SPECTRUM ASSIGNMENT IN COGNITIVE RADIO NETWORKS USING FUZZY LOGIC EMPOWERED ANTS

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Abstract. The prevalent communications networks suffer from lack of spectrum and spectrum inefficiency. This has motivated researchers to develop cognitive radio (CR) as a smart and dynamic radio access promised solution. A major challenge to this new technology is how to make fair assignment of available spectrum to unlicensed users, particularly for smart grids communication. This paper introduces an innovative approach to this key challenge in CR networks based on an empowered ant colony system (ACS) using fuzzy logic (FL). In order to evaluate performance of the proposed fuzzy logic-ant colony system spectrum assignment algorithm (FLACS-SAA), authors have particularly studied its performance versus the color sensitive graph coloring (CSGC) approach as well as a variety of bio-inspired based techniques referenced in the literature.

1. Introduction

The current spectrum convention in wireless networks is concentrated on certain portions which causes shortage of spectrum, so-called spectrum scarcity problem [24, 8]. This is while a significant amount of spectrum remains unutilized in these systems. The Federal Communication Commission (FCC) advocates the development of a new generation of programmable radios that can dynamically access various parts of the spectrum including the licensed bands [24, 11].

Smart grid is the new generation of electricity networks which combines a variety of state-of-the art technologies such as embedded sensing, adaptive control, and particulary wireless communication [22]. An efficient and reliable communication architecture plays a crucial role in the smart grid. By considering a huge number of wireless users as well as lack of frequency band for communication between different users of this network, cognitive radio can be a reliable and promised solution for spectrum management in smart grids [22].

Cognitive radio (CR) is a new communication paradigm to fully utilize the scarce spectrum resources in an opportunistic manner [8]. This technology is categorized into four stages, comprising spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility [1]. During the first stage, unused spectrums are detected and shared, taking care to avoid harmful interference with other users.

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The spectrum management stage captures the best available spectrum to meet user communications requirements. In the spectrum mobility stage, in order to have better spectrum availability, seamless communications during the transition are maintained. The final stage ensures fair spectrum scheduling among coexisting users [1].

Based on agreements imposed by legacy spectrum (primary) users, the spectrum assignment functionality of CR deals with how unlicensed (secondary) users opportunistically can utilize unused licensed spectrum on a non-interfering and leasing basis at any location over the entire spectrum [27]. While optimizing certain network utilities by allocating available channels to secondary users (SUs) is the primary goal of the CR networks, a good allocation scheme also needs to provide fairness across devices [28]. Many techniques such as game theory [18], pricing and auction mechanisms [9, 13] and local bargaining [3] have been developed in the literature on spectrum assignment in CR. In [31], based on the probabilities of channel availability obtained from spectrum sensing, a method is proposed which optimizes channel and power allocation in a multi-channel environment. In [19, 32], the spectrum assignment problem (SAP) is mapped to a NP-hard graph coloring problem (GCP) and a vertex labeling mechanism is put forward to overcome GCP [2]. An improved algorithm based on the graph coloring theory model is presented in [14] which reports almost similar spectrum utilization to CSGC, but with less simulation time. A novel distributed collusion mechanism is unveiled in [26] that allocates channels in the spectrum pool by using graph coloring and bidding theory. However, the simulation results does not conclusively demonstrate a better system performance compared to random based techniques.

Bio-inspired algorithms are well known for their approximate non-deterministic solutions. Such algorithms have received considerable attention for tackling NP-hard problems in the literature due to their low computational complexities as well as easy implementation characteristics [17, 21]. The harmony search algorithm (HSA), inspired by the behavior of music orchestra in the process of improvising a harmony, is used in [5] for spectrum allocation in CR networks. An adaptation method based on the particle swarm optimization (PSO) is employed in [30] to optimize CR parameters with respect to a set of objectives. In [28], three types of spectrum assignment algorithms (SAAs), which are genetic algorithm (GA), quantum genetic algorithm (QGA) and PSO are investigated for spectrum assignment in CR networks. The authors in [28] claim that the PSO algorithm can find optimal solution in all experiments under three specific objectives introduced in [19]. However, performance of this algorithm versus different number of primary users (PUs), SUs and available channels is not well investigated. In [20], an ACS approach to the SAP is disclosed which first converts the CR network topology to a GCP and then assigns spectrum to the unlicensed users using artificial ants. Performance of this approach is only studied for one of the objectives in [19]. The ACS scheme in [29] has modeled the SAP as an adaptive task assignment in ant colonies. A set of SUs are assigned to some available spectrum subject to minimal cost constraint. This solution assigns spectrums with an acceptable quality, however, its performance for many network topologies with different densities of users and available channels is

not yet well explored.
In this paper, we have authorized artificial ants with fuzzy logic (FL). The proposed fuzzy logic-ant colony system SAA (FLACS-SAA) enhances spectrum assignment performance in comparison with ACS-SAA [20], PSO-SAA, GA-SAA, QGA-SAA [28] and CSGC algorithm [19], approaches. In addition, performances of the above techniques are evaluated for various numbers of SUs and PUs as well as available channels under the objectives in [19]. Finally, further research challenges are suggested which aim to improve the FLACS-SAA performance.
The next section surveys principals of ACS as well as FL. The spectrum assignment algorithm is explained in section III and related simulations are discussed in section IV. Finally, the paper is concluded in section V.

2. A Survey on Ant Colony System and Fuzzy Logic

A short review on ACS as well as FL is presented in the following subsections. However, a more detailed overview of these topics is beyond the scope of this paper and the interested reader is referred to the abundant literature available on this topic (see for instance [6, 12]).

2.1. Ant Colony System.

The ant colony optimization (ACO) is a class of algorithm whose first member, called ant system (AS), was initially proposed by Colorni, Dorigo and Maniezzo [6]. Although real ants are blind, they are capable of finding shortest path from their nest to a food source by exploiting information of a liquid substance, called pheromone, which they release on the transit route. The more developed AS strategy attempts to simulate the behavior of real ants with the addition of several artificial characteristics: visibility, memory and discrete time to resolve many complex problems successfully such as the traveling salesman problem (TSP) [6] and transportation networks [21]. Even though many changes have been made to the ACO algorithms during the past years, their fundamental ant behavioral mechanism that is a positive feedback process demonstrated by a colony of ants, is still the same. Ants algorithm finds plenty of applications in different areas of wireless communications such as routing and resource management [10, 25], cell planning and user detection [23, 29] and spectrum assignment [11, 17]. Different steps of a simple ACS algorithm are as follow:
Problem Graph Depiction: Artificial ants move between discrete states in discrete environments. Since the problems solved by ACS algorithm are often discrete, they can be represented by a graph with N nodes and R routes.
Ants Distribution Initializing: A number of ants are placed on the origin nodes. Number of ants is determined by trial and error and number of nodes in the region.
Ants Probability Distribution Rule: Ants probabilistic transition between nodes can also be specified as node transition rule. The transition probability of ant k from node i to node j is given by

$$p_{ij}^{k} = \begin{cases} \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{h \notin tabu_k} \tau_{ih}^{\alpha}\eta_{ih}^{\beta}}, & j \notin tabu_k \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where τ_{ij} and η_{ij} are the pheromone intensity and the heuristic visibility (cost) of

direct route between nodes i and j respectively. Relative importance of τ_{ij} and η_{ij} are controlled by parameters α and β respectively. The is a set of unavailable routes for ant .

Update Global Trail: When every ant has assembled a solution at the end of each cycle, the intensity of pheromone is updated by a pheromone trail updating rule. This rule for ACS algorithm is given as

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{2}$$

where $0 < \rho < 1$ is a constant parameter named pheromone evaporation. The amount of pheromone laid on the route between nodes i and j by ant k is computed by

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{f_k}, & if route(i,j) is traversed by ant k \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where Q is a constant parameter and f_k is the cost value of the found solution by ant k.

Stopping Procedure: This procedure is completed after arriving at a predefined number of cycles, or the maximum number of cycles between two improvements of the global best solutions. Interested readers are referred to [6] for more details regarding philosophy of ACS.

2.2. **Fuzzy Logic.** The fuzzy set theory was initially introduced by Lotfi Zadeh in 1965. In this theory, the usual set theory is generalized so that an object cannot only be seen as an element of a set (membership value 1) or not an element of this set (membership value 0), but it can also have a membership value between 0 and 1. Therefore, a fuzzy set is defined by its membership functions which are allowed to assume any value in the interval [0,1] instead of their characteristic function, which is defined to assume the values 0 or 1 only [21].

Later in 1970, Assilian and Mamdani developed the fuzzy control concept to control complex processes particularly when no strict model of the processes exists [4, 15]. Fuzzy control can be described as a means of control working with conditional sentences called linguistic IF-THEN rules rather than mathematical equations. The deduction of the rule is called inference and requires definition of a membership function characterizing this inference. This function determines the degree of truth of each proposition [4].

Different stages of a simple fuzzy logic (FL) controlling system are as follows:

Fuzzification: Each fuzzy system is realized in the form of fuzzy rules such as:

$$\begin{aligned} Rule I: &\quad IF \quad M\ is\ p_1 \quad AND \quad N\ is\ q_1 \quad THEN \quad R\ is\ g_1 \\ Rule II: &\quad IF \quad M\ is\ p_2 \quad AND \quad N\ is\ q_2 \quad THEN \quad R\ is\ g_2 \end{aligned} \tag{4}$$

where M and N are variables of the condition part, R is variable of the action part and p_i , q_i and g_i are fuzzy parameters characterized by membership functions. The condition parts of control rules make use of measurements, which are usually real numbers [15].Figure 1 presents Mamdanis approach to the fuzzy inference procedure for two rules and arbitrary membership functions. By considering

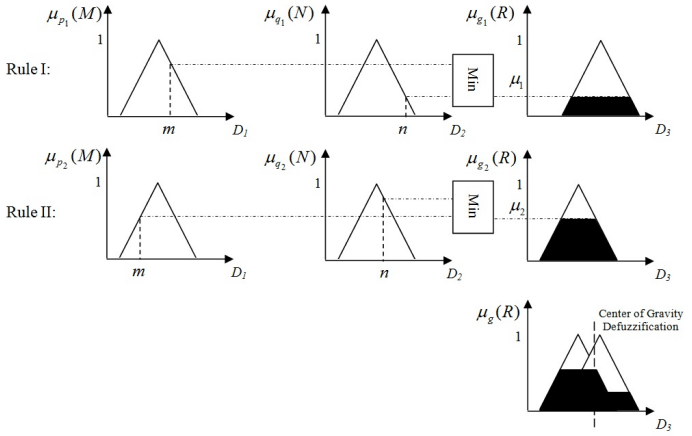


FIGURE 1. Fuzzy Inference Procedure for Two Rules Based on Mamdanis Type, [21]

D_1 and D_2 as value domains, the real valued measurements m and n are matched to their corresponding fuzzy variables by determining their membership values as $\mu_{p1}(m)$,$\mu_{q1}(n)$, $\mu_{p2}(m)$ and $\mu_{q2}(n)$.

Fuzzy Inference Engine: By considering $M = m$ and $N = n$ for all the control rules in the rule base, the truth value of each rule in the premise is derived by building the conjunctions of the matching membership values as

$$\begin{aligned} RuleI: &\qquad \mu_1 = \mu_{p1}(m) \wedge \mu_{q1}(n) \\ RuleII: &\qquad \mu_2 = \mu_{p2}(m) \wedge \mu_{q2}(n) \end{aligned} \tag{5}$$

where the $\wedge$ conjunction represents one of the Mamdanis implication such as min function [15]. The truth degree of rules I and II is represented by μ_1 and μ_2 respectively. These also define the membership values $\mu_{g1}(R)$ and $\mu_{g2}(R)$ of the fuzzy subsets $g_1(R)$ and $g_2(R)$ for the measurement m and n respectively. By considering D_3 as the value domain of the output variable, the fuzzy control output $g(R)$ is represented by the aggregation of all fuzzy subsets $g_i(R)$. Its membership values $\mu_{g_i}(R)$ are determined by disjunction of all the membership values, so that

$$\mu_g(R) = \mu_{c_1}(R) * \mu_{c_2}(R) \tag{6}$$

where the $'*'$ disjunction is the max function when used with Mamdanis implication [4, 15].

Defuzzification: The fuzzy result, which is outcome of the inferences, is transformed into a real value that can be used as control input. Since the desired output is a non-fuzzy outcome, a quantitative value of the control output is determined by defuzzifying $\mu_{g_i}(R)$. There are two common methods for defuzzification, which are the center of gravity and mean of maxima methods. Interested readers are referred to [4, 7, 15] for more details.

3. Spectrum Assignment Algorithm

3.1. **SAP Definition.** In order to demonstrate a sample SAP topology, separate specific channels are assigned to the PUs in Figure 2. This is while SUs, equipped with the orthogonal frequency division multiple access (OFDMA) technology, are distributed through the region and waiting for channel assignment. Since PUs within range of each other cannot use same channel, each PU x inhabits a channel m with a radius of protection area $dp_{x,m}$. The coverage area radius for SU n on channel m is adjustable by tuning the transmit power on this channel, which is defined as

$$ds_{n,m} = min(d_{max}, min(Dist_{x,n} - dp_{x,m})) \tag{7}$$

where $Dist_{x,n}$ is the distance between PU x and SU n. As a general rule, the interference range is bounded by the minimum and maximum transmit power that is $[d_{min}, d_{max}]$, [19]. Increasing the $ds_{n,m}$ also increases the probability of interfering with a neighboring user. Any radiation from each PU or SU into the coverage area of another user on channel m would cause interference [19].
By considering the above network topology, the problem is how to allocate available channels to SUs so as to avoid interference as well as to optimize certain network utilities. In the first stage of the proposed procedure in [19], network information such as number of SUs N , number of PUs X and number of channels M, are gathered. Then the binary channel availability matrix of users $L_{N\times M}$ is determined, where if $l_{n,m} = 1$, channel m is available for SU n, otherwise this user has no available channel. Subsequently, interferences between different SUs on each channel are gathered in binary interference matrix $C_{N\times N\times M}$. If $c_{n\times k\times m}$, SUs n and k interfere on channel m simultaneously. Maximum acquired throughput by SU n using channel m is considered as a reward in $B_{N\times M}$ that represents the maximum bandwidth or throughput which can be acquired (assuming no interference from neighbors) by user n using channel m.

According to [19], the reward can be the capacity of using a channel (assuming the signal to noise ratio (SNR) is a function of $ds_{n,m}$), defined as

$$B_{n,m} = log(1 + f(ds_{n,m}), \quad d_{min} \leqslant ds_{n,m} \leqslant d_{max} \tag{8}$$

or as coverage of SU n using channel m as

$$B_{n,m} = \begin{cases} ds_{n,m}^2, & d_{min} \leqslant ds_{n,m} \leqslant d_{max} \\ 0, & L_{n,m} = 0. \end{cases} \tag{9}$$

With respect to [19], the reward policy in (8) is considered in all understudy systems of this paper.

3.2. **Modeling SAP to a GCP.** In the GCP model of SAP, nodes of graph are considered as SUs and two interfering SUs construct an edge between these users [19]. In order to have a complete GCP, available channels are considered as available colors in a color pool. In this problem, each vertex is colored using a number of colors from its available color list under the constraint that two vertices linked by an edge cannot share the same color. The objective is to obtain a color assignment that maximizes a given utility function. Obtaining the optimal coloring

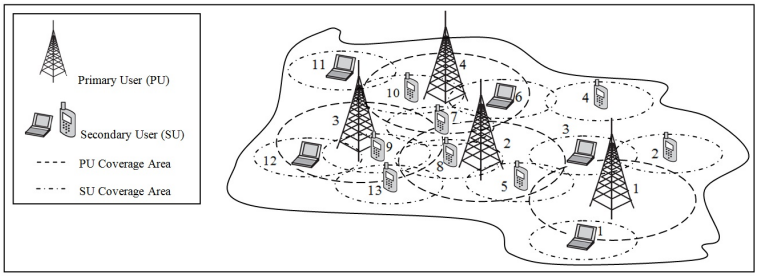


FIGURE 2. A Sample Cognitive Radio Network Topology, Illustrating Interferences Between Primary and Secondary Users

is known to be NP-hard [19, 28].
Having the above model specifications, the SAP is mapped into a GCP defined as $G = (V, L, C)$, where V is a set of nodes denoting the SUs, L is the list of available channels and C is the interference matrix between SUs. The binary matrix $A_{N\times M}$ represents channel assignment matrix. If channel m is assigned to SU n, $a_{n,m} = 1$, otherwise, $a_{n,m} = 0$. By considering $R = \{r_n = \sum_{m=1}^{M} a_{n,m}b_{n,m}\}_{N\times 1}$ as the reward vector that each SU obtains for a given channel m, the SAP is defined as the optimization problem, i.e.

$$A^* = arg\, max U_i(R), \quad for\ A \in \Lambda_{L,C},\ i \in \{MSR, MMR, MPF\} \tag{10}$$

where $Lambda_{L,C}$ is the set of conflict free channel assignment for a given L and C. The $U_i(R)$ is the network utilization where according to [19, 28], three functions Max-Sum-Reward (MSR), Max-Min-Reward (MMR) and Max-Proportional-Fair (MPF) are considered. The MSR function maximizes the total spectrum utilization in the system regardless of fairness as

$$U_{MSR}(R) = \sum_{n=1}^{N} r_n. \tag{11}$$

The MMR function maximizes the spectrum utilization regarding the user with the least allotted spectrum as

$$U_{MMR}(R) = min(r_n), \quad 1 \le n \le N. \tag{12}$$

This function gives the user with the lowest reward, the largest possible share while not wasting any network resources. The MPF function addresses fairness for single-hop, followed as

$$U_{MPF}(R) = (\prod_{n=1}^{N}(r_n + 10^{-6}))^{(}\frac{1}{N}). \tag{13}$$

Interested readers are referred to [12] for proofs and details.

3.3. **FLACS Approach to GCP Model.** In order to present a clear objective of the proposed FLACS approach, the graph obtained from GCP model of topology in Figure 2 is expanded as shown in Figure 3. In this graph, interferences between two SUs on a channel is illustrated separately as an edge. A colony of ants is considered on each node. Based on the pseudocode in Figure 4, in order to consider system fairness and allocate similar search opportunities to all SUs, search process runs for

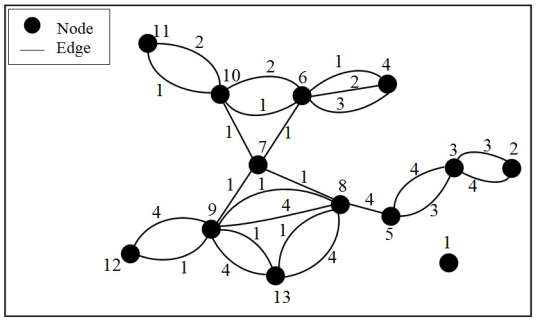


FIGURE 3. Formulating Interferences Between Secondary Users (SUs) in Figure 2 as a Graph. The Nodes Represent SUs and the Edges Between Nodes Represent Interference Between SUs on a Channel

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Procedure FLACS-SAA
Initialize
  For each iteration
    For each SU
      If the SU has available channel & interference
        For each active ant
          While the ant is active
            CH Probability
            CH Selection
            Update Ant Activation
          End While
        End For
      End If
        Local Pheromone Updating
    End For
      Global Pheromone Updating
  End For
  Result
End FLACS-SAA
```

FIGURE 4. Proposed FLACS-SAA in Pseudocode

each node respectively. In each journey, the traveler ant collects information of the transited edges and visited nodes. After arrive at a destination, based on analyze of the transited path by the fuzzy system, the ant releases pheromone on the edges. This procedure will be repeated for all ants, noting that further ants would consider pheromone release of the previous ants in their own edge selection process. the result of the mentioned procedure is a pheromone report, which presents pheromone amount of each node for each route, or in other words, reasonability of each channel for each SU. Finally, the channel with the most pheromone amount is selected for each SU. Pseudocode of the above procedure is illustrated in Figure 4. Different steps of the proposed algorithm are described in details as follow.

Initialize: Initial parameter values are set at this stage. Topology information such as number of SUs and PUs are imported to the algorithm regularly using the information in spectrum sensing step of the CR network. The active ants are also

located at each node respectively to start their journey at this step.

CH Probability: In each iteration, after locating or arrival of each active ant at a node, it must select an edge to continue its journey. Selection probability of each candidate edge i for active ant χ is

$$P_i^{\chi} = \begin{cases} 0, & \sum_{j=1}^{M} \acute{L}_{\acute{n},j} = 0 \\ \frac{T_{\acute{n},i,\xi}^{\alpha} \Delta_i^{-\beta}}{\sum_{i=1}^{I} [T_{\acute{n},i,\xi}^{\alpha} \Delta_i^{-\beta}]}, & \text{otherwise} \end{cases}$$

$$\forall i \in \acute{\Gamma}_{1\times I} \tag{14}$$

where for I number of potential edges, $\acute{\Gamma}_{1\times I}$ represents list of possible edges and $\acute{L}_{\acute{n},j}$ is binary list of available channels for candidate SU $\acute{n}$. The parameters α and β control relative importance of $T_{\acute{n},i,\xi}$ and Δ_i respectively. $T_{\acute{n},i,\xi}$ is the pheromone amount of the SU $\acute{n}$ using channel i in iteration ξ and Δ_i is the cost of candidate edge for active ant χ defined as

$$\Delta_i = (M^{-1} \sum_{j=1}^{M} \acute{L}_{\acute{n},j})^{\delta} (N^{-1} \sum_{k=1}^{N} \wedge_{\acute{n},k,i})^{\varphi} (d_{max}^{-1} ds_{\acute{n},i})^{\gamma} \tag{15}$$

where δ, φ and γ control relative importance of channel availability, interference and propagation radius factors respectively. The CH probability function is achieved by studying important parameters considered in spectrum assignment approaches. By combining them and studying several structures, based on trial and error, we could find the optimum probability function as (14).

CH Selection: After calculating probability of each possible edge, an edge must be selected. To do this, the random parameter g with uniform distribution in [0,1] is compared with the predefined parameter G, which is set to 0.9 based on trial and error [6, 20]. The result picks up one of the following selection methods

$$\acute{m} = \begin{cases} arg\ max(P_i^{\chi}), & g > G \\ Roulette\ Wheel(P_i^{\chi}), & \text{otherwise} \end{cases} \tag{16}$$

where $\acute{m}$ is the selected edge. Therefore, the active ant continues its journey through the selected edge to the next node (channel $\acute{m}$ aiming SU $\acute{n}$).

Update Ant Activation: In this algorithm, each ant can visit each node just once. If the current active ant χ, after its move toward $\acute{n}$, has no possible edge to continue its journey or SU $\acute{n}$ has no interference, this ant is blocked. The activation list $\Omega_{X\times N\times \Xi}$ for active ant χ is updated as

$$\Omega_{\chi,\acute{n},\xi} \begin{cases} 0, & \sum_{j}^{N} C_{\acute{n},j,\acute{m}} = 0 \\ 1, & \text{otherwise} \end{cases} \tag{17}$$

where $\Omega_{\chi,\acute{n},\xi} = 0$ indicates that ant χ is blocked at node $\acute{n}$ and is considered as a passive ant in the current iteration ξ. In this case, the termination condition is met for this ant.

Local Pheromone Updating: At this stage, some pheromone must be released on the transited edges by active ant χ. The pheromone amount of the selected channel $\acute{m}$ for the SU $\acute{n}$ is updated by

$$T_{\acute{n},\acute{m},\xi}^{new} = T_{\acute{n},\acute{m},\xi}^{old} + (\phi \times \Delta T) \tag{18}$$

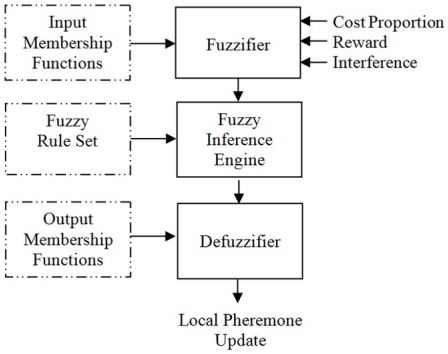


FIGURE 5. Architecture of the Fuzzy Logic System for the FLACS-SAA

where ΔT is the amount of local pheromone updating managed by a FL system and its impact can be adjusted by ϕ, which is set to one here. By considering the FL approach in subsection 2.2, and Mamdanis implication as our approach, structure of the employed FL system is illustrated in Figure 5. This model manages ΔT as output of the FL system by considering three inputs, which are Cost Proportion, Reward and Interference.

After all ants completed their journeys for each beginning node, total cost of the edges, which each ant has selected is calculated as

$$\Delta^{\chi}_{Total} = \sum_{\forall j \in LV} \Delta_j \tag{19}$$

where LV is the list of visited edges by ant χ through its journey. The Cost Proportion of each ant is obtained by

$$\Delta^{\chi}_{CP} = \frac{\Delta^{\chi}_{Total}}{max\Delta^{\acute{\chi}}_{Total}} \quad for\ \acute{\chi} = 1, 2, ..., X \tag{20}$$

where routes with high
$Delta^{\chi}_{CP}$ are not desired by the system and are punished by gaining few ΔT. The Reward is the sum of visited edges rewards $B_{n,m}$ by ant χ defined as

$$B^{\chi}_{Total} = \sum B_j \quad \forall j \in LV \tag{21}$$

where routes with high B^{χ}_{Total} are desired by the system and encouraged by achieving more ΔT. The Interference is the sum of interferences on the selected channels through the visited edges and is defined as

$$C^{\chi}_{Total} = \sum C_j \quad \forall j \in LV \tag{22}$$

where routes with high C^{χ}_{Total} are not desired by system and are punished by achieving less ΔT. By considering computing complexities, only two input fuzzy sets, Low and High, are defined for each input. The corresponding Trapezoidal-shaped membership functions of the input variables is plotted in Figures 6. Also, four fuzzy sets are considered for the output variable representing different levels of pheromone density, which are Very Low, Low, High, and Very High, respectively as shown in Figure 7.

Based on the above description, IF-THEN rules set of the FL system is presented in

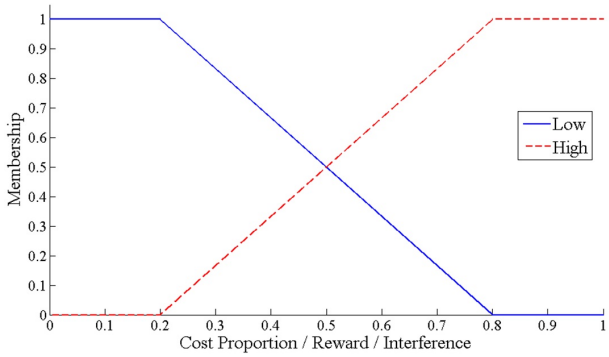


FIGURE 6. Membership Functions of Cost Proportion, Reward, and Interference Parameters

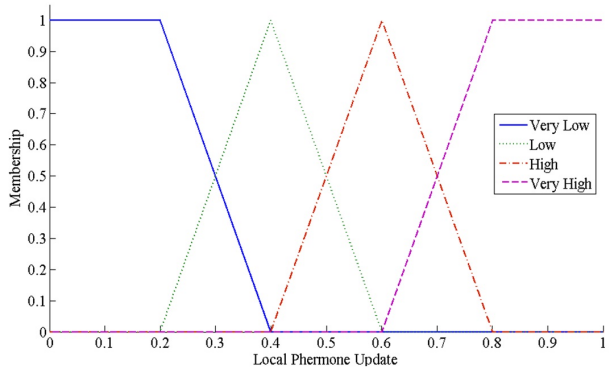


FIGURE 7. Membership Function of Local Pheromone Updating

Table I. by following the rules set, routes with the least Cost Proportion as well as Interference and the most Reward, gain the most local pheromone update. At the final stage, with respect to the defuzzification techniques mentioned in subsection 2.2, the center of gravity method is employed to resolve a single output value from the fuzzy set.

Global Pheromone Updating: The last traditional step of each completed iteration ξ is global pheromone updating as

$$T_{n,m,\xi}^{new} = \rho T_{n,m,\xi}^{old} \quad for\ n = 1, ..., N\ and\ m = 1, ..., M \tag{23}$$

where the parameter $0 < \rho < 1$ is the evaporation coefficient which is set to 0.9 based on trial and error [15, 21].

Result: In the last phase of the algorithm, after Ξ iterations, a channel ω_n is assigned to each SU n based on the corresponding pheromone amount of each SU given by

$$\omega_n = arg\ max(\frac{1}{\Xi}\sum_{\xi=1}^{\Xi} T_{n\times m\times \xi}). \tag{24}$$

In this manner, the channel with most obvious pheromone is selected for each SU. In some exceptional cases, where pheromone rate of channel ω_n is not so clear

Rule No.	IF			THEN
	Cost Proportion	Reward	Interference	Local Pheromone Update
1	Low	High	Low	Very High
2	High	High	Low	High
3	Low	High	High	High
4	Low	Low	Low	High
5	Low	Low	High	Low
6	High	Low	Low	Low
7	High	High	High	Low
8	High	Low	High	Very Low

TABLE 1. The IF THEN Rules Set for Proposed FLACS-SAA System

among other available channels to the same SU and can satisfy the threshold limit ϵ defined as

$$|\frac{1}{M \times \Xi} \sum_{m=1}^{M} \sum_{\xi=1}^{\Xi} T_{n \times m \times \xi} - Max(\frac{1}{\Xi} \sum_{\xi=1}^{\Xi} T_{n \times m \times \xi})| < \epsilon \tag{25}$$

or the SU has no available channel, corresponding SU cannot obtain any channel and is called starved. For the SUs with channel availability but without interference, a channel is assigned randomly.

4. **Simulations and Discussions**

In this section, performance of the proposed FLACS-SAA is analyzed from different aspects. In subsection 4.1 a sample network topology is considered and its SAP is solved by the proposed algorithm. This is then followed in the next subsection by a discussion on the performance of FLACS-SAA versus ACS-SAA [20], PSO-SAA, GA-SAA, QGA-SAA [28] and CSGC algorithm [19], approaches for the utilization functions (11), (12) and (13) considered in [19, 20, 28].

A desktop computer with Intel Core2Quad T9300 2.5 GHz CPU and 3 GB of RAM is employed for simulations in MATLAB 2009b. By following the method in [19, 20, 28] for simplicity, SUs are assumed to have fixed power control mechanism for adjusting their transmit power to the maximum permissible level in order to avoid interfering with PUs. In addition, the transmission and interference ranges are assumed identical. Different values of parameters are evaluated in order to achieve highest performance. Based on these evaluations, 15 ants are employed and the parameters are considered as in Table II throughout the simulations.

4.1. **Spectrum Assigning of a Sample Topology.** In a sample topology, 20 PUs and 10 SUs are randomly placed in a 10×10 region as in Figure 8. The spectrums of PUs are randomly assigned in Table III with uniform distribution in $[1, 10]$, so that interference between PUs on a same channel [19, 20]is avoided. In order

Parameter	Value
$C_{\max}$	10
$d_{\max}$	4
$d_{\min}$, ε	1
G , ρ	0.9
dp , δ , φ , γ , α , β	2

TABLE 2. Parameter Values for Simulations

Primary User ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Assigned Spectrum	3	6	8	4	1	5	10	7	1	9
Primary User ID	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Assigned Spectrum	4	2	9	6	7	3	8	10	5	4
Secondary User ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Spectrum (FLACS-SAA)	8	5	7	4	0	9	2	5	6	8
Spectrum (ACS-SAA)	2	4	0	9	9	4	7	3	0	4

TABLE 3. Primary Users and Secondary Users with Correspondent Spectrums for the FLACS-SAA and ACS-SAA Approaches

Iterations (Generation)	Algorithm	Average Reward (N=5 ; M=5)			Average Reward (N=20 ; M=20)		
		MSR	MMR	MPF	MSR	MMR	MPF
10	GA-SAA	150.6038	25.0771	53.8800	1170.9525	2.3642	62.4950
	QGA-SAA	151.0952	27.8634	65.1482	1206.1508	9.5613	37.0068
	PSO-SAA	151.0952	27.8634	64.8348	1204.7035	8.3244	13.7659
	ACS-SAA	152.9406	28.1875	67.2993	1206.8396	9.3964	43.6243
	FLACS-SAA	154.9752	32.5620	71.2254	1211.4250	11.6402	58.7432
50	GA-SAA	151.0952	25.6343	64.0926	1229.1568	7.2553	96.2020
	QGA-SAA	151.0952	27.8634	66.1267	1237.3000	39.5744	87.5857
	PSO-SAA	151.0952	27.8634	67.8842	1238.1758	28.0520	82.4346
	ACS-SAA	152.9406	30.9360	71.7630	1241.7378	42.7491	98.8839
	FLACS-SAA	154.9752	36.0753	80.8462	1252.4725	50.8461	103.6923
300	GA-SAA	151.0952	27.3061	64.5525	1238.9552	12.3750	116.7429
	QGA-SAA	151.0952	27.8634	66.1267	1238.9561	56.2500	118.0215
	PSO-SAA	151.0952	27.8634	67.9928	1240.1890	50.9594	120.5298
	ACS-SAA	152.9406	30.9360	71.7630	1241.7826	65.9205	137.3048
	FLACS-SAA	154.9752	33.8218	79.6230	1248.9041	71.0437	145.9418
	CSGC	138.3981	21.1016	56.0257	1206.0437	2.7769	60.1252

TABLE 4. Average Reward of the Proposed FLACS-SAA Versus ACS-SAA [20], PSO-SAA, GA-SAA, QGA-SAA [28] and CSGC Algorithm [19], Approaches

to study performance of the FL in local pheromone updating of FLACS-SAA, it is evaluated against the ACS-SAA approach in [20] in allocating 10 available channels to SUs in 30 iterations.

Final pheromone matrixes of the FLACS-SAA and ACS-SAA are presented in Figure 9. With respect to the selection criterions (24) and (25), SUs assigned channels

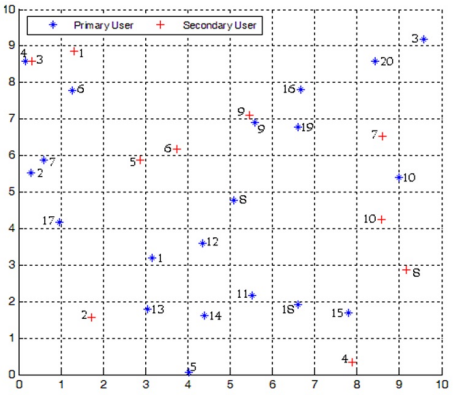


FIGURE 8. A 10×10 Region with Randomly Placed Primary and Secondary Users

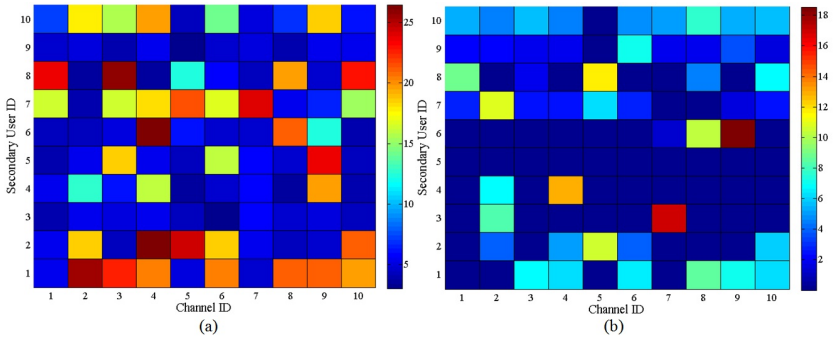


FIGURE 9. Output Pheromone Matrix of the a) ACS-SAA and b) FLACS-SAA Approaches

are presented in Table III. In this assignment, overlapped users (located on the broadcast range of each other) are not assigned the same channel. By setting the threshold limit to 1, pheromones of SUs 3 and 9 for the ACS-SAA and of SU 5 for the FLACS-SAA approaches are almost equal for their corresponding channels pool. Consequently, with respect to (25), these SUs could not obtain any channel and therefore, ACS-SAA has two starved SUs while the FLACS-SAA has one.

4.2. **Performance Analysis.** In [28], the GA, QGA and PSO evolutionary algorithms are studied for spectrum assignment in CR networks. It is reported that, PSO-SAA outperforms better than the QGA-SAA and GA-SAA, however, the impact of varying number of SUs, PUs, and channels on the PSO-SAA performance is not well studied. In [20], performance of the ACS-SAA model is evaluated versus CSGC method in [28]. It is reported that ACS-SAA performs better than CSGC for the MPF utilization function. Here, we first compare performance of the FLACS-SAA and the other understudy algorithms in [19, 20, 28] for the mentioned

variables with the MSR, MMR, and MPF utilization functions. Then, convergence time of the studied algorithms is evaluated.

4.2.1. **FLACS-SAA vs. ACS-SAA, PSO-SAA, GA-SAA, and QGA-SAA.** It is claimed in [28] that GA-SAA performs the worst compared to QGA-SAA and PSO-SAA and all three evolutionary algorithms perform far better than the proposed CSGC method in [19]. As it is illustrated in Table IV, average rewards of the algorithms over 50 experiments for two separate network topology properties ($N = 5; M = 5 and N = 20; M = 20$) and three iteration numbers 10, 50, and 300 under the MSR, MMR and MPF utilization functions are compared. Based on the reports in [28], PSO-SAA overall performs better than the QGA-SAA and GA-SAA under the MSR and MPF objectives. On the other side, under the MMR objective, QGA-SAA outperforms PSO-SAA and GA-SAA. In addition, from the MPF standpoint, GA-SAA has superior performance compared to QGA-SAA and PSO-SAA in the early stage for the second topology. This is while the average reward of ACS-SAA behaves better than reviewed algorithms, especially the PSO-SAA, under different number of iterations and with all three objective functions considered with respect to [20]. However, the fuzzy empowered ACS-SAA, called FLACS-SAA, due to the contribution of FL in local pheromone updating, exhibits superior performance compared to the ACS-SAA approach. As it will be discussed in the next subsection, this fact can validate superiority of the proposed algorithm over the methods introduced in [19, 20, 28]for different densities of SUs, PUs and channels.

4.2.2. **Impact Analysis: Number of Primary Users, Secondary Users, and Channels.** Configuration of PUs determines channel availability, reward and interference constraints seen by SUs. Increasing the number of PUs or increasing the protection range dp not only can expand the primary protection area but also force affected SUs to reduce their power and thus ds. This results in reduction of the available channels as well as channel reward at SUs and therefore, degrades spectrum utilization. In addition, the interference among SUs decreases the possibility of spectrum reuse by multiple SUs [12]. Figures 10-12 display average rewards of the understudy algorithms over 50 experiments for different number of PUs, SUs, and channels.

As can be seen from Figure 10, for N=10 and M=10, increasing the number of PUs would degrade all three utilities. A comparison of the studied algorithms reveals that the CSGC solution performs poorly in term of all three utilities. This is while ACS-SAA performs much better than its PSO-SAA and CSGC counterparts under the MSR and MMR objectives. However, under the MPF objective, the PSO-SAA and ACS-SAA performances are almost similar. As is evident, the FL has managed the local pheromone updating of the FLACS-SAA approach remarkably well and as a result, could gain more utilization than other algorithms versus dynamic alternations of number of PUs. In a simple CR network topology, by increasing the number of SUs, or in other words SUs density, more interference constraints are created. Therefore, as Figure 11 demonstrates for X=20 and M=10, all three

utilities degrade as the number of SUs increases. The algorithms behavior for varying number of SUs is almost similar to the PUs, except that the PSO-SAA and ACS-SAA performance are less different. Figure 12 quantifies the performance of different algorithms as the number of channels changes for N=10 and X=20. Despite of algorithms reaction versus varying number of PUs and SUs, by increasing the number of channels, all three utilities increases.
As Figures 10-12 demonstrate, the plots of bio-inspired algorithms are less smooth than the CSGC algorithm, which is due to the

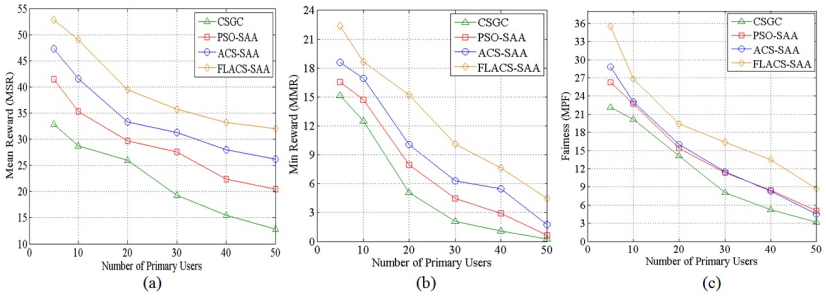


FIGURE 10. Spectrum Assignment with Varying Number of Primary Users Versus Three Utilization Functions: a) MSR; b) MMR; c) MPF

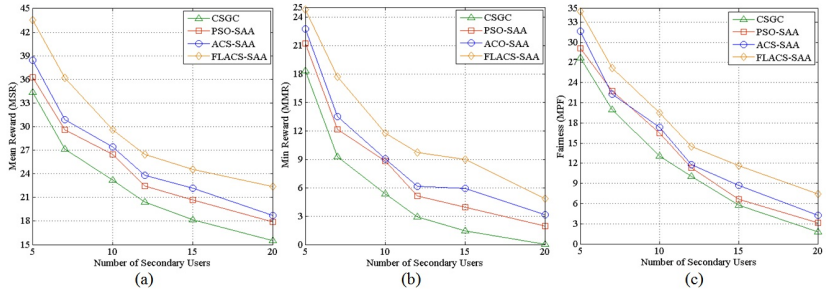


FIGURE 11. Spectrum Assignment with Varying Number of Secondary Users Versus Three Utilization Functions: a) MSR; b) MMR; c) MPF

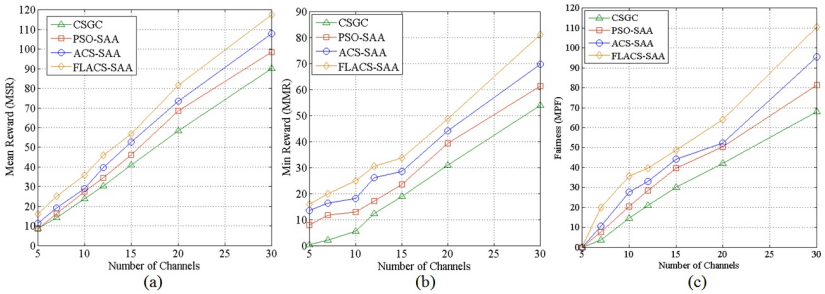


FIGURE 12. Spectrum Assignment with Varying Number of Channels Versus Three Utilization Functions:a) MSR; b) MMR; c) MPF

heuristic behavior of such algorithms. However, these algorithms perform far better than CSGC, which further validates the performance of these natural inspired-based spectrum allocation methods. Since in real scenarios, users are mostly mobile and network topology varies with time, we need a system capable of supporting such dynamic networks. The proposed bio-inspired algorithms in the literature [20, 28] and specifically, the FLACS-SAA perspective in this work, due to their low computational complexities as well as superior performance versus other studied systems in the literature can be an adequate low cost solution. Such approaches can quite easily be considered for real-time implementation too [21, 28].

5. **Conclusion and Future Works**

Since in practical cognitive radio (CR) scenarios, network topology is mostly complex and considered as NP-hard, there is the lack of fast, and low cost spectrum assignment systems. In this paper, the CR network topology is reconstructed as a graph coloring problem (GCP). Consequently, the proposed fuzzy logic-ant colony system (FLACS) algorithm employs ants, authorized by fuzzy logic (FL), for spectrum assignment of secondary users (SUs). Performance of this system versus different bio-inspired approaches in the literature and for various numbers of SUs, primary users (PUs) as well as available channels is investigated. The simulation results show that the proposed algorithm can enhance performance of spectrum assignment in CR networks in comparison with the other studied algorithms. In order to have a more dynamic algorithm and add more flexibility to the cost evaluation of candidate channels, we have considered some important rate parameters which control impact rate of each parameter. These parameters can also be assigned dynamically based on the networks topology characteristics. Studying these parameters and different techniques of controlling them to achieve better system performance remain as some research challenges. Currently, we are working on the mobility issue in bio-inspired approaches to spectrum assignment.

References

[1] I. F. Akyildiz, W. Lee, M. C. Vuran and S. Mohanty, *Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey*, Computer Networks, **50** (2006), 2127-2159.

[2] G. Audhya, K., Sinha, S. Ghosh and B. Sinha, *A survey on the channel assignment problem in wireless networks*, Wireless Communications and Mobile Computing, 2010.

[3] L. Cao and H. Zheng, *Distributed spectrum allocation via local bargaining*, IEEE DySPAN, (2005), 475-486.

[4] P. Chemouil, L. Khalfet and M. Lebourges, *A fuzzy control approach for adaptive traffic routing*, IEEE Communications Magazine, (1995), 70-76.

[5] J. Del Ser, M. Matinmikko, S. Gil-Lopez and M. Mustonen,*A novel harmony search based spectrum allocation technique for cognitive radio network*, 7th International Symposium on Wireless Communication Systems (ISWCS), (2010), 233–237.

[6] M. Dorigo and L. Gambardella,*Ant colony system: a cooperating learning approach to the traveling salesman problem*, Evolutionary Computing, IEEE Transactions on, **1(1)** (1997), 1-24.

[7] Fuzzy Logic Toolbox For Use with MATLAB, The MathWorks, Inc., 2006.

[8] S. Haykin, *Cognitive radio: brain-empowered wireless communications*, Selected Areas in Communications, IEEE Journal on, **23(2)** (2005), 201-220.

[9] J. Huang, R. Berry and M. Honig,*Auction-based spectrum sharing*, ACM Mobile Networks and Applications (MONET), **119(3)** (2006), 405-418.
[10] O. Hussein, T. Saadawi and M. Lee, *Probability routing algorithm for mobile ad hoc networks resources management*, Selected Areas in Communications, IEEE Journal on, **23(12)** (2005), 2248-2259.
[11] S. Khozeimeh x and S. Haykin, *Dynamic spectrum management for cognitive radio: an overview*, Wireless Communications and Mobile Computing, **9** (2009), 1447-1459.
[12] G. Klir and B. Yuan, *Fuzzy sets and fuzzy logic: theory and applications*, Prentice-Hall PTR, 1995.
[13] C. Kloeck, H. Jaekel and F. Jondral, *Dynamic and local combined pricing, allocation and billing system with cognitive radios*, IEEE DySPAN, (2005), 73-81.
[14] Y. Liu, G. Xu and X. Tan,*A novel spectrum allocation mechanism based on graph coloring and bidding theory*, International Conference on Computational Intelligence and Natural Computing, (2009), 155-158.
[15] E. Mamdani, *Application of fuzzy algorithms for control of simple dynamic plant*, Proceeding IEEE, (1974), 121-129.
[16] X. Mao and H. Ji, *Biologically-inspired Distributed Spectrum Access for Cognitive Radio Network*, 6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM), (2010), 1-4.
[17] R. Montemanni, D. Smith and S. Allen, *An ANTS algorithm for the minimum-span frequency-assignment problem with multiple interference*, Vehicular Technology, IEEE Transactions on, **51(5)** (2002), 949-953.
[18] N. Nie and C. Comaniciu, *Adaptive channel allocation spectrum etiquette for cognitive radio networks*, IEEE DySPAN, (2005), 269-278.
[19] C. Peng, H. Zheng and B. Zhao, *Utilization and fairness in spectrum assignment for opportunistic spectrum access*, ACM Mobile Networks and Applications (MONET), **11(4)** (2006), 555-576.
[20] H. Salehinejad, F. Pouladi and S. Talebi, *A metaheuristic approach to spectrum assignment for opportunistic spectrum access*, IEEE 17th International Conference on Telecommunications, (2010), 234-238.
[21] H. Salehinejad and S. Talebi, *Dynamic fuzzy logic-ant colony system based route selection system*, Journal of Applied Computational Intelligence and Soft Computing Article ID 428270, doi:10.1155/2010/428270, 2010.
[22] H. Salehinejad, S. Talebi, M. Rashidinejad and A. Rashidinejad, *PPM-UWB channel modeling for SCADA communications in offshore wind farms*, IEEE Proceedings of the 2nd Iranian Conference on Smart Grids, (2012), 1-6.
[23] R. Subrata and A. Y. Zomaya, *A comparison of three artificial life techniques for reporting cell planning in mobile computing*, Parallel and Distributed Systems, IEEE Transactions on, **14(2)** (2003), 142-153.
[24] E. Z. Tragos, S. Zeadally, A. G. Fragkiadakis and V. A. Siris, *Spectrum assignment in cognitive radio networks: a comprehensive survey communications surveys & tutorials*, IEEE, **15(3)** (2013), 1108-1135.
[25] J. Triay and C. Cervello-Pastor, *An ant-based algorithm for distributed routing and wavelength assignment in dynamic optical networks*, Selected Areas in Communications, IEEE Journal on, **28(4)** (2010), 542-552.
[26] J. Wang, Y. Huang and H. Jiang, *Improved algorithm of spectrum allocation based on graph coloring model in cognitive radio*, International Conference on Communications and Mobile Computing, (2009), 353-357.
[27] Q. Zhao and B. Sadler, *A survey of dynamic spectrum access: signal processing, networking, and regulatory policy*, IEEE Signal Processing magazine: Special Issue on Resource-Constrained Signal Processing, Communications, and Networking, (2007), 79-89.
[28] Z. Zhao, Z. Peng, S. Zheng and J. Shang, *Cognitive radio spectrum allocation using evolutionary algorithms*, Wireless Communications, IEEE Transactions on, **8(9)** (2009), 4421-4425.

[29] N. Zhao, Z. Wu, Y. Zhao and T. Quan, *A population declining mutated ant colony optimization multiuser detector for MC-CDMA*, IEEE Communications Letters, **14(6)** (2010), 497-499.
[30] Z. Zhao, S. Xu, S. Zheng and J. Shang, *Cognitive radio adaptation using particle swarm optimization*, Wireless Communications And Mobile Computing, **9** (2009), 875-881.
[31] H. Zheng and C. Peng, *Collaboration and fairness in opportunistic spectrum access*, 40th annual IEEE International Conference on Communications (ICC), (2005), 3132-3136.
[32] X. Zhou, G., D. Li, D. Wang, K. Soong, *Probabilistic resource allocation for opportunistic spectrum access*, Wireless Communications, IEEE Transactions on, **99** (2010), 1-10.

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