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*Research Article*

# A Genetic Algorithm with Location Intelligence Method for Energy Optimization in 5G Wireless Networks

**Ruchi Sachan, Tae Jong Choi, and Chang Wook Ahn**

*Department of Computer Engineering, Sungkyunkwan University, 2066 Seobu-ro, Jangan-gu, Suwon-si, Gyeonggi-do 16419, Republic of Korea*

Correspondence should be addressed to Chang Wook Ahn; cwan@skku.edu

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The exponential growth in data traffic due to the modernization of smart devices has resulted in the need for a high-capacity wireless network in the future. To successfully deploy 5G network, it must be capable of handling the growth in the data traffic. The increasing amount of traffic volume puts excessive stress on the important factors of the resource allocation methods such as scalability and throughput. In this paper, we define a network planning as an optimization problem with the decision variables such as transmission power and transmitter (BS) location in 5G networks. The decision variables lent themselves to interesting implementation using several heuristic approaches, such as differential evolution (DE) algorithm and Real-coded Genetic Algorithm (RGA). The key contribution of this paper is that we modified RGA-based method to find the optimal configuration of BSs not only by just offering an optimal coverage of underutilized BSs but also by optimizing the amounts of power consumption. A comparison is also carried out to evaluate the performance of the conventional approach of DE and standard RGA with our modified RGA approach. The experimental results showed that our modified RGA can find the optimal configuration of 5G/LTE network planning problems, which is better performed than DE and standard RGA.

## 1. Introduction

The green domain is a new stage which aims to protect Earth and contribute to reducing the global warming by efficiently optimizing the energy consumption. Thus, the need for energy efficient wireless networks has drawn significant attention and focuses on the need to cut operating expenses and power usage of the telecommunications infrastructure, where radio networks represent about 80% of energy consumption. Furthermore, it is widely known that base stations (BSs) consume a significant amount of the energy (above 50%) in a cellular network [1, 2], which requires optimization of the transmission power and location of a BS regarding green aspects as shown in Figure 1.

The current 3G and 4G communication technologies were introduced to fulfill the massive demand for enhancing the speed of data traffic. Although the current communications technology has progressed impressively, it is still facing the increasing demands due to the development of smart devices. For this reason, various intensive studies towards 5G networks are being developed beyond the current 4G/IMT-Advanced standards and are moving towards the next phase of mobile communication. The most important requirement for the development of 5G network is the enhanced data traffic; that is, it has to support robustly an exponentially increasing number of devices [3]. Moreover, Long-Term Evolution (LTE) which is expected to be used with 5G networks has to deal with the reduced cell size of a BS [4], which leads to an increase in the number of BSs and raises a concern about increasing energy consumption of BSs.

Fortunately, 5G networks would benefit from the position information and fittingly guide the wireless network designs and optimization. There are many ways to find precise location information in wireless networks along with related distances, velocities, angles, delays, and predictable user behavior [5] in 5G networks. The information obtained from location-aware technology can be used to address numerous issues by implementing sharing and coexistence approaches to the challenges in 5G networks based on the user's position. By getting more accurate information of the users, power

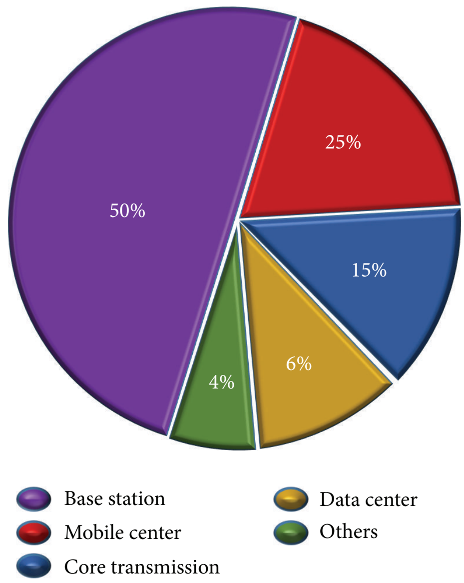


Figure 1: The energy consumption ratio in cellular networks.

efficiency can be improved by placing the sufficient base stations in a reasonable position based on the user's behavior. Overload and delay can also be reduced by using location-aware information.

In this paper, Real-coded Genetic Algorithm (RGA) was modified to allocate the base stations efficiently in a dense urban area regarding green aspects based on the user's optimal position. In other words, we modified RGA to solve our BSs allocation problem efficiently. We found out that standard RGA cannot converge to an optimal solution because its offspring is created by shuffling all chromosomes of its parents. By introducing BS Crossover Rate (BCR) to RGA and slight modification of mutation, our modified RGA can perform better than not only standard RGA but also differential evolution (DE) algorithm. Thus, the key contribution of this paper is that we modified RGA-based method to find the optimal configuration of BSs not only by just offering an optimal coverage of underutilized BSs but also by optimizing the amounts of power consumption.

In this study, we introduced a literature survey in Section 2 which dealt with optimizing the energy consumption in cellular networks. A system model which provided a description of the general framework for network planning in the context of 5G networks was explained in Section 3. The idea of implementing a modified RGA for optimizing the energy consumption of BSs was presented in Section 4. The experimental results obtained from our proposed method with the conclusion to this paper were illustrated in Sections 5 and 6, respectively.

## 2. Related Work

To date, many researchers have rigorously studied network design problems such as planning and optimizing performance in cellular networks with a considerable amount of published work, specifically on Universal Mobile Telecommunications System (UMTS) networks, LTE networks, and 5G networks. These studies aimed to estimate the optimal configuration for the locations of BSs, power requirement of each transmitter, antenna heights, relaying, and load balancing [6–8]. For instance, a variation of simulated annealing algorithm was proposed to find the optimal design for least cost and full coverage planning in Single Frequency Networks (SFNs) [9]. In this paper, it was stated that the worst solution found by the stochastic optimization algorithm based on numerical formulation is more efficient than the best solution found by the conventional coverage planning algorithm.

In [10], the authors stated that avoiding the maximum throughput regarding the minimizing energy consumption for designing an initial cell is efficient. When a coverage area is to be planned, network designers should estimate the calculations for neighbor interference, which is known as in-band Inter-Cell Interference (ICI). These methods are useful to avoid ICI while minimizing cell edge throughput.

In the network planning problem for WiMAX, the authors of [11] have determined a location-awareness issue by using the Evolutionary Algorithms (EAs) such as Artificial Bee Colony (ABC) and genetic algorithm (GA) to meet the traffic and coverage requirements for the targeted base stations efficiently. For minimizing the interference among cells and reducing energy consumption, the authors have divided a genetic algorithm into APS-GA (Genetic Algorithm with Adaptive Population Size) and FPS-GA (Genetic Algorithm with Fixed Population Size) to resolve the same problem for comparing these two algorithms efficiently. After the comparison of APS-GA and FPS-GA with ABC algorithms, it was observed that the ABC algorithm required minimum computational efforts, that is, less population and fewer evaluations, compared to the APS-GA and FPS-GA, while the balanced load could not efficiently satisfy the connected users.

In [12], the authors proposed an algorithm for joint uplink and downlink radio planning in a UMTS with the objective of minimizing the total energy consumption. The authors successively executed and subdivided the problem into two segments. Firstly, the authors tried to find the optimal positions of a fixed number of UMTS BSs in the given area of interest for targeting the optimization problem for best locations of BSs. The study aimed to minimize the total downlink power expense and at the same time the uplink outage that depends on the power abilities of Mobile Stations (MSs) under different restraints which sustain an acceptable Quality of Service (QoS) and satisfy the energy budget. In a second phase, they proposed an algorithm to select the minimal set of BSs with fixed locations based on the site awareness prospects.

In the perspective of energy consumption, some recent researchers [13, 14] have also discussed a method of achieving optimum power savings by switching off traffic underloaded BSs (eNBs) in LTE technologies. In the article [13], the vast amount of energy conservation is estimated by disabling unnecessary cells due to low traffic. As outlined by different studies that mostly tackle the sleep mode at mobile user's side, there is trade-off between outage of users and energy saving [14].

In [15], the authors have proposed a scheme on resource allocation for next-generation 5G networks. They calculated Signal to Interference Noise Ratio (SINR) based on the estimated path loss for each BSs and MSs pair. The power received from each user was compared with the given threshold value for the coverage area of macrocell and microcell as these cells come in the new features of the heterogeneous cell for the modern communication of LTE and LTE-Advance or beyond. In the conclusion, the authors had just proposed a scheme based on the radio planning for giving a good coverage to the users, but they did not care about optimizing the power consumption. Our paper has considered not only a good coverage but also power consumption by using the application of the EAs. There is scope for improving and optimizing network planning concerning the green aspects by using the new features available in 5G networks.

## 3. System Model

The system model assumes that we consider occupying the area of $[W \times H]$ Km$^2$ for 5G/LTE networks, where BSs can be installed in that given area with a set of candidate sites $H = \{h_1, h_2, h_3, \ldots, h_M\}$, which is given in this scenario. In order to place the BSs we need an installing cost which is associated with each of the candidate sites $C = \{c_1, c_2, c_3, \ldots, c_M\}$. The number of BSs in our simulation is denoted by $K$ and a set of BSs is denoted by $B = \{b_1, b_2, b_3, \ldots, b_K\}$.

As for the power of a transmitter, it is given that a BS has the transmission power in the range of 0.1 to 10 Watt. In reality, the value of antenna gain depends on the manufacture but, in our paper, it is assumed to be 18 dBi, and frequency is used as 1800 MHz [3, 16]. We employ the Cost-231 HATA urban propagation model as this model is also known as a radio propagation model, but it extends the urban HATA model to cover a more enlarged range of frequencies [17, 18]. The coverage probability in the area around the location $h_i$ with a threshold is less than the SINR. The SINR is calculated by using (1), where $M_g$ is the MHA gain, $P_t$ is the transmission power, and $I$ and $N$ refer to the interference and noise, respectively. Consider

$$\mathrm{SINR} = \frac{M_g \cdot P_t}{I + N}. \quad (1)$$

After calculating the value of SINR, the path loss (PL) is determined by

$$\mathrm{PL}\,[\mathrm{dB}] = P_t + G_t - L_b - \mathrm{SINR}, \quad (2)$$

where $G_t$ is the transmitter's antenna gain and $L_b$ is the body loss in dB. Also, the coverage area of a BS is formulated by

$$\mathrm{CA}_{b_i} = \sqrt[3]{3}\left(\frac{R^2}{2}\right), \quad (3)$$

where $R$ is the cell radius. The coverage probability in that area around the location $h_i$ with threshold $T$ is

$$P_c(h_i) = P(\mathrm{SINR}(h_i) > T). \quad (4)$$

Table 1: Decision variables.

| | |
|---|---|
| $Q_i$ | Available transmit power of a base station $b_i$ [0.1 to 10.0] Watt |
| $X_i$ | Location of a base station $b_i$ in $x$-axis |
| $Y_i$ | Location of a base station $b_i$ in $y$-axis |

## 4. The Proposed Algorithm

The application of EAs such as GA, DE, and RGA is a stochastic exploration technique for solving both constrained and unconstrained optimization problems, which are based on the natural selection. This procedure drives the biological evolution, in such a manner that a population of individual solutions is deceptively modified. At each phase, EA probabilistically selects promising individuals from the current population to be parents and then uses them to produce their offspring for the next-generation employing crossover and mutation mechanisms. As such, the application of EA provides satisfactory solutions to NP-hard optimization problems. Additionally, EA is also used to solve many practical problems such as finding an optimal position for a BS [9, 19] in a given area of interest.

Although EAs can solve NP-hard and several practical problems efficiently, designing the structure of EAs properly to a problem is required to achieve optimal performance. The problem that we tried to solve is as follows. Users are located in several dense areas, called urban areas, and we try to give service to as many users as possible by using least number of BSs and least transmit power by locating BSs to optimal positions. To solve this problem, we applied RGA because all the decision variables (transmit power and location) are continuous values. However, standard RGA could not find an optimal solution because the crossover of standard RGA shuffles all of the chromosomes, which makes a huge difference between parents and offspring. Besides, the mutation operator of standard RGA uses high standard deviation values, which also makes a huge difference. To solve this problem to make RGA perform better to solve network planning problem, we modified RGA by introducing BS Crossover Rate (BCR) to shuffle less and using small standard deviation values. These modifications make RGA outperform not only standard RGA but also DE approach in simulation results.

*4.1. Encoding.* The design of chromosomes is the essential aspect of EAs. The chromosome of EA is a set of decision variables that represents candidate solutions to an objective problem. As usual, a set of chromosomes is a possible solution to the target problem. We have to consider the design of chromosomes carefully for gaining a better representation of a solution to an objective problem while applying stochastic methods. The population consists of a set of individuals that contains the structure of chromosomes.

In this paper, the decision variables of our problem are given in the available transmit power ($Q_i$) and location of a BS ($X_i, Y_i$). In our chromosome representation, we used only continuous values. The proposed algorithm uses these decision variables for chromosomes as described in Table 1.

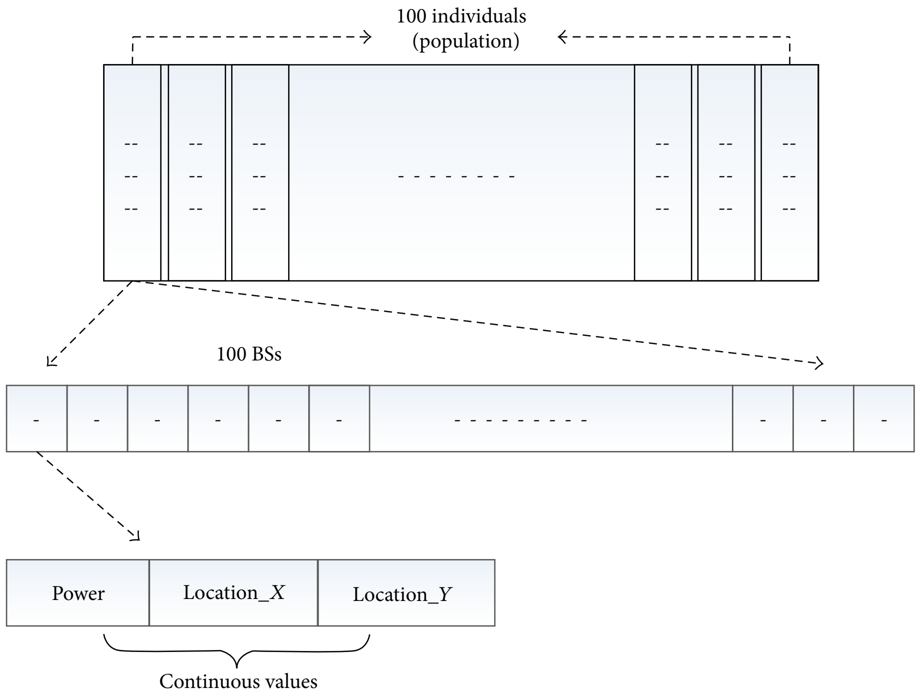


FIGURE 2: The structure of chromosomes.

In our encoding, the population consists of $P$ individuals and each individual is composed by $K$ BSs and one BS has three decision variables. In other words, a set of $K$ BSs falls within one individual, and a set of $P$ individuals falls within one population. Figure 2 shows how the structure of a population and individuals is organized in our encoding. The values that are out of the ranges given in this scenario for the BSs will be penalized by the given condition in an evaluation operator. By applying this mechanism, the modified RGA can find an optimal configuration.

*4.2. Genetic Operations.* In general, the operators of EAs consist of selection, crossover, and mutation. We apply roulette wheel selection for selecting potentially valuable solutions for recombination. According to the number of times, the roulette wheel is twisted equally to base on the size of the population and divides from the natural way. Each time the wheel stops it gives the fitter individual the greatest chance of being selected for the next generation and succeeding the mating pool. It can produce faster convergence speed, which has more potential to find fast optimal solutions.

The basic idea behind crossover is to increase genetic diversity. In this mechanism, it exchanges parent individuals' chromosomes and produces their offspring to make better individuals than both of their parents if they take the best characteristics from each of the parents. In our work, we applied box crossover. The upper bound and lower bound of two-dimensional bounded areas evaluate the range of the possible offspring. Box crossover is also a proper feature of RGA to maintain their population diversity efficiently. What we have modified in the standard RGA is that we introduce BCR by applying modified crossover in our proposed modified RGA means MRGA. As mentioned earlier, we found out that standard RGA cannot converge to an optimal solution because its offspring is created by shuffling all chromosomes of its parents. In our modified RGA, we are not shuffling every chromosome of an individual to the next generation by using BCR. Therefore, BCR prevents shuffle of all of the chromosomes, which makes a small difference between parents and offspring. The modified crossover is performed as Algorithm 1. In the Algorithm, the tilde indicates offspring.

Mutation is the part of a genetic operator which is also used to increase genetic diversity from one generation of a population to the next generation. It is meant to break frequently few chromosomes of a population to overcome a local optimum. We have applied slightly modified mutation in our modified RGA. The modified mutation is performed as Algorithm 2.

$D$ value contains a difference between standard RGA's mutation and our modified RGA. In standard RGA, $D$ value is fixed to use 10, while the modified RGA uses 100. Similar to BCR, this modification makes a small difference between parents and offspring, not a huge difference.

After crossover and mutation, our modified RGA conducts replacement operator. In replacement operator, if offspring has better fitness than a randomly selected individual from the population, then offspring replaces the individual. Otherwise, offspring discarded. The overall procedures of the proposed RGA are described in Algorithm 3.

*4.3. Fitness Evaluation.* A fitness function is used to help get a solution from the evaluation of chromosomes for the survival

**Begin**
  $r_1$ is a random individual from selected individuals
  $r_2$ is a random individual from selected individuals
  $r_{1,m}$ is a selected base station based on roulette wheel from $r_1$
  $r_{2,n}$ is a selected base station based on roulette wheel from $r_2$
  **For** $i = 0$ to $i = P$
    **For** $j = 0$ to $i = K$
      **If** a random number from $[0, 1]$ is less than BSR **Then**
        $\widetilde{Q_{i,j}}$= a random real number in $[\min(Q_{r_{1,m}}, Q_{r_{2,n}}), \max(Q_{r_{1,m}}, Q_{r_{2,n}})]$
        $\widetilde{X_{i,j}}$ = a random real number in $[\min(X_{r_{1,m}}, X_{r_{2,n}}), \max(X_{r_{1,m}}, X_{r_{2,n}})]$
        $\widetilde{Y_{i,j}}$ = a random real number in $[\min(Y_{r_{1,m}}, Y_{r_{2,n}}), \max(Y_{r_{1,m}}, Y_{r_{2,n}})]$
      **Else**
        $\widetilde{Q_{i,j}} = Q_{r_{1,m}}$
        $\widetilde{X_{i,j}} = X_{r_{1,m}}$
        $\widetilde{Y_{i,j}} = Y_{r_{1,m}}$
      **End If**
    **End For**
  **End For**
**End**

Algorithm 1: The modified crossover.

**Begin**
  **For** $i = 0$ to $i = P$
    **For** $j = 0$ to $i = K$
      **If** a random number from $[0, 1]$ is less than $M_r$ **Then**
        $\widetilde{Q_{i,j}} = \widetilde{Q_{i,j}} + N(0, (Q_{\max} - Q_{\min})/D)$
      **End If**
      **If** a random number from $[0, 1]$ is less than $M_r$ **Then**
        $\widetilde{X_{i,j}} = \widetilde{X_{i,j}} + N(0, (X_{\max} - X_{\min})/D)$
      **End If**
      **If** a random number from $[0, 1]$ is less than $M_r$ **Then**
        $\widetilde{Y_{i,j}} = \widetilde{Y_{i,j}} + N(0, (Y_{\max} - Y_{\min})/D)$
      **End If**
    **End For**
  **End For**
**End**

Algorithm 2: The modified mutation.

**Begin**
  Initialize Users
  Initialize Population
  Evaluate Population
  **While** Termination criteria does not met **Then**
    SelectedIndividuals = RouletteWheel(Population)
    Offspring = ModifiedBoxCrossover(SelectedIndividuals) (Algorithm 1)
    Offspring = ModifiedMutation(Offspring) (Algorithm 2)
    Replacement(Population, Offspring)
  **End While**
**End**

Algorithm 3: Pseudocode of modified RGA.

Table 2: Simulation parameters.

| | |
|---|---|
| Carrier frequency | 15 GHz |
| Frame structure | FDD |
| Population size | 100 |
| Maximum number of iterations | 50 |
| Maximum number of generations | 200 |
| Transmission power ($P_t$) | [0.1 to 10] Watt |
| Receiver antenna gain | 18 dBi |
| MHA gain ($M_g$) | 2 dB |
| Cable loss ($C_l$) | 2 dB |
| Noise figure ($N$) | 2 dB |
| Body loss ($L_b$) | 2 dB |
| Area | Urban |
| Maximum number of BSs | 100 |
| Longitude (upper-left $X$) | −100 |
| Latitude (upper-left $Y$) | 100 |
| Longitude (lower-right $X$) | 100 |
| Latitude (lower-right $Y$) | −100 |
| Number of users | 10000 |
| Propagation model | Cost-231 HATA Model |

of next generation. The objective function in our approach can be formulated for getting the fitness ($F$) of the optimal network configuration as follows:

$$F = \left[ \frac{UE^2}{T_P \times \text{ActiveBSs}^2} \right], \tag{5}$$

where $UE$ is the number of connected users to the BSs, $T_P$ is the total transmit power, and ActiveBSs is the number of BSs that connected to at least one user.

As for the termination criteria, we defined the maximum number of generations $T_g$. After executing simulation $T_g$ generations, the proposed algorithm terminates the procedure and returns the best-so-far solution.

## 5. Experimental Results

In this section, the performance evaluation of the modified RGA is presented. At first, the modified algorithm is evaluated concerning the best-optimized power level and its location for 5G BSs with standard RGA and DE. In this scenario, we obtained the experimental results regarding the number of active base stations and transmission power with the connected users and compared with conventional DE. Finally, we also conducted the best, average, and worst fitness, transmission power, the number of active base stations, and their connected users of the modified RGA.

Table 2 lists the simulation parameters which we have considered in this paper. In the table, there are some constant variables such as bandwidth, carrier frequency, frame structure, receiver antenna gain, MHA gain, cable loss, noise figure, and body loss and decision variables such as population size ($P$), maximum number of iterations, and transmission power (Q). In our experiments, the environment area is assumed to be representing $(X, Y)$ as $(-100.00, 100.00)$ and

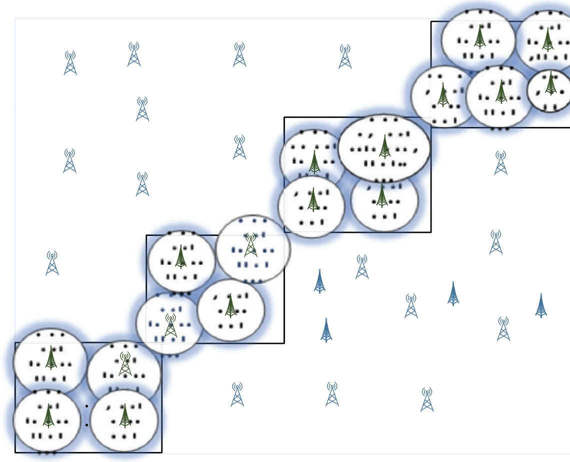

Figure 3: Simulation environment.

$(100.00, -100.00)$ in meter, where base stations and users are allocated in given area of interest. The users are allocated as an exact point by using their accuracy range in the given area as this is the new feature of 5G networks. Figure 3 shows a proposed simulation environment where we can see the following: rectangle boxes are representing cities with an area entirely covered with users mostly called urban area. The circle shapes are serving a coverage area by optimum base stations that were being proposed by the EA with the extended version of RGA.

We have performed the experiments and reported values to estimate the best configuration for 5G BSs. Our experimental results gathered over 50 independent runs. The compared algorithms are described as follows:

(i) The modified RGA, with BSR = 0.1 and $M_r$ = 0.2.

(ii) Standard DE(rand/1/bin) with SF = 0.5 and CR = 0.9.

(iii) Standard RGA with $M_r$ = 0.2.

First of all, Figure 4 shows the convergence graphs of the modified RGA, DE, and RGA. As we can see, the modified RGA's performance is better than DE and RGA towards the upcoming generation. By comparing the algorithms (the modified RGA, DE, and RGA), we notice that RGA is getting slightly the same and worse fitness value towards a generation. This is because of shuffling happening again and again by using box crossover, where the modified RGA and DE are better than RGA as they are not changing their chromosomes every time in crossover operator.

Figure 5 shows that DE and RGA can keep less activated BSs and serve similar users at the same time in comparison with the modified RGA. This result leads to less fitness value as it depends on the objective function. The randomness of the EAs provides more of a chance for the network operator to find better BS combinations. However, this advantage comes at the expense of higher computational complexity that depends on the standard crossover and mutation of DE and RGA. That is why the modified RGA increases the number of the base stations more with less power consumption than DE and RGA to achieve better fitness.

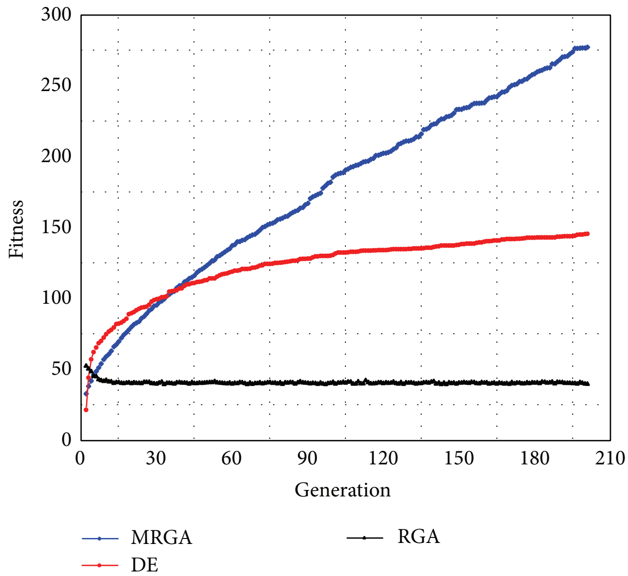


Figure 4: The convergence graphs.

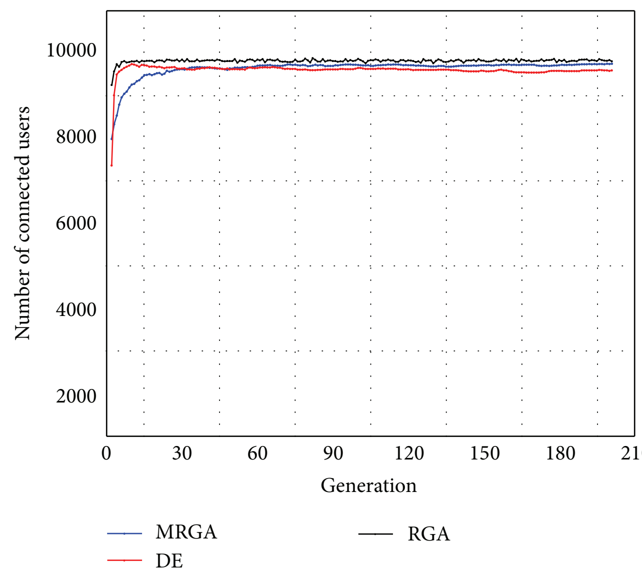


Figure 6: Comparison of the number of connected users.

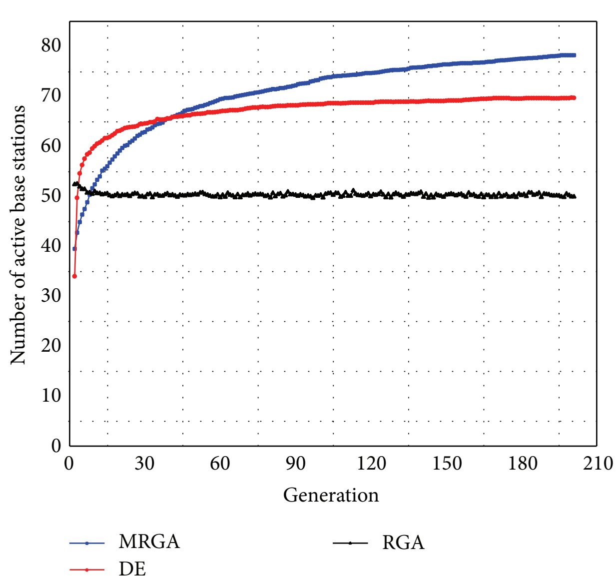


Figure 5: Comparison of the number of active BSs.

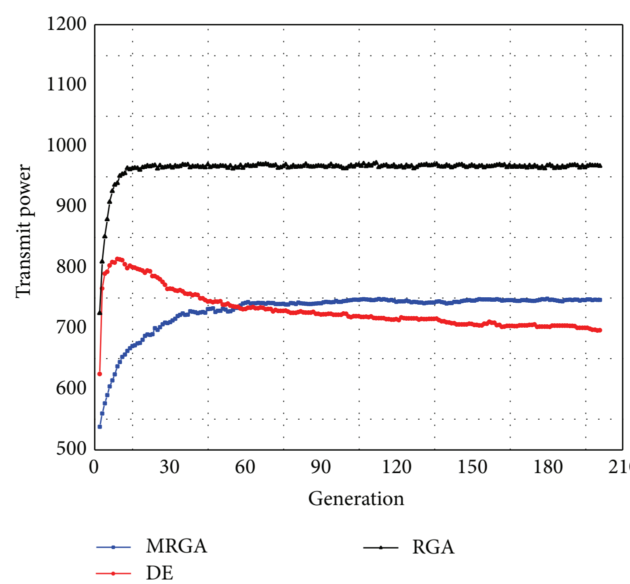


Figure 7: Comparison of the total transmit power.

In Figure 6, the most numbers of connected users are similar in the modified RGA, DE, and RGA, where we can see that coverage area is covered well for giving an excellent service to the connected users by using these three techniques. There is no much difference in performing to providing a good coverage in our simulation environment mentioned in Figure 3 by applying the modified RGA, DE, and RGA regarding the connected users.

Figure 7 plots the performance of transmission power consumption in between the modified RGA, DE, and RGA towards the upcoming generation, where we can see that DE and modified RGA are performing quite similarly after reaching around 60th generation due to replacing their chromosomes less than RGA. By doing less shuffling, the modified RGA and DE have performed well in terms of the power consumption. As a result, our goal of the mitigation of the energy consumption is reached by adjusting the BSs transmission power according to getting the optimal locations of BSs and covering the coverage area for satisfaction by the quality of service. In other words, our modified algorithm has less total power consumption in comparison to DE and RGA but still it can serve more users than DE and RGA, which makes the huge difference in their fitness.

At last, we have also gathered all the best, average, and worst results of our modified RGA approach. The results are plotted as fitness value in (a), transmission power in (b), a number of active base stations in (c), and the number of connected users in (d), respectively, in Figure 8.

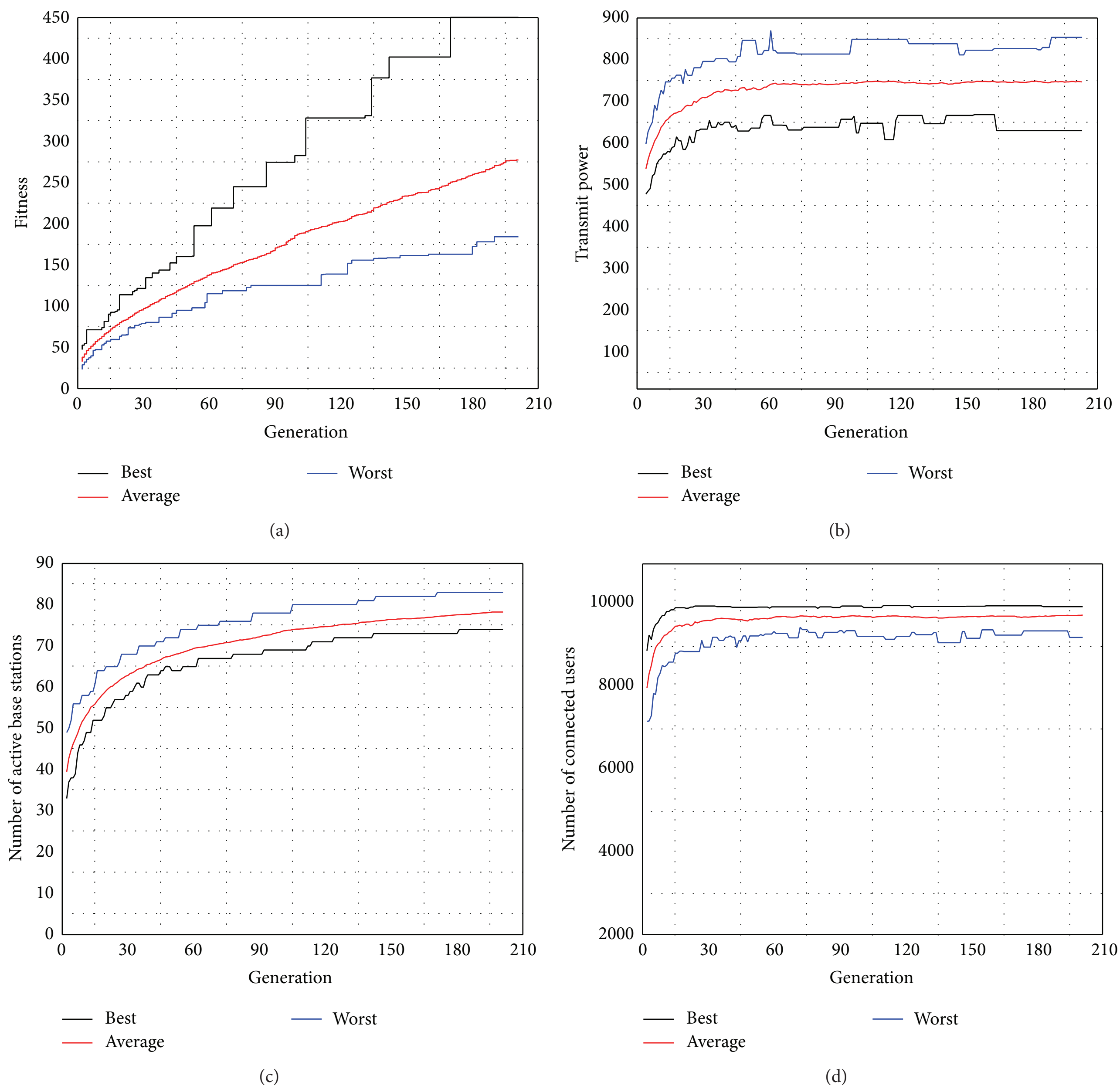


Figure 8: The best, average, and worst convergence graphs of the modified RGA.

Tables 3 and 4 show that our modified RGA is statistically significantly better than DE and RGA. As we can see in both of the tables, the $t$-value gives $2.01303E-22$ for DE and the modified RGA and $5.4306E-33$ for RGA and MRGA. Hence, it is proven that the modified RGA has statistically better performance than DE and RGA.

Table 3: The $t$-value of 49 degrees of freedom is significant at a QOS level of significance by two-tailed $t$-test for MRGA and DE.

| | The modified RGA | DE | $t$-value |
|---|---|---|---|
| Average | 277.270614 | 145.654808 | |
| St. dev. | 56.7086340687 | 15.8800909196 | $\mathbf{2.01303E-22}$ |

## 6. Conclusion

In this paper, we have offered the modified RGA method for allocating the optimal positions of the future 5G base stations. The modified RGA has achieved sufficiently better performance in terms of transmit power saving and total connected users for 5G networks with providing optimal coverage. We established to evaluate the location intelligence of the BSs to be in concession with green communications. The modified RGA has successfully found the considerable better configuration by comparing with conventional DE and RGA to locate proper location and adjusting the range of the power level additional to coverage constraints. In our ongoing and future

Table 4: The $t$-value of 49 degrees of freedom is significant at a QOS level of significance by two-tailed $t$-test for MRGA and RGA.

| | The modified RGA | RGA | $t$-value |
|---|---|---|---|
| Average | 277.270614 | 39.76453 | |
| St. dev. | 56.7086340687 | 2.399219965 | **5.4306*E*−33** |

work, we will study optimal BSs and their cost regarding frequency level using an advanced EA. We will also investigate the chronological evolution of the energy in the standard of satisfactory QoS.

## Competing Interests

The authors declare that there are no competing interests regarding the publication of this paper.

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