Optimizing the Location of 5G Network Base Stations Taking into Account Intra-System Interference

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Keywords: 5G, MmWave, Structure Optimization, Genetic Algorithm, Propagation Models, SINR.

Abstract: This work is devoted to the structural optimization of 5G networks, specifically addressing the problem of base station (BS) placement optimization in indoor network deployment. A method is proposed for determining the number and optimal spatial coordinates of BSs in indoor environments, such as shopping malls or telemedicine centers, under random user distribution to ensure maximum coverage and network throughput while explicitly accounting for intra-system interference. The problem is characterized by dynamic environmental conditions, high user density, heterogeneous service demands, and the requirement for guaranteed network quality indicators, as well as the need to ensure reliable coverage in complex indoor layouts. As a result, the BS placement task is formulated as a nonlinear NP-complete integer programming problem. A genetic algorithm was employed to solve it, incorporating adaptive selection, crossover, and mutation operators. The fitness function was mathematically formulated to maximize the average user data rate while including penalty terms for BS overload, excessive BS proximity, and violations of minimum quality of service (QoS) thresholds. Numerical simulations demonstrate the effectiveness of the proposed approach, confirming that the developed method allows for structural optimization of 5G networks through intelligent base station placement under the influence of intra-system interference.

1 INTRODUCTION

In the context of rapid digital transformation and the exponential growth of data volumes, 5G technology has acquired strategic importance as a foundational component of modern information infrastructure. The efficient deployment of 5G networks is critical for ensuring sustainable economic development, strengthening national security, and enhancing the quality of life for citizens.

Networks based on 5G serve as a fundamental service platform enabling a wide range of applications spanning various societal activity sectors. In particular, in telemedicine, 5G facilitates remote medical consultations and real-time patient monitoring [1]. Furthermore, 5G contributes to the development of intelligent transportation systems, providing seamless connectivity between vehicles and infrastructure, which enables traffic optimization and improves road safety.

In the industrial domain, 5G unlocks the potential for automation of production processes and implementation of remote control and equipment monitoring systems, thereby increasing operational efficiency and productivity. In the entertainment sector, 5G supports high-resolution video streaming and virtual and augmented reality technologies, creating new opportunities for interactive content delivery.

In this context, the problem of optimizing the network design process arises it is necessary to develop a network architecture capable of supporting the efficient operation of modern services, including telemedicine systems, intelligent transport infrastructure, industrial automation, and other innovative applications.

It is evident that 5G networks operate within a constantly evolving and dynamically changing environment, where the number of users, their mobility patterns, and service demands such as data rate and latency vary continuously. These ongoing environmental changes significantly impact on the characteristics, architecture, and operational trajectory of 5G networks. Given that such influences are persistent in nature, the structure and behavior of a 5G network transform every stage of its life cycle. Under these conditions, optimizing a 5G network as a complex and adaptive system becomes feasible only through continuous adaptation. One of the most practical and effective forms of such adaptation is structural optimization, particularly the optimization of BS placement. Accurate BS positioning is essential for ensuring adequate coverage, minimizing inter-cell interference, and maintaining high network performance under dynamic conditions. To account for the impact of electromagnetic interference on bandwidth allocation, an accelerated genetic algorithm can be used [2].

An important and highly relevant task is optimizing 5G BS placement in indoor environments, such as shopping malls, medical institutions, and educational facilities. In medical institutions, where services like telemedicine and remote health monitoring are in use, the optimization of BS placement becomes a matter of vital importance.

In shopping malls, where many visitors simultaneously use mobile devices for navigation, shopping, entertainment, and communication, optimal BS deployment is essential to ensure high-quality and reliable connectivity.

The high user density, the rapid fluctuation in user presence, the diversity of services, and the requirement for robust coverage in complex indoor layouts all indicate that the problem of 5G BS placement is a complex, multi-criteria optimization challenge. It demands a comprehensive analysis that accounts for numerous factors, including coverage, throughput capacity, deployment cost, and energy efficiency. Solving this problem would enable the network's structural optimization, provide uniform coverage, avoid network congestion, and ensure high-quality service delivery to end users.

The problem of optimizing the placement of BSs has been studied by numerous researchers who have proposed various approaches and methodologies. In [3], a method for planning the optimal deployment of 5G BSs is introduced, combining conventional techniques with differential evolution algorithms while considering parameters such as transmission speed, planning accuracy, and planning depth.

In [4], under the conditions of a heterogeneous network structure, a heuristic solution based on a genetic algorithm is proposed to solve the BS placement problem. In [5], the time complexity of solving such classes of problems is addressed through optimization based on a genetic algorithm, aiming to reduce computation time.

In [6], the optimal placement of BSs in open terrain is investigated. The solution is also based on a genetic algorithm and considers factors such as installation costs, Euclidean distances between BSs, maximization of the coverage area per BS, and guaranteed throughput per user.

In summary, it can be stated that the problem of structural optimization specifically, the placement of base stations in 5G networks remains a highly relevant research challenge that has attracted significant attention from the scientific community. The proposed solutions in the literature are largely based on the use of genetic algorithms, which enable adaptation to the dynamic nature of the problem.

However, it is important to note that many existing studies have been conducted under "ideal conditions" where critical factors such as intra-system interference were not considered. This simplification limits the applicability of such models in realistic deployment scenarios, particularly in dense indoor environments.

Intra-system interference, arising from signal collisions between neighboring base stations and between user terminals, is a critical factor that limits the performance and reliability of 5G networks. As the density of BS deployments and user terminals increases, the network becomes increasingly susceptible to significant degradation in communication quality.

Existing models often fail to account for intra-system interference, which leads to reduced throughput, increased latency, deterioration in user QoS, and inefficient utilization of the radio spectrum.

Therefore, studying base station placement optimization in 5G networks with explicit consideration of intra-system interference is a pressing research and engineering challenge. The development of advanced mathematical models and optimization algorithms aimed at minimizing the impact of interference is essential to enhancing network performance and reliability, ensuring high-quality service delivery, and improving the efficiency of spectrum usage. When developing a genetic algorithm, it is necessary to consider numerical analysis methods that can be used to optimize the algorithm's parameters [7]. For effective quality of service provisioning in wireless mesh networks, packet-level resource allocation methods can be used [8].

2 PROBLEM FORMULATION

This study aims to develop a method (algorithm) for determining the spatial coordinates of base stations (BSs) in the context of deploying a 5G network in indoor environments - such as shopping centers or telemedicine facilities - under conditions of random user distribution. The proposed solution aims to ensure maximum network coverage and throughput while explicitly considering the impact of intra-system interference arising from signal collisions between users and adjacent base stations.

It is evident that during the techno-economic justification of 5G network topology design, it is necessary to consider key performance indicators such as throughput, QoS, reliability, and deployment cost.

The described problem belongs to the class of structural optimization problems, and in terms of optimization theory, it can be formulated as follows:

There exists a bounded indoor environment (e.g., a business center or a medical facility) within which a 5G network must be deployed. The network consists of several BSs, each assigned a unique identifier and associated with spatial coordinates.

Within the boundaries of this object, a fixed number of user terminals (UEs) are randomly distributed across the area (see Fig. 1).

The objective is to determine the optimal number of base stations and their optimal locations in such a way as to provide effective signal coverage over the entire area, maximize the average data rate per user and account for indoor propagation conditions, where radio signals are affected by multipath, obstructions, and intra-system interference.

This interference arises from adjacent base stations and other nearby users operating within the same frequency bands. The resulting problem requires multi-criteria optimization, where spatial arrangement directly impacts performance indicators such as coverage, throughput, and QoS.

The formulated problem of 5G base station placement optimization is a nonlinear, NP-complete, integer programming task. Exact solutions to such problems typically require exhaustive search over the solution space; however, this approach becomes impractical for high-dimensional instances due to the exponential growth of computational complexity.

As a result, a wide range of heuristic methods have been developed and are commonly employed to obtain near-optimal solutions within acceptable computational time. Among the well-known heuristic approaches for nonlinear optimization are the penalty function method, the projected gradient method, the interior-point method, and the branch and bound technique. These methods are generally based on pseudo-random search strategies and systematically evaluating the explored solution space.

Figure 1: A typical shopping mall scenario.

In this context, nature-inspired algorithms, particularly genetic algorithms (GAs), have demonstrated significant potential. Thanks to their mutation mechanism, which introduces random perturbations into candidate solutions, GAs can escape local minima and explore broader regions of the search space.
Moreover, genetic algorithms are well suited to solving large-scale problems due to their:

- ability to handle a large number of variables;
- lack of dependence on gradient information and inherent parallelism allows for computational acceleration.

As noted in [9], GAs have been successfully applied to various optimization problems in infocommunications. For these reasons, a genetic algorithm was selected as the core method for solving the optimization problem described in this study.

3 PROPOSED METHOD

As input data for the model, we consider:

- a matrix of spatial coordinates for the base stations (BSs);
- the technical characteristics of the BSs;
- the geometric parameters of the deployment environment.

The environment is modeled as a square area of size $A \times A$ meters, containing N mobile users $n_i = (x_i, y_i)$ and M base stations $m_j = (x_j, y_j)$, which are initially randomly positioned using the Monte Carlo method.

The objective is to determine the coordinates of the base stations that maximize the average data rate for all users, while explicitly considering intra-system interference, including interference from neighboring BSs and nearby users (1).

$$M = \{m_1, m_2 ... m_K\}, \quad m_j = (x_j, y_j) \tag{1}$$

Accordingly, the objective function of the optimization problem can be formulated as follows (2):

$$\begin{aligned} \max F(M) = \frac{1}{N}\sum_{i=1}^{N} R_i - \alpha \sum_{i=1}^{N} \delta(R_i < R_{\min}) - \\ -\beta \sum_{i=1}^{N} \delta(n_j > n_{\max}) - \gamma \sum_{i=1}^{N}\sum_{i=1}^{N} \delta(\|b_j - b_k\| < d_{\min}) \end{aligned} \tag{2}$$

R_i is the data rate for user i, $R_{\min}$ is the minimum acceptable user rate, $n_{\max}$ is the maximum capacity per BS, $\delta(\cdot)$ is the indicator function, α, β and γ are penalty coefficients.

The achievable data rate for a given user i can be estimated (3) using the Shannon–Hartley theorem, which accounts for the signal-to-interference-plus-noise ratio (SINR):

$$R_i = B \cdot \log_2 \left(1 + \frac{P_{i,j^*}}{\sum_{k \neq j} P_{i,k} + N_0} \right) \tag{3}$$

where B is the available channel bandwidth (Hz),, P_{i,j^*} is the power received by user i from its serving base station j^*, $P_{i,k}$ is the interfering power received from base station, N_0 is the thermal noise power.

The power received by user i from its serving base station j^* calculated as follows (4):

$$P_{i,j^*} = \frac{P_{BS} G_{BS}}{PL_{i,j}}, \tag{4}$$

where P_{BS} is the transmit power of the base station, G_{BS} is the antenna gain of the base station, $PL_{i,j}$ is the path loss between BS j and user i.

For the selected environment (a shopping mall), we apply the Indoor Path Loss Model [10], which captures signal propagation characteristics in complex indoor scenarios with obstacles and dense user presence (5).

$$PL_{i,j} = PL(d_0) + 10v \log_{10}\left(\frac{d_{i,j}}{d_0}\right) + \sum_{k=1}^{K} L_k + X_\sigma, \tag{5}$$

where $PL(d_0)$ is the free-space loss at the reference distance., $d_{i,j} = \|n_i - m_j\|$ is the distance between the BS and user, v is the path loss exponent (environment-dependent, e.g., 2–4), L_k is the loss introduced by the k-th obstacle (e.g., wall, glass), K is the number of obstacles, $X_\sigma \sim N(0, \sigma^2)$ is a Gaussian random variable accounting for shadow fading,.

In terms of the genetic algorithm (GA), the solution space is represented as a population consisting of multiple individuals, where each individual encodes a candidate deployment configuration of M base stations.

Formally, an individual (chromosome) can be represented as (6):

$$X = \begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \dots & \dots \\ x_M & y_M \end{bmatrix} \in {}^{M\times 2}, \qquad (6)$$

At the next step, a total of K individuals (candidate solutions) are generated to form the initial population of the genetic algorithm. $\left\{X^{(1)},\dots,X^{(K)}\right\}$. The coordinates of each base station $m_j = \left(x_j, y_j\right)$ are randomly initialized within the boundaries of the selected area, ensuring that all initial placements lie within the defined indoor environment $A \times A$.

For each individual, the objective (fitness) function is evaluated based on the resulting network performance. Specifically, the data rate is calculated for every user, and the average user throughput is used as the primary fitness metric.

Individuals that achieve higher average user rates are selected to advance to the next generation. Among a randomly chosen subset of the population, the best-performing individual is identified as an elite solution and retained.

Next, a crossover operation is applied—this involves combining the coordinates of two parent individuals to generate an offspring. Formally, given two parent solutions (7), (8):

$$X_{child} = \lambda X_1 + \left(1-\lambda\right) X_2,\ \lambda \in [0,1], \qquad (7)$$

This operation blends the base station positions from two selected parents to produce a new candidate solution, promoting diversity and the exploration of promising regions in the solution space.

Another essential step of the genetic algorithm is the mutation operation, which involves a random displacement of a single base station within the boundaries of the deployment area.

$$m_j \leftarrow m_j + \delta,\ \delta \sim N\left(0,\sigma^2\right). \qquad (8)$$

4 EXPERIMENTAL RESULTS

Figure 2a illustrates the initial random placement of 10 base stations (red triangles) within a 100×100 meter indoor area containing 200 active users (blue dots), uniformly distributed using the Monte Carlo method. This initial configuration demonstrates non-uniform coverage, with evident clustering of base stations in certain regions and coverage holes or "dead zones".

Figure 2b shows the optimized deployment of base stations (green triangles) obtained through the genetic algorithm-based optimization. The base stations are now more evenly distributed, significantly reducing poor coverage areas and more effectively adapting to user density across the environment.

As shown in Figure 2, after optimization, the base stations were placed more uniformly across the service area, leading to improved coverage and reduced dead zones.

To provide a clear visual representation of how this optimized placement affects signal quality, SINR heatmaps are presented in Figures 3a and 3b, illustrating the spatial distribution of the signal-to-interference-plus-noise ratio (SINR) before and after optimization.

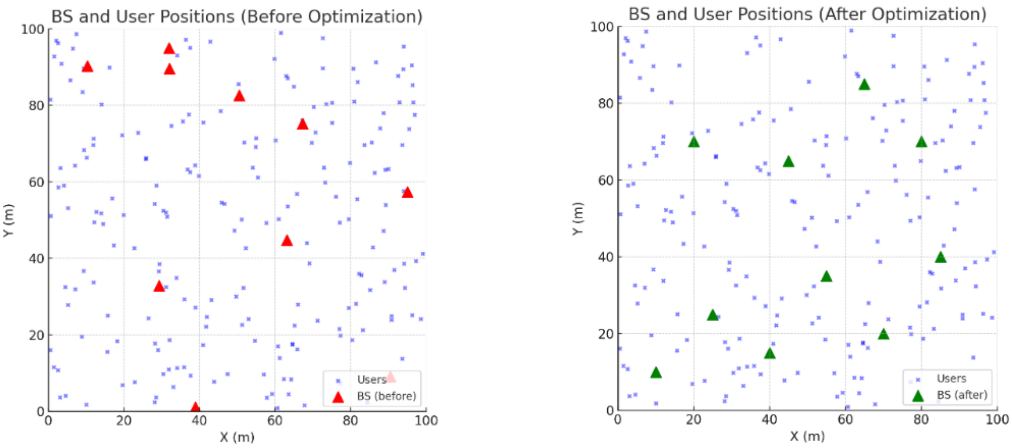
The improvement in SINR directly impacts user service quality, particularly on the achievable data rate. Figures 4a and 4b present the heatmaps of the estimated user data rates (in Mbps) before and after optimization, respectively.

It is evident that after optimization, a significant portion of the area achieves higher data rates, while low-throughput zones have been substantially minimized.

5 CONCLUSIONS

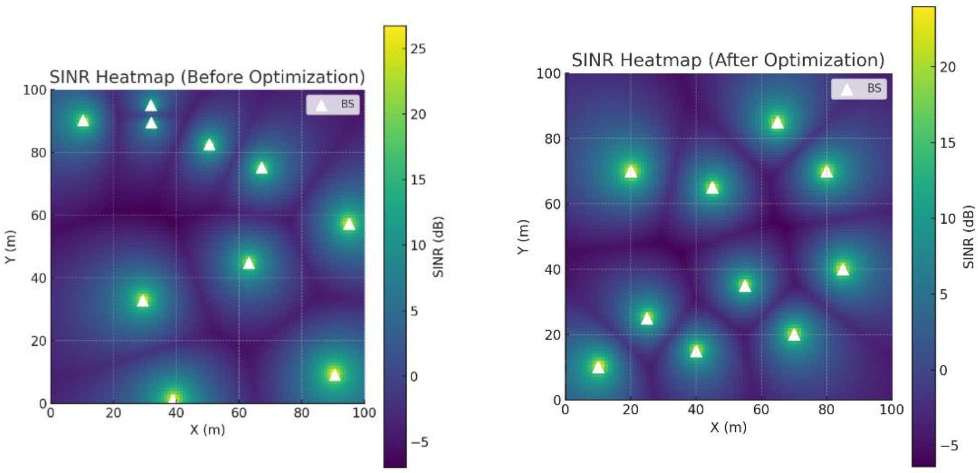
In this study, a comprehensive mathematical model of a fifth-generation (5G) mobile communication network was developed, considering the spatial distribution of base stations (BSs), intra-system interference, signal level, SINR, and data rate for each user. Particular attention was given to the problem of optimal BS placement in indoor environments, such as shopping malls and medical centers, which is especially relevant due to high user density and complex propagation conditions.

To solve the optimization problem, a genetic algorithm was implemented with adaptive operators for selection, crossover, and mutation. The mathematical formulation of the fitness function aimed to maximize the average user data rate, while incorporating penalties for base station overload, excessive deployment density, and violations of minimum quality of service (QoS) requirements.



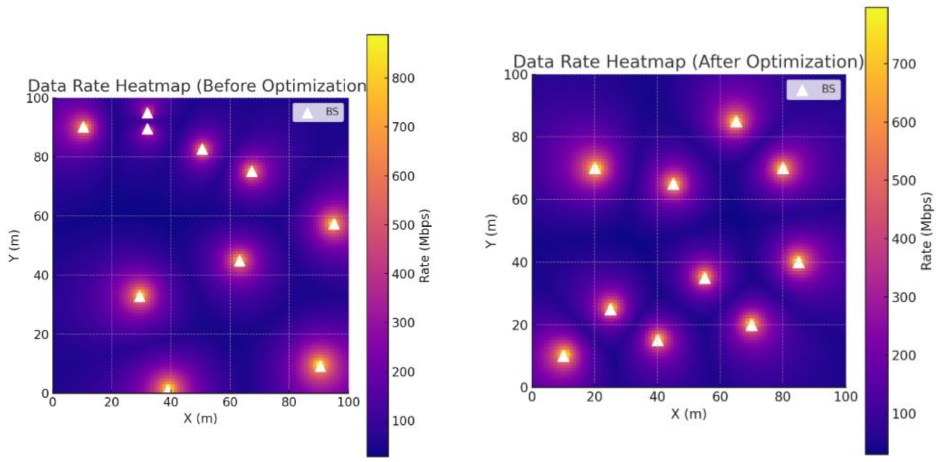
a) b)

Figure 2: Distribution of users (a) and base stations (b) within the considered area.



a) b)

Figure 3: SINR heatmap before (a) and after optimization (b).



a) b)

Figure 4: Rate heatmap before (a) and after optimization (b).

As a result of numerical simulations conducted for a 100×100 meter area with 200 users and 10 base stations, a significant improvement in key network performance metrics was observed. In particular, the average user data rate increased from approximately 123.25 Mbps to 133.76 Mbps after optimization.

Furthermore, the number of areas with poor coverage (i.e., low SINR) was significantly reduced, and users experiencing data rates below 5 Mbps were effectively eliminated. The heatmaps of SINR and data rate confirmed that the optimized BS placement provides a more uniform distribution of resources across the area and ensures effective coverage throughout the environment.

The research confirms the effectiveness of evolutionary approaches for solving the problem of radio network planning, particularly in high-density indoor environments with limited physical space.

Further development of the proposed model may include:

- support for multi-floor environments,
- path loss modeling those accounts for wall materials and obstructions,
- adaptive frequency resource management, and
- the application of deep learning methods for predictive base station placement based on user traffic patterns.

ACKNOWLEDGMENTS

We acknowledge support by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG) and the Open Access Publishing Fund of Anhalt University of Applied Sciences.

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