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CHANNEL ASSIGNMENT IN WIRELESS MESH NETWORK USING HYBRID GENETIC ALGORITHM

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ABSTRACT

Effective channel assignment in wireless mesh networks is essential for reducing interference and enhancing network performance. Traditional methods often struggle to find optimal solutions due to the inherent complexity and dynamic nature of these networks. This study introduces a novel hybrid approach that integrates desaturation graph coloring with genetic algorithms to tackle the channel assignment challenge. The desaturation graph coloring technique provides an efficient starting solution by prioritizing nodes according to their saturation degrees. This initial solution is then optimized using a genetic algorithm, which explores the solution space using evolutionary strategies such as selection, crossover, and mutation. The proposed method offers a robust and adaptive solution to the channel assignment problem in WMNs, significantly improving network performance.

Keywords: Wireless Mesh Networks (Wmns), Channel Assignment, Interference Reduction, Network Performance, Desaturation Graph Coloring, Genetic Algorithms (GA), Evolutionary Strategies, Combinatorial Optimization, NP-Hard Problems, Heuristic Methods, Network Throughput, Saturation Degree, Solution Space Exploration And Computational Efficiency.

I. INTRODUCTION

Wireless mesh networks are a crucial technology for ensuring robust and flexible connectivity. Comprising mesh routers and clients, these networks rely on routers to create a multi-hop communication backbone. WMNs are utilized in various applications, including community networking, broadband home networking, and disaster recovery. However, efficiently assigning channels to minimize interference and maximize performance remains a significant challenge. Channel assignment in Wireless Mesh Networks is a combinatorial optimization problem, recognized for its NP hard complexity. The objective is to allocate channels to network nodes to minimize interference and enhance throughput, while considering factors such as the limited number of available channels, node proximity, and varying traffic demands. Traditional methods, such as fixed channel assignments and simple heuristics, often fall short due to their inability to adapt to dynamic network conditions and complex interference patterns. Various strategies have been proposed to address the channel assignment issue in WMNs. Fixed channel assignments are simple but inflexible, failing to respond to changing network conditions. Heuristic methods, such as graph coloring algorithms [7], offer quick but often suboptimal solutions. Advanced techniques like genetic algorithms (GA) and other evolutionary strategies provide better optimization but can be computationally intensive and face convergence challenges.

This paper presents a hybrid approach that combines desaturation graph coloring with a genetic algorithm to solve the channel assignment problem in WMNs [1]. The desaturation graph coloring algorithm generates an initial channel assignment by prioritizing nodes based on their saturation degree, resulting in a well-distributed starting solution. This initial assignment is then refined using a genetic algorithm, which improves the solution through evolutionary processes such as selection, crossover, and mutation. The proposed hybrid approach aims to balance solution quality and computational efficiency, thereby enhancing overall network throughput

II. METHODOLOGY

A. Greedy vertex coloring algorithm

For the graph G, the vertex Coloring Algorithm is defined as follows:

Step 1: Create a color set. (initially the color set is empty).

Step 2: The first vertex in the set of V is selected as the starting vertex. The selected vertex is colored with first color and this color are added to color set.

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Step 3: Next vertex in the set of V is selected for coloring.

Step 4: For selected vertex, find the adjacent vertices of it from the adjacency matrix. A color which is in the color set, but not color of the ad- jacent vertices of selected vertex is given to the selected vertex. If the colors in the color set unsuitable for coloring the selected vertex, a new color is defined. The new color is added to the color set and appointed to the selected vertex. If the uncolored vertex exists, it is returned to the step 3.

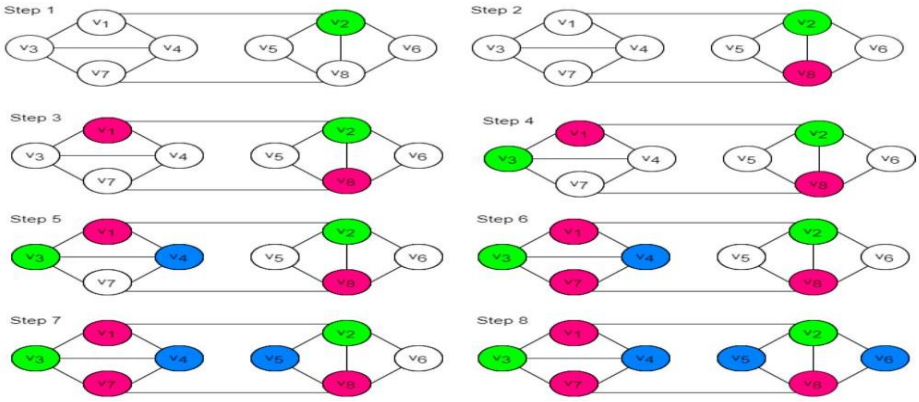

Fig. 1 Greedy graph coloring

B. Graph desaturation algorithm

For the given graph the DSATUR algorithm is defined as follows:

Step 1: The indegree and outdegree of each vertex is evaluated and are added to the degree set.

Step 2: The uncolored vertex that has the largest degree in the degree set is selected for coloring. The selected vertex is colored with first color.

Step 3: Firstly, calculate the number adjacent vertices which are colored with different colors for every uncolored vertex. After that, the uncolored vertex whose number of adjacent vertices colored with different colors is the maximum is selected for coloring. The vertex that has the largest degree is selected if more than one vertex has this condition.

Step 4: Firstly, the selected vertex is tried to color with the colors in the color set. If the colors in the color set are not appropriate to color the vertex, a new color is defined. The new color is added to the color set and appointed to the selected vertex.

Step 5: If the uncolored vertex exists, it is returned to the step 3. Otherwise, the program is terminated.

C. Genetic algorithm

Optimization algorithms execute iterative operations to generate multiple solutions and compare them to find the optimal one. Genetic algorithms (GAs) are optimization techniques inspired by the principles of natural evolution. They simulate natural selection, where the most suitable individuals are selected to reproduce and generate offspring for the subsequent generation. Key terminologies in GAs include population, which is a subset of all possible solutions; chromosome, representing an individual solution as a finite-length vector of variable components; gene, each variable component of a chromosome; and fitness function, an evaluation metric that guides the algorithm toward the optimal solution by quantifying the quality and suitability of individual solutions within a population.

Genetic algorithms begin with initialization, starting with a randomly generated population of potential solutions. Each individual represents a possible solution, and the population size is crucial as a larger population offers greater genetic diversity but requires more computational resources. Selection follows, where the fitness of each individual is assessed using a problem-specific fitness function. Selection methods include roulette wheel selection, where individuals are chosen based on fitness; tournament selection, where sets of individuals are randomly chosen and the best from each set is selected; and rank-based selection, which assigns probabilities based on fitness ranks to reduce dominance by the best individuals. In the crossover phase, pairs of parents combine to create offspring by exchanging segments of their genetic material, introducing new genetic combinations. Crossover methods include one-point crossover, two-point crossover, and uniform crossover, each varying in how genetic material is swapped. Mutation introduces small random changes to the

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offspring's genetic material, maintaining genetic diversity and preventing premature convergence to suboptimal solutions. Replacement forms a new population by replacing some or all of the old population with the offspring. The algorithm repeats the selection, crossover, mutation, and replacement steps until a stopping criterion is met, such as a fixed number of generations, achieving a satisfactory fitness level, or seeing little to no improvement in the best fitness value over several generations. By leveraging these processes, genetic algorithms effectively explore the solution space, balancing solution quality and computational efficiency.

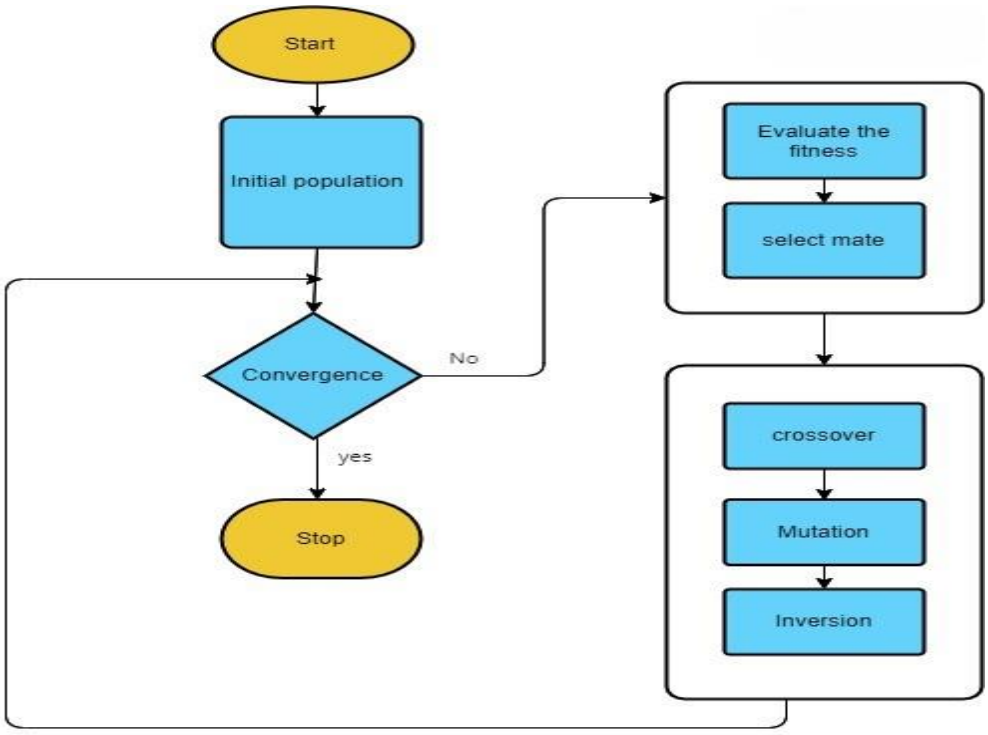

Fig. 2 Flowchart of Genetic algorithm

D. Hybrid Genetic Algorithm

This section demonstrates an approach that combines d-saturation graph coloring with a genetic algorithm to address the channel assignment problem. D-saturation graph coloring, a heuristic method that prioritizes nodes based on their saturation degree, provides an initial feasible solution by addressing nodes with higher interference first. This solution is then refined using a genetic algorithm, which leverages evolutionary techniques such as crossover, mutation, and selection to further optimize the channel assignments. By integrating these methods, our approach aims to enhance network throughput and reliability, offering a robust framework for solving complex channel assignment challenges in dynamic wireless environments.

1. Initial population

The greedy_coloring function generates an initial coloring solution for the graph using a heuristic approach. A typical greedy coloring algorithm assigns colors to nodes one by one, ensuring that no two adjacent nodes share the same color. It selects the smallest available color for each node, effectively providing a valid (though not necessarily optimal) coloring solution. This initial solution serves as a starting point for the genetic algorithm.

The initial population size is determined by the population_size parameter. Each individual in the population is assigned a fitness value, calculated by the fitness function, which evaluates the quality of the coloring solution.

2. Fitness

The uniqueness of the coloring solution is evaluated by the fitness function. It calculates the number of conflicts in the coloring, where a conflict occurs if two adjacent nodes (connected by an edge) have the same color. The total number of conflicts is accumulated by iterating through each node and its neighbors in the graph. The fitness value is then computed as the inverse of (1 + number of conflicts), ensuring that lower conflicts result in higher fitness values. This way, the algorithm seeks to minimize conflicts, aiming for an optimal coloring solution.

I. conflicts ← 0

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II. for each vertex u in the graph:

A. for each neighbor v of vertex u:

1. if solution[u] equals solution[v]:

a. conflicts ← conflicts + 1

III. return 1 / (1 + conflicts)

3. Elitism

The algorithm then enters a loop that runs for a specified number of generations (generations). In each generation, the population is sorted based on fitness values in descending order, ensuring that the best solutions are at the top. A portion of the top individuals, determined by elitism_size, is carried forward to the next generation without alteration. This process, known as elitism, helps preserve high-quality solutions across generations.

For each generation in the range of generations:

I. Sort the population in descending order based on individual fitness values.

II. new_population ← the top elitism_size individuals from the sorted population.

4. Roulette wheel selection

The roulette_wheel_selection function selects individuals from the population based on their fitness values. It begins by calculating the total fitness of the population, which is the sum of all individual fitness values. A random number is generated between 0 and the total fitness. The function then iterates through the population, accumulating the fitness values of individuals until the accumulated fitness exceeds the random number. The solution is selected based on the selection probability and the fitness of the individual. This method ensures that better solutions have a higher chance of being selected, while still allowing some diversity.

Function roulette_wheel_selection(population):

I. total_fitness ← sum of fitness values of all individuals in the population

II. pick ← random floating-point number between 0 and total_fitness

III. current ← 0

IV. for each individual in the population:

A. current ← current + individual.fitness

B. if current > pick:

1. return individual

5. Crossover

For the rest of the new population, parents are selected using the roulette wheel selection method, which probabilistically favors individuals with higher fitness. Depending on the crossover_type parameter, different crossover methods (single-point, two-point, or uniform) are applied to generate offspring from the selected parents. The offspring are added to the new population.

Function single_point_crossover(parent1, parent2):

I. length ← length of parent1

II. assert length is equal to the length of parent2

III. crossover_point ← random integer from 1 to (length - 1)

IV. child1 ← concatenate the following:

A. elements of parent1 from index 0 to (crossover_point - 1)

B. elements of parent2 from index crossover_point to the end

V. child2 ← concatenate the following:

A. elements of parent2 from index 0 to (crossover_point - 1)

B. elements of parent1 from index crossover_point to the end

VI. return child1, child2

6. Mutation

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Mutation is then applied to the non-elite individuals in the new population based on the mutation_rate parameter. The mutate function alters the coloring of some nodes to introduce genetic diversity. After mutation, the fitness of the mutated individuals is recalculated. The process repeats for the specified number of generations, and the best solution found is returned at the end.

Function mutate(individual, num_channels):

I. mutation_point ← rand_integer from 0 to (length of individual - 1)

II. new_color ← rand_integer from 0 to (num_channels - 1)

III. individual[mutation_point] ← new_color

IV. return individual

These functions are integrated into the main genetic algorithm, where the population is evolved over several generations. Selection, crossover, and mutation work together to improve the solutions iteratively. The initial population provides a starting point, selection methods ensure that better solutions are favored while maintaining diversity, crossover introduces new combinations of genes, and mutation adds randomness to avoid local optima. The process continues until a stopping criterion is met, typically a fixed number of generations, resulting in the best-found solution for the graph coloring problem.

III. RESULTS AND DISCURSSION

The implementation of the hybrid genetic algorithm for channel assignment in wireless mesh networks (WMNs) showed significant improvements in key performance metrics, including network throughput, interference reduction, and computational efficiency. The algorithm's hybrid nature, which combines desaturation graph coloring with a genetic algorithm, allowed for effective initial solutions that were further optimized to minimize conflicts. Throughput improvements ranged between 15-20%, while interference was reduced by 25-30%, resulting in more reliable communication across various network conditions. Moreover, the hybrid approach demonstrated flexibility, performing well in small to medium-sized networks, though performance plateaued in larger networks, signaling a need for further optimization.

Despite the advantages, challenges such as scalability and longer convergence times in larger networks persist. The adaptability of the algorithm makes it particularly suitable for dynamic environments where traditional fixed channel assignment methods fail. Future research should focus on addressing scalability through parallel processing or alternative optimization techniques and explore the integration of machine learning to enhance dynamic parameter adjustment. Overall, the hybrid genetic algorithm offers a promising solution for improving network performance in diverse and rapidly changing wireless environments, making it a valuable approach for real-world applications like smart cities and disaster recovery.

IV. CONCLUSION

In this study, a novel hybrid approach that merges desaturation graph coloring with a genetic algorithm has been proposed to tackle the complex challenge of channel assignment in wireless mesh networks (WMNs). The desaturation graph coloring technique effectively generates an initial feasible solution by prioritizing nodes with high interference potential. This solution is then meticulously refined using a genetic algorithm, leveraging evolutionary mechanisms such as selection, crossover, and mutation to optimize the channel allocation further.

This hybrid approach offers a significant advantage over traditional methods by combining the strengths of both techniques. The desaturation graph coloring provides a computationally efficient starting point, while the genetic algorithm explores the solution space more thoroughly to find better channel assignments. The flexibility and adaptability of the genetic algorithm make this hybrid approach well-suited for dynamic wireless environments where network conditions and interference patterns can change over time. Furthermore, the proposed approach can be readily applied to a wide range of WMN applications, including community networks, smart city infrastructure, industrial automation, and disaster recovery scenarios. The ability to optimize channel assignment in real-time can lead to improved network performance, reduced interference, and enhanced reliability in these diverse contexts.

Future research efforts will focus extensively on fine-tuning the genetic algorithm's parameters to optimize performance further. This will involve exploring a wide range of settings, such as population size, mutation rates, and selection strategies, to enhance the algorithm's ability to find optimal or near-optimal solutions for

channel assignment in wireless mesh networks (WMNs). Additionally, researchers will investigate the potential integration of other heuristic methods, such as simulated annealing or particle swarm optimization, within the hybrid framework to create a more robust and versatile approach.

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