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Next Generation Wireless Network Deployment using Machine Learning based Multi-Objective Genetic Algorithm

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Abstract

6G networks provides ubiquitous connectivity, reduced delay and high-speed gigabit connection. The Introduction of AI to the planning process of 5G beyond networks is crucial to ensure the efficient deployment of cells and the minimization of SINR (signal to interference plus noise ratio). The Multi-Objective Genetic Algorithm (MOGA) to take care of the planning issue in 5G and beyond network organizations. This is accomplished by expanding the already existing 4G and 5G infrastructure. The MOGA endeavors to limit the deployment cost, the interference between the cells and maximize the percentage of the clients being served. This work is the solution for deployment problem in next generation networks. The randomly deployment of the cells decreases the network performance, increases the interference and not effective in terms of deployment cost and leads to Dense Multi-Objective Deployment problem. An optimised deployment strategy is employed in the proposed work to address this issue. This work based on optimized utilization of the network through planning. This decreases the cost of deployment, interference and redundancy. It enhances the coverage capacity and quality of service. This excellent coverage of users which is close to 85% is obtained over existing 4G and 5G infrastructure, thereby reducing the total cost of deployment. The work is compared with the meta-heuristic algorithms. The comparison results shows that the proposed work achieves higher SINR, improved coverage capacity than the meta-heuristic algorithms.

Keywords: Genetic algorithm, MOGA, URLLC, 6G, Base stations, HelNet, SNIR, Fitness Function and EPC

1. INTRODUCTION

The next generation of cellular networks, or 5G or 6G, promise improved coverage, low latency, high-speed gigabit connections, greater data rates, and cost and energy effectiveness. According to general consensus, the aggregate data rate or area capacity of 5G networks will increase by 1000x compared to that of 4G, and the edge rate or 5% rate of 5G networks will be between 100 Mbps and as much as 1Gbps, which is approximately 100x more advanced than current 4G systems, which have a typical 5% rate of around 1Mbps. With 5G, which is an order of magnitude quicker than 4G, the latency for sending and receiving data might decrease to 1 millisecond from an average of 50 milliseconds in 4G. Extreme network densification, traffic offloading, and millimetre wave technology—which offers a constrained range of electromagnetic wave frequencies ranging from 30 to 300GHz—are the fundamental technologies enabling the aforementioned network performance. The improved spectral efficiency is a result of developments in Massive MIMO technology [1-3]. There are two basic techniques for 6G deployments: non-standalone and standalone 6G deployments [4]. In 88 countries, 224 mobile service providers are currently building 5G networks as of April 2019. Considering that 6G also supports non-public networks for industrial applications [5-6], The deployment of today's 4G and 5G networks aims to boost peak rate and spectrum efficiency, while in the 6G era, the emphasis is on dense HetNet architectures to improve network efficiency [6]. Massive MTC-Low cost, wide-spread, and long-lasting devices, such as wearables, sensors, actuators, and tracers. URLLC (C-MTC) Extremely low frequency, great availability, and high dependability [7]. Different base station types introduced by 6G are extremely important during deployment as they can be utilised to create or generate various deployment plans. many base stations, including Micro, Pico, Femto, and Macro [8-10]. In order to meet the strict requirements for latency, dependability, and high accuracy positioning that industry 4.0 scenarios will bring in the indoor and private areas, the coupling of 6G technology with enterprise network solutions becomes extremely important [11-12]. The Figure 1 depicts the integrated 6G network. To function, standalone 6G does not require an LTE EPC. Instead, it combines 6G radios with a 6G core network that is cloud-native [13-16].

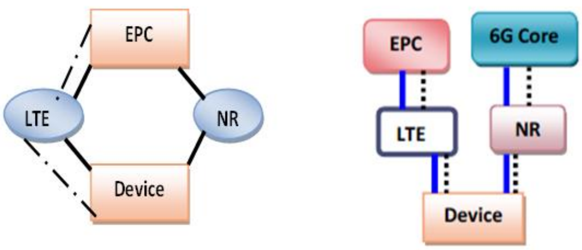

Figure 1. Non-standalone and standalone network

6G is a heterogeneous network that can accommodate a variety of user requirements and radio access technologies. To meet the requirement of heavy data traffic, heterogeneous networks have more cells in a certain location. The Femto, Pico, Micro, and Macro cells are the four different base stations as depicted in Figure 2.

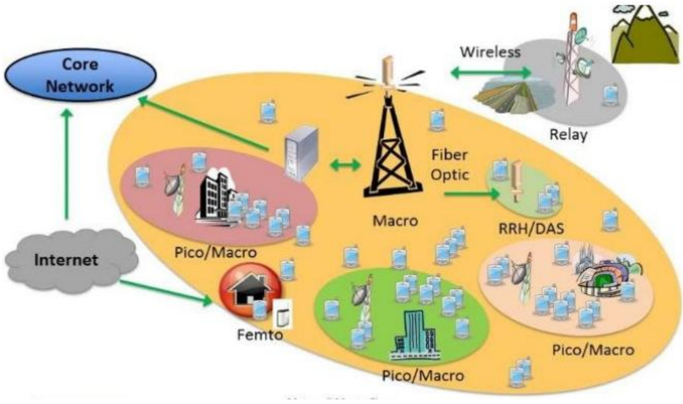

Figure 2. 6G heterogeneous network

1.1 Problem statement, motivation and scope

Since 6G employs a different spectrum and distinct base station types (Macro, Micro, Pico, and Femto), a new strategy is required to overcome the difficulties associated with using millimetre waves, which have shorter wavelengths. Since millimetre waves can only travel a short distance a greater number of cells or base stations have to be deployed to achieve exceptional capacities and ultra-low latencies. One of these challenges includes the cost of deployment and maintenance of Macro base stations. This is solved by effectively deciding on the type of cell that can be deployed to minimize the total cost and maximize user coverage and capacity. Using Evolutionary Search Techniques of Machine learning, an optimized deployment strategy is generated for deploying different base stations corresponding to 5G in an efficient manner so that maximum number of users are connected with quality internet speed and are provided with comprehensive coverage. Although 5G offers better bandwidths, the available bandwidth cannot keep up with the rising demand. more sensors, portable technology, and M2M connectivity Mobile data rates will continue to rise, and 6g, or new radio access technology, meets this need.

The paper is organized as abstract, introduction to the technology, problem statement, motivation and scope in section-1; Section-2 tells about the related work. Section-3 describes the proposed work originality. Section-4 depicts system design. Section-5 describes experiment and analysis and section-6 provides the conclusion and future work. In the proposed work, bottom-up approach is used, where initially individual components are designed and then integrate them together. This approach involves designing of different components like base station, network functions, generating candidate points for users and base station location and genetic algorithm which involve different genetic operators which help in determining the fitness of the plan generated [17-18]. Assumptions are made in this work such as factors such as rain attenuation, foliage loss such as tress; buildings, path loss, etc. do not affect or distort signals that are being transmitted [19].

2. RELATED WORKS

Numerous research papers about optimizing the base station deployment and technologies relevant to recent work. Inferences drawn by referring to different publications include different properties of base stations such as radius covered, power transmitted, maximum and minimum number of users that can connect to the base stations, factors affecting the deployment, algorithms for generation of efficient strategies, incorporating the techniques of Machine Learning with Networking to be able to generate best plans for deployment of base stations. "Expected to reach $4.7 Billion in annual spending by the end of 2020, private LTE and 5G networks are increasingly becoming the preferred approach to deliver wireless connectivity for critical communications, industrial IoT, enterprise and campus environments, and public venues. The market will further grow at a CAGR of 19% between 2020 and 2023, eventually accounting for nearly $8 billion by the end of 2023" [6-8]. "Deployment of Private 6G Networks are intended for sole use of the private entity with enhanced security, privacy and improved coverage within the organization which will enable their journey towards digitalization, helping them reduce operational inefficiencies and maximize business performance, thereby improving customer experience" [9].

This paper examines these subjects, distinguishing key difficulties for future examination and fundamental 5G normalization exercises, while giving a far-reaching outline of the current writing, and specifically of the papers showing up in this uncommon issue [20]. Unlike traditional industrial wireless technologies based on Wi-Fi and Bluetooth, 5G provides a definite QoS for critical industrial applications [21]. The major objective of this project is to enhance network connectivity and make it possible in areas where private networks are needed, particularly in industries. This is achieved by using the magma framework that provides network operators a flexible and extendable mobile core network solution [22]. The main objective of the paper is as per resource usage in C-RAN the BBU is put in the active or in-active mode to minimize energy consumption in C-RAN of 5G technology. As per our proposed C-RAN application, the proposed PSO algorithm 90% minimizes energy consumption and maximizes energy efficiency compared with existing work [23-24].

3. ORIGINALITY

The goal of this project is to put a Multi-Objective Genetic Algorithm (MOGA) to use in order to address the planning problem in 6G enterprises. This is achieved by building on the 3G, 4G, and 5G framework already in place and introducing the aforementioned tiny cells. Using Evolutionary Search

Technique, the deployment of the 6G network is improved. The MOGA aims to optimize the proportion of clients being serviced while minimizing deployment costs and cell interference. Genetic Algorithm along with properties of different base stations corresponding to 5G to generate an ideal deployment strategy of base stations which makes sure that utmost users are covered at the same time providing acceptable data rates and coverage. From experimental results obtained after running optimizations through several generations, we are able to summarize that a coverage of more than 85% is obtained. Graphs are plotted representing SINR, cost and fitness vs. generation indicating the trend in change in fitness. We are able to observe and draw insights that fitness value reaches a maximum and does not increase post that value even if a greater number of generations are used. The proposed implementation considers various types of base stations with their properties, user requirements, and optimization parameters such as cost of deployment, user coverage and interference. The results imply deploying multiple small cells with minimal cost instead of deploying macro cells. This significantly reduces the deployment cost by improving the user coverage. The paradigm of shift from macro cells to small cells in incorporated using mutation. Mutation is implemented as greedy algorithm, in which changing of types of cells is solely dependent on random selection following custom distribution rather than using uniform distribution. Custom distribution is based on the deployment cost at the particular state in the chromosome. The project can be extended to a point where the constants of the fitness formulae can be self learnt from generational learning, rather than assuming values in the initial phase.

4. SYSTEM DESIGN

This project used Multi-Objective Genetic Algorithm which is an unsupervised learning algorithm there's no labelled data set. The data is generated by an algorithm that uses efficient techniques to generate random positions in the form of coordinates for users as in depicted in Table 1 and based on these user points coordinates are generated for the base stations to be deployed. The generated data is fed to genetic algorithm for further optimizations which results in an efficient plan to deploy base stations such that utmost number of users are connected and are provided with acceptable data rates.

Table 1. A base station deployment plan's representation of cell coordinates

B0	B1	...	Bn
(100.7, 200.0)	(2000.007, 5.0)	...	(500.0, 3500.0)

4.1 A weighted MOGA-based strategy for the deployment of 6G cells

A weighted MOGA is a form of genetic algorithm that calculates the fitness value while attempting to balance many problem parameters. This is accomplished by creating one fitness value from the weighted sum of its parameters, which can then be minimized or maximized. An individual in the population was chosen to be represented using real value floating-point. A population's representation of each individual is made up of a group of components called genes. whereas the person is referred to as a chromosome. The term "pool" refers to the chromosomal collection. Each chromosome's gene has two values, an x value and a y value, which correspond to the coordinates of the cells in the area of interest. Each member of the population is a plan, each of which has cells and users currently connected to it and each of which has users associated with it. The phase involved in genetic algorithm is represented in Figure 3.

Figure 3. Different phases involved in genetic algorithm

A selection procedure is used on the population's current members to simulate the survival of the fittest. The candidate's "fitness" is a key consideration in the selection process. The exploitation of decent people is caused by selection, which forces the entire population to select fitter people in order to survive into the following generation. Tournament Selection, Roulette Wheel Selection, and Stochastic Universal Sampling are the three selection techniques that were used. However, it is crucial to first talk about the fitness value computation that establishes the chromosome's quality because it establishes the value that the selection methods will use. Using Equation (1), the fitness of a plan is determined.

$$\Gamma = \alpha \cdot \frac{\max(\phi) - \phi}{\max(\phi)} + \beta \cdot \frac{\Omega}{\max(\Omega)} + \gamma \cdot \frac{\max(\phi) - \phi}{\max(\phi)} \tag{1}$$

Where φ denotes the plan's cost, ψ denotes interference and α, β, γ denotes the weights assigned to each item in the equation, and Ω denotes coverage ratio. The goal of the genetic algorithm is to increase the value of Γ. The algorithm is known as a Multiple Objective Genetic Algorithm since the fitness value contains three parameters α, β, γ. The better individual fitness has an easier time surviving and reproducing, which improves the genetic makeup of the entire community. Equation (2) defines the coverage ratio and Equation (3) refers to the cost parameter.

$$\Omega = \beta \cdot \frac{U_{\text{covered}}}{|U|} \tag{2}$$

$$\phi = \sum_{i=1}^{F_n} \sum_{j=1}^{|C_i|} F_{i,j} \tag{3}$$

The weight of user coverage, |U| the number of users in the AOI, |U| covered the number of users covered by the cell. The number of cell types is indicated by Fn, and $F_{i,j}$ stands for the deployment costs of the j^{th} cell of the i^{th} type. The total number of deployed cells is represented by $|Ci|$. The interference value in Equation (1) is defined in Equation (4) as follows, presuming complete orthogonality between the subcarriers within the cell.

$$\psi = \sum_{k=1}^{n} \frac{P_{k,b(k)}}{\sigma^2 + I_k} \tag{4}$$

Where σ^2 is the thermal noise power, I_k is the inter-cell interference from nearby Base stations, and $P_{k,b(k)}$ is the received power on subcarrier n allotted for user k by its serving base station $b(k)$. All base stations are considered to be transmitting at their highest P_{BS} levels. The transmit power for the macro and micro base stations is designated as P_{BS} macro and P_{BS} micro respectively. The user's mobile node determines the received power using Equation (5) and the base station transmits with a power equivalent to P_{BS}/N_{SUB} depending on which cell the user connects to.

$$P_{k,i}(\text{dB}) = 10\log_{10} \frac{P_{\text{BS}}}{\kappa_{\text{BS}}} - L_{k,i} \tag{5}$$

$P_{k,i}$ is the power received in decibel by user k from ith base station. P_{BS} is the power of the base station in watts. K_{BS} is the maximum capacity of users for a particular base station. $L_{k,i}$ is the path loss between user k and its serving base station i. The path loss can be calculated using as shown in Equation (6).

$$L_{k,i}(\text{dB}) = 92.4 + 20\log_{10}(d_{k,i}) + 20\log_{10}(f) + A(d_{k,i}) + R(d_{k,i}) + F + h_{k,i} \tag{6}$$

Where f is the carrier frequency in GHz and $d_{k,i}$ is the Euclidean distance between the user k and the base station i. Small cells (Micro, Pico, and Femto) employ 28GHz while macro cells use 3.5GHz to transmit their signal. The atmospheric attenuation, $A(d_{k,i})$, is set at 0.06 at 28 GHz, while the rain attenuation, $R(d_{k,i})$, affects the power at higher frequencies. F is the foliage loss, which has an impact on 28GHz tiny cells. The channel gain (Shadowing, fading) between base station i and user k is represented by the random variable $h_{k,i}$. At 5G networks that operate at high frequencies, foliage losses for mmw frequencies should be taken into account because they are large. The calculation for the foliage loss F is as follows:

$$F = 0.2(f)^{0.3}(r)^{0.6} \tag{7}$$

where f is the frequency in MHz and r is the depth of the foliage in metres. The working of Genetic algorithm and control flow is depicted in Figure 4 and 5 respectively. The user locations are represented by two-dimensional coordinates. User density is determined for each grid by breaking the entire area of interest into chunks of varying sizes. The number of candidate points is chosen based on the user density in a specific grid. A particular grid needs additional base stations because of the higher user density. The domain for base station deployment in the initial population is a set of candidate sites. Pool-Sample from a population, a collection of the individuals who are the primary solutions and are eligible for application of genetic operator selection after which propagation to application of further genetic operators takes place.

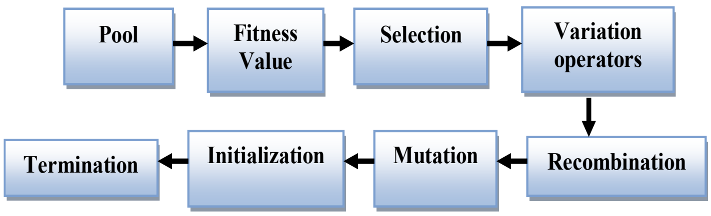

Figure 4. Genetic algorithm process

Fitness or Fitness value is a value that is used to determine the quality of the solution and it is determined based on the problem. The fitness can be made of one quality of an individual, or many, in which case the calculation is known as a Multiple Objective Genetic Algorithm (MOGA).

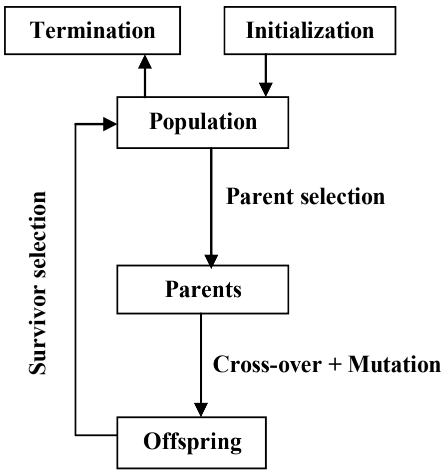

Figure 5. Working of Genetic algorithm and control flow

Selection is the first process or the first genetic operator that is used for optimization; it is the process of choosing individuals or parents that will allow surviving and propagating into the next generation to follow the principle of Survival of the fittest. Variation operators are the operators that are used for the introduction of new solutions into the population. There are two types in genetic algorithms, mutation or unary operator and crossover/recombination or n-ary. Mutation is a unary activity that is liable for presenting stochastic change on the qualities or genes of the chromosomes. Crossover or Recombination as it usually known, is the second kind of operator that is used for presenting new solutions or individuals into the pool, and it works by choosing at least two solutions from the pool to act like parents for creating offspring solution also known as new individual(s) by utilizing qualities from all parents included. Termination alludes to the method involved with halting the genetic algorithm, and there are numerous ways of carrying this out, however the most well-known ones are-Terminate after completion of N generations or Terminate after the genetic variety has fallen below a certain acceptable threshold.

Generation and Initialization phase

- Phase 1- Generation and initialization
- Generate Users
- Candidate points are allowed set of points for deploying base stations
- Generate Candidate points
- Populate Generation ‘0’

Evaluate the generation

- Select the best Offspring
- Phase 2 –Evaluation

A population is represented by each Generation. Each chromosome symbolises a plan, and a population is a set of chromosomes. A plan is a deployable unit that includes user locations, cell configuration, connections between users and base stations, and all of the deployment's features, including cost, SINR, and coverage. A chromosome's fitness can be used to determine its goodness. A high fitness value chromosome has a better chance of surviving one generation and moving into the following one. Selection is the process of choosing chromosomes for future generations that have greater coverage, cost, and SINR.

Evolution: phase-1 process

- Evolution
- Connect users and cells
- Disconnect Idle cells
- Connect cost of deployment
- Calculate SINR of Generation
- Calculate fitness of Generation

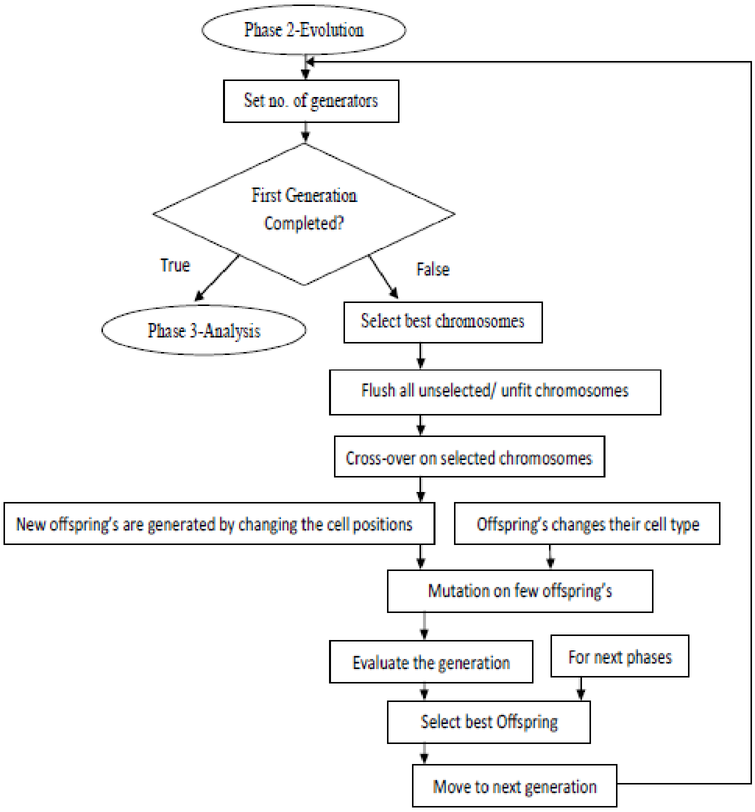

Figure 6. Evolution phase-2 process

The entire population must be assessed after creation, whether by populating the chromosomes or by crossover followed by mutation. Every chromosome in the population is evaluated, which entails connecting users to base stations, removing deployed base stations that do not meet user thresholds, and computing various metrics like the quantity of users connected, deployment cost, total power received SINR value, and fitness value. The SINR value, deployment cost, and user coverage of the plan are used to determine the fitness value for each chromosome. When choosing chromosomes for future generations, fitness value, which measures how effective a certain plan is crucial. Figure 6 shows the evaluation process in action.

5. EXPERIMENT AND ANALYSIS

The obtained results for a 4000 × 4000 km^2 area are analyzed below. Fixed Macro Base Station, Macro Base Station, Micro Base Station, Pico Base Station, and Femto Base Station are the base stations that were initially distributed randomly. Each base station has a distinct transmission power and area covered, correspondingly. Table 2 lists the number of base stations, the deployment's radius(km), power (watts), and the deployment's minimum and maximum users. This table lists the simulation parameters for each Base Station. The 4000 × 4000Km^2 spaces are distributed randomly among 900 people in the ideal setting. The bare minimum user count in a grid needed to produce a candidate point is known as the user threshold.

Table 2. Representation of cells co-ordinates in a base station deployment plan

Base station	No. of BS used	Radius in km	Power in watts	Minimum users	Maximum users
Fixed Macro	15	1000	40	10	30
Macro	15	1000	40	10	30
Micro	30	250	10	5	20
Pico	15	100	10	2	15
Femto	10	50	10	1	10

Figure 7 displays the simulation findings. User Density = (User / Threshold) in grid, keeping user threshold as 2.

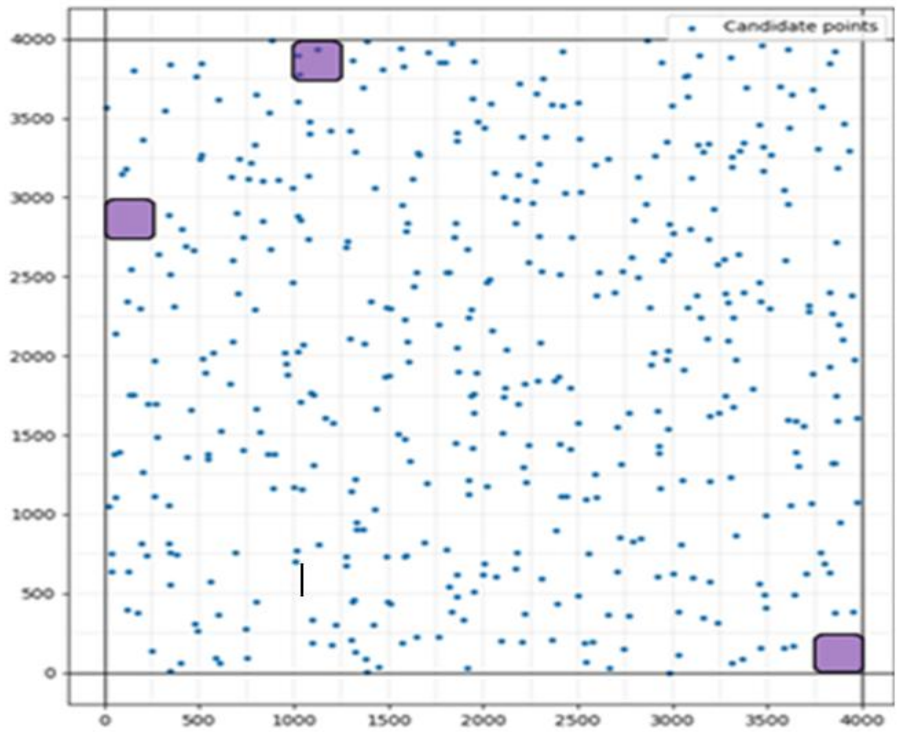

Figure 7. Candidate point's generation

Figure 8 depicts the generation of user points in two dimensional spaces. This image provides the information about the random distribution of user in a specified cell area.

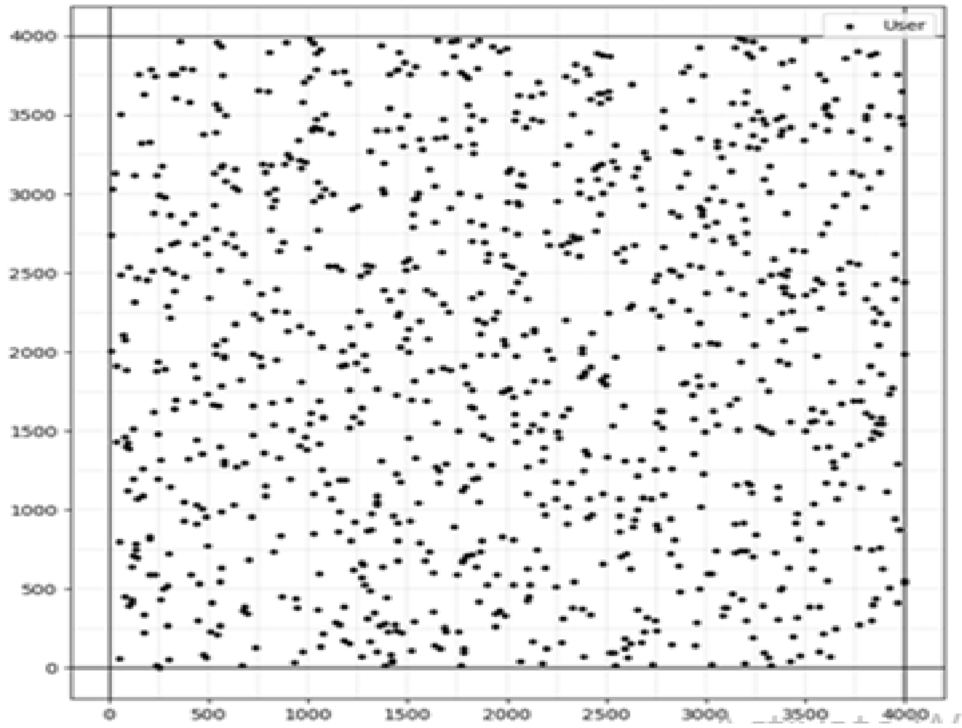

Figure 8. Generation of user points

The simulation results below in Figure 9, depicts the generation of initial population.

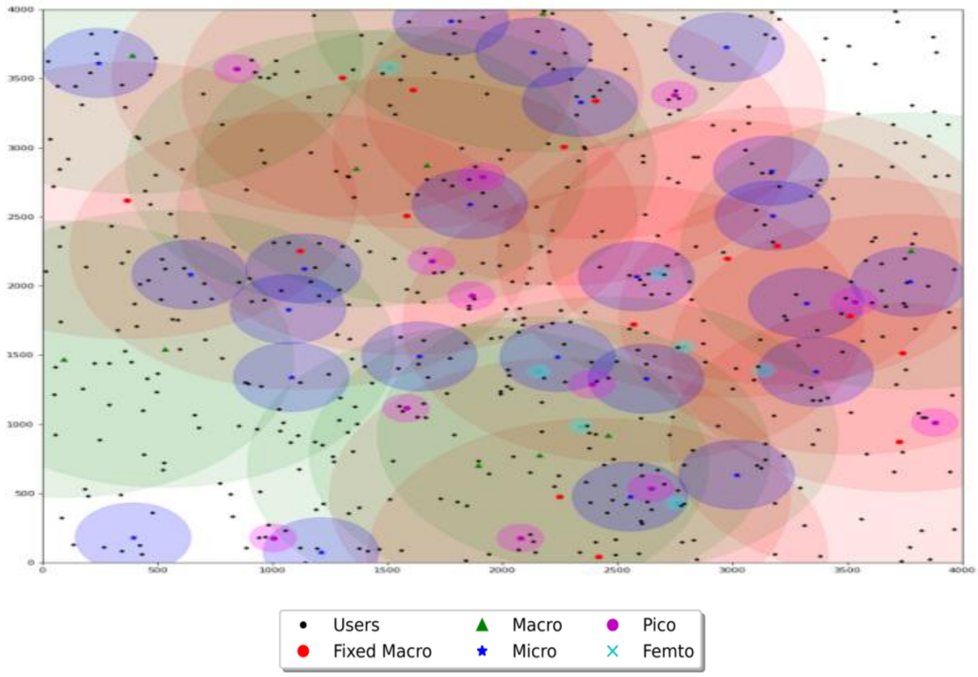

Figure 9. Generation of initial population

Figure 10, represents a class diagram. As per the work flow, the entire program module is divided in to five sub-modules namely User class, Generation class, BestBs class, Pan Class and Cell class. A specific task is assigned to each class. A user class has the information about the connected base stations, closed base stations and received power level. A cell contains the information about the maximum and minimum number of users connected to the cell area, the cell radius, state and power level etc. Similarly best base station, network plan and generation class's description and correlation between the classes are depicted.

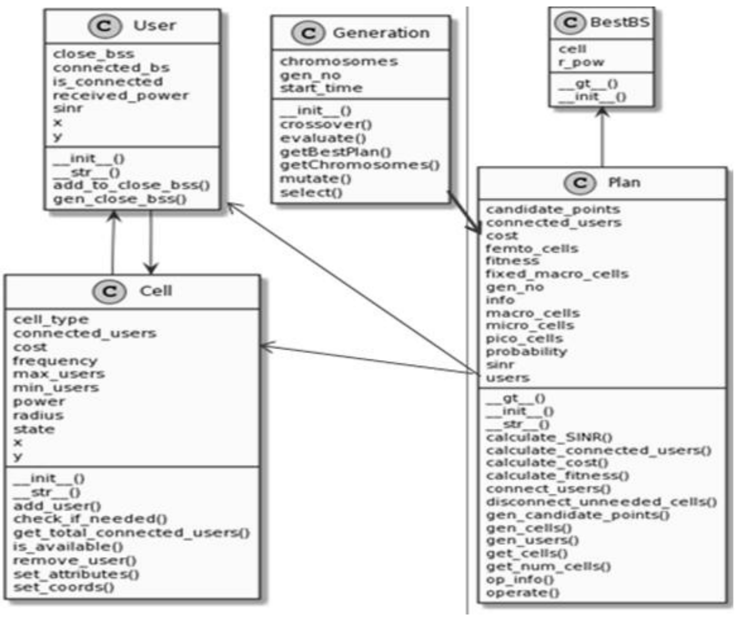

Figure 10. Class diagram

The result of the cell mutation in representing generation vs. Cost is depicted below in Figure 11. As the number of new generations increases the cost parameter decreases and the SINR value increases with the number of generations. The Fitness value improves with the new generations as depicted in Figure 12.

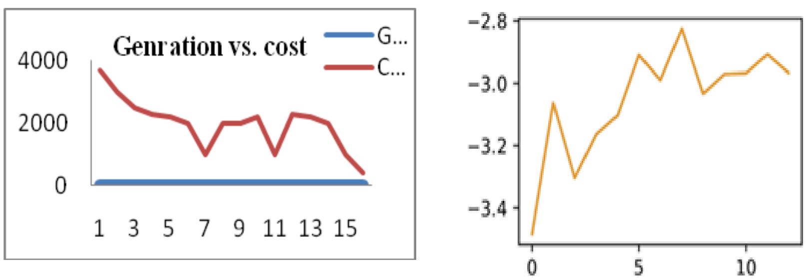

Figure 11. Gen # vs. cost and gen vs. SINR

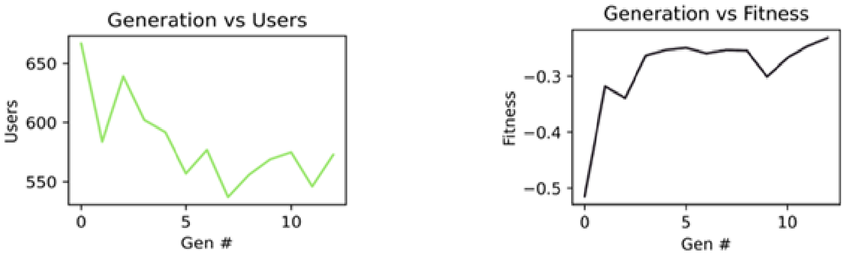

Figure 12. Gen vs. users and cell mutation generation vs. fitness

To produce new offspring, the chosen chromosomes are employed. The task of changing a base station's coordinates while preserving its type and all related properties would fall to Crossover. The following phase, known as mutation, on the other hand, would be in charge of altering the cell's type, which would then affect all of its properties while preserving its coordinates.

Only a small part of the population experiences mutations each generation because they are a rare process. Figure 13 shows the number of fixed macro, macro, micro, pico, and fempto base stations as well as connected users. Cell crossover, a new coordinate generation from the parent coordinate is illustrated in this figure.

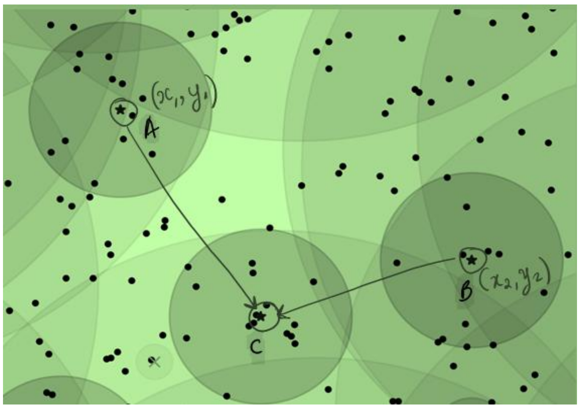

Figure 13. Cell crossover, a new coordinate generation from the parent coordinate

The initial deployment with the base stations being placed at random from generated candidate points. Candidate points are all potential locations for base station deployment. Based on the users' positions, these candidate points are created. It is clear from the initial deployment that a sizable portion of customers are not connected. After applying the algorithm, the base stations are moved to a better position, increasing the number of connected users and decreasing the SINR value, improving coverage and data rates. After repeated experiments, it can be concluded that the multi-objective genetic algorithm is capable of producing results where close to 85% of the users are covered. This excellent coverage of users which is close to 80% is obtained by using minimum number of 6G cells and existing 5G infrastructure, there by reducing the total cost of deployment. The following parameters aided in obtaining best results.

- Selection: Stochastic Universal Sampling
- Crossover: Whole Arithmetic
- Mutation: Cell Mutation

Genetic Algorithm along with properties of different base stations corresponding to 6G to generate an ideal deployment strategy of base stations which makes sure that utmost users are covered at the same time providing acceptable data rates and coverage. From experimental results obtained after running optimizations through several generations, it is summarized that coverage of more than 80% is obtained. Graphs are plotted representing SINR, cost and fitness vs generation indicating the trend in change in fitness.

It is observed that fitness value reaches a maximum and does not increase post that value even if a greater number of generations are used. Figure 14 shows that as and when new generations are acquired, the number of linked users grows. This aids in developing a deployable strategy that is effective, covers the greatest number of users, and has a low SINR value. Possessing a high crossover probability is always advised. This is because the only mutations present are local ones when the crossover chance is minimal. This indicates that change will be gradual and that it will be challenging to push your population past a local optimum. A low probability of mutation is advised. A divergence operation is a mutation. number of users increases with the Gen#.

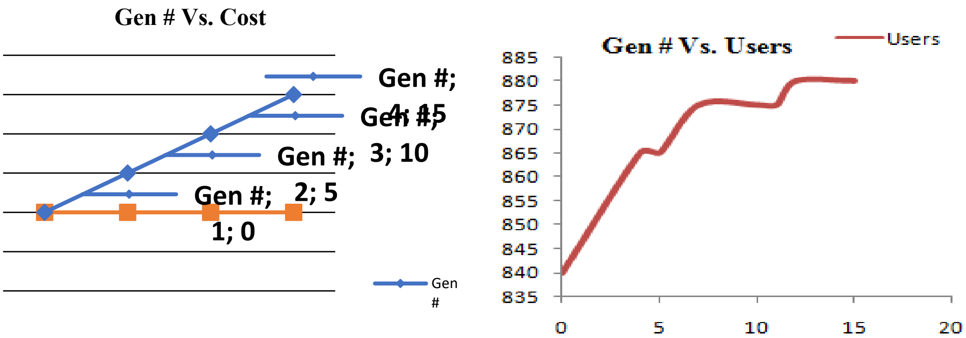

Figure 14. Gen# vs. cost and users

The Gen# Vs. SINR is represented in Figure 15, as the new generation arrives the SINR parameter decreases and Fitness value increases with new generations.

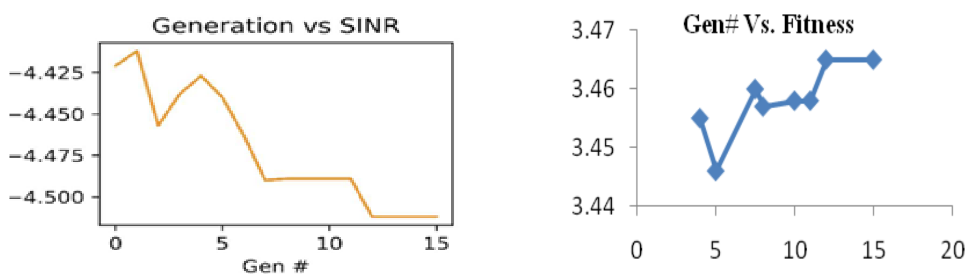

Figure 15. Gen# vs. SINR and fitness

In Table 3, the results comparison is made between the Signal to interference plus noise ratio (SINR) and the user density in the network using proposed Multi Objective Genetic Algorithm (MOGA) with Meta-heuristic algorithms. The value of SINR is marginally decreased as the number of generations increased. The user density in proposed work is improved in comparison with Meta-heuristic algorithm.

Table 3. SINR and No. of user's comparison

	SINR		Users	
Gen#	**Multi Objective Genetic Algorithm (MOGA)**	**Meta-heuristic algorithms**	**Multi Objective Genetic Algorithm (MOGA)**	**Meta-heuristic algorithms**
0	-4.425	-3.021	840	620
5	-4.450	-3.405	865	625
10	-4.475	-3.995	875	632
15	-4.500	-4.002	880	640

6. CONCLUSION

In this work multi-objective genetic algorithms is used to give an optimize solution to the next generation wireless networks. The suggested implementation considers different base station types, their characteristics, user needs, and optimization parameters like deployment cost, user coverage, and interference. The findings in this work suggests that several small cells can be deployed at low cost in place of large cells. As a result, better user coverage is achieved by greatly decreasing the deployment cost. Utilizing mutation, the paradigm shift from large to small cells is accomplished. According to the simulation results, there are 841 connected users in the initial deployment, and the deployment's SINR value is -4.421. When 880 users are connected and a SINR value of -4.512 is reached, base stations are deployed effectively. With effective deployment, the SINR value is decreased. As described in the result section, the better result is produced by taking into account Stochastic Universal Sampling Selection, full arithmetic crossover, and cell mutation. With each successive generation, the price stays the same. With an increase in the number of generations, the signal interference and noise ratio are lowered. With the rise of the new generation, there are more connected users and more significance placed on fitness. As more users become connected and more of the region is covered by moving base stations and employing mobile micro base stations rather than stationary macro stations, efficient deployment out-performs initial deployment in terms of results.

From experimental results and insights from different graphs we are able to conclude that Genetic Algorithm emphasizes combining information from good parents, it is inherently parallel and there is always a result. There are many ways to speed up and improve as GA-based application as knowledge about problem domain is gained. As a plan for future work, we need to focus on the genetic operators which include crossover and mutation which helps in obtaining better experimental results. Further modifications of constants that are related to properties of base stations which helps in improving the fitness. Formulae used in different network functions like calculating power received by user needs to be upgraded to mimic real environment scenarios.

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