2014 IEEE 28th International Conference on Advanced Information Networking and Applications

An Imperialist Competitive Algorithm For Interference-Aware Cluster-heads Selection in Ad hoc Networks

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***Abstract*—This paper presents the results of applying a new clustering algorithm in ad hoc networks. This algorithm is a centralized method and it is designed on the basis of an imperialist competitive algorithm (ICA). This algorithm aims to find a minimum number of cluster-heads while satisfying two constraints, connectivity and interference. This work is a part of an ongoing research to develop a distributed interference aware cluster-based channel allocation method. The results of the centralized method are required to provide an ideal case when investigating the performance of the distributed version. The suggested method is evaluated for several scenarios and compares the obtained results with the reported results of ant colony optimization-based methods.**

Keywords— Ad Hoc Network, Cluster Formation; Imperialist Competitive Algorithm.

I. INTRODUCTION

In an ad hoc network, the formation of a clustered network topology plays a crucial role to effectively utilize the resources and improve the network performance. In other words, a well-organized scalable network structure increases the efficiency of routing algorithms, power control mechanisms and spectrum management methods [1]-[4]. Various clustering algorithms have been developed to form an optimal clustered network structure. They mostly aim at improving network performance in terms of scalability, stability and communication control overheads. Thus, forming a stable clustered topology with a small number of clusters is a desirable way to reduce communication control overheads [1]-[8]. Using a graph theoretic approach to solve this problem and selecting a set of nodes to take the role as cluster heads has been defined as an equivalent to finding a dominating set in the corresponding graph [1]-[3], [8]. This problem has been proved as an NP-hard problem that can be effectively solved by applying meta-heuristic algorithms such as genetic algorithms (GAs), ant colony optimization (ACO) and imperialist competitive algorithm. methods [8]-[15].

Forming clusters with a minimum number of clusters has been investigated by genetic algorithm and ant colony optimization [10],[12]-[17]. However, forming a clustered structure that provides maximization in spectrum efficiency has not been sufficiently examined by the meta-heuristic methods. Thus, the main idea of this paper is to evaluate the use of a meta-heuristic method to form a clustered network structure to minimize the communication overheads and maximize spectrum efficiency. The suggested algorithm aims to provide an efficient method to find a near optimal solution for this problem.

The main contribution of this paper is to present a discrete version of the standard ICA as an applicable optimization method in the context of ad hoc networks. Thus, the suggested algorithm can be used for other combinatorial optimization problems e.g., rate, bandwidth allocation, , traffic scheduling, and multi-channel MAC scheme [18]-[19]. In addition, the obtained results can be compared with a new inspired optimization algorithm that will be suggested based on our pervious work related to brain emotional learning [20]-[22]. suggested algorithm can be part of a joint clustering and channel assignment algorithm in ad hoc networks. The suggested method can be applied to develop an ICA-based cognitive engine to solve optimization problems in cognitive radio ad hoc networks. Finally, the obtained results can be used to provide an upper level to evaluate the performance of the distributed method of ICA for the distributed interference aware cluster-based channel allocation method.

The rest of this paper is organized as follows: Section II, describes a review of related works in cluster formation. In Section III, the problem is described. The imperialist competitive algorithm (ICA) is illustrated in Section IV. The numerical studies and the results of simulation are presented in Section V. In Section VI, this paper concludes with some final notes.

II. RELATED STUDIES IN CLUSTER FORMATION

A clustering algorithm partitions the network into a set of connected clusters covering all nodes in the ad hoc network. A common clustered network topology encompasses three types of nodes: *cluster head, gateway* and *ordinary nodes* (see Fig. 1). The cluster head, the master of a cluster, is responsible for coordinating the intra- cluster communication [8]. The gateway, which is a common node between two or more clusters, provides the connectivity between the clusters. Other nodes are ordinary nodes that determine the boundary of clusters, which is dependent on the transmission range and the density of the nodes [2],[3].

In an ad hoc network, a clustered structure causes an increase in the manageability and scalability of the network; thus, numerous clustering algorithms have been developed to

1550-445X/14 $31.00 © 2014 IEEE
DOI 10.1109/AINA.2014.12

provide clustered structure networks. Simple clustering methods are 'identity based clustering' algorithms [1]-[4] (e.g. Lowest-ID and Max-min d-cluster algorithms), which select the cluster heads on the basis of the node identities. These algorithms aim at reducing the control communication overheads in the network and maximizing the stability of the clusters in terms of prolonging the lifetime of cluster heads [2],[3].

Another simple clustering algorithm is the highest connectivity clustering (HCC) algorithm, which is a type of 'connectivity-based clustering' algorithm [1]-[4]. The HCC has a similar objective as Lowest-ID; however, it uses the nodes' degree to form the clusters [1]-[4]. Other instances of connectivity-based clustering algorithms have objectives to satisfy the load balancing constraints or minimize the number of cluster heads [1]-[4]. Clustering algorithms that form the clusters by using the mobility metric (e.g. mobility based metric for clustering (MOBIC)), are referred to as mobility-aware clustering methods [1]-[4]. The main objective of these algorithms is to stabilize the intra-cluster connections or minimize the rate of re-affiliations [1]-[4].

Another clustering method is the combined–weight based clustering method. In this 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 algorithms. An example is the weighted clustering algorithm (WCA) that defines four metrics: degree, mobility, transmission power and battery power to select the cluster heads. The aim of this method is to minimize the number of clusters and the control communication overheads. In addition to the mentioned clustering algorithms, other algorithms such as power-aware, load balanced clustering and low cost of maintenance clustering algorithms have also been proposed [1]-[4]. They have shown the capability to provide an energy-efficient, well load balanced, scalable and stable hierarchical structure with a low control communication overhead [[3]. Most clustering algorithms have concentrated on selecting suitable nodes as the cluster heads and satisfying the connectivity of the clustered structure that are two main factors in maximizing the life time of a network.

In addition to the above methods, meta-heuristic algorithms e.g., genetic algorithms (GAs), and ant colony optimization methods have also been examined to form the clustered structure [10]-[17]. Good examples are GA-based algorithms that have been applied to modify the performance of a weighted clustering algorithm (WCA). In [10], the suggested algorithm forms a clustered topology with a minimum number of clusters while maximizing the connectivity. In [11], a distributed genetic-based algorithm has been proposed to improve the performance of WCA in selecting cluster heads, using the local information. Generally, in comparison with the centralized clustering schemes, the distributed clustering methods, especially GA-based methods, have proven to be efficient methods in terms of control communication overheads.

Other efficient schemes for clustering are based on ACO and often are modifications of weighted-combined algorithm (WCA) [12]-[14]. ACO-based clustering algorithms have also shown good results in forming clustered structures with maximizing the stability and throughput of networks. In [12], a probability function is calculated for each node. The probability is defined on the basis of two metrics, the degree and pheromone intensity and estimates the desirability of the node to be a cluster head. Testing this method for different sizes of networks has 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 has defined a new metrics 'computing power' [13] to improve the performance of WCA. The algorithm forms the clusters to maximize the throughput, load balancing and stability while minimizing the delay. Another type of ACO-base clustering algorithm is referred to as 'CAACO' that stands for Clustering Algorithm based on Ant Colony Optimization [14]. It uses a metric for the level of pheromone intensity of each node and a probability function is defined on the basis of this metric. A node with the highest probability is selected as a cluster head. The CAACO tries to reduce the control communication overheads as well as maximize the scalability and inter-cluster stability.

As previously mentioned, the majority of efforts made to form clustered structures have aimed to minimize the number of clusters. However, the idea of forming clusters to optimize the spectrum utilization by minimizing the number of interfering cluster heads has not been sufficiently studied. The fact is, that selecting a lower number of nodes as the cluster heads while optimizing the distance between the cluster heads causes a maximization of the spectrum efficiency. It should be noted that the cluster formation is not the final solution for maximizing the spectrum efficiency; a suitable channel assignment method can provide a significant increase in spectrum utilization.

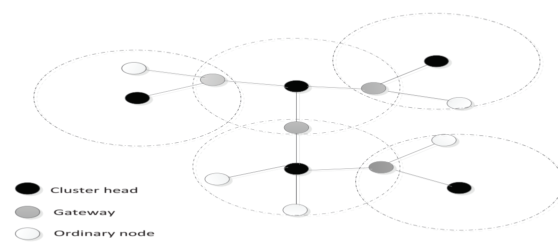

Fig. 1. A Clustered Structure.

III. PROBLEM FORMULATION

As was earlier discussed, this work presents preliminary results from an ongoing research applying ICA-based methods to solve optimization problems in cognitive radio ad hoc networks; thus, the formulation of this work is theoretical rather than practical. Graph-theoretic approaches have been used to solve the cluster formation problems; an ad hoc network can be represented by a connected unidirectional graph as $\mathcal{G}=(\mathcal{V},\mathcal{E})$. The set of the nodes and the set of the communication links are represented by $\mathcal{V}$ and $\mathcal{E}$, respectively. There is a communication link between each two nodes which are within transmission range of each other. Fig. 2 represents the communication graph, $\mathcal{G}$. The wireless nodes are shown by the circular nodes and each edge represents a possible communication link, i.e., two nodes are within transmission range of each other.

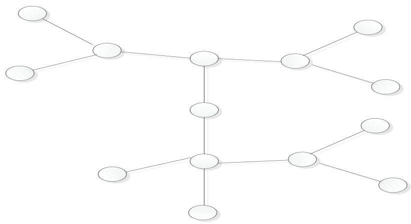

Fig. 2. A communication graph of the ad hoc network with 10 nodes

Using the above representation of an ad hoc network, the problem of cluster head selection is equivalent to finding a dominant set, $\mathcal{D}$, of a graph $\mathcal{G}$. The dominant set, $\mathcal{D}$, is a subset of the graph's nodes, $\mathcal{V}$, such that $\bigcup_{\mathcal{D}\in\mathcal{D}} \mathcal{N}(\mathcal{D})=\mathcal{V}$, where $\mathcal{N}(\mathcal{D})$ is the set of neighbors of $\mathcal{D}$ that is defined as equation (1).

$$\mathcal{N}(\mathcal{D})=\mathcal{D}\cup\{j\in\mathcal{V}|(i,j)\in\mathcal{E} \text{ and } i\in\mathcal{D}\} \tag{1}$$

The problem of cluster head selection can be represented as finding a minimum connected dominating set in $\mathcal{G}$. A dominating set can be defined as a set $\mathcal{D}\subseteq\mathcal{V}$ such that $\mathcal{N}(\mathcal{D})=\mathcal{D}\cup\{j\in\mathcal{V}|(i,j)\in\mathcal{E} \text{ and } i\in\mathcal{D}\}$. The minimum dominating set problem is defined as 'finding a dominating set of minimum cardinality' [23]. The minimum connected dominating set is defined as a dominating set $\mathcal{D}$ such that the sub graph $\mathcal{G}(\mathcal{D})=(\mathcal{D},\mathrm{E}(\mathcal{D}))$ is connected, where $\mathrm{E}(\mathcal{D})=\{\{i,j\}\in\mathrm{E}|i\in\mathcal{D} j\in\mathcal{D}\}$ [21]. The objective function can be formulated as equation (2) where x_j is a binary variable. If $x_j=1$ the j^{th} node has been selected as a cluster head, otherwise $x_j=0$.

$$\mathbf{x}^*=\arg\min_{x_j\in\ 0,1}\sum_{j\in\mathcal{V}}x_j \tag{2}$$

$$\sum_{\substack{j\in\mathcal{N}(\ i\ )\\ i\in\mathcal{V}}}x_j\geq 1 \tag{3}$$

$$connected(x) \tag{4}$$

Equation (2) find a minimum connected dominating set; while Equation (3) defines that the solution should be a dominating set. Equation (4) defines the connectivity condition of each minimum dominating set. In order to satisfy the connectivity constraint; it is clear that two selected cluster should have one common node as their neighbors. Equation (5) formulates this expression.

$$\mathcal{N}(i)\cap\mathcal{N}(j)\geq 1\ \forall i,j\in\mathcal{V} \text{ and } x_i=1,x_j=1 \tag{5}$$

$$\mathrm{int}\, erfernce(x) \tag{6}$$

Equation (6) satisfies the interference constraint. The interference model in this paper is a disk-shaped interference model that has been derived on the basis of the interference range of the wireless node. If each two cluster heads are within the interference range of each other, the minimum dominating set suffers from a potential interference. The interference constraint emphasizes that the selected cluster heads should not be within similar interference range. The interference constraint could be formulated using equation (7), where y_{ij} is a binary variable. If two nodes are within similar interference range in $\mathcal{G}$, $y_{ij}=1$, otherwise $y_{ij}=0$.

$$\sum_{\substack{i=1,j=1,i\neq j\\ x_j=1\ ,x_j=1}}^{|\mathcal{V}|}y_{ij}=0\quad\forall i,j\in\mathcal{V} \tag{7}$$

As was mentioned earlier, the clustering algorithm provides a clustered structure to maximize spectral efficiency. In order to evaluate the suggested method in terms of spectral utilization, a channel allocation scheme is used to assign channels to the cluster heads maximizing spatial reuse. This algorithm has just considered an inter-cluster communication and has ignored the intra-cluster communication. In order to formulate the channel assignment problem, let us assume that the ICA-based clustering algorithm has formed a clustered ad hoc network with a set of cluster heads as $\{C_1,...,C_{N_{cluster}}\}$ where $N_{cluster}$ is the number of clusters. There is a set of available channels as $\{ch_1,...,ch_{N_{Available\_ch}}\}$ where $N_{Available\_ch}$ is the number of available channels. Another graph as $\overline{\mathcal{G}}=(\overline{\mathcal{V}},\overline{\mathcal{E}})$ is defined; the nodes of this graph are $\overline{\mathcal{V}}$ and represent the cluster heads; the links of $\overline{\mathcal{G}}$ are $\overline{\mathcal{E}}$. Each link indicate that two cluster heads are neighbors. The neighbor relationship is defined as equation (5); considering that two nodes i and j are cluster heads.

A channel allocation scheme can be represented as an $N_{Available\_ch}\times N_{cluster}$ matrix, Z; where $z_{pq}=0$ or 1. If p^{th} channel, ch_p, is assigned to q^{th} cluster, C_q, then $z_{pq}=1$ otherwise it is 0. The optimization functions can be formulated according to equation (8); an optimal solution minimizes the number of used channels.

$$\min\sum_{p=1}^{N_{Availabel\_ch}}\sum_{q=1}^{N_{cluster}}z_{pq} \tag{8}$$

The ICA-based method can be applied to assign channels to the cluster heads to maximize spectral efficiency while avoiding co-channel interference. The detail of this method has been explained in [24]. Four performance measurement factors have been defined as follows:

- The connectivity factor is defined as equation (9).

$$\sum_{i,j\in\mathcal{V}\ \text{and}\ x_i=1,x_j=1} \mathcal{N}(i)\cap\mathcal{N}(j) \Bigg/ \sum_{i\in\mathcal{V}} x_j \tag{9}$$

- The interference factor is defined as the ratio of the cluster heads that are within a similar interference range to the number of clusters, equation (10).

$$\sum_{\substack{i=1,j=1,i\neq j\\ x_j=1,x_j=1}}^{|\mathcal{V}|} y_{ij}=0 \Bigg/ \sum_{i\in\mathcal{V}} x_j \tag{10}$$

- The load balancing factor calculates as equation (11) and 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. Here μ is calculated as $\mu=(N_{network-size}-N_{cluster})/N_{cluster}$.

$$\sum_{j=1}^{|\mathcal{V}|} x_j \Bigg/ \sum_{i=1,\bar{x}_i=1}^{|\mathcal{V}|} (|\mathcal{N}(\mathrm{i})|-\mu) \tag{11}$$

- The channel reuse efficiency is determined as the ratio of the number of cluster heads to the number of the used channels.

IV. IMPERIALIST COMPETITIVE ALGORITHM

The Imperialist Competitive Algorithm (ICA) inspired by the social behavior of humans [25] is a type of evolutionary optimization method (i.e., genetic algorithm). In ICA, each individual i.e., each solution is represented as a '*country*' [25]. Each country is a vector of optimization parameters, a_i s as equation (12). Where $N_{parameters}$ indicates the number of optimization parameters.

$$country = \; a_1,...,a_{N_{parameters}} \tag{12}$$

The initial population of ICA is a set of countries. A cost function is defined on the basis of the objective function is used to evaluate each country. The population is classified into two groups: the colonies and the imperialists according to the values of power. Equation (13) calculates the power, p_i , on the basis of the cost function. Countries with higher power, higher value of p_i , are considered as the imperialists; while the countries with the lower power are grouped as the colonies.

$$p_i=\left|\frac{Normalized\_Cost_i}{\sum_{i=1}^{N_{pop}} Normalized\_Cost_i}\right| \tag{13}$$

TABLE I. DESCRIPTION OF THE NOTATIONS AND THEIR CORRESPONDING VALUES

Notations	Description		
	Definition	***Algorithm's Graph***	***Formulation's Graph***
$\mathcal{G}$	Commuincation graph of ad hoc network $(\mathcal{V},\mathcal{E})$	no	yes
$\bar{\mathcal{G}}$	Communication graph of clustered ad hoc network $(\bar{\mathcal{V}},\bar{\mathcal{E}})$	no	yes

For the minimization problem, the normalized cost function, $Normalized\_Cost_i$, can be defined as equation (14). Here $\cos t_i$ is the value of the objective function for the country.

$$Normalized\_Cost_i=\cos t_i-\min(\mathbf{COST}) \tag{14}$$

The parameter **COST** is a set of cost functions of all countries, defined as equation (15), where N_{pop} denotes the total number of countries in the population.

$$\mathbf{COST}= \; \cos t_1...,\cos t_i,...\cos t_{N_{pop}} \tag{15}$$

One of the first steps in ICA is forming the empires that are created by the imperialists. They start to take possession of the colonies with the lower power [23]. Then, the evolutionary operators, assimilation operator, revolution operator, exchange operator and competition operator are applied to search for a good solution. They can be summarized as follows:

a) Assimilation operator: This operator is applied to change the parameters of each colony by assimilating it to the corresponding imperialists.

b) Revolution operator: This operator is applied to change the parameters of the imperialists or colonies. It updates the cost function of colonies by changing the parameters of colonies. The aim of the revolution operator is to change some parameters of the individual to prevent the algorithm from falling into local suboptimal solutions. If a colony reaches to a higher power than its corresponding imperialist, the position of the colony and its imperialist must be exchanged.

c) Exchange operator: This operator is applied to update the position state of imperialists and exchanges its position with a colony that has a higher power.

d) Competition operator: This operator is applied to update the position of the colonies by picking it from one imperialist and joining it to another imperialist. 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 [25]. The standard version of ICA has shown an excellent convergence characteristic for solving continuous optimization problems [25]. Thus, it is also interesting to develop a combinatorial optimization method based on such an efficient optimization algorithm.

V. IMPERIALIST COMPETITIVE ALGORITHM FOR COMBINATORIAL OPTIMIZATION PROBLEMS

In order to apply ICA for combinatorial optimization problem, two new terms: *province and resource* are defined. The province is the main component of each country and can simply be encoded by integer representation. The resource part is not a mandatory part; it can also be encoded by an integer number. In the ICA-based combinatorial optimization method, countries have different length; each country is assigned a random number, m , that represents the number of provinces of this country. The evolutionary operators (e.g., assimilation and revolution operators) are redefined to be applicable for discrete representation. The characteristics of ICA as a cluster head selection algorithm can be explained as follows.

a) Encoding and Initialization of Popualtion:

Let us assume that the cluster formation problem has been proposed in an ad hoc network with $N_{network-size}$ nodes that have assigned unique IDs. In order to encode this problem, the solution must be represented by the integer numbers that determine the nodes' IDs as equation (16).

$$country = \underbrace{n_i, n_j, ..., n_k}_{\text{Pr}ovince(Clusterhead)} \tag{16}$$

The parameters i, j, k are numbers between 1 and $N_{network-size}$. The node's identity of i^{th} node is represented by n_i . As was mentioned earlier, the lengths of countries in population are different from each other. For each country, the number of provinces is chosen from a uniform distribution as $U(0, N_{\max-clusterhead})$. This means that the number of clusters that can be formed by each individual is determined randomly. The maximum number of clusters, $N_{\max-clusterhead}$, is dependent upon the size of the ad hoc network and the transmission range of the wireless nodes.

In order to encode a country, first, the nodes are sorted according to their degrees. The degree of each node, d_i, is calculated as equation (17) and denotes the number of neighbors of that node. Then, the m nodes with the highest degree are chosen and the country is created using their node identities.

$$d_i = |\mathcal{N}(\mathrm{i})| \quad \mathrm{i} \in \mathcal{V} \tag{17}$$

b) Cost Function:

A multi-objective function as equation (18) is defined; it is defined as a weighted combination of equations (2), (3), (4) and (6).

$$\frac{1}{|\mathcal{V}|}\sum_{j=1}^{|\mathcal{V}|} x_j + \frac{1}{\sum\limits_{\substack{i=1,j=1\\x_i=1,x_j=1}}^{|\mathcal{V}|} |\mathcal{N}(\mathrm{i}) \cap \mathcal{N}(\mathrm{j})|} + \frac{1}{|\mathcal{V}|}\sum_{\substack{i=1,j=1\\x_i=1,x_j=1}}^{|\mathcal{V}|} y_{ij} \tag{18}$$

c) Evaluationary Operators:

For the ICA-based clustering algorithm, the assimilation and revolution operators are redefined. The assimilation operator replaces the worst node's identity of the assimilated colony with the best node's identity of its corresponding imperialist. Three policies are defined to determine the worst node's identity and the best node's identity as follows:¨

- The worst node's identity is related to the node with the lowest number of the neighbors. In contrast, the best node's identity is related to the node with the highest number of neighbors.
- The worst node's identity is related to the node with the lowest value of connectivity factor; in contrast, the best node's identity is related to the node with the highest value of connectivity factor. The connectivity factor is explained in detail in the next Section.
- The worst node's identity is related to the node with the highest number of interference factor. The best node's identity is related to the node with the lowest number of interference factor. The number of potential interfering nodes is explained in the next Section.

In the ICA-based clustering algorithm, the revelation operator removes the worst node's identity from the imperialist with the lowest power.

VI. SIMULATION RESULTS

We have simulated several scenarios of ad hoc networks taking the following assumptions:

- The allocated channels are orthogonal channels that can be exclusively used by each cluster head for intra cluster scheduling. We have omitted to explain how an intra-cluster communication can be managed and only considered the channel allocation to the demands for inter-cluster communication.
- No models for transmission activity and nodes' mobility have been considered.
- Each node has an omni-directional antenna. Each node has a disc-shape communication area and a disc-shape interference area.
- All of the nodes use similar transmission power, which is unchanged during the cluster formation and channel allocation procedure.
- To maximize the spectrum utilization, the same channels can be assigned to the cluster heads that are sufficiently far from each other (i.e., spatial channel reuse).

MATLAB is used to simulate different scenarios of ad hoc networks (each scenario is simulated 20 times) in order to evaluate the suggested method in terms of the load balancing factor, the connectivity, the number of potential interfering cluster heads and channel reuse efficiency. Moreover, we have considered the ICA-based method with two objective functions; the first one has been a single objective function and has been defined to find a solution with a minimum number of clusters; in contrast the second one has been a multi-objective function to seek a clustered structure with a minimum number of clusters thereby satisfying two constraints, which are connectivity and interference.

As the first experiment, networks with: 100, 200, 300 and 400 nodes are considered. The nodes are uniformly distributed in a 1000 times 1000 meters square area. The transmission range and interference range of each node are fixed and set to 250 and 500 meters, respectively. It should be noted that the aim of this experiment is to provide comparable results with other studies.

Table II lists the obtained results from different clustering algorithms such as the ICA-based algorithm, the Lowest-ID and the ACO-based algorithm that have been applied to form clusters. The results from a modified version of the weighted clustering algorithm that has been presented in [12] are also mentioned in Table II. It can be observed that a clustered topology network based on the ICA has a smaller number of clusters than the other methods. Thus, an ICA-based clustering algorithm can significantly reduce the communication control overheads. The convergence characteristics of the ICA-based algorithm for the single-objective and multi-objective functions are investigated in Fig. 3.

The curves of the minimum and mean values of the objective functions indicated that the multi-objective function is converging quicker than the single-objective function. Using the multi-objective function, the ICA-based algorithm is converging after 30 iterations; however, the curve of minimum value of the single-objective function is converging after 80 iterations.

The result of the performance factors have been depicted in Fig.4. As the graph in Fig.4(a) shows, an increase in the number of nodes causes a decrease in the load balancing factor for all clustering methods. Using a single-objective function, both ICA and ACO methods have similar values for load balancing factors; however, the ACO-based clustering algorithm has a slightly better value for the load balancing factor. Using the multi-objective function, the ACO method has higher values of load balancing factor than the ICA-based method (compare the dashed line and solid line). The values of the connectivity factor are given in the graph in Fig.4(b); it shows that the connectivity factor increases as the number of nodes rises.

It is noticeable that using the ACO-based method, the values of the connectivity factor are similar for single-objective and multi-objective functions. However, using the ICA-based methods the obtained results for the connectivity factor from the single-objective clustering algorithm are higher than the corresponding values of the multi-objective algorithm. It can be concluded that using the single objective function, the ICA-based clustering algorithm has the capability to form a connected clustered structure with a minimum number of clusters; however, it would not be able to minimize the number of potential interfering nodes (see Fig. 4 (c)). In contrast, using a multi-objective function, the ICA-based method has the ability to provide a connected clustered topology with a minimum number of the cluster heads and a minimum number of potential interfering nodes.

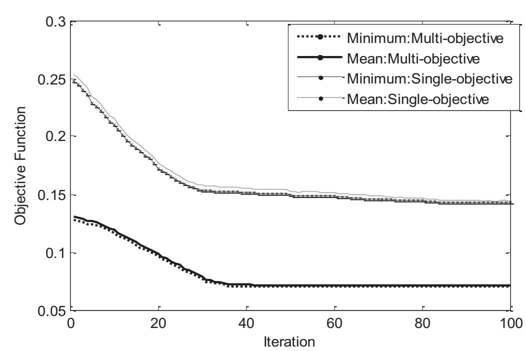

Fig. 3. The minimum and the average values of the objective functions versus the iterations.

The convergence behavior of the interference factor versus the iterations is given in Fig.5. The curves show that using a single-objective function, the number of interfering cluster heads increases during the iterations. The reason for the increase is that the single-objective function has no goal to minimize interference; however, using the multi-objective function of the ICA-based method causes a decrease in the number of interfering cluster heads. It can be concluded that the clustered structure that is formed by using a multi-objective function can satisfy the interference constraint.

TABLE II. COMPARISON BETWEEN DIFFERENT CLUSTERING ALGORITHMS

Method	Characteristic			
	Algorithm Specification		***No. of Nodes***	***No. of Cluster***
	No.of Population	***No.of Iteration***		
ACO: Single-objective [16]	7	50	100	12.8
	7	70	200	11.85
	12	100	300	12.45
	12	150	400	13.3
ACO: Multi-objective [16]	7	50	100	13.10
	7	70	200	14.4
	15	100	300	15
	15	150	400	14.95
Lowest-ID	--	--	100	5
	--	--	200	6
	--	--	300	8
	--	--	400	9
ICA: Single-objective	33	100	100	7
	67	100	200	8
	50	100	300	13
	40	100	400	15
ICA: Multi-objective	33	100	100	7.3
	67	100	200	8.25
	50	100	300	14
	40	100	400	16
WCA- based ACO[12]	--	--	100	5
	--	--	200	10
	--	--	300	15
	--	--	400	20

It should be noted that the depicted curves of the values of the interference factor are related to a worst case when one channel is assigned to all of the cluster heads. There is a significant decrease in the number of interfering cluster heads (i.e. the interference factor) when a channel assignment method is used.

Using the ICA-based clustering method can improve the spectrum efficiency while minimizing the average interference power in a network. This case has been investigated by utilizing an ICA-based channel assignment model for an ad hoc network with 100 nodes and 30 clusters. Figure 6 shows the obtained interference power from using the channel assignment method with the objective function to minimize the number of used channels. It shows that applying a multi-objective ICA-based method to select the cluster heads causes a significant decrease in the interference power in the network.

It should be noted that the obtained values for the interference factor for formed clustered structure by multi-objective of ICA is equal to 0.043. In contrast, this value in the clustered structure by single-objective ICA is 0.2023 that is a large value in comparison with the previous value. The interesting point is that the values of the channel reuse efficiency factor for the multi-objective of ICA and the single-objective ICA are equal to 2.457 and 2.456, respectively.

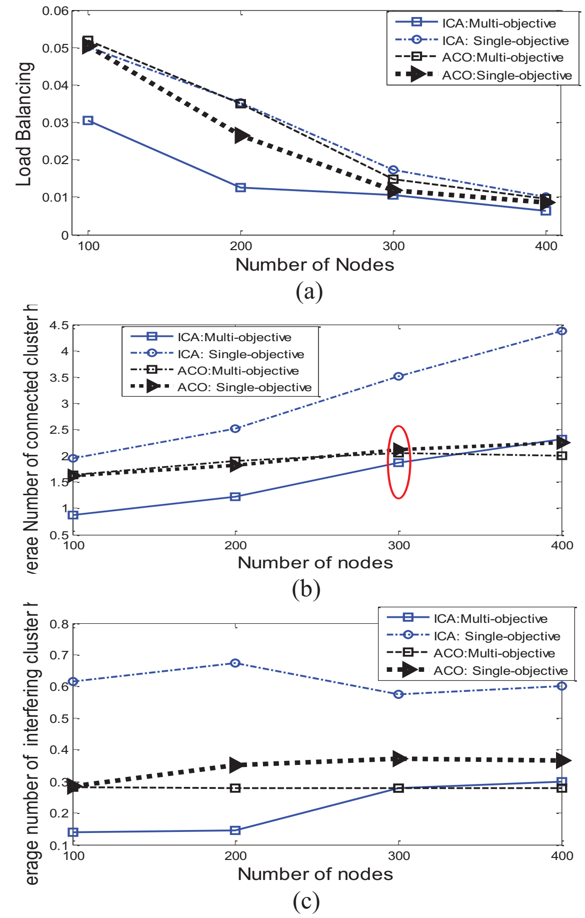

Fig. 4. The curves of different performance measures for ICA-based clustering algorithms and ACO-based clustering algorithms. (a). the load balancing factor. (b). the connectivity factor. (c). the interference factor.

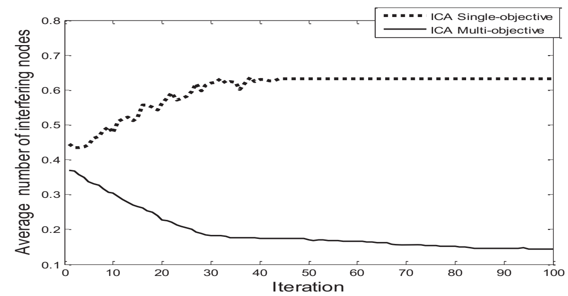

Fig. 5. The average number of interfering nodes versus the iterations.

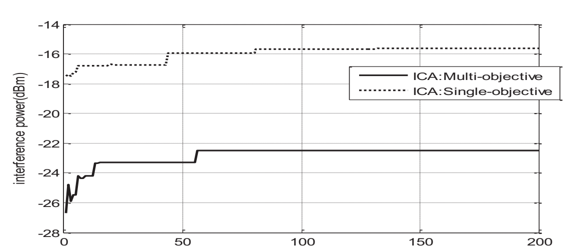

Fig. 6. The average of interference power using a channel assignment method for an ICA-based clustered topology structure.

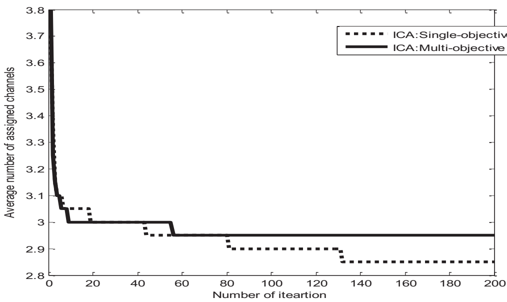

Fig. 7. The average number of used channels to a network with 30 cluster heads.

Thus, the ICA-based algorithm with the multi-objective function can form a clustered topology with high channel reuse efficiency and low interference power. Figure 7 depicts the graphs of the average number of used channels versus the iterations using the ICA-based clustering algorithm

VII. CONCLUSION

This paper proposed the use of ICA as an efficient optimization method to solve the cluster formation problems in ad hoc networks. A multi-objective function is designed to find a minimum number of cluster heads while satisfying the interference and connectivity constraints. The obtained results verify that the performance of the suggested algorithm is fairly good in comparison with ACO- based clustering algorithms. The experimental results also indicate that the capability of an ICA-based clustering algorithm in terms of scalability is better than other methods. The main drawback of the proposed algorithm is high time complexity; in particular, when the population size and network size are large. Modifying the evolutionary operators can cause a reduction in time complexity.

As future works, two more constraints can be added to control the transmission power of cluster heads and maximize the stability of the clustered structure. A distributed clustering method will be developed on the basis of ICA. Due to the reasonable performance of ICA, a cognitive radio engine based ICA will be designed.

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