A Merged Scheme of Two Evolutionary Algorithms for Spectrum Management in Mobile ad hoc Network (MANET)

Mahboobeh Parsapoor; Urban Bilstrup
(Halmstad University, Halmstad, Sweden)
mahbpar11@student.hh.se; urban.bilstrub@hh.se

ABSTRACT

The next generation tactical networks will be based on mobile ad hoc networks (MANETs). These networks require as well a stable clustered network structure as an efficient channel assignment optimization method. Efficient spatial channel reuse provides network scalability and high spectral efficiency. In this paper, a centralized scheme based on two evolutionary algorithms, ant colony optimization (ACO) and imperialist competitive algorithm (ICA), is suggested for forming clusters and assigning channels to the clusters. Ant colony optimization (ACO) is used to select the cluster heads in an as advantageous way as possible. A multi-objective function is designed to maximize the stability and scalability, minimize the number of clusters and inter-cluster interference power. The imperialist competitive algorithm is applied in conjunction with the ACO algorithm as a scheme for spatial channel assignment. In this case, a multi-objective function is defined to minimize interference and maximize spectral efficiency. The suggested algorithms are evaluated for numerous scenarios. Particularly, the performance of ACO-based clustering algorithm is compared with other clustering algorithms.

1. INTRODUCTION

Mobile ad hoc networks (MANETs) have crucial roles in the next generation tactical military networks and battlefield communications. Due to their characteristic, creating communication hierarchies out of sets of mobile nodes, it is essential to control the topology, effectively utilize resources and improve the networks' performance [1]. The procedure of creating a hierarchical structure in a MANET is referred to as *clustering*. The clustering algorithms partition the network into groups of mobile nodes to provide a well-organized scalable structure for routing algorithms, power control mechanisms and spectrum management methods [1]. A common structure for forming a clustered network topology is based on defining three types of nodes: *cluster head*, *gateway* and *ordinary nodes*. The cluster head, the master of a cluster, is responsible for allocating resources and coordinates the intra cluster communication. The gateway, which is a common node between two or more clusters, provides the connectivity between the clusters. Others nodes are ordinary nodes that determine the boundary of clusters, which is dependent on the transmission range and the node density [1]-[3].

Most clustering algorithms seek a scalable, energy efficient and low interference topology to improve the performance. It is also desirable that the clustering algorithm forms a stable topology with a small number of clusters to reduce the control communication overhead [3], [4]. Forming the clustered structure with a minimum number of cluster heads is equivalent to solving the dominating set problem, [4]-[6], finding the optimal solution is unfortunately an NP-hard problem. Most evolutionary algorithms that have been applied for forming clusters try to maximize scalability and stability while using a minimum number of cluster heads [5]-[7]. However, maximizing spectrum efficiency through forming clusters has not been sufficiently examined by evolutionary algorithms. A cluster-based topology can also address the spectrum scarcity issue by optimizing the spatial channel reuse. The essential objective of the channel assignment method is to assign the frequency channels to the clusters in order to maximize the spectrum efficiency. In MANET, the channel assignment problem is equivalent to the graph coloring problem, which also has been identified as an NP-hard class of problem [8].

In this paper, we suggest a procedure that is a merging of ant colony optimization and imperialist competitive algorithm for spectrum management. We apply the merged method to form clusters and assign the channels to these clusters. Two multi-objective functions are defined to seek the Pareto front that makes a tradeoff between several objectives.

This paper is organized as follows: in Section 2, related works in the area of channel assignment and cluster formation are reviewed. In Section 3, the problems that are sought for the optimal solutions are described. A new evolutionary method, ICA, in conjunction with ant colony optimization based algorithms, ACO-based, are explained and applied for solving the defined problems. The numerical studies and the results of simulation are presented in Section 4. In Section 5 we conclude with some significant notes.

2. RELATED WORKS

2.1. Related Studies in Channel Assignment Problems

Channel assignment is one of the most challenging tasks in MANET. A desirable channel assignment scheme addresses several issues, such as stability, throughput, connectivity and routing and fault tolerance [9], [10]. Although, the channel assignment problem was early defined in cellular communication systems [9], [10], finding an effective channel assignment scheme is also required to improve the performance of mobile ad hoc network (MANET) and cognitive radio network (CRN). So far, a large number of channel assignment schemes (e.g. greedy allocation, genetic algorithms (GA) [10] and ant colony optimization (ACO) [11]) have been proposed for the different types of networks; they can be classified as centralized, distributed, cooperative and non-cooperative, measurement and non-measurement methods [10]. Heuristic methods (e.g., greedy and genetic algorithms), can also be utilized as cluster-based channel assignment schemes. They seek a solution to assign orthogonal channels to 'neighbor clusters' and 'neighbor cluster neighbors' [12]. In this paper, a centralized evolutionary method, ICA, is applied to solve the cluster-based channel assignment problem. We suggest a multi-objective function to simultaneously maximize the spectral efficiency and minimize co-channel interference.

2.2. Related Studies in Cluster Formation

In MANET, a clustering algorithm divides a flat network topology into a set of connected clusters that cover all mobile nodes in the network. Generally, clustering algorithms have been proposed to increase the manageability and scalability of MANETs.

Simple clustering methods are 'identity based clustering' [4] algorithms (e.g. Lowest-ID and Max-min d-cluster algorithms) that select the cluster heads on the basis of the node's ID. These algorithms aim at reducing the control communication overhead in the network and maximizing the stability of the clusters in terms of prolonging the lifetime of cluster heads [4], [14]. The highest connectivity clustering (HCC) algorithm, which is a type of 'connectivity-based clustering' [4] algorithms, is another simple clustering algorithm with a similar objective as LID; however, it uses the node's degree to form the clusters [4], [14]. Other instances of connectivity-based clustering algorithms have objectives to satisfy the load balancing constraints or minimize the number of cluster heads (e.g. minimize the dominating set) [4]. Clustering algorithms that form the clusters by using mobility metric (e.g. mobility based metric for clustering (MOBIC)), are referred to as mobility-aware clustering methods [14], [15]. The main objective of these algorithms is to stabilize the intra-cluster connections or minimize the rate of re-affiliations [14]-[15]. In the combined–weight based clustering method, a weight, which is defined as a summation of several metrics, is assigned to each node. The node with minimum weight is more desirable to select as the cluster head. The metrics are dependent upon the objective of the clustering algorithm. In the weighted clustering algorithm (WCA), the weights are defined on the basis of four metrics: degree, mobility, transmission power and battery power. It aims to minimize the number of clusters and the control communication overhead. In addition to the above clustering algorithms, other algorithms such as power-aware clustering, load balanced clustering and low cost of maintenance clustering have also been proposed. They aim at providing an energy-efficient, well load balanced, scalable and stable hierarchical structure with low control communication overhead [14]-[15].

Forming clusters with minimizing the number of clusters, maximizing stability and scalability of clustered topology are the most desirable objectives of the clustering algorithms. Since these problems are NP-hard problems, evolutionary algorithms (e.g., GA) and swarm intelligent based methods (e.g., ACO) have been examined for solving them in polynomial time [5], [6], [8], [15]-[17]. As an example, a genetic algorithm is applied to modify the performance of weighted clustering algorithm (WCA) to minimize the dominating set [6] and maximize the connectivity [13]. In [6] the chromosome has been represented as a sequence of the selected nodes as cluster heads and its fitness function is defined as the summation of cluster head' weights. In [13], each individual corresponds to each node and is represented by the values of metrics. The node with the minimum value of fitness function, which is defined on the basis of the node's metric, is a more desirable choice as a cluster head. Á distributed WCA that defines a local cost function [15] has also been examined for forming clustered topology. Finding a local solution for clustering and overcoming the control communication overhead are the main contributions of this distributed method. In the GA-based distributed method, the cluster heads selection process is done by only using the local information [15]. In comparison with the centralized clustering schemes, the distributed clustering methods, especially GA-based methods have proven to be efficient methods in reducing control communication overhead.

Combinations of ant colony optimization (ACO) and weighted-combined algorithm (WCA) have been suggested as efficient schemes for clustering [5], [15]-[19]. They aim to minimize the number of clusters, re-affiliations, and also maximize the stability and throughput. In [16], each node calculates a probability function, which is defined on the basis of two metrics, the degree and pheromone intensity, to estimate the probability of a node to be selected as a cluster head. Examining this method for the different sizes of networks proved that it has the capability to find the minimum number of cluster heads while satisfying the connectivity and time complexity of the selection procedure. Another instance of ACO-based clustering schemes that was suggested in [5] defines a new metrics 'computing power' [5] and combines the WCA and the ACO to improve the performance of WCA. The algorithm forms the clusters to maximize the throughput and load balancing while minimizing the delay and the re-affiliations rate. Another type of ACO-base clustering algorithms was proposed in [17], it is referred to as 'CAACO', [17]. It assigns a metric to each node, which is represented by the level of pheromone intensity of that node. The probability function for each node is defined based on this metric; thus, a node with the highest probability is selected as a cluster head. The CAACO aims to reduce control communication overhead as well as maximize the scalability and inter-cluster stability.

As previously mentioned, most clustering algorithms form clustered network topology with a minimum number of clusters as the objective, which causes a reduction in control communication overhead. For such a clustered topology a lower number of channels is required. The spectrum efficiency is maximized by selecting a lower number of nodes as cluster heads while optimizing the distance and overlap between clusters. The spatial reuse clustering algorithms [14] investigate the possibilities of forming clusters to optimize spectrum utilization. However, selecting cluster heads to minimize inter-cluster interference has not been sufficiently studied. The cluster formation is not the final solution for maximizing the spectrum efficiency. An efficient channel assignment scheme has a significant role in the process of maximizing spatial reuse.

In this paper, a procedure that consists of two evolutionary algorithms is suggested for spectrum management through forming clusters and allocating channels to the formed clusters. We aim the merged scheme has the capability to maximize the spectrum efficiency and stability, as well as minimizing the interference power.

3. EVALUTIONARY BASED METHODS FOR SPECTRUM MANAGEMENT

In this section, we explain how to merge ant colony optimization (ACO) and imperialist competitive algorithm (ICA) to solve clustering formation and channel assignment problems in MANET. The main assumptions for our algorithms are as follows: 1) A centralized controller coordinates the clustering and channel allocation algorithms. In a real network, this structure can be implemented using a centralized access point and a set of mobile nodes [20]. 2) There is a global knowledge of the available channels and node state. 3) During the procedure of cluster formation and channel assignment to the clusters, it is assumed that there is no change in the network topology and the transmission power. 4) All nodes use similar transmission powers. 5) Each node has an omni-directional antenna. 6) The channel model and interference model are considered as free-space path loss model and disk graph model, respectively. 8) In general no specific models are considered for transmission activity (traffic model) and mobility of nodes**.**

A MANET can be represented as a unidirectional graph, $G=(V,E)$, where $|V|$ is the number of nodes and E represents the communication links [3], which are defined on the basis of the transmission range of the nodes. There is a communication link between each two neighbor nodes which are mutually within the transmission range of each other. Using the above representation of MANET, cluster head selection and channel assignment problem are equivalent to finding the dominating set of G and the chromatic number of G, respectively [5], [6], [7], [21].

3.1. Ant Colony Optimization Meta-heuristic

Ant colony optimization meta-heuristic (ACO_MH) is a collection of algorithms which are inspired by the 'foraging behavior of real ants' [22]. Real ants start from the start node and use both local and global knowledge to construct the shortest path to the destination node. The ACO-based algorithms imitate this behavior to find the optimal sequence of nodes, i.e. the path with the minimum cost [22]. To solve an optimization problem using ACO-based algorithms, the problem is represented by a graph $G'=(V',E')$ to construct a sequence of nodes, a solution. In this graph, G' , the nodes, V' , represent the components of the problem and the links, E' , show the transition between nodes.

The general components of ACO-based algorithm are summarized as follows [21]-[23]:

1. A population of ants which memorize the traversed paths.
2. A graph that represents the optimization problem.
3. An initial state which is assigned to each ant and determines the starting node for that ant.
4. A 'probabilistic transition rule' [22] is used by each ant to make a decision to move to the next node. It is defined on the basis of heuristic information and pheromone intensity.
5. A Heuristic function, which is 'problem dependent function' [22], to indicate the desirability of selected node.
6. Pheromone intensity that represents the desirability of selected path. This desirability of each path is described from the perspective of other ants.
7. An updating rule for pheromone intensity is used to determine the effect of the previous deposited pheromones. In this paper, we adopt the updating rule that is defined according to 'ant colony system' [22]. Hence, the pheromone is updated by the best global ant.
8. A set of feasible nodes, N_i^k , in order to avoid forming a loop during the path construction. It shows the feasible nodes from the perspective of ant k when it is placed on i th node.
9. A cost function is assigned to each complete path to show how profitable the path is.

For the ACO-based clustering algorithms the following assumptions are made:

1. The completed path is a sequence of nodes which are selected as cluster heads and satisfies the problems' constraints. Ants construct the solution by incrementally choosing one node as a cluster head until they reach the termination condition.

2. The node is selected as the cluster head and the nodes are chosen as its members are removed from the feasible set.
3. The ACO-based clustering seeks a dominating set as $\mathbf{x}^*$ that is defined as (1).

$$\mathbf{x}^* = \arg \min_{x \in \prod DS} f(\mathbf{x}) \tag{1}$$

Where, DS is a dominating set of V', $\mathbf{x}$ is the set of feasible solutions and $f(\mathbf{x})$ is the objective function. In the following, we describe three different ACO-based clustering algorithms, which differ in the designed objective functions and the defined heuristic functions.

3.1.1. ACO-based Clustering for Minimizing Dominating Set

ACO-based clustering for minimizing dominating set (ACO_MDS) selects the cluster heads in order to reduce the number of clusters. The characteristics of this algorithm are as follows:

1. The ants are placed on the nodes with the lower weight to construct solution. The weight is defined as equation (2). The set of neighbors of node i and the degree of node $\boldsymbol{i}$ are defined by $N(i)$ and d_i, respectively; their formulations have been defined in [15].The $D_{N(i),i}$ is the set of the distances between node $\boldsymbol{i}$ and its neighbors.

$$W(i) = \frac{d_i}{(\max_{j \in N(i)} \{D_{N(i),i}\})} \tag{2}$$

2. The node that is selected as the cluster head and its members (i.e. its neighbors) are removed from the feasible set.
3. The heuristic function is simply defined as $\eta_{ij} = d_j$.
4. Assuming $\mathbf{x}^k$ is a solution that is constructed by ant k, the cost function is calculated as (3).

$$F_{ACO\#1}(\mathbf{x}^k) = \frac{|\mathbf{x}^k|}{(|V'| + n_{cc})} \tag{3}$$

The parameters: $|\mathbf{x}^k|$ and $|V'|$ are the number of cluster heads and the total number of nodes, respectively. And, $\boldsymbol{n_{cc}}$ is the number of vertices of a sub graph of $\boldsymbol{G''}$ with the maximum length of connected nodes. A sequence of nodes that are selected as cluster heads, induces another graph, $\boldsymbol{G''=(V'',E'')}$. The vertices of $\boldsymbol{G''}$, $\boldsymbol{V''}$ is the set of cluster heads and the links, $\boldsymbol{E''}$, which represents the adjacency between the clusters. For two cluster heads, $\boldsymbol{u}$ and $\boldsymbol{v}$, if there is a common node in the sets of their members, they are mutually adjacent and have a link in $\boldsymbol{G''}$.

3.1.2. ACO-based Clustering for Maximizing Spatial Reuse and Minimizing Dominating Set

ACO-based clustering for maximizing spatial reuse and minimizing dominating set (ACO_MSR) forms a clustered topology finding a minimum dominating set while maximizing channel spatial reuse. The main objective of this algorithm is to achieve high channel utilization through optimizing the spatial separation of cluster heads. This algorithm aims at reducing the potential interference between clusters increasing the spatial separation between the cluster heads. A feasible solution partitions the network into a minimum number of clusters while maximizing the spatial separation of cluster heads. Some characteristics of this algorithm are explained as follows:

1. The ants are placed on the nodes with the higher degree to initiate a solution.
2. The node that is selected as the cluster head and all its members (i.e. its neighbors) are removed from the feasible set.
3. The heuristic function is defined as equation (4) and calculated as a weighted summation of the node degree and the cardinality of I_{C_i}.

$$\eta_{ij} = w_1 \times d_j + w_2 \times \frac{|I_{C_i}|}{|C_i|} \tag{4}$$

The parameter I_{C_i} is defined as (5), and is a set of nodes (e.g., u) that are belonged to C_i and have a potential interference with the selected cluster head i.

$$I_{C_i} = \bigcup_{u \in C_i, u \neq j} \{u \,|\, dist(i,u) < 2 \times tx_{range}\} \tag{5}$$

The set of the covered nodes by the current dominating set is shown by C_i. This algorithm optimizes a multi-objective function which is designed as (6). It is a weighted summation of two objective functions, F_1 and F_2.

$$\mathrm{F}_{ACO\#2}(\mathbf{x}^k) = w_1 \, \mathrm{F}_1(\mathbf{x}^k) + w_2 \, \mathrm{F}_2(\mathbf{x}^k) \tag{6}$$

These objective functions F_1 and F_2 are defined as (7) and (8) respectively.

$$\mathrm{F}_1(\mathbf{x}^k) = (1/ \; |\mathbf{x}^k|^2) \times \sum_{i=1}^{|\mathbf{x}^k|} |I_{CH_i}| \tag{7}$$

$$\mathrm{F}_2(\mathbf{x}^k) = |\mathbf{x}^k| / |V'| \tag{8}$$

The parameter I_{CH_i} shows the subset of cluster heads' set, CH and is defined as (9). Each node (e.g., u) that is belonged to I_{CH_i} is a potential interferer with respect to the i th cluster head. The cardinality of I_{CH_i} is given by $\left|I_{CH_i}\right|$.

$$I_{CH_i} = \bigcup_{u \in CH_i, u \neq i} \{u \,|\, dist(u,i) < 2 \times tx_{range}\} \tag{9}$$

3.1. 3 ACO-based Clustering for Maximizing Stability, Spatial reuse and Minimizing Dominating Set

ACO-based clustering for maximizing stability, spatial reuse and minimizing dominating set (ACO_MSSR) seeks a stable minimum dominating set that minimizes the potential inter-cluster interference. In this algorithm, each node is assigned a stability factor that is a weighted summation of three variables: 'relative mobility, average sum of distances' [24] and average of speeds. The characteristics of *ASO_MSSR* are explained as follows:

1. The ants are placed on the nodes that have the lowest value of the stability factor.
2. The node that is selected as the cluster head and its entire members are removed from the feasible set. The set of members of each cluster head, Mem_{CH_i} , is the subset of the neighbors' set. Each node (e.g., u) that belongs to Mem_{CH_i} satisfies the condition given by equation (10).

$$Mem_{CH_i} = \bigcup_{u \in N(i), u \neq i} \{u \,|\, dist(u_{next}, i) < tx_{range}\} \tag{10}$$

The parameter u_{next} is a predicted next location of node u which is calculated using the average of previous speeds and directions.

3. The heuristic function is defined as (11).

$$\eta_{ij} = \frac{1}{S_j} \tag{11}$$

The stability factor s_j is calculated as the weighted summation of three factors (12).

$$S_j = w_1 M_j + w_2 D_{sum-j} + w_3 \bar{v}_j \tag{12}$$

The first variable M_j is a relative speed between node j and all its neighbors; it is calculated according to [24]. The second variable of the stability factor is D_{sum_j} , that is defined as 'the average sum of distance' [24]. The last variable is the average speed of node jth, $\bar{v}_j$, that is calculated as the average of all pervious speeds of node j . A node with a lower stability factor is more desirable to select as a cluster head. This algorithm is a multi-objective optimization method; thus, the multi-objective function is defined as similar to ACO_MSR. However, the weights are different and the found solution should satisfy the constraint defined as (13).

$$\max_{CH_i \in x} Mem_{CH_i} \leq |x| / |V| \tag{13}$$

This equation aims to form a high load balanced clustered network.

3.2. Imperialist Competitive Algorithm (ICA)

3.2.1 ICA: A New Optimization Method

Evolutionary methods in particular genetic algorithm and ant colony optimization have shown reasonable results in solving NP-hard problems [25],[26].

Imperialist Competitive Algorithm (ICA) is an evolutionary optimization method inspired by "*imperialist competition"* [27]. ICA defines the term 'country' [27] for the individual. Thus, an initial population for ICA is a set of countries. A vector of optimization parameters is named country. The population, the countries, is classified into two groups: the colonies and the imperialists. The countries that have the higher power are considered as the imperialists that start to take possession of the countries with the lower power, which are referred to as the colonies. In this way, each imperialist creates its empire; then the movement of colonies toward the imperialists is started (assimilation operator). If a colony reaches to a higher power than its imperialist, the position of the colony and its imperialist must be exchanged. Finally, imperialists start a competition to take possession of the weakest colonies of the weakest empires. During the competition, the weakest colony from the weakest empire is picked and joined to the most powerful imperialist. The weakest empires, whose colonies are joined to other empires, will be eliminated. The algorithm is converged to the global optimum when there is one empire [27]. The evolutionary operators of ICA are summarized as follows:

1. Assimilation operator: This operator updates the cost function of colonies by moving them to their corresponding imperialists.
2. Revolution operator: This operator updates the cost function of colonies by changing the elements of colonies. The goal of the revolution operator is to change some parameters of the individual in order to prevent the algorithm from falling into local suboptimal solutions
3. Exchange operator: It updates the position state of colonies and imperialists.
4. Competition operator: It updates the position of the colonies by picking it from one imperialist and joining it to another.

So far, the ICA has been applied for several benchmark optimization problems [27]. The results have shown that it has the ability to converge to the global minimum of problem quickly. Thus, it is interesting to define a method for channel assignment based on such an efficient optimization algorithm.

3.2.1 ICA-based Channel Assignment Algorithm

In order to apply ICA for the channel assignment problem, a new representation of an individual is suggested. It is referred to as grouping imperialist competition algorithm (GICA). In the GICA, an individual is divided into two parts which are defined as *province* and *resource*. Equation (14) describes this representation for the channel assignment problem.

$$\underbrace{f_2 f_3 f_1 f_3 f_1 f_2 f_1 f_1}_{\text{Province(Clusterheads)}} : \quad \underbrace{f_3 f_1 f_2}_{\text{Resource(FrequecyChannels)}} \tag{14}$$

When using ICA to solve the channel assignment problem in a cluster-based MANET, the province part contains information of assigned channels to the clusters and the resource part contains the permutation order of the available channels. The constraint of this problem is that the adjacent clusters should be assigned by different frequency channels. At initialization state, the channels of the resource part are assigned to the element of the province part, using a heuristic function to initiate feasible solutions. The evolutionary operators of GICA are applied on the resource part, and then the province part is re-assigned according to the available channels of the resource part. The assimilation and the revolution operators have been changed, while the exchange operator and competition operator are as similar as ICA. In GICA, for each empire, the weaker colonies that have lower power are selected to assimilate using the following procedure:

1. One element of the imperialist's resource part is randomly selected.
2. The selected element is injected as the first element of the colony's resource part.
3. The province part of the colony is overwritten by the new element according to the province part of its imperialist.
4. Because of the second and the third step, there are some elements of the resource part of the colony that lose their assignment. These elements are removed from the resource part.
5. Consequently, the province part should be reassigned using the remaining elements in the resource part to satisfy the constraints.
6. The steps two to five are repeated for each colony that is chosen to assimilate.

In GICA, the revolution operator has two levels:

1. First level: Colonies with the lowest power are selected and then some elements of their resource parts are removed.
2. Second level: Additional elements are added to the resource part of imperialists.

After each level, the province part is reassigned according to the available channels of the resource part. Due to this representation and its related operators, individuals of a population are not of the same length. As was discussed, GICA seeks a solution to assign the channels to the clusters in order to minimize the number of assigned channels. To avoid co-channel interference, i.e. adjacent clusters should be assigned by different channels. To solve the channel assignment problem with GICA, we suggest two objective functions: a single-objective and a multi-objective function. Assigning channels to clusters with regard to minimizing the total number of used channels, i.e. maximizing the spectral efficiency is considered as the single optimization problem. In GICA, a solution as $\mathbf{x}$ is an individual with two parts: the province part, $\mathbf{x}_P$, and the resource part, $\mathbf{x}_R$. The single objective function is defined as (15).

$$\mathrm{F}_{SOF}(x) = (|\mathbf{x}_R| - f_l) + \sum_{k=1}^{|\mathbf{x}_R|} g(\mathbf{x}_R, f_k)) \tag{15}$$

The parameter $|\mathbf{x}_R|$ is the number of available frequency channels and f_l is the minimum number of available channels. The number of elements in $\mathbf{x}_P$ that is allocated by f_k, the k th element of $\mathbf{x}_R$, is defined by $g(\mathbf{x}_P, f_k)$.

For multi-objective optimization, the 'objective function' [28] is defined as an exponential function according to (16). It aims at finding a solution for channel assignment for the purpose of maximizing the spectral efficiency and minimizing inter-cluster interference. The weights w_1, w_2 and w_3 are adjusted to0.3, 0.4 and 0.3 respectively.

$$F_{MOF} = \exp(-abs(\sum_{k=1}^{3} w_k F_k)) \tag{16}$$

The functions, F_1, F_2 and F_3 are defined according to equations (17), (18) and (19), respectively.

$$F_1(x) = \frac{(|\mathbf{x}_R| - f_l) + \sum_{k=1}^{|x_R|} g(|\mathbf{x}_R|, f_k))}{(|\mathbf{x}_P| \times f_u) + (|\mathbf{x}_R| - f_l)} \tag{17}$$

The second objective function, F_2, represents the number of elements of $\mathbf{x}_P$, i.e., number of clusters, that are assigned the same channel. It is calculated according to equation (18).

$$\mathrm{F}_2(\mathbf{x}) = \frac{\sum_{i=1}^{|x_P|} |I_{f\to i}|}{|\mathbf{x}_P|^2} \tag{18}$$

$$I_{f\to i} = \bigcup_{,j \neq i} \{ j | x_P(i) = x_P(j) \} \tag{19}$$

The parameter $|I_{f\to i}|$ is the cardinality of the set of clusters that have been assigned the same channel as i th cluster. The third objective function is given by (20), It represents the average level of inter-cluster interference.

$$\mathrm{F}_{3(x)} = \sum_{i=1}^{|x_P|} \frac{\mathrm{P}_i}{|x_P|} \times \hat{I}(x_P(i)) \tag{20}$$

$$\hat{I}(x_P(i)) = \frac{\sum_{j=1}^{|I_i|} \mathrm{D}_j^{\,-n}}{\sum_{j=1, j\neq i}^{|x_P|} \mathrm{D}_j^{\,-n}} \tag{21}$$

The average level of inter-cluster interference for i th cluster is calculated using (21). The numerator of $\hat{I}(x_P(i))$ is calculated for all clusters that are assigned the same channel as the i th cluster. In contrast, the denominator of $\hat{I}(x_P(i))$ is calculated for all clusters inside the network. Where D_j is the distance between the i th cluster head and the j th cluster head. The path loss exponent and transmission power of the i th node are shown by n and P_i respectively. In this paper, we assume that the path loss propagation exponent n is equal to 2.7.

4. SIMULATION RESULTS

The suggested algorithms are evaluated by several scenarios. The simulated models assume that *N* nodes are placed in an *m* x *m* meter square. The position of each individual node has coordinates, x and y . Each coordinate is drawn from a uniform distribution $[0,m]$. We use three factors: the average number of clusters, the load balancing factor [2] and the number of re-affiliations [6] to evaluate the performance of the ACO-based clustering algorithms. The load balancing factor defines a quantity to measure how the mobile nodes are distributed among the clusters. A well balanced clustered topology has a high value for the load balancing factor [2]. The 're-affiliation factor' [6] is a measure to show the stability of the clustered topology. This factor calculates the number of cluster members that gets disassociated from theirs clusters and are added to the other clusters.

4.1. Different Network Sizes

4.1.1. Small Sized MANETs

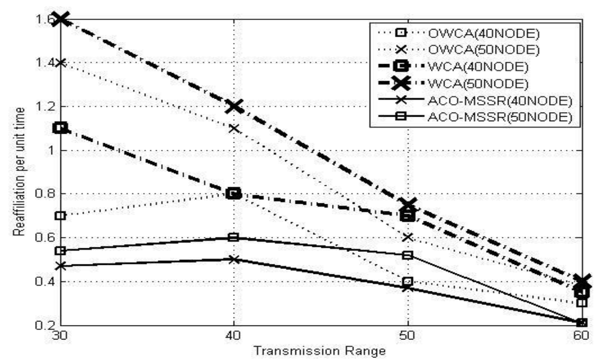
As the first experiment, the stability factor of ASO_MSSR is evaluated. The small sized MANETs, 30, 40 and 50 nodes are examined. The nodes are placed in a 100 x 100 meter square area using uniform distribution. The transmission range and the maximum speed of nodes are set to 30 meters and 5 meters per second respectively. The random walk model is assumed for the node mobility. The obtained results of these simulations are compared with the presented results in [6]. In this part, we follow the assumptions that have been taken in [6]. Table I lists the obtained results from applying ASO_MSSR, 'original WCA' and 'Optimized WCA' [6] to form clusters in terms of the number of clusters and the number of re-affiliations per unit time. It shows that increasing the number of nodes causes an increase in the number of re-affiliations. However, the clustered topology based on ASO_MSSR is more stable than the two previous methods. It can also be observed that by using ACO_MSSR to form clusters, there is no sharp rise in the number of re-affiliations, as the number of nodes increases.

The stability of ACO_MSSR based clustered MANETs is also evaluated for MANETs with two different sizes of nodes, 40 and 50 and different transmission ranges that varies from 30, 40, 50 and 60 meters. The number of re-affiliations for different clustered topologies (different transmission ranges) is depicted in Fig. 1. An obvious result is that the number of re-affiliations has a significant reduction when the transmission range is increased.

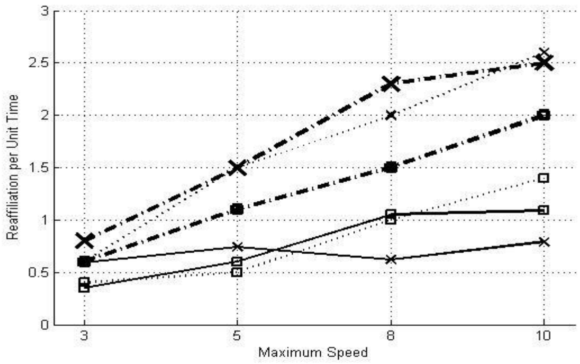
It can also be observed that a clustering scheme based on ASO_MSSR provides almost identical results for various transmissions ranges (see Fig. 1(a)). The stability of ASO_MSSR clustering algorithm is evaluated for different mobility: 3, 5, 8 and 10 meters per second. Figure 1.b depicted the number of re-affiliations that are obtained for different clustering schemes. It can be seen that as the maximum speed of nodes increases, the number of re-affiliations increases. However, the ASO_MSSR has a smaller number of re-affiliations in comparison with the two other methods. It should be noted the depicted values of 'original WCA' and 'Optimized WCA' are extracted from [6].

TABLE I. COMPARISON BETWEEN THREE CLUSTERING ALGORITHMS FOR MANETS WITH DIFFERENT SIZES OF NODES.

Method	Specification		
	No. of Nodes	***No. of Cluster***	***No .of Re-affiliation***
ACO_MSSR	30	7.3	0.21
	40	6	0.33
	50	7.6	0.4
Optimized WCA [6]	30	6.5	0.41
	40	7.3	0.8
	50	8.3	1.3
Original WCA[6]	30	7.8	0.8
	40	8.3	1.1
	50	8.5	1.8



(a)



(b)

Fig. 1. The number of re-affiliations per unit time for three clustering algorithms (a). Versus the transmission range, (b). Versus the maximum speed.

4.1.2. Medium Sized MANETs

In this experiment the load balancing factor (LBF) of three different clustering algorithms: ACO_MDS, ACO_MSR and LID are compared. For this purpose, MANETs with different sizes, 70, 100, 150, 200 and 250 nodes are investigated. The transmission range of the nodes varies from 100, 150 and 250 meters. The nodes are uniformly distributed in a 1000 x 1000 meter square area. The load balancing factor, LBF, versus number of nodes for the different clustering methods is depicted in Fig. 2. It shows that for all methods, the LBF decreases while increasing the size of the network (i.e. the number of nodes). However, using the LID, the LBF has a lower value than others and it becomes lower as the transmission range becomes larger. This means that the LID is not a well-balanced clustering algorithm. The LBF of ACO-based clustering algorithms are higher than LID, for all different transmission ranges. We can conclude that the two clustering schemes, ACO_MDS and ACO_MSR, create more balanced topologies than others. For a network that has 100 nodes with transmission range 200 meters, the ACO_MSR shows better performance than other methods in terms of load balancing factor. The reason is that it provides a large number of clusters, i.e. 15 clusters; thus it has the ability to uniformly partition the network.

Figure 3 indicates that the number of clusters becomes smaller by incresing the transmission range (comapres solid lines and dotted lines in Fig. 3). By increasing the transmission range, the degradation of the number of clusters in the LID is more significant than for the other methods (see red solid line and dotted line in Fig. 3). It is noticable that the number of clusters which is formed by ACO_MSR are almost similar for all different transmission ranges and numberof nodes (see black lines in Fig. 3).

4.1.3. Large Sized MANETs

Here the suggested clustering algorithms are evaluated in terms of the number of clusters formed for different number of nodes: 100, 200, 300 and 400. The nodes are uniformly distributed in a 1000 x 1000 meter square area. The transmission range of nodes is fixed and set to 250 meters. The LID and the three ACO-based clustering algorithms are examined to form the clustered network topology. Table II presents the obtained results from LID, ACO-based clustering algorithms and the proposed methods in [5]; it lists the number of cluster heads and the characteristics of the compared methods. Table II indicates that a clustered topology network based on ACO has a smaller number of clusters for the networks with 300 to and 400 nodes than the number of clusters using WCA.

4.2 MANETs with Different Size of Clusters

In this section, the channel assignment in cluster-based MANETs with sizes is investigated. The nodes are uniformly distributed in a 1000 x 1000 meter square area. The transmission ranges of nodes are set to 250 meters. The ICA-based scheme is applied as a cluster-based channel assignment method. The bar charts in Fig. 4 show the numbers of channels that are allocated to the different clustered topologies. The number of required channels is dependent upon the number of clusters. However, for the topologies with similar number of clusters, the average number of assigned channels by the multi-objective ICA is smaller than for the single-objective ICA (see Fig. 4). Fig. 4(a) also shows that by using the multi-objective ICA and the ACO_MSR algorithm, the smallest number of channels is achieved.

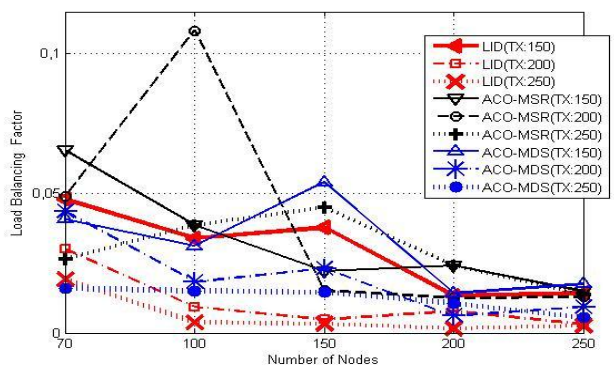


Fig. 2. The obtained LBF of different clustering methods in MANETs with the different numbers of nodes.

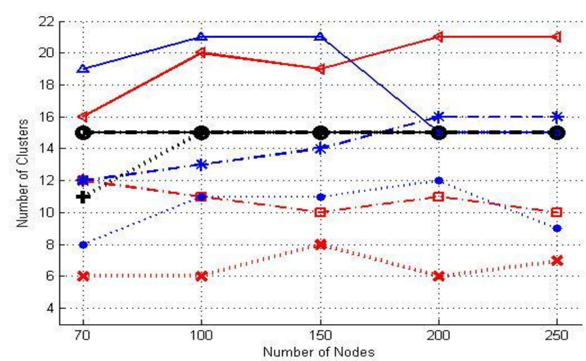
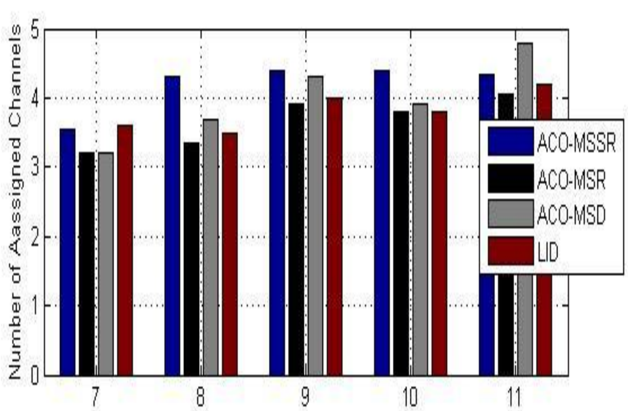


Fig. 3. The number of cluster heads that are selected by the different clustering methods for MANETs with the different numbers of nodes (the legends are similar to Fig. 2.).

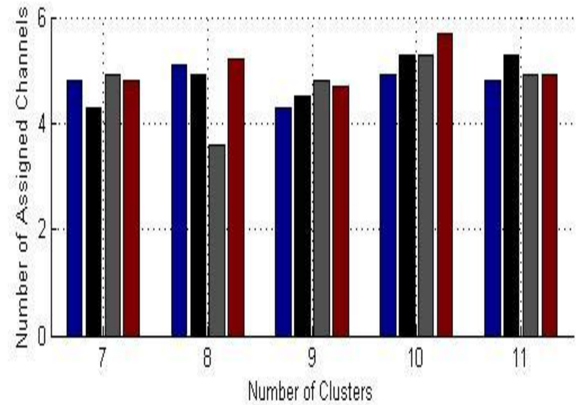
TABLE II. COMPARISON BETWEEN FOUR CLUSTERING ALGORITHMS FOR MANETS WITH DIFFERENT SIZES OF NODES.

Method	**Characteristic**		
	No. of Ants and Iterations	***No. of Nodes***	***No. of Cluster***
ACO_MSD: One Objective	7,50	100	10.75
	7,70	200	11.45
	12,100	300	11.05
	15,150	400	12.5
ACO_MSR: Two Objective	7,50	100	11.8
	7,70	200	14.3
	15,100	300	14.9
	15,150	400	15
LID	----	100	6
	----	200	6
	----	300	8
	----	400	8
ACO_MSSR: Two Objective	4,15	100	13
	4,15	200	13
	4,10	300	13
	4,10	400	13
WCA- based ACO[5]	----	100	5
	----	200	10
	----	300	15
	----	400	20

The average of inter-cluster interference that is obtained using ICA-based channel assignment schemes is depicted in Fig.5. Figure 5(a) shows that using all ACO-based clustering algorithms, the average of inter-cluster interference monotonically increases with increasing number of clusters. However, the obtained results from combining ACO_MSSR and ICA show that the interference level increases very slowly (solid line in Fig. 5(a)). Indeed, assigning channels by the single-objective ICA causes a significant reduction in the level of inter-cluster interference power (see Fig. 5(b)). For single objective function, ACO_MSD has the lowest value of interference power. The combination of single-objective GICA with ACO_MSD is a desirable channel assignment scheme to maximize the spectrum efficiency (see grey bar in Fig. 4 (b)). Moreover, using this method, the increase in the number of used channels is slow when the size of the network (number of clusters) increases. It indicates that this method might be a scalable and feasible method for a large sized MANET (from the perspective of number of clusters).

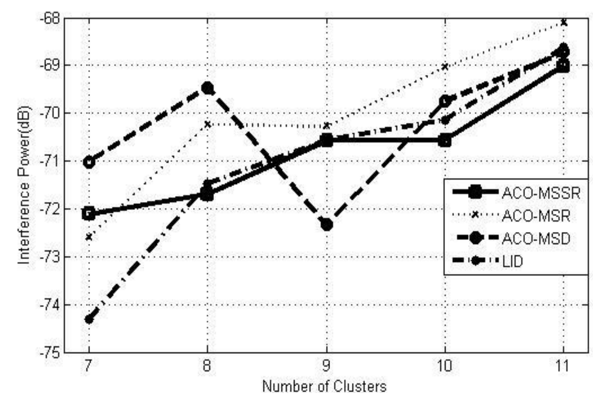


(a)

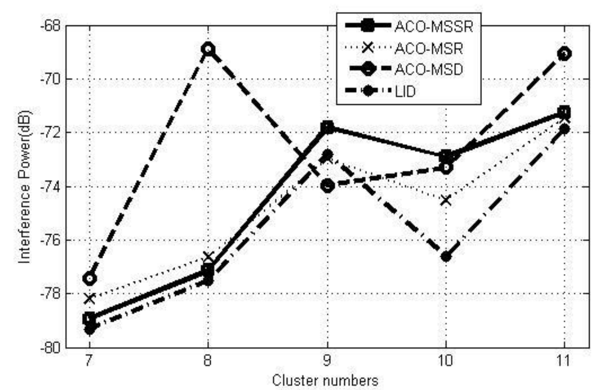


(b)

Fig. 4. The number of assigned channels to the MANETs with different numbers of clusters; The MANETs are clustered using the different clustering algorithms. (a) The number of assigned channels using the multi-objective ICA. (b) The number of assigned channels using the single-objective ICA.



(a)



(b)

Fig. 5. The averages of inter-cluster interference (a). Multi objective-algorithm based on ICA is used as channel assignment method. (b). Single-objective algorithm based on ICA is used as channel assignment method.

5. CONCLUSION

This paper presents evolutionary-based algorithms for optimization problems in spectrum management. We have proposed three ACO-based clustering algorithms for forming clusters and one ICA-based channel assignment scheme. Different multi-objective functions are investigated to solve the underlying multi-objective optimization problems of spectrum management. We aim to merge ACO and ICA schemes to present a feasible hybrid method for cluster formation in conjunction with the channel assignment.

The suggested methods are examined for several scenarios and their performances are compared with previous studies. Among the suggested ACO-based clustering algorithms, ACO_MSSR and ACO_MSR are more capable to create a scalable and stable clustered network structure. The obtained results indicate that ACO_MSSR finds better approximations of Pareto solutions in terms of minimizing the number of clusters, inter-cluster interference, maximizing stability and spectrum efficiency. The ACO_MSSR and the ACO_MSR, also contribute in forming interference aware clusters. The merging of ICA with ACO-based clustering algorithms improves the spectrum efficiency and minimizes the average level of inter-cluster interference inside the network.

The definition of a distributed method on the basis of the proposed centralized algorithm is considered as future work. Due to the reasonable performance of ICA, ICA-based clustering algorithms will also be suggested for cluster formation.

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