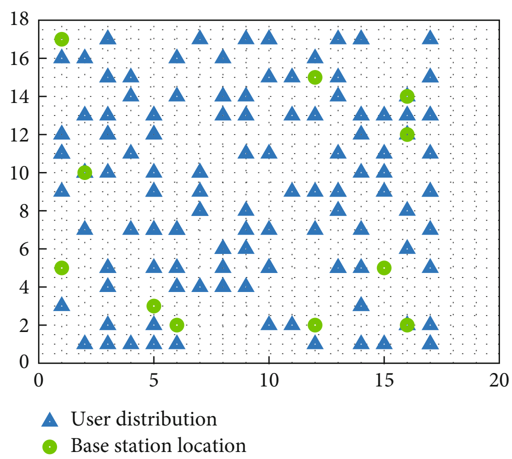

Figure 1: Test area for eNodeB location setup and evaluation.

BSs with configurations is one of the leading objectives of the mobile networking industry [10–13]. This objective can only be achieved if a good evolved node base station (eNodeB) placement and configuration method considers the propagation environment in place [14–16].

The traditional method of eNodeB placement and configurations depends mainly on the imported propagation models such as the Hata and COST 231 Hata that do not capture the actual characteristics of the radio signal propagation environment [17–20]. The limitations posed by these models used to characterize the environment often lead to unreliable network planning, resulting in poor quality of service at the subscribers' equipment terminals. To this end, this study focuses on investigating and developing a robust eNodeB placement and configuration algorithm that considers the investigated radio signal propagation environment.

The genetic algorithm (GA) is preferred to other heuristic optimization algorithms and deterministic approaches owing to its capability to handle continuous and discrete parameters, insensibility to local minima, model generality, and robustness of the GA program code [21–24]. These characteristics presents the genetic algorithm (GA) as the natural choice for optimization in this investigation. In particular, the optimization problem is quantitatively described as a maximization or minimization of the function $f(x_1, x_2, \cdots, x_n)$, where n indicates the number of parameters. The minimization and maximization can be replaced by each other if the function is multiplied by a minus sign.

The cellular network infrastructure comprises several eNodeBs deployed over the service coverage area. Each eNodeB creates or produces a coverage area referred to as a cell [25, 26]. The users geographically located inside the cell are provided with the different network services by the associated eNodeB. The optimal placement of the eNodeB to varying locations over the tested geographical area to meet the desired service coverage quality and satisfy the diverse subscribers' multifarious demands poses a challenge due to several dynamic factors and steps involved, leading to an eNodeB placement problem worthy of investigation. The eNodeB placement problems deal with determining the type of eNodeB antennas, the number of eNodeBs, the configuration of the eNodeB antennas (tilt, sectors, and azimuth), and the positioning of the eNodeBs on potential cell sites to meet the coverage, capacity, and service quality demands [12, 27–31].

There exist several methods of handling automatic base station placement problems. In the existing literature, Císcar and Pino [32] presented a solution-based technique that employs a heuristic search algorithm that combines ray tracing and direct ray methods to determine the received signal power level at a given location. In the works of [33–37], pattern search algorithms were explored to determine the antenna location placement considering bit error rate and power coverage constraints. In the pattern search algorithm, the coverage area is separated into different receiver location grids, followed by an iterative search initiated until some enhanced and workable solutions are attained. In [10], a robust method similar to the current study is proposed. Base stations are automatically determined and distributed over an area to meet the coverage constraint and traffic capacity demands.

In [38], a nonlinear programming problem with constrained multivariables is formulated to determine the location of nodes and their data transmission patterns. The constraints were targeted at minimizing the total cost and maximizing the network lifetime. Furthermore, the authors assumed that all nodes possess the same energy, making them suitable for only first-round wireless network deployment. A related study [39] proposed a multiobjective metric method to handle base station placement in WSNs. The metrics are coverage, fault tolerance, energy consumption, and average delay. Their results showed optimal base station performance.

From the preceding literature, it is apparent that there is a need to investigate the coverage, capacity, and power consumption of eNodeBs as a combined multiobjective problem employing a genetic algorithm. Thus, this paper proposes a multiobjective genetic algorithm that integrates coverage, capacity, and power consumption for optimal eNodeB placement in a typical 4G LTE network. The main contributions of this paper are outlined as follows:

(i) A multiobjective optimization method is proposed for evaluating the combined coverage, capacity, and power consumption problem for optimal eNodeB placement in a typical 4G LTE network

(ii) The effect of different population sizes on the cost of placing the eNodeBs and the percentage coverage of the eNodeBs in a given cell is investigated

(iii) The optimal selection technique minimizes the total network cost without compromising the desired coverage and capacity benchmarks determined

The remaining part of this paper is given as follows: Section 2 presents the preliminaries. Section 3 captures the experimental measurements, and Section 4 presents the results and discussions. Finally, Section 5 gives a brief conclusion to the paper.

Input: eNodeB placement model parameters
Input: GA control operators
Input: I (population size)
Output: O (Pareto front approximation)
Steps
i: Define fitness functions
ii: Create an initial random population, P_i
iii: Compute fitness values of each chromosome in P_i
iv: Rank the individuals in the population using a fast nondominated sort
v: Compute the crowding distance of each solution
vi: While the maximum iteration number is not reached yet, do
vii: Choose parents from P_i through binary tournament selection with crowding distance
viii: Employ the GA operators (crossover and mutation) to create a set of new solutions, P_n
ix: Evaluate fitness values of solutions in P_n
x: Merge I ← [I, P_n]
xi: Rank each solution in P_1 using a fast nondominated sort
xii: Compute the crowding distance meant for each solution in P_n
xiii: Change solutions in P_i with the I best solution in P_n
xiv: End while

Algorithm 1: The adopted NSGA-II pseudocode.

2. Preliminaries

This section presents the design of the base station placement model, maximization of service coverage areas, maximization of the covered user capacity, minimization of cost of power consumption, and model formulation.

2.1. Base Station Placement Model. The core aim is to find a BS placement procedure that maximizes the coverage and user capacity, whose power radiation is equal to or below maximum transmit power, P_{th}. In order to provide a mathematical depiction of this model, it is essential to introduce a set of variables. Mainly each BS_i, $i = 1, \cdots, k$, is linked to a binary variable x_i with the following meaning: x_i is equal to 1 if an eNB is selected and placed in the intended location equal to 0, or otherwise. Figure 1 shows the setup created for the eNodeB placement and evaluation method with the randomly distributed user traffic. The design is as follows: the total area of interest and the BS transceiver is $17 \times 17\,\text{km}^2$, and the eNodeB can be placed at any location in this area. Eleven base stations with three sectored directional antennas are intended to be distributed randomly in the investigated area. All base stations are assumed to possess the same transmission power (20 W) and are of the same height (30 m).

2.2. Maximization of Service Coverage Areas. The first objective is to minimize the network dead zones/coverage hole areas. Dead zones/coverage holes are the areas of interest close to the cell edges where the network services are very poor or unavailable. This first objective is geared toward maximizing the network coverage area. Thus, this fitness function $f_{cov}(x)$, in equation (1), has been formally evaluated by [40, 41].

$$f_{cov}(x) = \text{Max}\left(\frac{\text{Coverage rate}\,(x)}{\text{Number of antennas}\,(x)}\right), \tag{1}$$

where the coverage rate expresses the coverage percentage value of the measurement test points.

2.3. Maximization of the Covered User Capacity. The second objective is targeted at minimizing the uncovered user capacity. In other words, the objective is directed at maximizing the system capacity in the network area of interest [42, 43]. This objective can be expressed by

$$f_{cap}(x) = \text{Max}\left(\frac{\left(M_{erl} \times K \times N_{sec} \times S_{spec} \times B \times L_f \times A_c\right)(x)}{R_{th}^{DL}}\right). \tag{2}$$

2.4. Minimization of Cost of Power Consumption. Cellular network planners are always interested in reducing users' exposure to electromagnetic radiation emanating from the BSs and the cost of energy consumption to maximize revenue. Thus, the key objective is to minimize network energy consumption and reduce users' exposure to electromagnetic radiation emanating from the eNodeBs [44]. This objective can be formulated as follows:

$$f_{po}(x) = \text{Min}\,\frac{\sum_{s=1}^{N_{BS}} P_s(x)}{P_{max}}, \tag{3}$$

where P_s indicate the BS transmit power, N_{BS} is the number of eNodeBs, and P_{max} is the maximum BS transmit power given in equation (4), and it can be determined by [24].

$$P_{max} = P_t + 10\,\log_{10} N_{NB}. \tag{4}$$

2.5. Model Formulation. The optimal placement of no more than some k BSs attains a suitable trade-off among

$$f_1 = \max f_{cov}(x), \tag{5}$$

$$f_2 = \max f_{\text{cap}}(x), \tag{6}$$

$$f_3 = \min f_{\text{cost}}(x). \tag{7}$$

Subject to the constraints given,

$$\begin{cases} n \\ i \end{cases} \le k, \tag{8}$$

$$f_{\text{cov}}(x) \le C(r), \tag{9}$$

$$f_{\text{cap}}(x) \le S_{i,c}, \tag{10}$$

$$f_{\text{pow}}(x) \le P_T\{\max\}, \tag{11}$$

where $S_{i,c}$ indicates the channel capacity for user i, considering a channel c. $P_T\{\max\}$ indicates the maximum BS transmit power. A receiver r is said to be properly covered by a base station if the RSRP is greater than the threshold, which is given by

$$C(r) = \begin{cases} 1 & \text{if } r \text{ is covered by a BS,} \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

A binary decision vector $x = [x_1, x_2, \cdots, x_n]^T$, satisfying equations (8)–(11), is termed a feasible solution.

3. Proposed Multiobjective Optimization Method

There exist several GA stochastic optimization methods. This work engages the nondominated sorting genetic algorithm-II (NSGA-II) optimization method. The NSGA-II is a fast elitist multiobjective optimization algorithm [45, 46] resolving problems by converging to a Pareto front. The NSGA-II is utilized to select the optimal BS locations from a subset of the predefined candidate sites and guide an evolutionary procedure toward attaining feasible solutions with better service coverage, desired user capacity, and lower cost function. At the same time, it retains a population of the best-fit solutions. The adopted NSGA-II pseudocode is given in Algorithm 1. The key GA parameters include the following:

(a) *Population size*: this expresses the number of individuals (chromosomes) that are available in a population for each generation

(b) *Crossover fraction*: this defines the population fraction at the succeeding (next) generation

(c) *Selection function*: a key evolutionary process operator that assists individuals to undergo better variation and produce offspring in the succeeding generation employing their fitness scores

(d) *Pareto function*: this regulates the elite population members at each generation to keep up the population diversity before converging to the optimal Pareto front

Table 1: Simulation parameters used in the multiobjective genetic algorithm.

Operation/parameter	Value(s) of options/parameter
Population size	10, 40, 70, and 100
Population type	Double vector
Elite count	1
Pareto fraction	0.75
Crossover fraction	0.8
Mutation function	Adaptive feasible
Migration direction	Both
Migration interval	20
Constraint tolerance	1.0000e-03
Measure function for distance	{@distancecrowding 'phenotype'}
Time limit	Inf
Fitness limit	-Inf
MaxStall generation	100
MaxGenerations	200 × number of variables
MaxTime	Inf

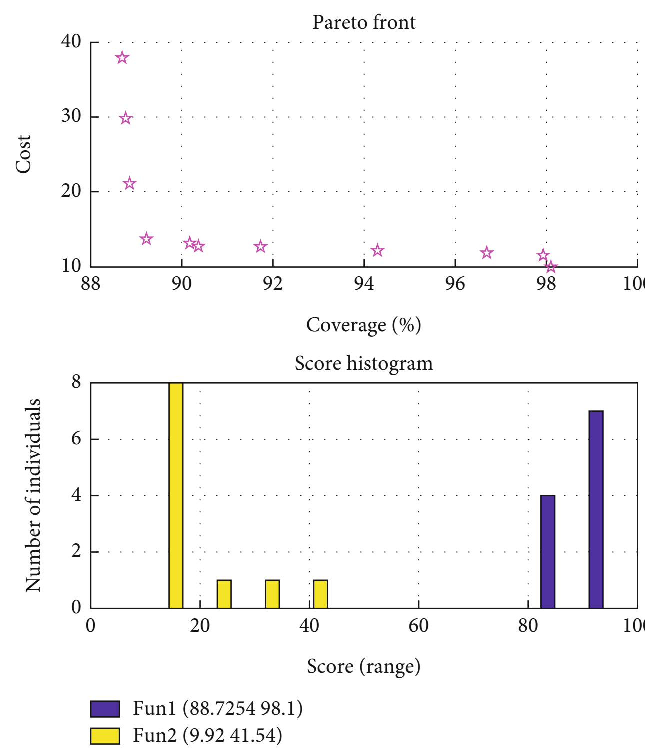

Figure 2: Pareto plot and the score histogram obtained with 10 population size for scenario 1.

(e) *Generation*: iteratively, the control of the number of chromosome evaluations during the optimization process (run)

3.1. Representation and Encoding. In the proposed multiobjective GA, chromosomes represent the solution that

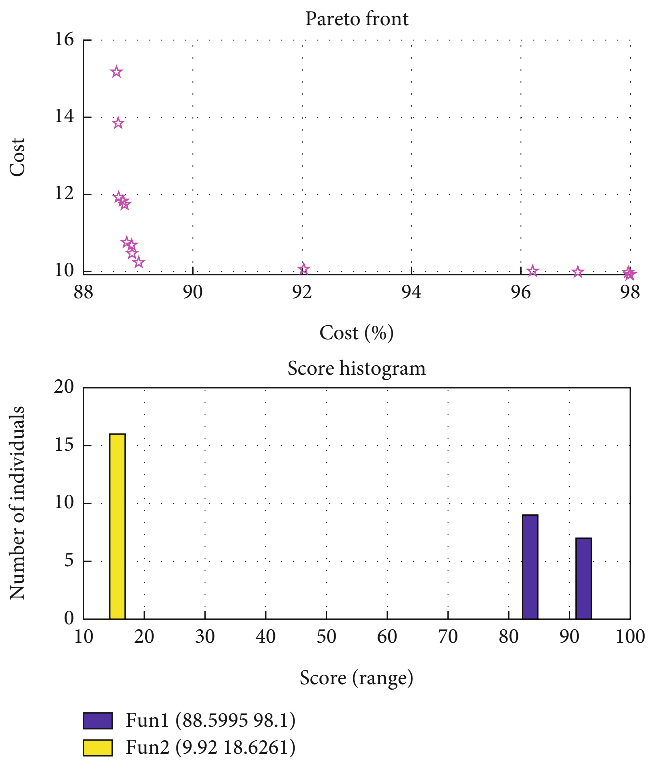

FIGURE 3: Pareto plot and the score histogram obtained with 40 population size for scenario 1.

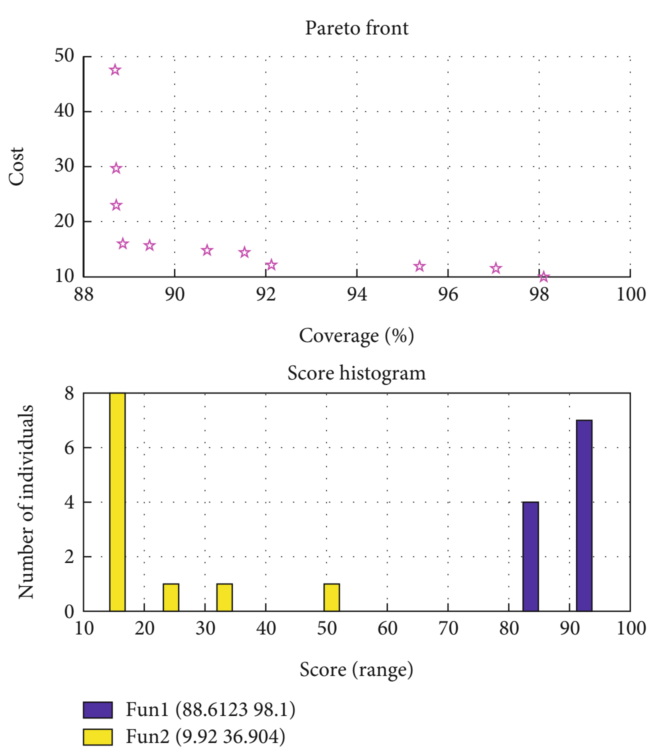

FIGURE 4: Pareto plot and the score histogram obtained with 70 population size for scenario 1.

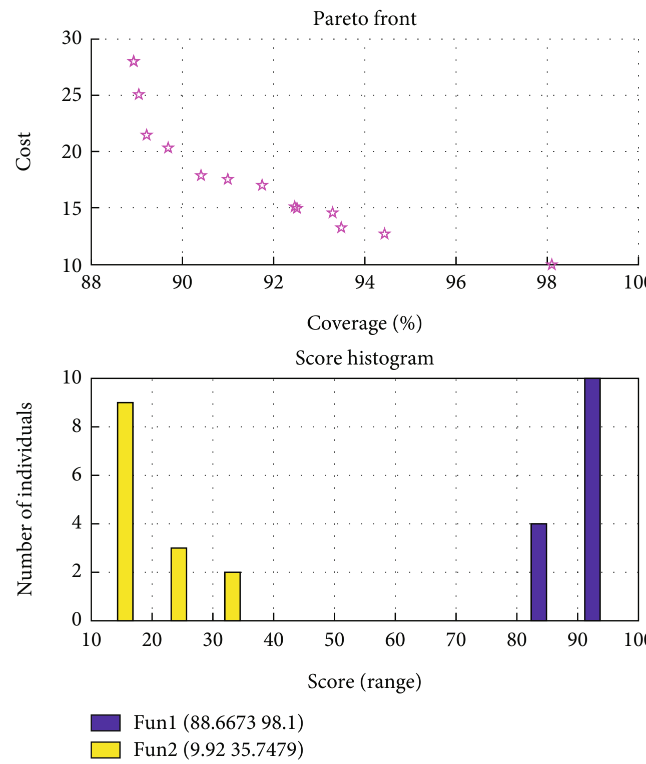

FIGURE 5: Pareto plot and the score histogram obtained with 100 population size for scenario 1.

TABLE 2: Coverage versus cost performance statistics.

	Cost				Coverage (%)			
Trial	Mean	STD	Min	Max	Mean	STD	Min	Max
1	9.94	0.03	9.93	10.01	91.95	2.54	88.60	95.91
2	9.93	0.01	9.92	9.96	90.75	1.15	86.60	93.09
3	10.03	0.17	9.92	10.37	91.73	3.25	86.60	97.06
4	11.01	0.80	9.92	12.52	92.68	3.35	88.62	98.10
5	15.78	4.37	9.92	23.21	90.05	2.83	88.65	98.10
6	13.27	2.42	9.92	17.45	90.08	3.33	88.62	98.10
7	15.64	4.62	9.92	23.13	90.19	3.00	88.61	98.10
8	13.88	2.98	9.92	18.94	90.49	3.08	88.63	98.10
9	13.13	2.36	9.92	16.68	90.46	3.07	88.65	98.10
10	30.98	14.94	9.92	53.80	90.10	2.86	88.64	98.10

designates the locations (positions) of the potential BS sites. A location is modeled as an (x, y) coordinate point. Each chromosome is encoded in the GA algorithm using binary values (i.e., tilt strings of 1 s and 0 s), with one at each bit for a potential BS location; otherwise, it is 0. Thus, the coordinates represent the location of each BS in the optimization area such that $b_{s1} = \{x_1, y_1\}$ is called the gene and $\mathrm{BSs} = \{b_{s1}, b_{s2}, \cdots, b_{sk}\}$ are termed the chromosomes, where k indicates the number of BSs. Table 1 gives the simulation parameters used in the proposed multiobjective genetic algorithm.

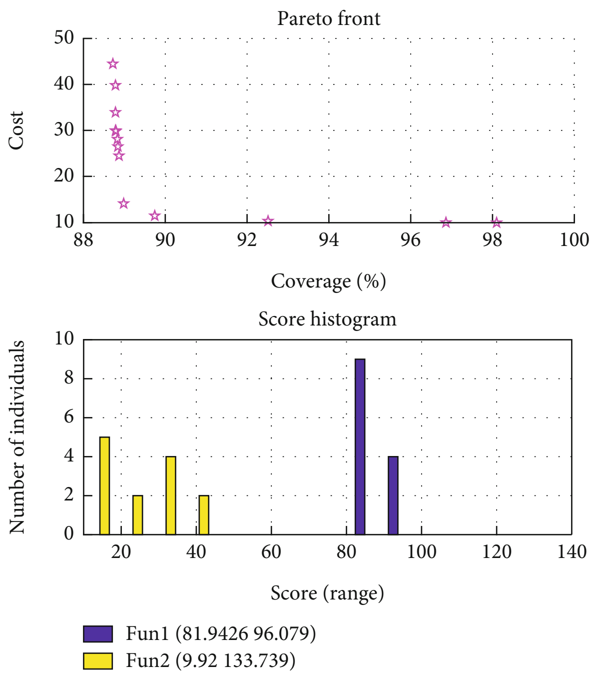

Figure 6: Pareto plot and the score histogram obtained with 10 population size for scenario 2.

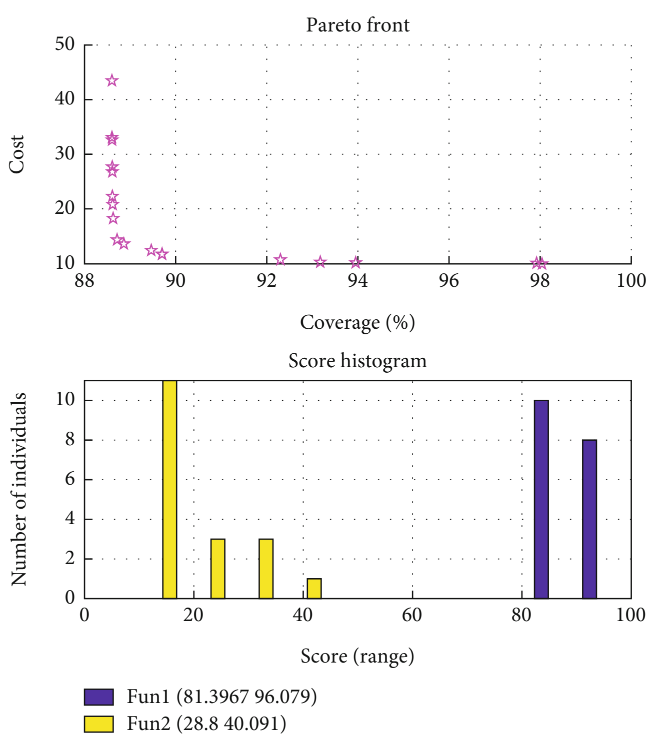

Figure 7: Pareto plot and the score histogram obtained with 40 population size for scenario 2.

4. Results and Discussion

The GA simulations are performed using a PC/Intel Core i5-500 CPU at 2.5.00 GHz, 3 GB Memory (RAM), and

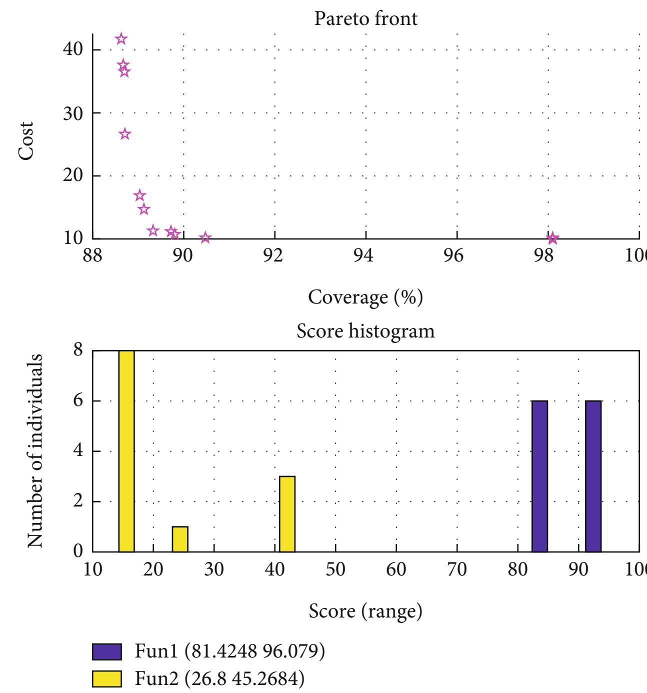

Figure 8: Pareto plot and the score histogram obtained with 70 population size for scenario 2.

Window 7 with 64-bit operating system in MATLAB 2018a environment. The GA embroils searching and tuning (optimizing) several key parameters to attain its desired optimal performance. The key parameters considered include population size, mutation, and crossover organizations. In order to obtain good results, several simulated tests were performed to ascertain the proper population size within the range of 10 to 100 individuals. In the simulation, two scenarios were considered. Scenario 1 considers optimal eNodeB placement with coverage and cost optimization, and scenario 2 considers optimal eNodeB placement with coverage plus user capacity and cost optimization. The key GA simulation parameters are provided in Table 1.

The first scenario considers optimal eNodeB placement with coverage and cost optimization. Here, the effect of different population sizes (10, 40, 70, and 100) on the cost of placing the eNodeBs (fun 2) and the percentage coverage of the eNodeBs (fun 1) are presented in Figures 2–5. Each figure's upper and lower parts indicate the optimal Pareto front and the minimum/maximum scores achieved after the simulation. An inspection of the statistics reveals that the cost objective function (fun 2) reduces as the population sizes grow larger until 70. Then, a further increase in the population to 100 produced a reduced population size. Thus, the maximum population size of 70 is simulated using the GA simulation parameters in Table 1. The results in Table 2 show the respective optimal coverage plus capacity and cost performance over ten simulation runs. This result implies that a population size of 70 individuals produced the best coverage performances of 88.59 and 98.10%, but at the cost of 9.92 and 36.90, respectively.

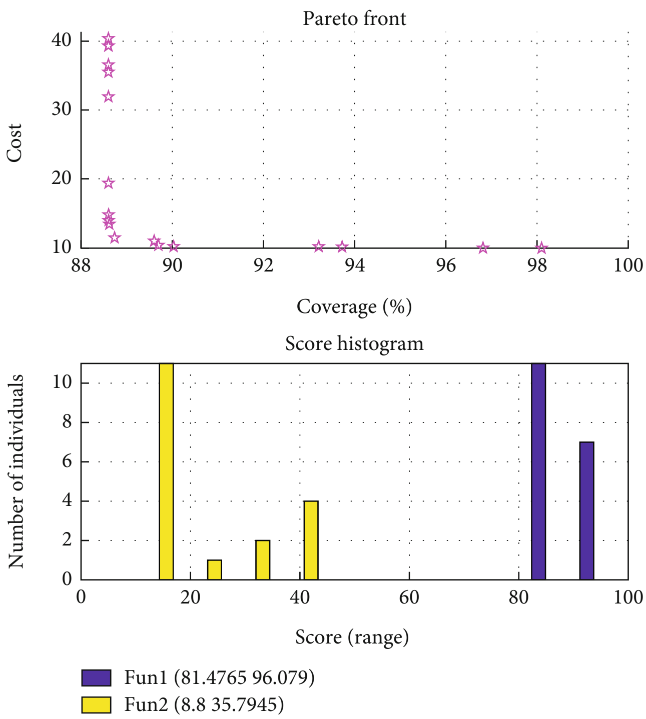

Figure 9: Pareto plot and the score histogram obtained with 100 population size for scenario 2.

Table 3: Coverage plus capacity versus cost performance statistics.

	Cost				Coverage (%)			
Trial	Mean	STD	Min	Max	Mean	STD	Min	Max
1	35.68	7.73	26.8	48.56	85.81	4.72	81.40	96.08
2	31.60	4.45	26.8	40.09	86.36	5.21	81.39	96.07
3	39.33	9.98	26.8	57.31	85.51	5.18	81.42	96.08
4	36.96	8.15	26.8	49.71	85.65	5.48	81.51	96.08
5	34.94	5.97	26.8	46.44	87.09	5.02	81.44	96.08
6	49.99	20.32	26.8	85.99	84.45	4.83	81.47	96.08
7	31.81	3.74	26.8	37.72	84.43	4.87	81.42	96.07
8	47.72	14.23	26.8	72.95	85.65	4.42	81.74	96.07
9	32.89	4.32	26.8	40.16	87.14	4.77	82.00	96.08
10	60.72	26.72	26.8	107.15	83.59	4.13	81.46	96.08

The second scenario considers optimal eNodeB placement with coverage plus user capacity and cost optimization. Here, the effect of different population sizes (10, 40, 70, and 100) on the cost of placing the eNodeBs (fun 2) and the percentage coverage of the eNodeBs (fun 1) are presented in Figures 6–9. The upper and lower parts of each figure indicate the optimal Pareto front attained and the minimum/maximum scores achieved after the simulation. An inspection of the figures reveals that the cost objective function (fun 2) reduces as the population sizes grow larger until 70. Further, an increase in population size to 100 produced a better solution by using the 70 population size with other GA parameters (Table 1). The results in Table 2 show the respective optimal coverage plus capacity and cost performance over 10 simulation runs. Again, the results imply that with a population size of 70 individuals, the best coverage plus capacity performances of 81.42 and 96.07% were produced at the cost of 26.80 and 35.26, respectively. Lastly, the coverage plus capacity versus cost performance statistics is presented in Table 3.

5. Conclusion

This study has presented a multiobjective genetic algorithm that integrates network coverage, capacity, and power consumption for optimal eNodeB placement in a simulated 4G LTE network. Optimal minimization of the cost of planning cellular networks generally calls for the most favorable selection and positioning of the eNodeB transmitter stations to meet the required coverage and capacity quality under certain constraints. Capacity and coverage planning are interconnected in contextual broadband wireless networks like 4G LTE. However, the ever-growing nonuniform user capacity demands coupled with mixed cellular network settings make the selection and location of eNodeB transmitter stations a nontrivial task. In order to address this problem, this paper proposes a multiobjective genetic algorithm-based methodology that performs optimal selection and location of base stations robustly. The optimal selection process minimizes the total network cost without compromising the desired coverage and capacity benchmarks. The proposed method performed favorably and can be explored to optimize a cellular network planning process in a related wireless environment.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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