Paper

Multicriteria Oppositional-Learnt Dragonfly Resource-Optimized QoS Driven Channel Selection for CRNs

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Abstract — Cognitive radio networks (CRNs) allow their users to achieve adequate QoS while communicating. The major concern related to CRN is linked to guaranteeing free channel selection to secondary users (SUs) in order to maintain the network's throughput. Many techniques have been designed in the literature for channel selection in CRNs, but the throughput of the network has not been enhanced yet. Here, an efficient technique, known as multicriteria oppositional-learnt dragonfly resource-optimized QoS-driven channel selection (MOLDRO-QoSDCS) is proposed to select the best available channel with the expected QoS metrics. The MOLDRO-QoSDCS technique is designed to improve energy efficiency and throughput, simultaneously reducing the sensing time. By relying on oppositional-learnt multiobjective dragonfly optimization, the optimal available channel is selected depending on signal-to-noise ratio, power consumption, and spectrum utilization. In the optimization process, the population of the available channels is initialized. Then, using multiple criteria, the fitness function is determined and the available channel with the best resource availability is selected. Using the selected optimal channel, data transmission is effectively performed to increase the network's throughput and to minimize the sensing time. The simulated outputs obtained with the use of Matlab are compared with conventional algorithms in order to verify the performance of the solution. The MOLDRO-QoSDCS technique performs better than other methods in terms of throughput, sensing time, and energy efficiency.

Keywords — cognitive ratio network (CRN), multicriteria dragonfly optimization, oppositional learning, optimal available channel, QoS metric

1. Introduction

Back in the days, efficient channel allocation was achieved in CRNs was by means of the adjustable multi-radio channel hopping (AMCH) protocol [1]. Although the protocol solves the rendezvous concern in CRN, the throughput of the network has not been improved. To handle this problem, a novel MOLDRO-QoSDCS optimization technique has been designed, relying on multiple criteria for enhancing the throughput performance of CRNs.

Machine learning was used in [2] for developing a three-phase target channel sequence (TCS) generation and allocation scheme for dynamic channel allocation in CRNs. It solves the fairness, individuality, and dynamic TCS generation issues, but the sensing time was not minimized. To solve this issue, the oppositional learning concept was designed to arrive at a global solution quicker.

Better throughput and shorter service times were obtained in CRNs by applying the extended generalized predictive channel selection algorithm (EXGPCSA), as presented in [3]. However, energy consumption of the network was not minimized. The Q learning-based dynamic optimal band and channel selection technique was developed in [4] for improving the accessible transmission time. Although the data rate was increased, QoS-aware channel selection was not performed. The cross-layered channel assignment algorithm was presented in [5] to offer a consistent route scheme in CRNs. However, the delay of the network was not reduced due to the congestion in the routes. In [6], QoS-aware routing protocols were described for selecting the channel and the route in CRNs. The research conducted has contributed to optimizing throughput and delay, but energy efficiency was not improved.

To solve these issues, this paper proposes the MOLDRO-QoSDCS technique for improving the performance of CRNs. This paper addresses the major issue of energy efficiency in the CRN channel allocation process. It also solves the issues of higher power consumption, signal-to-noise ratio sensing time, and lower spectrum utilization in QoS-aware channel selection in data communication. The proposed MOLDRO-QoSDCS technique offers the following innovative approaches:

– It uses the multicriteria dragonfly optimization algorithm to select the optimal channel available in a CRN. Such a process integrates the oppositional learning concept for finding the optimal available channel via the fitness function. On the contrary to other optimization techniques, the proposed dragonfly optimization algorithm computes multiple criteria, such as signal-to-noise ratio (SNR), power consumption and spectrum utilization in the course of the channel selection process;

– Multicriteria dragonfly optimization exploits the oppositional learning concept to initialize the opposite population with the current population for obtaining a global optimum solution in the channel selection process;
– The ranking method is employed to minimize the sensing time for obtaining the local optimal solution from the current and opposite populations. With this approach, the global optimum solution is obtained within shorter times;
– To evaluate performance of the MOLDRO-QoSDCS technique and to compare it to contemporary state-of-the-art methods, a Matlab simulation analysis is performed. It shows that the proposed method outperforms the state-of-the-art models in terms of various metrics.

The rest of this paper is organized as follows. Section 2 offers a review of the literature. Section 3 presents, in detail, the proposed MOLDRO-QoSDCS technique. Section 4 describes and discusses the simulation settings and evaluation metrics. Finally, Section 5 summarizes the paper.

2. Related Works

The joint FD-aware channel assignment and route selection protocol for CRN was presented, under time-changing channel conditions in [7]. However, QoS metrics are not considered in the channel selection process. An intelligent access network selection algorithm was designed in [8], depending on multiple attribute decision-making (MADM), but the throughput was not improved. A new approach was presented in [9] to assign the resources and distribution depending on the cooperative game theory in order to ensure maximized payoff. However, time and complexity have remained higher. Reinforcement learning (RL) based schemes were introduced in [10] to assign the resources in CRNs. However, no optimal channel allocation approach was proposed.

In article [11], the cross-layer algorithm, defined as multicast routing, channel selection, scheduling, and call admission control (MRCSC), was designed for the purpose of multi-radio CRNs. Utilization of the network's bandwidth was improved, but the sensing time was not measured. The cross-layer routing scheme that supports adaptive bitrate multimedia (ABM) was developed in [12] to enhance the efficiency of channel utilization, but the optimal channel selection was not researched.

A two-phase spectrum handoff methodology was presented in [13] to choose the best channel and minimize channel drop in CRNs. However, throughput was not improved. The discrete quality factors aware channel scheduling (DQFACS) method was researched in [14] to lower the recurrent transmission in a cognitive radio ad-hoc network (CRAN), but QoS-related metrics were not considered when scheduling the channels. A game theory-based algorithm was considered in [15] to assign sensors to diverse channels in order to minimize energy consumption by satisfying a few channels sensing-related constraints. Unfortunately, the throughput was lower. Another new method was designed in [16] by integrating artificial intelligence techniques and spectrum detection algorithms to allocate channels in CRNs. However, time consumption has remained higher in such an approach.

A dynamic channel selection mechanism was developed in [17]. It relies on the fuzzy inference system (FIS). It selects the channel for lowering re-transmission probability. The expected throughput, data latency, and communication reliability were achieved, but the issue of energy use was not researched. A second order Kalman filter technique was analyzed in [18] to estimate channels for sensing the spectrum in CRNs. Unfortunately, the sensing time was not reduced.

To select channels in CRNs, the multi-objective optimization based on a ratio analysis (MOORA) algorithm was developed in [19]. However, the energy efficiency of the CRN was not improved. A proactive spectrum handoff scheme was developed in [20] for choosing the target channel in CRN, but the channel collision failed to be minimized. The Brownian motion-based dragonfly algorithm (DA) was designed in [21] to address the spectrum assignment (SA) problem. However, multiple criteria were not used there. Finally, the adaptive threshold-based dragonfly optimization method was introduced in [22] for cooperative spectrum sensing in CRN in order to identify spectrum holes.

3. Proposed Method

The MOLDRO-QoSDCS technique is dedicated to improving cognitive radio networks by selecting the optimal channel with a better QoS. A block diagram of a QoS-aware channel selection process using the proposed MOLDRO-QoSDCS technique is shown in Fig. 1.

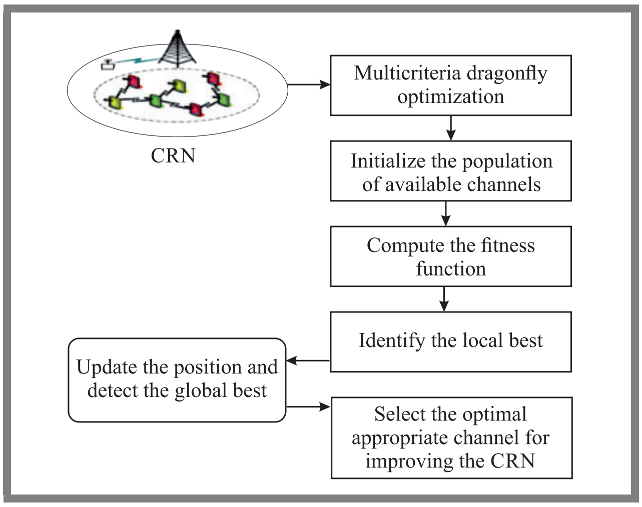

Fig. 1. Block diagram of the proposed MOLDRO-QoSDCS technique.

Let us consider a CRN consisting of n primary users (PU) and m secondary users (SU) with the available channels identified as $C = C_1, C_2, \ldots, C_n$. The proposed multicriteria oppositional-learnt dragonfly resource optimization technique is categorized as a meta-heuristic technique that is applied to determine the solution of an optimization problem. In MOLDRO-QoSDCS, the multicriteria include SNR, power consumption, and spectrum utilization. In contrast to conventional approaches, the newly developed technique utilizes an oppositional-based learning model for acquiring the global best result within the population in a shorter period of time. By using the oppositional-based learning optimization algorithm, such parameters as convergence speed, flexibility, error tolerance, and accuracy are improved.

Roaming and searching for food sources is a natural activity of dragonflies. In the proposed technique, the dragonfly is related to the number of available channels and the food source is related to multi-criteria functions, i.e. signal-to-noise ratio, power consumption, and spectrum utilization. The population of dragonflies (i.e. available channels) is initialized and the dragonflies move within the search space.

To begin the optimization process, the channel population existing in the search space is first initialized and is given by:

$$A = \{C_1, C_2, \ldots, C_n\}, \tag{1}$$

where A is the current population of channels $C_1, C_2, \ldots, C_n$. To obtain the global best solution, the proposed technique creates an opposite population from the current population through the opposition-based learning concept as:

$$A' = x_i + y_i - A, \tag{2}$$

where A' is the opposite population generated based on the current population A, x_i and y_i are the lower and higher values of A. With this, the current A and the opposite A' population are created in the search space. Upon completing the population generation process, the objective function is evaluated for each dragonfly (i.e. channel) in A and A' according to the abovementioned multiple criteria.

First, SNR is calculated using the number of users and their transmission rates:

$$S_{nr} = \frac{T_p \cdot G}{\sigma^2 + I_p}, \tag{3}$$

where T_p symbolizes the transmission power, G is the gain, σ^2 represents the noise power, and I_p stands for the power of interference created by other users. Subsequently, spectrum utilization is:

$$S_u = \frac{T_{\mathrm{BR}}}{\mathrm{BW}_c}, \tag{4}$$

where S_u represents the spectrum utilization, T_{BR} refers to the transmitted bitrate that is measured in bps, and BW_c refers to the channel's bandwidth (in Hz). Afterwards, power consumption of the channel is determined as:

$$P_{\mathrm{con}} = P_T - P_{ut}, \tag{5}$$

where P_{con} indicates the channel's power consumption, P_T is the total power and P_{ut} denotes the amount of power used. Depending on the above-calculated metrics, fitness is calculated as follows:

$$\alpha_F = \{S_{nr}, S_u, P_{\mathrm{con}}\}, \tag{6}$$

where the maximum spectrum utilization is S_u and the minimum signal-to-noise ratio is S_{nr}. Power consumption of the channel selected in CRN is P_{con}. Following fitness estimation, the current and opposite populations are merged into one and the dragonflies are sorted with respect to their fitness value. The channel with higher S_u and lower S_{nr} and P_{con} values is positioned first.

$$C = \alpha_F(C_1) > \alpha_F(C_2) > \ldots > \alpha_F(C_b). \tag{7}$$

With this, n best available channels are chosen from in order to identify the global best solution. Depending on fitness, the global best dragonfly in the search space is determined by performing such processes as separation, alignment, cohesion, and attraction towards the food source. To begin with the separation process, the current position of the dragonfly and its neighboring position is estimated as:

$$w = \sum_{j=1}^{n} \left[g(t) - g_j(t)\right], \tag{8}$$

where w is the separation process, $g(t)$ is the present position of an available channel at time t, $g_j(t)$ is the neighboring channel at time t and m indicates the number of neighboring dragonflies. Velocity of the dragonflies is determined and the neighborhood matching procedure is performed in the alignment process. It is computed as:

$$x = \sum_{j=1}^{m} \frac{\theta_j(t)}{m}, \tag{9}$$

where x is the alignment, $\theta_j(t)$ is the velocity of neighboring dragonflies, and m is the number of several neighboring dragonflies. Another process is called cohesion. Dragonflies tend to travel to the middle of their neighborhood. It is calculated as:

$$y = \sum_{j-1}^{m} \frac{g_j(t) - g(t)}{m}, \tag{10}$$

where y indicates the cohesion of the dragonfly, $g_j(t)$ is the position of an adjacent dragonfly, $g(t)$ stands for the position of a recent dragonfly, m is the neighborhood. Lastly, the attraction towards food sources is calculated:

$$z = g_F(t) - g(t), \tag{11}$$

where z is the attraction function, $g_F(t)$ is the location of the food source, and $g(t)$ is the present dragonfly location. Finally, the position of the dragonfly gets updated to discover the global best solution as:

$$g_{t+1} = g(t) + \nabla g_{t+1}, \tag{12}$$

where g_{t+1} refers to the updated dragonfly position, $g(t)$ determines the dragonfly's current position, and ∇g_{t+1} indicates the step vector for detecting the movement direction of the dragonfly as:

$$\nabla g_{t+1} = \{l_1 w + l_2 x + l_3 y + Fz\} + W \cdot g(t), \tag{13}$$

where l_1 indicates the weight of separation (w), l_2 refers to the weight of alignment x, l_3 is the weight of cohesion y, F is a food vector, z identifies "magnetism" of the food source, W indicates an inactivity weight for managing the convergence optimization, $g(t)$ represents a recent position of the dragonfly at time t. Next, the global best dragonfly is determined.

Algorithm 1. The pseudocode for of MOLDRO-QoSDCS technique.

Input: available channels $C = C_1, C_2, \ldots, C_n$, cognitive nodes $N = N_1, N_2, \ldots, N_n$, primary users PUs, secondary users SUs
1. **For each** C
2. Initialize channel populations $A = \{C_1, C_2, \ldots, C_n\}$
3. Initialize opposite population of dragonfly A'
4. **For each** C **in** A and A'
5. Determine objective functions
6. Measure the fitness φ_F
7. Combine A and A'
8. Order the channel $C_1, C_2, \ldots, C_n$
9. Choose local optimum
10. Calculate w, x, γ, z
11. **If** $\alpha_{F_a} > \alpha_{F_b}$ **then**
12. Update the position of the dragonfly
13. Obtain global best dragonfly
14. **Else**
15. Go to step 6
16. **End if**
17. **End for**
18. **End for**
19. **End**

Output: Identify the channel with optimal QoS

Algorithm 1 shows the computation procedure of MOLDRO-QoSDCS. The current and opposite population of several channels is determined. For each population the fitness function is computed depending on the multiple criteria. Both populations are merged and the order of the dragonfly is set using the fitness score. From that, the local optimum solution is obtained. Subsequently, four different processes are performed. Then, the position of the dragonfly is updated and the optimal solution is detected for improving CRN throughput.

4. Performance Simulation

The performance of the proposed MOLDRO-QoSDCS technique was simulated using Matlab with 1000 cognitive radio network nodes and several users during a 10 ms period. The results are compared with a conventional adjustable multi-radio channel hopping (AMCH) protocol and an ML-enabled three-phase TCS generation and allocation scheme. Testing metrics used to evaluate the performance of both the proposed and other existing methods include sensing time, throughput, and energy efficiency.

4.1. Sensing Time

Sensing time determines the channel selection period. In addition, sensing time is referred to as the number of channels sensed by SUs for data transmission. It is estimated as:

$$S_T = T[S_C] \cdot N \tag{14}$$

Simulation results of sensing time for MOLDRO-QoSDCS and methods [1] and [2] versus the number of CRN nodes are shown in Tab. 1. The MOLDRO-QoSDCS technique offers the shortest sensing time for improving the performance of CRN and the results obtained are lower than those of state-of-the-art methods (Fig. 2).

Tab. 1. Sensing time comparison.

Number of CRN nodes	Sensing time [ms]		
	ML-enabled three-phase TCS generation and allocation scheme	AMCH protocol	MOLDRO-QoSDCS technique
100	8.2	5.6	3.4
200	10.6	8.2	5.6
300	13.5	11.3	8.2
400	14.5	12.6	9.1
500	18.6	15.4	12.3
600	21.4	18.9	15.4
700	27.6	24.1	20.6
800	29.5	26.8	22.5
900	34.2	31.3	26.8
1000	36.4	33.5	30.4

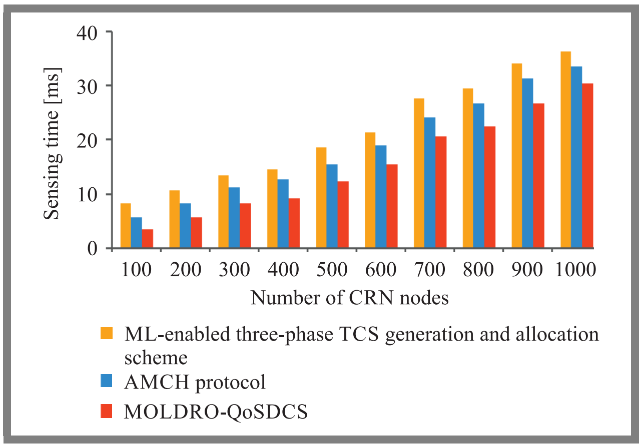

Fig. 2. Sensing time versus the number of nodes.

The lower sensing time achieved with the use of the MOLDRO-QoSDCS technique results from the oppositional learning concept. The ranking method detects the local optimum from the population. Contrary to existing approaches, more available optimal channels are sensed and determined in a CRN. Besides, the best channels are determined and ranked to find the local optimal one. This leads to a decrease (of up to 22%) in sensing time during the channel selection process compared to [1] and, to a decrease of 33% compared to [2].

4.2. Throughput

The formula for calculating throughput is:

$$\textit{Throughput} = \frac{\mathrm{DR}}{t}, \tag{15}$$

where DR is the data rate and t is the time interval (considered to be 1 s). It is determined in bits per second (bps) i.e. data transmission speed.

Table 2 shows throughput-related performance of three different methods: MOLDRO-QoSDCS, [1] and [2] for different

CRN nodes. The data obtained shows that the throughput of the proposed technique is higher than that of [1], [2] (by up to 21% compared with [1] and by 35% compared with [2]) (Fig. 3).

Tab. 2. Comparison of throughput for researched methods.

Number of CRN nodes	Throughput [bps]		
	ML-enabled three-phase TCS generation and allocation scheme	AMCH proto-col	MOLDRO-QoSDCS technique
100	100	120	165
200	140	160	210
300	190	220	280
400	240	270	330
500	330	360	420
600	390	410	490
700	450	480	560
800	500	550	640
900	610	650	720
1000	690	740	860

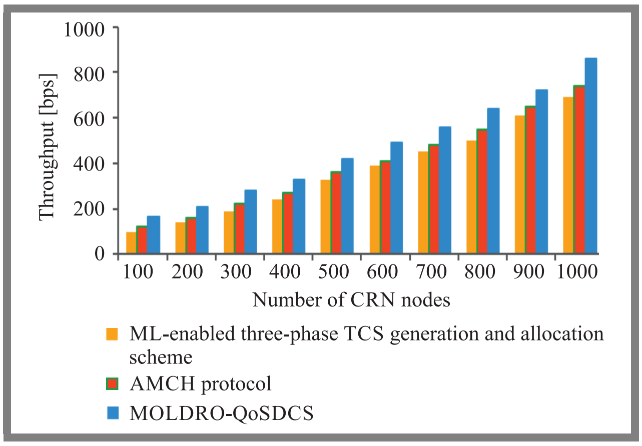

Fig. 3. Throughput comparison.

The newly designed optimization technique also finds the global best solution among the population through fitness function based on optimal SNR ratio, power consumption, and spectrum utilization. This additionally helps increase the throughput.

4.3. Energy Efficiency

Energy efficiency is measured as the ratio between output energy and input energy used for communication in a CRN:

$$\mathrm{EE} = \frac{R_{\mathrm{out}}}{E_{\mathrm{in}}} \cdot 100\% \tag{16}$$

where EE denotes the energy efficiency, E_{out} is the output energy, and $E_{\in}$ is the input energy.

Table 3 shows the energy efficiency simulation results for the three methods, depending on the number of CRN nodes. From the table, it is evident that the proposed MOLDRO-QoSDC technique enhances energy efficiency to a greater extent than the two existing methods.

Tab. 3. Comparison of energy efficiency.

Number of CRN nodes	Energy efficiency [%]		
	ML-enabled three-phase TCS generation and allocation scheme	AMCH proto-col	MOLDRO-QoSDCS technique
100	73	78	85
200	75	80	87
300	76	81	88
400	75	80	86
500	76	81	87
600	77	83	89
700	76	82	88
800	78	83	90
900	75	81	89
1000	76	80	88

Figure 4 illustrates the energy efficiency performance depending on the number of CRN nodes (varying from 100 to 1000). The MOLDRO-QoSDC technique allows to achieve energy efficiency of 85% for 100-node networks, while values of 78% and 73% are obtained using [1] and [2]. The average outputs show that the energy efficiency of the MOLDRO-QoSDC technique is increased by 8% compared with [1] and by 16% compared with [2].

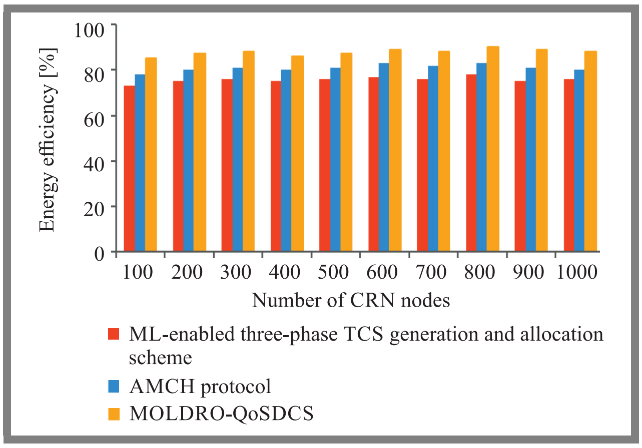

Fig. 4. Energy efficiency comparison graph.

5. Conclusion

An efficient MOLDRO-QoSDC technique is proposed to improve throughput-related performance of CRNs. MOLDRO-QoSDC increases energy efficiency and reduces the sensing time in CRNs. With the calculation of the fitness function, an optimal channel is chosen for CRN communication. Consequently, throughput is improved as well as the sensing time is shortened.

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