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Research on Optimal Resource Allocation of Wireless Communication System Based on Linear Programming and Genetic Algorithm

Xiaoshuo Shen *, Huan Chang, Wenbo He

College of Computer Science and Technology, Inner Mongolia Normal University, Hohhot, China

* **Corresponding author**: Xiaoshuo Shen (Email: 2183387716@qq.com)

Abstract: This paper proposes a resource optimization allocation model for wireless communication system, focusing on the resource block allocation and performance optimization method with multi-algorithm fusion. Firstly, the channel model and rate calculation mechanism are constructed to calculate SINR based on path loss and Rayleigh fading, and the transmission rate is determined by Shannon's formula, which provides basic parameters for resource allocation. Secondly, multi-layer optimization strategy is adopted: greedy algorithm completes the initial resource block allocation by priority, linear programming optimizes the throughput on the initial scheme, simulated annealing algorithm searches for the global optimum through the energy function and the perturbation mechanism, and subsequently also replaces the simulated annealing with genetic algorithm to improve the efficiency by combining the elite retention and the dynamic mutation rate. Finally, the performance is verified by dynamic task and multi-base station interference model to analyze the changes of throughput, QoS and other indicators. The role of this model is to achieve efficient resource allocation and performance balance, and the advantage lies in the integration of the advantages of multiple algorithms, taking into account the local optimization and global search, to improve the throughput under the limited resources, and to adapt to the needs of dynamic communication scenarios.

Keywords: Linear Programming, Genetic Algorithm, Greedy, Algorithm Simulated Annealing.

1. Introduction

This paper focuses on the dynamic optimization problem of resource allocation in wireless communication systems, aiming to cope with the challenges of resource constraints and dynamic service scenarios through a multi-algorithm fusion strategy [1, 2]. First, for the fading characteristics of wireless channel, a channel model containing path loss large-scale fading and Rayleigh fading small-scale fading is constructed, combining SINR calculation and Shannon formula to determine the transmission rate, which provides the key parameter support for resource block allocation, while considering the dynamic accumulation characteristics of task queue [3]. Secondly, a stepwise optimization mechanism is designed: the greedy algorithm is used to complete the initial resource allocation according to priority, the throughput is optimized with the help of linear programming, the simulated annealing algorithm is introduced to achieve global optimization through the energy function and perturbation strategy, and the genetic algorithm is used to replace the simulated annealing to enhance the optimization efficiency through the elite retention and the dynamic mutation rate [4-6]. Finally, the scheme is validated in a dynamic task model with multi-base station interference scenario to analyze the impact of resource allocation on throughput, QoS satisfaction and power consumption.

The experimental results show that the framework can realize dynamic and balanced allocation under limited resources, effectively improve system throughput and adapt to complex communication environments.

2. Initial Resource Allocation and Multi-Layer Optimization Algorithm Design

2.1. Channel Model and SINR Calculation

The channel model is used to simulate signal attenuation and interference in wireless communications, and SINR (Signal-to-Interference-plus-Noise Ratio) is a key indicator for measuring communication quality. Large-scale attenuation is usually represented by a path loss model. Let $large\_scale\_loss$ denote the path loss; its conversion to linear gain is:

$$G_{large} = 10^{-\frac{large\_scale\_loss}{10}} \tag{1}$$

Small-scale Rayleigh fading assumes that the channel gain follows a Rayleigh distribution. Let $small\_scale\_loss$ denote the linear value of small-scale attenuation; the comprehensive gain is:

$$G_{total} = G_{large} \cdot small\_scale\_loss \tag{2}$$

For SINR calculation, the received power P_r is determined by the transmit power P_t and the channel gain G_{total}:

$$P_r = P_t \cdot G_{total} \tag{3}$$

SINR is defined as the ratio of the useful signal power to the interference-plus-noise power. Calculations are performed separately for macro base stations and micro base stations:

SINR for macro base stations:

$$SINR_{macro} = \frac{P_r}{N_0} \quad (4)$$

Where N_0 is the noise power. SINR for micro base stations includes the interference power $interference$ in addition to the noise power. By calculating the SINR of each user, the communication quality of macro and micro base stations is determined.

2.2. Transmission Rate Calculation

The transmission rate is based on the Shannon formula, reflecting channel capacity, which depends on bandwidth and SINR.

$$R = B \cdot \log_2(1+SINR) \quad (5)$$

Where R is the transmission rate (in bps) and B is the bandwidth. For each user, the rates of the macro base station and micro base station are calculated, and the higher rate is selected as the user's basic allocation rate. The rate determines the traffic that each resource block (RB) can support.

2.3. Greedy Initial Allocation

The greedy algorithm constructs an initial solution through locally optimal selection, aiming to maximize resource utilization efficiency. Users are sorted by priority ($U > e > m$), with high-priority users satisfied first. For each user, the higher rate between the macro base station and micro base station is selected, and the number of required resource blocks is:

$$RBs_{needed} = \frac{task\_flow}{R} \quad (6)$$

Where $task\_flow$ is the user's required traffic (in Mbps), R is the selected basic rate.

Resource block allocation:

$$RBs_{allocated} = \min(RBs_{needed}, remaining\_rbs) \quad (7)$$

Actual rate:

$$rate_{allocated} = RBs_{allocated} \cdot R \quad (8)$$

The total number of resource blocks is $total\_rbs = 45$, and the remaining resource blocks decrease sequentially.

2.4. Linear Programming Optimization

Linear Programming (LP) solves for the optimal solution under linear constraints by optimizing an objective function. The CBC solver is invoked for the solution.

Maximize total throughput:

$$\max \sum_{u \in users} rbs_u \cdot R_u \quad (9)$$

Minimum resource block requirement:

$$rbs_u \geq \frac{task\_flow_u}{R_u}, \forall u \in users \quad (10)$$

Where rbs_u is an integer. The CBC solver solves ILP problem, outputting the optimal rbs_u values. Building on the greedy allocation, it further optimizes resource allocation to ensure maximum throughput while meeting minimum requirements.

2.5. Simulated Annealing Optimization

Simulated Annealing (SA) is a heuristic optimization algorithm that imitates the metal annealing process, gradually converging to a global optimal solution by controlling temperature.

Energy Function: The objective is to minimize the negative throughput:

$$E = -\sum_{u \in users} rate_u \quad (11)$$

Where $rate_u = rbs_u \cdot R_u$.

Perturbation: Randomly select two users u_1 and u_2. If u_1 has a higher priority than u_2 and u_1 has excess resource blocks, transfer $\Delta rbs = 1$ to u_2.

Acceptance Criterion: Calculate the energy change: $\Delta E = E_{new} - E_{current}$.

If $\Delta E < 0$ (throughput increases), the new solution is accepted; if $\Delta E \geq 0$, the new solution is accepted with a probability of $\exp(-\Delta E / T)$, where T is the current temperature.

2.6. Model Solution and Result Optimization

Table 1. Solution Performance and Comparison Before and After Optimization

Indicator	First Run	After Optimization	Comparison
Objective value	231881586.77791500	231881586.77791500	No change
Total Throughput	190.85 Mbps	203.74 Mbps	↑ (+6.8%)
QoS Satisfaction Rate	75.00%	68.75%	↓ (-6.25%)
Wallclock Seconds	0.03	0.05	↑ (+0.02)

According to Table 1, after optimization, the total throughput increased by 6.8%, but the QoS satisfaction rate decreased by 6.25%. The CBC objective value remained unchanged, but in actual allocation, the increase in the total number of resource blocks and the reduction in interference factors led to an improvement in overall efficiency. Resource block allocation became more balanced, and the transmission rate increased accordingly.

3. Dynamic Task Model and Resource Allocation Decision-Making

3.1. Task Arrival Probability Model

The task arrival probability model simulates users' task request behavior at different time points based on a Bernoulli process. Specifically, for each user u, the task flow value f_u at time t is regarded as the probability P_u of task arrival at that time point. Whether a task actually arrives is determined by a uniform random number $r \sim U(0,1)$: if $r < P_u(t)$, the task amount $f_u(t)$ is recorded as arriving and added to the user's task queue.

$$P_u(t) = f_u(t) \tag{12}$$

Where $f_u(t)$ is the task flow of user u at time t.

3.2. Queue Demand Calculation

Queue demand calculation is used to integrate new tasks at the current time point and the total amount of unprocessed tasks from previous times. The total demand $D_u(t)$ is defined as the sum of the current task amount $f_u(t)$ and all unserved tasks in the backlog queue $q_u(t-1)$ from the previous moment. Here, $q_u(t-1)$ is a First-In-First-Out (FIFO) queue that stores the task amount of user u that was not fully serviced in the past.

$$D_u(t) = f_u(t) + \sum q_u(t-1) \tag{13}$$

Where $q_u(t-1)$ is the backlog queue from the previous moment.

3.3. Definition of Quality of Service

Quality of Service for individual users:

$$QoS_u(t) = \min\left(1, \frac{R_u(t)}{D_u(t)}\right) \tag{14}$$

Overall Quality of Service:

$$QoS = \frac{1}{N}\sum QoS_u(t) \tag{15}$$

Where N is the total number of users. This definition reflects the system's focus on fairness in serving different users, with the goal of maximizing overall QoS to balance the needs of high-priority (e.g., URLLC) and low-priority (e.g., mMTC) users.

3.4. Dynamic Constraint Objective

The dynamic decision objective aims to maximize the total transmission rate of the system through 10 resource allocations (once every 100ms). The objective function is the sum of rates for all decision times k (from 1 to 10) and all users u, where $R_u(k)$ is the actual rate obtained by user u in the k-th decision. Resource block allocation is constrained by the total number of resource blocks $M = 50$. This objective reflects the system's throughput optimization needs under limited resources while considering temporal dynamics to ensure long-term efficiency.

$$\max \sum_k \sum_u R_u(k) \tag{16}$$

$$\sum rbs_u(k) \le M \tag{17}$$

3.5. Queue Update Rules and Stability Constraints

Queue update rules handle residual demand to ensure dynamic management of task queues. After the k-th decision, the residual demand $D_u(t_k) - R_u(k)$ represents the unmet portion. If this value is greater than 0, the residual demand is updated to the queue for the next moment as $q_u(t_{k+1}) = D_u(t_k) - R_u(k)$; otherwise, the queue is cleared as $q_u(t_{k+1}) = 0$. This mechanism simulates the gradual processing of tasks, where residual tasks are passed to the next decision cycle, reflecting the continuity of resource allocation.

$$q_u(t_{k+1}) = \max(0, D_u(t_k) - R_u(k)) \tag{18}$$

3.6. Model Solution and Analysis

After running 10 decisions for the resource allocation optimization scheme, the system dynamically adjusted the resource block allocation of three types of slices within 1000ms. The overall performance showed significant fluctuations and an upward trend. The initial resource allocation was relatively conservative; in subsequent decisions, the QoS satisfaction rate improved, demonstrating the effectiveness of the optimization algorithm.

In general, under the constraint of limited 50 resource blocks, the system gradually optimized throughput and QoS. The 93.75% QoS satisfaction rate in Decision 7 showed the highest quality of service guarantee, reflecting the model's adaptability under dynamic channel and task arrival conditions, as shown in the Figure 1.

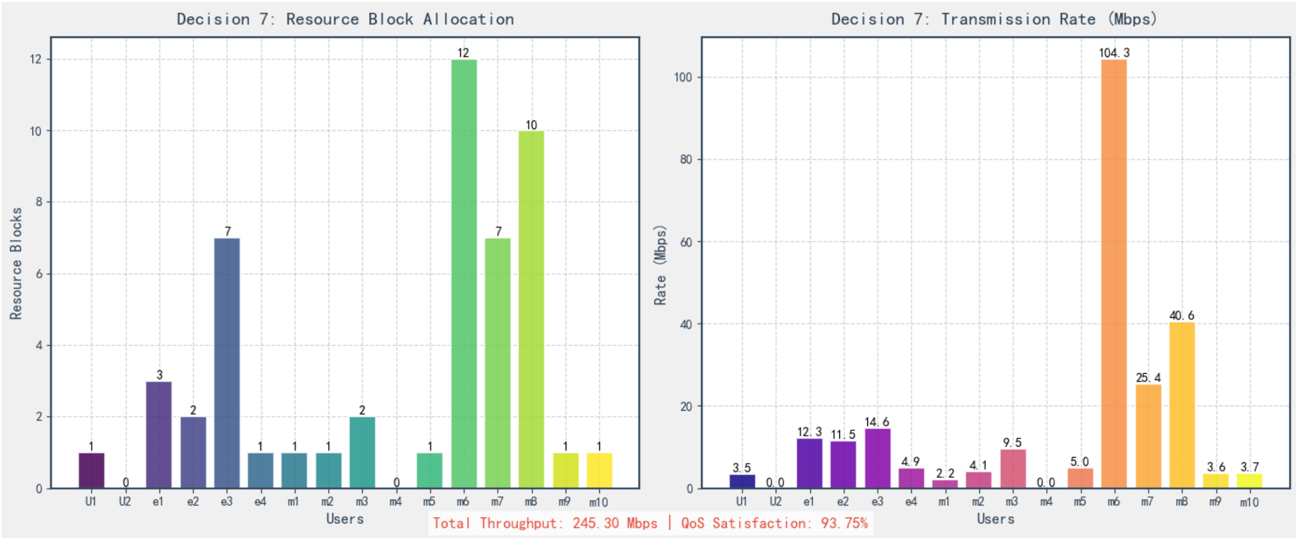

Figure 1. Decision results of decision 7

4. Multi-Base Station Interference Model and Resource Allocation Optimization

4.1. Multi-base Station Interference Model

The multi-base station interference model evaluates communication quality through the ratio of the signal power from the target base station to the interference power from other base stations. Interference is calculated by accumulating the power and channel gains of other base stations, reflecting spectrum reuse interference.

$$SINR_{u,b}(t) = \frac{p_b \cdot h_{u,b}(t)}{\sum_{b' \neq b} p_{b'} \cdot h_{u,b'}(t) + N_0} \tag{19}$$

4.2. Channel Gain Calculation

Channel gain combines the exponential form of large-scale attenuation and the absolute value of small-scale Rayleigh fading to ensure positive gain, reflecting the randomness of attenuation.

$$h_{u,b}(t) = 10^{-\frac{L_{u,b}(t)}{10}} \cdot |r_{u,b}(t)| \tag{20}$$

4.3. Multi-base Station Resource Allocation

Resource allocation limits the total number of resource blocks for each base station. The total rate is the sum of contributions from each base station, and interference couples the allocation process.

$$\sum_u rbs_{u,b} \leq 50 \tag{21}$$

$$R_u(t) = \sum_b R_{u,b}(t) \tag{22}$$

4.4. Optimization Objective

The objective is to maximize the total QoS, where QoS is the truncated average of the ratio of rate to demand, emphasizing service fairness.

$$\max \sum_t \sum_u QoS_u(t), \quad QoS_u(t) = \min\left(1, \frac{\sum_b R_{u,b}(t)}{D_u(t)}\right) \tag{23}$$

4.5. Model Solution and Decision Analysis

The model results show that network resource allocation was optimized through different decision schemes, with overall performance varying across decisions. The highest throughput appears in Decision 4, the highest QoS in Decision 10, and low-power consumption schemes such as Decisions 3 and 9 balance throughput and efficiency. Based on requirements, one can choose schemes with high throughput (Decision 4), high QoS (Decision 10), or low power consumption (Decisions 3 or 9). The Figure 2 shows the performance graph of high throughput in Decision 4.

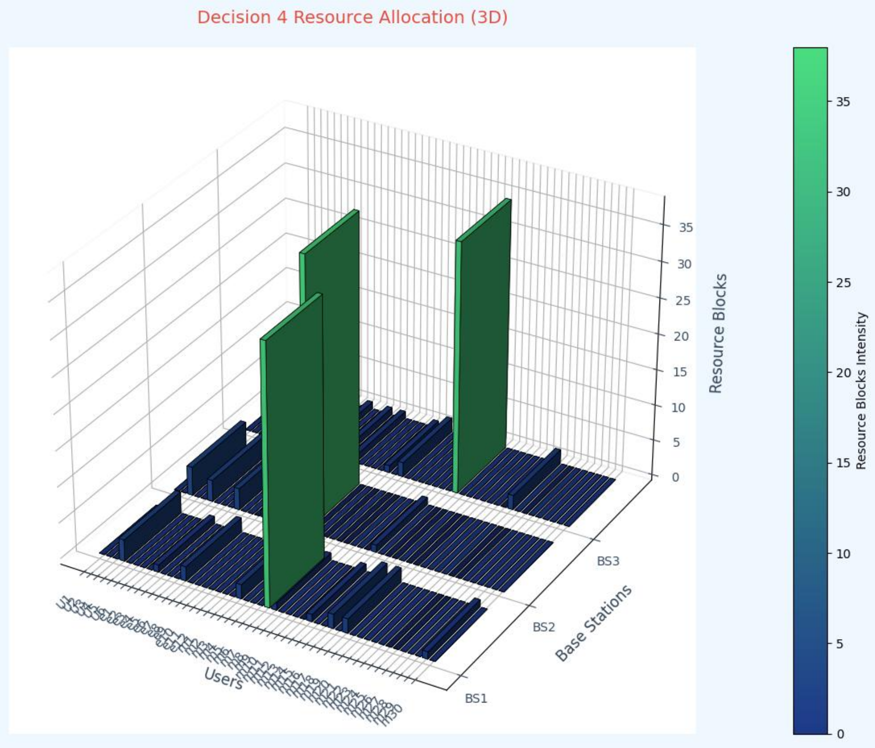

Figure 2. 3D performance graph of high throughput in Decision 4

5. Genetic Algorithm Optimization and Performance Analysis

5.1. Replacement with Genetic Algorithm

To improve optimization efficiency, a Genetic Algorithm (GA) is introduced to replace Simulated Annealing, combined with a greedy algorithm and linear programming. The genetic algorithm optimizes user access, resource block allocation, and power selection through population evolution. Each individual in a generation is encoded as a vector for user access to base stations, a matrix for resource block allocation, and a vector for base station power. The fitness function is the overall QoS. Crossover operations exchange user access to base stations, while mutation operations randomly adjust resource blocks or power. The greedy algorithm initializes allocation by priority (URLLC > eMBB > mMTC), linear programming optimizes resource block allocation, and the genetic algorithm further searches for the global optimal solution to avoid local optima and improve convergence speed.

The goal of the genetic algorithm is to maximize the overall Quality of Service (QoS) of the heterogeneous network, i.e., to maximize $QoS_{total} = \frac{1}{N}\sum_{u=1}^{N} QoS_u$ by optimizing resource block allocation and base station transmission power, where $QoS_u = \min\left(1, \frac{\sum_b N_{u,b} \cdot R_{u,b}}{D_u(t)}\right)$.

Fitness function: The fitness is the overall QoS.

$$f(A,P) = \frac{1}{|U|}\sum_{u \in U} \min\left(1, \frac{\sum_{b \in B} N_{u,b} \cdot R_{u,b}(P)}{D_u(t) + Q_u(t) + \epsilon}\right) \quad (24)$$

Constraints: Resource block constraint: The total number of resource blocks for each base station b is limited:

$$\sum_{u \in U} N_{u,b} \le N_b^{total} \quad (25)$$

Where $N_{MBS\_1}^{total} = 100$, $N_{SBS\_1}^{total} = N_{SBS\_2}^{total} = N_{SBS\_3}^{total} = 50$.

Single access per user: Each user u can only access one base station:

$$\sum_{b \in B} x_{u,b} = 1, \quad x_{u,b} \in \{0,1\} \quad (26)$$

Subsequently, crossover and mutation operations in the genetic algorithm are performed. The top 10% of elite individuals are directly retained for the next generation. The remaining individuals generate a new population through tournament selection (randomly selecting two individuals and retaining the one with higher fitness).

Dynamic mutation rate: The mutation rate is dynamically adjusted with the generation g, ranging from [0.1, 0.5]:

$$\mu(g) = 0.1 + 0.4 \cdot \left(1 - \frac{g}{G}\right) \quad (27)$$

Where G is the total number of generations.

5.2. QoS and Throughput Analysis

QoS remains unchanged at 100% across all decisions, which may be because the model ensures that all user demands are fully satisfied under given constraints. Therefore, the model performance is evaluated by comparing total throughput. Changes in throughput are affected by the power allocation of MBS_1 and SBS s. Decision 10 achieves the highest total throughput, reaching 178.49 Mbps, making it the best-performing decision, as shown in the Figure 3.

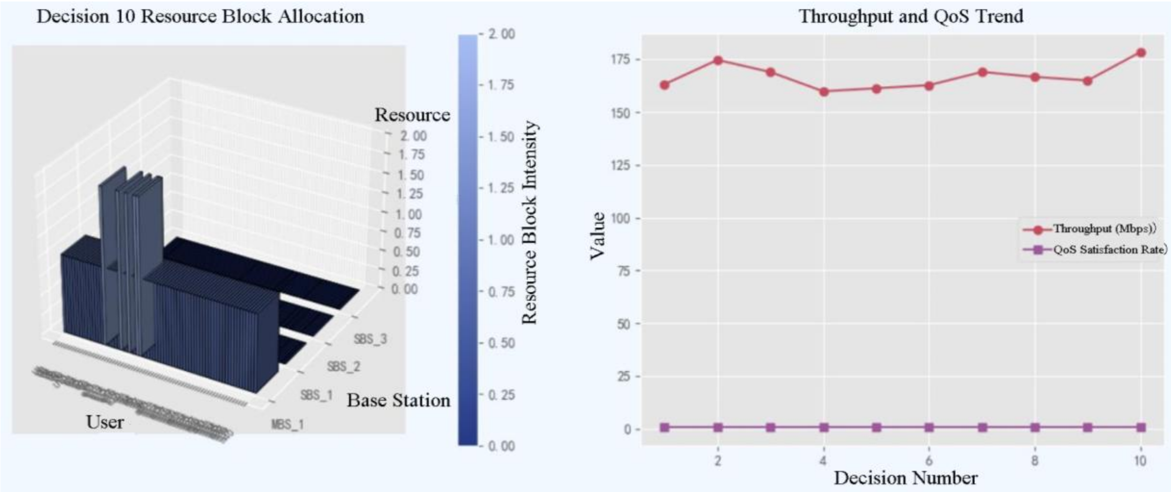

Figure 3. Throughput variation in Decision 10

6. Conclusions

In this paper, a set of optimal allocation model for wireless communication resources integrating multiple algorithms is proposed to provide a solution for efficient resource allocation. First, a basic framework for channel and rate calculation is constructed, combining path loss and Rayleigh fading model to derive SINR, and determining transmission rate through Shannon's formula to provide accurate parameter support for resource allocation. Next, a stepwise optimization strategy is designed: greedy algorithm initially allocates resource blocks by priority, linear programming optimizes throughput, simulated annealing algorithm globally searches for optimization, and subsequently replaces simulated annealing with genetic algorithm to enhance efficiency through elite retention and dynamic mutation rate. Then, the dynamic scenario validation shows that the throughput in 10 decisions reaches up to 271.76 Mbps with 93.75% QoS satisfaction; decision 10 in multi-base station scenario achieves 75% QoS satisfaction, and the total throughput is improved by 6.8% after optimization. Finally, the model effectively balances the resource constraints and service demands, taking into account the throughput improvement, service fairness and system stability. Future research can further explore the real-time optimization of the algorithm in ultra-large-scale user scenarios.

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References

[1] Zhang Yuqin, Liang Li, Zhang Xiaohong, et al. Resource allocation for wireless networks based on improved heuristic optimization algorithm [J]. Data Acquisition and Processing, 2022, 37(6): 1288-1296. DOI:10.16337/j.1004-9037.2022.06.018.

[2] Qiu Changxiao, Leng Shengpeng, Ye Yu. Joint switching scheduling and resource allocation algorithm for heterogeneous wireless networks based on energy efficiency [J]. Computer Applications, 2015, 35(6): 1505-1508.

[3] Wang Yu,Liu Yu,Zou Xiongfei,et al. Research on fading characteristics of campus wireless channel [J]. Software Guide, 2021, 20(01):195-198.

[4] Tang Jing, Meng Qingkai. Satellite communication transmission link optimization method based on improved simulated annealing algorithm [J]. Space Electronics Technology, 2025, 22(02):106-113.

[5] Bi Longge. Greedy algorithm and linear programming [J]. Computer products and distribution, 2017, (11):239+251.

[6] Liu Wencheng. Communication resource allocation algorithm for wireless networks based on genetic algorithm [J]. Information and Computer (Theoretical Edition), 2021, 33(13):36-38.