NATIONAL AND KAPODISTRIAN UNIVERSITY OF ATHENS

SCHOOL OF SCIENCE
DEPARTMENT OF INFORMATICS AND TELECOMMUNICATION

MSc THESIS

AI-based resource management in future mobile networks

Ulzhan Zh.Zhumakeldi

Supervisor (or supervisors):	**Dr. Nikos Passas,** Research Group Leader at National Kapodistrian University of Athens

ATHENS

OCTOBER 2022

MSc THESIS

AI-based resource management
in future mobile networks

Ulzhan Zh.Zhumakeldi
S.N.: 7115192100003

Supervisor (or supervisors): **Dr. Nikos Passas,**
Research Group Leader at National Kapodistrian University of Athens

SUMMARY

The 5G and beyond networks supported by Artificial Intelligence algorithms in solving network optimization problems are recently studied to meet the quality-of-service requirements regarding coverage, capacity, and cost. One of the essential necessities is the optimized deployment of network base stations. This work proposes the meta-heuristic algorithm Genetic Algorithm to solve optimization problems considering the demand constraints. The main goal is present the alternative solution, which is using the Genetic Algorithm to optimize BSs network deployment. This deployment provides the same services as existing deployments and minimizes the network infrastructure's energy consumption, including using homogenous and heterogenous scenarios of base stations. The simulations were performed in Python programming language, and the results as the best plans for each generation were presented and saved.

A comparison of the macro base station deployment and small base station deployment was made on top of the existing one. By applying the small base stations, the network deployment will enable user coverage enhancements and reduce the deployment cost, energy consumption, and inter-cell interference. All the scenarios were assembled in user density area A, user density area B, and user density area C areas of interest. In meeting the requirements for QoS and UE, the small base station deployment is beneficial, namely in hotspot areas.

SUBJECT AREA: Mobile networks, Artificial Intelligence, resource management

KEYWORDS: 5G and beyond networks, artificial intelligence, base stations, Genetic Algorithm, network deployment

To my beloved family for their support and love, especially my parents for providing me with the best they have to ensure I would have an opportunity to pursue a high-quality education. Dedication to my family for supporting me morally, emotionally, and financially.

To my friends for giving me strength in challenging situations.

Erasmus Mundus Joint Master's Degree

"SMART Telecom and Sensing NETworks" (SMARTNET) (2020/2022 intake)

Aston University, Triangle, B4 7ET / Birmingham, UK

Email: aipt_smartnet@aston.ac.uk / Web-site: smartnet.astonphotonics.uk/

Acknowledgment

This Master Thesis has been accomplished in the framework of the European Funded Project: **SMART Telecom and Sensing Networks (SMARTNET) -** Erasmus+ Programme Key Action 1: Erasmus Mundus Joint Master Degrees – Ref. Number 2017 – 2734/001 – 001, Project number - 586686-EPP-1-2017-1-UK-EPPKA1-JMD-MOB, coordinated by **Aston University,** and with the participation of **Télécom SudParis, member of IP Paris** and **National and Kapodistrian University of Athens.**

ACKNOWLEDGEMENT

Primarily, I would like to praise Allah, the most gracious and merciful, for the blessing provided to me throughout the process of completing this thesis.

My warmest gratitude to my supervisor Nikos Passas for allowing me to work under his supervision and be part of his research team. I am also sincerely thankful to Dimitris Tsolkas for helping and supporting me and guiding me with a well-organized project plan. Special thanks to Anastasios-Stavros Charismiadis, who has been a great advisor with the simulation part, as well as suggesting the approaches for the report. Not to mention, even if most meetings were held online, all my supervisors were reachable.

I am also grateful to SMARTNET MSc Programme Director Stylianos Sygletos for his work throughout the duration of the whole program, including the situations with remote work and unexcepted circumstances and coordinators Tetyana Gordienko and Eirini-Zoi Mpousmpoura for always being there whenever needed. Appreciations to the opportunity of being part of this program.

My friends have also been a significant part of my academy life; I would like to thank Umid Narziev for his help and patient explanations, Safiya Jassim for her high level of empathy, and Danara Aisina, who was emotional and moral support at both Aston University and the University of Athens.

Last but not least, I would like to acknowledge my family for their inspiration, for always being by my side and for trusting me to follow my path, and for all their advice.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

5G and beyond networks are expected to play a significant role in various sectors such as healthcare, agriculture, industry 4.0, and entertainment in terms of cost-effectiveness, enhanced architecture, improved capacity, and low latency. When the previous network technologies, such as 3G and 4G, were mainly focused on enhancing data rate and spectral efficiency, starting from 5G, mobile networks are working on architecture enhancements, such as the concurrent operation of macro-, micro-, pico-, and femtocells, termed as heterogeneous networks (HetNets), to improve the network efficiency. Generally, 5G base stations, called gNBs (next generation NodeB), are deployed densely within heterogeneous networks. Most users use indoor services (pico- and femtocells) more willingly than outdoors (macro-cells), as capacity is usually more substantial, and the user can have better service quality and experience. Employing the small base stations to cover more considerable indoor network traffic will enable the optimization of coverage, capacity improvement, and reduced latency. In addition, base station deployment closer to the users will minimize the round-trip delay and maximize the availability of resources. Hence, network planning is essential considering the constraints of demand, cost optimization, coverage, and capacity.

The energy consumption from the communication systems is becoming critical as the base stations are deployed more densely. The energy consumption of the Information and Communication Technology (ICT) industry is coming to almost 20% of the total and has an increasing trend between 6 and 9%. For instance, the power consumption of 5G is above 11,000W when the previous Network, 4G, has been below 7,00 [2].

A countermeasure to the increase in energy consumption can be reducing the number of BSs without decreasing the quality of service considering coverage, interference, and capacity. This challenge is an optimization problem that can be dealt with the benefits of the AI toolset.

Mainly, the interconnection of AI and wireless communications allows the appearing paradigms, particularly AI-empowered wireless communication systems and edge intelligence. In the prior paradigm, AI and ML models are employed as data-driven mathematical methods, contrary to conventional model-driven methods, to optimize the wireless communication system in enhancing performance. In the subsequent paradigm, the capabilities of AI and mobile edge computing integrated into BSs and access points at the edge to allow intelligent applications, for instance, industrial autonomous and autonomous driving to meet extended computation and communication requirements [1]. AI has great potential to address challenging system design and optimization issues. An indicative example where energy consumption can be optimized is the base station (BS) deployment process. The deployment of BS has several steps to follow: 1) the number and location of new BSs based on user requirements should be decided; 2) optimize the field measurements and evaluate coverage using propagation models for the decision of BSs' exact addresses; 3) deployment starts in this step [2] It is a significant problem to optimize the number of base stations, allocate them efficiently and select the proper configurations for the base stations in the deployment of the wireless networks. The commonly used macro base stations manage to meet the coverage requirements, also mobility and signaling challenges. The usage of micro base stations is beneficial in enhancing capacity. This thesis presents a deployment framework, including small cells coexisting with macro cell base stations.

The primary objective of this thesis is to examine alternative solutions (e.g., by using a Genetic Algorithm) that will allow the optimized network deployment of BSs. This deployment aims to support the same services and thus reduce the network infrastructure's energy needs, considering both homogenous (using the same type of base station, e.g., macro-BS) and heterogenous (using different kinds of the base station) cellular networks.

2. BACKGROUND

2.1 5G and B5G

Mobile networks before LTE were based on specialized protocols and carried out on specific hardware. Every succeeding decade, advancements are made in the generations of mobile networks. The most critical requirements for the following wireless communications were low latency, high bandwidth, and data rate. 5G networks not only meet the criteria mentioned above but also provide improved quality of service (QoS), better coverage, low latency that is five times reduced compared with 4G, and better energy efficiency. Three services are provided in 5G cellular networks: enhanced mobile broadband (eMBB) with bandwidth-consuming and throughput-driving requirements to new services, ultra-reliable low latency service (URLLC), and massive machine-type communications (mMTC). For enhancing spectrum efficiency (SE) and energy efficiency (EE), intelligence embracement in 5G and beyond networks will provide different solutions in radio resource management (RRM), mobility management (MM), and management and orchestration (MANO) [3]. eMBB offers high-speed internet connectivity, wide bandwidth, UltraHD streaming videos, and virtual and augmented reality media. Service mMTC provides a high data rate and reduces power consumption; using simple device complexity extends the coverage. URLLC delivers low latency, high reliability, and enhanced quality of service. And this service allows real-time interaction, for instance, remote surgery, smart grids, and intelligent transport systems. This reliable Network and the fastness of 5G have better-controlled operations that have no delays compared with previous networks.

The architecture of 5G is based on three main concepts:

1. ***Splitting of control and user plane.*** This offers connection among 4G core and 5G core elements, e.g., Access and Mobility Management Function (AMF), Session Management Function (SMF), and User Plane Function (UPF). AMF is responsible for registration, access control, and mobility management, while SMF allows the creation, update, and removal of PDU sessions. Moreover, SMF does the session management with UPF, and IP address allocation for users plays a DHCP role. UPF oversees packet forwarding and routing and acts as an anchor point for mobility.
2. ***Network slicing.*** In general, a network slice is an end-to-end logical Network involving Radio Access and Core Network. These logical networks provide various services to satisfy user communication requirements. It introduces the concept of a network-as-a-service model that allocates and flexibly reallocates the resources based on the dynamic demands considering network slices' customization for complex 5G communication cases. Furthermore, network slices are able to isolate the network resources of specific services from others; the configurations between different slices do not impact each other. Hence, the security and reliability of each slice can be improved [4].
3. ***Service-Based Architecture.*** Virtualization of cellular networks began to be developed from LTE, including Service Based Architecture (SBA) which is the evolution of the virtualization process. Hence, this process was planned to be employed in 5G and beyond cellular networks. This model provides the services operating the set of Network Functions. The 3GPP introduces the SBA for the core network of 5G with a set of Network Functions (NF) that are interconnected, allowing access to services among each other. These network functions are implemented in

software, for instance, in the cloud, and may provide more than one service. The interface comes together with well-defined APIs and a client-server model. Some benefits of SBA are cost-effectiveness, reliability, scalability, modularity, and simplicity of deployment [5].

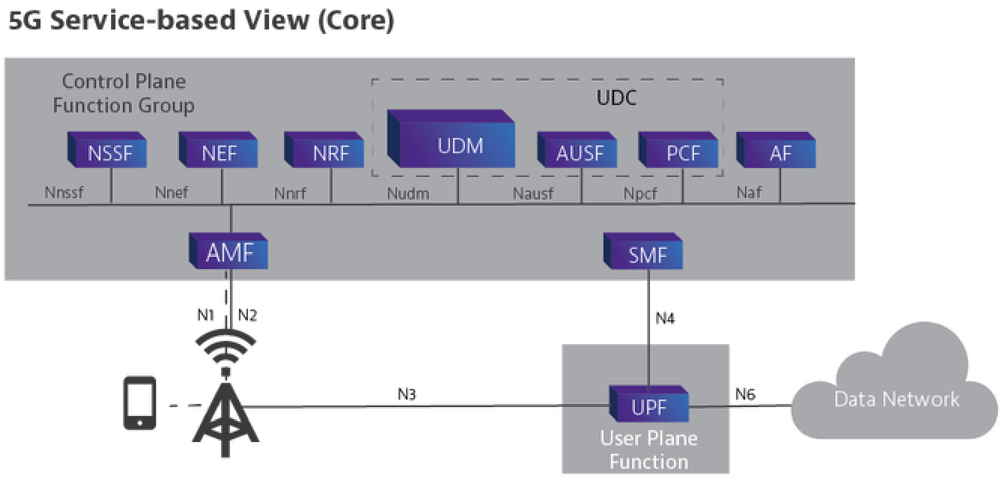


Figure 1: 5G Core Service-Based Architecture [6]

Two key components of 5G are network slicing and network functions virtualization. The researchers are practising the use of network slicing, referring to the creation of several logical network instances, in other words, slices throughout the Network, which can be automatically optimized depending on some criteria and perhaps owned by various organizations. Physical infrastructure handles the share of computing, storage, and network resources in network slicing, giving the companies a chance to simulate the softwarized network services.

The vertical industries, namely manufacturing, healthcare, energy, automotive, media, and entertainment, are needed to be supported in 5G and beyond networks. In order to efficiently accommodate this, the network architecture should be improved concerning current network deployments. One of the potential solutions for that is network softwarization, which is the concept of enabling networks to apply software-based tools. Technologies such as Network functions virtualization (NFV) and software-defined networking (SDN) as part of network softwarization will allow flexibility, programmability, and modularity in meeting the virtual network creation requirements. NFV needs to be studied to enhance end-to-end network performance and advance multiuser cooperative transmissions. Verification and debugging of NFV-based network services were examined in [7].

The primary connection in 5G architecture is between gNodeB and the 5G Core Network. The gNodeB acts based on the New Radio air interface and signalling protocols concerning the end-user device. It is also connected to 5G Core Network Element AMF for signalling in the control plane, and to transfer the application data connection with UPF is made. The gNodeB are interconnected visa Xn interface. gNodeB is possibly connected to more than one AMF and UPF, and the first AMF is selected for each user. The connection between them is reached using the Next Generation Control Plane interface, which employs Next Generation Application Protocol for signalling message transmission. The signalling among users and AMF is executed using Non-Access Stratum signalling messages. SMF makes the selection of UPF for each session. The connection is possible based on the Next Generation User Plane interface that utilizes GRPS tunnelling protocol. That interface is used for packet transmission between UDP and IP.

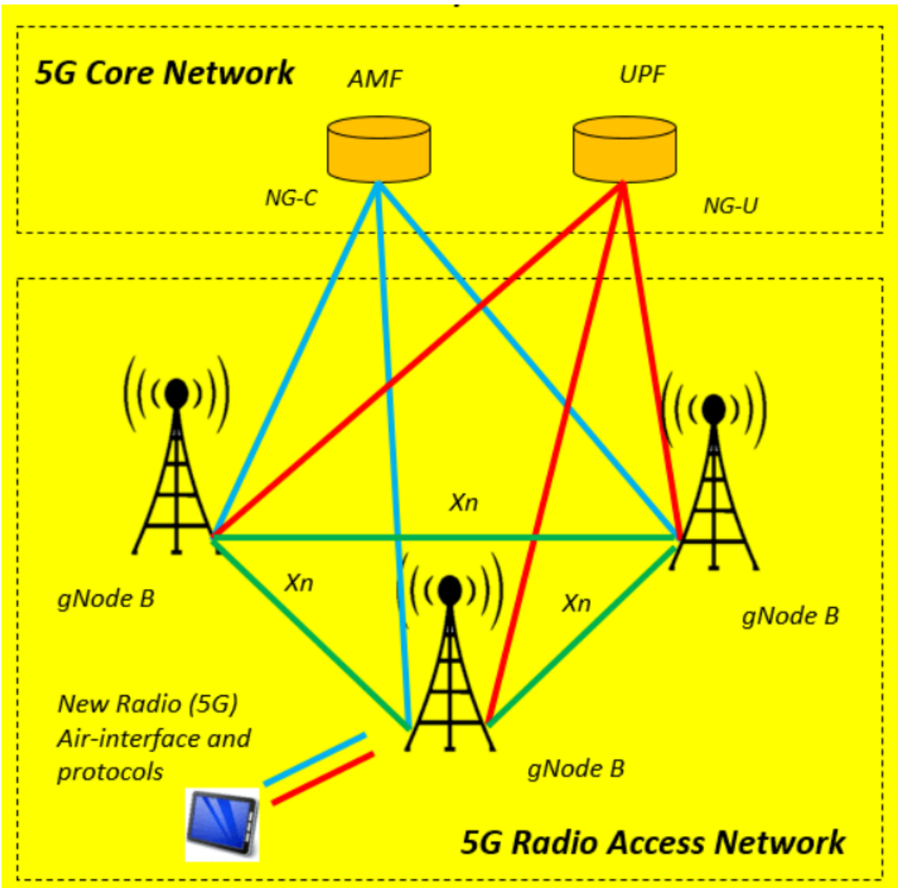


Figure 2: Base Station Architecture in 5G [8]

2.1.1 5G coverage requirements

Managing full (100%) coverage will be essential to meet the 99,9% network availability and reliability requirement in 5G and beyond. The network coverage represents the geographical area throughout the base station, where communication is accessible between the access point and the user for any service requests. The radius of the cell is the maximum distance between the base station and the user where the services are provided without interruption, and it represents the boundary of cell coverage. That means the user will not have any kind of connection beyond that boundary. Another directly proportional value to network coverage is the antenna's transmission power.

In the case Mobile Network Operators are required to make the deployments of more than one small cell to cover an area, the adjacent small cell should sustain inter-site distance (ISD). For maintaining the quality of coverage in mobile terminals, multi-cell cooperative communication is the unavoidable solution for future mobile networks [9].

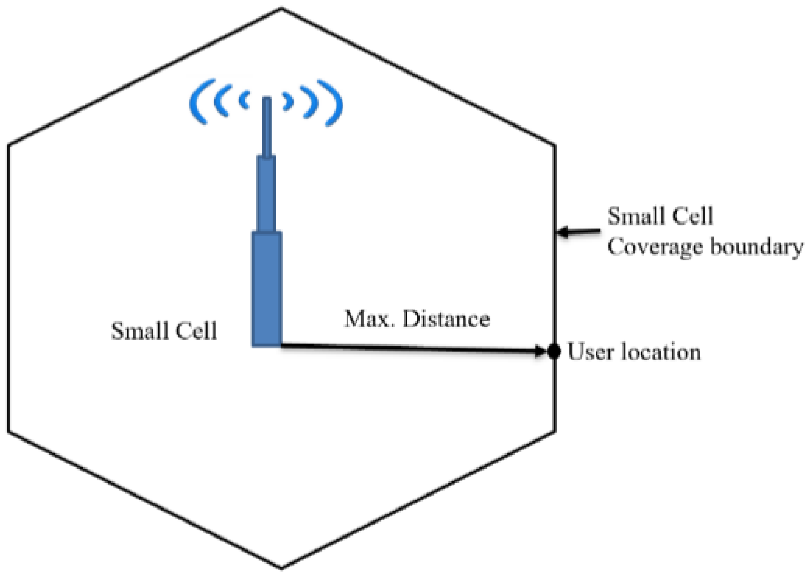


Figure 3: Small cell network coverage [10]

Cell coverage is a crucial parameter to ensure the required level of QoS. For that, it is mandatory to be familiar with UE resources, guaranteeing the throughput resolved by UE's intended service.

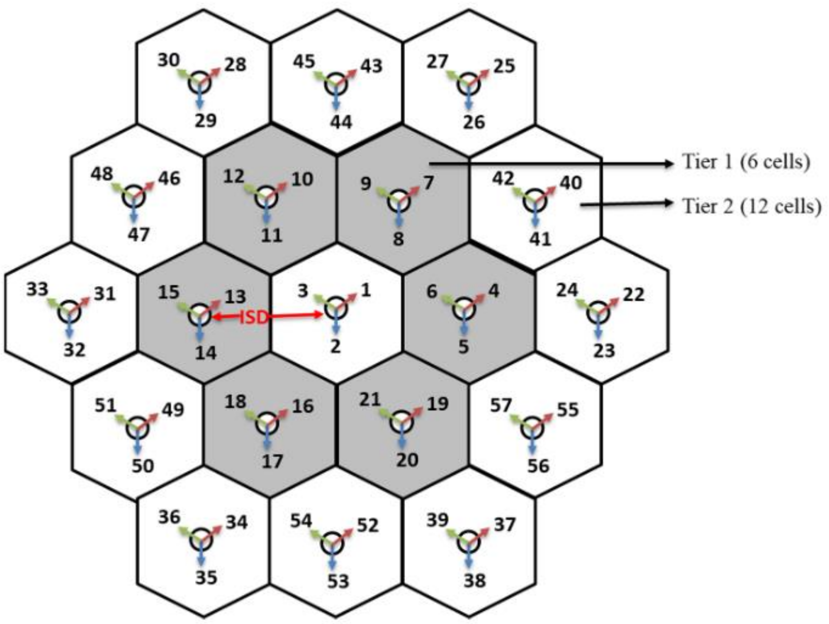


Figure 4: 5G Network layout

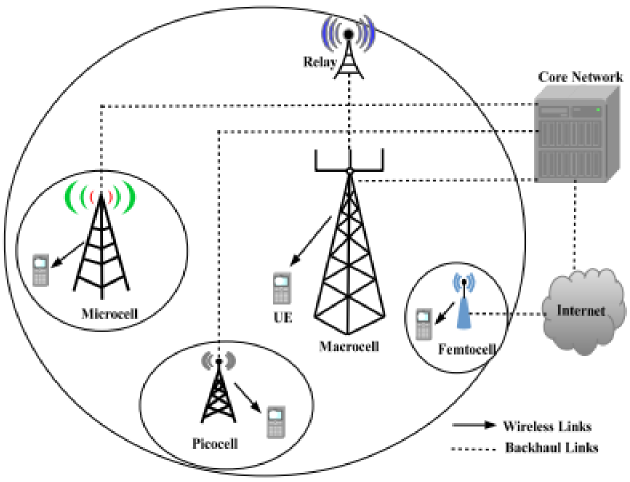


Figure 5: 5G Network Architecture [11]

In 5G architecture, the access network is comprised of different types of cells (macro-, micro-, pico-, and femtocells). The connection between the core network and the base stations is handled by the backhaul network using wireless, wired, or mixed methods.

2.2 Artificial Intelligence and categories

Artificial Intelligence is an interdisciplinary branch of Computer Science and can be identified in several ways. In the literature, it is introduced as the discipline where an intelligent machine predicts the feature or set of procedures that give machines the chance to perform reasoning, perception, and actions. Another author describes that AI aims to imitate and act as human intelligence, applying different algorithms for decision-making, problem-solving, and human communication understanding [12].

In [14], AI is divided into categories such as Symbolic AI, Machine Learning, Heuristics, and Hybrids. Each of them has its algorithms based on specific purposes and logic.

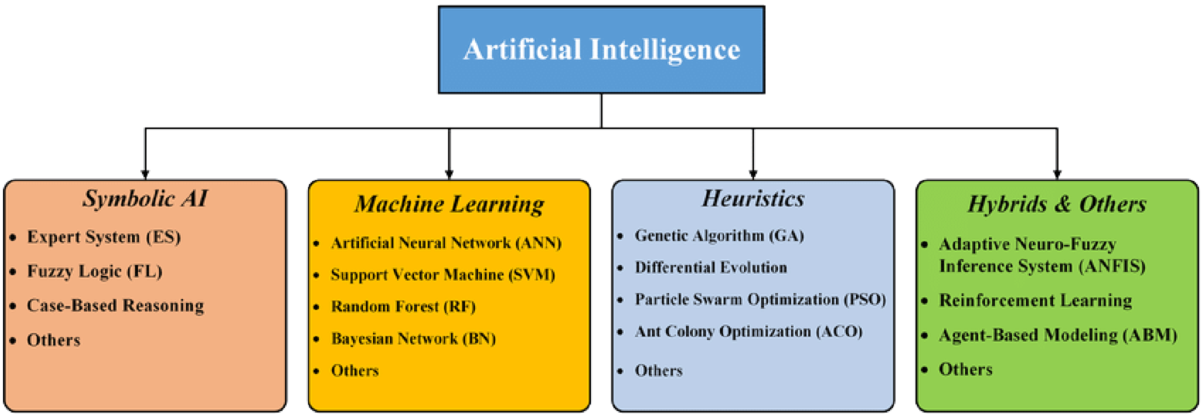


Figure 6: AI categories and techniques [13]

Among these four main categories, the first one is dedicated to ***Symbolic AI***, which considers symbols for cognition representation and imitates the human cognition process using deductive logic. Deductive logic or deductive reasoning is the reasoning process containing statements to outreach a logical conclusion. Expert System (ES) is an example of Symbolic AI, which plays an essential role in its application's decision-making, production planning, and scheduling areas. They solve problems that are complex with the help of knowledge reasoning that is based on if-then rules [14]. The main components of ES are the knowledge base, inference engine, and user interface. Fuzzy Logic (FL) has a similar approach to the rules; in addition, it introduces the term called membership function, which is a degree indication between 0 and 1. However, the difference between Fuzzy logic and the Expert system is that the expert system is computer-based and endures facts and rules using an automated reasoning process.

In contrast, fuzzy logic uses fuzzy sets and membership functions to describe the situation. Linguistic variables define labelled fuzzy sets; for example, the temperature can be identified as terms {low, below average, average, above average, high} [15]. Another problem-solving method in AI that has contrast with other paradigms is Case-Based Reasoning, as it has the opportunity to use specific information from the past. Currently, it is applied for nursing care systematization, where the experiences of nurses are saved in the form of cases, and the compilation of data could assist the workers in exploring new diagnoses. Besides that, nurses may analyze the past case studied, which was solved in [16].

The following category is ***Machine learning***, which may be separated into three steps: exploring the data, learning from it, and applying what has been retained to make the decisions. The system analyses the given tasks' performance and behaviour to improve their execution with experience. Generally, ML can be categorized into supervised and unsupervised learning. Classification is the supervised learning algorithm that classifies the data and makes the prediction of class according to the data—for example, text classification in plagiarism-detecting tasks. The most known predictive analysis algorithms are KNN, SVM, Naïve Bayes, Decision Tree, and Random Forest. Regression problems under supervised learning algorithms predict the output values subject to the input data in the system. Logistic, linear, Lasso, and Multiple Multivariate are kinds of regression algorithms. Next comes clustering, which is an unsupervised learning category that deals with the problem of dividing the same or similar data points of a dataset into the same group. Efficient usage of clustering algorithms could be addressed in smart resource orchestration in order to differentiate the similarity for the collection of objects. Four examples of clustering methods are K-means clustering, Fuzzy C-Means, Expectation-Maximization (EM) Algorithm, and Hierarchical Algorithm.

Deep Learning is a category of ML that uses the hierarchical architectures of concepts and representations to learn high-level abstractions in data and has been used in NLP, computer vision, and communication networks [17]. Computer vision examples such as image classification, semantic segmentation, and object detection are only a small portion of use cases where DL has been adopted. CNN is a widely used DL algorithm, which stands for Convolutional Neural Networks. AlexNet is the known method and architecture of CNN where two forms of data augmentation are performed, data augmentation and intensities alteration of RGB. Artificial Neural Network (ANN) is also a commonly applied method of AI where the human cognition system inspires the model. The totality was consisting single units, artificial neurons that relate to weights (coefficients) that lead to neural structure or processing elements. Processing elements have three main components: weighted inputs, transfer function, and output [18].

Genetic Algorithms, Differential Evolution, Particle Swarm Optimization, and others are considered as ***heuristic methods*** in Artificial Intelligence. Heuristic methods can be very efficient in optimization problems with dynamic environments that can have uncertain or incomplete data [19]. Search and optimization methods of this category are divided into heuristics and metaheuristics. Heuristics depend on the problem, while metaheuristics are independent of the problem (can be used as black box solutions) and, as a result, can have a broad range of applications. A metaheuristic is a high-level algorithmic framework that offers a set of guidelines or strategies for developing heuristic algorithms for optimization [20]. The Genetic Algorithm (GA) was first introduced in 1975 by American scientist John H. Holland [21], and it is a metaheuristic method imitating the natural selection and evolution process. The term gene is considered a design variable, and chromosomes tend to be potential solutions that are stored in each iteration. When the individuals of the population are evaluated, the fitness value is found, and two individuals are chosen using selection, crossover, and mutation methods for new generation creation.

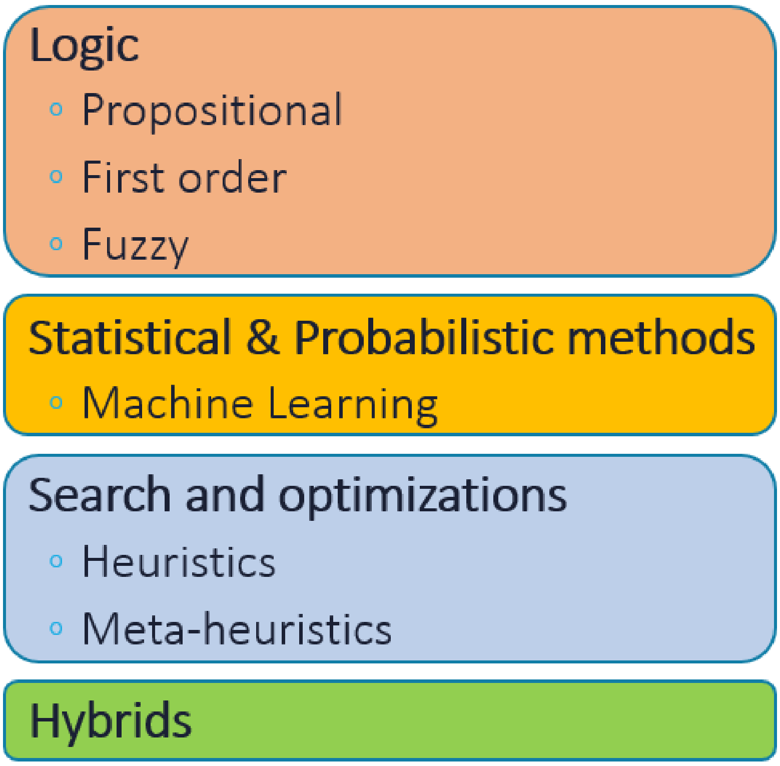


Figure 7: Tools of AI categories

Ant Colony Optimization (ACO), as the name says, imitates the ants' behaviour in the searching trail between colony and food source, in other words, optimal path exploration. This approach has been used to solve scheduling problems of manufacturing, assembly line balancing, travelling salesman problem (TSP), and others. [21].

The combination of deterministic and stochastic models forms the ***hybrid*** category. These models have a wide range of applications as they can employ the various algorithms' strengths. For instance, in [22], personalized recommendation for users using a hybrid algorithm was proposed, enhancing the accuracy of previous models and robustness. Big companies such as Amazon, IBM, and IFS Business Software developed AI planning and optimization projects. It can be applied in automation and cybersecurity domains. Dynamic programming, reinforcement learning, and combinational optimization are proper methods for this objective.

2.2.1 AI in 5G and B5G

The enhancement of AI technology revolutionizes telecom industries and values the connectivity of big data, IoT, and other network concepts. AI will strengthen mobile communication technologies, e.g., diminish the gap in the performance between computing and computing on Edge devices [23]. In addition, more functionalities for 5G and beyond networks will be enabled with the help of AI.

The performance in terms of latency, efficiency, and reliability of network applications will be much higher with the integration of AI. The decisions could be made by intelligent BS, and mobile devices will create adaptable clusters of the learned data.

Open challenges into which AI can be integrated are the following:

Mobility Management.

Providing continuous and robust communication is essential. The development of wireless communications allows the necessities of network operators and users to be performed in a less complex and improved way. In [24], the authors aim to track network dynamics and user mobility challenges by applying the online learning model keeping the periodical iodates in real-time. The behaviour is captured using hierarchical Markov Models, and load trace generation of each femtocell is performed with high accuracy. Fitness is calculated according to results. RL models are employed in [25] for channel optimization. Network mobility challenge causes energy-efficiency problems because packet transmissions can be lost on the way. Offloading methods are presented in [26], [27] to improve energy efficiency in heterogenous wireless communications. To offload the data traffic in Wi-Fi access points or femtocells, the authors propose the mobility prediction and apply the pre-fetching technique in [26]. At the same time, researchers from [27] are continuing this approach and writing about the ability to download the delay-tolerant traffic while UE is in the radius of a Wi-Fi hotspot or femtocell rather than macro-cell usage. Another kind of delay, handover delay, and failure were studied in [28] where authors presented a new mobility management design named Software Handover Management Engine (SDHME). Four main steps were followed, including data collection, data processing, virtual cell creation, and finally, the execution of the handover. The mechanism was implemented in the control plane, the application plane was responsible for the definition, and performance was performed in the data plan. All the process was accomplished according to the SDN architecture. The authors finally reached their purpose, which was reducing the handover delay and failure.

Nonlinearities in the physical layer of wireless communications can be mitigated by applying AI methods [29]. Recurrent neural networks (RNN) were used first to deal with linear programming problems; however, they can also automatically extract the environment-invariant features of the nonlinear system and outperform existing approaches [30]. 5G networks based on AI are valuable in solving existing research challenges in terms of heterogeneity and various levels of context awareness.

Resource allocation.

Practical and advanced allocation schemes are necessary because of the complexity of resource requirements. Resource management plays a significant role in any cellular network as it allows end-users, partners, and customers' access. Power and energy control, bandwidth allocation, and deployment strategies are considered resources in the system [31].

To handle the drawbacks of line-of-sight (LOS) transmission and mobility robustness in visible light communications, researchers from [32] studied energy-aware network selection and resource allocation for heterogenous radiofrequency and visible light communication networks. Authors in [33] focused on security-aware power and subchannel allocation issue for heterogenous cognitive communications with inter-network cooperation. The dual decomposition method was proposed to solve the bi-convex optimization problem. A greedy algorithm was employed to efficiently allocate the power and subchannel that allowed to enhance the throughput. In [34], resource allocation was reviewed from the point of spectrum allocation among microwave bands and mm-wave bands for multiple pairs of D2D. The transmission rate is used as an optimization metric to maximize the system performance. Compared to the usual mm-wave transmission scheme, the performance of the system was improved by almost 40%. D2D communications were studied in terms of relay nodes in [34], [35] to maximize energy-efficient resource allocation and cell selection. D2D relay nodes were applied for macrocell coverage extension. The concave fractional problem was converted to a concave optimization problem based on the transformation of the Charness-Copper, which is solved by the outer approximation method. Energy efficiency improves when the number of users increases.

The authors in [36] apply RL and heuristic learning to allocate the resources in 5G cellular networks for public safety communications. They divided the solution into two groups: heuristic-based and RL-based. The challenge in RL-based algorithms implementation is in improving the high scalability and dealing with problems immediately concerning speed and finding global optima. As the cloud computing environment has a growing trend from people who use it for personal activities to businesses and corporates, and a high volume of data and resources in the cloud. UE and cost-efficient solutions should be supported.

Latency minimization or scheduling.

The transmission delays are significant as the number of BSs increases, also leading to scheduling delays. In the article [37], the authors propose an improved Auto Regressive Moving Average (ARMA) algorithm, present the prediction error of aggregate traffic records taken from China Mobile [38] and the prediction of service-level traffic by extracting a traffic model from realistic records and apply a stable model-based compressive sensing algorithm [37]. Regarding the scheduling problem, authors from [39] presented an intelligent resource scheduling method for 5G radio access network slicing. A collaborative learning framework was embedded, comprised of deep learning and reinforcement learning to handle large and small-time scales. DL model is applied to predict the volume of traffic for optimized resource allocation, and a computing-based A3C RL model on clearing up resource scheduling in a small timescale.

Energy efficiency.

In the literature, the challenge of energy efficiency is studied deeply. Power allocation should be performed in energy-saving mode. An analysis of the trade-off between the application performance should be done. More attention is needed to learn the efficiency of beamforming. The software elements would enable faster decision-making about resource management, human interactions concerning network characterization, and optimization will be replaced by performing ML algorithms that lead to cost-effective solutions in management, and the paper discusses the areas for AI research in cellular networks. The authors define various algorithms for physical, MAC, and network layers. Supervised and reinforcement algorithms for symbol detection, end-to-end learning, channel estimation and prediction, channel coding, and dynamic spectrum access applications. And for energy optimization, fault recovery and analysis, resource management and scheduling, and cell-sectorization supervised/unsupervised and reinforcement learning are proposed [40]. Authors from [41] considered the interference-aware energy efficiency in 5G ultra-dense networks. Spectral efficiency is employed where the macro cells cover small cells and share the bandwidth to reach energy efficiency. Small cells are part of the maximization of energy efficiency based on game theoretic methodology, where the Nash product is utilized.

Network Scalability.

Large-scale networks demand practical algorithms regarding channel state information (CSI). Attention is mandatory for the complex challenge of network scalability. This problem was studied in [42] as interference, and green deployment challenges are more complicated because of intrinsic densification and scalability. Authors in this research worked on the maximization of energy efficiency with the exploration and exploitation of different cooperative gains. The model was game-based and aimed to reach the optimal spectral efficiency of each small cell, leading to enhanced energy efficiency. Utility function was used in the maximization of energy efficiency without spectral efficiency loss. Authors from [43] presented the analysis of network scalability that was performed systemically in a 5G core network. The authors proposed a Performance Evaluation Process Algebra-based model for scalability analysis and core network performance of 5G network slicing. The Network is specified with a sequential approach, and the proposed model demonstrated the assessment and modelling based on the session scalability and performance.

Network Security.

Improving the security and creditability of collaboration among network entities can be supported by a blockchain that does not require a centralized network controller [44]. The authors from [45] pointed out link-layer security in 6G networks and introduced an adaptive method for security configuration. Users can employ the prediction results, and they can select security suites that guarantee uninterrupted services. And provided services are protected, enhancing the Quality of Experience

(QoE). It is known that the necessity of security architecture requirements is not ignorable for each developed generation. The design of artificial noise and beamforming of MIMO was presented in [47] [48] to secure heterogenous wireless communications. In [48]a new approach to the mathematical framework was proposed that allows the maximization of the performance of reliability and security by analyzing the network-wide secrecy throughput. At the same time, in [47], two spectrum allocation strategies were presented to maximize the user secrecy rate.

In 5G and B5G networks, the network expense of operators will increase because multiple iterations of testing with related equipment and tools should be performed. AI-based technology is beneficial for using deep learning and dynamic modelling in CAPEX planning tools. According to Ericsson's research, almost half of communications service providers (CSP) are testing AI capabilities, which reduces CAPEX nowadays [49]. This paper will focus on network optimization and efficiency as part of resource allocation problems.

2.3 Network optimization using AI

Network optimization in wireless networks is a kind of technical challenge that is complex to model. These challenges may include network deployment and planning, coverage, interference, neighbouring cell selection, and handover. The requirements for 5G planning include energy and power consumption optimization, cost-optimized deployment, and traffic-aware scenarios. The placement of core and radio network elements is vital to provide better performance and the lowest possible latency, considering the significant part of the Base Station. In this work, the problem of optimizing the locations of base stations was taken as a basis.

2.3.1 Recent works

Network optimization would be an excellent opportunity to solve the significant operational and economic concerns in telecommunication fields, particularly in mobile networks. From earlier works and literature, it cannot be denied that exponential growth in network traffic and the increased number of connected devices led to studying and analyzing the concept of energy efficiency for mobile networks. In addition, energy efficiency is helpful for industries and companies in achieving sustainability goals. Within this context, the identification of new challenges in energy efficiency is forthcoming.

For further research, the authors in [50] focus on AI for green communication transmission enhancement when there are multiple communications. The same paper also discusses the existing literature and methods on how AI can be adopted in future communications systems. They divide research issues into three communication scenarios that are Cellular Network Communications (CNC), Machine Type Communications (MTC), and Computation Oriented Communications (COC). In this paper, the CNC scenario is chosen, and BS deployment in BS Management topic will be studied to balance energy efficiency and QoS.

BS deployment is a significant aspect of obtaining better network performance and optimizing consuming energy. The energy cost of 5G and beyond networks is intuitive as the number of required BSs increases. Both academia and industry came up to separate into two groups in energy consumption mitigation solutions:arvesting and adopting energy-efficient network management algorithms' development [51]. For example, energy harvesting will alleviate the drawbacks of constrained battery and computation capacity. The study and development of energy efficiency models considering computations and transmission power will enhance the overall performance of mobile networks. In addition, joint optimization algorithms can be studied to overcome the abovementioned challenges.

The survey undertaken by authors in [52] to determine the challenges and open research issues proposes that clustering methods taking into account the reconfigurable ultra-dense BS design should be taken into consideration.

In the first decade of the 2000s, researchers studied automatic base stations in 3G and LTE. Authors from [53] introduce a method for automatically distributing BSs in specific scenarios, sustaining the coverage requirement, and allowing the distribution of traffic transmission. The optimizing tasks and planning rely on the K-means clustering algorithm, in which they cluster the demands and perform cell settings. The results are numerical, and the method allows to reach total coverage while all traffic demands services are also granted. However, it was proposed that previous cellular networks and other algorithms, such as RRC, should be used to reduce the number of BSs.

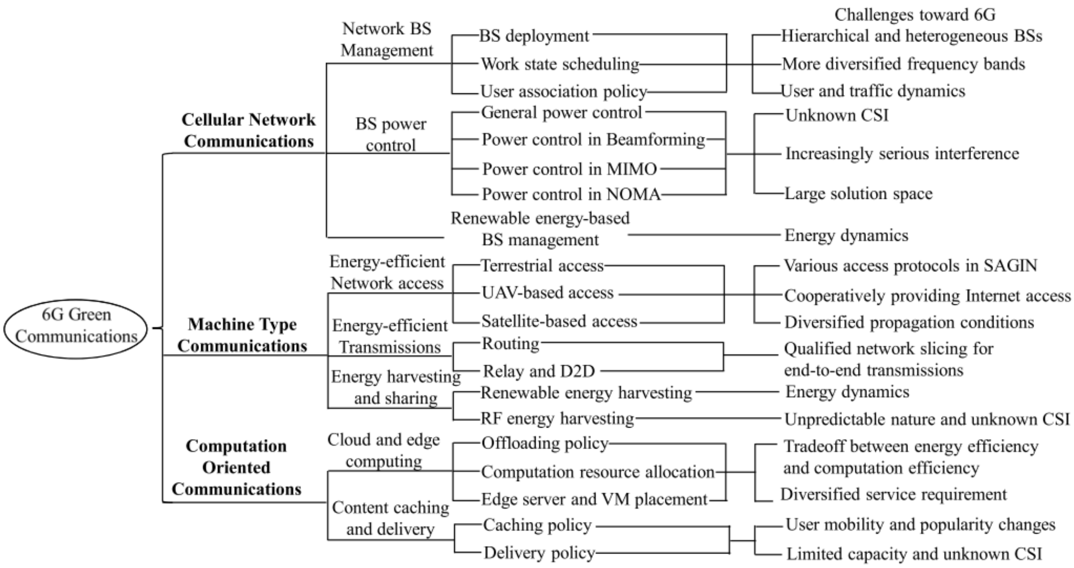


Figure 8: Challenges in communication systems towards 6G [1]

Article [54] considers aerial BS regarding user mobility. To save energy and manage the number of BSs, aerial BS is used to assist traditional BSs. Q-learning algorithm is applied to find the optimal solution, and simulation results prove it enhanced QoS according to user positions. The advantage of this approach is flexibility and agility, which could be helpful in future communication networks.

Authors from [55] formulate user scheduling and resource allocation based on energy efficiency by applying the RL framework. Network capacity and coverage can be increased by deploying the heterogeneous small-cell BSs (SBS); for this reason, cell edge users get a chance to have a high data-rate service with low power transmission consumption. As it is known, the SBS is associated with being closer than traditional or macro base stations (MBS). The actor-critic Algorithm learns the stochastic policy where the actor part provides parameterized policy while value function evaluation is done by critic one.

The authors in [2] present a multi-objective Genetic Algorithm (GA) to solve the BSs deployment quantity issue. The method initially obtains the key features for the determination of the Received Signal Strength (RSS) 's strength. The relation between obtained features and RSS values in the ML algorithms as KNN, SVM, MLP, and random forest are adopted. Secondly, the proposed multi-objective GA is applied to optimize locations and operating parameters. The number of BSs selected changes on every episode of the Algorithm, and the least number that fits the coverage requirements is finally chosen. Finally, the optimal solution is found by the ML methods mentioned above.

A similar approach, i.e., a combination of ML and GA in mobile networks' design, is studied in [56]. SVM training is executed offline and taken as a QoS regressor with data. Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) received deriving from serving neighbouring eNBs. In the forwarding step, the implementation of the GA algorithm is made for optimal solution accomplishment with eNBs' configuration parameters. UE measurements in each optimal solution are used as SVM inputs, and the fitness function is calculated from the predicted QoS result. Iterations of GA help receive better BS configuration through minimization of Physical Resource Block (PRB) per transmitted Mb.

The earlier research states that deployment policy could be optimized by adopting iterative algorithms such as GA when ML methods are applied for multiple network parameters' prediction or fitness function evaluation.

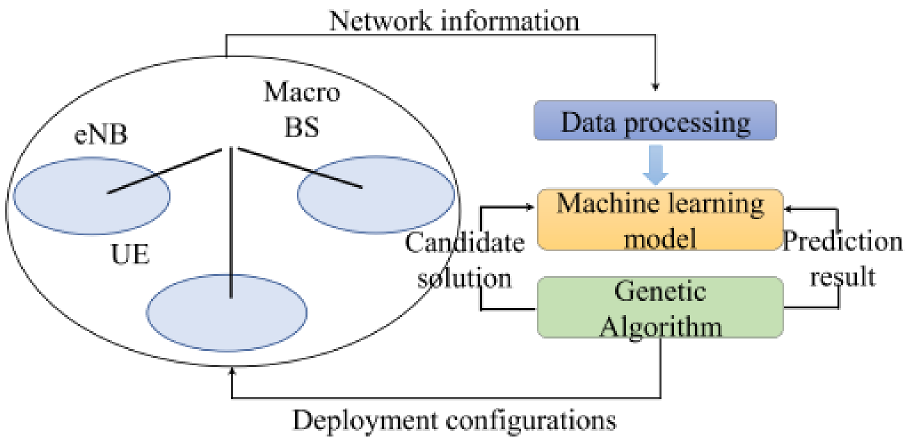


Figure 9: Intelligent BS deployment [56]

The heuristic algorithms are advantageous as they are less complex, and ML algorithms improve efficiency. A hybrid solution is perhaps feasible for B5G networks.

On the other hand, heuristic algorithms may drop to a local optimum while searching for the optimal solution.

User association policy should also be optimized to turn off redundant BSs for energy saving. The locations of users contribute to the changes in traffic loads, and authors in [57] [58] use this information to find an optimal BS switch on/off policy. RL is utilized for BS selection in order to minimize the system power based on traffic patterns. Despite that and considering the user association policy after switching off several BSs, papers ignore the QoS.

2.4 Network planning

Generally, the process of network planning contains not less than three concurrent or recursive phases, mainly as follows:

1. Network Dimensioning. It is the first step in which link budget analysis is assembled to get the approximate number of base stations to meet the high-level coverage and capacity requirements in a specific planning area.
2. Detailed Network Planning. This phase employs the network dimension approximation for the accurate number of required base stations, their placement, and initial network parameters.
3. Post-deployment optimization. The repetition of the optimization process runs in production networks to manage or enhance performance in case of unpredicted or dynamic factors that were not taken into consideration in the previous phase. Factors can be various, for example, network failures or decreasing quality, changes in demand due to new services, the increasing trend of users, and so forth [59].

The complex network planning involves cost, coverage, ElectroMagnetic Field (EMF) limitations, and impacts on both the costs of CAPEX experienced by the operator and the Quality of Service accessed by UEs. Operators have to minimize expenses in cellular network deployments and installation. At the same time, try to enhance the performance in terms of throughput and delay to meet users' Quality of Experience. This research work focuses on the detailed network planning phase [60]. One of the well-known algorithms for network optimization problems, and particularly network planning, is the Genetic Algorithm having an excellent performance in terms of complexity of computation quality of solutions. Authors in [61] presented a data-driven planning framework using a Genetic Algorithm reviewing practical issues met in 5G heterogenous deployments. The experiments were made applying the case study of the urban macrocell-based Network in Addis Ababa, Ethiopia, according to 3G and 4G network configurations. Spatial traffic statistics were made, and data as street furniture's existing backbone was collected. In addition, the authors studied a variety of papers and found out that research on optimizing BS locations is limited, especially in a realistic approach for small cells. A new method for a 5G heterogeneous network was proposed in [62]. Three levels of base stations and their placements are performed based on the principles of Voronoi tessellation. An adaptive formation model is suggested to increase network capacity and QoS. The efficient use of resources can be reached by utilizing a dynamically distributing model to avoid inter-cell interference.

The authors from [63] proposed the new indoor network planning relied on machine learning and genetic Algorithm as well. Pathloss was estimated using the Decision

Tree model. As a result, they got 15 times faster, their model is flexible in terms of replanning, and access points are satisfied with the given conditions. The other work [64] was dedicated to random deployment cases dealing with coverage hole problems using a Genetic Algorithm. The results of simulations showed that coverage could be enhanced by evaluating the minimum number of additional mobile nodes.

To get optimal network performance, the coverage has a vital role in affecting the number of required BSS. In [65], the authors present the GA algorithm's usage for adjusting the femtocell's coverage and optimizing the coverage holes, coverage leakage, and load balance. Moreover, those three metrics are utilized for fitness function determination in evaluating the solutions during the process of evolution. The inaccurate coverage estimations can lead to the network performance decline remarkably, firstly, coverage underestimation, which can be the source of overlapped coverage of neighbouring cells, will raise the out-of-cell interferences, and the level of the received signal will be lower than the given threshold at the cell edge. Consequently, coverage planning and signal analysis are the prioritized conditions that enable 100% network coverage [66].

3. SYSTEM MODEL

3.1 Problem Statement

Suboptimal deployment of BSs can lead to weak network performance. In order to solve this issue, the number of deployed BS in an area should be minimized while at the same time not violating coverage, QoS, and energy efficiency requirements. We adopt the problem statement as presented in [2], expanding its concept by taking into consideration interference and different types of base stations. However, due to the lack of data, which is a common problem, we apply only the Genetic Algorithm, and the network planning architecture is described in the following figure.

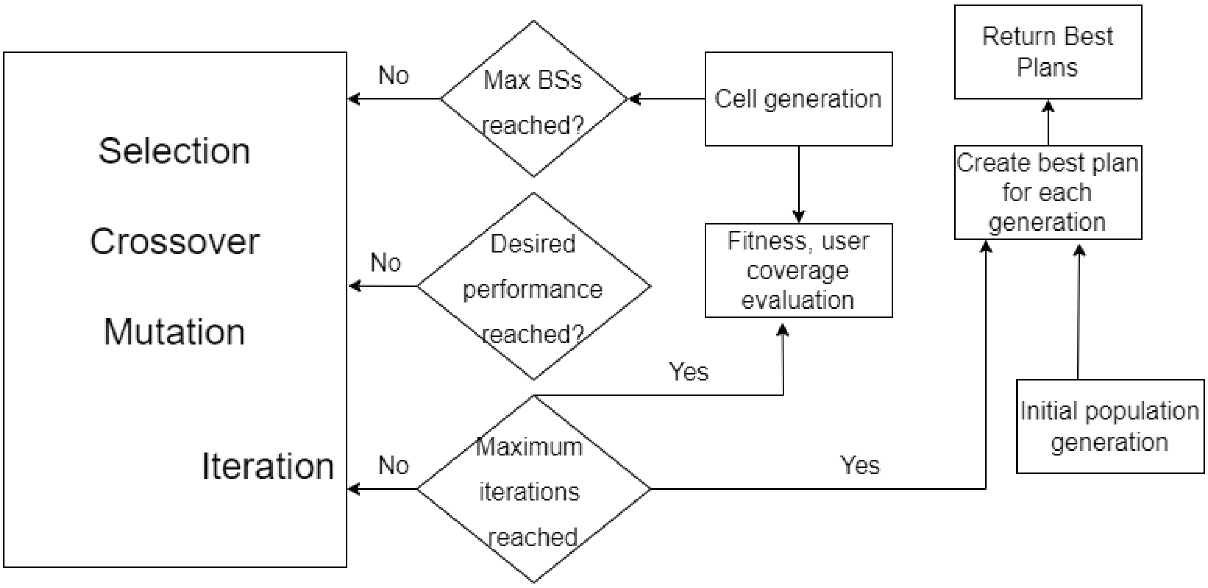


Figure 10: Network planning architecture

The employment of AI in 5G network planning is essential and enables efficient base station deployment by minimization of Signal to Interference Ration (SINR) and enhancing user coverage. This work aims to implement the Genetic Algorithm, an AI algorithm of the Meta-Heuristic category, to deal with planning challenges in 5G cellular communications.

The multi-objective Genetic Algorithm (GA) algorithm is applied to find the optimal number and locations of BSs in an area of interest based on a specific objective function. Two different network scenarios are considered: Homogenous, i.e., consisting of one type of base station (macro cells in our case), and heterogenous, i.e., composed of several types of base stations (microcells, femtocells, picocells, and microcells). Each generation or iteration returns the best plans containing fitness, SINR, and number of active cells depending on the type of it. The population of optimal solutions is randomly generated in every GA iteration. Different types of BSs are presented, such as macrocell, microcell, femtocell, and picocell base stations. This variety allows us to reduce the cost and energy consumption of 5G network planning. The proposed Algorithm tries to minimize the deployment cost and inter-cell interference and maximize user coverage. The areas of interest differ from each other in the density of users within them. Three areas are considered: C area - 4 km^2 and 1000 users, B area - 16 km^2 and 1000 users, and A area - 16 km^2 and 600 users.

The total number of Base Stations for heterogenous BSs is taken as 100; for the homogenous one, the number equals 80. Each generation or iteration returns the best plans containing fitness, SINR, and number of active cells depending on the type of it. The population of optimal solutions is randomly generated in every GA iteration. Different types of BSs are presented, such as macrocell, microcell, femtocell, and picocell base stations. This variety allows us to reduce the cost and energy consumption of 5G network planning. The proposed Algorithm tries to reduce the deployment cost and inter-cell interference and maximize user coverage.

Contributions of this paper are described below:

1) The authors in [2] primarily focused on coverage, while in this work, the Algorithm is also taking the interference into account, which is more practical and closer to the real case.
2) Different types of base stations are presented, thus making the problem fit better to real-world 5G deployments.
3) Three different areas were considered for the precise performance of GA and comparison analysis.

3.2 Proposed Algorithm

3.2.1 Genetic Algorithm Background

Genetic Algorithm is an evolution-based metaheuristic algorithm based on the theory of evolution of species, mainly attributed to complex search and optimization problems. The same approach as in biology is considered: a chromosome is generated and reproduced through a set of processes, i.e., selection, crossover, and mutation. A chromosome represents a possible solution to the problem, and a gene is a part of the solution. The number of generations is directly proportional to the fitness function because the quality in succeeding generations will perform better. From the perspective of biology, fitness is a measure that defines the chromosome's reproductive effectiveness. The fitness function in GA is getting the candidate solution as input and, depending on the solution's fit or goodness, produces the output. It leads to higher fitness value allowing individuals to be selected for the next generation [67]. A description of each process is presented below:

Initialization.

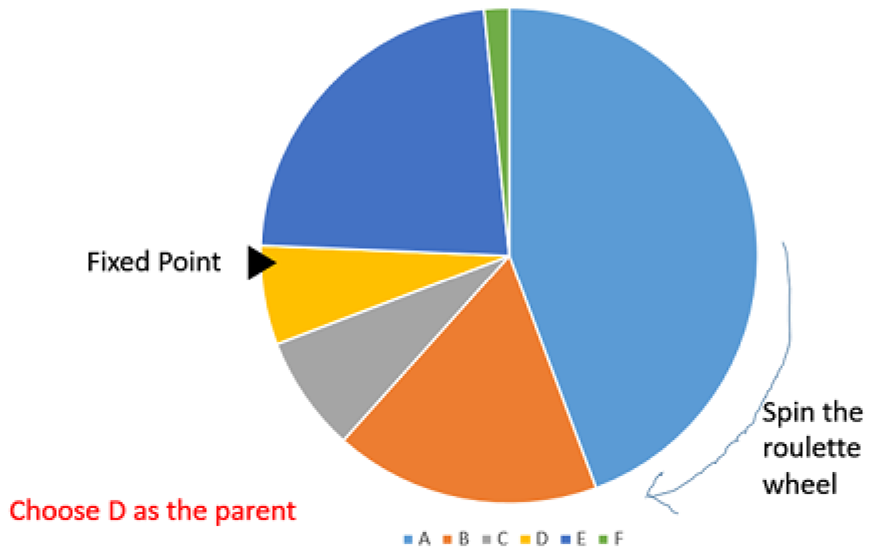
An initial population of chromosomes (i.e., solutions) is randomly generated.

Selection.

The selection or reproduction process is the first operator applied to a population and executed for breeding the new generation. The solutions received after the fitness function are most likely for selection. Certain types of selection exist 1) roulette wheel selection, 2) tournament selection, and 3) stochastic universal selection.

Roulette wheel selection.

The wheel is divided into n parts, where n denotes the number of chromosomes. Each chromosome gets a proportional share in the wheel according to its fitness value. One point is chosen as fixed, and the wheel is rotated. The corresponding parent is selected in whichever part the fixed point is stopped. The exact process is repeated as it is mandatory to have two parents for the next-generation formulation. In total, two iterations are made for parent selection.



Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Figure 11: Roulette wheel selection [68]

The procedure is as follows:

1) The sum of the fitness values of all chromosomes is calculated (S).
2) A random number among 0 and S is generated.
3) Adding S for the partial sum P until P is less than S beginning from the top of the population. The partial sum is the population and sum of finesses, denoted as P between 0 and 1.
4) The individual is chosen when P exceeds the value of S.

Stochastic Universal Sampling.

The difference from roulette wheel selection is that there are multiple fixed points in this type; therefore, making more iterations than one is not mandatory.

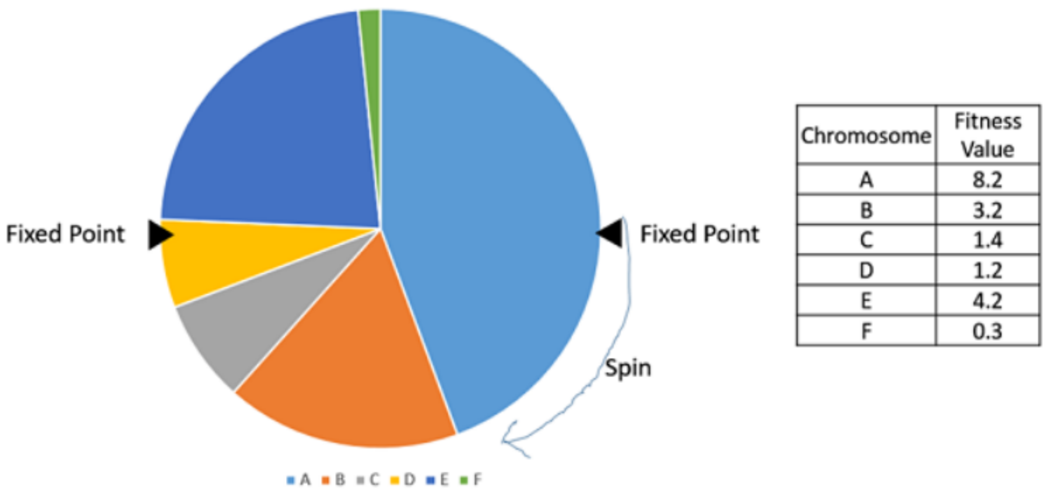


Figure 12: Stochastic Universal Sampling selection

It should be pointed out that selection methods that are based on fitness proportions are not feasible for negative fitness value cases.

Tournament selection.

It is also known as the K-way tournament selection. Random individuals, denoted as K, are selected among the population, and the best one is chosen as the parent. The process is repeated for the selection of the next parent. This method is beneficial for cases with negative fitness values and is most applied.

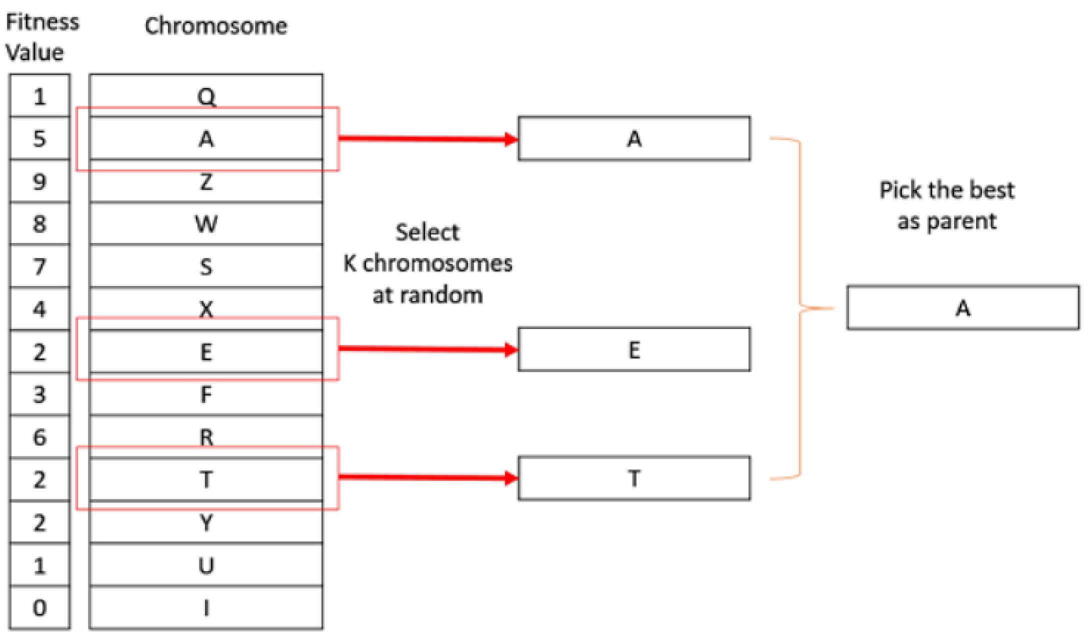


Figure 13: Tournament selection

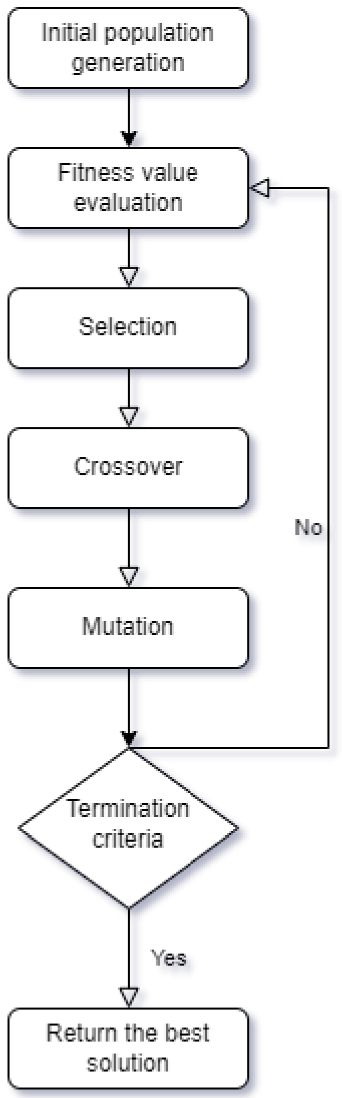


Figure 14: Genetic Algorithm process

Crossover.

It is a GA operator for the recombination of two strings to receive a better string. Mostly implemented one is the arithmetic crossover which has three types: single arithmetic crossover, simple arithmetic crossover, and whole arithmetic crossover. In the arithmetic crossover, two chromosomes are chosen for recombination, and two offspring are made for the result [69].

Single Arithmetic Crossover. Selection of a random single gene k is performed. In the same position, the arithmetic average of two parents is taken. Parents can be denoted as <x_1,…, x_n> and <y,…, y_n>.

Arithmetic operation on parents' genes calculates the gene in that position. Mathematically it can be written as [70]:

$$< x_1, \ldots, x_k, \alpha \times y_k + (1-\alpha) \times x_k, \ldots, x_n >,$$

where α – variable multiplier with value in the range between 0 and 1.

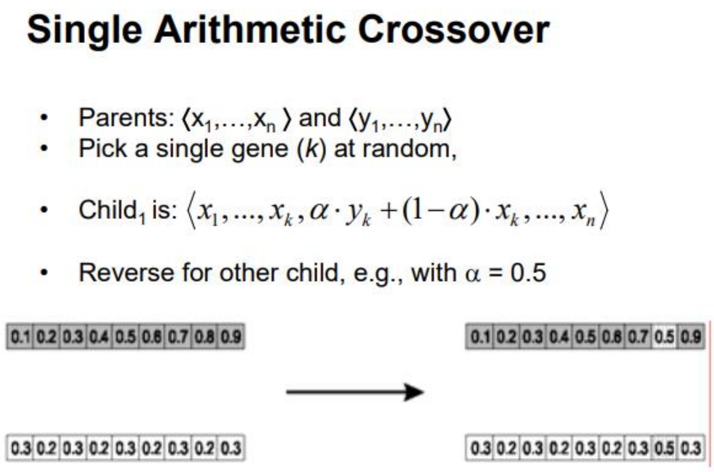


Figure 15: Single Arithmetic Crossover

Simple arithmetic crossover. In this type of random crossover, the number is selected as intersection point k among 0 and each parent's chromosomes. Then the first value k of the randomly selected parent is copied to the child. So, the first child can be written as follows:

$$< x_1, \ldots, x_k, \alpha \times y_{k+1} + (1-\alpha) \times x_{k+1}, \ldots, y_n + (1-\alpha) \times x_n >$$

Parents are represented as <x_1,…, x_n> and <y,…, y_n>.

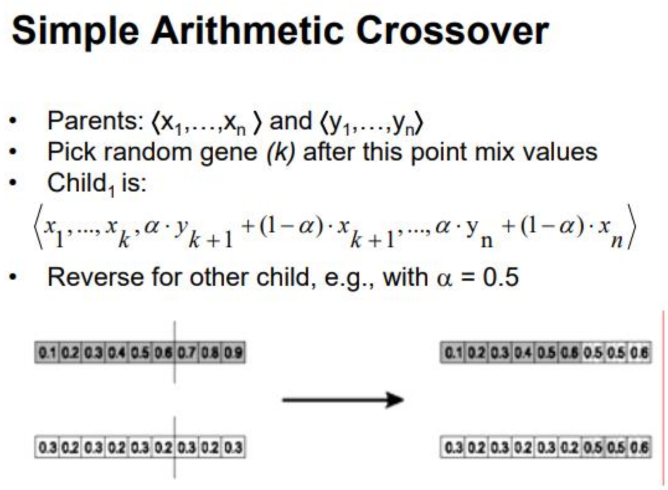


Figure 16: Simple Arithmetic Crossover

Whole arithmetic crossover. It is the most used crossover type, and the procedure is about getting the weighted sum considering the same α value of two parents for each gene.

$$< a \times \bar{x} + (1 - \mathrm{a}) \times \bar{y} >$$

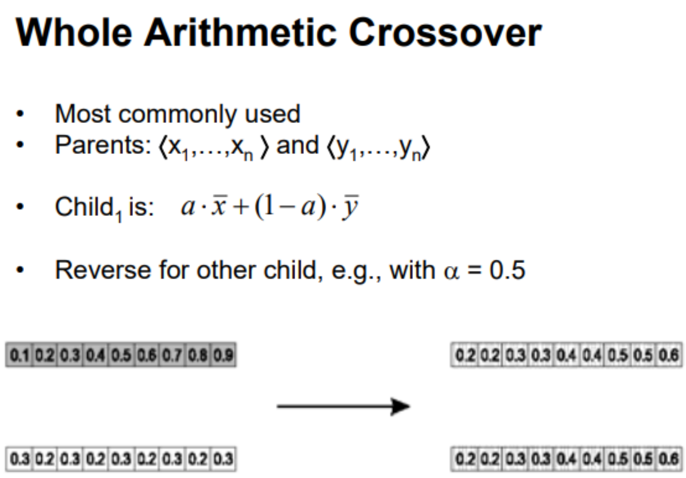


Figure 17: Whole Arithmetic Crossover

Mutation.

The mutation is a random tweaking of chromosomes to get the new solution.

Uniform mutation. Choosing a part of genes randomly and setting random values to them.

Non-uniform mutation. The mutation rate changes depending on how the population fits, for example, reducing the mutations as time passes.

3.3 Mapping of problem to Genetic Algorithm

The 5G base station is the gene; the chromosome is the set of base stations chosen to serve an area noted as plan, and the fitness function is taken as the sum of interference and user coverage; cell means the base station type. The population is depicted by each generation. The generation of initial populations is represented as a pool in the implementation, and the best plans are chosen from the initial population. The initial population includes a number of base stations, all types of base stations, their radiuses, users, and candidate points. Candidate points are used to plant the cell considering the area, step size which is the inter-site distance in our case, and user threshold, which is the minimum number of users per grid. The plan includes the base stations and users demonstrating the single plan. Users are allocated randomly in a uniform way, and they are connected to available cells based on the coordinates of the cells and users as well. Some cells can be disconnected if they do not have enough users to be active. If the number of users is less than the minimum, the cell is turned off, and users are left unconnected.
In the end, all the active cells with their SINR value, fitness values, and how many users are connected employing active cells are considered as best plans for all given generations.

3.3.1 Experiment Parameters

Table 1: Initial parameters of the heterogenous network scenario

Area (m^2)	4000
Step size	125
Number of chromosomes	20
Number of users	1000
Type of base stations	Macro-, micro-, pico-, femtocells
Number of base stations	100
Coverage weight	0.8
Maximum coverage	90
Interference weight	0.2
Selection method	stochastic
Crossover method	whole arithmetic
Mutation method	non-uniform
Mutation type	gaussian

Table 2: Initial parameters of the homogenous network scenario

Area (m^2)	4000
Step size	125
User Threshold	2
Number of generations (iterations)	20
Number of chromosomes	20
Number of users	1000
Type of base stations	homogenous
Number of base stations	100
Coverage weight	0.8
Maximum coverage	90
Interference weight	0.2
Selection method	stochastic
Crossover method	whole arithmetic
Mutation method	non-uniform
Mutation type	gaussian

The genetic Algorithm gives the best plans with active cells (all types), the number of connected users out of 1000 provided, and coverage. In each generation of GA, the optimal solutions were generated randomly and saved for the next operation.

The genetic Algorithm is tested for 18 different cases considering two types of networks (homogenous, heterogenous), three density cases (A, B, C), and three iteration numbers (20, 50, 70). Each case has been run five times, and an average has been calculated for each one of the parameters we study (processing time, number of selected BSs, and user coverage).

3.3.2 Genetic Algorithm process workflow

The reference code from [71] was studied, analyzed, and mapped to the Base Station distribution problem.

Before starting the Genetic Algorithm, some preparation steps have to be followed:

1) Set environment parameters

This step includes the configuration of two parameters: area size in m^2 and the number of users. Both are indicated in the constants.py file.

2) Generate candidate points.

The step size parameter, which is the inter-cite distance (which is equal to 125 in our case), and the threshold of users (equivalent to 2) are utilized to generate cells randomly in the areas of interest by applying the random attribute Numpy library.

3) Pool or Initial Population Generation.

This step generates an initial chromosome population (i.e., possible solutions).

Then according to the given generation, GA operates using this initial population as input and implements the necessary operations such as connecting users, disconnecting the unnecessary cells, and calculating the fitness. Afterwards, the selection method (stochastic universal selection) is applied for a given population and returns plans representing the new pool. Any type among the three: stochastic universal sampling, tournament selection and roulette wheel can be chosen as all of them are depicted in the simulation part.

The exchange of chromosomes is performed in the crossover part of the GA method; the whole arithmetic method is chosen in our case. Each crossover generates two offspring. Following the mutation operator applied over the whole pool, the entire population should be evaluated. This evaluation is performed for all the chromosomes in the population considering the connection between users and base stations, removing the deployed base stations that do not meet such requirements as user threshold, calculating the number of connected users, received power, SINR, and fitness values.

Gaussian distribution and non-uniform mutation type are performed. The crossover probability is 0.6, the mutation probability is 0.4 correspondingly, and the alpha parameter is 0.4. The alpha value is a multiplier factor, and it has an influence on diversity. In the end, the best plans from each generation are selected. Best plans and times are saved in csv files that can be opened and used for other purposes, for example, analysis and comparison. Mutation does not happen frequently and is used only for a small amount of the population in each generation. Generally, the probability of mutation is low; however, the growth of this value may affect the results, which can be uncertain in the end.

The operator adds a random unit Gaussian distribution value to a selected gene in Gaussian mutation. The value is thus added to each element of the gene carrier's vector, which causes the development of a new offspring.

```
# user generation
users = generate_users(NUM_USERS, AREA)

# generate candidate points (used to plant cells)
candidate_points = generate_candidate_points(AREA,
                                             STEP_SIZE,
                                             copy.deepcopy(users),
                                             USERS_THRESHOLD)

# generate initial population
pool = generate_initial_population(NUM_CHROMOSOMES,
                                   candidate_points,
                                   users,
                                   NUM_FIXED_MACRO,
                                   FIXED_MACRO_RADIUS,
                                   NUM_MACRO,
                                   MACRO_RADIUS,
                                   NUM_MICRO,
                                   MICRO_RADIUS,
                                   NUM_PICO,
                                   PICO_RADIUS,
                                   NUM_FEMTO,
                                   FEMTO_RADIUS)
start_time = time.time()
# add the best plan from the initial population
for plan in pool:
    plan.operate()
best_plans.append(find_best_plan(pool))
```

Figure 18: Initial steps for GA

The plan represents the single plan, taking into consideration the users and cells, particularly the distribution of cells according to the user location. The user can be known with x and y coordinates, attribute "close_bss" shows cells(BSs) close to the user, and this User class notes the base station to which the user is currently connected. The "received_power" is the power received from the connected base station; the SINR value for each user can also be taken from this class. User location is crucial in implementing network planning. The whole area of interest is divided into chunk-sized grids; user density is found for each of these grids. The number of candidate points, namely base station locations in deployment, are resolved according to user density. If the user density has high values, it designates the necessity of more base stations in a specific grid.

In addition to saving the best plans in a csv (comma-separated) file, for each generation, the best plan is demonstrated by the image and saved as a png file in the figures folder.

```
# GA start
for generation in range(NUM_GENERATIONS):
    print("GENERATION #{}".format(generation + 1))
    for plan in pool:
        plan.operate()
        print(plan.pprint())

    # selection
    pool = selection(pool, SELECTION_METHOD)

    # crossover
    cross_point = random.randint(1, len(pool) - 1)
    pool = crossover(pool, CROSSOVER_PROBABILTY, cross_point, CROSSOVER_METHOD, ALPHA)

    # mutation
    mutation(pool, AREA, MUTATION_PROBABILTY, MUTATION_METHOD)

    # selection of the best plan from each generation
    best_plans.append(find_best_plan(pool))
```

Figure 19: Genetic Algorithm implementation in Python

Euclidean distance is examined to determine whether a user is close to at least one base station. Gaussian distribution was employed in the Algorithm to design and construct the fitness function.

Mathematically, Euclidean distance can be represented as:

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

Fitness function considering the coverage and interference is modelled as:

fitness = coverage + interference

The fitness value is the representation of how "good" a particular plan/solution is, which is a significant metric in chromosome selection for future generations.

The signal-to-interference ratio (SINR) is calculated for interference determination.

$$SINR = \frac{BS\ power}{Thermal\ Noise^2 + interference + 30}$$

For the determination of received power, let us define the term path loss. Apart from noise signals, transmission can be distorted by losses. The common losses considered in the link budget design for wireless networks include atmospheric absorption loss, reflection and diffraction loss, path loss, and scattering loss which includes rain attenuation. Path Loss is the loss or electromagnetic signal propagation that comes across its path between transmitter and receiver, and it can be represented as:

$$P_L = \frac{P_t}{P_r},$$

where P_t - transmitter power,

P_r – received power.

Channel path loss is also defined in dB:

$$P_L(dB) = 10log_{10}\frac{P_t}{P_r}dB$$

When there is a case of LOS in a communication system without any other impairment, the loss is called free space loss or propagation model free network.

In our case, the path loss is calculated as below:

$$P_L = 20log_{10}(frequency) + 0.06\,(distance) + rain + fooliage$$

The values of rain and foliage are taken as zero, which means free space loss is taken for our model.

Received power can be represented as follows:

$$P_r = 10log_{10}\frac{P_{BS}}{N_{BS}} - P_L + 30\,,$$

where P_{BS} – the power of the base station

N_{BS} – number of base stations

P_L – path loss.

```
num_bs = self.get_num_cells(desired.get_cell_type())
power1 = received_power(desired.get_power(),
                        num_bs,
                        dist1,
                        desired.get_frequency(), 0, 0)

num_bs = self.get_num_cells(tested_cell.get_cell_type())
power2 = received_power(tested_cell.get_power(),
                        num_bs,
                        dist2,
                        tested_cell.get_frequency(), 0, 0)
```

Figure 20: Power calculation in Python

3.3.3 Model implementation parameters

The General Parameters for both homogenous and heterogeneous scenarios are demonstrated in the table below. As mentioned above, the interference was taken into consideration, and its weight is equivalent to 0.2, and the weight of coverage equals 0.8. A crossover probability of 1.0 represents that all the selected chromosomes are utilized in the reproduction process, meaning there are no survivors. But, empirical studies have clarified that better results may be achieved by crossover probability from 0.6 to 0.85, which implies that the probability of the selected chromosomes surviving to the next generation remains stable, not counting the changes from a mutation between 0.4 to 0.15. The minimum number of users in order for cells to be created is 2; the mutation type is Gaussian. The gaussian mutation is a search mutation and retrieval function by enhancing the Genetic Algorithm enhancing the local search ability, for example, search range and direction. Thermal noise is -112,240257 dBm/Hz, and the signal-to-interference threshold is -9.

All the simulations were performed in Python programming language using the PyCharm tool. It should be pointed out that all the simulations were executed on Windows 11Home-64 bit with Intel Core i7 2.8GHZ and 16GB RAM.

Table 3: General Parameters of the proposed model

Parameter Name	Type/Method/Value
Selection Method	Stochastic Universal Sampling
Crossover Method	Whole Arithmetic
Mutation Method	Non-uniform
Mutation Type	Gaussian
Crossover Probability	0.6
Mutation Probability	0.4
Alpha	0.4
User Threshold	2
Number of Chromosomes	20
Thermal Noise	-112,240257
SINR Threshold (dBm)	-9
Coverage Weight	0.8
Interference Weight	0.2
Maximum Interference	1
Number of Fixed Macro Cells	15
Number of Macro Cells (for heterogenous case)	15
Number of Macro Cells (for homogenous case)	100
Number of Micro Cells	30
Number of Pico Cells	20
Number of Femto Cells	20
Total Number of Base Stations	100
Fixed Macro Radius (m)	1000
Macrocell Radius (m) (for heterogenous case)	1000
Macrocell Radius (m) (for homogenous case)	500
Microcell Radius (m)	250
Picocell Radius (m)	100
Femtocell radius (m)	50
Macro Cell Frequency (GHz)	3.5
Micro Cell Frequency (GHz)	28
Fixed Macro, Macrocell power (W)	40
Microcell, femtocell, picocell power (W)	10

4. RESULTS

The experiments are performed for three cases of areas: 600 users in 4000 m × 4000 m area considered as user density area A, user density area B involving 1000 users in 4000 m × 4000 m area, while in the user density area C 1000 users should be connected to base stations in 2000 m × 2000 m area. Users are represented by blue dots, base stations with circles where fixed macrocells are noted in blue, macrocells in red, microcells in pink, femtocells in lime, and picocells in green and there are figures to represent each of the cells in a circle.

4.1 Results for the areas of interest

4.1.1 User density area A

From the simulation part, it is known that the results are based on the best plans for each generation. GA is tested for three different numbers of iterations, namely 20, 50, and 70.

As it was noted in previous sections, GA is also tested for homogenous and heterogenous network scenarios.

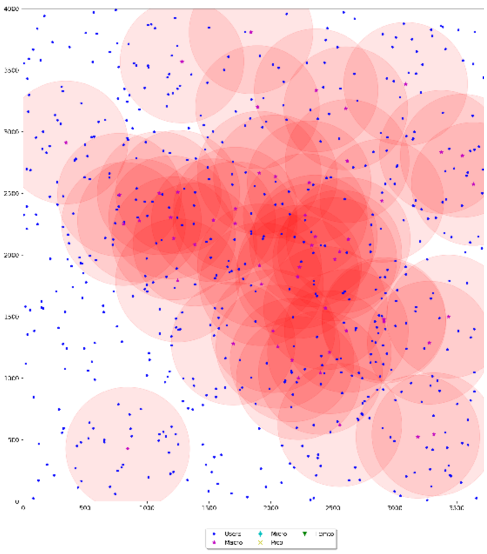


Figure 21: Non- optimized BSs allocation in a homogenous network scenario

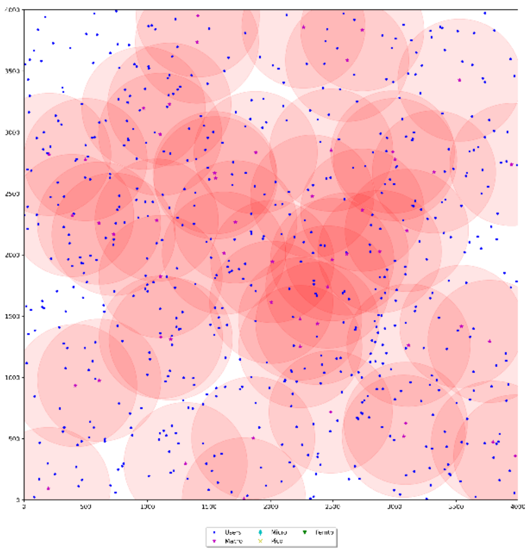


Figure 22: Optimized BS allocation in a homogenous network scenario

Figures 21-24 demonstrate the deployment of base stations in a non-optimized and optimized way in homogenous and heterogenous network scenarios. In the initial deployment, the base stations are installed randomly on candidate points (possible positions for BS deployment) according to the UE locations. From the figure on the left, it is evident that many users are not connected to the base stations, which leads to no-optimized BS deployment.

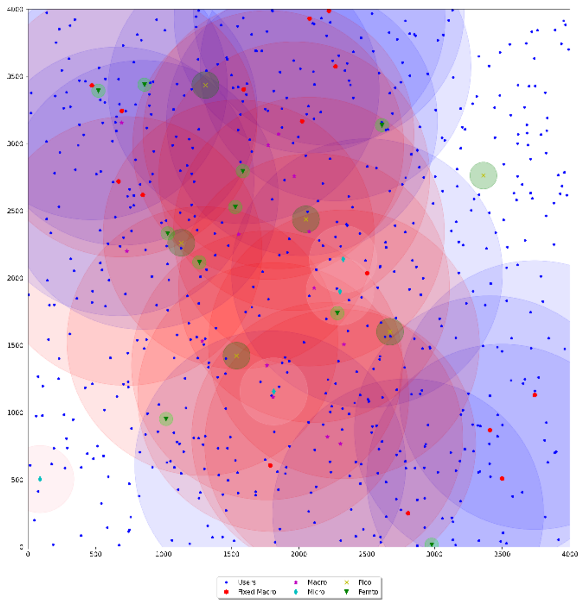


Figure 23: Non-optimized BSs allocation in a heterogenous network scenario

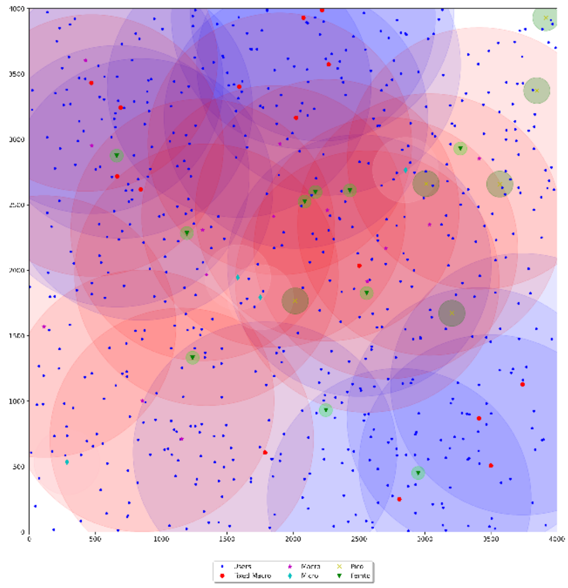


Figure 24: Optimized BS allocation in a heterogenous network scenario

Table 4: User-density area A - homogenous network results

Homogenous Network			
Iterations	20	50	70
Average			
Processing time (sec)	417.5105	828.7947	1033.712
Quality (final user coverage) (%)	99.55	99.52	99.18
Number of Base stations	33	36.2	34.2
SINR	-4.992	-4.9784	-4.9558

After applying the Genetic Algorithm, the optimized BS locations can be found in the figure on the right side. Enhanced user coverage is reached by using the Algorithm.

The results of simulations are written in the table depending on the area of interest. The data is distinguished with parameters such as processing time (in seconds), final user coverage (%), and the number of selected BSs. All scenarios are simulated five times, and the average is retained for future analysis.

Table 5: User-density area A - heterogenous network results

Heterogenous Network			
Iterations	20	50	70
Average			
Processing time (sec)	497.5708	870.9255	1276.678
Quality (final user coverage) (%)	96.02	95.32	96.18
Number of Base stations	38.6	40.2	37.2
SINR	-5.3756	-5.3978	-5.3924

4.1.2 User density area B

Table 6: User-density area B - homogenous network results

Homogenous Network			
Iterations	20	50	70
Average			
Processing time (sec)	254.33	792.4779	995.6182
Quality (final user coverage) (%)	97.18	97.4	97.28
Number of Base stations	43.2	42.8	40.2
SINR	-5.048	-5.0582	-5.0266

Table 7: User-density area B – heterogenous network results

Heterogenous Network			
Iterations	20	50	70
Average			
Processing time (sec)	456.1047	1044.853	1371.042
Quality (final user coverage) (%)	88.66	91.38	89.9
Number of Base stations	35	28.8	29.2
SINR	-4.8134	-4.8508	-5.0124

4.1.3 User density area C

Table 8: User-density area C – homogenous network results

Homogenous Network			
Iterations	20	50	70
Average			
Processing time (sec)	417.5105	828.7947	1033.712
Quality (final user coverage) (%)	99.55	99.52	99.18
Number of Base stations	33	36.2	34.2
SINR	-4.992	-4.9784	-4.9558

Table 9: User-density area C -heterogenous network results

Heterogenous Network			
Iterations	20	50	70
Average			
Processing time (sec)	497.5708	870.9255	1276.678
Quality (final user coverage) (%)	96.02	95.32	96.18
Number of Base stations	38.6	40.2	37.2
SINR	-5.3756	-5.3978	-5.3924

4.2 Analysis and Insights

4.2.1 User coverage

The chart below demonstrates the average user coverage for all three areas of interest.

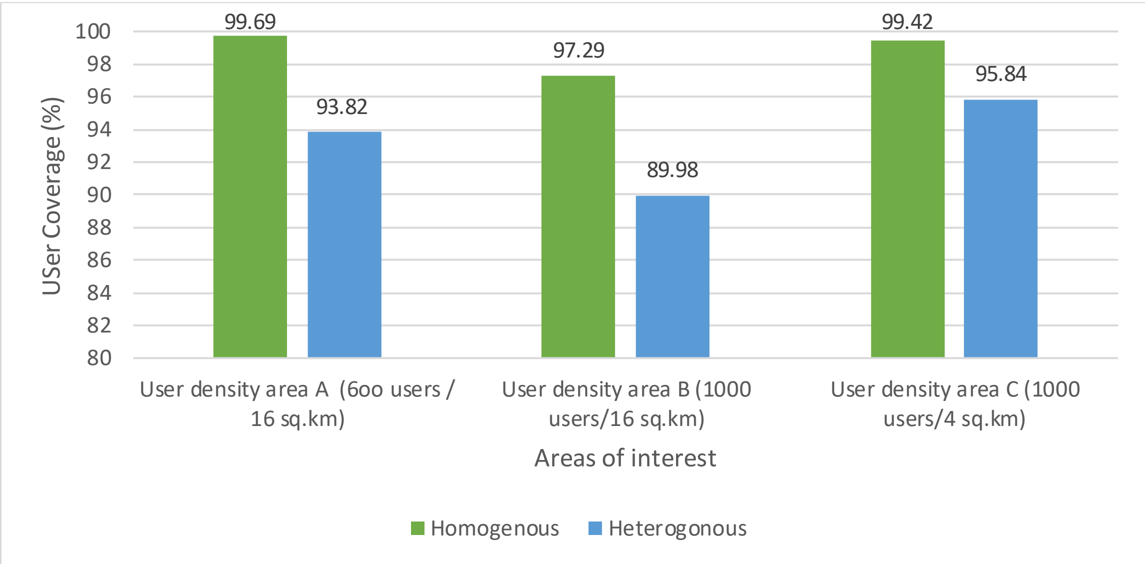


Figure 25: User Coverage Chart

A and C user density areas in the homogenous network scenario have approximately the same user coverage percentage, while about 97,29% of users were covered in the user density area B. Unlike the first scenario, in the heterogenous Network, the maximum coverage equals 95.84%, which corresponds to the user density area C, while A and B cases showed 93.82% and 89.98 respectively. Generally, GA seems to give better results in dense areas, which is very promising, as the majority of the networks in 5G will be of high user density. Consequently, as the mobile network networks beyond 5G are expected to be even denser than 5G, the application of GA can be beneficial.

4.2.2 Number of selected Base Stations

The following important parameter that should be compared and analyzed is the number of selected base stations. The total number of BSs before the GA runs is 100. The number of base stations in the heterogenous scenario is less than the homogenous one for the two first cases. On the other hand, in the user-density area C, the two network scenarios are very close, with the homogenous case having an advantage.

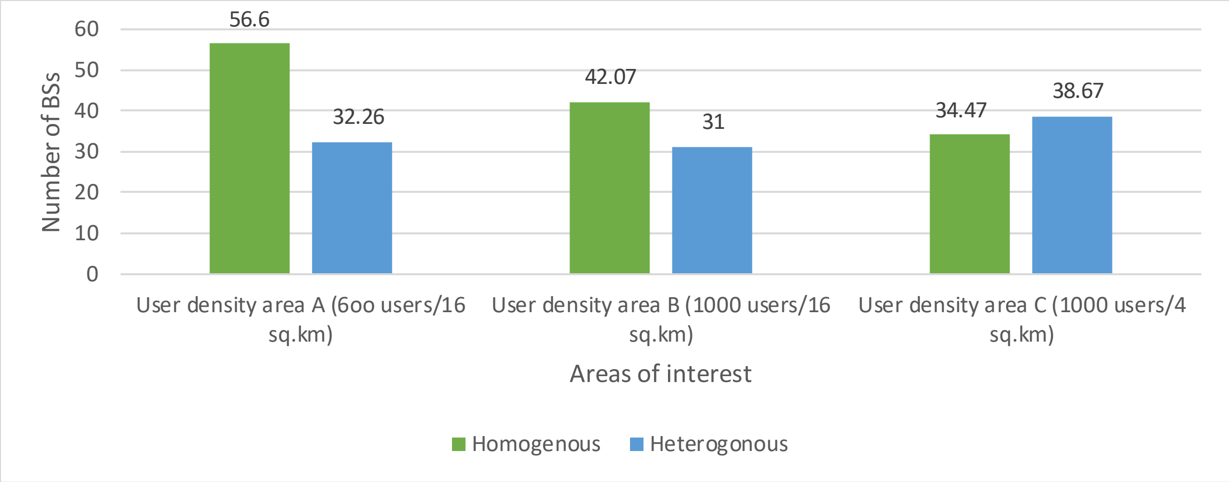


Figure 26: Required number of Base Stations chart

From the results of user coverage and the number of BSs in the homogenous scenario, the percentage of user coverage and the number of selected BSs are directly proportional. In other words, more BSs are necessary to serve as many users as possible. However, the purpose of this work is to have the highest served users and optimized (less) number of required BSs. The performance of GA is better in heterogenous Networks because it can reduce the number of selected BSs to approximately 30% in all density cases.

4.2.3 Processing time result analysis

The processing time of applying the Genetic Algorithm and its execution is another significant parameter in any simulation results. In this case, time is identified in seconds; six lines represent the areas and types of scenarios. All the homogenous scenarios are designated in red and heterogenous scenarios are in green color. A Square demonstrates the A area; a triangle is utilized for a user-density area B, and a circle represents user-density area C. The heterogeneous scenario in the user-density area B had the most prolonged duration.

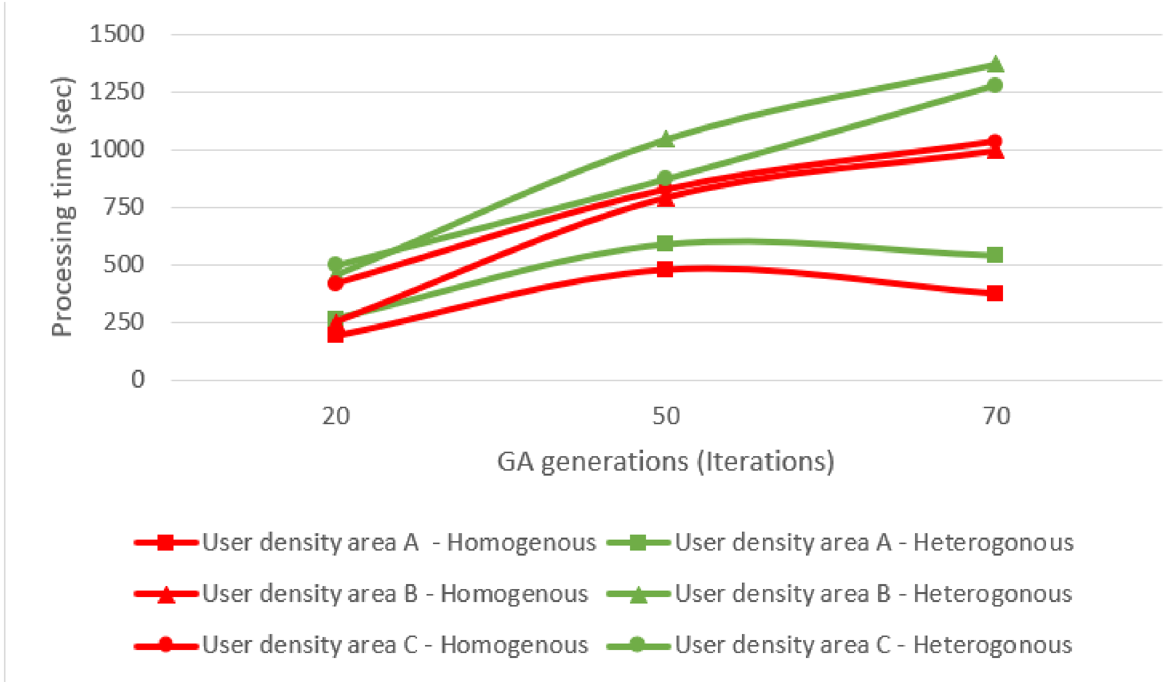


Figure 27: Processing time chart

In the processing time chart, square points represent 20,50, and 70 iterations, respectively. Most of the cases have an increasing trend according to the growth of iterations, which is predictable. One more parameter strongly related to the processing time is the number of base stations due to the data collection during simulations.

4.2.4 SINR result analysis

Minimization of SINR ensures the efficient deployment of base stations. The chart shows that the lowest values of SINR that is close to -5.5 dBm correspond to user-density area C in heterogeneous networks. In comparison, the user-density area A in both heterogenous and homogenous networks represents the highest SINR, approximately -3 dBm. Also, it is noteworthy that a higher number of iterations have lower values of SINR, which is promising in reaching better network performance.

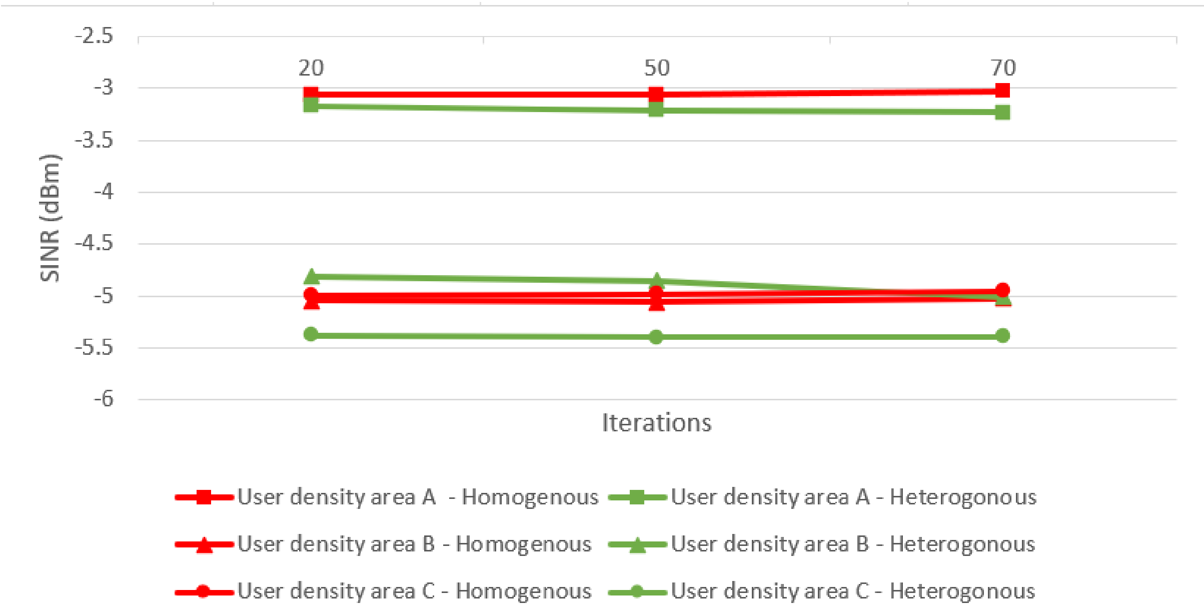


Figure 28: SINR vs. Iterations chart

Analyzing all the results that were found for the four approaches, even if the highest number of served users corresponds to the A area that uses only macro base stations, on the contrary, the number of base stations is increased. Hence, we cannot consider it as the best performance. On the other hand, the heterogeneous scenario in a user density area B shows the results of 31 required BSs and 89% user coverage, which is a mediocre result concerning the coverage but very energy efficient, as the number of selected BSs is limited. Correlating the processing time, the number of base stations, user coverage noted in per cent, the use of various types of base stations, i.e., the heterogonous scenario in the user-density area A took a maximum of 591 seconds for simulating the Genetic Algorithm and returning the best plans with figures covering 94% of users that corresponds to 563 users out of 600 can be considered as the best and optimized solution. The maximum number of connected users and reduced SINR value could be adjusted to specific requirements. The usage of small cells meets the QoS UE requirements, especially in hotspot areas, as well as propagation conditions at higher frequencies.

CONCLUSIONS AND FUTURE WORK

This paper proposes a network planning scheme integrating the metaheuristic Genetic Algorithm for the optimization of BS deployment. The research aims to maximize the served users while reducing the number of deployed numbers of base stations, also considering the processing time for the simulation. The proposed framework of heterogenous network planning outperforms the existing macro cell homogeneous deployment mentioned as the homogenous scenario in this work. It is utilized for the analysis purpose of comparing the heterogeneous scenario. The application of GA is advantageous in the case of heterogeneous networks for a reason, the number of selected BSs can be minimized by almost 30%. Besides that, developing mobile networks requires the best performance in densely distributed areas; from the results, it can be clearly seen that GA presents success in this area of interest.

Further studies must consider user mobility for this specific network planning scheme. Other benchmark algorithms can be studied and analyzed for comparison and have a deeper performance examination. In addition, the dataset can be created using the proposed Algorithm for prediction tasks. The losses, such as foliage and rain attenuation, can be reviewed since, in this simulator, they are mentioned, however, taken as zero. As it is widely known, the number of served users starting from 5G is assumed to be increased up to 1 mln devices per square kilometre; the proposed approach can be studied further with densely distributed users.

Additionally, as resource allocation is a significant aspect of all communications systems, other parameters that may also impact the network performance, such as geographical data, including azimuth, mechanical and electrical downlit, and the height of base stations, should also be considered.

ABBREVIATIONS – ACRONYMS

3G	3rd generation mobile network technology
4G	4th generation mobile network technology
5G	5th generation mobile network technology
6G	6th generation mobile network technology
ACO	Ant Colony Optimization
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARMA	Auto Regressive Moving Average
B5G	Beyond 5G
BS	Base Station
CAPEX	Capital Expenditures
CNC	Cellular Network Communications
COC	Computation-Oriented Communications
CSI	Channel State Information
CSP	Communications Service Providers
DL	Deep Learning
EE	Energy Efficiency
eMBB	enhanced Mobile Broadband
eNBs	evolved Node B
FL	Fuzzy Logic
GA	Genetic Algorithm
ICT	Information and Communication Technology
KNN	k-Nearest Neighbours
LOS	Line-Of-Sight
LTE	Long-Term Evolution
MAC	Medium Access Control
MANO	Management and orchestration

GA	Genetic Algorithm
MBS	Macro Base Stations
ML	Machine Learning
MLP	Multilayer Perceptron
MM	Mobility Management
mMTC	massive Machine-Type Communications
MTC	Machine Type Communications
multi-RAT	multiple Radio Access Technology
NFV	Network Function Virtualization
PRB	Physical Resource Block
QoE	Quality of Experience
QoS	Quality of Service
RL	Reinforcement Learning
RRC	Radio Resource Control
RRM	Radio Resource Management
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
RSS	Received Signal Strength
SBS	Small-cell Base Stations
SE	Spectrum Efficiency
SVM	Support Vector Machines
TSP	Traveling Salesman Problem
UE	User Equipment
URLLC	Ultra-Reliable Low Latency Communications

REFERENCES

[1] Q. Wu *et al.*, "A Comprehensive Overview on 5G-and-Beyond Networks With UAVs: From Communications to Sensing and Intelligence," *IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS*, vol. 39, no. 10, 2021, doi: 10.1109/JSAC.2021.3088681.

[2] L. Dai and H. Zhang, "Propagation-model-free base station deployment for mobile networks: Integrating machine learning and heuristic methods," *IEEE Access*, vol. 8, pp. 83375–83386, 2020, doi: 10.1109/ACCESS.2020.2990631.

[3] R. Li *et al.*, "Intelligent 5G: When Cellular Networks Meet Artificial Intelligence," *IEEE Wirel Commun*, vol. 24, no. 5, pp. 175–183, Oct. 2017, doi: 10.1109/MWC.2017.1600304WC.

[4] X. Li, M. Samaka, H. A. Chan, L. Gupta, C. Guo, and R. Jain, "5G Network Slicing for 5G: Challenges and Opportunities," 2017, doi: 10.1109/LANMAN.2016.7548842.

[5] Marin Ivezic, "Introduction to 5G Core Service-Based Architecture (SBA) Components," Aug. 16, 2020.

[6] "5G Core Service Based Architecture," 2019.

[7] M.-K. Shin, Y. Choi, H. H. Kwak, S. Pack, M. Kang, and J.-Y. Choi, *Verification for NFV-enabled network services; Verification for NFV-enabled network services*. 2015. doi: 10.1109/ICTC.2015.7354672.

[8] "Standalone Base Station Architecture in 5G."

[9] X. Ge *et al.*, "Spatial Spectrum and Energy Efficiency of Random Cellular Networks," *IEEE TRANSACTIONS ON COMMUNICATIONS*, vol. 63, no. 3, p. 1019, 2015, doi: 10.1109/TCOMM.2015.2394386.

[10] M. M. Ahamed and S. Faruque, "5G Network Coverage Planning and Analysis of the Deployment Challenges," *Sensors*, vol. 21, no. 19, p. 6608, Oct. 2021, doi: 10.3390/s21196608.

[11] M. M. Mowla, I. Ahmad, D. Habibi, and Q. V. Phung, "A Green Communication Model for 5G Systems," *IEEE Transactions on Green Communications and Networking*, vol. 1, no. 3, pp. 264–280, Sep. 2017, doi: 10.1109/TGCN.2017.2700855.

[12] S. Russell, L. Chen, and P. Norvig, "Artificial Intelligence A Modern Approach Third Edition," 2010.

[13] M. Liao and Y. Yao, "Applications of artificial intelligence-based modeling for bioenergy systems: A review," *GCB Bioenergy*, vol. 13, no. 5, pp. 774–802, May 2021, doi: 10.1111/gcbb.12816.

[14] S. S. Rao, A. Nahm, Z. Shi, X. Deng, and A. Syamil, "Artificial intelligence and expert systems applications in new product development—a survey," *J Intell Manuf*, vol. 10, no. 3/4, pp. 231–244, 1999, doi: 10.1023/A:1008943723141.

[15] C. Moraga, "Introduction to fuzzy logic," *Facta universitatis - series: Electronics and Energetics*, vol. 18, no. 2, pp. 319–328, 2005, doi: 10.2298/FUEE0502319M.

[16] M. B. Alazzam, N. Tayyib, S. Zuhair Alshawwa, and M. K. Ahmed, "Nursing Care Systematization with Case-Based Reasoning and Artificial Intelligence," 2022, doi: 10.1155/2022/1959371.

[17] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," *Neurocomputing*, vol. 187, pp. 27–48, Apr. 2016, doi: 10.1016/j.neucom.2015.09.116.

[18] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *J Pharm Biomed Anal*, vol. 22, no. 5, pp. 717–727, Jun. 2000, doi: 10.1016/S0731-7085(99)00272-1.

[19] W. Zhang, R. Dechter, and R. E. Korf, "Heuristic search in artificial intelligence," *Artif Intell*, vol. 129, no. 1–2, pp. 1–4, Jun. 2001, doi: 10.1016/S0004-3702(01)00111-4.

[20] K. Sörensen, "Metaheuristics-the metaphor exposed," *International Transactions in Operational Research*, vol. 22, no. 1, pp. 3–18, Jan. 2015, doi: 10.1111/itor.12001.

[21] K. Castillo-Villar, "Metaheuristic Algorithms Applied to Bioenergy Supply Chain Problems: Theory, Review, Challenges, and Future," *Energies (Basel)*, vol. 7, no. 11, pp. 7640–7672, Nov. 2014, doi: 10.3390/en7117640.

[22] Z. Chunrong, H. Tao, and X. Xianglin, "Design and Implementation of Reading System Based on Improved Personalized Recommendation Hybrid Algorithm; Design and Implementation of Reading System Based

on Improved Personalized Recommendation Hybrid Algorithm," *2022 IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, vol. 10, 2022, doi: 10.1109/ITAIC54216.2022.9836614.

[23] M. Yao, M. Sohul, V. Marojevic, and J. H. Reed, "Artificial Intelligence Defined 5G Radio Access Networks," *IEEE Communications Magazine*, vol. 57, no. 3, pp. 14–20, Mar. 2019, doi: 10.1109/MCOM.2019.1800629.

[24] Murphy and Kevin P, *Machine learning: a probabilistic perspective*. Cambridge: MA: MIT Press, 2012.

[25] B. Zhao, J. Liu, Z. Wei, I. You, and S. Member, "SPECIAL SECTION ON GREEN COMMUNICATIONS ON WIRELESS NETWORKS A Deep Reinforcement Learning Based Approach for Energy-Efficient Channel Allocation in Satellite Internet of Things", doi: 10.1109/ACCESS.2020.2983437.

[26] V. A. Siris and M. Anagnostopoulou, *Performance and Energy Efficiency of Mobile Data Offloading with Mobility Prediction and Prefetching*. 2013. doi: 10.1109/WoWMoM.2013.6583450.

[27] N. Ristanovic, J.-Y. le Boudec EPFL, A. Chaintreau, and V. Erramilli, "Energy Efficient Offloading of 3G Networks," 2011, doi: 10.1109/MASS.2011.27.

[28] A. Gharsallah, F. Zarai, and M. Neji, "SDN/NFV-based handover management approach for ultradense 5G mobile networks," 2018, doi: 10.1002/dac.3831.

[29] P. Hemrajani, V. S. Dhaka, M. K. Bohra, and A. K. Gupta, "Artificial Intelligence in Wireless Communication," in *Artificial Intelligent Techniques for Wireless Communication and Networking*, Wiley, 2022, pp. 317–334. doi: 10.1002/9781119821809.ch20.

[30] M. Yao, M. M. Sohul, X. Ma, V. Marojevic, and J. H. Reed, "Sustainable green networking: exploiting degrees of freedom towards energy-efficient 5G systems," *Wireless Networks*, vol. 25, no. 3, pp. 951–960, Apr. 2019, doi: 10.1007/s11276-017-1626-7.

[31] M. A. Kamal, H. W. Raza, M. M. Alam, M. M. Su'ud, and A. binti A. B. Sajak, “Resource Allocation Schemes for 5G Network: A Systematic Review,” *Sensors*, vol. 21, no. 19, p. 6588, Oct. 2021, doi: 10.3390/s21196588.

[32] W. Wu, F. Zhou, S. Member, and Q. Yang, "Adaptive Network Resource Optimization for Heterogeneous VLC/RF Wireless Networks," *IEEE TRANSACTIONS ON COMMUNICATIONS*, vol. 66, no. 11, 2018, doi: 10.1109/TCOMM.2018.2831207.

[33] L. Xu *et al.*, "Security-Aware Proportional Fairness Resource Allocation for Cognitive Heterogeneous Networks; Security-Aware Proportional Fairness Resource Allocation for Cognitive Heterogeneous Networks," *IEEE Trans Veh Technol*, vol. 67, no. 12, 2018, doi: 10.1109/TVT.2018.2873139.

[34] Y. Chen *et al.*, "Resource Allocation for Device-to-Device Communications in Multi-Cell Multi-Band Heterogeneous Cellular Networks; Resource Allocation for Device-to-Device Communications in Multi-Cell Multi-Band Heterogeneous Cellular Networks," *IEEE Trans Veh Technol*, vol. 68, no. 5, 2019, doi: 10.1109/TVT.2019.2903858.

[35] M. Ali, S. Qaisar, M. Naeem, S. Mumtaz, and M. Ali, "SPECIAL SECTION ON GREEN COMMUNICATIONS AND NETWORKING FOR 5G WIRELESS Energy Efficient Resource Allocation in D2D-Assisted Heterogeneous Networks with Relays", doi: 10.1109/ACCESS.2016.2598736.

[36] A. Othman and N. A. Nayan, "Efficient admission control and resource allocation mechanisms for public safety communications over 5G network slice," *Telecommun Syst*, vol. 72, no. 4, pp. 595–607, Dec. 2019, doi: 10.1007/s11235-019-00600-9.

[37] R. Li, Z. Zhao, J. Zheng, C. Mei, Y. Cai, and H. Zhang, "The Learning and Prediction of Application-Level Traffic Data in Cellular Networks," *IEEE Trans Wirel Commun*, vol. 16, no. 6, pp. 3899–3912, Jun. 2017, doi: 10.1109/TWC.2017.2689772.

[38] R. Li, Z. Zhao, X. Zhou, and H. Zhang, "Energy savings scheme in radio access networks via compressive sensing-based traffic load prediction," *TRANSACTIONS ON EMERGING TELECOMMUNICATIONS TECHNOLOGIES Trans. Emerging Tel. Tech*, 2012, doi: 10.1002/ett.2583.

[39] M. Yan, J. Zhou, Y. Sun, and Y.-C. Liang, "Intelligent Resource Scheduling for 5G Radio Access Network Slicing; Intelligent Resource Scheduling for 5G Radio Access Network Slicing," *IEEE Trans Veh Technol*, vol. 68, no. 8, p. 7691, 2019, doi: 10.1109/TVT.2019.2922668.

[40] Camps-Mur *et al.*, "AI and ML – Enablers for Beyond 5G Networks," 2021. https://www.researchgate.net/publication/352551034_AI_and_ML_-_Enablers_for_Beyond_5G_Networks (accessed Jul. 06, 2022).

[41] C. Yang, J. Li, S. Member, Q. Ni, A. Anpalagan, and M. Guizani, "Interference-Aware Energy Efficiency Maximization in 5G Ultra-Dense Networks," *IEEE TRANSACTIONS ON COMMUNICATIONS*, vol. 65, no. 2, 2017, doi: 10.1109/TCOMM.2016.2638906.

[42] I. Alawe, Y. Hadjadj-Aoul, A. Ksentini, P. Bertin, and D. Darche, *On the scalability of 5G core network: The AMF case; On the scalability of 5G core network: The AMF case*. 2018. doi: 10.1109/CCNC.2018.8319194.

[43] C. Hernan, T. Arteaga, A. Ordoñez, O. Mauricio, and C. Rendon, "Scalability and Performance Analysis in 5G Core Network Slicing", doi: 10.1109/ACCESS.2020.3013597.

[44] V. S. Pana, O. P. Babalola, and V. Balyan, "5G radio access networks: A survey," *Array*, vol. 14, p. 100170, Jul. 2022, doi: 10.1016/j.array.2022.100170.

[45] B. Mao, Y. Kawamoto, and N. Kato, "AI-Based Joint Optimization of QoS and Security for 6G Energy Harvesting Internet of Things; AI-Based Joint Optimization of QoS and Security for 6G Energy Harvesting Internet of Things," *IEEE Internet Things J*, vol. 7, no. 8, 2020, doi: 10.1109/JIOT.2020.2982417.

[46] "(No Title)."

[47] T. Lv, H. Gao, and S. Yang, "Secrecy Transmit Beamforming for Heterogeneous Networks; Secrecy Transmit Beamforming for Heterogeneous Networks," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 6, 2015, doi: 10.1109/JSAC.2015.2416984.

[48] L. Wang, K.-K. Wong, M. Elkashlan, A. Nallanathan, S. Member, and S. Lambotharan, "Secrecy and Energy Efficiency in Massive MIMO Aided Heterogeneous C-RAN: A New Look at Interference," *IEEE J Sel Top Signal Process*, vol. 10, no. 8, p. 1375, 2016, doi: 10.1109/JSTSP.2016.2600520.

[49] Ericsson, "Employing AI techniques to enhance returns on 5G network investments".

[50] B. Mao, F. Tang, Y. Kawamoto, and N. Kato, "AI Models for Green Communications Towards 6G," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 1, pp. 210–247, Nov. 2022, doi: 10.1109/COMST.2021.3130901.

[51] M. Bashar *et al.*, “Exploiting Deep Learning in Limited-Fronthaul Cell-Free Massive MIMO Uplink,” *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 8, pp. 1678–1697, Aug. 2020, doi: 10.1109/JSAC.2020.3000812.

[52] M. A. Kamal, H. W. Raza, M. M. Alam, M. M. Su’ud, and A. binti A. B. Sajak, “Resource Allocation Schemes for 5G Network: A Systematic Review,” *Sensors*, vol. 21, no. 19, p. 6588, Oct. 2021, doi: 10.3390/s21196588.

[53] I. Törős and P. Fazekas, "An Algorithm for Automatic Base Station Placement in Cellular Network Deployment," 2010, pp. 21–30. doi: 10.1007/978-3-642-13971-0_3.

[54] R. Ghanavi, E. Kalantari, M. Sabbaghian, H. Yanikomeroglu, and A. Yongacoglu, "Efficient 3D Aerial Base Station Placement Considering Users Mobility by Reinforcement Learning," 2018.

[55] Y. Wei, F. R. Yu, M. Song, and Z. Han, "User Scheduling and Resource Allocation in HetNets With Hybrid Energy Supply: An Actor-Critic Reinforcement Learning Approach," *IEEE Trans Wirel Commun*, vol. 17, no. 1, pp. 680–692, Jan. 2018, doi: 10.1109/TWC.2017.2769644.

[56] J. Moysen, L. Giupponi, and J. Mangues-Bafalluy, "A machine learning enabled network planning tool," Dec. 2016. doi: 10.1109/PIMRC.2016.7794909.

[57] S. Sharma, S. J. Darak, and A. Srivastava, "Energy saving in heterogeneous cellular network via transfer reinforcement learning based policy," in *2017 9th International Conference on Communication Systems and Networks (COMSNETS)*, Jan. 2017, pp. 397–398. doi: 10.1109/COMSNETS.2017.7945411.

[58] S. Sharma, S. J. Darak, and A. Srivastava, "Transfer Reinforcement Learning based Framework for Energy Savings in Cellular Base Station Network," in *2019 URSI Asia-Pacific Radio Science Conference (AP-RASC)*, Mar. 2019, pp. 1–4. doi: 10.23919/URSIAP-RASC.2019.8738418.

[59] B. Berehanu Haile, E. Mutafungwa, and J. Hämäläinen, "A Data-Driven Multi-objective Optimization Framework for Hyperdense 5G Network Planning", doi: 10.1109/ACCESS.2020.3023452.

[60] L. Chiaraviglio, C. di Paolo, and N. Blefari-Melazzi, "5G Network Planning Under Service and EMF Constraints: Formulation and Solutions; 5G Network Planning Under Service and EMF Constraints: Formulation and Solutions," *IEEE Trans Mob Comput*, vol. 21, 2022, doi: 10.1109/TMC.2021.3054482.

[61] B. Berehanu Haile, E. Mutafungwa, and J. Hämäläinen, "A Data-Driven Multi-objective Optimization Framework for Hyperdense 5G Network Planning", doi: 10.1109/ACCESS.2020.3023452.

[62] J. Su *et al.*, "5G multi-tier radio access network planning based on voronoi diagram," *Measurement*, vol. 192, p. 110814, Mar. 2022, doi: 10.1016/j.measurement.2022.110814.

[63] Y. Hervis Santana, R. Martinez Alonso, G. Guillen Nieto, L. Martens, W. Joseph, and D. Plets, "Indoor Genetic Algorithm-Based 5G Network Planning Using a Machine Learning Model for Path Loss Estimation," *Applied Sciences*, vol. 12, no. 8, p. 3923, Apr. 2022, doi: 10.3390/app12083923.

[64] O. Banimelhem, M. Mowafi, and W. Aljoby, "Genetic Algorithm Based Node Deployment in Hybrid Wireless Sensor Networks," *Communications and Network*, vol. 05, no. 04, pp. 273–279, 2013, doi: 10.4236/cn.2013.54034.

[65] L. Ho, H. Claussen, and D. Cherubini, *Online evolution of femtocell coverage algorithms using genetic programming*. 2013. doi: 10.1109/PIMRC.2013.6666667.

[66] M. Ahamed and S. Faruque, "5G Network Coverage Planning and Analysis of the Deployment Challenges," 2021, doi: 10.3390/s21196608.

[67] A. Lambora, K. Gupta, and K. Chopra, "Genetic Algorithm- A Literature Review," in *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, Feb. 2019, pp. 380–384. doi: 10.1109/COMITCon.2019.8862255.

[68] "Genetic Algorithms - Parent Selection." tutorialspoint.com/genetic_algorithms/genetic_algorithms_parent_selection.htm (accessed Aug. 20, 2022).

[69] C. Ryan, *Automatic re-engineering of software using genetic programming*. Kluwer Academic, 2014.

[70] M. Furqan, E. Ongko, M. Ikhsan, and C. Author, "Performance of Arithmetic Crossover and Heuristic Crossover in Genetic Algorithm Based on Alpha Parameter," vol. 19, no. 5, pp. 31–36, doi: 10.9790/0661-1905013136.

[71] "5G planning using GA," Dec. 23, 2019. https://github.com/pisceswolf96/5G-planning-using-a-GA (accessed Oct. 11, 2022).