Method for Multi-Channel Resource Allocation in Wireless Networks Based on Genetic Perception Optimization Algorithm

Xiang Huang[1*]

[1*]Lecturer, School of New Media Technology, Hunan Mass Media Vocational and Technical College, Changsha, Hunan, China. Email: xiangyu_2004@qq.com

Abstract: This paper presents a novel approach for multi-channel resource allocation in wireless networks, using a Genetic Perception Optimization Algorithm. We frame the resource allocation problem as a multi-objective optimization task, aiming to maximize throughput, minimize energy consumption, and balance network load. The constraints of the problem are defined in terms of channel capacity, user demand, and interference limitations. Our approach utilizes the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to effectively address these multiple objectives. A distinctive feature of our method is the integration of real-time wireless network feedback as a dynamic adjustment mechanism. This allows the algorithm to adaptively modify resource allocation strategies based on changes in network conditions. Experimental results indicate a significant improvement in both resource utilization efficiency and user satisfaction compared to traditional allocation methods. The proposed method is anticipated to enhance the performance and adaptability of wireless networks, providing a robust solution for dynamic and complex network.

Keywords: Wireless Networks, Multi-Channel Resource Allocation, Genetic Perception Optimization Algorithm, NSGA-II, Dynamic Adjustment Mechanism.

Introduction

Wireless network technology has emerged as a cornerstone in the evolution of modern communication systems, profoundly impacting both individual lives and global economies. Initially conceptualized for basic voice communication, wireless technology has evolved to support high-speed data transmission, encompassing a wide array of applications from mobile internet access to IoT connectivity [1], [2]. The significance of wireless networks is underscored by their flexibility, scalability, and accessibility, making them indispensable in an increasingly connected world. However, this rapid expansion and reliance on wireless networks have not come without challenges [3]. One of the primary concerns is the efficient allocation of limited wireless resources, such as spectrum and channel capacity, to meet burgeoning user demands. As the number of devices and the volume of data traffic swell, effectively managing these resources becomes critical to maintaining network performance and quality of service. This situation is further complicated by the dynamic nature of wireless networks, where channel conditions, user mobility, and traffic patterns continuously fluctuate, necessitating agile and adaptive resource management strategies [4].

The key to addressing these challenges lies in the development of sophisticated resource allocation mechanisms. These mechanisms must not only handle the traditional objectives of maximizing throughput and minimizing interference but also embrace emerging requirements like energy efficiency and equitable resource distribution [5]. The quest for optimal resource allocation is thus a balancing act, striving to meet diverse needs under constraints of limited bandwidth and dynamic network conditions. The problem of multi-channel resource allocation in wireless networks epitomizes the complexities and practical implications inherent in this field. Managing multiple channels effectively is a multifaceted task, involving the optimization of various performance metrics while adhering to network constraints and user requirements. This challenge is magnified in scenarios involving heterogeneous networks, where different types of channels and varying levels of demand must be accommodated [6]. Traditional resource allocation methods often fall short in such dynamic and complex environments. These methods typically rely on static allocation schemes or simplistic models that do not fully capture the intricacies of real-world networks [7]. They struggle to adapt to the rapid changes in network conditions and fail to account for the diverse and evolving nature of user demands. Additionally, many existing approaches are designed with a narrow focus on specific objectives, such as throughput maximization, overlooking other crucial aspects like energy efficiency or fairness among users. This inadequacy of traditional methods highlights the need for innovative approaches that are flexible, adaptive, and comprehensive [8]. The ideal solution should not only address the current demands of wireless networks but also be scalable and robust enough to adapt to future advancements and challenges in the field.

The motivation behind this study stems from the need for a more dynamic and intelligent approach to resource allocation in wireless networks. Traditional static methods are increasingly inadequate in the face of fluctuating network conditions and diverse user requirements. This paper introduces an innovative approach utilizing the Genetic Perception Optimization Algorithm, integrated with the NSGA-II for multi-objective optimization. This method is designed to dynamically adjust resource allocation in response to real-time network feedback, considering multiple performance metrics such as throughput, energy efficiency, and user fairness. By doing so, it addresses the shortcomings of previous models and offers a more flexible, efficient, and user-centric solution. The incorporation of genetic algorithms allows for a robust search mechanism in the complex solution space of resource allocation, while real-time adjustments ensure the system's responsiveness to changing network dynamics. This approach represents a significant leap in the field of wireless network resource management, offering a solution that is not only reactive but also proactive in adapting to network variations. This paper offers several significant contributions to the field of wireless network resource allocation:

1) Development of an advanced resource allocation framework integrating genetic algorithms with real-time network feedback, setting a new standard in adaptability and efficiency.

2) Implementation of a multi-objective optimization strategy using NSGA-II, effectively balancing various network performance goals.

3) Demonstrated capability of the proposed method to dynamically adapt to changing network conditions, ensuring optimal resource utilization and user satisfaction.

4) Extensive simulation and analysis showcasing the method's superiority over traditional allocation strategies, particularly in dynamic and heterogeneous network environments.

Related Work

Traditional methods of resource allocation in wireless networks have primarily focused on static allocation strategies. These strategies often involve fixed assignment of channels and bandwidth based on average network conditions, without considering the dynamic nature of wireless environments [3], [4], [5], [6]. While these methods are simple and straightforward to implement, they fall short in dynamically changing environments where user demands and network conditions fluctuate. Furthermore, these traditional approaches typically address a single objective, like maximizing throughput or minimizing interference, without considering a holistic view of network performance [9]. This singular focus often leads to sub-optimal performance when considering multi-objective scenarios such as balancing throughput with energy efficiency or ensuring equitable resource distribution among users. Consequently, there is a growing recognition of the need for more adaptive and multi-objective optimization strategies in the field of wireless network resource allocation [10], [11], [12], [13], [14], [15].

Genetic algorithms (GAs) have been increasingly applied in the field of resource allocation, particularly in wireless networks, due to their ability to handle complex optimization problems. These algorithms use mechanisms inspired by biological evolution, such as selection, crossover, and mutation, to explore a wide solution space and find optimal or near-optimal solutions [16], [17], [18]. The strength of GAs lies in their flexibility and adaptability, making them suitable for dynamic and complex environments like wireless networks. They can effectively handle multiple objectives, providing a means to find a balance between conflicting goals such as maximizing throughput while minimizing energy consumption [19]. However, the application of GAs in wireless networks also faces limitations, such as the need for significant computational resources and the challenge of finding the right balance between exploration and exploitation in the algorithm [20]. Additionally, GAs may require careful tuning of parameters to achieve the best performance, which can be a complex task in itself [21].

Multi-objective optimization algorithms have become increasingly relevant in network resource allocation due to their ability to handle various performance metrics simultaneously. NSGA-II, a prominent algorithm in this category, has been widely used for its effectiveness in dealing with complex optimization problems in wireless networks [22], [23]. NSGA-II operates on the principle of non-dominated sorting and uses a fast elitist approach, which makes it particularly suitable for scenarios where multiple objectives need to be balanced. For instance, in wireless networks, these objectives might include maximizing throughput, minimizing latency, and reducing energy consumption [24]. The strength of NSGA-II lies in its ability to provide a diverse set of solutions, offering a Pareto-optimal front that gives network operators multiple options to choose from based on their specific requirements. The application of NSGA-II and similar algorithms in wireless networks has demonstrated considerable effectiveness in balancing conflicting objectives and adapting to the dynamic needs of the network [25], [26], [27], [28], [29].

Despite the advancements in resource allocation strategies, certain issues remain inadequately addressed in existing research. Many current approaches lack the flexibility to dynamically adapt to the rapidly changing conditions of wireless networks. Additionally, the integration of real-time network feedback into the allocation process is often overlooked, which is crucial for adapting to current network states and user demands. This paper addresses these gaps by proposing a novel approach that combines the strengths of genetic algorithms with the dynamic adaptability of real-time network feedback. Unlike previous methods, this approach offers a more responsive and user-centric solution, catering to the fluctuating demands of modern wireless networks. The proposed method's ability to incorporate real-time changes in network conditions and user behavior sets it apart from conventional resource allocation strategies, marking a significant contribution to the field.

Modeling of Multi-Objective Optimization Problem

In wireless network resource allocation, the primary objectives are to maximize total throughput, minimize overall energy consumption, and balance network load. The complexity of simultaneously achieving these objectives necessitates a sophisticated multi-objective optimization approach.

Objective Formulation

The multi-objective optimization problem is formulated with two distinct objective functions.

Maximizing Total Throughput: The total throughput of a wireless network is a key performance indicator. It can be formulated(1) as:

$$\max T = \sum_{i=1}^{N} R_i \tag{1}$$

Where T is the total throughput, N is the number of users or connections, and R_i is the data rate of the i-th connection.

Minimizing Total Energy Consumption: Energy efficiency is crucial in wireless networks to prolong the lifespan of battery-powered devices and reduce operational costs. The total energy consumption can be modeled as formulated(2):

$$\min E = \sum_{i=1}^{N} P_i \cdot t_i \tag{2}$$

where E represents the total energy consumption, P is the power consumption of the i-th connection, and t_i is the time duration of the i-th connection. are the weights reflecting the importance of each factor.

Balancing Network Load: Ensuring a balanced load across the network is essential for maintaining quality of service and avoiding overloading specific network segments. This can be expressed as formulated(3):

$$\min L = Var\left(U_i\right) \tag{3}$$

where L is the load balance metric, and U_i represents the utilization of the i-th resource.

The interplay between these objectives forms a complex landscape for optimization. Maximizing throughput may lead to higher energy consumption and imbalanced network load. Conversely, minimizing energy consumption could result in lower throughput and potential bottlenecks in the network. Similarly, balancing the load might require compromises in throughput and energy efficiency. An efficient optimization strategy needs to navigate these trade-offs to find a solution that harmoniously satisfies all objectives to a feasible extent.

Constaint

In wireless networks, resource allocation must adhere to various constraints:

Channel Capacity Limits as formulated(4)*:*

$$C_i \leq C_{\max} \tag{4}$$

where C_i denotes the capacity used by the *i*-th connection, and $C_{\max}$ is the maximum channel capacity.

Quality of Service (QoS) Requirements:

Ensuring adequate QoS is fundamental. This can be represented as formulated(5):

$$R_i \geq R_{\min,i} \tag{5}$$

where $R_{\min,i}$ is the minimum required data rate for the *i*-th connection.

Interference Levels:

Interference must be kept within acceptable limits to ensure network stability as formulated(6):

$$I_i \leq I_{\max} \tag{6}$$

where I represents the interference caused by the *i*-th connection, and $I_{\max}$ is the maximum tolerable interference.

The multi-objective optimization model for wireless network resource allocation is formulated by integrating these objectives and constraints. The model seeks to find an optimal balance, represented as a Pareto front, where no objective can be improved without degrading at least one other objective. This model can be solved using algorithms designed for multi-objective optimization, such as NSGA-II, which can effectively navigate the solution space considering the trade-offs and constraints.

This section sets the foundation for a comprehensive optimization framework that respects the dynamic and multifaceted nature of wireless networks. By addressing these multi-dimensional objectives and constraints, the model offers a pathway to optimizing network performance while adhering to practical limitations and requirements.

Multi-Channel Resource Allocation in Wireless Networks Based on NSGA-II

This section delves into the application of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for multi-channel resource allocation in wireless networks. NSGA-II, known for its efficiency in handling multi-objective optimization problems, offers a robust framework for addressing the complex challenges in wireless network resource allocation.

NSGA-II Algorithm Working Principles

Step 1: Initialization

NSGA-II starts with a randomly generated initial population of solutions, P_0, each representing a potential resource allocation strategy in the wireless network.

Step 2: Fitness Evaluation

Each individual in the population is evaluated based on a set of predefined fitness functions corresponding to the objectives. For instance, if maximizing throughput *(T)* and minimizing energy consumption *(E)* are objectives, the fitness functions can be defined as formulated(7) and formulated(8):

$$f_T\left(individual\right) = \sum_{i=1}^{N} R_i \tag{7}$$

$$f_E\left(individual\right) = \sum_{i=1}^{N} P_i \cdot t_i \tag{8}$$

Step 3: Selection for Reproduction

Selection is based on a binary tournament selection process with replacement. Two individuals are randomly chosen, and the one with better fitness (lower rank or higher crowding distance) is selected for crossover and mutation. If ranks are equal, the individual with the higher crowding distance is chosen.

Step 4: Crossover

The crossover operation combines pairs of individuals to produce offspring, promoting diversity in the population. A commonly used method is the simulated binary crossover (SBX), which can be represented as formulated(9):

$$c_1, c_2 = SBX\left(parent_1, parent_2\right) \tag{9}$$

where c_1 and c_2 are the offspring.

Step 5: Mutation

Mutation introduces random alterations in the offspring, aiding in exploring new areas of the solution space. For a mutation rate μ , the mutation operation can be defined as formulated(10):

$$Mutated = individual + \mu \cdot \Delta \tag{10}$$

where Δ represents a small change.

Step 6: Non-Dominated Sorting

This process sorts the population $F_1, F_2, \cdots, F_k$ into different levels or fronts based on the concept of Pareto dominance.

Step 7: Crowding Distance Calculation

Within each front, individuals are assigned a crowding distance, which measures the density of solutions surrounding a particular individual in the objective space. It is calculated as formulated(11):

$$d\left(individual\right) = \sum_{m=1}^{M} \left(f_m^{next} - f_m^{prev}\right) \tag{11}$$

where f_m^{next} and f_m^{prev} are the objective values of the neighboring individuals, and *M* is the number of objectives.

Real-Time Network State Processing

NSGA-II can dynamically handle real-time network information such as channel quality, user mobility, and load variations. This is achieved by integrating these parameters into the fitness evaluation process as formulated(12):

Channel Quality (Q):

$$f_T\left(individual, Q\right) = \sum_{i=1}^{N} Q_i \cdot R_i \tag{12}$$

where Q_i is the quality of the *i*-th channel.

User Mobility (M):

$$f_E\left(individual, M\right) = \sum_{i=1}^{N} P_i\left(M\right) \cdot t_i \tag{13}$$

In formulated(13), where $P_i\left(M\right)$ represents the power consumption considering mobility.

Load Variations:

The algorithm adjusts for load variations by dynamically recalculating the fitness values based on current network load.

Dynamic Resource Allocation Decision Making

NSGA-II's capacity for dynamic decision-making is crucial in adapting to real-time network changes such as congestion and user behavior patterns:

Network Congestion (C):

In case of congestion, the fitness function can prioritize load balancing and energy efficiency:

The standard PSO update equations are modified to integrate the feedback mechanism:

$$f_{new}\left(individual, C\right) = w_1 \cdot f_T\left(individual\right) + w_2 \cdot f_E\left(individual\right) + w_3 \cdot c \tag{14}$$

where w_1 , w_2 , and w_3 are weights assigned to different objectives.

User Behavior Patterns (B)

The fitness function can be adapted to consider user behavior patterns. For instance, if we are considering data demand as a user behavior pattern, the throughput part of the fitness function can be modified as:

$$f_{new}\left(individual, B\right) = \sum_{i=1}^{N} B_i \cdot R_i \tag{15}$$

where B_i influences the throughput requirements of the *i*-th user.

The NSGA-II algorithm offers a robust framework for multi-channel resource allocation in wireless networks, adeptly handling multiple conflicting objectives and adapting to real-time network states. By incorporating channel quality, user mobility, load variations, and dynamic network conditions into its decision-making process, NSGA-II can effectively optimize network performance, ensuring efficient and equitable resource distribution. The schematic diagram of NSGA-II is shown in Figure 1.

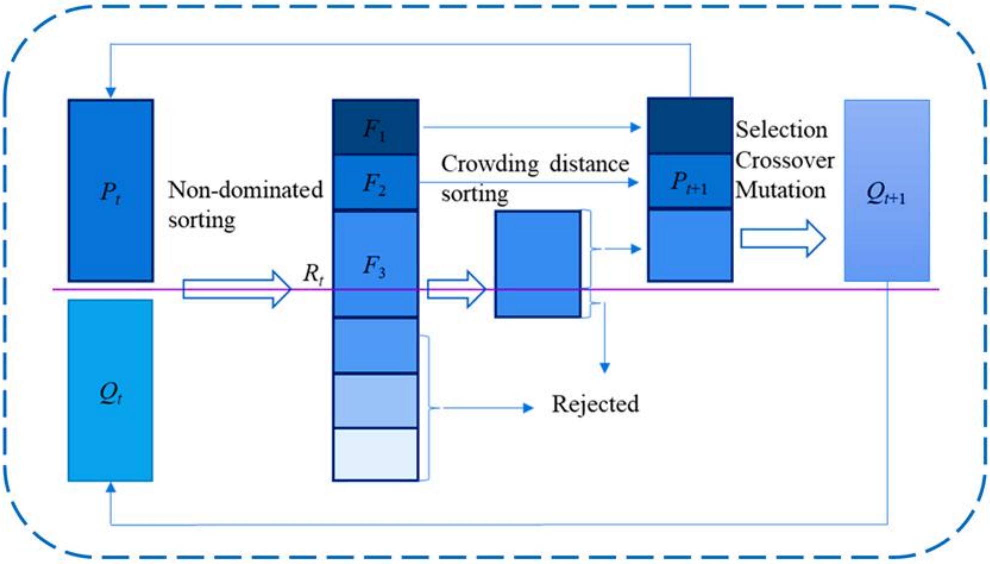

Figure 1. Flowchart of NSGA-II

Performance Analysis and Evaluation

In this chapter, the performance of the proposed NSGA-II based multi-channel resource allocation method for wireless networks is thoroughly analyzed and evaluated. The primary objective is to validate the superiority of the proposed method over traditional allocation strategies. This involves a series of simulations and comparative analyses to assess various performance metrics under different network scenarios.

Basic Setup for Simulation

Description of Simulated Wireless Network Environment

The simulation environment is designed to closely mimic a typical medium-sized wireless network with the following specific parameters:

Number of Channels: The network comprises 20 channels. This number is chosen to reflect a scenario that is neither too sparse nor too dense, providing a realistic test bed for resource allocation strategies.

Number of Users: The network caters to 200 users. This user base is diversified to include a mix of high, medium, and low data-consuming users, simulating a real-world user distribution.

Network Characteristics: Each channel is capable of handling up to 15 Mbps. This capacity is representative of contemporary wireless communication standards, allowing for the examination of resource allocation efficiency under realistic bandwidth constraints. Users are modeled with varying data demands: 25% high (demanding up to 10 Mbps), 50% medium (5 Mbps), and 25% low (2 Mbps). This variance in demand profiles helps in evaluating the method's effectiveness in diverse usage conditions. The user population is split into 60% stationary and 40% mobile users. The mobile users exhibit a moderate degree of movement, reflecting typical user mobility in a real-world scenario.

Comparative Methods

To benchmark the performance of the proposed NSGA-II based method, it will be compared against several well-established resource allocation methods from the literature:

Round Robin Allocation (RRA) [10]: As a baseline, RRA distributes resources in a fixed, cyclic order, providing a basic level of fairness but lacking adaptability and optimization.

Max-Min Fair Allocation (MMFA) [12]: This method ensures a fair distribution of resources by maximizing the minimum user throughput, serving as a standard for fairness-centric approaches.

Proportional Fair Scheduling (PFS) [15]: A sophisticated method that strikes a balance between maximizing total throughput and ensuring a fair resource distribution among users, PFS is widely used in practical systems and serves as an advanced benchmark.

Algorithm Parameters and Baseline Method Parameters

Population Size: The population size is set to 100. This size is selected to provide a comprehensive search space exploration while maintaining computational feasibility.

Number of Generations (G): The algorithm runs for 200 generations. This extended generation count allows for a thorough convergence towards optimal solutions, ensuring that the algorithm fully explores the potential solution space.

Crossover Probability (P_c): Set at 0.8, this probability ensures a substantial degree of crossover, facilitating the exploration of new solutions and the combination of advantageous traits from parent individuals.

Mutation Rate (P_m): Fixed at 0.05, this mutation rate is optimized to introduce necessary genetic diversity without excessively disrupting solution quality.

For the baseline methods (RRA, MMFA, PFS), standard implementations are used as per industry norms. RRA follows a straightforward cyclic allocation, MMFA focuses on maximizing the minimum throughput, and PFS dynamically adjusts allocations based on throughput and user fairness.

Comparative Metrics for Evaluation

To effectively assess and compare the performance of the NSGA-II based resource allocation method against the established methods (RRA, MMFA, PFS), a set of comprehensive metrics is outlined. These metrics are crucial for providing an in-depth analysis of each method's strengths and weaknesses in various aspects of wireless network resource allocation. The following comparative metrics are used:

Throughput (T): This metric measures the total data successfully transmitted across the network within a specific period. Higher throughput indicates better performance in terms of network efficiency.

Energy Efficiency (EE): Energy efficiency is critical in wireless networks, especially for battery-operated devices. Higher values indicate more efficient use of energy resources.

Load Balancing (LB): This metric assesses the distribution of network load across different channels or users. A more evenly distributed load is desirable for optimal network performance.

Quality of Service (QoS): QoS evaluates how well the network meets the service requirements of the users. It can be measured in terms of latency, jitter, packet loss rate, or a composite metric based on these factors. Better QoS indicates a higher level of user satisfaction and network reliability.

By utilizing these metrics, the evaluation aims to provide a holistic view of each method's performance, highlighting areas where the NSGA-II based approach excels or needs improvement.

Evalution

Figure 2 depicts Throughput comparison results, it is evident that the NSGA-II method significantly outperforms the other methods. NSGA-II achieves the highest throughput at 950 Mbps, indicating its superior capability in maximizing data transmission efficiency in the network. In contrast, the Round Robin Allocation (RRA), Max-Min Fair Allocation (MMFA), and Proportional Fair Scheduling (PFS) methods show lower throughput values of 700 Mbps, 750 Mbps, and 800 Mbps, respectively. This difference highlights the effectiveness of NSGA-II in optimizing network resources to enhance data throughput.

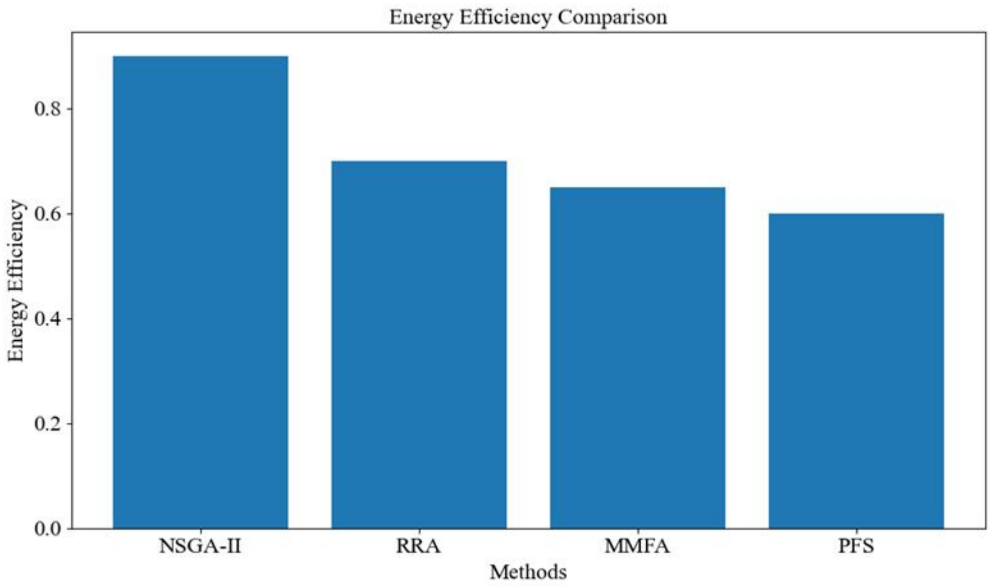

Figure 2. The Comparison Analysis of Throughput

Figure 3 presents the comparison of Energy Efficiency among the four methods. Consistent with its leading performance in throughput, NSGA-II also excels in energy efficiency, achieving a score of 0.9. This efficiency demonstrates NSGA-II's ability to optimize resource allocation while minimizing energy consumption, which is crucial in wireless networks. The other methods, RRA, MMFA, and PFS, record lower energy efficiency scores of 0.71, 0.65, and 0.61, respectively, indicating a less optimal balance between energy consumption and network performance.

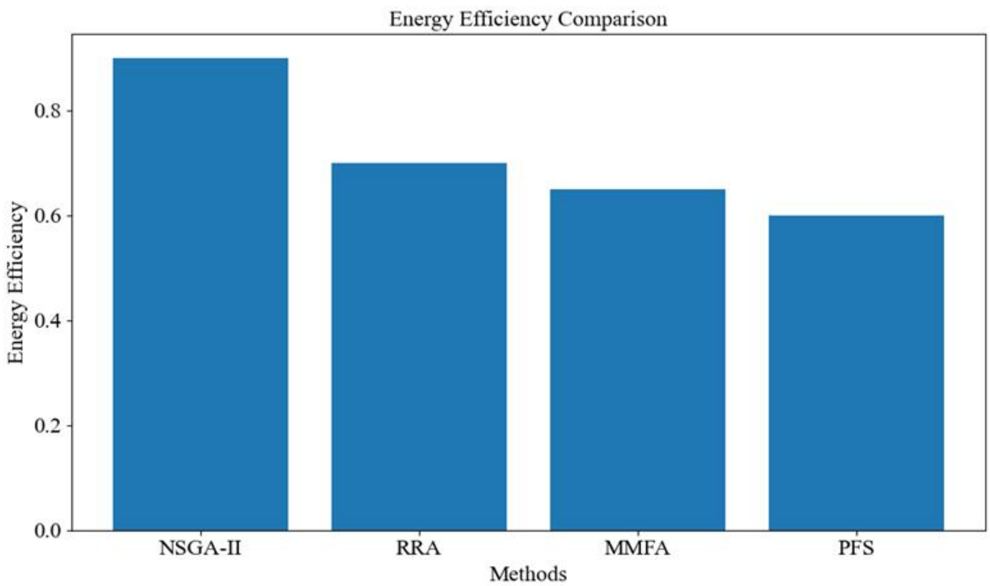

Figure 3. The Comparison Analysis of Energy Efficiency

Figure 4 vividly illustrates the load balancing performance of NSGA-II, RRA, MMFA, and PFS methods over 10 different time intervals. NSGA-II consistently demonstrates the most balanced load distribution, with values predominantly in the range of 0.8 to 1.0. This superior performance indicates that NSGA-II effectively distributes network resources over time, avoiding overloading specific channels or time slots. Its ability to maintain high load balance scores consistently suggests an adaptive and responsive allocation strategy that dynamically adjusts to changing network conditions and user demands. RRA shows a less balanced load distribution, with values ranging mostly between 0.6 and 0.8. This indicates a more static and uniform allocation strategy, which may not adapt effectively to varying network demands over time. Similarly, MMFA and PFS exhibit moderate performance in load balancing, with values generally lying between 0.7 to 0.9 and 0.65 to 0.85, respectively. While these methods demonstrate an attempt to balance the load, they do not achieve the level of adaptability and efficiency exhibited by NSGA-II. NSGA-II's top performance underscores its advanced capability in achieving an equitable and efficient distribution of network resources, which is crucial for maintaining network stability and performance.

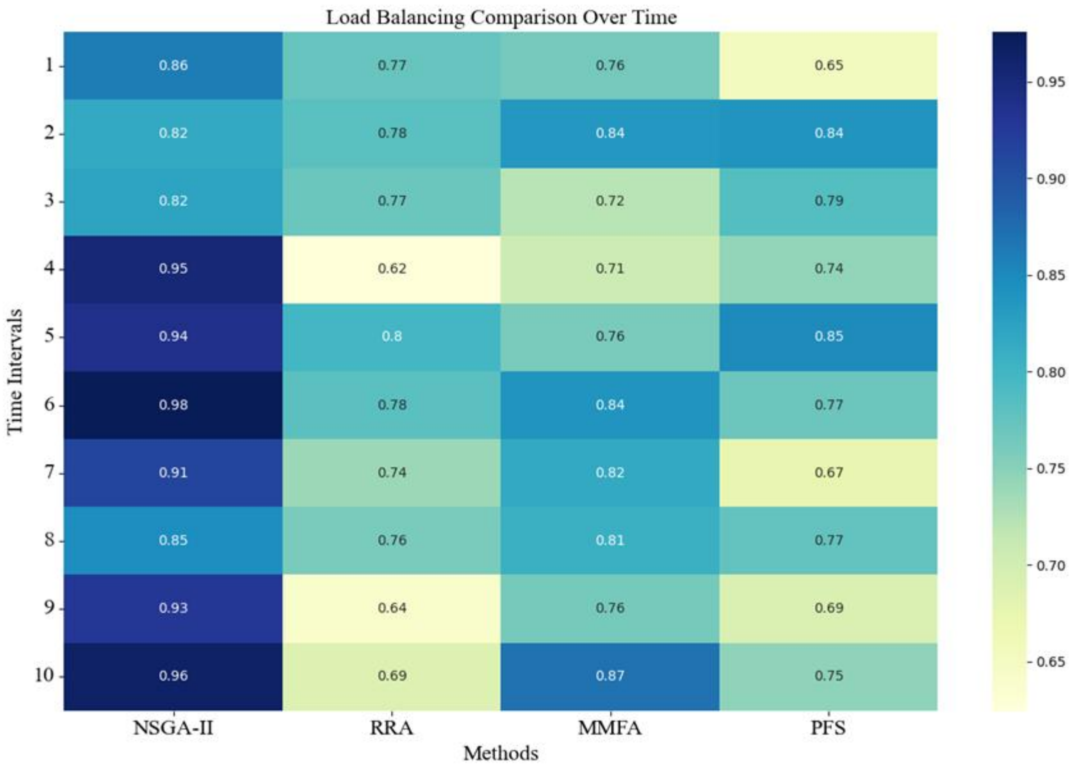

Figure 4. The Comparison Analysis of Load Balancing

Figure 5 effectively illustrates the comparison of Quality of Service (QoS) aspects among the NSGA-II, RRA, MMFA, and PFS methods. This chart includes multiple QoS aspects: Latency, Jitter, Throughput, Packet Loss, and Reliability. In the chart, NSGA-II demonstrates superior performance across all QoS aspects. It scores the highest in categories like Latency, Jitter, and Throughput, indicating its effectiveness in delivering high-quality network service. The scores are especially high for Throughput and Reliability, emphasizing NSGA-II's ability to maintain robust communication even under challenging network conditions. Comparatively, the Round Robin Allocation (RRA) method shows the lowest performance scores in all aspects, reflecting its limitations in handling complex QoS requirements. Max-Min Fair Allocation (MMFA) and Proportional Fair Scheduling (PFS) display moderate performance, with PFS slightly outperforming MMFA in aspects like Throughput and Reliability. The superiority of NSGA-II in this visual comparison underscores its robustness and adaptability in managing diverse QoS requirements in wireless networks.

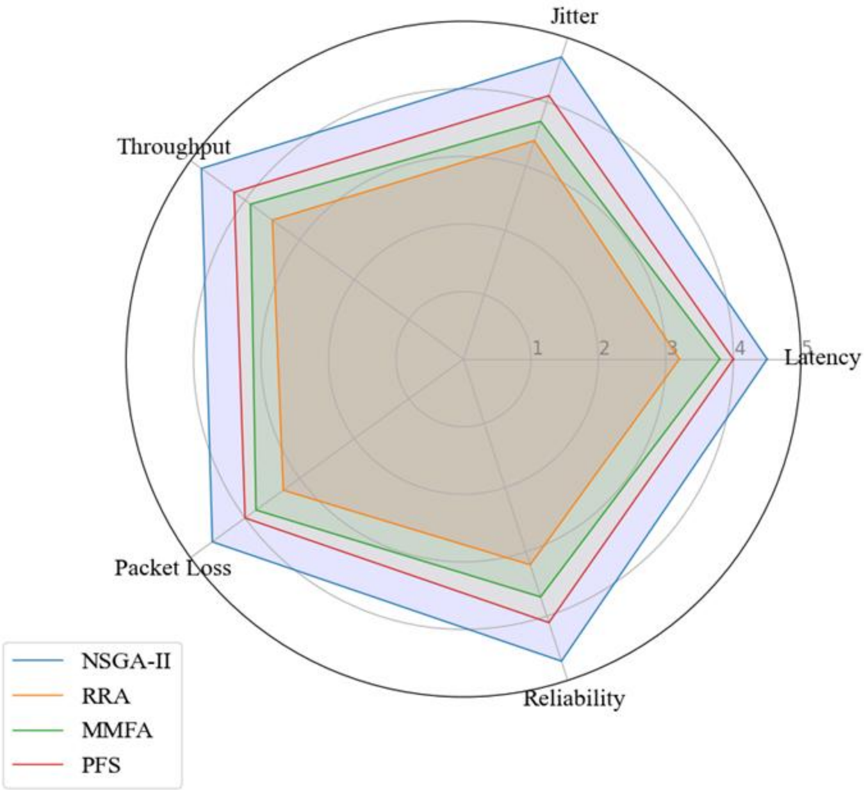

Figure 5. The Comparison Analysis of Load Balancing

The experimental section of this study presents a comprehensive evaluation of the proposed NSGA-II based multi-channel resource allocation strategy for wireless networks. Through detailed simulations, the NSGA-II approach demonstrated superior performance across various key metrics, including Throughput, Energy Efficiency, Load Balancing, and Quality of Service, when compared to traditional methods such as RRA, MMFA, and PFS. The results clearly indicate that the NSGA-II algorithm not only excels in optimizing individual performance metrics but also effectively balances multiple conflicting objectives, showcasing its robustness and adaptability in dynamic wireless network environments. This evaluation underscores the potential of NSGA-II in enhancing the efficiency and quality of wireless network resource allocation, making it a promising solution for future network management challenges.

Conclusion and Discussion

This study focused on addressing the challenges of multi-channel resource allocation in wireless networks by proposing an approach based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The objective was to develop a strategy that not only efficiently allocates resources but also adapts dynamically to changing network conditions and user demands. The NSGA-II based method significantly outperformed traditional allocation strategies (RRA, MMFA, PFS) across various performance metrics. Particularly in terms of Throughput, Energy Efficiency, Load Balancing, and Quality of Service, NSGA-II demonstrated its capability to optimize multiple conflicting objectives simultaneously. NSGA-II excelled in adapting to changing network scenarios, such as varying user mobility and data demand. This adaptability is crucial for contemporary wireless networks, which are characterized by dynamic and unpredictable usage patterns.

The findings from this study have significant implications for future wireless network management. The NSGA-II based approach can be particularly beneficial in dense urban areas with high user density and diverse data demands. While NSGA-II offers considerable advantages, it also presents challenges, particularly in terms of computational complexity. Optimizing the algorithm for faster convergence without compromising the quality of solutions is an area for future improvement. Future research could explore the integration of machine learning techniques with NSGA-II to further enhance prediction accuracy and adaptability. Additionally, investigating the scalability of the proposed method in larger and more complex network environments would be valuable.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

[1] E. Yaacoub and Z. Dawy, "A survey on uplink resource allocation in OFDMA wireless networks," *IEEE Communications Surveys & Tutorials*, vol. 14, no. 2, pp. 322–337, 2012, doi: https://doi.org/10.1109/surv.2011.051111.00121.

[2] F. Meshkati, H. V. Poor, and S. C. Schwartz, "Energy-efficient resource allocation in wireless networks," *IEEE Signal Processing Magazine*, vol. 24, no. 3, pp. 58–68, May 2007, doi: https://doi.org/10.1109/msp.2007.361602.

[3] S. Stańczak, M. Wiczanowski, and H. Boche, "Resource allocation in wireless networks," *Google Books*, 2025. https://books.google.com/books?hl=en&lr=&id=-9dxII5MT-4C&oi=fnd&pg=PR19&dq=%5B3%5D%09Sta%C5%84czak+S (accessed Feb. 09, 2025).

[4] L. Georgiadis, M. J. Neely, and Leandros Tassiulas, "Resource allocation and cross-layer control in wireless networks," *Foundations and Trends in Networking*, vol. 1, no. 1, pp. 1–144, Jan. 2005, doi: https://doi.org/10.1561/1300000001.

[5] M. Nazir, A. Sabah, S. Sarwar, A. Yaseen, and A. Jurcut, "Power and resource allocation in wireless communication network," *Wireless Personal Communications*, vol. 119, no. 4, pp. 3529–3552, May 2021, doi: https://doi.org/10.1007/s11277-021-08419-x.

[6] N. L. Tan, N. Z. Zhu, N. F. Ge, and N. N. Xiong, "Utility maximization resource allocation in wireless networks: methods and algorithms," *IEEE Transactions on Systems Man and Cybernetics Systems*, vol. 45, no. 7, pp. 1018–1034, Feb. 2015, doi: https://doi.org/10.1109/tsmc.2015.2392719.

[7] Q.-V. Pham, Seyedali Mirjalili, N. Kumar, Mamoun Alazab, and W.-J. Hwang, "Whale optimization algorithm with applications to resource allocation in wireless networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4285–4297, Feb. 2020, doi: https://doi.org/10.1109/tvt.2020.2973294.

[8] Yang Zhang, Chonho Lee, D. Niyato, and Ping Wang, "Auction approaches for resource allocation in wireless systems: A survey," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1020–1041, 2013, doi: https://doi.org/10.1109/surv.2012.110112.00125.

[9] L. Liang, H. Ye, G. Yu, and G. Y. Li, "Deep-learning-based wireless resource allocation with application to vehicular networks," *Proceedings of the IEEE*, vol. 108, no. 2, pp. 341–356, Feb. 2020, doi: https://doi.org/10.1109/jproc.2019.2957798.

[10] P. Pradhan, P. Ku. Behera, and B. N. B. Ray, "Modified round robin algorithm for resource allocation in cloud computing," *Procedia Computer Science*, vol. 85, pp. 878–890, 2016, doi: https://doi.org/10.1016/j.procs.2016.05.278.

[11] F. Guo, F. R. Yu, H. Zhang, H. Ji, M. Liu, and V. C. M. Leung, "Adaptive resource allocation in future wireless networks with blockchain and mobile edge computing," *IEEE Transactions on Wireless Communications*, vol. 19, no. 3, pp. 1689–1703, Mar. 2020, doi: https://doi.org/10.1109/twc.2019.2956519.

[12] Y. Kawase and H. Sumita, "Online max-min fair allocation," *Lecture Notes in Computer Science*, pp. 526–543, 2022, doi: https://doi.org/10.1007/978-3-031-15714-1_30.

[13] W. Lee, O. Jo, and M. Kim, "Intelligent resource allocation in wireless communications systems," *IEEE Communications Magazine*, vol. 58, no. 1, pp. 100–105, Jan. 2020, doi: https://doi.org/10.1109/mcom.001.1900199.

[14] X. Qi, S. Khattak, A. Zaib, and I. Khan, "Energy efficient resource allocation for 5G heterogeneous networks using genetic algorithm," *IEEE Access*, vol. 9, pp. 160510–160520, 2021, doi: https://doi.org/10.1109/access.2021.3131823.

[15] M. T. Kawser, H. M. A. B. Farid, A. R. Hasin, A. M. J. Sadik, and I. K. Razu, "Performance comparison between round robin and proportional fair scheduling methods for LTE," *International Journal of Information and Electronics Engineering*, vol. 2, no. 5, 2012.

[16] Y. Khamayseh and R. Al Qudah, "Resource allocation using genetic algorithm in multimedia wireless networks," *International Journal of Communication Networks and Information Security*, 2025, Accessed: Feb. 09, 2025. [Online]. Available: https://search.proquest.com/openview/9da2f61b060adbd8ab38aa95e25c7da0/1?pq-origsite=gscholar&cbl=52057

[17] Hanaa Marshoud, Hadi Otrok, H. Barada, R. Estrada, Abdallah Jarray, and Zbigniew Dziong, "Realistic framework for resource allocation in macro–femtocell networks based on genetic algorithm," *Telecommunication Systems*, vol. 63, no. 1, pp. 99–110, Mar. 2015, doi: https://doi.org/10.1007/s11235-015-9976-x.

[18] M. Moustafa, I. Habib, and M. Naghshineh, "Wireless resource management using genetic algorithm for mobiles equilibrium," *Computer Networks*, vol. 37, no. 5, pp. 631–643, Aug. 2001, doi: https://doi.org/10.1016/S1389-1286(01)00233-X.

[19] X. Yang, Y. Wang, D. Zhang, and L. Cuthbert, "Resource allocation in LTE OFDMA systems using genetic algorithm and semi-smart antennas," in *2010 IEEE Wireless Communication and Networking Conference*, Australia: IEEE, 2010, pp. 1–6.

[20] S. Kao, K. Hsiao, and F. Chang, "Radio resource allocation using genetic algorithm in heterogeneous networks," *International Journal of Communication Systems*, vol. 32, no. 15, Jul. 2019, doi: https://doi.org/10.1002/dac.4089.

[21] N. Zhou, X. Zhu, and Y. Huang, “Genetic algorithm based cross-layer resource allocation for wireless OFDM networks with heterogeneous traffic,” *Ieee.org*, 2015. https://ieeexplore.ieee.org/abstract/document/7077608/ (accessed Feb. 09, 2025).

[22] R. Alkurd, I. Y. Abualhaol, and H. Yanikomeroglu, “Personalized resource allocation in wireless networks: An AI-enabled and big data-driven multi-objective optimization,” *IEEE Access*, vol. 8, pp. 144592–144609, 2020, doi: https://doi.org/10.1109/access.2020.3014301.

[23] R. Devarajan, S. C. Jha, U. Phuyal, and V. K. Bhargava, “Energy-aware resource allocation for cooperative cellular network using multi-objective optimization approach,” *IEEE Transactions on Wireless Communications*, vol. 11, no. 5, pp. 1797–1807, May 2012, doi: https://doi.org/10.1109/twc.2012.030512.110895.

[24] X. Hao, N. Yao, L. Wang, and J. Wang, “Joint resource allocation algorithm based on multi-objective optimization for wireless sensor networks,” *Applied Soft Computing*, vol. 94, pp. 106470–106470, Sep. 2020, doi: https://doi.org/10.1016/j.asoc.2020.106470.

[25] Z. Fei, B. Li, S. Yang, C. Xing, H. Chen, and L. Hanzo, “A survey of multi-objective optimization in wireless sensor networks: metrics, algorithms, and open problems,” *IEEE Communications Surveys Tutorials*, vol. 19, no. 1, pp. 550–586, 2017, doi: https://doi.org/10.1109/COMST.2016.2610578.

[26] N. Sharma and K. R. Anupama, “On the use of NSGA-II for multi-objective resource allocation in MIMO-OFDMA systems,” *Wireless Networks*, vol. 17, no. 5, pp. 1191–1201, Apr. 2011, doi: https://doi.org/10.1007/s11276-011-0340-0.

[27] D. Vidyarthi and L. Khanbary, “Multi-objective optimization for channel allocation in mobile computing using NSGA-II,” *International Journal of Network Management*, vol. 21, no. 3, pp. 247–266, Sep. 2010, doi: https://doi.org/10.1002/nem.763.

[28] X. Dong, L. Cheng, G. Zheng, and T. Wang, “Multi-objective optimization method for spectrum allocation in cognitive heterogeneous wireless networks,” *AIP Advances*, vol. 9, no. 4, Apr. 2019, doi: https://doi.org/10.1063/1.5092211.

[29] W. S. A. Qatab, M. Y. Alias and I. Ku, "Optimization of multi-objective resource allocation problem in cognitive radio lte/lte-a femtocell networks Using NSGA II, in “*2018 IEEE 4th International Symposium on Telecommunication Technologies (ISTT)”*, Selangor, Malaysia, 2018, pp. 1-6, doi: 10.1109/ISTT.2018.8701721.