A Genetic Approach for Gateway Placement in Wireless Mesh Networks

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Summary
Recently, Wireless Mesh Network (WMN) has gained important roles in current communication technologies. It has been used in several applications, which the majorities of them are critical applications such as surveillance and rescue systems. Hence, the WMN attracts a bunch of attention from many researchers. WMN consists of mainly mesh clients (MC) s and mesh routers (MR) s, some of the latter are functionalized by additional functions to serve as internet gateways (IG) s. Thus, most of the network traffic is acting toward IGs. Therefore, the network performance largely depends on the MRs' placement, especially the IGs. Since the gateway placement problem (GPP) has been proven as NP-Hard. Therefore, finding the optimal resolution is difficult or it takes polynomial time. Thus, finding near optimal solution is essential to improve the net operation. This paper proposes a novel approach to solve this problem using Genetic Algorithm (GA) to achieve a near optimal solution, considering the number of IGs and the number of hops that the packet traverses between the IG and the source/ destination MR (MR-IG). The main objective of the proposed approach is to minimize the variation of MR-IG- hop counts (VAR-MR-IG-Hop) among MRs to insure that the IGs are placed in the appropriate positions. Finally, we evaluated the proposed algorithm using many generated instances using different parameters (population size, tournament size, crossover type, mutation type), the experimental results had shown that the high convergence rate using different parameters. Moreover, the algorithm has considerable scalability and robustness to solve the GPP in large and small networks as well as the positive significance of VAR-MR-IG-hop in comparison with the AVG-MR-IG-hop on enhancing the network performance.

Keywords:
Wireless Mesh Network, Gateway Placement, Genetic Algorithm, optimization

1. INTRODUCTION

Wireless Mesh Network (WMN) is a communication technology used for last-mile internet access [1] [3] and in numerous applications such as neighborhood networking [3], surveillance, emergency and rescue systems [1] [3]. WMN mainly consists of mesh routers (MR) s and mesh clients (MC) s. Some of the MRs are functionalized by additional features and have external interfaces to connect the internal network with the internet called internet gateways (IG) s. Most of the network traffic in such network either inside the network between the MCs via MRs or from/to the internet via the IGs and this may result in many problems such as these IGs may be potential bottleneck points because all traffics should be passed through these IGs. If the IGs placed, too far from the MRs this will increase the transmission time by increasing the number of hops that the packets will traverse from the source to the destination, which will result in delay. Thus, packet loss may happen, and if they placed close to MRs, the transmission time decreases, but the network cost will increase due to the high cost of the IG installation because of using physical links to be connected to the internet. Therefore, IG placement optimization is essential in planning and designing of the WMN, especially in the earlier stages of network design, which usually based on topology considerations to minimize overheads of using sophisticated protocols that will be used in the future to overcome the problem of IG placement in high levels of network planning and configuration. Therefore, the network performance depends largely on the optimal placement of MRs especially the IGs. Since the gateway placement problem (GPP) is considered as NP-Hard problem [2] [5] and computationally can be modelled as a combinatorial optimization problem. Thus, the optimal solution may be difficult or it may take polynomial time. Consequently, some sorts of (Meta) heuristic methods are required to find the near optimal solution. Genetic Algorithms (GAs) recently proved their usefulness and efficacy to solve optimization problems in reasonable time

Manuscript received July 5, 2015
Manuscript revised July 20, 2015

[1] [19] [20]. This paper proposes a new approach using the GA to find near optimal solutions for the GPP. The approach aims to minimize the variation among the MRs in the whole network in term of hop counts that the packet traverses to the nearest IG (VAR-MR-IG-Hop). Since each MR is associated to a specific IG that considering the pervious objective.
The next sections of this paper are organized as follows: section 2 presents and investigates the previous research works related to the proposed solution. Section 3 discusses the details of the proposed solution that contains the problem formulation and how the network is modelled besides the proposed GA approach. Section 4 presents and discusses experimental and numerical results of the proposed algorithm. Finally, section 5 presents the conclusion and the future works.

2. Related Works

Many research efforts have been proposed that addressing the GPP in different aspects using different techniques and methods such as Leaner Programming (LP), Integer Leaner Programming (ILP) based methods or metaheuristic methods such as Genetic Algorithm (GA). This section presents and investigates most of the related research works to the proposed approach. In [6], a fixed WMN configuration model has been offered to find the maximum and the optimal throughput depending on fixed wireless nodes with specified locations where the data streams were generated logically as well as finding out how the network can be configured to attain the optimum throughput. They prepared and investigated optimization framework to determine the optimal throughput and to lay the network configuration [3], enumerative method has been applied to bring different insights about the network structure considering the optimal routes, schedules, and physical layer factors. The model assists in determining the achievable throughput in correspondent scenario [3]. In [7], an IG placement approach to minimize the number of IGs considering the bandwidth requirements in the MRs, where the Problem has been formulated as a network flow problem. A max-flow min-cut based algorithm has been developed for IG selection. An MR may be attached to multiple IGs through multiple paths [3]. In [8], a new approach has been proposed for solving the IGs' bottleneck problem in WMN, which aimed to optimize the network performance. Firstly, MRs were distributed and treated as normal nodes. Hence, a weighted objective function has been designed using the logarithm normal distribution model to guarantee the connectivity of all nodes, including the IGs then the nodes with higher throughput and better connectivity configured as IGs using TSP algorithm to choose among MRs [3]. In [9], grid-based IG deployment method has been proposed using cross-layer throughput optimization. LP-Flow-Throughput based on the LP is used to evaluate the model. The result shows that, the model effectively exploits available resources and performs better than the random and fixed deployment methods [3]. In [10], a method addressing GPP depending on the ILP considering quality of service constraints has been proposed. GDTSP algorithm has been used to make comparisons amongst existing solutions and finally heuristic algorithm has been developed. However, the solution concentrated only on cost minimization [3]. In [14], the GPP has been studied and formulated as an ILP; two heuristic algorithms have been developed in order to minimize the number of IGs while satisfying the MR throughput. However, the very important contribution is that the IGs placement optimization problem proved as NP-hard by reduction from capacitated facility location (CFL) [17]. In [11], a model to generate many heuristics to get an optimal position for a single IG in WMN has been proposed, they used the proposed model in [6] to generate multiple scenarios and then compare their relative performance in terms of the network throughput. However the proposed solution can achieve a good performance by a achieving the optimum through, but the solution can be used in networks with a single IG only. In [13], a new algorithm to solve the GPP based on clustering technique in four stages: starts with choosing the cluster heads, assign nodes to these clusters considering the delay constraints, beak down the clusters that do not satisfy the required constraints and finally select the IGs [3]. However, the algorithm did not consider the competitive performance because there is no global information about the whole network when identifying the clusters' heads and assigning MRs to these clusters and this may generate new clusters without considering assigning MRs to them. Hence, some unnecessary clusters will be created as well as increasing the number of clusters significantly [3]. In [18] a new approach has been proposed for load balancing considering the number of IGs, the average IG-MR hop count (AVG-MR-IG-Hop) and the load balance in the IGs. However, many research works have been proposed to address the GPP. Some of them based on a fixed network or ready network, which makes the enhancement chances very limited since the enhancement became in the later stages of network design. Some of them based on LP, which has been proven, has limited capabilities for finding a near optimal solution in large networks. The research work that is very close to our model is that the solution, which proposed in [18]. Nevertheless, the main difference is, our model aims to minimize the variation of hop count between the MRs and their nearest IGs (VAR-MR-IG-Hop) among MRs in the network to insure that the IGs are placed in the appropriate positions, whereas the approach proposed in [18] is aimed to minimize the AVG-MR-IG-Hop.

The GAs have been used in many research works and had shown their usefulness on solving optimization problems. In [15], a new scheme has been proposed using GA to plan and optimize to WMN backbone focusing on routing and channel assignment. The scheme achieves a good solution when dealing with large-scale WMN in relatively small computation time. The results show the effectiveness of GA operators [15]. In [16], a new scheme has been proposed for planning and optimizing WMN, GA used for planning the location of IGs and MRs as well as for routing and channel allocation optimization. However, the solution results show that the proposed algorithms outperform the introduced greedy algorithm.

3. The Proposed Approach

This section presents the proposed approach to solve the GPP using the GA and aiming to find a near optimal solution to minimize the VAR-MR-IG-Hop. Hence, the network performance will be improved. We will present the mathematical formulation for this problem as well as discussing all parameters that will be used and the details GA approach.

3.1 The problem formulation

The network here is defined as a set R= $\{R_1, R_2, \dots, R_r\}$ of r MRs, which construct the network, a subset N = $\{n_1, n_2, \dots, n_n\}$ of n MRs that act as none IGs nodes, a subset Gn= $\{g_1, g_2, \dots, g_g\}$ of g IGs connected the internet as $G \subseteq R$ where $1 < g < n$, and a set E of m edges that connecting MRs denoted as $e_{ij} \subseteq E$ where e_{ij} represents the link between node i and node j. Thus, the network can be denoted as a graph G(R, E), r=|R| is the number of MRs in the network including the IGs. The number of IGs is g=r-n where (1<=g<r). In addition, the graph here is an undirected graph and all its edges have the same weights of the value one because we concentrate only on the number of nodes between each node and the nearest IG. The previous description will be used during all the next processes of the proposed solution and the notations that will be employed in the problem formulation and the other model stages are presented in table 1.

Table 1: List of symbols

Symbol	Description
R	The set of all MRs
r	The number of all MRs.
N	The set of none IG nodes.
N	The number of none IG nodes.
E	The set of all links between each MRs.
Gn	The set of IGs.
g	The number of internet IGs
l_{ij}	Indicator with a value 1 if the path between the MR i and the IG j is the smallest path between the MR i and each other IGs otherwise the indicator should be 0.
D_{ij}	The distance between the MR i and the IG j.
g_{nj}	The number of all MRs associated (all the MRs that their nearest IG is IG j) with the IG j.
x_i	The distance between the MR i and the nearest IG.
$\overline{x}$	The average hop counts among all MRs.
σ	The variance between all MRs in term of hop counts to the nearest IG (VAR-MRs-IGs-Hop)

The problem is formulated as follows:

$$\text{Min } \sigma = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right) \quad , where\ n \geq 1 \tag{1}$$

Such that

$$x_i = \min_{j=1,\dots,g} \left(D(n_i, g_j) \right), \text{where } i = 1, \dots, n \tag{2}$$

$$D(i,j) = \begin{cases} 1, \text{if } i \neq j \text{ and if } i \text{ and } j \text{ are adjecent} \\ 0 \quad , \text{if } i = j \end{cases} \tag{3}$$

$$\text{where } i = 1, \dots, n\ ;\ j = 1, \dots, g \ \text{ and } \ 1 \leq g < n$$

$$l_{ij} = \begin{cases} 1 \ , \text{if } x_i = \min(D(n_i, g_j)) \\ 0 \quad \text{otherwise} \end{cases} \tag{4}$$

$$\text{where } i = 1, \dots, n\ ;\ j = 1, \dots, g \ \text{ and } \ 1 \leq g < n$$

$$\overline{x} = \frac{1}{(n)}\sum_{i=1}^{n} x_i \ , \text{where } i = 1, \dots, n \ \text{ and } n \geq 1 \tag{5}$$

$$\left(\sum_{i=1}^{n} l_{ij}\right) \geq 1 \tag{6}$$

$$\text{where } i = 1, \dots, n\ ;\ j = 1, \dots, g \ \text{ and } \ 1 \leq g < n$$

$$\forall\, n_i, g_j \in R \tag{7}$$

$$\forall\, n_i \in N \text{ and } \forall\, g_i \in Gn \tag{8}$$

$$\nexists\, \mathrm{n_i} \in \mathrm{Gn} \text{ and } \nexists\, g_j \in N \tag{9}$$

The objective (1) means minimizing the variation of hop counts between nodes and the near IGs (VAR-MR-IG-Hop). This, to guarantee that each IG is placed in the near optimal position to serve a group of selected nodes that were selected based on the shortest paths between the nodes and the nearest IG, the decision variable, which is defined by Eq (2) is used to calculate the shortest paths between the corresponding node and all IGs in the network using Dijkstra's algorithm. Then, the shortest one will be returned and this node will be associated with the IG that satisfy this constraint, constraint (3) defines a rule for adjacent nodes as well as each node with itself. Constraint (4) returns the value one when the IG satisfies constraint (2) otherwise return the value zero. Equation (5) used to calculate the average hop counts from the MRs (Nodes) to their nearest IGs (AVG-MR-IG-Hop), which is subject to the constraint (2).

3.2 Genetic Algorithm Approach

The following subsections present the GA representation for the GPP. The GA operators that will be discussed are chromosome representation (network encoding) to represent the network in the real world, fitness function that will be used to evaluate the quality of the individuals besides crossover, mutation, and selection operators that will be used in the proposed approach. This section shows the detailed algorithm based on the GA as follows.

3.2.1 Network's encoding

The encoding process is the first and the core process of GA to represent the real-world problem. In this work, all MRs are labelled from one to n where n is the number of MRs including those that were chosen as IGs. The binary string is used to represent the chromosome as shown in Fig. 1. The order of the gene in the string (chromosome) determines the node ID in the graph (network) and the value of this gene determines either this node is selected as an IG, which is represented by one or as a normal MR, which is represented by zero.

0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1

Fig. 1: Chromosome's encoding

3.2.2 Initial population

The initial population will be generated randomly from a given number of MRs and IGs, which are represented by the graph. A number of genes will be selected randomly to represent the IGs according the number of IGs.

3.2.3 Fitness Function

The fitness function is used to evaluate the quality of each individual in the current generation based on the objective defined in Eq. (1) and subject to the constraints defined in the equations from 2 through 9. The individual with the highest fitness value will be selected as elite to be kept in the new generation, while the remaining individuals of the new generation will be generated using crossover and mutation operators. This function considers the objective (1) so, that the aim is, to minimize the VAR-MR-IG-Hop according to the following formula.

$$f_1 = \min(\sigma)$$

$$Fitness = 1/f_1$$

The individual of the minimum VAR-MR-IG has the highest fitness value.

3.2.4 Selection Operator

The tournament selection is used to select a number of individuals from the current generation based on a specific probability so-called the tournament probability denoted by T_p then, the selected individuals will be ranked according to their fitness values and the individual with the highest fitness value will be used to reproduce the offspring by applying crossover and mutation operators.

3.2.5 Crossover operator

Three types of crossover, single point, two point, and uniform have been used alternatively for further optimization.

3.2.5.1 Single Point Crossover

The Single-Point crossover is used to generate the new offspring's, which is done by selecting a single point within the parents. Copies the genes before this point points from the first parent in the corresponding positions of the child (offspring) and then fill the remaining genes of the child from the second parent with the genes in the positions after the selected point. Fig.2 shows the single-point crossover.

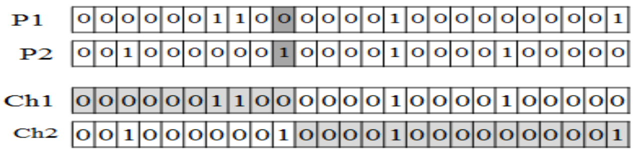

Fig. 2: Single Point Crossover

3.2.5.2 Two Point Crossover

Two-Points crossover has been used to generate the new offspring's, which is done by selecting two points within the parents, then copy the genes between these points from the first parent in the corresponding positions of the child and fill the remaining genes of the child from the second parent as illustrated in Fig. 3.

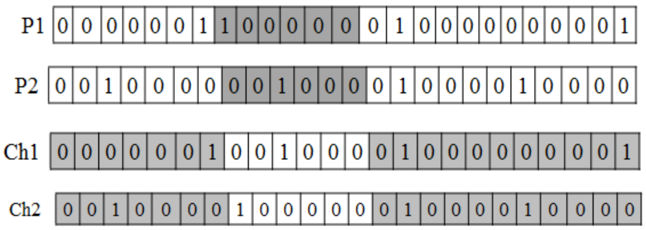

Fig. 3: Two point crossover

3.2.5.3 Uniform Crossover

The uniform crossover is used to generate the new offspring's based on a fixed mixing ratio between two parents. Unlike one- and two-point crossover, the Uniform Crossover enables the parent chromosomes to contribute the gene level rather than the segment level. Therefore, we use this type for further optimization and compare the results of different crossover types. Here, the genes' exchange operation uses a specific probability called crossover probability and denoted by P_c then, a random mask of 1s and 0s will be generated with a chromosome length as follows:

(i). Generate a random number P_R per each gene in the chromosome.

(ii). Generate the random mask according to the following formula:

$$corresponding\ mask\ gene = \begin{cases} 1 & if\ P_R < P_c \\ 0 & ,otherwise \end{cases}$$

(iii). The final mask will be as shown in Fig.4

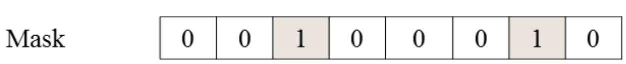

Fig. 4 :: Mask Sample in Uniform Crossover

(iv). The one value indicates that, the corresponding gene in the child will filled from the first parent, and the zero value from the second parent. Fig.5 illustrates these steps.

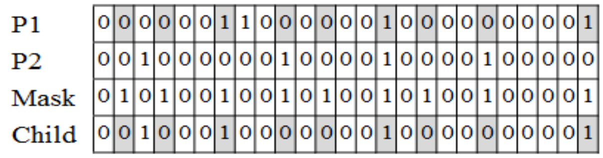

Fig. 5: Uniform Crossover

3.2.6 Mutation Operator

Swap mutation is used to modify the individual, which selects two positions within the individual randomly and swaps the genes in these positions to produce a new individual and prevent GA from falling on the local optimum solution as shown in Fig. 6.

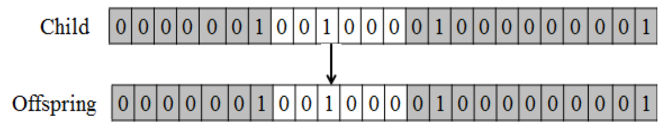

Fig. 6: Mutation Operator

3.2.7 Repair Procedure

The number of IGs is fixed in this solution and we use designated parameter to keep this number in the network but due to the GA operations processes, which cause continuous changing within the individuals the number of the IGs may either increase or decrease. Hence, we use this procedure to alter the individual that violates the constraint of IGs number.

3.2.8 Termination's Condition

The termination's condition is used to indicate when the GA will stop processing. Here, The GA will stop when the number of current generations is greater than the maximum number of allowed generations.

3.2.9 The Proposed GA Template

Algorithm 1: GA Procedure
Set iteration counter i=0. Set initial parameters: Termination condition: T_c; Population Size: Z; tournament probability: T_p Step 1: Generate the initial population P_i With the size Z. Step 2: Evaluate P_i If P_i Pass the Step 3: Do while not T_c Select Elite = the best individual P_i According to fitness value For j =2 to z Selects two parents (Pr1, Pr2) using selection operator with

probability T_p
'Generate the offspring using crossover on the selected individuals using following formula:
Offspring=crossover(Pr1, Pr2)
'Checks the validity of the offspring if not passes, then apply repair procedure.
If not checkIndividual (offspring) then
RepairGenes(offspring)
End if
'Add offspring to the crossover population
$\mathbf{P_i^c}$.Add (offspring)
Next j
'Apply mutation using the following formula:
$\mathbf{P_i^m} = \mathbf{mutate}(\mathbf{P_i^c})$.
Create a new generation $\mathbf{P_{i+1}}$ From the Elite the individuals in $\mathbf{P_i^m}$
I=i+1
Loop

4. Computational Results

The experiments have been performed on Hewlett-Packard HP 2000 Notebook PC with Intel core-i3 2.40GHz processor and 4.00GB of RAM. The algorithms have been coded in Visual Basic .Net 2010 using Microsoft Visual Studio 2010 and tested under Windows 7 (32-bit) operating system.

We investigated the population evolution to demonstrate the effectiveness of the GA. In order to prove the correct functionality of the GA the growth of the fitness over the must be observed over the new generations, which are produced by the genetic operators. Thus, we investigated the effects of these operators to show the effectiveness of the GA. Therefore, we evaluated the algorithm using different conditions such as the effects of population size 50,100 and 150, crossover types with crossover probability of 0.5, mutation type with probability of 0.08 and the tournament size with different tournament size 6,10,15,20 and 30. The evaluation process is aimed to show the convergence rate of the proposed algorithm as well as showing the robustness and the scalability of the proposed algorithm, which they be used in high intensity situation. Moreover, the evaluation also aimed to show the significance of the objective function on solving the GPP and how it is different from the existing research works that aimed to minimize the AVG-MR-IG-Hop to enhance the network performance. The following subsections present and discuss the generated results.

The following figure shows the generated result using population size of 100, two-point crossover type, inversion mutation and tournament size of 10. The number of MRs is 100 with 10 IGs and we ran the algorithm for four rounds for only ten generations per each round, the figure below shows that the algorithm always get good results, and this indicates that the algorithm will get better result in the next generations. In addition, the results show a positive convergence rate at each round.

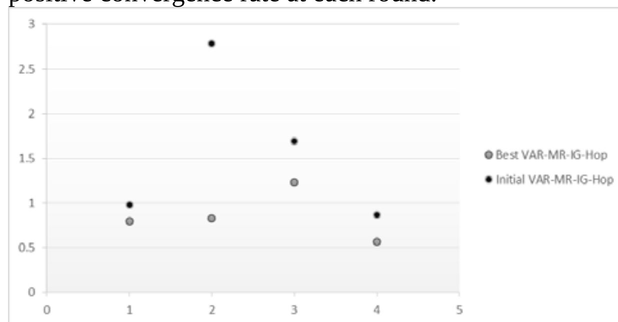

Fig. 7: Initial GA results for four rounds and ten generations

4.1 The effect of population size on convergence rate

We studied the effect of population size on the convergence rate, and the algorithm parameters that were used in the experiments as shown in Table 2.

Table 2: Parameters used to evaluate the effect of population size

Parameter	Value
Crossover type	2-points
Mutation type	Inversion
Tournament size	10
Number of MRs	25
Number of IGs	4
Population sizes	50,100,150
Maximum generations' No.	6000

Fig. 8 shows the VAR-MR-IG-Hop of the best solution of the initial population and the current generation when the population size is 100. The results show the variation of hop-counts among MRs. Fig. 9 shows the convergence rate using different population sizes: 50,100,150 and the results show that the algorithm has a good convergence rate at different population size but the best population size with the parameters' values shown in Table 2 is 100, which shows the lowest variation (highest convergence rate).

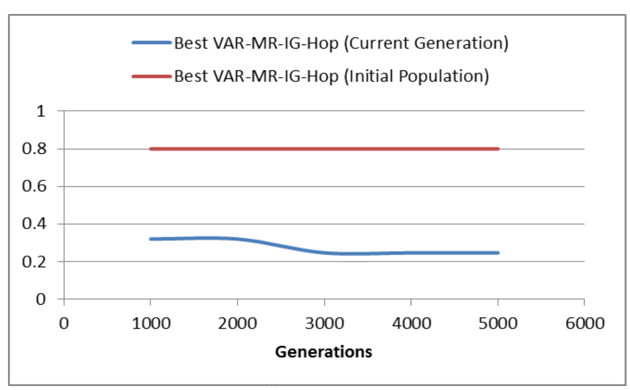

Fig. 7: VAR-MR-IG-Hop difference (initial population and the current

generation)

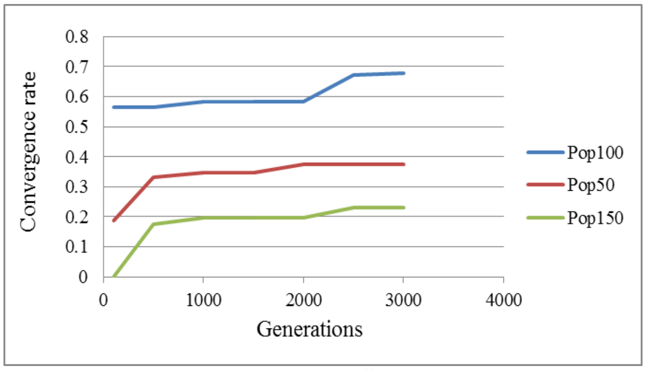

Fig. 8:Convergence rate using different population sizes

We run the three instances of the algorithm using the population sizes 50,100,150 and we compared the fitness values of each instance at 3000 generations. The algorithm has shown good results for different population sizes, but the highest quality (highest fitness value) at population size of 100. The result, as shown in Fig. 10.

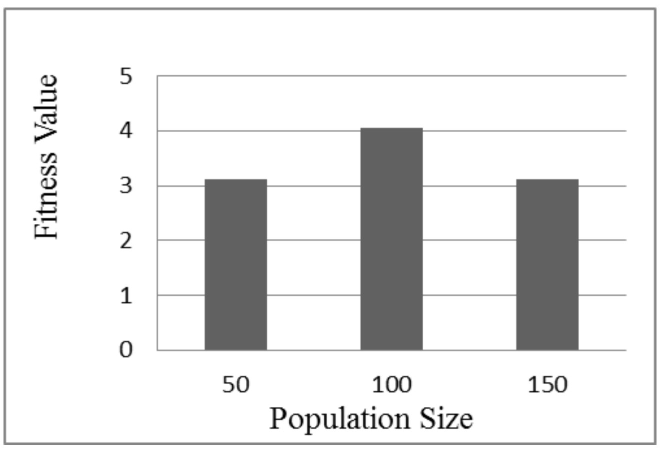

Fig. 9: Fitness values over 3000 generations

4.2 The effect of tournament size on the convergence rate

We have tested the algorithm using different tournament sizes and parameters that have been used shown in Table 3. Fig. 11 shows the convergence rate of four instances of the algorithm for a number of generations using different tournament sizes shown in Table 3. The results show that the algorithm can achieve a good convergence rate in different tournament sizes, but the highest convergence rate of 30-tournament size for 2000 generations, which means 30% of the population.

Table 3: Parameters used to evaluate the effect of tournament size

Parameter	Value
Crossover type	2-points
Mutation type	Inversion
Tournament size	6,10,15,20,30
Number of MRs	25
Number of IGs	4
Population size	100
Maximum generations' No.	6000

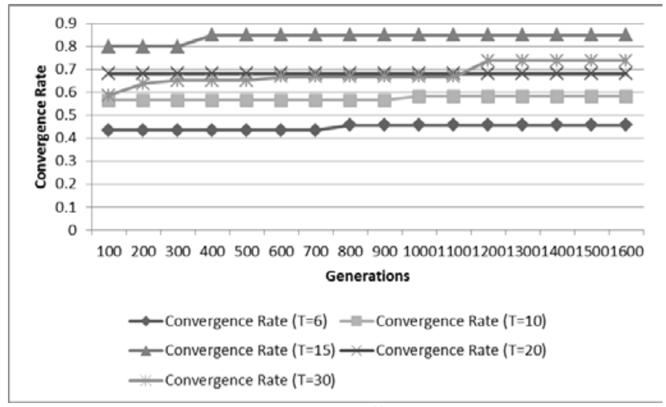

Fig. 10: Convergence rate using different tournament sizes

4.3 The effect of crossover type on the convergence rate

From the previous results the best population size is 100 and the best tournament size, 30% of the population where the total number of MRs is 25 (individual size) with four IGs. The previous tests have done using 2-point crossover; in the following section will present the effect of using different crossover types and the parameters that will be used as shows in Table 4.

Table 4: The Parameters used to evaluate the effect of crossover type

Parameter	Value
Crossover type	Single point, 2-points, Uniform
Mutation type	Inversion
Tournament size	30
Number of MRs	25
Number of IGs	4
Population size	100
Maximum generations' No.	1600

Table 5 shows the effects of the crossover type on the convergence rate and also shows AVG-MR-IG-Hop through 1600 generations. The results show that the algorithm has a good convergence rate using the three crossover types, but the two-point crossover has the best result in comparison with single point and uniform crossover.

Table 5: Effect of different crossover types

	Single Point crossover		2-Points Crossover		Uniform Crossover	
Generation No.	Convergence Rate	AVG-MR-IG-Hop	Convergence Rate	AVG-MR-IG-Hop	Convergence Rate	AVG-MR-IG-Hop
100	0.5805	1.8095	0.5857	1.8095	0.3482	2.0476
200	0.5805	1.6667	0.6381	1.8571	0.3482	2.8571
300	0.5805	1.6667	0.6524	2.0000	0.3482	1.8095
400	0.5805	2.0000	0.6524	1.9524	0.3482	2.2381
500	0.5977	1.7619	0.6524	2.4762	0.3482	1.9048
600	0.5977	2.0476	0.6667	2.2381	0.3482	1.9524
700	0.6839	2.0952	0.6667	1.9524	0.3482	2.4286
800	0.6839	1.9048	0.6667	1.9524	0.3482	1.7619
900	0.6839	1.9524	0.6667	2.0952	0.3482	1.8571
1000	0.6839	1.8095	0.6667	2.1429	0.3482	1.8571
1100	0.6839	2.1905	0.6667	2.0952	0.3482	1.9524
1200	0.6839	1.8095	0.7381	1.7619	0.3482	2.2381
1300	0.6839	2.1905	0.7381	1.8571	0.3482	1.9048
1400	0.6897	1.6190	0.7381	1.7619	0.3482	2.3810
1500	0.6897	1.7619	0.7381	2.0952	0.3482	2.1905
1600	0.6897	1.9524	0.7381	2.1905	0.3482	1.8571

Fig. 11 shows the convergence rate of the three crossover types.

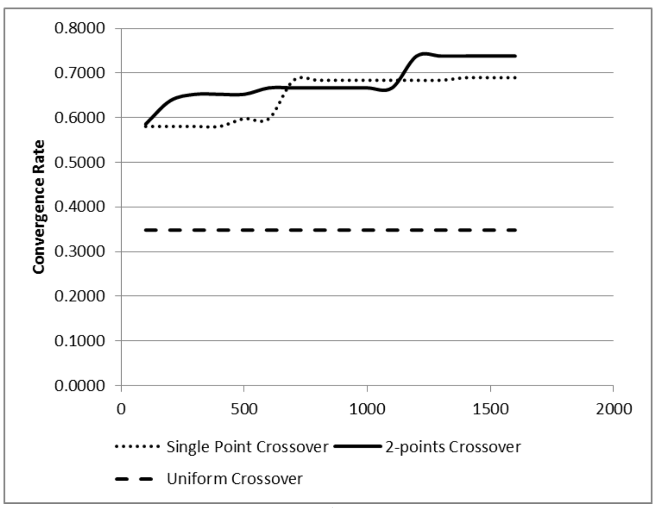

Fig. 11: Convergence rate of the three crossover types

4.4 The significance of the VAR-MR-IG-Hop

As mentioned before in this paper, the objective is to minimize the VAR-MR-IG-hop among MRs to enhance the overall network performance. Fig. 13 shows the relationship between the AVG-MR-IG-hop and VAR-MR-IG-hop. Many research works have aimed to minimize the AVG-MR-IG-hop count to minimize the bandwidth consumption, delay, the transmission time and maximize the network throughput, but using this metric may lead to high variation in MR-IG-Hop in the overall network. From the result shown in Fig. 13 the VAR-MR-IG-Hop always, keep minimizing with different AVG-MR-IG-Hop values. Therefore, minimizing only the AVG-MR-IG-Hop may lead to high variation on MR-IG-Hop in the network. Hence, some MRs may have low throughput while the other have high throughput due to the variation in the distance between the MRs and IGs in the network.

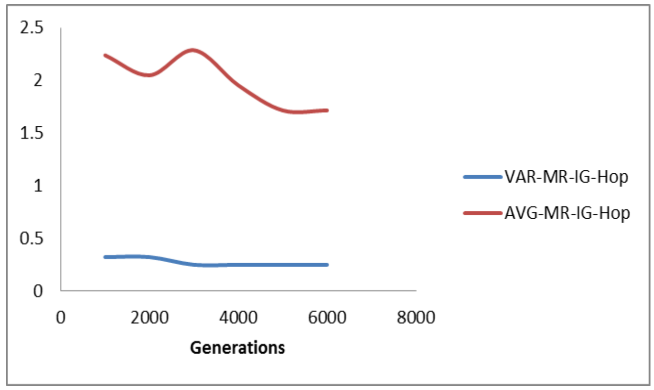

Fig. 12: the AVG- MR-IG-Hop and VAR-MR-IG-Hop) when the population size=100

5. Conclusion

In this paper, the GPP in WMN has been studied and addressed, a novel approach had been proposed using GA to find a near optimal solution for this problem. The proposed approach aimed to minimize the VAR-MR-IG-Hop counts among MRs in the network to insure that each MRs were placed in a near optimal position from its nearest IG as well as to insure the MRs were distributed equally among the IGs. The problem had been formulated as a mathematical model and the network was represented by undirected graph of a one-unit weights. The Dijkstra's algorithm had been used to calculate the shortest path between the MRs and the IGs. The GA had been used to find the near optimal solution based on the objective function in the mathematical model. The proposed algorithms had been evaluated based on generating instances to show the convergence rate of the algorithm and the scalability and the robustness of the algorithm. In addition, for more optimization, the algorithm had been tested using different parameters' values. The parameters that have been considered in the test are population size, tournament size and crossover type. The results had shown that the algorithm could achieve good results in different situations in high intensity and low intensity. Moreover, the results had shown the positive significance of VAR-MR-IG-hop in comparison with the AVG-MR-IG-hop on enhancing the network performance. Hence, the algorithm has considerable scalability and robustness to solve the GPP in large and small networks.

In the future work, we intended to propose a new algorithm for more optimization.

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