Multiobjective Memetic Optimization for Spectrum Sensing and Power Allocation in Cognitive Wireless Networks

Hieu V. Dang and Witold Kinsner
Department of Electrical and Computer Engineering
University of Manitoba, Winnipeg, Canada
Email: {dangh@myumanitoba.ca|witold.kinsner@umanitoba.ca}

***Abstract*—The paper presents a multiobjective memetic optimization algorithm for a joint spectrum sensing and power allocation problem in a multichannel, multiple-user cognitive wireless networks. In particular, we apply a multiobjective memetic algorithm to design efficient spectrum sensing and power allocation techniques to maximize the throughputs and minimize the interferences of the network. To maximize the throughputs of secondary users and minimize the interferences to primary users, it requires for a joint determination of the sensing and transmission parameters of the secondary users, such as sensing times, decision threshold vectors, and power allocation vectors. There is a conflict between these two objectives, thus a multiobjective optimization problem is introduced. The proposed algorithm evolutionarily learns to find optimal spectrum sensing times, decision threshold vectors, and power allocation vectors to maximize the averaged opportunistic throughput and minimize the averaged interference (or maximize the averaged transmission gain) of the cognitive network.**

I. Introduction

Evolutionary algorithms (EA), like *genetic algorithms* (GA), are search-and-optimization techniques that work on a principle inspired by the natural evolution theory of Darwin [1], [2]. Inspired by models of adaptation in natural systems that combine the evolutionary adaptation of a population with individual learning within the lifetimes of its members, *memetic algorithms* (MA) have been introduced by Moscato [3] as extentions of EA that adopt the hybridization between EA and local searches to refine the individuals under consideration [1], [3]. The use of MA for multiobjective optimization (*Mutiobjective memetic algorithms* - MOMA) has attracted much attention and efford in recent years. In the literature, MOMA has been demonstrated to be much more effective and efficient than the EA and the tranditional optimization searches for some specific optimization problem domains [1], [4], [5], [6], [7]. The reports on the applications of MOMA to real engineering problems are still limited in the literature.

Cognitive radios have been proposed to be the next generation wireless devices that can share underutilized spectrum [8], [9]. Spectrum sensing and dynamic spectrum access are main principles of cognitive radios. In spectrum sensing, cognitive radio users (*secondary users* - SU) sense the spectrum of licenced users (*primary users* -PU) to detect and utilize spectrum holes within the PUs' spectrum. The cognitive radio networks adopt a hierarchical access structure by considering PUs as the legacy spectrum holders and SUs as the unlicensed users.

The challenge for a reliable sensing algorithm is to identify suitable transmission opportunities without compromising the integrity of the PUs [10], [11]. The efficiency of the employed spectrum sensing technique plays a key role in maximizing the cognitive radio network throughput while protecting the PUs from interference. The popular criteria in designing sensing techniques is to minimize the probability of false alarm as low as possible [11], [10]. Besides, in order to limit the probability of interfering with PUs, it is desirable to keep the missed detection probability as low as possible. The sensing time is the tradeoff factor between the quality and the speed of sensing. Increasing the sensing times allows to have both low false alarm and low missed detection probabilities, but reduces the time available for transmissions which results in low throughputs of SUs. Another tradeoff factor between the false alarm and the missed detection probabilities is the detection thresholds. Low detection thresholds will result in high false alarm probability and low missed detection probability and vice versa. Thus, to maximize the throughput of SUs, it requires for a joint optimization of the sensing and transmission parameters of the SUs. They are sensing times, decision threshold vectors, and power allocation vectors.

In this paper, we model the joint optimization problem between spectrum sensing and power allocation for a multichannel, multiple user cognitive radio network as a multiobjective optimization problem. Two conflicting objectives are the throughput of SUs and the interference created by SUs. We propose to use MOMA to search for optimal sensing times, decision vector, and power allocation vector of each SU to maximize the averaged throughput and minimize the averaged interference of the cognitive network. The main contributions of this work are as follows.

1. A multiobjective joint optimization problem between spectrum sensing and power allocation for a multichannel multiple SU cognitive wireless network is introduced.
2. A novel multiobjective joint spectrum sensing and power allocation method is proposed based on MOMA. This is the first approach to solve the joint optimization problem

using MOMA.

The rest of the paper is organized as follows. Sec. II gives a background on MOMA. Sec. III describes the joint spectrum sensing and power allocation problem, and the proposed solution based on MOMA. Sec. IV discusses experimental results. Finally, the paper ends with the conclusions.

II. MULTIOBJECTIVE MEMETIC ALGORITHMS

In multiobjective optimization problems, the solution is a family of points known as a Pareto-optimal set (i.e., Pareto solution set), where each objective component of any member in the set can only be improved by degrading at least one of its other objective components [12], [13]. The values of objectives of the Pareto solutions in the Pareto-optimal set form a Pareto front. Multiobjective optimization algorithms can be categorized into two groups: (*i*) algorithms that use the combinations of objectives to select new individuals; (*ii*) algorithms that do not combine objectives and do the selection by means of dominance based criterion [5]. In the first category, the multiple objectives are combined to create a single objective by adopting a weight values. Thus, the algorithm does not detect a Pareto front, but only one solution. This class of algorithms has the drawback that the selection of a proper set of weights must be performed to allow a natural dispersion of the solutions. In the second approach, the selection is based on dominance-based rankings of all the solutions of the population. A multiobjective memetic optimization can be developed based on the combination of objectives for a single objective optimization, or based on dominance-based criteria. In this work, we focus only on the second approach that is based on the Pareto front criteria for effective MOMA.

The performance of MOMA not only relies on the evolutionary framework, but also depends on the local search. The best tradeoff between a local search and the global search provided by evolution is the foremost issue in MOMA [1]. There are different MOMA frameworks introduced in the literature for domain-specific applications [18], [14]. Ishibuchi et al. [4] introduced a MOMA framework for combinatorial optimization problems. This work adopts a hybridization of the multiobjective genetic algorithm NSGA-II introduced by Deb and coworkers [15] and a local search to produce a MOMA for the Knapsack combinatorial optimization problem. In this work, a local search is employed to refine the offsprings with a weighted sum-based scheme. The selection criterion are based on Pareto ranking and crowding distance sorting used in NSGA-II. Motivated by the work of Ishibuchi et al. [4], the framework of the MOMA for our data hiding problem is described in the Algorithm 1.

Algorithm 1 is a hybrid between NSGA-II and a local search. The procedures "Fast Non-Dominated Sort", "Crowding Distance Assignment" are parts of the NSGA-II described in details in [15], [2]. The procedure "Generate Offspring Population" is genetic operation procedure consisting of crossover and mutation operations. In this application, we use the real-coded crossover algorithm with probability p_x, and real-coded

Algorithm 1 Multiobjective Memetic Algorithm (MOMA)

procedure MOMA(N, p_{ls})
    Generate Random Population P size N
    Objectives Evaluation
    Fast Non-Dominated Sort
    Crowding Distance Assignment
    repeat
        Generate Offspring Population P_{offs}
        $P_{impr} \leftarrow$Local-Search(P_{offs}, p_{ls})
        $P_{inter} \leftarrow P \cup P_{offs} \cup P_{impr}$
        Fast Non-Dominated Sort
        Crowding Distance Assignment
        Update Population $P \leftarrow$ Selection(P_{inter})
    until Terminated Conditions
    return Non-Dominated Population P
end procedure

mutation with probability p_m [16], [15]. The offsprings are refined by the local search with probability of p_{ls}. In the local search, we use weighted-sum fitness as being recommended by Ishibuchi et al. [4]. The k objectives $(f_1, f_2, ...f_k)$ are weighted to be a single objective by

$$f(x) = \sum_{i=1}^{k} \lambda_i f_i(x) \tag{1}$$

where $(\lambda_1, \lambda_2, ..., \lambda_k)$ are random normalized weights generated according to [17]

$$\begin{cases} \lambda_1 = 1 - \sqrt[k-1]{rand()} \\ ... \\ \lambda_j = (1 - \sum_{l=1}^{j-1} \lambda_l)(1 - \sqrt[k-1-j]{rand()}) \\ ... \\ \lambda_k = 1 - \sum_{l=1}^{k-1} \lambda_l \end{cases} \tag{2}$$

The local search procedure is performed only on the best individuals of a given offspring generation. Firstly, a random weight vector is generated by Eq. (2). Based on the generated random weights, the initial solution for local search is selected from offspring population using tournament selection with replacement. The same random weights are then used for the local search to produce improved population P_{impr} from selected initial indivisual. The intermediate population P_{inter} is produced by combining the current population P, the offspring population P_{offs}, and the improved population P_{impr}. The non-dominated population P is finally updated by the selection with replacement based on the Pareto ranks and crowding distances. The algorithm finishes when it meets certain terminated conditions such as predefined number of iterations. The details of applying this MOMA to our multi-objective joint optimization problem are discribed in the next section.

III. MULTIOBJECTIVE JOINT SPECTRUM SENSING AND POWER ALLOCATION USING MOMA

A. Formulation of Multiobjective Joint Spectrum Sensing and Power Allocation Problem

The model is considered with Q active SUs, each formed by a transmitter-receiver pair, coexisting in the same area and sharing the same band. We assume that the medium access control (MAC) frame is divided in two time slots: τ-sensing slot, and $T-\tau$ data slot. During the sensing slot τ, the SUs stay silent and sense the electromagnetic environment looking for the spectrum holes. During the data slot $T-\tau$, the SUs transmit simultaneously over the portions of the licensed spectrum detected as available. The sensing problem is introduced in a CR scenario that consists of one active PU.

The spectrum sensing problem of SU $i = 1, ..., Q$ on subcarrier $k = 1, ...N$ is formulated as a binary hypothesis testing at time index $n = 1, 2, ..., K_i$. Based on the Neyman-Pearson frame work, the decision rule of SU i over carrier k based on the energy detector is [19], [10]

$$D(Y_{i,k}) = \frac{1}{K_i}\sum_{n=1}^{K_i}|y_{i,k}[n]|^2 \underset{\mathcal{H}_{k|0}}{\overset{\mathcal{H}_{k|1}}{\gtrless}} \gamma_{i,k} \tag{3}$$

where $\gamma_{i,k}$ is the decision threshold of SU i for the carrier k to be chosen to meet the required false alarm rate. Under this framework, the probability of false alarm and probability of detection are approximated as follows

$$P_{i,k}^{fa}(\gamma_{i,k}, \tau_i) = \mathcal{Q}\left(\sqrt{\tau_i f_i}\frac{\gamma_{i,k} - \mu_{i,k|0}}{\sigma_{i,k|0}}\right) \tag{4}$$

$$P_{i,k}^{d}(\gamma_{i,k}, \tau_i) = \mathcal{Q}\left(\sqrt{\tau_i f_i}\frac{\gamma_{i,k} - \mu_{i,k|1}}{\sigma_{i,k|1}}\right) \tag{5}$$

where the function $\mathcal{Q}(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-t^2/2}dt$; and $\mu_{i,k|0}$, $\mu_{i,k|1}$, $\sigma_{i,k|0}$, and $\sigma_{i,k|1}$ are constant parameters given in [10]. The missed detection probability is then calculated by

$$P_{i,k}^{md} = 1 - P_{i,k}^{d} \tag{6}$$

The sensing problem is to find optimal values of the detection thresholds $\gamma_{i,k}$ and the sensing time τ_i in order to minimize both $P_{i,k}^{fa}$ and $P_{i,k}^{md}$. However, Eqs. (4) and (5) show that there exists a tradeoff between probability of false alarm and the detection probability when selecting the optimal values of $\gamma_{i,k}$ and τ_i. Thus, the optimality of the sensing system cannot be obtained if we just focus on the detection problem to select the parameters $\gamma_{i,k}$ and τ_i. The optimal choice of the detection thresholds and sensing time should be the result of a joint optimization of the sensing and transmission processes.

The transmission strategy of each SU i is the power allocation vector $p_i = \{p_{i,k}\}_{k=1}^N$ over the N subcarriers. The opportunistic throughput of SU i is given by [10]

$$R_i(\tau_i, \boldsymbol{p}, \boldsymbol{\gamma}_i) = (1 - \frac{\tau_i}{T})\sum_{k=1}^{N}[1 - P_{i,k}^{fa}(\gamma_{i,k}, \tau_i)]r_{i,k}(\boldsymbol{p}) \tag{7}$$

where the maximum achievable rate $r_{i,k}(\boldsymbol{p})$ for a specific power allocation profile $p_{1,k}, ..., p_{Q,k}$ is

$$r_{i,k}(\boldsymbol{p}) = log\left(1 + \frac{|H_{ii}(k)|^2 p_{i,k}}{\sigma_{i,k}^2 + \sum_{r\neq i}|H_{ri}(k)|^2 p_{r,k}}\right) \tag{8}$$

where $\{H_{ii}(k)\}_{k=1}^N$ is the channel transfer function of the direct link i and $\{H_{ri}(k)\}_{k=1}^N$ is the cross-channel transfer function between the secondary transmitter r and the secondary receiver i.

Missed detections at the SUs will produce the interferences to the PU. We define the interference and the transmission gain created by cognitive user i to the PU given by

$$I_i(\tau_i, \boldsymbol{\gamma}_i, \boldsymbol{p}_i) = \sum_{k=1}^{N} P_{i,k}^{md}(\gamma_{i,k}, \tau_i).p_{i,k} \tag{9}$$

$$G_i(\tau_i, \boldsymbol{\gamma}_i, \boldsymbol{p}_i) = \sum_{k=1}^{N}(1 - P_{i,k}^{md}(\gamma_{i,k}, \tau_i)).p_{i,k} \tag{10}$$

Our objective is to find the optimal sensing time τ_i, the decision threshold vector $\boldsymbol{\gamma}_i$, and the power allocation vector $\boldsymbol{p}_i$ to maximize the throughput R_i and to minimize the interference I_i (or equivalent to maximize the transmission gain G_i) at each SU i, $i = 1, ..., Q$.

Movivated from centralized cooperative spectrum sensing methods [20], [21], a centralized cooperative joint sensing and power allocation mechanism is proposed in this work. In this centralized cooperative sensing and power allocation, a central unit is used to collect sensing information from cognitive devices, identifies and determines optimal parameters for spectrum sensing and power allocation, and then broadcasts these informations to other cognitive radios. The central unit is also called the fusion center [20]. In this context, SUs will send its sensing statistics and parameters to the fusion center. At the fusion center, the probability of false alarm P^{fa} and probability of miss detection P^{md} are calculated, and so the throughput R_i and the transmission gain G_i of SU i. The averaged throughput and the averaged transmission gain of the network are then calculated at the fusion center by

$$R(\boldsymbol{\tau}, \boldsymbol{p}, \boldsymbol{\gamma}) = \frac{1}{Q}\sum_{i=1}^{Q} R_i(\tau_i, \boldsymbol{p}, \boldsymbol{\gamma}_i) \tag{11}$$

$$G(\boldsymbol{\tau}, \boldsymbol{\gamma}, \boldsymbol{p}) = \frac{1}{Q}\sum_{i=1}^{Q} G_i(\tau_i, \boldsymbol{\gamma}_i, \boldsymbol{p}_i) \tag{12}$$

The multiobjective joint optimization problem between spectrum sensing and power allocation is now formulated by

$$\begin{cases} \underset{\boldsymbol{\tau},\boldsymbol{\gamma},\boldsymbol{p}}{\text{maximize}}\ R(\boldsymbol{\tau}, \boldsymbol{p}, \boldsymbol{\gamma}) \\ \underset{\boldsymbol{\tau},\boldsymbol{\gamma},\boldsymbol{p}}{\text{maximize}}\ G(\boldsymbol{\tau}, \boldsymbol{\gamma}, \boldsymbol{p}) \end{cases} \tag{13}$$

where $\boldsymbol{\tau} = \{\tau_i\}_{i=1}^Q$; $\boldsymbol{p} = \{p_{i,k}\}_{i=1,k=1}^{Q,N}$; and $\boldsymbol{\gamma} = \{\gamma_{i,k}\}_{i=1,k=1}^{Q,N}$.

We propose to use multiobjective memetic learning algorithms to solve the joint optimization in Eq. (13). The algorithms are described in the next section.

B. MOMA Based Joint Spectrum Sensing and Power Allocation (MOMA-JSSPA)

In this joint spectrum sensing and power allocation problem, there always exists two conflicting objectives. These are the averaged throughput and the averaged transmission gain of the network. In this work, we apply MOMA to search for the optimal decision policy (sensing time τ_i, decision threshold vector $\boldsymbol{\gamma}_i$, and power allocation vector $\boldsymbol{p}_i$) for each SU i. The pseudocode of the proposed algorithm is described in Algorithm 2.

Algorithm 2 MOMA_JSSPA

procedure MOMA_JSSPA($Q, N_{pop}, N_c, p_{ls}, MaxItrs$)
  Compute Number of Decision Variables: $V \leftarrow 3 * Q$
  Generate Random Population P size N_{pop}
  $P \leftarrow$ OBJ_EVAL(P, V, Q, N_c) ▷ Evaluate Objectives
  Fast Non-Dominated Sort
  Crowding Distance Assignment
  $itrs \leftarrow 0$
  repeat
    $itrs \leftarrow itrs + 1$
    Generate Offspring Population P_{offs}
    $P_{offs} \leftarrow$ OBJ_EVAL(P_{offs}, V, Q, N_c)
    $P_{impr} \leftarrow$ LOCAL_SEARCH(P_{offs}, p_{ls}, M, V)
    $P_{inter} \leftarrow P \cup P_{offs} \cup P_{impr}$
    Fast Non-Dominated Sort
    Crowding Distance Assignment
    Update Population: $P \leftarrow$ SELECTION(P_{inter})
  until $itrs \geq MaxItrs$
  $S_{best} \leftarrow$ SOL_SELECT(P)
  $\{\hat{\boldsymbol{\tau}}\}, \{\hat{\boldsymbol{\gamma}}\}, \{\hat{\boldsymbol{p}}\}, \{\hat{R}\}, \{\hat{I}\} \leftarrow$ POST_PROCESS(S_{best})
  return $\{\hat{\boldsymbol{\tau}}\}, \{\hat{\boldsymbol{\gamma}}\}, \{\hat{\boldsymbol{p}}\}, \{\hat{R}\}, \{\hat{I}\}$
end procedure

The inputs consist of N_{pop} chromosomes in population P, Q number of cognitive users, Nc number of channels, the probability of local search p_{ls}, and the max number $MaxItrs$ of evolutionary iterations. Each chromosome consists of $Q + 2 * N_c * Q$ genes. The first Q variables are Q genes which represent for the sensing times of Q SUs. The next Q variables are $Q * N_c$ genes representing for decision threshold vectors of Q SUs with N_c channels. The last Q variables are $Q * N_c$ genes representing for power allocation vector of Q SUs with N_c channels. The procedure OBJ_EVAL is used to evaluate objectives for each chromosome in the population. In this work, we search for optimal sensing times, decision threshold vectors, and power allocation vectors to maximize two objectives. They are the averaged throughput of the network R, and the averaged transmission gain G defined in Eqs. (11) and (12) respectively. The Tabu search [22] is employed as an effective local search for WAT-MOMA. The Tabu local search uses the random weighted fitness as discribed in the next section, and the random weights obtained from Eq. (2).

The best solution or best chromosome (S_{best}) will be selected from the non dominated population POP. Finally, the optimal sensing time, the optimal decision threshold vector, the optimal power allocation vector, the resulted throughput, and the resulted interference of each SU are obtained from post processing function POST_PROCESS of the best chromosome. The initialization, objective evaluation, local search, and genetic operation algorithms are discussed as follows.

1) *Initialization*: Each chromsome represents $(1 + 2N_c)Q$ real nonnegative parameters to be searched. The first Q parameters are sensing time parameters of Q SUs, which are searched in the range from τ_{min} to τ_{max}. The next QxN_c parameters are Q decision threshold vectors (each of size 1xN_c) of Q SUs, which are searched in the range from γ_{min} to γ_{max}. The last QxN_c parameters are Q power allocation vectors (each of size 1xN_c) of Q SUs, which are search in the range from p_{min} to p_{max}.

2) *Objective Evaluation Function*: In literature, the objective function is also called the fitness function. The objective function uses the averaged throughput R in Eq. (11), and the averaged transmission gain G in Eq. (12) as the two objectives to be maximized. We denote $\hat{\boldsymbol{\alpha}} = [\bar{\alpha}_1, \bar{\alpha}_2, ..., \bar{\alpha}_{3Q}]$ as the parameters to be searched, where $\{\bar{\alpha}_i\}_{i=1}^{Q}$ are sensing times of Q SUs, $\{\bar{\alpha}_{i,k}\}_{i=Q+1,k=1}^{2Q,N_c}$ are decision threshold vectors of Q SUs for N_c channels, and $\{\bar{\alpha}_{i,k}\}_{i=2Q+1,k=1}^{3Q,N_c}$ are power allocation vectors of Q SUs for N_c channels. The objectives function is then set up as

$$\bar{f}(\hat{\boldsymbol{\alpha}}) = [f_1(\hat{\boldsymbol{\alpha}}), f_2(\hat{\boldsymbol{\alpha}})] \tag{14}$$

where

$$f_1(\hat{\boldsymbol{\alpha}}) = R(\hat{\boldsymbol{\alpha}}) = R(\bar{\alpha}_1, \bar{\alpha}_2, ..., \bar{\alpha}_{3Q})$$
$$f_2(\hat{\boldsymbol{\alpha}}) = G(\hat{\boldsymbol{\alpha}}) = G(\bar{\alpha}_1, \bar{\alpha}_2, ..., \bar{\alpha}_{3Q})$$

Our joint optimization problem is to search the optimal parameter $\hat{\boldsymbol{\alpha}}$ that can be formed by

$$\max_{\hat{\boldsymbol{\alpha}}} \bar{f}(\hat{\boldsymbol{\alpha}}) = \max_{\hat{\boldsymbol{\alpha}}} [f_1(\hat{\boldsymbol{\alpha}}), f_2(\hat{\boldsymbol{\alpha}})] \tag{15}$$

The pseudocode of our objective evaluation function is described in the Algorithm 3.

3) *Local Search*: In this work we employ the principle of Tabu local search [22] with random normalized weights generated by Eq. (2). The best initial solution for the local search is selected by doing a tournament selection between chromosomes in the population P_{offs}. The procedure finally returns the N_{LS} better solutions, P_{impr}.

4) *Crossover, Mutation, and Selection with Replacement Operations*: Genetic operators including crossover and mutation are used to generate offspring population in each evolutionary loop. In this work, the real-coded crossover and mutation introduced in [16], [15] are adopted with crossover probability $p_x = 0.8$ and mutation probability $p_m = 0.05$. The non-dominated chromosomes are selected in each evolutionary loop by using the selection with replacement based on the Pareto ranks and crowding distances as described in [15], [2].

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this scope of the paper, we setup the system for simulation with $Q = 10$ SUs; the available bandwidth is divided in $N = 12$ subchannels; the time sensing frame for each SU is $Tf = 2\ ms$; minimum sensing time for each SU for a channel

Algorithm 3 OBJ_EVAL

procedure OBJ_EVAL($Chromosome, V, Q, N_c$)
  for $i \leftarrow 1, Q$ **do**
    $\tau(i) \leftarrow Chromosome(i, 1)$
    for $k \leftarrow 1, N_c$ **do**
      $\gamma(i, k) \leftarrow Chromosome(Q + i, k)$
      $p(i, k) \leftarrow Chromosome(2Q + i, k)$
    end for
  end for
  $[\boldsymbol{H}_{qq}, \boldsymbol{H}_{rq}] \leftarrow$ Channel_tf(Q, N_c) ▷ Channel parameters
  for $i \leftarrow 1, Q$ **do**
    for $i \leftarrow 1, N_c$ **do**
      Calculate $P^{fa}_{i,k}$ by Eq. (4)
      Calculate $P^{de}_{i,k}$ by Eq. (5)
      Calculate $P^{md}_{i,k}$ by Eq. (6)
      Calculate archivable rate $r_{i,k}$ by Eq. (8)
    end for
  end for
  for $i \leftarrow 1, Q$ **do**
    Calculate the throughput $R(i)$ by Eq. (7)
    Calculate the transmission gain $G(i)$ by Eq. (10)
  end for
  $f(1) \leftarrow R$ calculated by Eq. (11) ▷ Objective 1
  $f(2) \leftarrow G$ calculated by Eq. (12) ▷ Objective 2
  return f
end procedure

is $\tau_{min} = 15\ \mu s$, and maximum sensing time for each SU for a channel is $\tau_{max} = 100\ \mu s$; the minimum power allocated for a channel is $p_{min} = -15\ dbm$; the maximum power allocated for a channel is $p_{max} = 20\ dbm$; the minimum decision threshold for a channel is $\gamma_{min} = -20\ db$; the maximum decision threshold for a channel is $\gamma_{max} = 20\ db$. The transmited power of the primary signal is $1\ w$.

In the MOMA_JSSPA algorithm, the number of initial population N_{pop} is setup to 100, the local search is applied to refine the offspring population with the probability of 0.5 and the number of iterations is 50. These local search parameters are selected based on the analystical results in [4]. The performance of MOMA_JSSPA is also compared with the performance of NSGA2_JSSPA (the joint spectrum sensing and power allocation based on NSGA2 in [15]). The initial population of NSGA2_JSSPA is also setup to 100 chromosomes.

The initial populations consisting of 100 chromosomes are described in Fig. 1. The obtained Pareto fronts after 100 iterations are reported in Fig. 2. The results reveal that MOMA obtain a better quality of nondominated solutions in comparison to NSGA2. Since there is a conflict between the averaged throughput R and the averaged transmission gain G, the optimally selected solution is a balance between R and G objectives. It is observed that the nondominated solutions offered by MOMA is larger than that offered by NSGA2, and the solutions offered by MOMA are dominating the solutions offered by NSGA2. The sensing times of Q SUs from the best solution produced by MOMA_JSSPA is illustrated in Fig. 3. From the figure we see that the sensing times of SUs vary differently from the min sensing time of 18.598 μs (SU 9) to the max sensing time of 98.2018 μs (SU 7). The decision threshold vectors γ, and the power allocation vectors p of Q SUs are displayed in Fig. 4 and Fig. 5 respectively.

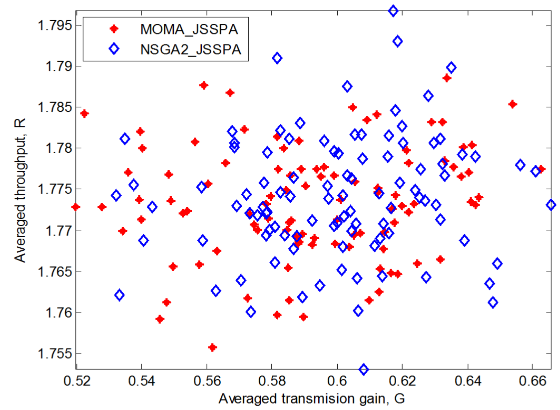

Fig. 1. The initial populations.

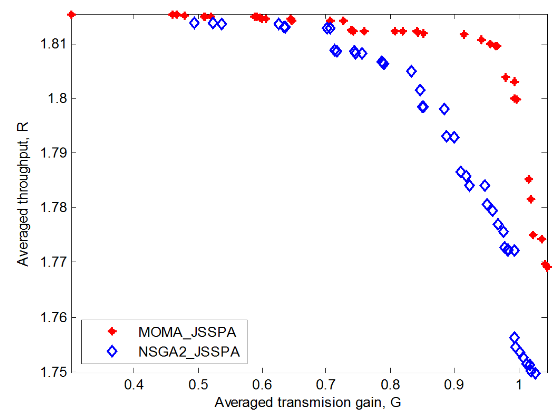

Fig. 2. The Pareto fronts of the populations after 100 iterations.

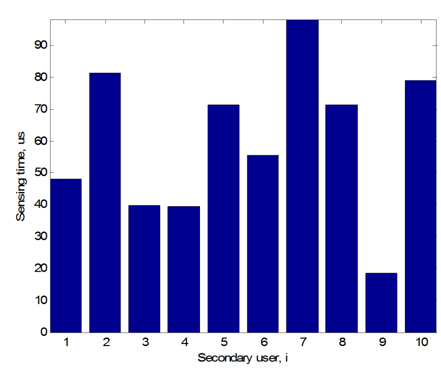

Fig. 3. The sensing times of SUs from the best solution.

V. CONCLUSIONS

In this paper, a joint spectrum sensing and power allocation problem of a multiple user multiple channel network is formu-

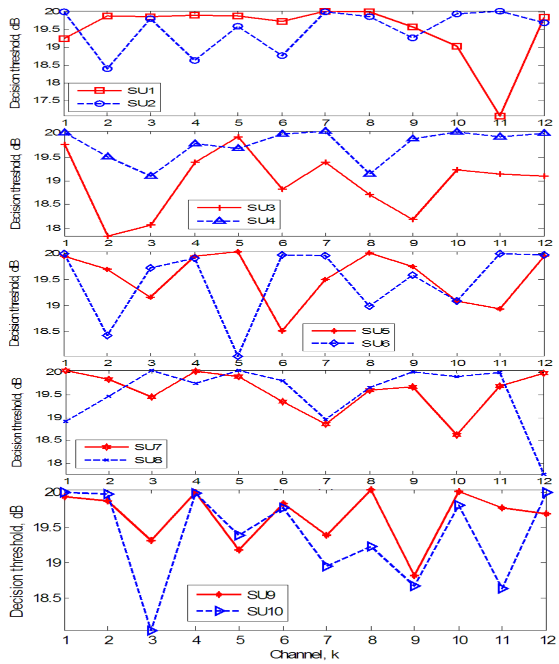

Fig. 4. The decision threshold vectors of SUs from the best solution.

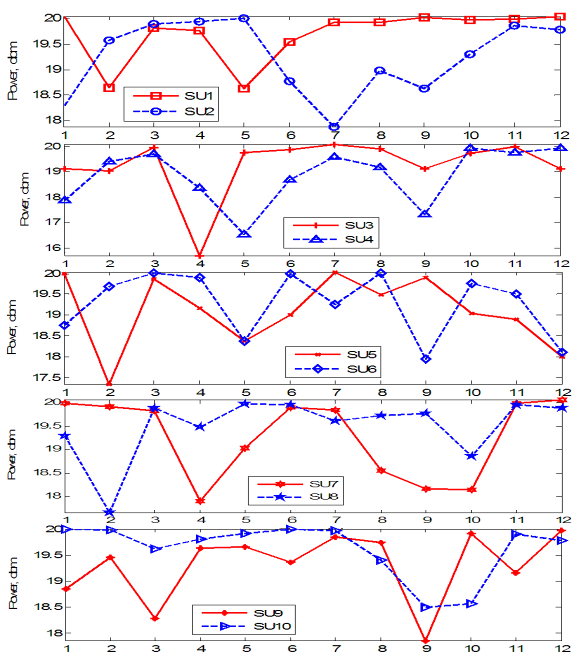

Fig. 5. The power allocation vectors of SUs from the best solution.

lated as a multiobjective optimization of finding sensing times, decision threshold vector, and power allocation vector of each cognitive user to maximize the network throughput and minimize the interferences. A multiobjective memetic algorithm is proposed to solve this challenging join optimization problem. The simulation results show that the proposed method obtains very good performance and dynamic parameters in cooperative spectrum sensing and power allocation for cognitive radios. The effectiveness of applying memetic learning algorithm in solving multiobjective optimization is also stressed in the paper.

References

[1] Natalio Krasnogor and Jim Smith, "A tutorial for competent memetic algorithms: model, taxonomy, and design issues," *IEEE Trans. Evol. Comput.*, vol. 9, no. 5, pp. 474-488, Oct. 2005.

[2] K.C.Tan, E.F.Khor, and T.H.Lee, *Multiobjective evolutionary algorithms and applications*, London UK: Springer, 2010, 295 pp.

[3] P. Moscato, "On evolution, search, optimization, genetic algorithms and martial arts: Toward memetic algorithms," California Inst. Technol., Pasadena, CA, Tech. Rep. Caltech Concurrent Comput. Prog. Rep. 826, 1989.

[4] Hisao Ishibuchi, Yasuhiro Hitotsuyanagi, Noritaka Tsukamoto, and Yusuke Nojima, "Implementation of multiobjective memetic algorithms for combinatorial optimization problems: a Knapsack problem case study," in *Multi-Objective Memetic Algorithms*, Chi-Keong Goh, Yew-Soon Ong, and Kay Chen Tan, Eds. Springer Berlin, pp. 27-49, 2009.

[5] Ferrante Neri and Carlos Cotta, "Memetic algorithms and memetic computing optimization: a literature review," *Swarm and Evolutionary Computation*, vol. 2, pp. 1-14, Feb. 2012.

[6] Xian Chen, Yew-Soon Ong, Meng-Hiot Lim, and Kay Chen Tan, "A multi-facet survey on memetic computation," *IEEE Trans. Evol. Comput.*, vol. 15, no. 5, pp. 591-607, Oct. 2011.

[7] Christoph Bergmeir, Issac Triguero, Daniel Molina, Jose L. Aznarte, and Jose Manuel Benitez, "Time series modeling and forcasting using memetic algorithms for regime-switching models," *IEEE Trans. Neural Netw. Learning Syst.*, vol. 23, no. 11, Nov. 2012.

[8] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, Feb. 2005.

[9] Ekram Hossain and Vijay K. Bhargava, *Cognitive Wireless Communication Networks*, (edited volume), New York, Springer, 2007, 440 pp.

[10] Jong-Shi Pang, and Gesualdo Scutari, "Joint sensing and power allocation in nonconvex cognitive radio games: Quasi-Nash equilibria," *IEEE Trans. Sig. Process.*, vol. 61, no. 9, pp. 2366-2382, May 2013.

[11] Sami M. Almalfouh, and Gordon L. Stuber, "Joint spectrum-sensing design and power control in cognitive radio networks: a stochastic approach," *IEEE Trans. Wireless Comm.*, Vol. 11, No. 12, Dec. 2012.

[12] David E. Goldberg, *Genetic algorithm in search, optimization, and machine learning*, Addison-Wesley, Reading, Massachusetts, 1989, 423 pp.

[13] kay C. Tan, Eik F. Khor, Tong H. Lee, and Ramasubramainan Sathikannan, "An evolutionary algorithm with advanced goal and priority specification for multi-objective optimization," *Journal of Artificial Intelligence Research*, vol. 18, pp. 182-215, 2003.

[14] Andriana Lara, Gustavo Sanchez, Carlos A. Coello, and Oliver Schutze, "HCS: A new local serach strategy for memetic multiobjective evolutionary algorithms," *IEEE Trans. Evol. Comput.*, vol. 14, no. 1, pp. 112-132, Feb. 2010.

[15] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and T. Meyaruvan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comp.*, vol. 6, no. 2, pp. 182-197,April 2002.

[16] K. Deb and R. B. Agrawal, "Simulated binary crossover for continuous search space," *Complex Syst.*, vol. 9, pp. 115-148, 1995.

[17] Andrzej Jaszkiewicz, "Genetic local search for multi-objective combinatorial optimization," *European Journal of Operational Research*, vol. 137, no. 1, pp.50-71, Feb. 2002.

[18] Daniel Molina, Manuel Lozano, Carlos Garcia-Martinez, and Francisco Herrera, "Memetic algorithms for continuous optimisation based on local search chains," *Evolutionary Computation*, vol. 18, no. 1, pp.27-63, 2010.

[19] Rahul Tandra, and Anant Sahai, "SNR walls for signal detection," *IEEE J. Selected Topics in Signal Process.*, vol. 2, no. 1, pp. 4-17, Feb. 2008.

[20] Tevfik Yucek, and Huseyin Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Comm. Surveys & Tutorials*, Vol. 11, No. 1, pp. 116-130, March 2009.

[21] Karaputugala M. Thilina, Kae W. Choi, Nazmus Saquib, and Ekram Hossain, "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks," *IEEE J. Selected Areas in Communications*, vol. 31, no. 11, pp. 2209-2221, Nov. 2013.

[22] F. Glover, "Tabu search: a tutorial," *Interfaces*, vol. 20, no. 4, pp. 74-94, 1990.