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Power Optimization in Multi-Tier Heterogeneous Networks Using Genetic Algorithm

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Abstract: The Internet of Things (IoT) connects numerous sensor nodes and devices, resulting in an increase in the bandwidth and data rates. However, this has led to a surge in data-hungry applications, which consume significant energy at battery-limited IoT nodes, causing rapid battery drainage. As a result, it is imperative to find a reliable solution that reduces the power consumption. A power optimization model utilizing a modified genetic algorithm is proposed to manage power resources efficiently and reduce high power consumption. In this model, each access point computes the optimal power using the modified genetic algorithm until it meets the fitness criteria and assigns it to each cellular user. Additionally, a weight-based user-scheduling algorithm is proposed to enhance network efficiency. This algorithm considers both the distance and received signal strength indicator (RSSI) to select a user for a specific base station. Furthermore, it assigns appropriate weights for the distance, and the RSSI helps increase the spectral efficiency performance. In this paper, the user-scheduling algorithm was assigned equal weights and combined with the power optimization model to analyze the power consumption and spectral efficiency performance metrics. The results demonstrated that the weight-based user-scheduling algorithm performed better and was supported by the optimal allocation of weights using a modified genetic algorithm. The outcome proved that the optimal allocation of transmission power for users reduced the cellular users' power consumption and improved the spectral efficiency.

Keywords: successive interference cancellation; spectral efficiency; heterogeneous network; power optimization

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1. Introduction

The blooming of emerging technologies is becoming unified through mobile communication to revolutionize our future by integrating entire global elements: transportation infrastructures, mailboxes, light switches, humans, cars, appliances, utilities, and any other entity that might take advantage of heterogeneous connectivity [1]. Presently, the utilization of existing mobile network infrastructure is reaching its limits due to massive mobile data services and a huge increase in user elements. Therefore, the preceding enhancement to achieve an ultrahigh mobile network bandwidth in the Fifth-Generation (5G) communication is pursued through the advanced utilization of the millimeter-wave (mmWave) frequency [2]. This emerging 5G deploymentmodel can be categorized into three types, including "Enhanced mobile broadband", with ultimate data rates well above 1 Gbps, "Massive Machine Type", with highly dense levels up to one-million devices/km^2, and "Ultrareliable and low-latency" communications [3].

However, there are several limitations, especially in achieving the optimized propagation of mmWave radio signals such as scattering, fading, time delay, multipath effects, and interference [4]. Moreover, 5G communication also contains challenges in utilizing resource-constrained devices with the forecasted specifications of high capacity and low-cost spectral efficiency. The 5G communication architecture is required to accommodate thousands of devices through reliable and acceptable links [5]. Therefore, interference stands as a major challenge in such a scenario, where all the neighboring devices are simultaneously striving to establish connectivity [6]. Due to the interference issues, 5G communication has been extensively researched to incorporate efficient interference cancellation techniques [7]. The 5G network architecture contains multi-tier heterogeneous nodes and the cell architecture, including macrocells, femtocells, picocells, and device-to-device (D2D) connectivity [8]. Similarly, the user end devices have the ability to establish multiple communication paths to distinct base stations (BSs) or access points (APs) through single or multiple radio access technologies (RATs). Therefore, the 5G multi-tier architecture demands optimum coordination between all the tiers in the network to reduce interference issues among the heterogeneously connected devices. Moreover, a higher bandwidth achievement in 5G is highly dependent on interference cancellation and spectrum power management techniques [9]. Fundamentally, the interference phenomenon occurs due to the negative interaction of signals transmitted by the other devices, resulting in the reduced specification of the wireless link, such as a decreased bandwidth, higherlatency, and low QoS [10]. Interference in 5G networks can be categorized into several architectural multi-tier elements, such as inter-cell interference, intra-cell interference, and inter-system interference. Therefore, power optimization techniques are widely researched to reduce the interference effects to achieve the forecasted higher bandwidth, reliability, and enhanced quality of service (QoS). Similarly, successive interference cancellation (SIC) is a widely researched interference mitigation technique for the maximum exploitation of the mmWave spectrum [11]. Hence, we suggest power optimization in multi-tier heterogeneous networks by utilizing SIC.

The rapid expansion of mobile data services and the surge in the number of users is putting pressure on the current communication capacities of network infrastructure [12]. The 5G network is faced with the significant challenge of delivering low-power, more spectrally efficient, high-capacity, high-performance, and cost-effective devices [13]. It also provides dependable connectivity and a suitable interface for communication among devices in close proximity. Interference has become a significant concern in multi-tier heterogeneous networks as hundreds of devices are attempting to connect in the same environment.

2. Related Work

Wireless communication networks are bound to have a robust, reliable, and efficient spectrum power management mechanism. Similarly, 5G communication is no exception. All expected enhanced QoS parameters for 5G, such as higher bandwidth and lower power consumption, depend on improved energy efficiency (EE) and spectrum efficiency (SE) techniques. In the recent past, several research efforts have been made to propose optimum techniques and frameworks for power minimization in multi-tier 5G heterogeneous networks. The study in [14] suggested a hybrid model containing both on-grid and off-grid small cell base stations (SBS) in a heterogeneous network. Energy optimization has been achieved by controlling the on- or off-grid ratio. Similarly, the authors in [15] proposed an improved wakeup/sleep technique in D2D communication to counter the coverage gaps caused by closely located BSs. They suggested a joint implementation of fuzzy control and Q-learning to achieve a fuzzy interference system in a dynamic environment with varying BS availability. Likewise, the authors in [16] suggested the utilization of dynamic time-division duplexing and full-duplexing for optimum adaptive transmissions according to network services and traffic matching. Moreover, the authors in [17] provided a detailed analysis and discussion of the limitations and various available solutions to accommodate resource-constrained devices in 5G networks. It highlighted several requirements for spectrum control to provide an optimum power management solution for a 5G multi-tier heterogeneous network. The proliferation of wireless networks has resulted in increased interference among them, making the use of interference mitigation techniques necessary. A statistical framework for throughput analysis [18] has been proposed with successive interference cancellation to mitigate interference in 5G networks.

Similarly, the study [19] highlighted the challenges associated with the expected tremendous expansion of smart infrastructures related to traffic chocking the bandwidthin next-generation mobile communication. They proposed a joint resource optimization approach by combining D2D communication with the 5G edge network architecture. The computations performed through modular approaches in this study involved local nodes, edge nodes, and fog nodes linked to a joint energy consumption model, latency model, and task scheduling model. The proposed solution was evaluated through a simulated environment of 5G mobile networks. The study in [20] highlighted the challenges related to spectrum shortage due to the massive deployment of Internet-enabled devices and services linked to Big Data. They suggested a time-switching method enabled by a power-splitting technique for minimum extra power transmission and optimum resource utilization. The study dealt with the joint optimization through two separate approaches, including rate control according to the transmissions from user end devices and maximizing the device transmissions under the spectrum-constrained condition of 5G. The simulation results of the proposed solution indicated substantial enhancement in power optimization. The authors in [21] presented a solution for the optimum control of the data rate and transmissions from IoT devices. The solution contained three distinct approaches, a fixed data rate, a fixed power level, and the optimal combination of both. The solution was evaluated through simulations to establish the significance of the energy savings in the overall communication. The authors in [4] exploited SIC to enhance the network performance through improved throughput, success probability, outage probability, coverage, and ergodic probability. The study indicated the high potential of SIC techniques for the control and optimization of spectrum use. Therefore, as an extension of the above-mentioned study, this paper presents an approach for utilizing the SIC technique for power optimization in a multi-tier heterogeneous network.

An accurate prediction of power consumption in distributed areas necessitates a trained deep learning model. This requires the optimization of the hyperparameters for a provided environment. To address this issue, a technique was presented in [22] to identify the best parameter values for learning. Furthermore, genetic algorithms were utilized to optimize the layer parameters of the deep learning models. The paper [23] presented a technique for tuning the trainable layers of pre-trained models using a genetic algorithm. This approach was applied to a classification task on single-channel image datasets, consisting of grayscale images and log-Mel spectrograms generated from preprocessed audio signals.

2.1. Power Optimization in Wireless Networks

In 5G technology, a major objective is to enhance the energy efficiency (EE) and spectrum efficiency (SE) to meet the increasing demand for high-quality service (QoS) while utilizing energy and spectrum resources more efficiently to achieve higher data rates. To examine the challenges related to spectrum efficiency and energy efficiency in 5G networks, a fuzzy-based approach [24] was implemented, aided by a look-up table. This approach achieved an efficient balanced trade-off between the two, thereby improving the system's overall performance. To fulfill the demands of increased capacity, faster data rates, and better quality of service in next-generation networks, the adoption of energy-efficient architectures is necessary [25]. Additionally, reducing the power consumption in wireless networks is important with respect to environmental and social responsibility, as reducing the carbon footprint is a pressing issue. Thus, green communication has become a critical need.

In situations where congestion is not complete, the power optimization for low interference and throughput enhancement (POLITE) approach can significantly reduce the transmission power of active cells. Furthermore, the design of POLITE allows compatibility with other MAC components, such as scheduling and beam selection techniques, making its implementation in real-world systems both practical and possible. The experiment showcased the impact of various traffic loads managed by base link adaptation (BLA) and POLITE [26], emphasizing the latter's benefits in terms of reduced power consumption, decreased interference, and enhanced capacity in densely populated cells.

The rapid growth of connected devices and mobile terminals in IoT networks is putting a significant strain on energy consumption, leading to concerns about energy sustainability. To address this challenge, a dynamic energy management model was presented in the paper [27] that aimed to improve the energy efficiency. Two new user scheduling strategies combined with power optimization resulted in enhanced network performance. The network efficiency was evaluated for a number of APs and by examining the performance of various precoding techniques. The study compared the results of various power allocation techniques, and it was proposed that the APs can utilize these algorithms to regulate the power distribution to user nodes.

Cooperative relay (CR) is a cost-effective solution for improving spectral efficiency and expanding cell coverage. However, its widespread use can result in high power consumption due to the large number of relay nodes (RNs) used in the network. Furthermore, full channel state information (CSI) is not always available in dynamic environments, leading to increased overhead delay and power consumption if the RNs cannot quickly adjust to the channel changes. To tackle these challenges, the modified genetic algorithm (modified GA) described in [28] integrated the probability-based selection rules and fitness evaluations. The performance was measured using the symbol error rate (SER), network capacity, energy consumption, and power improvement metrics.

2.2. Power Optimization Issues in 5G

The effectiveness of a cognitive radio (CR) network can be gauged by several QoS metrics, including energy consumption, power improvement, network capacity, and the SER. However, in a CR network, the addition of RNs to the BS often results in a gradual increase in the power consumption. To mitigate this issue, several power allocation (PA) schemes can be utilized, such as equal PA, the particle swarm optimization (PSO) algorithm, and the GA-based optimization scheme [29–31].

Power optimization is an important concern in designing and deploying 5G networks, as 5G systems are expected to consume significantly more power than previous generations of mobile networks. Some specific power optimization issues that may arise in 5G networks include:

1. High power consumption of 5G access points: The implementation of 5G technology has already begun globally in a non-standalone setup along with Long-Term Evolution (LTE) macro-structures. However, LTE has shortcomings for long-term use, and 5G's electronic design aims to conserve energy in idle states through reduced transmissions in an always-on mode, compared to LTE's brief sleep time of less than 1ms and limited fast activation components. In a standalone setup, the large projected device density of one-million per square kilometer would put a significant strain on the 5G base station in a cell sector, presenting a challenge in terms of reducing energy consumption and ensuring the network's sustainability. Two revised power consumption models [32] that precisely reflect the energy usage of a 5G base station in a standalone network have been proposed. A new routing protocol has also been introduced to distribute the load across base stations during inter-cellular communication evenly. The trade-off between latency and power consumption is considered to create a sustainable 5G network that meets the quality of service requirements, taking into account the energy-intensive nature of reducing power dissipation.
2. Power optimization of small cells: With the expected surge in 5G users, there will be a significant increase in power usage for transmitters and receivers. Researchers are looking for ways to optimize power consumption. One approach to optimizing

the algorithm design is the application of convex optimization. A mathematical method for deploying small cell access points [33] has been proposed to reduce energy consumption in massive MIMO and small cell environments.

3. Power optimization of user equipment: The increased number of 5G users is expected to result in higher power consumption by user equipment such as smartphones and tablets. It is essential to optimize the power consumption of user equipment in order to extend the battery life and decrease the overall energy consumption of the 5G network. Various approaches can be employed to tackle these power optimization challenges in 5G networks, including enhanced power management algorithms, advanced hardware design, and the implementation of energy-efficient components.

3. Motivation and Contribution

In the context of massive IoT, many devices are connected to the Internet and interact with one another to share and gather information. This requires a large amount of bandwidth and a high data rate. An increase in data-hungry applications drains the battery-powered IoT nodes at a higher rate, leading to the battery drainage and energy exhaustion challenges. Hence, the current research needs a sustainable energy solution for future wireless networks. This paper proposes a weight-based user-scheduling algorithm and a genetic-algorithm-based power optimization model in a multi-tier heterogeneous network. The SIC-based interference cancellation technique was used at the receiving end to mitigate the interference challenges.

The key contributions are as follows:

- A modified genetic-algorithm-based optimization model is proposed to allocate optimal power with which a particular access point transmits to a specific user to increase network efficiency.
- A weighted user-scheduling algorithm is proposed, which takes both the distances and received signal strength into account to select a user for downlink transmission.
- The suggested algorithms were evaluated for their effectiveness and compared with other techniques, including those based on particle swarm optimization, equal power, and genetic algorithms.

4. System Model

The system architecture includes APs, relay nodes, cellular users, and D2D devices as shown in Figure 1. The placement of network components was randomly dispersed within a geographical area using a Poisson point process. The Poisson point processes for the relay nodes, cellular users, and D2D users are represented by φ_R, φ_{CU}, and φ_D, respectively. The given area is served by the APs with a total of U single-antenna users distributed all over the network. Users were assigned to APs based on their needs, with each AP serving a specific group of users. The densities of the relay nodes, cellular users, and device-to-device users are represented by λ_R, λ_{CU}, and λ_D, respectively. In our network, we considered various channels, including the channel from an access point to a relay node $|H_{AP_i,R_i}|$, the channel from relay to relay $|H_{R_j,R_i}|$, the channel from the relay to the cellular user $|H_{R_j,CU_i}|$, the channel from the cellular to the relay user $|H_{CU_j,R_i}|$, the channel from the cellular to the cellular user $|H_{CU_i,CU_i}|$, and the channel from the D2D to the cellular user $|H_{D_i,CU_j}|$, all of which experience Rician fading with an exponent of σ and a path loss exponent of γ. The notations used in paper and their descriptions are provided in Table 1.

Table 1. Notations and their descriptions.

Notation	Description
φ_R	PPP of relay nodes
φ_{CU}	PPP of cellular users
φ_D	PPP of D2D users
γ	path loss exponent
h, f, g	fading factor
ρ_{AP}	transmission power of access point
ρ_R	transmission power of relay node
ρ_{CU}	transmission power of cellular user
x_{AP}	transmit signal of access point
x_R	transmit signal from relay station
λ_R	density of relay nodes
λ_{CU}	density of cellular user
λ_D	density of D2D users
x_{CU}	transmit signal at cellular user
H_{AP_i,R_i}	channel between access point to relay node
H_{R_j,R_i}	channel between relay node to relay node
H_{R_j,CU_i}	channel between relay node to cellular user
H_{CU_j,R_i}	channel between cellular user to relay node
H_{CU_i,CU_i}	channel between cellular to cellular user
H_{D_i,CU_j}	channel between device-to-device to cellular user
y_R	received signal
$P_{A,R}$	path loss between access point and relay node
$P_{R,R}$	path loss between relay nodes
n_R	received noise
$P_{R,U}$	path loss between relay nodes and cellular user
$P_{U,U}$	path loss between cellular users
z_{D_j}	D2D user signal
SIR_T	SIR threshold
$I_{CU_i}^{eq(k)}$	total interference at the cellular user

4.1. Channel Model

The access point AP_i transmits the information signal x_{AP_i}, which is connected via relay node R_i. It is fed with multiple signals y_R, including the desired signal (DS) from access points through a channel with path loss $P_{A,R}$ between the access point and relay nodes, the inter-relay interference (IRI) from R_j through the channel $|H_{R_j,R_i}|$ with path loss $P_{R,R}$ between relay nodes, the relay self-interference (RSI) through the channel $|H_{R_i,R_i}|$, and the received noise n_R. To acquire channel estimates, a total of l_p pilots are transmitted in the uplink, which are mutually orthogonal. The channel coefficients for the downlink are obtained by assuming channel reciprocity.

4.2. Successive Interference Cancellation Technique

Successive interference cancellation (SIC) is a well-studied technique for canceling interference in wireless networks with room for enhancement. It works by recreating the interfering signals and then removing them from the received combined signal, thereby enhancing the desired signal's signal-to-interference ratio (SIR). The SIC receiver technique shown in Figure 2. starts by decoding the strongest interfering signal while considering other signals as noise. It then regenerates the analog signal from the decoded information and subtracts it from the received combined signal. This results in the desired signal being free from the strongest interfering signal. The receiver then moves on to decoding, regenerating, and canceling the second-strongest interfering signal from the remaining signal, repeating this process until the desired signal can be successfully decoded.

4.3. SIR Calculation with and without Interference Cancellation Technique

The cellular user link comprises two stages: the connection from the AP to the RN and the connection from the RN to the CU. In this context, we determine the SINR for the first link between the AP and RN. The received signal at R_i is a combination of the desired signal plus all the interference from the surrounding RNs.

$$IRI = \sqrt{\rho_{R_j} P_{R,R} \alpha^{-\frac{\gamma}{2}}} \parallel H_{R_j,R_i} \parallel x_{R_j} \tag{1}$$

$$RSI = \sqrt{\rho_{R_i}} \parallel H_{R_i,R_i} \parallel x_{R_i} \tag{2}$$

$$DS = \sqrt{\rho_{AP_i} P_{A,R} \alpha^{-\frac{\gamma}{2}}} \parallel H_{AP_i,R_i} \parallel x_{AP_i} \tag{3}$$

$$y_{R_i} = DS + RSI + IRI + \eta_{R_i} \tag{4}$$

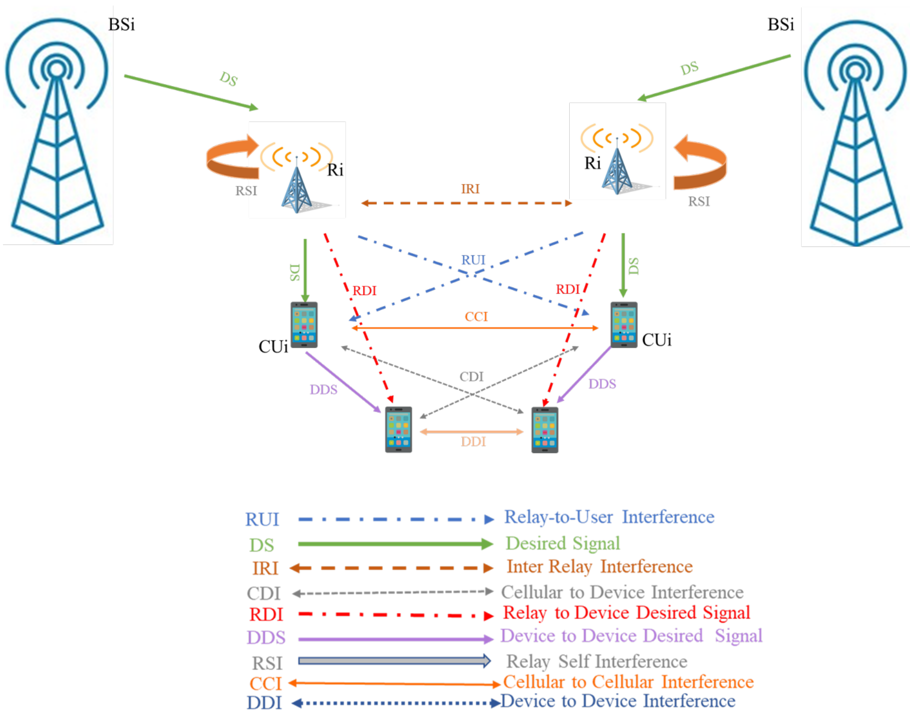

Figure 1. Multi-tier heterogeneous network.

The first part of the equation represents the desired signal from AP_i plus the noise received at R_i; the second part represents the RSI, and the third part represents the inter-relay interference (IRI) from the neighboring relay node R_j. Given the received signal, the SINR at R_i is calculatedas

$$SINR_{R_i} = \frac{\rho_{AP_i} P_{A,R} \alpha_i^{-\gamma} \parallel H_{AP_i,R_i} \parallel^2}{I_{R_i} + \eta_{R_i}} \tag{5}$$

where I_{R_i} is the total interference at R_i, which includes both the RSI and IRI.

$$I_{R_i} = \sqrt{\rho_{R_i}} \parallel H_{R_i,R_i} \parallel x_{R_i} + \sqrt{\rho_{R_j} P_{R,R} \alpha^{-\frac{\gamma}{2}}} \parallel H_{R_j,R_i} \parallel x_{R_j} \tag{6}$$

For the second hop, from the RN to the CU, the received signal at CU_i is composed of the desired signal from R_i plus the noise received, the relay-to-user interference (RUI) from R_j, the cellular-to-cellular interference (CCI) from CU_j, and the cellular-to-device interference (CDI) from D_j.

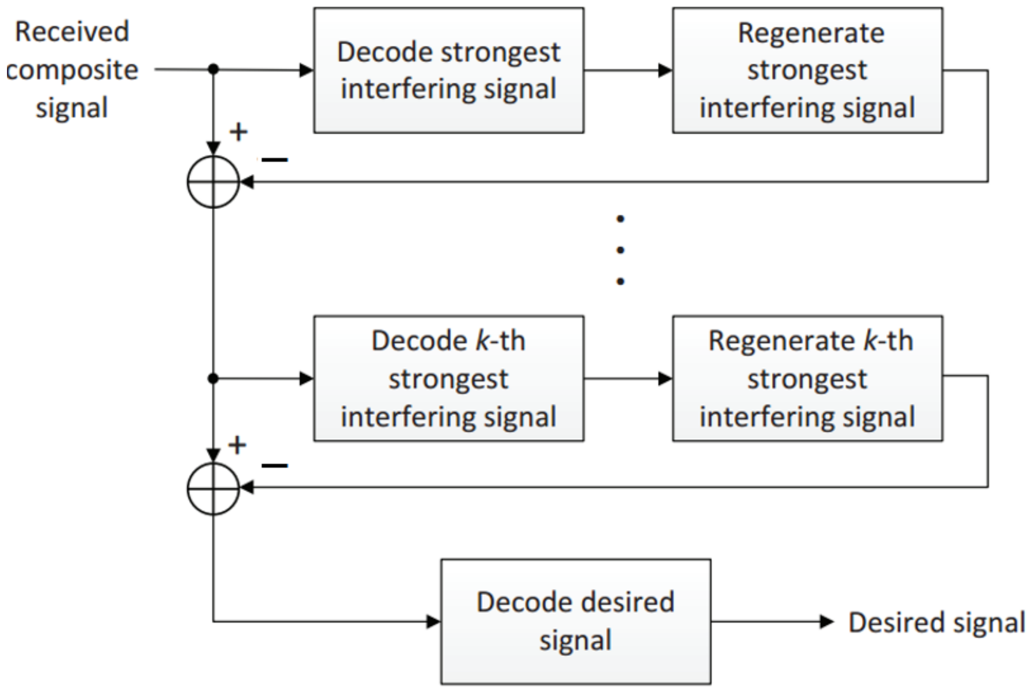

Figure 2. Block diagram of the SIC technique.

The SINR at CU_i is determined from the received signal.

$$SINR_{CU_i} = \frac{\rho_{R_i} P_{R,C} h_i^{-\gamma} \parallel H_{R_i,CU_i} \parallel^2}{I_{CU_i} + \eta_{CU_i}} \tag{7}$$

where I_{CU_i} is the total interference at CU_i, which encompasses the RUI [34], the CCI, and the CDI [35,36]. The SINR is calculated as the ratio of the desired signal to the interference from various network elements. The RUI, CDI, and CCI are estimated as

$$RUI = \sqrt{\rho_{R_j}} P_{R,C} h^{-\gamma/2} \parallel H_{R_j,CU_i} \parallel x_{R_j} \tag{8}$$

$$CDI = \sum_{y_j \in \lambda_{CU}} \sqrt{\rho_{CU_j}} P_{C,D} f^{-\gamma/2} \parallel H_{CU_j CU_i} \parallel y_{D_j} \tag{9}$$

$$CCI = \sum_{z_j \in \lambda_{CU}} \sqrt{\rho_{CU_j}} P_{C,C} g^{-\gamma/2} \parallel H_{CU_j CU_i} \parallel z_{CU_j} \tag{10}$$

$$I_{CU_i} = RUI + CDI + CCI \tag{11}$$

For a given network, The total SINR at CU_i is the cumulative product of the SINR at R_i and CU_i and can be represented as

$$SINR_{T_{CU_i}} = SINR_{R_i} * SINR_{CU_i} \tag{12}$$

In our network, due to several interferences from nearby devices, the environment is considered to be interference-limited; therefore, noise can be neglected.

$$SINR_{T_{CU_i}} = SIR_{TCU_i} = \frac{\rho_{R_i} P_{R,C} h_i^{-\gamma} \parallel H_o \parallel^2}{I_{TCU_i}} \tag{13}$$

where I_{TCU_i} is the combination of all the interferences from the other relay nodes, D2D users, and cellular users. H_o is the combination of H_{AP_i,R_i} and H_{R_i,CU_i}.

The SIR for the interference cancellation technique is estimated by examining its impact on cellular users CU_i. The total interference at CU_i includes the summation of the RUI, CCI, and CDI. As the k strongest equivalent interferers have been canceled, the received SIR at the cellular user can be estimated by comparing it with Equation (13).

$$SIR^k_{CU_i} = \frac{\rho_{R_i} P_{R,C} h_i^{-\gamma} \parallel H_o \parallel^2}{I^{eq(k)}_{CU_i}} \tag{14}$$

where $I^{eq(k)}_{CU_i}$ is the cumulative interferences at the cellular user from the kth strongest interferer. Hence, Equation (14) shows the SIR for the kth strongest equivalent interferer, while $k-1$ stronger interferers have already been canceled.

5. Power Optimization

Power optimization involves assigning the optimal power to the users by the access points. The symbol ρ_{max} represents the maximum transmit power of the access point. The user distance or channel conditions are used by the AP to determine the power allocation to different users. The downlink power coefficients ρ_{CU} are defined as $[\rho_{CU_1}, \rho_{CU_2} \cdots \rho_{CU_n}]^T$. The power allocated to the nth cellular user by all the serving APs is represented by ρ_{CU_n}. The SIR estimated in the downlink is dependent on ρ_{CU} and can be represented as follows, based on various power allocation [27] methods:

- Equal power allocation: The equal power allocation scheme assigns the same power to all the users served by an access point. Each AP can serve a maximum of l_x users, and hence, the power for each user is assigned as follows:

$$\rho_{CU_n} = \frac{\rho_{max}}{l_x} \tag{15}$$

- Fractional power allocation: The fraction of power is allocated to users within a serving AP and is proportional to the channel gains.

$$\rho_{CU_n} = \rho_{max} \frac{(\sum_{a \epsilon A_u} \beta_{ua})^{\mu}}{max_{i \epsilon Au} (\sum_{a \epsilon A_i} \beta_{ia})^{\mu}} \tag{16}$$

where the channel gains are β_{ua}; a 3GPP urban microcell large-scale fading model [37] is given as

$$\beta_{ua}[\text{dB}] = -30.5 - 36.7 log_{10} \frac{d_{ua}}{1\text{ m}} + F_{ua} \tag{17}$$

Here, F_{ua} represents shadow fading, and d_{ua} is the distance between UE u and access point a. μ is a variable that influences the power allocation behavior.

- GA-based power allocation: The goal of the design is to reduce the total power used by the users while still meeting their required SIR. This design provides a flexible relaying strategy that can satisfy each user's needs and achieve the desired quality of service. The problem of minimizing the total power at the UEs while meeting their desired SIR targets is stated as

$$min \sum_{i=1}^{n} \rho_{CU_i} \tag{18}$$

The power at each user equipment with optimized weighting can be represented as

$$\rho_{CU_i} = w_i \rho_i \tag{19}$$

The goal is to find the best values of the weights, w_i, that minimize the total power in a network with different types of users, by using the power amplification factor, ρ_i, at each UE, subject to $SIR_{CU_i} > SIR_T$, where SIR_T is the SIR threshold at the UE.

6. Proposed Algorithm

This section introduces a scheduling algorithm that uses weights to determine to which access point a user is assigned. The probable users are chosen based on the distance and received signal strength between the user and the access point.

Weight-Based User-Scheduling Algorithm

Various scheduling algorithms have been proposed that consider the minimum distance between a user and an access point and the maximum channel gain between a user and an access point to improve network efficiency. The scenario under consideration involves a multi-layer heterogeneous network with a large number of APs located in a specific geographical area. Each AP serves a portion of the total number of users (C_U) distributed randomly within the network, with a group of users referred to as C_{U_a}.

The flowchart of Weight-based user-scheduling algorithm is depicted in Figure 3. Let us consider $\{C_{U_1}, C_{U_2}, C_{U_3}, \ldots, C_{U_A}\}$ the subset of users assigned to a group of APs $\{1, 2, \ldots A\}$. The pilot channels are sent to obtain the channel estimates before sending the data in the downlink. In the communication scenario under consideration, a large number of APs are deployed in a certain geographical area, and a group of randomly distributed users is served by the APs in the network. A set of l_x mutually orthogonal pilot sequences is transmitted in the uplink to minimize interference from subsequent pilot transmissions. The pilot assignment to users starts by selecting an AP, a^*. In the weight-based user-scheduling Algorithm 1, the access point uses a hybrid approach that considers both the distance and received signal strength indicator (RSSI) of each user. The RSSI value of each user is frequently monitored by its serving and neighboring access point. A weight is then assigned to both the distance and RSSI. Finally, the user with the maximum value is assigned a subset of particular access points. Consider w_d the weight assigned to the distance and w_β the weight assigned to the RSSI value. To estimate the RSSI, the Alpha-Beta-Gamma (ABG) path loss model [38] is used and is given by

$$PL^{ABG}(f,d)[\text{dB}] = 10\alpha_A log_{10}(\frac{d_{ua}}{1\text{ m}}) + \beta_B + 10\gamma_G log_{10}(\frac{f}{1\text{ GHz}}) + \chi_\sigma^{ABG} \quad (20)$$

where $PL^{ABG}(f,d)[\text{dB}]$ denotes the path loss in dB over the frequency and distance, α_A and γ_G are the coefficients, which are dependent on the frequency and distance, respectively, and β_B is the optimized set value for path loss in dB. χ_σ^{ABG} is the standard deviation describing the large signal fluctuations about the mean path loss over the distance.

$$R_{ua} = \rho_{CU_i} - PL^{ABG}(f,d) \quad (21)$$

where ρ_{CU_i} represents the power allocated to the ith cellular user by all the serving APs. For each user u, the access point A_i calculates a value that is given by the equation:

$$\tau_{u_a} = w_d G_{ua} + w_\beta R_{ua} \quad (22)$$

where G_{ua} denotes the free space loss in decibels between the access point and the user. f is the frequency of communication. R_{ua} denotes the RSSI value between the access point and user.

$$G_{u_a}[\text{dB}] = 20log_{10}(d_{ua})\text{km} + 20log_{10}(f) - 147.55 \quad (23)$$

A user with a maximum value of τ_{u_a}, $max(\tau_{u_a})$, is selected by the AP. This process repeats until the APs select all the user subsets.

Algorithm 1 Weight-based user-scheduling algorithm.

Input: A, l_p, C_U
Output: C_{U_a}, $a\epsilon\{1, 2, \ldots A\}$
Initialization: $\{C_{U_1} = C_{U_2} = \ldots = C_{U_A} = \phi\}$
  $y \leftarrow 1$
  $X \leftarrow x$
  $N \leftarrow n$
  while $u < l_x$ **do**
    $lu \leftarrow u$
    while $u > l_x$ **do**
      find $a*$
      $a* \leftarrow max(\tau_{u_a})$
      $l' \leftarrow argmin_{l\epsilon\{1,2,\ldots,l_x\}} \sum_{i=1,l_i=l}^{u-1} \beta_{ia*}$
      $l_u \leftarrow l'$
      c = 1
      while $c < A$ **do**
        c = c+1
        l = 1
        while $l < l_x$ **do**
          l = l+1
          $i \leftarrow argmax_{u\epsilon\{1,2,\ldots,C_U\}} \tau_{u_a}$
          $C_{U_i} \leftarrow C_{U_i} \cup \{u\}$
        end while
      end while
    end while
  end while

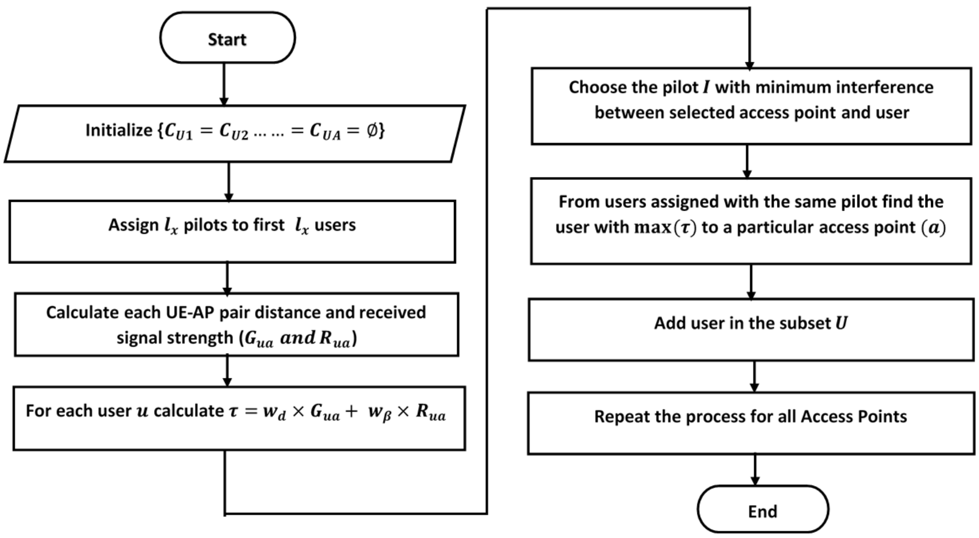

Figure 3. Flowchart of weighted user-scheduling algorithm.

7. Genetic Algorithm

The genetic algorithm (GA) is a type of evolutionary algorithm, which was inspired by biological evolution. In biological evolution, the process involves choosing parents and with the ultimate goal of producing offspring that are biologically superior to their parents through reproduction and mutation. The fundamental idea is to choose the most-exceptional individuals as parents from a group and then extend their lineage by generating new chromosomes through the exchange or blending of genes from healthier parents, a process referred to as crossover. The genes are then mutated, and this process leads to a healthier generation. The performance of chromosomes and fitness is evaluated using a cost function in which the best genes are selected using this function. The new generation is created from parent chromosomes after crossover and mutation, ensuring that the children's chromosomes satisfy the fitness function. The use of GA was motivated by the following characteristics [39]:

- Versatility: GAs are utilized to tackle complex issues that possess large search spaces. GAs excel at traversing extensive areas and quickly discovering the best-possible solution. Although GAs do not promise the optimal solution, they are beneficial to prevent local optima with a high likelihood.
- Ability to find good building blocks: The GA operates within a population composed of numerous chromosomes, allowing it to form various solutions in order to identify the building blocks. Chromosomes are referred to as building blocks, and in biological terms, the genes are mixed and interchanged to form healthier offspring out of the parent chromosomes. These chromosomes again act as a parent and reproduce new offspring. In this way, a GA can evolve to better solutions through a series of biological events to form good building blocks.
- Support for multi-objective function: The GA optimization problem supports multiple parameters since real-time practical problems in various wireless networks require solving more than one parameter. In practical scenarios involving wireless networks, the objectives in a multi-objective function may potentially contradict each other.
- Parallel nature and scalability: The GA uses evolutionary approaches to test, improve, and produce new solutions using various techniques such as selection, crossover, mutation, and recombination. These parallel approaches in the GA help it become a suitable framework for optimization and solve various scalable problems in wireless networks.
- Support for global optimization: The GA supports global optimization, which involves finding the optimal solution to problems containing local optima and is suited to global optimization because of a number of properties: (1) searching by means of a population of individuals; (2) encoding multiple parameters; (3) using a fitness function to evaluate its merit; (4) probabilistic search.

8. Optimization Using the Modified GA Approach

A GA is a form of heuristic search that falls under the category of evolutionary algorithms. It is used to tackle search and optimization problems. The natural evolutionary processes, such as inheritance, mutation, selection, and crossover, inspired the approach of the GA. The modified GA is a type of GA that has a different approach to clustering. At each iteration, the modified GA groups the fittest chromosomes, which then again reproduce offspring chromosomes. In the modified GA, the best solution is computed that moves closer to the optimal solution in every iteration. The next best chromosomes are selected based on selection, crossover, and mutation. After these processes, the chromosomes with low fitness values are eliminated and only high-quality chromosomes go forward to the next step, which then again act as the parent chromosomes. In crossover, the chromosomes are mixed to produce stronger chromosomes, which inherit the properties from the parents, and then, the genes of the chromosomes are mutated, which is controlled by a mutation parameter and the step size. Lastly, elitism helps prevent the loss of the best chromosomes in the current iteration.

In the modified GA, chromosomes are called solutions and the value of the solutions is evaluated by a fitness function as either "good" or "bad". The solutions that are "good" can move forward to the next step and are then used to form a new set of solutions, whereas the "bad" solutions are terminated. This new set of solutions again reproduces a set of solutions through the same process and then has to pass the test at each iteration. This cycle is repeated until an optimal solution is found. Once the optimal solution is found, it provides us the best cost. The illustration in Figure 4. depicts the proposed modified GA approach. The important elements of the modified GA are explained further below.

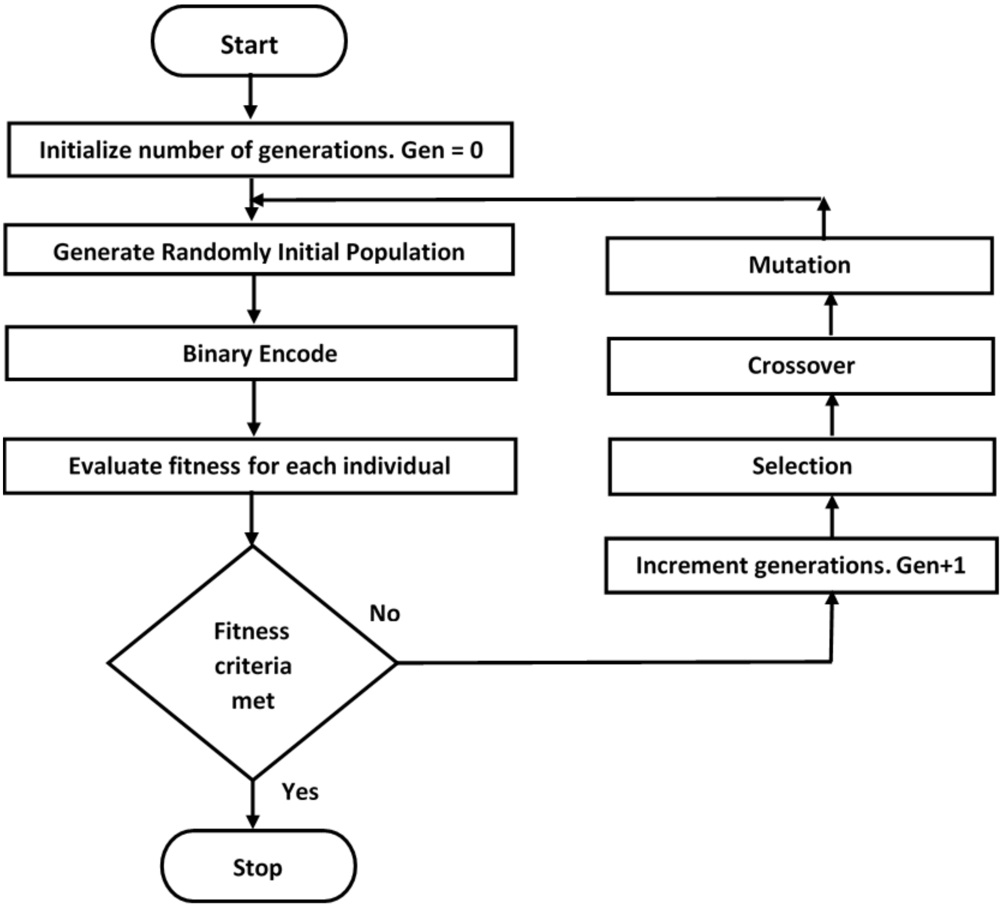

Figure 4. Flowchart of the modified GA.

8.1. Population Size

The population size refers to the number of individuals in each iteration and must be determined based on the extent of the search area. A larger population size results in a more precise search of the solution space, but a too large population can lead to divergence.

8.2. Selection

The algorithm starts with a randomly generated population. The population of size N is selected, and a dictionary is created to hold the population. Each individual is associated with chromosomes (positions) and a cost function. Each position in a chromosome is filled with randomly generated values between the lower limit of -1 and the upper limit of +1, which are called genes. Among the various selection methods, the roulette wheel was adopted, where the probability of individuals is calculated as

$$P_i = \frac{F_i}{\sum_{i=1}^{N} F_i} \tag{24}$$

where F_i is the fitness function and N is the population size. In order to increase the average fitness of the population, a new population is generated from the previous one. It has a higher probability to be included in the new generation depending on the fitness value of the chromosomes. The fitness value is computed for each chromosome as $\sum_{i=1}^{n} F_i$.

The fitness function F_i is given by

$$F_i = min \sum_{i=1}^{N} \rho_{CU_i} \tag{25}$$

In Figure 5. entire set of boxes outlined in green color is a chromosome. A chromosome is made up of genes. The green colored box within a chromosome is called a gene and collection of chromosomes is called a population.

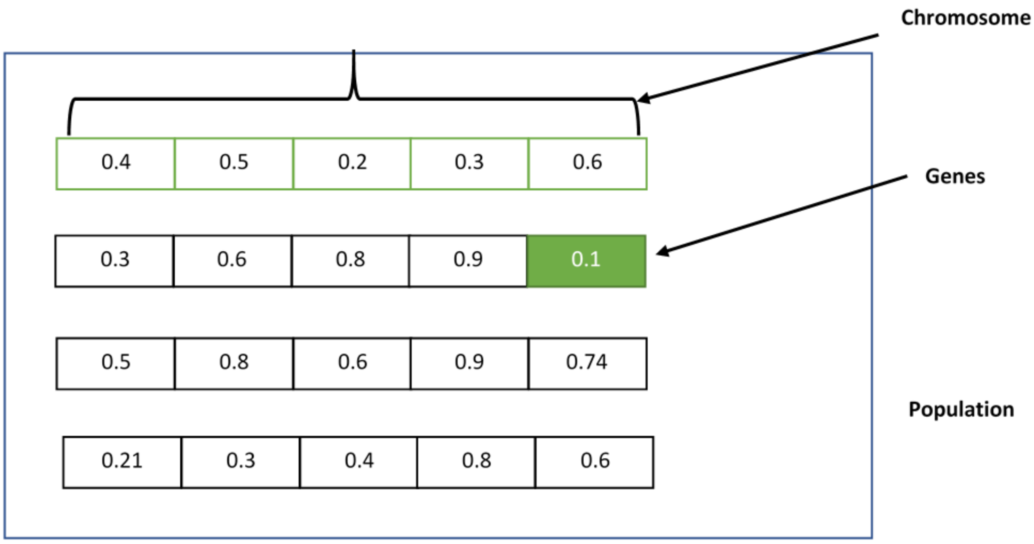

Figure 5. Selection process.

8.3. Crossover Operation

Crossover is a process in which genes are exchanged between two chromosomes to create a new population. In the current generation, crossover occurs at designated points, chosen randomly, and can take place at multiple points. The probability of crossover, typically set at a high value between 80% and 95%, controls the crossover operation and aims to enhance the genes in the chromosome structure. We considered a uniform crossover operation for our optimization algorithm. The chromosomes from two parents are inherited to create the offspring chromosomes. In this operation shown in Figure 6, each gene from Parent 1 is multiplied by θ and by $(1 - \theta)$ for Parent 2, and then, results are added to generate a single gene of the offspring chromosome, where θ is the crossover rate. The operation for crossover is explained in Algorithm 2, in which a set of Chromosomes $C = \{C_1, C_2, C_3 \ldots C_n\}$ and N (Population size) is taken as input. The loop executes for each population and from each population n chromosomes are chosen for crossover process. The output is then the offsprings which are stronger and better than their parents.

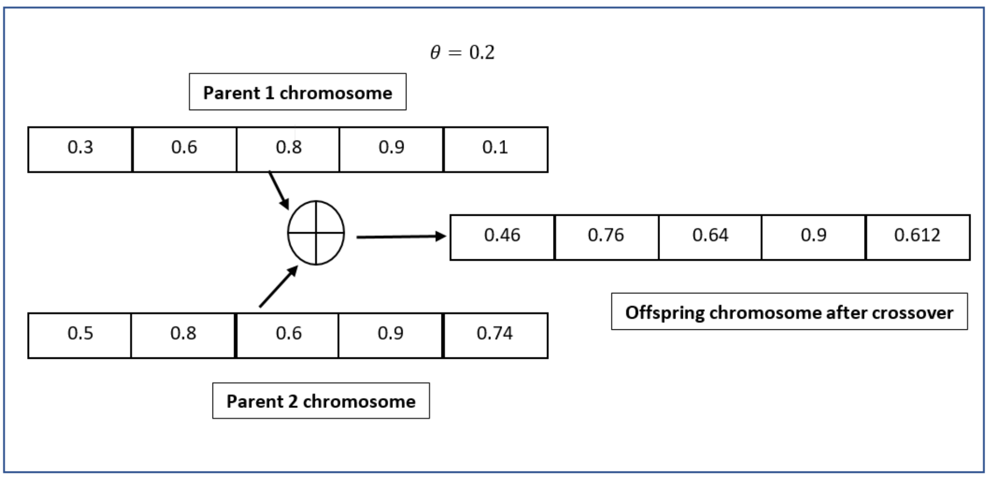

Figure 6. Crossover operation.

Algorithm 2 Crossover operation.

Input: $C = \{C_1, C_2, C_3 \ldots C_n\}$, N
i = 0
  while (i < N) **do**
    $i = i + 1$
    $P_{1_i} = C_i$;
    $P_{2_i} = C_{i+1}$;
    θ_i = random value between -1 and 1;
    $C_{1_i} = P_{1_i} * \theta_i + (1 - \theta_i) * P_{2_i}$
  end while

8.4. Mutation Parameter

Mutating the chromosomes is necessary in genetic algorithms because it may result in a revolutionary solution that can solve our complex problems more efficiently. It consists of three parameters: child chromosomes, the mutation rate (m), and the step size (Δ). The mutation rate is used to define the number of genes in a child chromosome that will undergo mutation. A random value is generated, which is compared to that of the mutation rate, and if the value is less than the mutation rate, new genes are generated by multiplying the original gene value by the step size. In Figure 7, the genes in blue are the chromosomes that are to be mutated and are multiplied by the step size, which results in a mutated chromosome. Algorithm 3. takes a number of chromosomes (n), mutation rate (m), step size (Δ) as input and loops over each chromosome. If a random number generated is less than a mutation factor a gene gets multiplied by a step and this process is repeated for each chromosome.

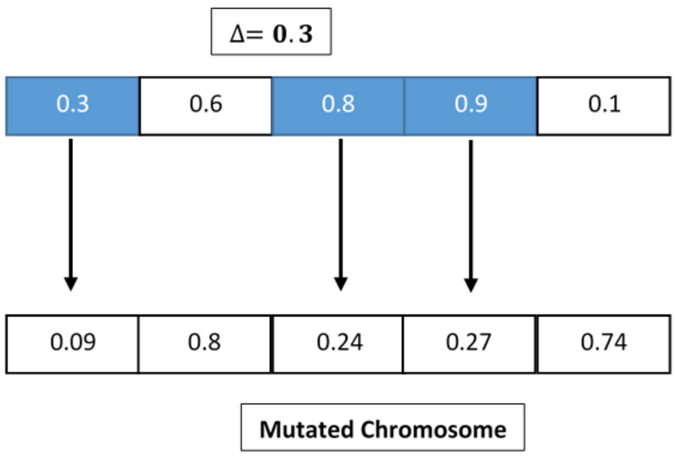

Figure 7. Mutation operation.

Algorithm 3 Mutation operation.

Input: C_i, m, Δ, n (number of chromosomes)
i = 0
  while (i<n) **do**
    generate a random number V
    if $(V < m)$
      $C_i k = C_i k * \Delta$
    end if
    i = i + 1
  end while

8.5. Elitism

Elitism selects some of the strongest chromosomes from the population and ensures that they are carried over to the next iteration unchanged, without undergoing any other GA operations such as crossover or mutation. This prevents the loss of the best chromosomes in that iteration. By utilizing elitism, the fittest chromosomes from the current generation are automatically included in the next iteration. In the modified GA, the constraints are formulated as follows:

1. Bound constraint: $0 \leq \rho_{CU_i} \leq \rho_{max}$
2. Linear constraint: $SIR_{CU_i} > SIR_T$

Algorithm 4, shows the process of modified GA used for power optimization model. Population size, number of chromosomes and number of genes in a chromosome are taken as input parameter and optimum weights are returned as output. Initial population of size N is generated and random weights between -1 and 1 are initialized to each chromosome and binary encoded. The fitness of each chromosome is computed until a criteria for a fitness function is met. The function of selection, crossover and mutation takes place in a loop and in each loop fitness function is checked and then finally returns optimum weights.

Algorithm 4 Power optimization model using the modified GA.

Input: N (population size), n (number of randomly selected chromosomes), k (number of genes in a chromosome)
Output: optimum weights w_{i_k}
Initialization: $gen = 0$, r = 0.85 (crossover fraction)
random weights assigned to each chromosome: w_{i_k}
$Generate\ the\ initial\ population$
$Binary\ Encode$
$Compute\ fitness(i)\ for\ each\ i \in w_{i_k}$
while (fitness criteria are not met) **do**
  gen = gen + 1
  roulette wheel selection
  crossover
  mutation
  compute fitness (i) for each $i \in w_{i_k}$
end while
  Return the fittest individual from w_{i_k}

9. Results and Discussion

This paper evaluated the performance of the suggested model by using a power optimization technique. The optimal weight was calculated to improve the system's performance. The simulation was performed using MATLAB. The power transmission of the access point and the relay node was fixed at 43 dBm and 23 dBm, respectively. A Monte Carlo simulation with 5000 iterations was carried out. The simulation model involved multiple macrocell and multiple femtocells, picocells, and users evenly spread out within the coverage area of the macrocell as shown in Figure 8. A network area of 2.5 × 2.5 km with 100–400 randomly placed access points was utilized. The users were evenly spread within the coverage area. The simulation was run with different parameter variations and power optimization techniques. The $PL^{ABG}(f,d)$[dB] in Equation (20) was utilized for the path losses $P_{A,R}$ (access point to relay node), $P_{R,R}$ (relay to relay node), and $P_{R,U}$ (relay to user node) for the implementation in the MATLAB simulation. The simulation parameters are listed below in Table 2.

SIR_T is an important metric for ensuring the reliability of wireless communication systems and is used in conjunction with the SIR to maintain a minimum quality threshold for a reliable communication. When the SIR decreases below a given threshold, the signal becomes weak and is unable to be detected at the receiver, leading to errors. Hence, the condition $(SIR_{CU_i} \geq SIR_T)$ should be met for the proper communication between a pair of a transmitter and a receiver. The SIR is a bottleneck for any transmitter and receiver pair in wireless networks. We made the assumption that the background noise is zero, and hence, the $SINR$ is equal to the SIR. For a successful transmission, the SIR of each cellular user

SIR_{CU_i} should be greater than the SIR threshold SIR_T. The condition ($SIR_{CU_i} \geq SIR_T$) is also known as the coverage probability. Hence, SIR_T is set for a given system, and then, performance metrics such as power consumption and spectral efficiency are calculated for those users that meet the condition ($SIR_{CU_i} \geq SIR_T$). Similarly, the power consumption and spectral efficiency are calculated for a set of SIR_T and plotted.

Table 2. Parameter specification.

Parameter	Default Value
Frequency (f)	2.3 GHz
Bandwidth	20 MHz
T_c (Coherence time)	2 ms
B_c (Coherence bandwidth)	100 kHz
A	100
σ^2	−94 dBm
Transmit power	46 dBm
Fading model	Rayleigh fading
Path loss exponent	3
Transmission range	500 m
SIR threshold (SIR_T)	−10 dB to 30 dB
Transmit antenna	2
Receive antenna	2
Population size	50
Crossover fraction	0.85
Mutation probability	1
Function tolerance	1×10^8
Iteration	100
w_d	0.5
w_β	0.5
α_A	2
β_B	31.4 dB
γ_G	2.1
σ_X	2.9 dB

A comparison of various related works with proposed algorithm has been done and is presented in tabular format in Table 3. In table, it points out the methodology, strategies, algorithms and performance metrics that has been used in related works as compared to that of proposed model.

Figure 9 shows that the modified genetic algorithm converged faster than the other algorithms and the best cost for the modified GA was 0.000013698. The modified GA evaluates solutions as chromosomes, classifying them as "good" or "bad" based on the fitness function. The proposed algorithm's results indicated that it reduced the power consumption and increased the network spectral efficiency, as compared to other methods such as equal power allocation, particle swarm optimization, and genetic algorithm.

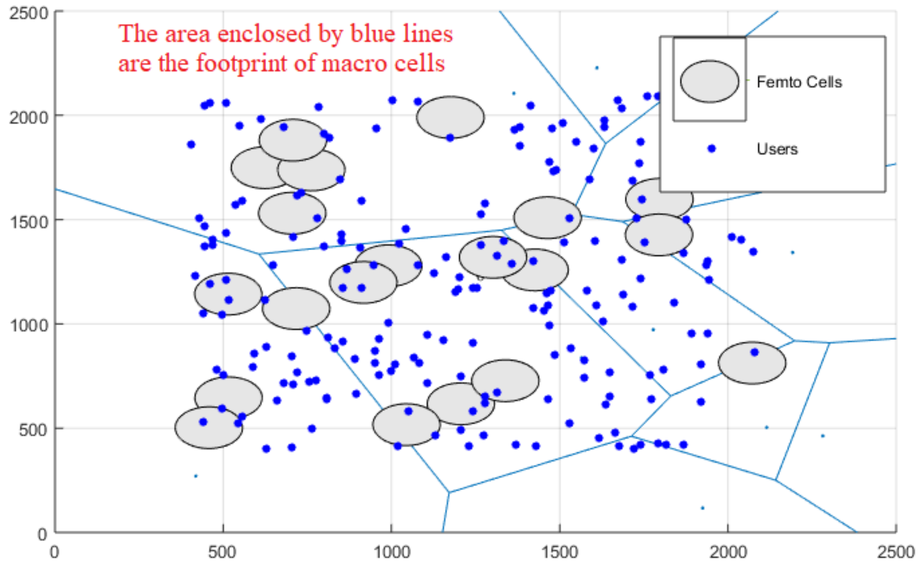

Figure 8. Simulation model of a heterogeneous network.

Table 3. Comparison table.

Reference	Related Works	Proposed Work
[24]	1. A fuzzy-based optimization was used to meet the demands for a higher data rate and high spectral efficiency. 2. Maximized the energy efficiency by optimizing the transmission power. 3. Assumption of infinite battery capacities during flooding, which is impractical.	1. A modified-GA-based optimization was proposed for power optimization and high spectral efficiency. 2. Minimized the power at user nodes and increased the spectral efficiency. 3. Battery capacity was limited and tried to optimize the use of the battery of a cellular user.
[25]	1. Presented an energy-efficient architecture for power optimization. 2. Analyzed the impact of carbon emissions on the life cycle of the mobile device. 3. Handoff and coverage problems between adjacent small cells impacted the energy efficiency (EE).	1. Presented a scheduling and optimization algorithm in a heterogeneous environment. 2. Analyzed the minimization of the transmit power and also met the QoS demands.
[27]	1. A fractional power allocation scheme was used along with the minimum channel gain and minimum distance scheduling techniques. 2. A centralized transmit pre-coding scheme at the downlink was used to cancel out interference. 3. Degradation in network performance with the spatial correlation with both the maximal ration (MR) and local partial minimum-mean-squared error (LPMMSE).	1. The modified genetic algorithm (GA) along with a weighted user scheduling technique was used. 2. A mathematical model for the successive interference cancellation technique was used to suppress interference in a multi-tier heterogeneous network. 3. Improved the network performance with both the GA and scheduling approach.
[28]	1. A cooperative-relay-based technique along with GA-based power optimization. 2. Increased spectral efficiency and enhanced the coverage area. 3. The optimization algorithm took a longer time to converge when the number of relay nodes increased.	1. Minimized the power of the cellular user, and the optimization took place at the access points. 2. Enhanced spectral efficiency by the use of the interference cancellation technique and also improved the transmission success probability. 3. The convergence rate was higher since the scheduling algorithm checked the number of users that can access the channel.

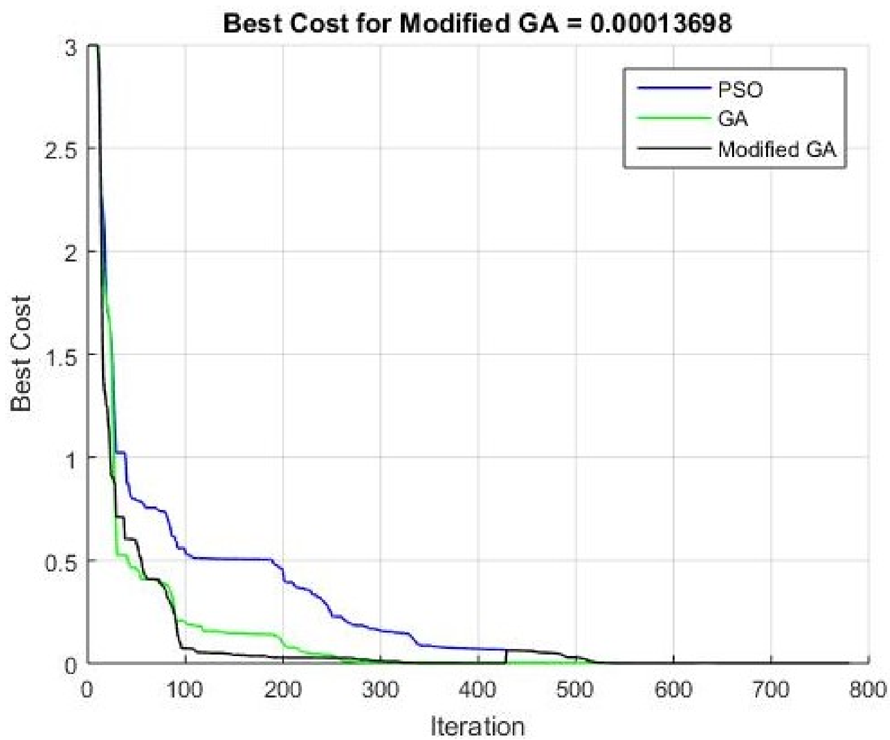

Figure 9. Best Cost vs. Iteration using various optimization techniques.

9.1. Power Consumption Performance

As 5G networks require much less energy to transmit the same data as 4G, they are more efficient in the ratio of power consumption to traffic. However, 5G's higher speed and bandwidth might also increase the number of devices using the network extensively; this could become a problem. In particular, IoT devices equipped with multiple sensors can present a challenge due to their constant transmission of large amounts of data, as they are not connected to the electrical grid. On the other hand, a sensor that transmits data seldom can do this sporadically in a 5G network, while in 4G environments, it has to be constantly transmitting. Likewise, while 5G's power consumption will require more access points per square kilometer, these will only need as much power as required—whereas predecessor networks were always "on".

In this section, the power consumption of a network is analyzed based on the number of users and the signal-to-interference ratio threshold (SIR_T) using various power optimization techniques in the proposed model. Power optimization refers to finding the best weights for transmitting access points to each user, increasing the spectral efficiency. Three different optimization techniques, (i) particle swarm optimization, (ii) the genetic algorithm, and (iii) the modified genetic algorithm, were used to optimize the weights with which the access point transmits to each user. Each user selects the access point according to the proposed user-scheduling algorithm, and then, the access point assigns an optimal power for downlink transmission, then this power is calculated, which is shown in Figure 10. The graph shows that the downlink power consumption for each access point increases with the increase in the number of users attached to a given access point. SIC-based hybrid transmit precoding is used to cancel out interference in multi-tier heterogeneous networks. However, transmitting data from an AP to one user can interfere with neighboring users. This interference can be mitigated by using an SIC-based receiver, but it still contributes to the overall energy consumption during the data capture and communication processes. The energy consumption from transmission and reception is modeled as

$$E_{rx}(b) = E_{elec}b \tag{26}$$

$$E_{tx}(d,b) = E_{elec}b + E_{amp}bd^n \tag{27}$$

where E_{elec} represents the electronic transmission energy, E_{amp} represents the amplification energy, d represents the distance between the transmitter and receiver, b represents the number of bits, and n represents the path loss exponent. The power consumption of each user for a given period of time t is now calculated as

$$P_{tot} = \frac{E_{tot}}{t} = \frac{E_{rx}(b) + E_{tx}(d,b)}{t} \tag{28}$$

As the number of nodes increases, the users' power consumption also increases. This is because there is more interference and more transmission is required to achieve the desired signal-to-interference ratio threshold. Power consumption is lower for the modified genetic algorithm as it optimizes the weights and transmission power. It shows that the power consumption for equal power allocation is the highest as it allocates equal power to all the users irrespective of the distance and channel gain.

In Figure 11, the SIR threshold is gradually increased from −5 dB to 20 dB, and then, the power consumption is evaluated for the fixed number of users. The number of users was fixed to be 50. The result showed that the power consumption from −5 dB to 5 dB remained almost constant using all of three optimization techniques because the given SIR threshold can be achieved with less power; hence, the power consumption was lower at a lesser SIR threshold. As the SIR threshold increased, power consumption also increased. For an SIR threshold greater than 5 dB, the power consumption increased exponentially because more power was required for transmission to achieve the given threshold and maintain the quality of service. The figure shows that the power consumption using the modified genetic algorithm was relatively lower than the other two optimization algorithms.

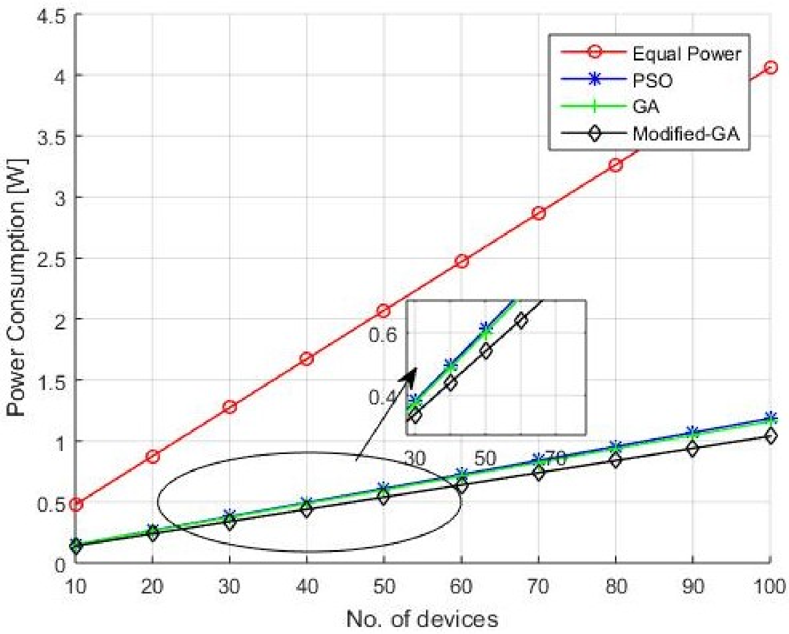

Figure 10. Power consumption vs. number of users for different optimization techniques.

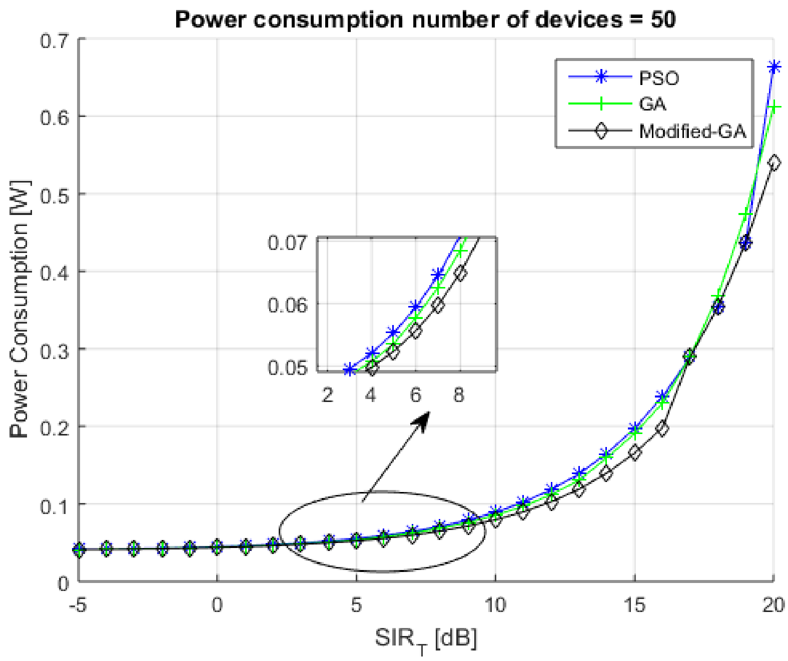

Figure 11. Power consumption vs. the SIR threshold using different optimization techniques.

9.2. Spectral Efficiency Performance

The average spectral efficiency [40] is determined by dividing the total throughput of all users by the effective bandwidth and the number of transreceivers (T_{R_x}). If there are N users, each with M T_{R_x}, and they are transmitting with a BW effective bandwidth, the average spectral efficiency ν_{avg} can be calculated as follows:

$$\nu_{avg} = \frac{\sum_{i=1}^{N} R_i(T)}{T.BW.M} \tag{29}$$

where $R_i(T)$ is the number of correctly received bits by user i over a period of time T and BW is the bandwidth. In our proposed weight-based user-scheduling algorithm, we took into consideration both the distance and received signal strength to select a user by a particular access point. Basically, for downlink transmission, low transmission power is allocated to the user near the base station and high power is assigned to the user away from the base station [41]. Similarly, transmission power is allocated based on the channel gain of the user. If a user has a low channel gain, he/she receives a high transmission power, and if a user has a high one, he/she receives a low transmission power. Boosting the transmission power improves the data rate and signal-to-noise ratio and increases interference to nearby stations. Thus, it is important to allocate the transmission power optimally to enhance the network efficiency.

Thus, this paper considered both the distance and received signal strength for a user to select an access point. Equal weight is provided to both the distance and received signal strength, and the base station calculates the resultant value depending on which access point decides which user to be selected. The weight is essential in selecting a user and improving the spectral efficiency. In our research, we took equal weights; however, future work can study the varying of the weight.

Here, throughput increased with the increase in the signal-to-noise ratio of each individual user, and hence, the spectral efficiency shown in Figure 12 increased, whereas the power optimization was carried out to allocate the optimal power for each user; the SIC-based receiver led to better interference suppression in a multi-tier heterogeneous environment, resulting in improved spectral efficiency (SE) performance. The optimal power allocation optimized the combined spectral efficiency of a set of users by allocating the appropriate transmission power, resulting in increased spectral efficiency for most of the users.

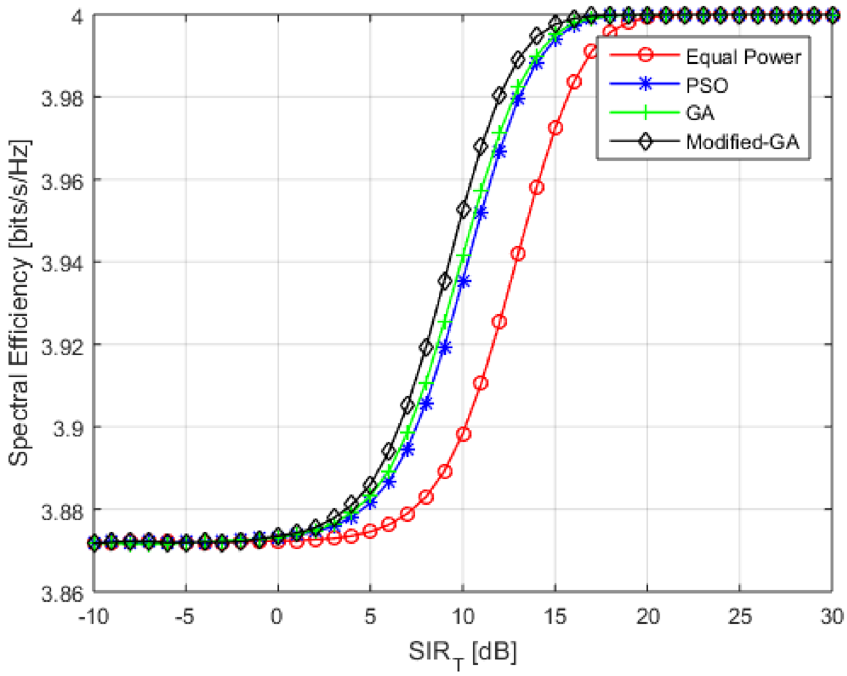

Figure 12. Spectral efficiency with respect to SIR_T for different power allocation schemes.

In Figure 13, spectral efficiency is analyzed for three different scheduling algorithms in a multi-tier heterogeneous network. The SIC-based receiver was used for a weight-based scheduling algorithm, and optimal power allocation for the users associated with a particular access point was performed using a modified genetic algorithm. In contrast, in the minimum distance scheduling and maximum channel gain algorithm, the local minimum-mean-squared error (LMMSE) precoding [27] technique was used. It uses fractional power allocation for optimal power allocation. In the minimum distance scheduling algorithm, the user u is assigned to access point A^* based on the shortest distance between them. The user with the shortest distance is assigned the highest power, while the user with the farthest distance is assigned the lowest power using fractional power allocation. Therefore, the spectral efficiency is better for MDS at lower distances. In the case of maximum channel gain scheduling (MCS) algorithm, the maximum power is allocated to the user with strong channel conditions and the minimum power to users with the worst conditions. The weight-based user-scheduling algorithm takes into account both the distance and received signal strength and allocates optimal power using an iterative GA approach to increase the spectral efficiency. The SIC-based interference cancellation technique is used at the receiver in order to mitigate interference in a multi-tier heterogeneous network. Thus, the proposed method, which uses weighting to assign different power levels to multiplexed users to minimize interference [42], performed better in terms of spectral efficiency compared to the minimum distance scheduling (MDS) and MCS algorithms.

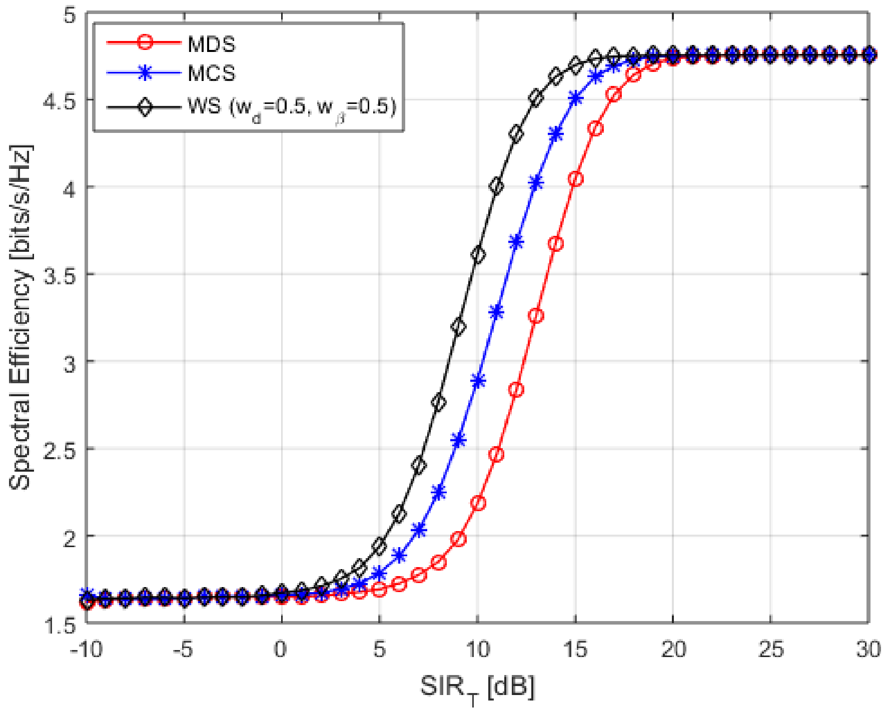

Figure 13. Spectral efficiency with respect to SIR_T for various user-scheduling algorithms.

10. Conclusions

In massive IoT networks, large numbers of devices are connected for various applications, and hence, the power consumption of these devices is a crucial factor in determining sustainability and cost-effectiveness. The power consumption of such devices depends on two main factors:

1. Types of devices: power-hungry applications and the type of sensors, communication, and processing power consumption;
2. Communication frequency and data rate: a device will consume more power with frequent communication at a high data rate

Hence, to minimize power in massive IoT networks, energy-efficient hardware and power-saving strategies must be applied to low-power communicating protocols. To decrease the energy consumption in devices with limited battery power, network providers are seeking environmentally friendly energy solutions to fulfill the energy needs of these networks. This paper presented an optimization technique along with a user-scheduling algorithm that allocates optimal power to each user and increases the network performance. A weight-based user-scheduling algorithm was proposed in which equal weights were assigned to the distance and received signal strength to select a set of users to be served by each AP. A perfect CSI was assumed for downlink transmission, and the performance of the proposed scheduling algorithm was evaluated with a modified genetic algorithm for optimal power allocation. The performance was measured in terms of the power consumption and spectral efficiency. The results showed the improvement in power consumption with the use of the genetic approach, which helped in the optimal assignment of powers to each users, so that the received SIR was always greater than SIR_T. The current research on the proposed weighted user-scheduling algorithm considered an equal weight; however, further improvements can be made and the performance can be evaluated under various weights. Moreover, the assignment of a proper weight helps in the enhancement of the performance metrics.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

Abbreviations

The following abbreviations are used in this manuscript:

IoT	Internet of Things
D2D	Device-to-device
BS	Base station
RAT	Radio access technology
SIC	Successive interference cancellation
EE	Energy efficiency
SE	Spectrum efficiency
SBS	Small cell base station
POLITE	Power optimization for low interference and throughput enhancement
BLA	Baseline link adaptation
MDS	Minimum distance scheduling
MCS	Maximum channel gain scheduling
CR	Cooperative relay
CSI	Channel state information
SER	Symbol error rate
PSO	Particle swarm optimization
GA	Genetic algorithm
LTE	Long-Term Evolution
MIMO	Multiple-input, multiple-output
SIR	Signal-to-interference ratio
CU	Cellular user
RUI	Relay-to-user interference
CCI	Cellular-to-cellular user interference
DDI	Device-to-device interference
CDI	Cellular-to-device interference

References

1. Siddiqui, M.U.A.; Qamar, F.; Kazmi, S.H.A.; Hassan, R.; Arfeen, A.; Nguyen, Q.N. A Study on Multi-Antenna and Pertinent Technologies with AI/ML Approaches for B5G/6G Networks. *Electronics* **2023**, *12*, 189. [CrossRef]
2. Siddiqui, M.U.A.; Qamar, F.; Tayyab, M.; Hindia, M.N.; Nguyen, Q.N.; Hassan, R. Mobility Management Issues and Solutions in 5G-and-Beyond Networks: A Comprehensive Review. *Electronics* **2022**, *11*, 1366. [CrossRef]
3. Kazmi, S.H.A.; Qamar, F.; Hassan, R.; Nisar, K.; Chowdhry, B.S. *Survey on Joint Paradigm of 5G and SDN Emerging Mobile Technologies: Architecture, Security, Challenges and Research Directions*; Research Square: Eindhoven, The Netherlands, 2022.
4. Gachhadar, A.; Maharjan, R.K.; Shrestha, S.; Adhikari, N.B.; Qamar, F. A 5G Framework and Its Analysis of Interference Cancellation in Multi-Tier Heterogeneous Networks. In Proceedings of the 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Mauritius, Mauritius, 7–8 October 2021.
5. Siddiqui, M.U.A.; Qamar, F.; Ahmed, F.; Nguyen, Q.N.; Hassan, R. Interference management in 5G and beyond network: Requirements, challenges and future directions. *IEEE Access* **2021**, *9*, 68932–68965. [CrossRef]
6. Kazmi, S.H.A.; Qamar, F.; Hassan, R.; Nisar, K. Interference Resistant Position Awareness for Collision Avoidance in Dense Drones Swarming. In Proceedings of the IEEE 15th International Conference on Application of Information and Communication Technologies (AICT), Washington, DC, USA, 12–14 October 2022.
7. Alzubaidi, O.T.H.; Hindia, M.N.; Dimyati, K.; Noordin, K.A.; Wahab, A.N.A.; Qamar, F.; Hassan, R. Interference Challenges and Management in B5G Network Design: A Comprehensive Review. *Electronics* **2022**, *11*, 2842. [CrossRef]
8. Qamar, F.; Hindia, M.N.; Rahman, T.A.; Hassan, R.; Saleem, S. Outdoor propagation channel investigation at 26 GHz for 5G mmWave communication. In Proceedings of the 2020 IEEE Student Conference on Research and Development (SCOReD), Batu Pahat, Malaysia, 27–29 September 2020.
9. Kazmi, S.H.A.; Qamar, F.; Hassan, R.; Nisar, K. Routing-Based Interference Mitigation in SDN Enabled Beyond 5G Communication Networks: A Comprehensive Survey. *IEEE Access* **2023**, *11*, 4023–4041. [CrossRef]
10. Malathy, S.; Porkodi, V.; Sampathkumar, A.; Hindia, M.H.D.N.; Dimyati, K.; Tilwari, V.; Qamar, F.; Amiri, I.S. An optimal network coding based backpressure routing approach for massive IoT network. *Wirel. Netw.* **2020**, *26*, 3657–3674. [CrossRef]
11. Qamar, F.; Hindia, M.H.D.N.; Dimyati, K.; Noordin, K.A.; Amiri, I.S. Interference management issues for the future 5G network: A review. *Telecommun. Syst.* **2019**, *71*, 627–643. [CrossRef]
12. Xu, C.; Zhang, P.; Jia, S.; Wang M.; Muntean, G.M. Video Streaming in Content-Centric Mobile Networks: Challenges and Solutions. *IEEE Wirel. Commun.* **2017**, *24*, 157–165. [CrossRef]
13. Chen, S.; Zhao, J. The Requirements, Challenges, and Technologies for 5G of Terrestrial Mobile Telecommunication. *IEEE Commun. Mag.* **2014**, *52*, 36–43. [CrossRef]
14. Yao, Y.; Chen, X.; Li, X.; Song, X. Hybrid small cell base station deployment in heterogeneous cellular networks with wireless power transfer. *Inf. Sci.* **2018**, *454*, 16–29. [CrossRef]
15. Panahi, F.H.; Panahi, F.H.; Hattab, G.; Ohtsuki, T.; Cabric, D. Green heterogeneous networks via an intelligent sleep/wake-up mechanism and D2D communications. *IEEE Trans. Green Commun. Netw.* **2018**, *2*, 915–931. [CrossRef]
16. Zhong, Y.; Ge, X.; Yang, H.H.; Han, T.; Li, Q. Traffic matching in 5G ultra-dense networks. *IEEE Commun. Mag.* **2018**, *56*, 100–105. [CrossRef]
17. Awoyemi, B.S.; Alfa, A.S.; Maharaj, B.T. Resource optimisation in 5G and Internet-ofthings networking. *Wirel. Pers. Commun.* **2020**, *111*, 2671–2702. [CrossRef]
18. Gachhadar, A.; Maharjan, R.K.; Shrestha, S.; Adhikari, N.B. Analysis of Throughput Gain in Multi-Tier Heterogeneous Networks. In *Intelligent Sustainable Systems*; Nagar, A.K., Singh Jat, D., Mishra, D.K., Joshi, A., Eds.; Lecture Notes in Networks and Systems; Springer: Singapore, 2023; Volume 579.
19. Yang, S. A joint optimization scheme for task offloading and resource allocation based on edge computing in 5G communication networks. *Comput. Commun.* **2020**, *160*, 759–768. [CrossRef]
20. Liu, X.; Zhang, X. Rate and energy efficiency improvements for 5G-based IoT with simultaneous transfer. *IEEE Internet Things J.* **2018**, *6*, 5971–5980. [CrossRef]
21. Al Homssi, B.; Al-Hourani, A.; Chavez, K.G.; Chandrasekharan, S.; Kandeepan, S. Energy-efficient IoT for 5G: A framework for adaptive power and rate control. In Proceedings of the 2018 12th International Conference on Signal Processing and Communication Systems (ICSPCS), Cairns, QLD, Australia, 17–19 December 2018.
22. Oh, S.; Yoon, J.; Choi, Y.; Jung, Y.-A.; Kim, J. Genetic Algorithm for the Optimization of a Building Power Consumption Prediction Model. *Electronics* **2022**, *11*, 3591. [CrossRef]
23. Jeong, J.-C.; Yu, G.-H.; Song, M.-G.; Vu, D.T.; Anh, L.H.; Jung, Y.-A.; Choi, Y.-A.; Um, T.-W.; Kim, J.-Y. Selective Layer Tuning and Performance Study of Pre-Trained Models Using Genetic Algorithm. *Electronics* **2022**, *11*, 2985. [CrossRef]
24. Khalaf, O.I.; Ogudo, K.A.; Singh, M. A Fuzzy-Based Optimization Technique for the Energy and Spectrum Efficiencies Trade-Off in Cognitive Radio-Enabled 5G Network. *Symmetry* **2021**, *13*, 47. [CrossRef]
25. Abrol, A.; Jha, R.K. Power Optimization in 5G Networks: A Step Towards GrEEn Communication. *IEEE Access* **2016**, *4*, 1355–1374. [CrossRef]
26. Mandelli, S.; Lieto, A.; Razenberg, M.; Weber, A.; Wild, T. Reducing interference via link adaptation in delay-critical wireless networks. *J. Wirel. Commun. Netw.* **2022**, *2022*, 109. [CrossRef]

27. Taneja, A.; Saluja, N.; Taneja, N.; Alqahtani, A.; Elmagzoub, M.A.; Shaikh, A.; Koundal, D. Power Optimization Model for Energy Sustainability in 6G Wireless Networks. *Sustainability* **2022**, *14*, 7310. [CrossRef]
28. Gachhadar, A.; Hindia, M.N.; Qamar, F.; Siddiqui, M.H.S.; Noordin, K.A.; Amiri, I.S. Modified genetic algorithm based power allocation scheme for amplify-and-forward cooperative relay network. *Comput. Electr. Eng.* **2018**, *69*, 628–641. [CrossRef]
29. Bansal, J.C.; Joshi, S.K.; Sharma, H. Modified global best artificial bee colony for constrained optimization problems. *Comput. Electr. Eng.* **2017**, *67*, 365–382. [CrossRef]
30. Nancharaiah, B.; Mohan, B.C. The performance of a hybrid routing intelligent algorithm in a mobile ad hoc network. *Comput. Electr. Eng.* **2014**, *40*, 1255–1264. [CrossRef]
31. Bhatia, T.; Kansal, S.; Goel, S.; Verma, A. A genetic algorithm based distance-aware routing protocol for wireless sensor networks. *Comput. Electr. Eng.* **2016**, *56*, 441–455. [CrossRef]
32. Sharma, D.; Singhal, S.; Rai, A.; Singh, A. Analysis of power consumption in standalone 5G network and enhancement in energy efficiency using a novel routing protocol. *Sustain. Energy Grids Netw.* **2021**, *26*, 100427. [CrossRef]
33. Gupta, A.; Jha, R.K. Power optimization using optimal small cell arrangements in different deployment scenarios. *Int. J. Commun. Syst.* **2017**, *30*, e3279. [CrossRef]
34. Hindia, M.N.; Qamar, F.; Abbas, T.; Dimyati, K.; Abu Talip, M.S.; Amiri, I.S. Interference cancelation for high-density fifth-generation relaying network using stochastic geometrical approach. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 1–16. [CrossRef]
35. Ma, C.; Wu, W.; Cui, Y.; Wang, X. On the performance of successive interference cancellation in D2D-enabled cellular networks. In Proceedings of the 2015 IEEE Conference on Computer Communications (INFOCOM), Hong Kong, China, 26 April–1 May 2015; pp. 37–45.
36. Zhang, Y.; Zhao, X.; Geng, S.; Zhou, Z.; Qin, P.; Zhang, L.; Yang, L. Power allocation algorithms for stable successive interference cancellation in millimeter wave NOMA systems. *IEEE Trans. Veh. Technol.* **2021**, *70*, 5833–5847. [CrossRef]
37. 3GPP. Further Advancements for E-UTRA Physical Layer Aspects (Release 9). In *3GPP Technical Specification 36.814*; 3GPP: Valbonne, France, 2017.
38. Sun, S.; Rappaport, T.S.; Rangan, S.; Thomas, T.A.; Ghosh, A.; Kovacs, I.Z.; Rodriguez, I.; Koymen, O.; Partyka, A.; Jarvelainen, J. Propagation Path Loss Models for 5G Urban Micro- and Macro-Cellular Scenarios. In Proceedings of the 2016 IEEE 83rd Vehicular Technology Conference (VTC Spring), Nanjing, China, 15–18 May 2016; pp. 1–6.
39. Mehboob, U.; Qadir, J.; Ali, S.; Vasilakos, A. Genetic algorithms in wireless networking: Techniques, applications, and issues. *Soft Comput.* **2016**, *20*, 2467–2501. [CrossRef]
40. Fuentes, M.; Carcel, J.L.; Dietrich, C.; Yu, L.; Garro, E.; Pauli, V.; Lazarakis, F.I.; Grondalen, O.; Bulakci, O.; Yu, J.; et al. 5G New Radio Evaluation Against IMT-2020 Key Performance Indicators. *IEEE Access* **2020**, *8*, 110880–110896. [CrossRef]
41. Benjebbovu, A.; Li, A.; Saito, Y.; Kishiyama, Y.; Harada, A.; Nakamura, T. System-level performance of downlink NOMA for future LTE enhancements. In Proceedings of the 2013 IEEE Globecom Workshops (GC Wkshps), Atlanta, GA, USA, 2013; pp. 66–70.
42. Al-Abbasi, Z.Q.; So, D.K.C. Resource Allocation in Non-Orthogonal and Hybrid Multiple Access System with Proportional Rate Constraint. *IEEE Trans. Wirel. Commun.* **2017**, *16*, 6309–6320. [CrossRef]