Relay Selection Scheme Based on Quantum Differential Evolution Algorithm in Relay Networks

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Abstract

It is a classical integer optimization difficulty to design an optimal selection scheme in cooperative relay networks considering co-channel interference (CCI). In this paper, we solve single-objective and multi-objective relay selection problem. For the single-objective relay selection problem, in order to attain optimal system performance of cooperative relay network, a novel quantum differential evolutionary algorithm (QDEA) is proposed to resolve the optimization difficulty of optimal relay selection, and the proposed optimal relay selection scheme is called as optimal relay selection based on quantum differential evolutionary algorithm (QDEA). The proposed QDEA combines the advantages of quantum computing theory and differential evolutionary algorithm (DEA) to improve exploring and exploiting potency of DEA. So QDEA has the capability to find the optimal relay selection scheme in cooperative relay networks. For the multi-objective relay selection problem, we propose a novel non-dominated sorting quantum differential evolutionary algorithm (NSQDEA) to solve the relay selection problem which considers two objectives. Simulation results indicate that the proposed relay selection scheme based on QDEA is superior to other intelligent relay selection schemes based on differential evolutionary algorithm, artificial bee colony optimization and quantum bee colony optimization in terms of convergence speed and accuracy for the single-objective relay selection problem. Meanwhile, the simulation results also show that the proposed relay selection scheme based on NSQDEA has a good performance on multi-objective relay selection.

Keywords: Cooperative relay networks, multiple relay selection, co-channel interference, single-objective optimization, multi-objective optimization

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1. Introduction

Relaying is an emerging and effective communication technology which can overcome the limitation of cell coverage, cell edge users' throughput and improve overall performance of wireless networks [1]. Relay nodes (RNs) mainly play a key role in ad hoc networks and other wireless networks such as wireless sensor networks for improving the spatial diversity order and increasing the network longevity [2-4].In order to exploit the advantages of the RNs deployment in the wireless networks, relay selection, power and bandwidth allocation for RNs have been investigated respectively by researchers, and relay selection is becoming the key issue of the radio resource management (RRM) in relaying networks [5]. The most common relay selection schemes considering the channel state information (CSI) is based on physical distance, path loss or signal to noise ratio (SNR), where they focus on the scenario of single source-destination pairing with multiple RNs [6-8]. Since the interference does not exist in such scenario, the criterion of relay selection is straightforward. Recently, there is increasing interest in relay networks with multiple source-destination pairs, referred to as multi-user relay networks. Typical multi-user relay networks include ad hoc, sensor and mesh networks. However, relay selection schemes proposed for single-user with multiple candidate relays cannot be simply extended to multi-user relay networks straightforwardly due to the difficulties in the performance evaluation, the competition among users and the increased computing complexity [9].

In the past, research efforts on relay selection schemes in multi-user networks are rather limited. In [10], for a multi-user network, a relay grouping algorithm is designed to maximize the minimum achievable rate among users or the network sum-rate. In [11-12], a relay selection method that maximizes the minimum achievable rate for all users is proposed. But it is assumed that there is no CCI between multiple users in [10-12]. So, in order to resolve the difficulty, multi-user relay selection method considering CCI between multiple users is proposed in [13]. However, only a sub-optimal solution for relay selection can be obtained.

For optimal relay selection problem, multiple relay selection is a typical integer optimization, and many previous continuous intelligent algorithms cannot be directly applied to solve this problem. Some intelligent algorithms are added post-processing of each iteration to resolve this problem, such as artificial bee colony (ABC) [14] and opposition-based quantum firework algorithm (OQFA) [15]. Although quantum bee colony optimization designed in [16] is for relay selection of multiple relay networks, it yet has the weakness of slow convergence rate and poor convergence value for complex relay selection problem.

In recent years, differential evolutionary algorithm (DEA) is an effective continuous optimization method, which is widely researched [17]. In this paper, for single-objective relay selection scheme, we propose a novel intelligence algorithm which combines the DEA proposed in [17] with quantum evolutionary theory [15]. That is called as quantum differential evolutionary algorithm (QDEA), which has the advantage of both DEA and quantum evolutionary algorithm, and then has a better performance for the integer optimization of multiple relay selection. To our knowledge, no existing QDEA is proposed for integer optimization. So， it is the first time that QDEA is designed and applied to the single-objective relay selection problem of multi-user relay networks. For multi-objective relay selection scheme, we propose NSQDEA to solve the problem. In principle, multi-objective optimization problems are different from single objective optimization problems. In single objective optimization, the goal is to obtain the best design or decision, which is usually the global minimum or global maximum depending on the optimization problem of minimization or maximization. In multi-objective optimization, however, there does not exist one solution which is best with respect to all objectives. In a typical multi-objective optimization problem, there exist a set of solutions which are superior to the rest of solutions in the search space when all objectives are considered but are inferior to other solutions in the space in one or more objectives. The solutions are known as Pareto front solutions or non-dominated solutions. The rest of the solutions are known as dominated solutions. A number of multi-objective evolutionary algorithms have been proposed in literature [17-21]. [22] proposes a hybrid evolutionary multi-objective optimization framework. These algorithms are shown to be efficient in the field of multi-criteria optimization and many researchers have investigated their use in different applications. In order to solve multi-objective relay selection problem, we apply the concept of non-dominated sorting proposed in NSGA II [19] and propose a NSQDEA scheme for integer optimization problems. To our knowledge, no existing paper addresses NSQDEA for difficult problem of multi-objective relay selection.

2. System Model

2.1 System Model

In this paper, a cooperative multi-user relaying system model is considered. N SNs have information to transmit to its own destination, thus formulating N SN-DN transmission pairs. Other M nodes are potential RNs. Usually M is larger than N [12]. Each SN-DN transmission pair can select one RN to help to transmit. Each RN can help at most one SN-DN transmission pair. There is only one available channel. A two-step decode-and-forward (DF) protocol is used to send information. Two time slots (TSs) are available, i.e., the SNs transmit in TS1 and the RNs transmit in TS2. The RNs can receive in TS1, while the DNs can combine the signals received from SNs and RNs in TS2. Maximum ratio combining (MRC) is used to combine the signals received from SNs and RNs. The transmissions from SNs and RNs are separated into two TSs, so the interference between SNs and RNs is avoided.

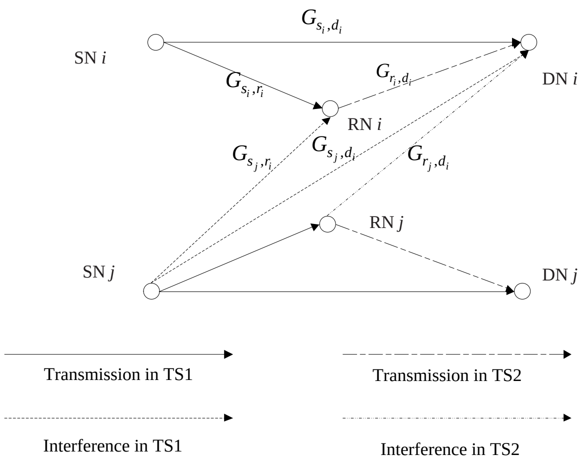

Fig. 1. System model of multi-user wireless relay network

In TS1, the channel state information (CSI) from the ith $(i = 1, 2, ..., N)$ SN to the ith RN is denoted as G_{s_i,r_i} and the CSI from the ith SN to the ith DN is denoted as G_{s_i,d_i} . The CCI from the *j*th $(j \neq i)$ SN to the *i*th RN is denoted as G_{s_j,r_i} and the CCI from the *j*th SN to the *i*th DN is denoted as G_{s_j,d_i}. In TS2, the CSI from the *i*th RN to the *i*th DN is denoted as G_{r_i,d_i} and the CCI from the *j*th RN to the *i*th DN is denoted as G_{r_j,d_i}. For each transmission, the power used at the *i*th SN and the *i*th RN are P_{s_i} and P_{r_i}, respectively, the power used at the *j*th SN and the *j*th RN are P_{s_j} and P_{r_j}, respectively . In TS1, the *i*th SN sends z_i, where the information symbol is z_i. If z_i is normalized as $E|z_i|^2 = 1$, the average power used at the *i*th SN is P_{s_i}.

The signal received at the *i*th DN in TS1 is

$$y_i^{(sd)} = \sqrt{G_{s_i,d_i}}\sqrt{P_{s_i}}z_i + \sum_{j=1, j\neq i}^{N} \sqrt{G_{s_j,d_i}}\sqrt{P_{s_j}}z_j + w_{s_i,d_i}, \tag{1}$$

where w_{s_i,d_i} is additive white Gaussian noise (AWGN) between the *i*th SN and the *i*th DN with power η_1. Therefore the signal to interference plus noise ratio (SINR) of SN-DN link can be calculated by

$$\gamma_i^{(sd)} = G_{s_i,d_i}P_{s_i} \Bigg/ \left(\sum_{j=1, j\neq i}^{N} G_{s_j,d_i}P_{s_j} + \eta_1 \right). \tag{2}$$

The signal received at the *i*th RN in TS1 can be written as

$$y_i^{(sr)} = \sqrt{G_{s_i,r_i}}\sqrt{P_{s_i}}z_i + \sum_{j=1, j\neq i}^{N} \sqrt{G_{s_j,r_i}}\sqrt{P_{s_j}}z_j + w_{s_i,r_i} \quad . \tag{3}$$

where w_{s_i,r_i} is the AWGN between the *i*th SN and the *i*th RN with power η_2.

Therefore the SINR of SN-RN link can be given by

$$\gamma_i^{(sr)} = G_{s_i,r_i}P_{s_i} \Bigg/ \left(\sum_{j=1, j\neq i}^{N} G_{s_j,r_i}P_{s_j} + \eta_2 \right). \tag{4}$$

In TS2, the RN receives and decodes the information, then recodes the decoded information and sends the recoded information to the DN, so the signal received at the *i*th DN is

$$y_i^{(rd)} = \sqrt{G_{r_i,d_i}}\sqrt{P_{r_i}}z_i' + \sum_{j=1, j\neq i}^{N} \sqrt{G_{r_j,d_i}}\sqrt{P_{r_j}}z_j' + w_{r_i,d_i}, \tag{5}$$

where z_i' is the recoded symbol of z_i. w_{r_i,d_i} is the AWGN between the *i*th RN and the *i*th DN with power η_3

Therefore the SINR of RN-DN link can be expressed as

$$\gamma_i^{(rd)} = G_{r_i,d_i} P_{r_i} \Bigg/ \left(\sum_{j=1, j\neq i}^{N} G_{r_j,d_i} P_{r_j} + \eta_3 \right) . \tag{6}$$

For DF relaying, the achievable data rate under the two-time-slot structure given by [16,23] is

$$\begin{aligned} R_i &= \frac{1}{2} W \log_2 (1+\gamma_i) = \frac{1}{2} W \log_2 (1+\min\{\gamma_i^{(sr)}, \gamma_i^{(sd)} + \gamma_i^{(rd)}\}) \\ &= \frac{1}{2} W \min\{\log_2 (1+\gamma_i^{(sr)}), \log_2 (1+\gamma_i^{(sd)} + \gamma_i^{(rd)})\} \end{aligned} \tag{7}$$

where W is the bandwidth of the available channel, γ_i is the end-to-end SINR of SN-DN pair *i*, $\gamma_i^{(sr)}$ is the SINR of SN-RN pair *i*, $\gamma_i^{(sd)}$ is the SINR of SN-DN pair *i*, and $\gamma_i^{(rd)}$ is the SINR of RN-DN pair *i*. Three single-objective relay selection schemes are used to optimize: Max-Average-Reward (MAR), Max-Proportional-Fair (MPF) and Max-Min-Reward (MMR). The objective of MAR is to maximize the average throughput of the network. The optimization problem of MAR can be formulated as

$$\begin{aligned} &\max_{\boldsymbol{r}} \{U_{MAR}(\boldsymbol{r}) = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2} W \log(1+\gamma_i)\} \\ &\text{subject to } \quad r_i \neq r_j, \forall i \neq j \end{aligned} \tag{8}$$

The objective of MPF is to maximize the fairness of throughput between different users in the relay networks. The optimization problem of MPF can be defined as

$$\begin{aligned} &\max_{\boldsymbol{r}} \{U_{MPF}(\boldsymbol{r}) = (\prod_{i=1}^{N} R_i)^{\frac{1}{N}} = (\prod_{i=1}^{N} \frac{1}{2} W \log(1+\gamma_i))^{\frac{1}{N}} \} \\ &\text{subject to } \quad r_i \neq r_j, \forall i \neq j \end{aligned} \tag{9}$$

The objective of MMR is to maximize the minimum throughput among all the users in the relay networks. The optimization problem of MMR can be expressed as

$$\begin{aligned} &\max_{\boldsymbol{r}} \{U_{MMR}(\boldsymbol{r}) \triangleq \min_{1\leq i\leq N} \{R_i\} = \min\{\frac{1}{2} W \log(1+\gamma_i)\} \} \\ &\text{subject to } \quad r_i \neq r_j, \forall i \neq j \end{aligned} \tag{10}$$

where $\boldsymbol{r} = [r_1, r_2, ..., r_N]$ is the relay selection scheme, and the constraint means that each RN can help at most one SN-DN transmission pair. Each element $r_i (i = 1, 2, ..., N)$ denotes the RN selected by SN-DN transmission pair *i*, so if RN $k (k = 1, 2, ..., M)$ is assigned to SN-DN transmission pair *i*, then $r_i = k$. In this paper, a novel intelligence algorithm, QDEA, is proposed to resolve this single-objective integer optimization problem.

Since the MAR only considers the average throughput of network, the relay selection scheme which has the largest MAR value cannot obtain the largest MPF or MMR. Also, the relay selection which has the largest MMR cannot obtain the largest MPF. Considering two objectives simultaneously, three multi-objective relay selection problems are formulated as follows:

$$\max_{\boldsymbol{r}} \{U_{MAR}(\boldsymbol{r}) = \frac{1}{N}\sum_{i=1}^{N} R_i, U_{MPF}(\boldsymbol{r}) = \left(\prod_{i=1}^{N} R_i\right)^{\frac{1}{N}} \}, \text{subject to } \quad r_i \neq r_j, \forall i \neq j \tag{11}$$

$$\max_{\boldsymbol{r}} \{U_{MAR}(\boldsymbol{r}) = \frac{1}{N}\sum_{i=1}^{N} R_i, U_{MMR}(\boldsymbol{r}) = \min_{1\leq i\leq N} R_i \}, \text{subject to } \quad r_i \neq r_j, \forall i \neq j \tag{12}$$

$$\max_{\boldsymbol{r}}\{U_{MPF}(\boldsymbol{r})=\left(\prod_{i=1}^{N}R_i\right)^{\frac{1}{N}},\ \ U_{MMR}(\boldsymbol{r})=\min_{1\le i\le N}R_i\},\text{subject to } \ r_i\neq r_j,\forall i\neq j \tag{13}$$

To optimize this multi-objective relay selection problem is a hard progress, because CCI makes this optimization problem become complicated to solve. The exhaustive search method to optimize this multi-objective relay selection problem needs to involve the following procedures. First, for all the relay selection solutions, we need to compute all the SNRs between the SNs, DNs and RNs. Then according to all the SINRs, we can calculate the objective function value. But there are $M!/(M-N)!$ (the number of ordered sequences of N elements selected from a set of M elements) relay selection schemes that should be calculated and compared. Since the calculation quantity grows faster than the exponential function, the complexity of the exhaustive search is intolerable for realistic values of M and N. In this article, we propose the QDEA and NSQDEA, which are used to solve the single-objective and multi-objective problem.

3. Single-objective Relay Selection Scheme Based on Quantum Differential Evolutionary Algorithm

3.1 QDEA for Integer Programming

QDEA is a novel multi-agent optimization system modified by DEA. There are H quantum individuals in an N-dimensional space, where N represents the maximal dimension of the optimization problem (N represents the number of SN-DN transmission pairs in the multi-user relay selection problem). Each quantum individual is composed of a series of quantum bits. The hth(h=1,2,...,H) quantum individual at the tth generation is defined as

$$\boldsymbol{x}_h^t=\begin{bmatrix}\alpha_{h1}^t,\alpha_{h2}^t,...,\alpha_{hN}^t\\ \beta_{h1}^t,\beta_{h2}^t,...,\beta_{hN}^t\end{bmatrix} \tag{14}$$

where $|\alpha_{hn}^t|^2+|\beta_{hn}^t|^2=1$ and $n=1,2,...,N$. To simplify QDEA, we define $0\le\alpha_{hn}^t\le1$, $0\le\beta_{hn}^t\le1$ and $\beta_{hn}^t=\sqrt{1-(\alpha_{hn}^t)^2}$. The hth quantum individual may be simplified as[24]

$$\boldsymbol{x}_h^t=[\alpha_{h1}^t,\alpha_{h2}^t,...,\alpha_{hN}^t]=[x_{h1}^t,x_{h2}^t,...,x_{hN}^t] \tag{15}$$

where $0\le x_{hn}^t\le1$ ($n=1,2,...,N$) and x_{hn}^t represents quantum bit.

The quantum individual is mapped to definition domain of the individual, and the rule can be described as follow:

$$\bar{x}_{hn}^t=l_n+x_{hn}^t(u_n-l_n), \tag{16}$$

where l_n is the lower bound of the nth dimension variant, u_n is the upper bound of the nth dimension variant. In the multi-user relay selection scheme, there are M potential relays which can be chosen, so $l_n=1$, $u_n=M$ for all $n=1,2,...,N$.

Since the multi-user relay selection problem is an integer optimization problem, we should map the real number into the integer number, the rule is as follow

$$\bar{\bar{x}}_{hn}^t=\text{round}(\bar{x}_{hn}^t), \tag{17}$$

where $\text{round}(\bar{x}_{hn}^t)$ means rounding up $\bar{x}_{hn}^t$ to an integer number $\bar{\bar{x}}_{hn}^t$, and $\bar{\bar{\boldsymbol{x}}}_h^t=[\bar{\bar{x}}_{h1}^t,\bar{\bar{x}}_{h2}^t,...,\bar{\bar{x}}_{hN}^t]$.

The fitness of the hth quantum individual is computed by $f(\bar{\bar{x}}_h^t)=\begin{cases} f(\bar{\bar{x}}_h^t), & \bar{\bar{x}}_{hi}^{t+1}\neq\bar{\bar{x}}_{hn}^{t+1}(\forall i\neq n,\ \ i,n=1,2,...,N) \\ 0, & \text{else}\end{cases}$. In this equation, penalty factor is used to delete the infeasible solutions. That is to say, if one solution does not satisfy $\bar{\bar{x}}_{hi}^{t+1}\neq\bar{\bar{x}}_{hn}^{t+1}(\forall i\neq n,\ \ i,n=1,2,...,N)$, the fitness of the solution is set as zero.

The evolutionary process of quantum individuals is mainly implemented by quantum rotation angles and simulated quantum rotation gate. Until the tth generation, the global optimal quantum individual discovered by the whole quantum population is $\boldsymbol{p}_g^t=[p_{g1}^t,p_{g2}^t,...,p_{gN}^t]$.

For the hth ($h=1,2,...,H$) quantum individual, generate a uniform distributed random number ξ_1 from zero to one. When ξ_1 is less than 0.5, the nth ($n=1,2,...,N$) quantum rotation angle and the nth quantum bit are updated as:

$$\theta_{hn}^{t+1}=\xi_2(p_{gn}^t-x_{hn}^t)+\frac{1}{2}\cdot\xi_3\cdot\text{sign}(f(\bar{\bar{x}}_a^t)-f(\bar{\bar{x}}_h^t))\cdot(x_{an}^t-x_{hn}^t) \tag{18}$$

$$p_{hn}^{t+1}=\begin{cases}\text{abs}(x_{hn}^t\cdot\cos\mu_{hn}^{t+1}+\sqrt{1-(x_{hn}^t)^2}\cdot\sin\mu_{hn}^{t+1}),\text{if } \varepsilon_{hn}^{t+1}\leq 0.01) \\ \text{abs}(x_{hn}^t\cdot\cos\theta_{hn}^{t+1}+\sqrt{1-(x_{hn}^t)^2}\cdot\sin\theta_{hn}^{t+1}),\text{otherwise}\end{cases} \tag{19}$$

where ξ_2 , ξ_3 and ε_{hn}^{t+1} are uniform distributed random numbers from zero to one, $\text{sign}()$ means sign function. μ_{hn}^{t+1} is a Gaussian distributed random number with zero mean and unit variance. $a\in\{1,2,...,H\}$ is a random integer.

When ξ_1 is no less than 0.5, the nth quantum rotation angle and the nth quantum bit of the hth quantum individual are updated as:

$$\theta_{hn}^{t+1}=\gamma_{hn}^{t+1}\cdot(x_{bn}^t-x_{hn}^t) \tag{20}$$

$$p_{hn}^{t+1}=\begin{cases}\text{abs}(x_{hn}^t\cdot\cos\varphi_{hn}^{t+1}+\sqrt{1-(x_{hn}^t)^2}\cdot\sin\varphi_{hn}^{t+1}),\text{if } \eta_{hn}^{t+1}\leq 0.01) \\ \text{abs}(x_{hn}^t\cdot\cos\theta_{hn}^{t+1}+\sqrt{1-(x_{hn}^t)^2}\cdot\sin\theta_{hn}^{t+1}),\text{otherwise}\end{cases} \tag{21}$$

where η_{hn}^{t+1} is a uniform distributed random number from zero to one, $\text{sign}()$ means sign function. φ_{hn}^{t+1}, γ_{hn}^{t+1} are Gaussian distributed random numbers with zero mean and unit variance, and $b\in\{1,2,...,H\}$ is a random integer, mutually different from a, when $n=1,2,...,N$.

In order to increase the diversity of the quantum individuals, crossover is introduced:

$$v_{hn}^{t+1}=\begin{cases}x_{hn}^t & \text{if } \xi_4>CR \text{ and } d\neq n \\ p_{hn}^{t+1} & ,\text{else}\end{cases} \tag{22}$$

where ξ_4 is a uniform distributed random number from zero to one, $d\in\{1,2,...,N\}$ is a random integer, $CR=0.01+(0.4t)/K$, and K is the maximum number of generation.

The quantum individual $\boldsymbol{v}_h^{t+1}$ ($h=1,2,...,H$) is mapped into integer number vector $\bar{\bar{\boldsymbol{v}}}_h^{t+1}$. Then the fitness of $\bar{\bar{\boldsymbol{v}}}_h^{t+1}$ is computed by fitness function. If the fitness of $\bar{\bar{\boldsymbol{v}}}_h^{t+1}$ is better than that of $\bar{\bar{\boldsymbol{x}}}_h^t$, $\boldsymbol{x}_h^{t+1}$=$\boldsymbol{v}_h^{t+1}$; else $\boldsymbol{x}_h^{t+1}$=$\boldsymbol{x}_h^t$. At last, the best quantum individual of current generation is used to update the global optimal quantum individual.

3.2 The Process of QDEA Based Single-objective Relay Selection Scheme

Based on what we have discussed, QDEA can be applied to solve single-objective multi-user relay selection problem in cooperative relay networks. The process of relay selection scheme based on QDEA is shown below:

Step1: Assume that the centre controller knows all CSI and the centre controller completes the relay selection process.

Step2: Randomly generate an initial population of H quantum individuals based on quantum coding mechanism. Calculate the fitness and find the global optimal quantum individual in the initial population.

Step3: According to the evolutionary process of quantum individual, perform the evolution scheme.

Step4: Calculate the fitness, then renew each quantum individual and update the global optimal quantum individual.

Step5: If it reaches the predefined value of the maximum generation, stop the process, and then transfer the outcome to the relay selection scheme, if not, go to Step3.

Step6: The centre controller broadcasts the relay assignments on a predefined channel to the SNs, RNs and DNs. The relay selection process is ended.

4. Multi-objective Relay Selection Scheme Based on Non-dominated Sorting Quantum Differential Evolutionary Algorithm

4.1 Non-dominated Sorting

To solve two objectives simultaneously, i.e., MAR and MPF , or MAR and MMR , or MMR and MPF , we propose the NSQDEA to solve the multi-objective relay selection problems. The NSQDEA makes use of Pareto dominance concept to select a set of Pareto front solutions. The solutions in the Pareto front can cover different tradeoffs of the objective problems. The NSQDEA is based on non-dominated sorting and crowding distance[20]. By this way, the entire population is sorted into various non-dominated levels. This provides the means for selecting the solutions in the better fronts, hence providing the necessary selection pressure to push the population towards the Pareto front.

First, we will introduce the non-dominated solutions. If we want to maximize a problem $f_i(\boldsymbol{x})(i=1,\cdots,m)$, where m is the number of objects that we will optimize, then there exist $\boldsymbol{u}$ and $\boldsymbol{v}$. If $\forall i=1,\cdots,m$, $f_i(\boldsymbol{u}) \geq f_i(\boldsymbol{v})$, and $\exists i=1,\cdots,m$, $f_i(\boldsymbol{u}) > f_i(\boldsymbol{v})$ then define $\boldsymbol{u}$ dominates $\boldsymbol{v}$, and $\boldsymbol{u}$ is the non-dominated solution of $\boldsymbol{v}$. It means that the solution $\boldsymbol{u}$ is better than solution $\boldsymbol{v}$ for each object. Then we can describe the progress of non-dominated sorting: first we will get some information of the solution $\boldsymbol{u}$, and for each solution $\boldsymbol{u}$, we can calculate u_{count}, which is the dominated count and $\boldsymbol{S}_u$, which is the set of solutions that are being dominated by the solution $\boldsymbol{u}$. The method of calculating u_{count} is as following: At the beginning for each solution $\boldsymbol{u}$, we will initialize u_{count} to zero. Then by comparing with every other solution $\boldsymbol{v}$ in the whole population $\boldsymbol{S}$, if $\boldsymbol{v}$ is the non-dominated solution of $\boldsymbol{u}$, $u_{count}=u_{count}+1$. If $\boldsymbol{u}$ is the non-dominated solution of $\boldsymbol{v}$, put $\boldsymbol{v}$ into the set of dominated solution $\boldsymbol{S}_u$. So we can get the dominated count of $\boldsymbol{u}$, and if $u_{count}=0$,that means there is no solution that can dominate $\boldsymbol{u}$ and this solution is in the first non-dominated front. Put these solutions into a separate list $\boldsymbol{F}_1$, and then for each first non-dominated front solution $\boldsymbol{u}$, we will process the set of dominated solutions $\boldsymbol{S}_u$. For each solution in $\boldsymbol{S}_u$, reduce its domination count by one. By executing this process, if the domination count becomes zero, this solution will be put into another separate list $\boldsymbol{F}_2$. The solutions in $\boldsymbol{F}_2$ belong to the second non-dominated front. Now the above procedure is continued again with the rest of the solutions in $\boldsymbol{S}_u$. These solutions which are selected belong to the third non-dominated front and will be put into list $\boldsymbol{F}_3$. This procedure continues until all fronts are indentified and there is no solution in $\boldsymbol{S}_u$. The solutions in the first non-dominated front are the non-dominated solutions among all solutions.

4.2 The Calculation of Crowding-distance

Next we will discuss how to calculate the crowding-distance. It is desired that the algorithm maintains a good spread of solutions in the obtained set of solutions along with convergence to the Pareto-optimal set. So we will calculate the proximity distance of two points along with each of the objectives. By calculating the crowding-distance we can preserve population diversity. The process of calculating crowding-distance will be described as follows.

Computing crowding-distance requires sorting the whole population according to each object value. The solution in every front is sorted according to the ascending order. For each objective function, initialize the crowding-distance of other solutions as zero. For the boundary solutions (the solutions which have the smallest or largest object value), the crowding-distance of them are assigned an infinite distance value. Then, calculate the crowding-distance of every other intermediate solution by (23):

$$I(k)_{\text{distance}} = I(k)_{\text{distance}} + \frac{I(k+1)_i - I(k-1)_i}{f_i^{\max} - f_i^{\min}} \tag{23}$$

where $I(k)_{\text{distance}}$ is the crowding-distance of the *k*th solution, $I(k)_i$ is the *i*th objective function value of the *k*th solution. $f_i^{\max}$ is the maximum value of the *i*th objective function and $f_i^{\min}$ is the minimum value of the *i*th objective function.

For other objective functions, this method of calculation is continued. At last, the overall crowding-distance value is calculated by the sum of individual distance values which are computed by every object function. Then sort the solutions in the same non-dominated front through the value of crowding distance in descending order.

Through the method of non-dominated sorting and calculation of crowding-distance, the solutions with better front and larger crowding-distance are better than other solutions.

4.3 Non-dominated Sorting Quantum Differential Evolution Algorithm

The NSQDEA is an algorithm which can solve multi-objective problem. The NSQDEA uses the idea of QDEA which is proposed in part three. There are three populations in the *N*-dimensional space, which are $\boldsymbol{S}$, $\boldsymbol{S}_2$ and $\boldsymbol{S}_3$. Each population has *H* quantum individuals and different population has its own evolutionary method. The progress can be summarized as following:

Step 1: Initialize $\boldsymbol{S}$, $\boldsymbol{S}_2$ and $\boldsymbol{S}_3$ in the *N*-dimensional space. The population $\boldsymbol{S}$ is used to evolve the non-dominated solutions. For the population $\boldsymbol{S}$, we can sort population according to non-dominated sorting and calculate the crowding-distance of this population.

Step 2: For each solution in the population ***S***, we evolve each solution according to the QDEA relay selection scheme, then we formulate *H* new solutions. In the progress of evolving new solutions, the global optimal quantum individual is chosen through one of objective function(MAR, MPF or MMR). These solutions are put into the population ***S***.

Step 3: Formulate another H new solutions according to another objective function through the QDEA. These solutions are also put into the population $\boldsymbol{S}$.

Step 4: Sort $\boldsymbol{S}$ according to no-dominated sorting and then calculate the crowding-distance. Select the H best solutions in the population $\boldsymbol{S}$ as the non-dominated solutions $\boldsymbol{S}_E$. Next, make $\boldsymbol{S}=\boldsymbol{S}_E$. These quantum individuals in $\boldsymbol{S}$ will take part in next iteration.

Step 5: For the population $\boldsymbol{S}_2$, evolve each quantum individual by using one object(MAR, MPF or MMR) as the evolutionary direction according to the QDEA.

Step 6: For the population $\boldsymbol{S}_3$, evolve each quantum individual by using another object(MAR, MPF or MMR) as the evolutionary direction according to the QDEA.

Step 7: During the process of iteration, we will perform the following steps every $K/10$ times iteration. Compare each quantum individual in population $\boldsymbol{S}_E$ and $\boldsymbol{S}_2$ with a same single-objective function f_1, f_1 is MAR, MPF or MMR. If the fitness of quantum individual which is in the population $\boldsymbol{S}_E$ is better than the quantum individual which is in the population $\boldsymbol{S}_2$, quantum individual in $\boldsymbol{S}_2$ is replaced by the quantum individual in $\boldsymbol{S}_E$. If the fitness of quantum individual in $\boldsymbol{S}_E$ is worse than the quantum individual which is in the population $\boldsymbol{S}_2$, quantum individual in $\boldsymbol{S}_E$ is replaced by the quantum individual in $\boldsymbol{S}_2$. Meanwhile, compare each quantum individual in population $\boldsymbol{S}_E$ and $\boldsymbol{S}_3$ with a same single-objective function f_2, which is MAR, MPF or MMR. If the fitness of quantum individual which is in the population $\boldsymbol{S}_E$ is better than the quantum individual which is in the population $\boldsymbol{S}_3$, quantum individual in $\boldsymbol{S}_3$ is replaced by the quantum individual in $\boldsymbol{S}_E$. If the fitness of quantum individual in $\boldsymbol{S}_E$ is worse than the quantum individual which is in the population $\boldsymbol{S}_3$, quantum individual in $\boldsymbol{S}_E$ is replaced by the quantum individual in $\boldsymbol{S}_3$.

Step 8: If it reaches the maximum iteration number, stop the progress. The solutions in $\boldsymbol{S}_E$ are the non-dominated solutions. If it doesn't reach the maximum generation number, go to Step 2, until the maximum generation number reaches.

From the above process, in each iteration, we select the non-dominated solutions in the current population and reject the dominated solutions. Through the iteration of evolutionary process, we can obtain the Pareto front solutions.

4.4 The Process of NSQDEA Based Multi-objective Relay Selection Scheme

According to what we have discussed above, the NSQDEA can solve the multi-objective relay selection problem. The process is as following:

Step1: Assume that the centre controller knows all CSI and the centre controller completes the relay selection process.

Step2: Use NSQDEA scheme to obtain the Pareto front solutions.

Step3: The centre controller chooses one solution from the Pareto solutions according to the tradeoff of MAR and MPF or the tradeoff of MAR and MMR or the tradeoff of MMR and MPF. The centre controller broadcasts the relay assignments on a predefined channel to the SNs, RNs and DNs. The relay selection process ends.

5. Simulation Results and Analysis

5.1 Simulations based on QDEA for single-objective relay selection scheme

In this section, we present the simulation results of optimal single-objective relay network. The used relay selection methods are as follows: quantum bee colony optimization (QBCO) based optimal relay selection, differential evolutionary algorithm (DEA) based optimal relay selection, artificial bee colony (ABC) based optimal relay selection, and the proposed quantum differential evolutionary algorithm (QDEA). For more details of ABC algorithm, please refer to [14].

In the simulation, the bandwidth is set as 10MHz for the available channel [11]. Wireless links and nodes are uniformly distributed over a square field with $D \times D$ dimensions, and in the simulation process, set $D = 100\text{m}$. In each simulation, N SNs are randomly generated and their corresponding DNs are generated around them in the area. The distance of the source node and destination node is uniformly distributed between $[d_{\min}, d_{\max}]$, so that they are not too far away from each other, and in the simulation, $d_{\min} = 25\text{m}$, $d_{\max} = 35\text{m}$. Then M candidate relays are generated in the area. The power of different SNs is the same, as well as the power of RNs. The power of the additive white Gaussian noise (AWGN) is 10^{-3}W at all nodes, i.e., $\eta_1 = \eta_2 = \eta_3 = 10^{-3}$. For QBCO, DEA, ABC and QDEA, the maximal iteration is set as 1000 and the population size H is set as 20. For ABC, the parameter settings of ABC can refer to [14]. For DEA, the parameter settings can refer to [17]. For QBCO, the parameter settings of QBCO can refer to [16]. In the Rayleigh fading channel, the path gain G_{s_i,d_i}, G_{s_i,r_i} and G_{r_i,d_i} will follow exponential distribution. The parameters of them are λ_{s_i,d_i}, λ_{s_i,r_i} and λ_{r_i,d_i} respectively. Therefore, the probability density function of (PDF) G_{s_i,d_i} is given as

$$f_{s_i,d_i}(x) = \lambda_{s_i,d_i} e^{-\lambda_{s_i,d_i} x} \tag{24}$$

where $\lambda_{s_i,d_i} = E\{G_{s_i,d_i}\} = d^{\beta}_{s_i,d_i}$, d is the distance between two nodes, and β is the path-loss exponent. Based the channel model we have proposed, we can get simulation results as following:

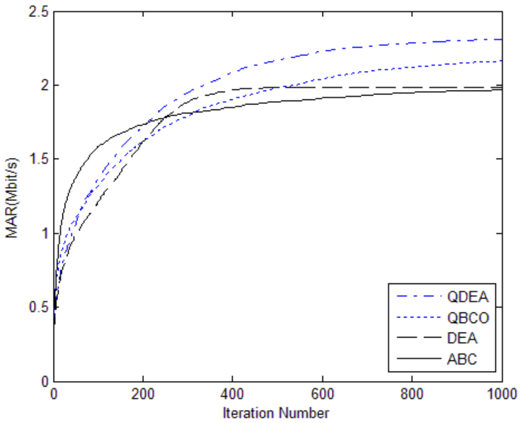

Fig. 2(a). Convergence curves of 4 different schemes with 20 RNs (MAR) with random Rayleigh fading

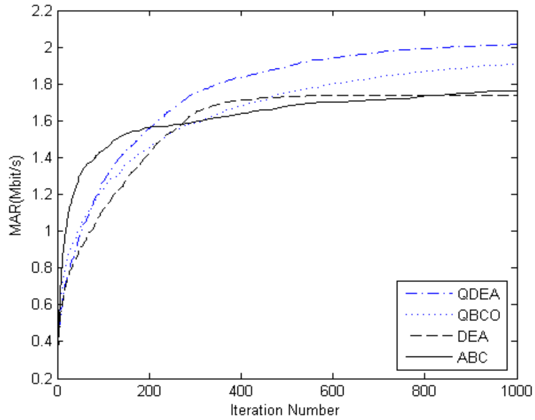

Fig. 2(b) Convergence curves of 4 different schemes with 20 RNs (MAR) with fixed Rayleigh fading

Fig. 2(a) shows the convergence curves of 4 different schemes with 20 RNs when considering the channel satisfies random Rayleigh fading. In order to guarantee the accuracy of the results, the simulation result is averaged over 5000 trials. The parameter of exponential distribution is $\lambda_{s_i,d_i}=E\{G_{s_i,d_i}\}=d^{\beta}_{s_i,d_i}$. In the simulation, β is equal to -3. From the simulation result, we can see the performance of the relay selection scheme we have proposed is better than QBCO, DEA and ABC. To simplify the random of Rayleigh fading, we can make channel state information (CSI) G_{s_i,d_i} , G_{s_i,r_i} and G_{r_i,d_i} as the Rayleigh fading expected value. That is to say, G_{s_i,d_i} is equal to λ_{s_i,d_i} , G_{s_i,r_i} is equal to λ_{s_i,r_i} and G_{r_i,d_i} is equal to λ_{r_i,d_i} . **Fig. 2(b)** is the simulation result of convergence curves of 4 different schemes with 20 RNs when considering the fixed Rayleigh fading. The simulation result is averaged over 200 trials. From **Fig. 2(a)** and **Fig. 2(b)**, we can see the scale of simulation result is the same. That is to say, the Rayleigh fading is a just a parameter and it doesn't influent the performance of simulation results. To reduce the time of simulation, the next simulation results only consider the fixed Rayleigh fading. All results are averaged over 200 trials.

Fig. 3 and **Fig. 4** consider the case where the MPF or MMR varies respectively with the iteration number for QBCO, DEA, ABC and QDEA when N=10, M=20, the SN power is 20W and the RN power is 18W. From these simulation results, QDEA can obtain the result which is better than the results obtained by other algorithms. It is clear that the performance of QDEA is superior to QBCO, DEA and ABC.

The proposed QDEA applies the quantum computing theory to the differential evolution algorithm. In this algorithm, each quantum individual is updated by using differential evolution theory and quantum computing. The differential evolution algorithm is able to locate the appropriate regions for a solution in the search place, but fairly slow to find the near-optimal solution. Because the updating equations are random in searching the near-optimal solution. It has the disadvantage of local convergence. However, the proposed QDEA has the advantages of both differential evolution theory and the quantum computing, so it can find the near-optimal solution compared to other intelligence algorithms. Besides, the proposed QDEA combines two evolution methods together, not only increases the speed of convergence, but also promotes the diversity of population. In summary, the proposed QDEA can overcome the disadvantages of the previous intelligence algorithms.

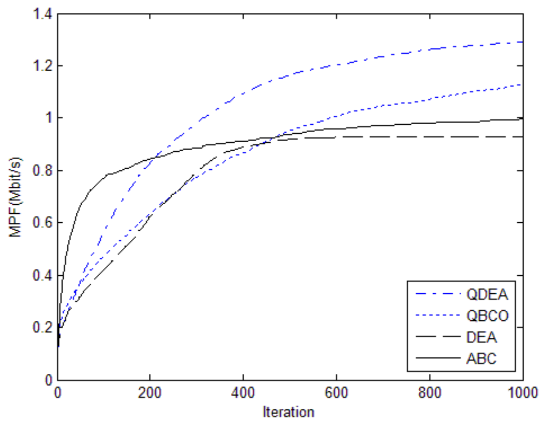

Fig. 3. Convergence curves of 4 different schemes with 20 RNs (MPF)

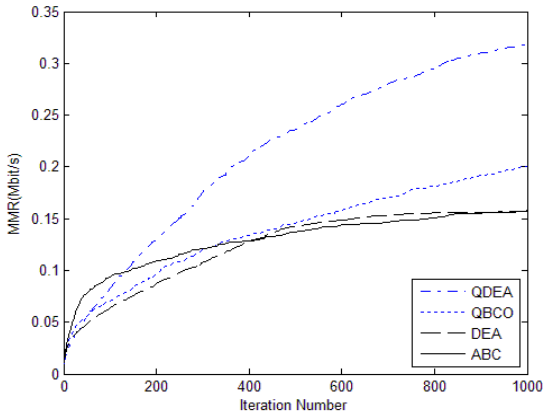

Fig. 4. Convergence curves of 4 different schemes with 20 RNs (MMR)

The MAR, MPF or MMR varies with the RN number is considered. In the simulation, N=10 but M varies from 20 to 35. The SN power is 20W while the RN power is 18W. Simulation results are shown in **Fig. 5**, **Fig. 6** and **Fig. 7**. It can be seen that MAR, MPF or MMR increases almost linearly with the RN number. From **Fig. 5**, **Fig. 6** and **Fig. 7**, it can also be seen that ABC performs worse than QDEA, QBCO and DEA, while QBCO performs better than DEA and ABC, but QDEA performs the best. The gain of QDEA is almost 0.3Mbit/s compared with QBCO when MAR is considered.

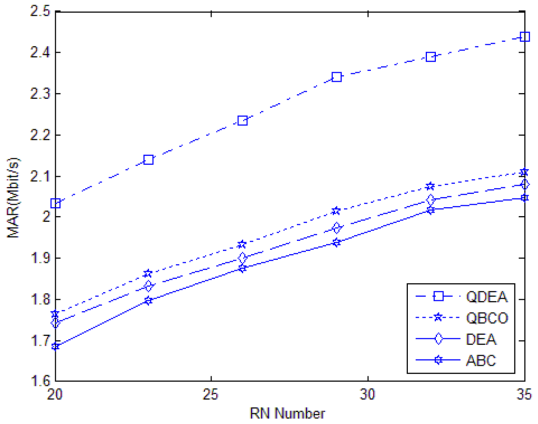

Fig. 5. MAR comparison of 4 schemes with different RN number

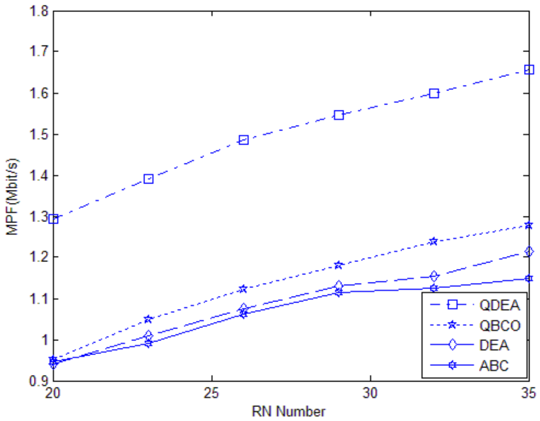

Fig. 6. MPF comparison of 4 schemes with different RN number

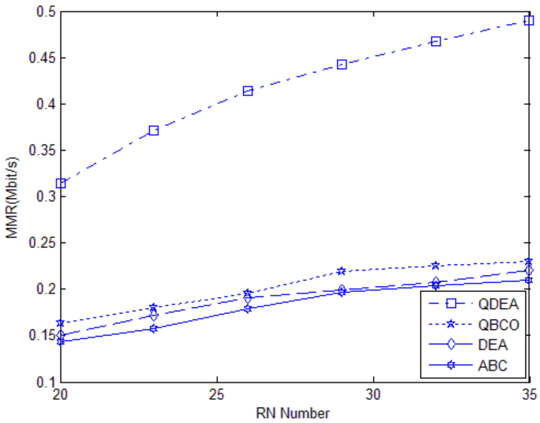

Fig. 7. MMR comparison of 4 schemes with different RN number

5.2 Simulations based on NSQDEA for multi-objective relay selection scheme

In this section, we will present the simulation results of multi-objective relay selection schemes based on NSQDEA. For NSQDEA scheme, the maximal iteration number is 500 and the number of quantum individuals in each population is the same. The number is 50. Other simulation parameters are the same as the single-objective relay selection scheme. The parameter settings of NSQBCO can refer to [24].

Fig. 8, **Fig. 9** and **Fig. 10** consider the performance of multi-objective relay selection scheme when N=5, M=7. The SN power is 20W. The RN power is 18W. **Fig. 8** considers the multi-objective of MAR and MPF, and it can be seen that there is no relay selection scheme that can maximize MAR and MPF simultaneously. When one solution maximizes one object, another object can't get the best performance. Also, we can find that the solutions we get through NSQDEA are the non-dominated solutions. **Fig. 9** considers MAR and MMR, **Fig. 10** considers MMR and MPF, which has the same phenomenon. Also, the solutions obtained by NSQDEA are all Pareto front solutions, which means there does not exist one solution that has a better performance in both objectives compared with these solutions. The simulation results show that the NSQDEA we have proposed is effective to solve multi-objective problems and can get the same non-dominated relay selection scheme as the exhaustive search.

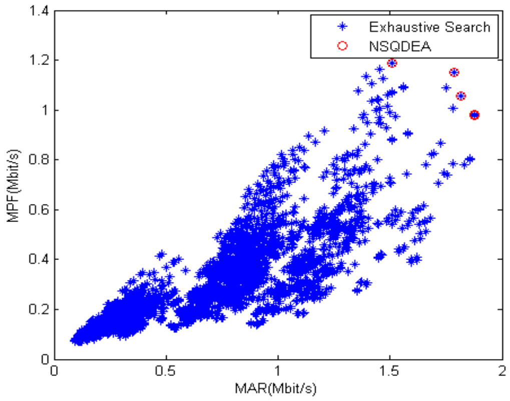

Fig. 8. The performance of all exhaustive solutions and solutions obtained by NSQDEA considering MAR and MPF

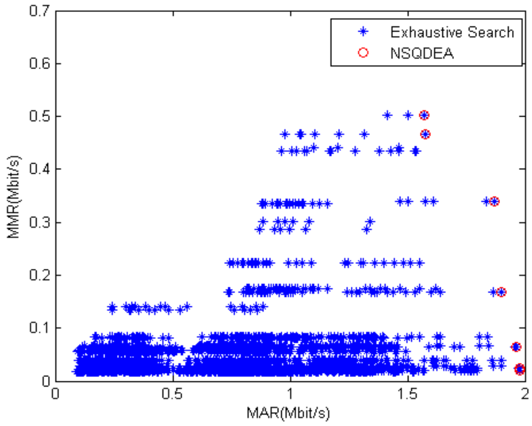

Fig. 9. The performance of all exhaustive solutions and solutions obtained by NSQDEA considering MAR and MMR

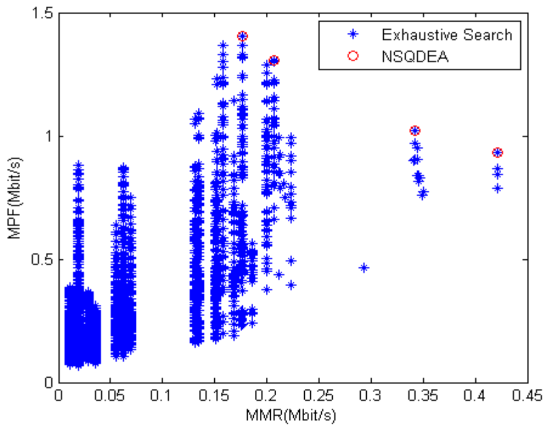

Fig. 10. The performance of all exhaustive solutions and solutions obtained by NSQDEA considering MMR and MPF

Fig. 11 and **Fig. 12** show the performance of NSQDEA for the multi-object of MAR and MPF when M=20, N=10. For one object MAR or MPF, the QBCO, DEA and ABC are used to optimize one object. The maximal iteration number of QBCO, DEA and ABC is 500, and the number of each population is 50. The SN power is 20W. The RN power is 18W. The settings of other simulation parameters are the same as the situation which only considers one object. From **Fig. 11** and **Fig. 12** we can see the solutions which are evolved by NSQDEA. And for one object, the solutions calculated by QBCO, DEA and ABC are dominated by the solutions which are evolved by NSQDEA. The simulation results show that the NSQDEA that we have proposed can get a good performance on solving multi-objective problem, and the solutions are non-dominated solutions.

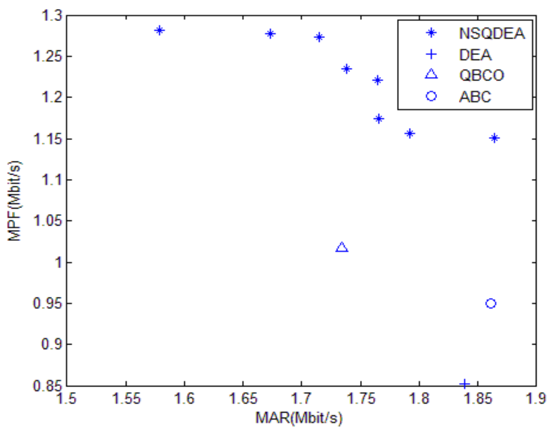

Fig. 11. The performance of solutions obtained by NSQDEA (considering MAR and MPF) and DEA, QBCO, ABC(considering MAR) in one relay selection case

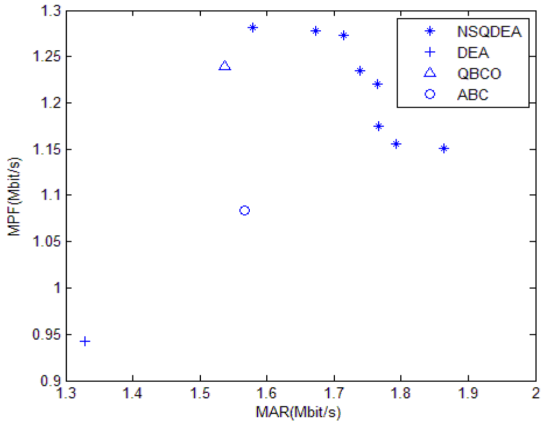

Fig. 12. The performance of solutions obtained by NSQDEA (considering MAR and MPF) and DEA, QBCO, ABC(considering MPF) in one relay selection case

Fig. 13 and **Fig. 14** show the performance of NSQDEA for the multi-object of MAR and MMR. The QBCO, DEA and ABC are used to optimize one object, MAR or MMR. The settings of other simulation parameters are the same as **Fig. 11** and **Fig. 12**. From **Fig. 13** and **Fig. 14** we can see that the solutions which are evolved by NSQDEA can dominate the solutions calculated by QBCO, DEA and ABC. The simulation results show that the algorithm NSQDEA that we have proposed can get a good performance when considering MAR and MMR.

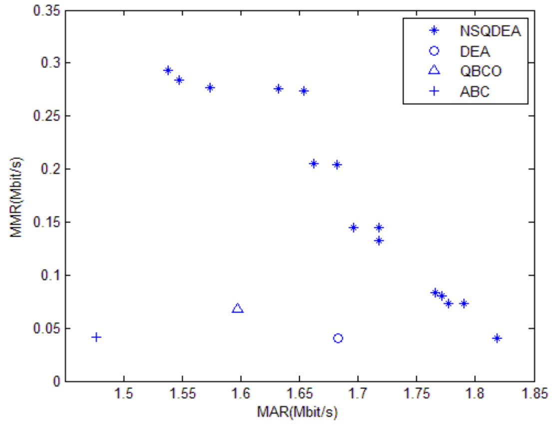

Fig. 13. The performance of solutions obtained by NSQDEA (considering MAR and MMR) and DEA, QBCO, ABC(considering MAR) in one relay selection case

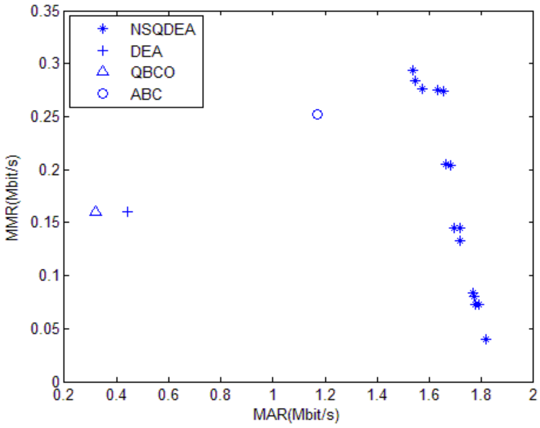

Fig. 14. The performance of solutions obtained by NSQDEA (considering MAR and MMR) and DEA, QBCO, ABC (considering MMR) in one relay selection case

Fig. 15 and **Fig. 16** show the performance of NSQDEA for the multi-object of MMR and MPF when M=20, N=10. The relay selection schemes obtained by QBCO, DEA and ABC are presented to compare. The SN power is 20W and the RN power is 18W. The settings of other simulation parameters are the same as **Fig. 11** and **Fig. 12**. The simulation results show that the multi-objective relay selection scheme NSQDEA has a wider application even if compared with single-objective relay selection scheme.

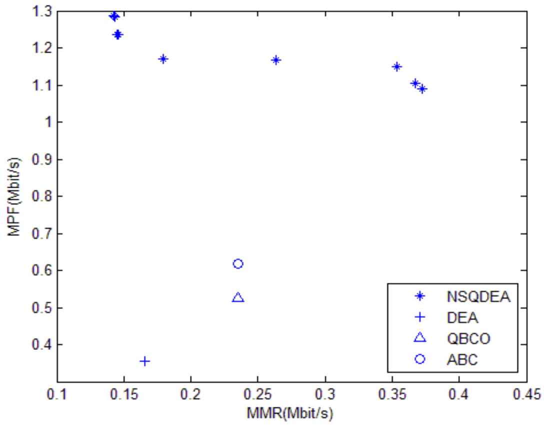

Fig. 15. The performance of solutions obtained by NSQDEA (considering MMR and MPF) and DEA, QBCO, ABC (considering MMR) in one relay selection case

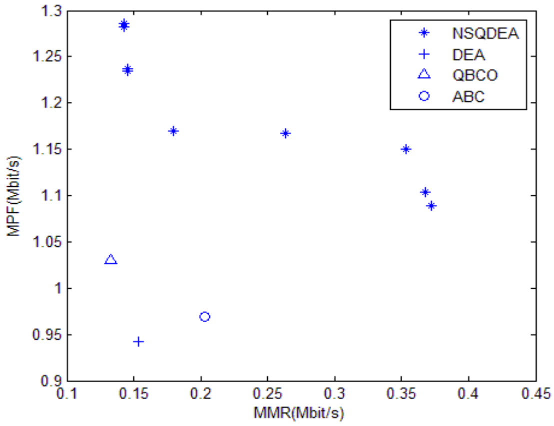

Fig. 16. The performance of solutions obtained by NSQDEA and NSQBCO (considering MMR and MPF) in one relay selection case

Fig. 17, **Fig. 18** and **Fig. 19** show the preformance of NSQDEA and NSQBCO for the multi-object of MMR and MPF, MAR and MMR or MMR and MPF. In this simulation, the maximal iteration number is 500, the SN power is 20W and the RN power is 18W. The simulation parameters of NSQBCO can be referred to [24]. The simulation results show that NSQDEA performs better than NSQBCO in multi-objective relay selection scheme. From **Fig. 17-19**, the gap between NSQDEA and NSQBCO is obvious when the multi-objective is different. All simulations illustrate that NSQDEA has the best performance under different simulation conditions.

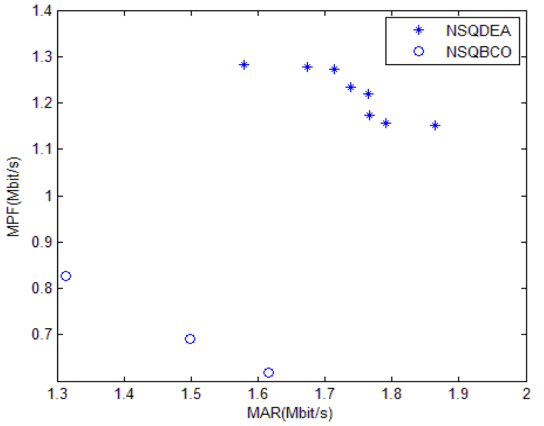

Fig. 17. The performance of solutions obtained by NSQDEA and NSQBCO (considering MAR and MPF) in one relay selection case

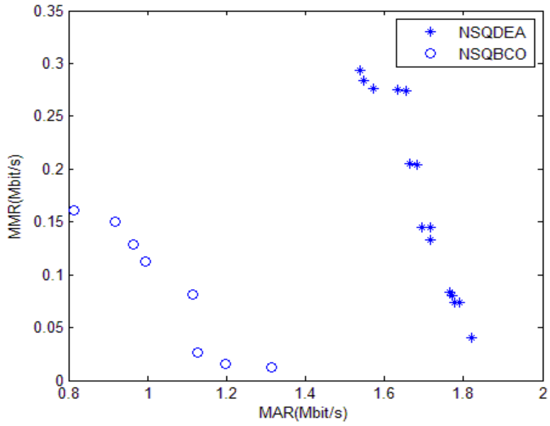

Fig. 18. The performance of solutions obtained by NSQDEA and NSQBCO (considering MAR and MPF) in one relay selection case

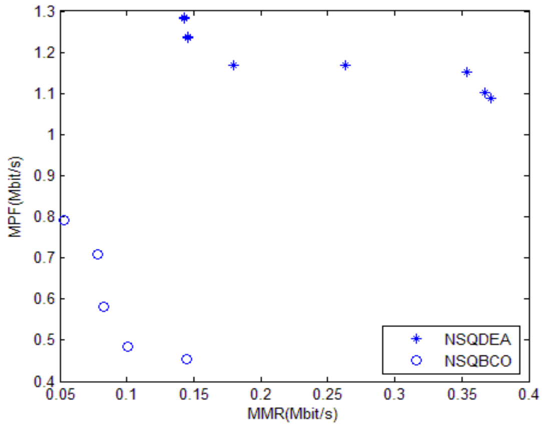

Fig. 19. The performance of solutions obtained by NSQDEA and NSQBCO (considering MMR and MPF) in one relay selection case

6. Conclusion

This paper has proposed QDEA based single-objective relay selection scheme and NSQDEA based multi-objective relay selection scheme considering CCI to other SN-DN transmission pairs in the cooperative relay networks. Compared with QBCO, DEA, and ABC based single-objective relay selection schemes, the proposed QDEA scheme has a much better performance on different objective functions under different simulation scenarios. NSQDEA based multi-objective relay selection scheme is proposed to obtain Pareto front solutions for MAR and MPF optimization, MAR and MMR optimization, or MPF and MMR optimization. Comparing NSQDEA with NSQBCO, simulation results illustrate the effectiveness of NSQDEA scheme, which has a better performance than NSQBCO in multi-objective relay selection scheme. Besides, the simulation results also validate that the multi-objective relay selection scheme NSQDEA has a much more wider application.

Acknowledgment

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