

Joint Optimal Channel Allocation, Interface Assignment and Routing in Multi-hop Wireless Networks

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Abstract—Multi-hop wireless networks have advantages over the single-hop ones in terms of reliability and coverage range. Moreover, the capacity of multi-hop wireless network can be substantially increased via multiple radios tuned to non-overlapping channels. However, the channel allocation, network interface cards assignment and routing remain challenging due to the interference of the neighboring transmissions. These three problems have proved to be a NP-hard problem. Previous studies separating the routing from the channel allocation, instead of considering the three problems as a whole, cannot get the overall optimal solution. In this work, we employ an improved Multi-Objective Genetic Algorithm to optimize the channel allocation, interface assignment and the routing, so as to minimize the overall network interference. The proposed algorithm includes two parts: 1) dynamic genetic mutation based on diversity measure; and 2) elite preservation based on ideal points. In order to eliminate illegal solutions, a new individual encoding method is proposed. In addition, an interference model taking into account the effects of channel separation and the traffic of neighbor links is applied to evaluate the quality of the interference of the network. Finally, a fitness function is defined to obtain the best search results. Simulation results show that our improved Multi-Objective Genetic Algorithm can reduce the interference and cost of total network compared to the standard Genetic Algorithm.

Keywords—Multi-objective genetic algorithm, channel allocation, interface assignment, routing, multi-hop wireless network.

I. INTRODUCTION

Multi-hop wireless network (MWN), an attractive novel technology with large network capacity, has been adopted in many applications, such as the last-mile broadband Internet access [1], campus networks [2], and traffic control networks [3]. A MWN consists of several wireless nodes, which brings both benefits and challenges to optimize the overall network utility. On one hand, the wireless nodes equipping multiple interfaces provide orthogonal channels, which further increase the network capacity by transmitting data over multiple radios simultaneously[4], [5]. On the other hand, channel allocation, routing and interface assignment are correlated to each other, which complicates the performance optimization of MWNs.

Genetic algorithms (GA) have become popular as effective heuristics for NP-hard combinatorial optimisation problems [6]. By mimicking the biological principles of evolution and Mendelian principles of inheritance [7], GAs encode a potential solution to a specific problem on a simple data

structure and apply recombination operators to these structures so as to preserve critical information for searching the optimal solution. Owing to the strong search ability of a GA, it can be well utilized to optimize MWNs.

In this paper, we introduce multi-objective genetic algorithm (MOGA) to jointly solve the channel allocation, interface assignment and routing problems. And in order to tackle the problem that a MOGA is difficult to converge to the true Pareto-optimal front, we develop an improved MOGA with two methods. The contributions of our work different from the existing channel allocation approaches are as follows.

- 1) To evaluate the interference of network, an interference model is proposed, which takes into account the channel separation and the traffic of neighbor links;
- 2) To eliminate illegal solutions, a new individual encoding and production method has been designed. Each individual includes reference table, channel table, and path table. Especially, the reference table for a new individual is generated by the channel tables rather than the reference table of the previous ones;
- 3) A fitness function is designed to achieve the best search results;
- 4) In order to search Pareto-optimal front as more as possible, a dynamic genetic mutation based on diversity measure is proposed;
- 5) An elite preservation based on ideal points is used to search all the Pareto-optimal solutions and to improve convergence speed.

The rest of the paper is organized as follows. In Section II we introduce the network model, interference model, conflict graph, and the formulation of problem. In Section III we describe the improved MOGA and discuss their applications in our case study. The simulation and experimental results are presented in Section IV. Section V contains our conclusions.

II. PROBLEM FORMULATION

In this section, the network model, interference model, and the conflict graph are introduced.

A. Network Model

In the network under consideration, the n nodes in the network are stationary and each node is equipped with a certain, *not necessarily the same*, number of interfaces. The network can be sketched by a general undirected graph, where the nodes and the connections between them are represented by an undirected graph $G = (V, E)$, with V the set of nodes

and E the set of links. A given link $l \in E$ is regarded as active when there is a transmission through it. The scenario considered in this paper is shown in Fig. 1.

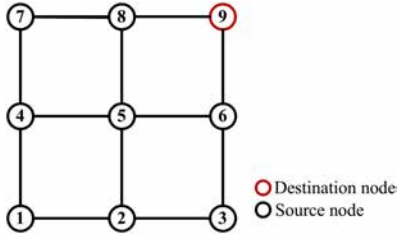


Fig. 1. The structure of network.

In Fig. 1, node $n=9$ is the destination node. All the other nodes can be used as source nodes or routes. The source nodes will send data to the destination node by a path, and the links in a path will be allocated channels. However, there may be various choices for the paths and channels, which lead to different total network interference. As a result, how to select the transmission paths and channels for the links affects the performance of network greatly.

B. Interference Model

The transmissions in neighbor links may interfere each other, so the neighbor relationship is a factor that causes the interference in the network. And the traffic size of neighbor links can also affect the interference. Furthermore, in this paper, since at least two channels will be used for channel allocation, the interference between two channels [8] will also be considered. Therefore, the interference model in this paper considers three factors: neighbor relationship of links, traffic size, and channel separation between the channels [9]. So for link l the interference can be written as

$$I^{link}(l) = \rho_1 \cdot \sum_{\forall j \in N_l^1} T(j) \delta(l, j) + \rho_2 \cdot \sum_{\forall k \in N_l^2} T(k) \delta(l, k) \quad (1)$$

where N_l^1 and N_l^2 are the sets of neighbor links of l with one hop and two hops, respectively, and ρ is the interference coefficient of neighbor link. T denotes the traffic size of the neighbor link. δ indicates the degree of channel separation. By $I^{link}(l)$, we can obtain the total interference of the network.

$$I = \sum_{l=1}^L I^{link}(l) \quad (2)$$

where L is the number of links in the network.

C. Conflict Graph

Given an interference model, the set of pairs of communication links that interfere with each other can be represented by a conflict graph [10]. Let V_c represent the set of communication links in the network. In particular,

$$V_c = \{l_{i,j} | (i,j) \text{ is a communication link}\}.$$

The conflict graph, as shown in Fig. 2, can be denoted as $G_c(V_c, E_c)$, where V_c is the vertices set of G_c , and edges set

E_c denotes the conflict relationship between the links in the conflict graph.

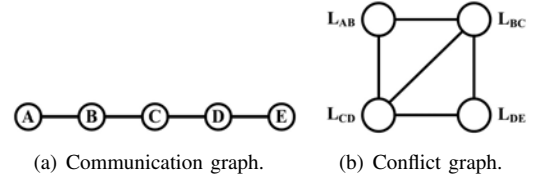


Fig. 2. The Communication graph and the corresponding conflict graph.

Figure 2(a) shows the communication graph of network with 5 nodes (A,B,C,D,E) and 4 communication links. The conflict graph corresponding to the communication graph is shown in Fig. 2(b), which has 4 vertices and each of them represents a link. The connection between two vertices indicates that there may be interference between two links.

III. MOGA-BASED NETWORK RESOURCE ALLOCATION

In this section, the improved MOGA is discussed. Firstly, the basic operations based on problem considered are described in detail. Then two improved methods, designed for searching more Pareto-optimal solutions, are introduced.

A. Basic Operations of Improved MOGA

1) *Individual Encoding*: The individual encoding is the first and most important step for a GA, and it is the way of encoding a solution to the problem under consideration. In this paper, each individual contains three parts: reference table (R_Tab), channel table (CA_Tab), and path table (PA_Tab). They all use real-number encoding. The CA_Tab and PA_Tab are generated according to the R_Tab. As shown in Fig. 3, for an example of 9 nodes network, these three tables are $n \times n$ matrix. The details of individual is as follows.

Reference table: The R_Tab points out all the pairs of communicable nodes in the network by nonzero real numbers, and the value of the nonzero real number denotes the available channel number (eg. 1~11). The row number and column number denote the node ID number. '0' means that there is no link between the nodes in reference to the row and column numbers. At initial, R_Tab is generated randomly, provided that each node can communicate with at least one of its neighbor nodes. The R_Tab of next generation will be generated by the CA_Tab of previous generation under operators such as elite reservation, crossover, and mutation.

Channel table: The nonzero real numbers in CA_Tab are selected randomly from R_Tab, and there is at least one nonzero real number in each row. The selection process of node 1 is indicated by blue arrows in Fig. 3(a). Along the direction of the arrows, all the selected nonzero real numbers are highlighted in yellow. The CA_Tab (shown as Fig. 3(b)) will be obtained after each link is allocated a channel.

Path table: The row number denotes the node ID number, and column number denotes the hop of path. In PA_Tab, the nonzero real numbers in each row represent a path from source node to destination node. The column numbers of the yellow

highlighted non-zero real numbers in Fig. 3(a) point out the path from the node 1 to node 9. Figure 3(c) shows a PA_Tab.

	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

(a) Reference table.

	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

(b) Channel table.

	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0

(c) Path table.

Fig. 3. Individual encoding.

2) *Objective Function*: The better solution, the less interference in the network and the less cost are. Therefore, two measures (i.e. network interference and interfaces number) will be considered as objectives.

Pareto solution: Pareto solutions are the solutions that are optimal in some sense [11]. For a problem with multi-objective function ($f_j, j = 1, \dots, M$ and $M > 1$), there will be a dominant relationship between any two solutions $x(1)$ and $x(2)$ - one dominates the other or none dominates the other. A solution $x(1)$ is considered to dominate the other solution $x(2)$, if the following two conditions are true: 1) The solution $x(1)$ is no worse (say the operator $<$ denotes worse and $>$ denotes better) than $x(2)$ in all objectives, or $f_j(x(1)) \not\prec f_j(x(2))$ for $j = 1, 2, \dots, M$ objectives; 2) The solution $x(1)$ is strictly better than $x(2)$ in at least one objective, or $f_{\bar{j}}(x(1)) > f_{\bar{j}}(x(2))$ for at least one $\bar{j} \in 1, 2, \dots, M$. If any of the above condition is violated, the solution $x(1)$ does not dominate the solution $x(2)$.

From the above discussion we know that a multi-objective optimization problem usually results in a set of Pareto-optimal solutions, instead of one single optimal solution. The multi-objective problem in this paper is defined as

$$\min f_1 = I \quad (3)$$

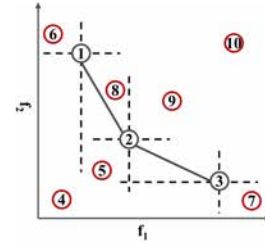
$$\min f_2 = \sum_{i=1}^n C_i \quad (4)$$

where C_i is the number of interfaces on node i .

3) *Fitness Function*: The fitness value indicates the quality of an individual (or a solution). The fitness value associated with a solution indicates 'how good' the solution is in terms of the original optimisation problem under consideration. The higher the fitness value is, the better the solution. Thus, measuring the fitness value enables us to rank the individuals and to decide which ones should be retained to the next generation.

Figure 4 is a $f_1 - f_2$ plot, the two objectives can be shown in a coordinate system.

The distribution area of the new solutions can be divided into four quadrants according to each existing Pareto solution. The new solutions in different quadrants have different dominance relations with the Pareto solutions, which will be

Fig. 4. The $f_1 - f_2$ plot.

denoted by a Rank (Rank1 > Rank2 > 0, Rank3 < 0). Moreover, the distance between the new solution and the Pareto solutions reflects the importance of the new solution. Therefore, the fitness function depends on two factors, the 'Rank' and the 'Distance',

$$Fit(i) = \sum_{p=1}^P R(i, p) \cdot D(i, p), \quad (5)$$

where R is the Rank of solution i marked by Pareto solution p , and D is the distance between i and p . P is the number of all the Pareto solutions. From Eq. (5), we can see that the fitness value of solution i depends on all the Pareto solutions, not only one of them.

It is important to assign Rank value for the solutions according to their relative positions with the Pareto solutions. Taking Fig. 4 as an example, the detailed allocation method is stated as below.

- The solution in the 3^{rd} quadrant of a Pareto solution will not be dominated by any Pareto solution. Solutions 4 and 5 are marked by Rank1, which is helpful to find the optimal solution.
- The solution whose one objective is better than all the Pareto solutions' and the other objective is inferior to all the Pareto solutions' will not be dominated by any Pareto solution. Solutions 6 and 7 are marked by Rank2, which is helpful to extend the search scope.
- The solution in the vicinity of two adjacent Pareto solutions is a new Pareto solution. Solution 8 is marked by Rank2, which is helpful to find more Pareto solutions.
- The solution in the first quadrant of a Pareto solution will be dominated by at least one Pareto solution. Solutions 9 and 10 are marked by Rank3, so as to reduce their fitness value.

4) *Crossover Operator*: A two-point strategy is used for this operator. In order to avoid illegal solution, the crossover operator is performed only between the CA_Tabs of individuals of the previous generation. As shown by the blue arrows in Fig. 5, the results obtained will serve as R_Tabs for the new individuals of the next generation.

5) *Mutation Operator*: The Mutation operator is only about the R_Tab. The nonzero real numbers in the R_Tab can be any random integers between 1 to 11. Once the R_Tabs are generated, CA_Tabs and PA_Tabs can be obtained by the processes described above.

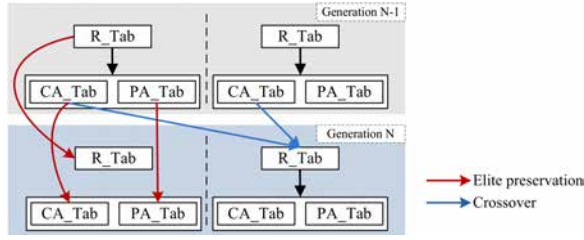


Fig. 5. The crossover operator.

B. Dynamic Genetic Mutation based on Diversity Measure

It is important for a multi-objective GA to search solutions in the true Pareto-optimal front, but still as diverse as possible. However, the optimum solutions may be localized only in a small area of the whole search space. Since the diversity of the generated solutions is reduced, there is no more useful information in the newly generated individuals. Therefore, more and more solutions are aggregated into one or a few points and trapped in local optimizations, which makes the crossover operator ineffective. In this section, to maintain a diversity of population while searching all the Pareto-optimal solutions, a dynamic genetic mutation is applied.

1) *Diversity Measurement*: In order to avoid local optimum, the diversity of population will be measured at each iteration. Suppose there are S different solutions in each generation, and N_s^G is the number of individuals of a solution $s \in (1, S)$. The diversity measurement becomes

$$Div = 1 - \sum_{s=1}^S \left(\frac{N_s^G \cdot T_s}{N^P} \right), \quad (6)$$

$$T_s = \begin{cases} 1 & \frac{N_s^G}{N^P} \geq Thr \\ 0 & otherwise \end{cases}, \quad (7)$$

where N^P is the population size, and Thr is the threshold of the ratio N_s^G/N^P . Eq. (6) indicates that the diversity of the population decreases with aggregating the same individuals.

2) *Dynamic Genetic Mutation*: The mutation rate will be set dynamically if Div is less than a lower limit, and will be improved after certain steps. The higher it is, the more probably the search process oversteps the local optimum. However, the search process will not converge if the mutation rate is too high, so it is necessary to set an upper limit for the dynamic mutation rate. In this paper, the mutation step is set to be 0.001, and the upper limit of the mutation rate is 0.1.

C. The Elite Preservation based on Ideal Points

Although dynamic mutation can make the search process out of local optimum, it is not always possible to find all the Pareto solutions. In addition, the improved mutation rate will decrease the converging speed of the algorithm. To circumvent these drawbacks, we propose an elite preservation based on ideal points in this section.

1) *The Ideal Points*: An ideal point is one of the best solutions of the problem. For example, in this paper the ideal points are $f_1 = 0$ and $f_2 = n$ in the n nodes network. Therefore, the selection strategy should be conducive to the discovery of the ideal points. The methods we use in this paper are:

- All the Pareto solutions will be retained to the next generation, as shown by the red arrows in Fig. 5 (The CA_Tab and PA_Tab of the left individuals of Generation N are retained from the previous generation, rather than generated by R_Tab);
- The solutions approximate to the ideal points will be preserved;
- The solution yielding more Pareto solutions will be preserved.

2) *Reward and Punishment*: As shown in Fig. 6(a), the solution space can be divided into different regions according to the ranks. The areas in favor of finding the Pareto solutions are shaded in red. In contrast, the gray areas are those unfavorable for finding Pareto solutions. The darker the color, the greater the impact is.

In order to speed up the converging rate and search as many solutions as possible, the search process should be in certain directions, as shown by yellow arrows in Fig. 6(b)), which are benefit for searching all the optimal solutions. From Fig. 6, the reward and punishment are:

- Solution 6 (7) is in the 2nd (4th) quadrant of all the Pareto solutions, so it is significant for searching the Ideal Points $f_1 = 0$ ($f_2 = n$). We then set solutions 6 and 7 to be Rank_Sup (Rank_Sup > Rank1) for a reward;
- Solutions 11 and 12 are close to the areas where the Ideal Points are located. Since they are very likely to contain the genes that are beneficial to search for the optimal solutions, solutions 11 and 12 will be set to be Rank1 for a reward;
- Solution 10 is in the first quadrant of all the Pareto solutions. It will play a negative role in searching for the optimal solutions, so the fitness value of solution 10 will be set to be Rand_L (Rand_L << Rank3) as a punishment.

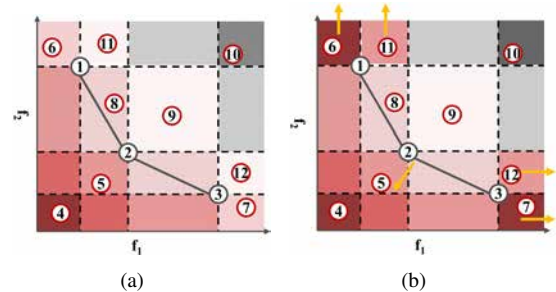


Fig. 6. The reward and punishment according to the ideal points.

IV. SIMULATION RESULTS

In order to verify the performance of the proposed algorithm, we have performed several simulations with MATLAB.

A. Simulation Setup

We consider n -node ($n = 9, 16, 25, 36, 49$) grid topology network deployed in $\sqrt{n} \times \sqrt{n}$ rectangular region. The ID number of the destination node is n , and all the other nodes are source nodes. The nodes $1 \sim n-1$ will transmit data to the destination node respectively. Each node is randomly assigned the number of interfaces, but the maximum number of the interfaces is set to 4. The communication range and the carrier sensing/interference range are 250m and 450m, respectively. Two nodes are connected by a communication link if they are in each other's transmission range. All 11 partially-overlapping frequency channels in the IEEE 802.11b 2.4 GHz band are being used.

Then, the control parameters of GA are set. The initial generation size is set to be 2000. The other parameters are: population size = 500, the crossover probability $P_c = 0.1$, and the mutation probability $P_m = 0.01$.

B. Simulation Results

We start our simulation by considering five networks based on grids with 9, 16, 25, 36 and 49 devices deployed in a square area. Due to the space limit, only the results of 9-node and 49-node networks are shown in Figs. 7 and 8. The total computation time is small, about 172.67s and 9046.98s, respectively. In order to visually verify the effectiveness of the configuration results, we consider only the interference between one hop neighbors in the interference model.

Figures 7(a) and 8(a) show the network configuration results under the principle of minimum interference. (The red lines indicate the paths from the source nodes to the destination node, and blue numbers the allocated channel numbers for links.) The [Number of interface, Interference] of two networks are [16, 0] and [96, 0], which reached the ideal values. We can see that in the interference model of one hop, only three orthogonal channels (1, 6, 11) have been involved in channel assignment.

Figures 7(b) and 8(b) show the network configuration results under the principle of minimum number of interfaces. The [Number of interface, Interference] of two networks are [9, 47] and [49, 823]. The results show that the number of the interfaces is equal to the number of nodes in the network, which reached the ideal value.

Figures 7(c) and 8(c) show the convergence of solutions in each iteration. We can see that more and more Pareto solutions are searched as the number of iterations increases.

Figures 7(d) and 8(d) show the Pareto-front and all the Pareto-optimal solutions for the issue considered in this paper.

The above simulation results show that the proposed multi-objective GA can search sufficient and well distributed optimal solutions, including the solutions of the minimum interference and of the minimum number of interfaces.

Figure 9 compares the calculation time our proposed GA and the standard one with the numbers of nodes in the network varying in 9, 16, 25, 36, and 49. It shows that our multi-objective GA is more efficient, and the differences are enlarged with increasing the number of nodes.

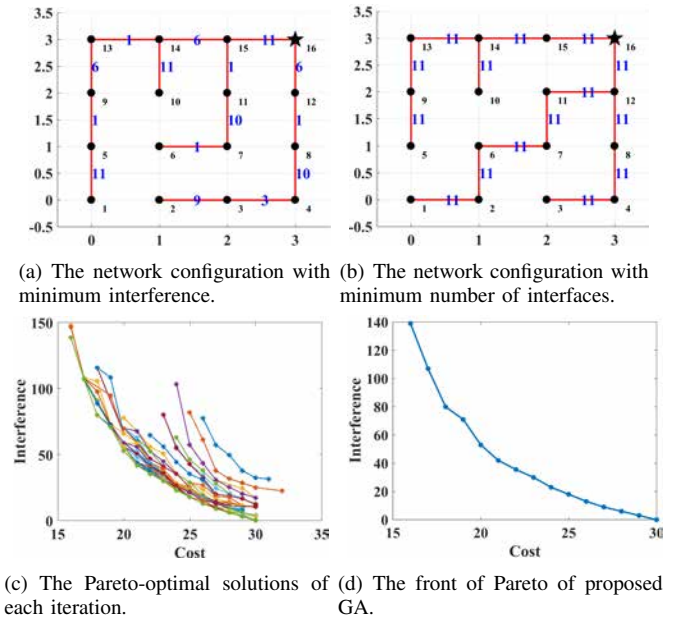


Fig. 7. The simulation results of 9 nodes network.

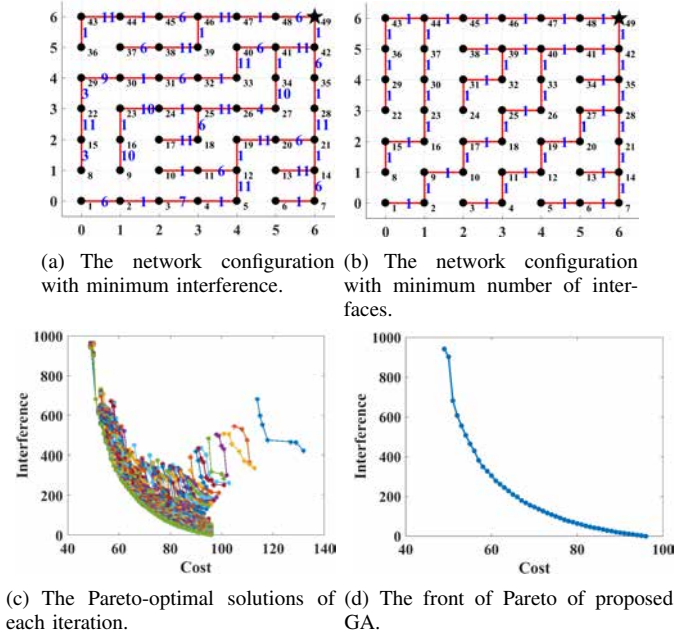


Fig. 8. The simulation results of 49 nodes network.

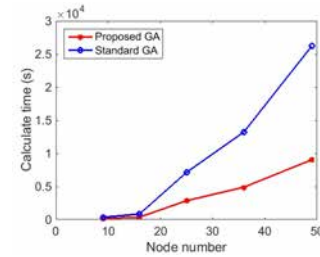


Fig. 9. The comparison of calculation time under two GAs.

V. CONCLUSION

In this paper, we have jointly approached the assignment of multi-channel, multi-interface and routing in multi-hop wireless networks by an improved multi-objective Genetic Algorithm with the objectives of minimizing overall network interference and cost.

In order to make the algorithm search as many Pareto solutions as possible and converge fast, the proposed multi-objective GA consists of: 1) the dynamic genetic mutation based on diversity measure; and 2) the elite preservation based on ideal points.

In addition, some crucial improvements have been made for the proposed algorithm. First, a new individual encoding method that avoids illegal solutions was proposed. Secondly, an interference model is applied to assign not only the non-overlapping (orthogonal) channels, but also the partially overlapping channels within the IEEE 802.11 frequency bands. Thirdly, an effective fitness function was designed to achieve the best search results. The validity of the proposed network resource allocation method has been experimentally verified. The results show that the maximum network capacity can be achieved with less computation time compared to the standard Genetic Algorithm.

For future work, we plan to evaluate our proposed method for video transmission in multi-hop wireless networks.

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