A Genetic Algorithm for Multiple Relay Selection in Two-Way Relaying Cognitive Radio Networks

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***Abstract*—In this paper, we investigate a multiple relay selection scheme for two-way relaying cognitive radio networks where primary users and secondary users operate on the same frequency band. More specifically, cooperative relays using Amplify-and-Forward (AF) protocol are optimally selected to maximize the sum rate of the secondary users without degrading the Quality of Service (QoS) of the primary users by respecting a tolerated interference threshold. A strong optimization tool based on genetic algorithm is employed to solve our formulated optimization problem where discrete relay power levels are considered. Our simulation results show that the practical heuristic approach achieves almost the same performance of the optimal multiple relay selection scheme either with discrete or continuous power distributions.**

***Index Terms*—Cooperative cognitive radio network, two-way relaying, genetic algorithm.**

I. Introduction

A light of improving both the spectrum usage and the data rate has been recently attracted researchers in wireless communications in both academic centers and industrial companies. Indeed, Cognitive Radio (CR) and cooperative communication provide smart solutions towards a more efficient usage of the frequency band and data rate. CR was introduced as one of the promising ideas for more efficient spectrum utilization in wireless communication [1]. CR spectrum sharing allows Secondary Users (SUs) known also as unlicensed users to access the frequency band allocated by Primary Users (PUs) known also as licensed users. As such and in order to protect the PUs, several works suggest that the sum of the interference power due to the Secondary Network (SN) should be kept below a certain tolerance called the interference temperature limit [2].

Bidirectional transmission known also as Two-Way Relaying (TWR) has also attracted significant attention during the last years. In conventional TWR, the transmission process takes place in two time slots. In the first time slot, the terminals transmit their signals simultaneously to the relay. Then, in the second time slot, the relay broadcasts the signal to the terminals. For instance, the authors in [3] proposed a useful framework to solve the optimal power allocation problem for TWR network. Their work shows that the TWR provides an improvement of spectral efficiency compared with unidirectional transmission known also as One-Way Relaying (OWR). The work in [4] deals with joint single relay selection TWR-CR network using Amplify-and-Forward (AF) protocol in the high Signal-to-Noise (SNR) regime. In addition, the work presented by Xu *et. al* in [5] propose to employ Genetic Algorithm (GA) [6] for multiple relay selection problem in OWR AF protocol in order to maximize the SNR at the receiver. It is assumed that each relay can be either activated with full power or keep silent, (i.e., ON-OFF mode, where a relay can either cooperates with its maximum power or does not cooperate at all). However, to the best knowledge of the authors, the multiple relay selection problem in TWR-CR networks has not been discussed so far as it is the case for OWR-CR networks.

In this study, we investigate the performance of a multiple relay selection scheme for TWR-CR networks with AF protocol where selected relays amplify the received signal before broadcasting it to destinations. We assume that the system works in a half duplex mode and channel reciprocity is considered. The main contributions of this paper can be summarized as follows: (i) Formulate an optimization problem to maximize the sum rate of a TWR secondary network with AF protocol by taking into account the power budget of the system and the interference level tolerated by the PU, (ii) Design a practical heuristic approach based on GA with discrete power levels to solve the formulated optimization problem, (iii) Compare the performance of the proposed GA with the performance of the optimal and Exhaustive Search (ES) solutions in addition to the performance of our proposed Iterative Algorithm (IA) presented in [7], and (iv) Analyze the impact of some GA parameters on the system performance.

In this work, we introduce discrete power levels to offer more degrees of freedom to the system. In fact, each cognitive relay is assumed to operate with one of the available power levels (i.e., from zero to the maximum available power budget) instead of just on an ON-OFF mode only as performed in [5].

The rest of this paper is organized as follows. The system model of TWR-CR network with AF protocol is presented in Section II. The problem formulation is described in Section III and the proposed heuristic approach based on GA is presented in Section IV. Simulation results are discussed in Section V. Finally, concluding remarks are given in Section VI.

This work was funded by an NPRP grant from Qatar National Research Fund (A member of Qatar Foundation).

II. System Model

We consider a CR system consisting of one PU and a SN. The SN is constituted of two cognitive transceiver terminals T_1 and T_2 and L single antenna cognitive relays. A Non-Line of Sight (NLOS) link between T_1 and T_2 is considered. During the first phase, known also as the Multiple Access Channel (MAC) phase, T_1 and T_2 transmit their signals to the relays simultaneously with a power denoted P_1 and P_2, respectively. In the second phase, known also as the Broadcast Channel (BC) phase, the selected relays transmit the amplified signal to the terminals with a power denoted P_{r_i}, where $i = 1, ..., L$. Half duplex channel case is considered as illustrated in Fig.1. In this work, we assume that the PU and SU's utilize the spectrum at the same time. In order to protect the PU, the received interference power due the secondary nodes should be below a specific interference threshold denoted I_{th}. Without loss of generality, all the noise variances are assumed to be equal to σ_n^2.

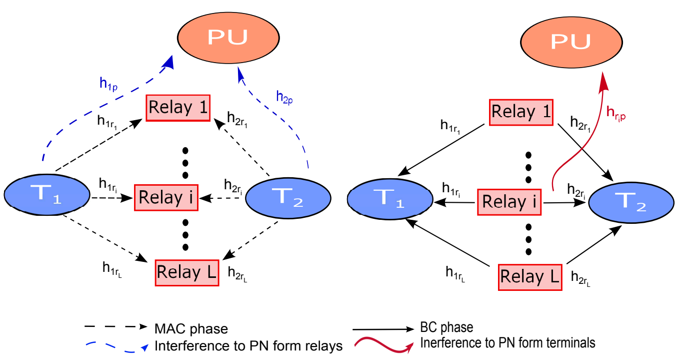

Fig. 1. System model of cooperative two way relaying cognitive radio.

Let us define $\bar{P}, \bar{P}_r, h_{1r_i}, h_{2r_i}, h_{r_ip}, h_{1p}$, and h_{2p} as peak power at the transceiver terminals, peak power at each relay, the channel gain between T_1 and the i^{th} relay, the channel gain between T_2 and the i^{th} relay, the channel gain between the i^{th} relay and the PU, the channel gain between T_1 and the PU, and the channel gain between T_2 and the PU, respectively. All the channel gains adopted in our framework are assumed to be Rayleigh fading channel gains and constant during the two transmission time slots. Furthermore, full Channel State Information (CSI) is considered. We denote by x_1 and x_2 the signals transmitted by T_1 and T_2, respectively. It is assumed that $\mathbb{E}\left(|x_1|^2\right) = \mathbb{E}\left(|x_2|^2\right) = 1$, where $\mathbb{E}\left(\cdot\right)$ denotes the expectation operator.

III. Multiple Relay Selection and Problem Formulation

For simplicity and without loss of generality, we assume that $P_1 = P_2 = P$, where P is the transmitted power allocated for the cognitive transceivers. In the first time slot, the received signal at the i^{th} relay is given by

$$y_{r_i} = \sqrt{P} h_{1r_i} x_1 + \sqrt{P} h_{2r_i} x_2 + n_{r_i}, \tag{1}$$

where n_{r_i} is the additive Gaussian noise at the i^{th} relay.

During the second time slot, each active relay amplifies y_{r_i} by multiplying it by w_i and broadcasts it to the terminals T_1 and T_2. The received signals in the BC phase are given by

$$\begin{aligned} y_1 &= \sum_{i=1}^{L} \epsilon_i w_i \left(\sqrt{P} \left(h_{1r_i} h_{1r_i} x_1 + h_{1r_i} h_{2r_i} x_2 \right) + h_{1r_i} n_i \right) + n_1, \\ y_2 &= \sum_{i=1}^{L} \epsilon_i w_i \left(\sqrt{P} \left(h_{2r_i} h_{1r_i} x_1 + h_{2r_i} h_{2r_i} x_2 \right) + h_{2r_i} n_i \right) + n_2, \end{aligned} \tag{2}$$

where n_1 and n_2 are the additive Gaussian noise at T_1 and T_2, respectively. In (1), ϵ_i is a binary variable denoting whether the i^{th} relay is active or not and it is given by

$$\epsilon_i = \begin{cases} 1, & \text{if the } i^{th} \text{ relay is selected.} \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

By using the knowledge of the CSI and channel reciprocity, the terminals can remove the self interference by eliminating their own signal (i.e., x_1 for T_1 and x_2 for T_2). After the self interference cancelation, the SNR at T_1 and T_2 are given by

$$\begin{aligned} \gamma_1 &= \frac{P \left(\sum\limits_{i=1}^{L} \epsilon_i |w_i h_{1r_i} h_{2r_i}| \right)^2}{\sigma_n^2 \left(1 + \sum\limits_{i=1}^{L} \epsilon_i |w_i h_{1r_i}|^2 \right)}, \\ \gamma_2 &= \frac{P \left(\sum\limits_{i=1}^{L} \epsilon_i |w_i h_{1r_i} h_{2r_i}| \right)^2}{\sigma_n^2 \left(1 + \sum\limits_{i=1}^{L} \epsilon_i |w_i h_{2r_i}|^2 \right)}, \end{aligned} \tag{4}$$

respectively. The relay power of the i^{th} relay node can be expressed as

$$P_{r_i} = \mathbb{E}\left(|w_i y_{r_i}|^2\right) = \left(P|h_{1r_i}|^2 + P|h_{2r_i}|^2 + \sigma_n^2 \right) |w_i|^2. \tag{5}$$

From equation (5), the value of $|w_i|$ can be expressed as

$$|w_i| = \frac{\sqrt{P_{r_i}}}{\sqrt{P|h_{1r_i}|^2 + P|h_{2r_i}|^2 + \sigma_n^2}}. \tag{6}$$

By substituting the value of $|w_i|^2$ into (4), the SNRs become

$$\begin{aligned} \gamma_1 &= \frac{P \left(\sum\limits_{i=1}^{L} \epsilon_i \frac{\sqrt{P_{r_i}} |h_{1r_i}| |h_{2r_i}|}{\sqrt{P\left(|h_{1r_i}|^2 + |h_{2r_i}|^2\right) + \sigma_n^2}} \right)^2}{\sigma_n^2 \left(1 + \sum\limits_{i=1}^{L} \epsilon_i \frac{P_{r_i} |h_{1r_i}|^2}{P\left(|h_{1r_i}|^2 + |h_{2r_i}|^2\right) + \sigma_n^2} \right)}, \\ \gamma_2 &= \frac{P \left(\sum\limits_{i=1}^{L} \epsilon_i \frac{\sqrt{P_{r_i}} |h_{1r_i}| |h_{2r_i}|}{\sqrt{P\left(|h_{1r_i}|^2 + |h_{2r_i}|^2\right) + \sigma_n^2}} \right)^2}{\sigma_n^2 \left(1 + \sum\limits_{i=1}^{L} \epsilon_i \frac{P_{r_i} |h_{2r_i}|^2}{P\left(|h_{1r_i}|^2 + |h_{2r_i}|^2\right) + \sigma_n^2} \right)}. \end{aligned} \tag{7}$$

Thus, the sum rate of the TWR can be written as

$$R = \frac{1}{2} \log_2(1 + \gamma_1) + \frac{1}{2} \log_2(1 + \gamma_2). \tag{8}$$

The sum rate maximization optimization problem of TWR-CR multiple relay selection can now be formulated as

$$\max_{P,\boldsymbol{P_r},\boldsymbol{\epsilon}} \quad R \tag{9}$$

$$\text{s.t} \quad 0 \leq P \leq \bar{P}, \tag{10}$$

$$0 \leq P_{r_i} \leq \bar{P}_r, \quad \forall i = 1, ..., L, \tag{11}$$

$$P(|h_{1p}|^2 + |h_{2p}|^2) \leq I_{th}, \tag{12}$$

$$\sum_{i=1}^{L} \epsilon_i P_{r_i} |h_{r_i p}|^2 \leq I_{th}, \tag{13}$$

$$\epsilon_i \in \{0, 1\}, \quad \forall i = 1, ..., L, \tag{14}$$

where $\boldsymbol{\epsilon} = [\epsilon_1, ..., \epsilon_L]$ and $\boldsymbol{P_r} = [P_{r_1}, ..., P_{r_L}]$ are the decision variables of our formulated optimization problem that contain the state and the transmit power of each relay, respectively. The constraints (10) and (11) represent the peak power constraint at the terminals, and at each cognitive relay, respectively, while the constraints (12) and (13) represent the interference constraint in the first time slot, and in the second time slot, respectively.

IV. Proposed Genetic Algorithm with Discrete Power Levels

In order to simplify the formulated optimization problem in Section III, we solve this problem in a time slot per time slot fashion. During the MAC phase, the power allocation of both terminals depends essentially on two constraints: the peak power constraint (10) and the interference constraint (12). For this reason, the optimal power at the terminals P^* can be expressed as

$$P^* = \min\left(\frac{I_{th}}{|h_{1p}|^2 + |h_{2p}|^2}, \bar{P}\right). \tag{15}$$

Indeed, if the power at the terminals $\bar{P}$ affects the performance of the PU, then the power is reduced to $\frac{I_{th}}{|h_{1p}|^2+|h_{2p}|^2}$. In the BC phase, we need to find the optimal power allocation over relays (i.e., $\boldsymbol{P_r^*}$) in order to maximize the sum rate of SN without affecting the Quality of Service (QoS) of the PU measured by I_{th}. The optimization problem during the second time slot is therefore given by

$$\max_{\boldsymbol{P_r},\boldsymbol{\epsilon}} \quad R \tag{16}$$

$$\text{s.t} \quad (11), (13), (14).$$

The optimal solution for our non linear optimization problem formulated in (16) is difficult to find due the existence of binary variables ϵ_i, $i = 1, ..., L$ [8]. Therefore, we propose to use a GA based approach to find suboptimal solution to the problem. This approach relies essentially on a random natural evolution. At the beginning, it generates a random initial population consisted by a certain number of strings. During each generation, GA survives the strong strings, while the weak strings die out. Then from the survival strings, GA generates new strings using genetic operators such as survivor selection, reproduction, crossover, and mutation [6].

A. Coding Scheme

Each relay can transmit the amplified signal using an amount of power between 0 and $\bar{P}_r$. In our approach, we propose to divide the interval of power into N power levels as follows $\left(P_{r_i} \in \left\{0, \frac{\bar{P}_r}{N-1}, \frac{2\bar{P}_r}{N-1}, ..., \frac{(N-2)\bar{P}_r}{N-1}, \bar{P}_r\right\}\right)$ and the relay can transmit its signal using one of these power levels between 0 and $\bar{P}_r$. Consequently, cognitive relays have more flexibility to allocate their powers in the case where continuous power distribution is not available and they become not limited to the ON-OFF mode where relays can either transmit or keep silent.

In order to employ the GA, we propose to encode these power levels into binary words $b^{(i)}, \forall i = 1, \cdots, L$ such that each power levels is designed by a binary word. The length of the binary words $b^{(i)}$ depends on N (i.e., the number of quantization levels) as follows: length$(b^{(i)}) = \lceil \log_2 N \rceil$ where $\lceil . \rceil$ denotes the integer round towards $+\infty$. For instance, if $N = 4$, two bits are sufficient to encode these levels. If $N = 11$, four bits are used to encode the code levels. In the last case, the number of required words is not a power of 2, some binary words are redundant and they correspond to any valid word. Several solutions were proposed to solve this problem by discarding these words as illegal, assigning them a low utility or mapping them to a valid word with fixed, random or probabilistic remapping [9].

B. Genetic Algorithm

In our GA based approach, we generate randomly T binary strings to form the initial population set where T denotes the population length. Each string S_t, $\forall t = 1, \cdots, T$, is built by concatenating L binary words $b^{(i)}$ corresponding to a power level of each relay. Thus, the length of a string is equal to $L \log_2 N$. Once the power level of each relay in a string S_t is known and thus the values of $\epsilon_i, \forall i = 1, \cdots, L$, (i.e., if $b^{(i)}$ refers to a zero power level, then $\epsilon_i = 0$, otherwise, $\epsilon_i = 1$), the algorithm verifies whether the constraint (13) is satisfied or not. If it is the case, the algorithm computes the corresponding data rate $R^{(t)}$ which plays the role of the fitness of the string S_t. Otherwise, $R^{(t)} = 0$. Then, the algorithm selects $\tau, 1 \leq \tau \leq T$, strings that provide the highest data rates and keeps them to the next population while the $T - \tau$ remaining strings are generated by applying crossovers and mutations to the τ survived parents. Crossovers consist of cutting two selected random parent strings at a correspond point which is chosen randomly between 1 and $L \lceil \log_2(N) \rceil$. The obtained fragments are then swapped and recombined to produce two new strings. After that, mutation (i.e., changing a bit value of the string randomly) is applied with a probability p. This procedure is repeated until reaching convergence or maximum generation number denoted I.

In some particular cases, most of randomly generated strings do not satisfy constraint (13) and thus most of the corresponding data rates are zeros. In fact, it is difficult to obtain combinations that fits constraint (13) mainly at high SNR. For this reason, we propose to select the best strings based on another fitness $D^{(t)}$ which corresponds to the difference between I_{th}

and the PU interference term, $D^{(t)} = \| \sum_{i=1}^{L} \epsilon_i P_{r_i} |h_{r_ip}|^2 - I_{th} \|$. Indeed, the best selected strings in this case, are those who provide these lowest $D^{(t)}$. The proposed GA with discrete power levels is detailed in Algorithm 1.

Algorithm 1 Proposed Genetic Algorithm with Discrete Power Levels

- **Input:** $N, I_{th}, \sigma_n^2, \bar{P}, \bar{P}_r, L, I, h_{1r_i}, h_{2r_i}, h_{r_ip}, h_{1p}$, and h_{2p}.
- $P^* = \min\left(\frac{I_{th}}{|h_{1p}|^2+|h_{2p}|^2}, \bar{P}\right)$.
- **Initialization:** $R_{max} = 0$.
- Generate a random initial population containing all S_t, $\forall t = 1, \cdots, T$.
- $itr = 1$.

while ($itr \leq I$ or not converge) **do**
  for $t = 1 : T$ **do**
    - Find P_{r_i}, $\forall i = 1, \cdots, L$ corresponding to the string S_t.
    - Compute $D^{(t)} = \| \sum_{i=1}^{L} \epsilon_i P_{r_i} |h_{r_ip}|^2 - I_{th} \|$.
    if interference constraint is satisfied (13) **then**
      - Compute the sum rate $R^{(t)}$ using (8).
    else
      - Set $R^{(t)}$ to 0.
    end if
  end for
  - Save R_{max} such that $R_{max} = \max_t \boldsymbol{R^{(t)}}$.
  - Keep the best τ strings providing the highest data rates to the next population and offering the lowest $D^{(t)}$.
  - From the survived τ strings, generate $T - \tau$ new strings by applying crossovers and mutations to generate a new population set.
  - $itr = itr + 1$.
end while

V. Simulation Results

In this section, simulation results are presented to show the performance of the proposed GA for multiple relay selection TWR-CR networks as described in the scenario given in Fig.1. The variance σ_n^2 is assumed to be equal to 10^{-4}. Also, we assume that all cognitive elements have the same peak power, i.e., $\bar{P}_r = \bar{P}$ and that all channels are assumed to be independent and identically distributed (i.i.d) Rayleigh fading channels. The GA is executed using these parameters: the mutation probability p is set to 0.5, $\tau = 0.25T$, and the maximum generation number $I = 35$.

Fig.2 shows a comparison between the performance of the proposed GA and the optimal solution with continuous power distributions. Starting by generating $T = 32$ random initial strings, we plot the achieved secondary sum rate versus $\bar{P}_r$ for different values of $I_{th} = \{10, 20\}$ dBm and different values of $L = \{6, 10\}$. In the low SNR region, we can notice that the proposed algorithm and the optimal solution have almost the same sum rate, while in the high SNR region, a small gap between both methods is observed. This gap is increasing with

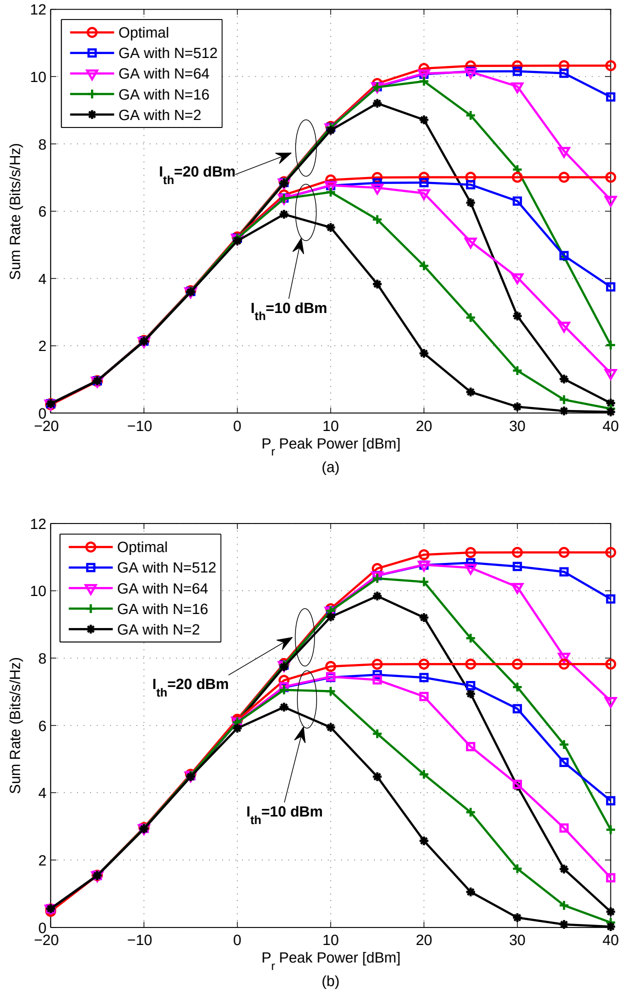

Fig. 2. Achieved sum rate versus the peak power $\bar{P}_r$ for the optimal and the proposed GA with different values of I_{th} and N (a) $L = 6$, (b) $L = 10$.

higher $\bar{P}_r$ values due to the fact that starting from a certain value of $\bar{P}_r$ the system can no more supply all relays with their whole power budget because the system has to respect constraint (13). Hence, more relays are deactivated. To cope with this, we have introduced the discretization set to get more degrees of freedom. Indeed, by increasing N we enhance the secondary sum rate and reduce the gap with the optimal solution. For instance, for $L = 10$ and $I_{th} = 20$ dBm, we were able to triple the achievable sum rate by going from less than 2 bits/s/Hz to around 5.5 bits/s/Hz by having $N = 16$ instead of $N = 2$ (i.e., ON-OFF mode) when $\bar{P}_r = 35$ dBm. It should be noted that using the proposed GA with discrete power levels, we achieve the performance of the optimal solution when $N \to \infty$.

In Fig.3, we compare the performances of the ES algorithm, IA, and GA (with $T = 32$) for discrete P_{r_i}. The IA presented in [7] attempts to solve the proposed optimization problem iteratively. At the beginning, it selects the relay and its maximum possible power that offer the highest sum rate and satisfy the constraint (13) simultaneously. Then, it tries to add the maximum number of relays that can contribute in maximizing the sum rate. If, during this process, constraint

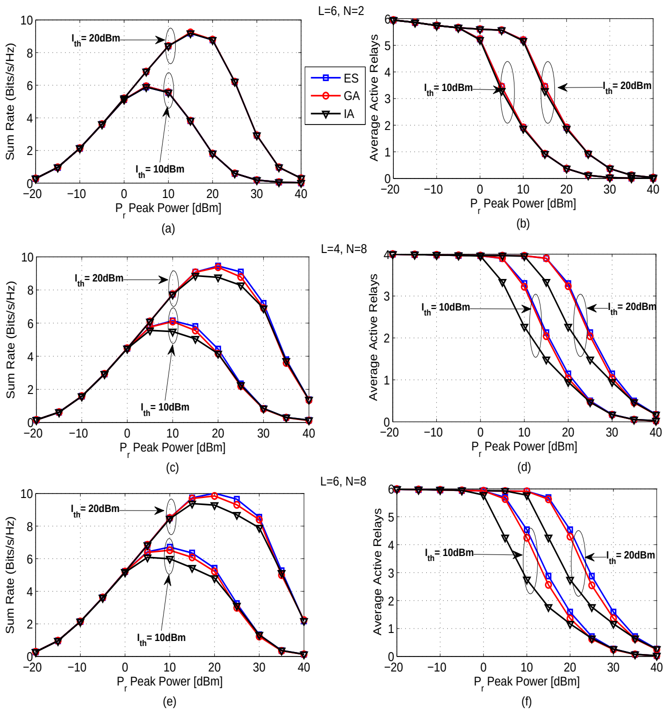

Fig. 3. The performance of the ES algorithm, the IA algorithm, and the GA algorithm with different values of I_{th}, L, and N versus $\bar{P}_r$, (a,c,e) achieved sum rate, (b,d,f) average active relays.

(13) is affected, then the new active relays have to be supplied with the next lower power existing in the discrete quantization set. Fig.3(a) and Fig.3(b) plot the secondary sum rate and the average number of active relays versus the peak relay power, respectively for $L = 6$ and $N = 2$. It is shown that the GA and IA achieve the same performance of the ES algorithm by powering the same number of relays. However, by increasing N and/or L, we observe, in Fig.3(c)-Fig.3(f), a degradation of the performance of IA comparing to ES method. However, our proposed GA maintains the same performance as ES method even for high values of L and N. Hence, it is more beneficial for TWR-CR network to employ GA instead of IA since the former outperforms the latter for all values of $\bar{P}_r, L, N,$ and I_{th}. Indeed, thanks to its random evolution process, GA provides more chance to find a better combination than IA. Furthermore, the added fitness $D^{(t)}$ in GA can contribute in enhancing the sum rate mainly at the peak. In terms of computational complexity, an important saving specially for large values of N and L is obtained comparing to the ES algorithm. Our proposed GA requires at most TI times to compute the rate until reaching convergence, while ES algorithm and IA need N^L and $(N-1)L^2$ operations to compute the rate and find the optimal or suboptimal solution, respectively. However, the GA requires more processing time than IA due to the genetic operators (i.e., selection, crossover, and mutation).

The impact of the initial population size T is investigated in Fig.4 where we plot the achieved secondary sum rate of the proposed GA versus the peak power $\bar{P}_r$ with $N = 64$, $L = 6$, and different values of I_{th}. We can notice that, in low SNR region, the proposed GA has almost the same achieved sum

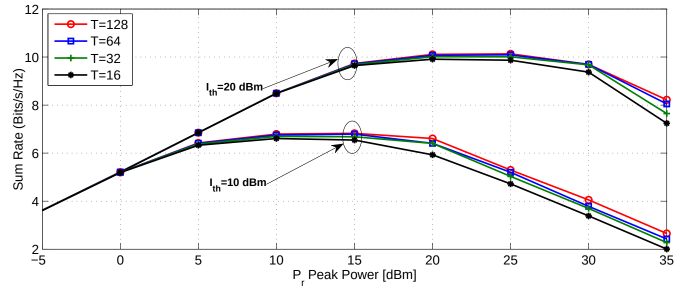

Fig. 4. Achieved sum rate versus the peak power $\bar{P}_r$ for the the GA with $N = 64$ and $L = 6$ with different values of I_{th} and T.

rate for any values of T, however, in high SNR region, if we increase T, we obtain a small improvement which indicates that, the proposed GA does not require a high population size T to reach acceptable performance. Nevertheless, with high values of T, more random combinations are involved by the GA and thus, it becomes able to find a better solution.

VI. Conclusion

In this paper, we proposed a practical heuristic algorithm based on GA to maximize the secondary achievable sum rate of a multiple relay selection scheme for TWR-CR system with discrete power distributions. We showed that the proposed approach achieves almost the same performance of both ES method and optimal solution with continuous power distributions. In addition, we showed that thanks to its random evolution, the GA provides a better performance than our previously proposed IA. In our ongoing task, we are working on applying our algorithm to OWR-CR networks and generalizing our model to a multiple relay scheme with multi-antenna system.

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