Quantum Bee Colony Optimization and Non-dominated Sorting Quantum Bee Colony Optimization Based Multi-relay Selection Scheme

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Abstract

In cooperative multi-relay networks, the relay nodes which are selected are very important to the system performance. How to choose the best cooperative relay nodes is an optimization problem. In this paper, multi-relay selection schemes which consider either single objective or multi-objective are proposed based on evolutionary algorithms. Firstly, the single objective optimization problems of multi-relay selection considering signal to noise ratio (SNR) or power efficiency maximization are solved based on the quantum bee colony optimization (QBCO). Then the multi-objective optimization problems of multi-relay selection considering SNR maximization and power consumption minimization (two contradictive objectives) or SNR maximization and power efficiency maximization (also two contradictive objectives) are solved based on non-dominated sorting quantum bee colony optimization (NSQBCO), which can obtain the Pareto front solutions considering two contradictive objectives simultaneously. Simulation results show that QBCO based multi-relay selection schemes have the ability to search global optimal solution compared with other multi-relay selection schemes in literature, while NSQBCO based multi-relay selection schemes can obtain the same Pareto front solutions as exhaustive search when the number of relays is not very large. When the number of relays is very large, exhaustive search cannot be used due to complexity but NSQBCO based multi-relay selection schemes can still be used to solve the problems. All simulation results demonstrate the effectiveness of the proposed schemes.

Keywords: cooperative relaying; relay selection; power efficiency; quantum bee colony optimization; non-dominated sorting quantum bee colony optimization

1. Introduction

It is well known that the relay nodes play an import role in conventional cellular networks to help enlarge the coverage of base station or increase the overall cell throughput in 3GPP Long Term Evolution-Advanced (LTE-A) [1]. Relaying is an effective and important technology to overcome the limitation of cell coverage and especially cell-edge users' throughput[2-3]. Relay technology is very important in other cooperative networks, such as ad hoc networks. In order to exploit the advantage of the relay node deployment in the wireless networks, relay selection, power and bandwidth allocation have been investigated in the literature, in which relay selection is the key issue of the radio resource management (RRM) in relaying systems. Most of the relay selection researches are based on certain function of channel state information (CSI), which are physical distance, path loss or end-to-end SNR [4]. In this scenario, the receiver knows all of the CSI between the source and the relay and all of the CSI between the relay and the destination thus chooses one relay according to certain function of CSI [5-6]. However, selecting single relay in wireless networks may result in imbalance of resource utilization, and moreover, the "emergence" diversity gain among multiple relays cannot be achieved. Furthermore, single assisted relay may have the disadvantage of heavy load. In order to solve this problem, [7] has proposed a load-based relay selection scheme. However, single relay selections cannot avoid the fading effect of wireless channels, therefore multi-relay selection schemes are widely researched. It has the ability of both improving the stability of network and maximizing the end-to-end SNR or power efficiency. It is especially useful for wireless relay networks with multiple relays and many complex constraints. However, with the number of relays increasing, the network may have the problems of much more interference and resource crashing. Thus, how to choose a set of suitable relays is very important. As it is well known, energy efficiency or power efficiency is of great importance in green communications, which is also the same in the relay networks. In [8], several relay selection strategies for multi-relay scenarios are proposed, which takes the instantaneous error rate and fast fading channels into consideration. In [9], a novel relay selection scheme considering energy-efficiency is proposed and the relay node which has the best energy efficiency is selected. In [10], a relay ordering based relay selection scheme which considers end-to-end SNR and end-to-end power efficiency is proposed. But the scheme for energy-efficiency only can get a sub-optimal solution, and the results of simulation in [10] illustrate that the solution given by the relay ordering scheme has a large gap compared with exhaustive search scheme.

The relay selection problems in [7-10] are all single objective optimization multi-relay selection problems, which can be modeled as '0-1' optimization problem. Intelligence algorithm can be used to solve the problems, which can get an approximate optimal solution. Some classical intelligence algorithms are widely researched and applied, like particle swarm optimization (PSO) [11]. Quantum genetic algorithm (QGA) is the combination of quantum theory and genetic algorithm therefore has the advantage of faster convergence rate, stronger searching abilities, less computing time. Quantum particle swarm optimization (QPSO) which combines PSO with quantum computing theory is a novel swarm intelligence algorithm, which has a better performance for multi-relay selection problem [12]. Quantum bee colony optimization (QBCO) is a novel swarm intelligence algorithm for solving cognitive radio spectrum allocation problem which is proposed in [13]. Quantum theory has great efficiency and effectiveness in the intelligence algorithm domain, therefore QBCO is designed to solve single objective multi-relay selection problems.

Single objective optimization based multi-relay selection schemes have some limitations. In SNR maximization based multi-relay selection scheme, we can only obtain the solution which has the maximum SNR value. However, it can’t reveal the relationship between power consumption and the marginal effect of the SNR. It may be energy inefficiency in high SNR region. Decreasing the transmission power only has little impact on the obtained SNR. Therefore we can decrease the consumed power with the cost of little SNR degradation. In power efficiency maximization based multi-relay selection scheme, we can only obtain the solution which has the maximum power efficiency value. However, such optimization doesn’t consider the obtained SNR and data rate. It may give the largest power efficiency with very low obtained SNR. Obviously, such solution can’t fulfill the SNR requirement for quality of service (QoS) guarantee in the transmission. In this optimization problem, the optimal power efficiency solution is not “optimal transmission”. In order to overcome the disadvantage of single objective optimization based multi-relay selection schemes, we propose the multi-relay selection problems considering multiple objectives (SNR maximization and power consumption minimization or SNR maximization and power efficiency maximization). Multi-objective optimization problems represent an important class of real-world problems. In principle, they are very different from the 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 on a particular performance indicator depending on the optimization problem of minimization or maximization. In multi-objective optimization, however, there does not exist one solution which is the best with respect to all objectives. Typically such problems involve tradeoffs. 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 are considered. 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, such as classical NSGA [14], NSGA-II [15], SPEA [16] and SPEA2 [17]. [18-23] have done reaserch on multi-objective algorithms based on classical algorithms. In order to improve convergence and diversity of solutions of Pareto front, [18] improves solutions diversity of Pareto front of a well known multi-objective optimization algorithm NSGA-II. [19] proposes a new solution based on multi-objective optimization using the genetic algorithm NSGA-II for security, QoS, and energy efficiency in Wireless Sensor Networks (WSNs). Resource constraints as well as QoS requirements are respected through use of optimal security level based on evolutionary strategy. [20] has researched the multi-objective combinatorial optimization in the design of fiber-based distribution networks. In [21], a multi-objective two-nested genetic algorithm is used to solve clustering homogeneous wireless sensor networks. [22] proposes a new Multi-Objective Optimization Algorithm Based on Non-Dominated Sorting and Bidirectional Local Search (NSBLS) to solve high-dimensional big data. [23] considers many-objective problems and proposes an early-developed and computationally expensive strength Pareto based evolutionary algorithm by introducing an efficient reference direction based density estimator, a new fitness assignment scheme, and a new environmental selection strategy. The majority of multi-objective algorithms make use of the Pareto dominance concept to assign a single fitness value for each individual in the population. This is used to select a set of Pareto front solutions. The diversity of solutions in the Pareto front to cover different tradeoffs of the problem objectives and the distance to the actual front (optimal solutions) are two main issues that should be considered carefully and are affected by the fitness assignment and Pareto front individual selection techniques. Using an external memory (archive) to store non-dominated solutions found during the search process is a common approach to maintain the Pareto front. In multi-objective optimization, it is also important to choose the evolutionary method. Due to the effectiveness of QBCO [13], we choose QBCO as the evolutionary method. Therefore we propose the NSQBCO to solve the multi-objective multi-relay selection problem (SNR maximization and power consumption minimization or SNR maximization and power efficiency maximization).

The rest of the paper is organized as follows. The network model and problem illustration are described in Section 2. The QBCO based single objective multi-relay selection scheme is proposed in Section 3. Section 4 gives the NSQBCO based multi-objective multi-relay selection scheme. Section 5 analyses the simulation. Section 6 concludes the paper.

2. Network model and problem statement

In this section, a cooperative wireless relay system model is considered, which consists of one transmitter for transmission and one receiver for reception and R relays for cooperation as described in **Fig. 1**.

With relay selection schemes, a set of relays is selected from the R potential relays which maximize SNR or power efficiency proposed later. There is no direct link between the transmitter and the receiver. However, the results can be applied to the case with a direct link straightforwardly.

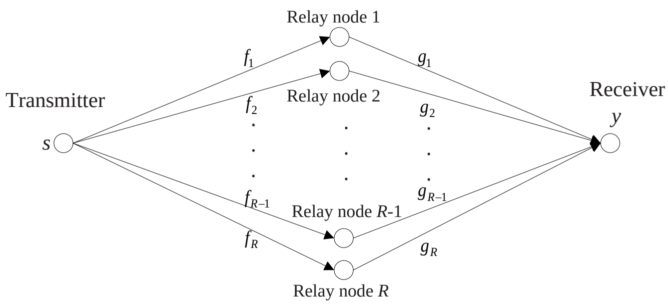


Fig. 1. Cooperative wireless relay network

It is assumed that each relay has only one antenna which can be used for both transmission and reception. Denote f_i as CSI from s to the i-th relay and g_i as CSI from the i-th relay to y. It is assumed that f_i and g_i are full known by the i-th relay, all CSI $f_1, f_2, \cdots, f_R$ and $g_1, g_2, \cdots, g_R$ are full known by the receiver. Assume that all CSI are normalized independent identical distribution (i.i.d.) Rayleigh random variables. P denotes the transmission power of the transmitter, and P_i denotes the transmission power of the i-th relay. Note that power control is not considered in the model, that is to say, the transmitter or relay cannot save power and sponsor the transmissions with better channels. A relay only has two choises, either cooperate or not cooperate at all. A two-step AF protocol is used to forward information without decoding. The transmitter sends the signal $\sqrt{P}z$ to all the other relay nodes in the first transmission process, where z is the signal to transmit and z is normalized as $E|z|^2 = 1$. The

i-th relay (if chosen) amplifies the signal received and forwards it to the receiver with power P_i in the second transmission process.

Firstly, existing relay selection scheme which selecting one relay based on SNR is reviewed and the cumulative distribution function (CDF) is derived and simulated.

Considering the system model in **Fig. 1**, the received signal at the i-th relay is

$$x_i = f_i \sqrt{P} z + v_i, \quad (i = 1, \cdots, R) \tag{1}$$

where v_i represents the additive white Gaussian noise (AWGN) with zero-mean and unit-variance at the i-th relay. The relay scales the signal received from the transmitter, then forwards it to the receiver, therefore the received signal at the receiver can be represented by

$$y_i = g_i \sqrt{\frac{P_i}{1 + P|f_i|^2}} x_i + w, \quad (i = 1, \cdots, R) \tag{2}$$

where w represents the AWGN with zero-mean and unit-variance at the receiver. The overall SNR of the transmission is

$$\gamma_i = \frac{|f_i g_i|^2 PP_i}{1 + |f_i|^2 P + |g_i|^2 P_i} \tag{3}$$

In the relay selection, the relay which has the largest SNR will be chosen to amplify and forward the transmitting data from the source to the destination. Set $P = P_i = 1$ for simplicity, and considering only one relay is selected among R available relays, the CDF of transmission SNR can be derived as

$$F(\gamma_0) = \left(1 - 2\mathrm{e}^{-2\gamma_0} \sqrt{\gamma_0{}^2 + \gamma_0} \times I_1\left(2\sqrt{\gamma_0{}^2 + \gamma_0}\right)\right)^R \tag{4}$$

where γ_0 represents the SNR value of between the transmitter and the receiver, and $I_1(\cdot)$ represents the first order modified Bessel function of the second kind.

Proof：The CDF of $F(\gamma_0)$ can be derived from single transmitter, single relay and single receiver scenario, which is defined as $F_{S,R,D}(\gamma_0)$. First, we calculate the CDF of $F_{S,R,D}(\gamma_0)$:

$$F_{S,R,D}(\gamma_0) = \Pr\left(\Gamma_{S,R,D} \le \gamma_0\right) = \iint_D f_X(x) f_Y(y) \mathrm{d}x\mathrm{d}y$$

where $X = \Gamma_{S,R} = |f|^2$ represents SNR from transmitter to relay, $Y = \Gamma_{R,D} = |g|^2$ represents SNR from relay to receiver. Therefore, $\Pr(X \le \gamma_0) = 1 - \mathrm{e}^{-\gamma_0}$, $\Pr(Y \le \gamma_0) = 1 - \mathrm{e}^{-\gamma_0}$ and we use two regions to calculate the integration, that is, $D_1 = \{X < \gamma_0\} \cup \{Y < \gamma_0\}$, $D_2 = D - D_1$. So the result of the integral can be written as $F_{S,R,D} = F_1 + F_2$.

$$\begin{aligned} F_1(\gamma_0) &= \Pr(X \le \gamma_0) + \Pr(Y \le \gamma_0) - \Pr(X \le \gamma_0, Y \le \gamma_0) \\ &= 1 - e^{-\gamma_0} + 1 - e^{-\gamma_0} - \left(1 - e^{-\gamma_0}\right)\left(1 - e^{-\gamma_0}\right) \\ &= 1 - e^{-2\gamma_0} \end{aligned}$$

Define $X_1 = X - \gamma_0, Y_1 = Y - \gamma_0$. Since $\frac{XY}{X+Y+1} = \gamma_0$, we can obtain $X_1 Y_1 = \gamma_0^2 + \gamma_0$. Therefore,

$$F_2(\gamma_0) = \int_0^\infty \int_0^{\frac{\gamma_0^2+\gamma_0}{y_1}} e^{-(\gamma_0 + x_1)} e^{-(\gamma_0 + y_1)} \mathrm{d}x_1 \mathrm{d}y_1 = -e^{-2\gamma_0} \int_0^\infty e^{-\frac{\gamma_0^2+\gamma_0}{y_1} - y_1} \mathrm{d}y_1 + e^{-2\gamma_0}$$

The above integral has the same form with the following:

$$\phi(a,b) = \int_0^\infty e^{\left(-\frac{a}{y_1} - by_1\right)} \mathrm{d}y_1 = \sqrt{\frac{a}{b}} \int_0^\infty e^{-\sqrt{ab}\left(\frac{1}{z} + z\right)} \mathrm{d}z$$

Assume $z = e^t$, and place it into the above equations, we can obtain

$$\phi(a,b) = \int_0^\infty e^{-2\sqrt{ab}\cosh t}\, 2\cosh t \mathrm{d}t$$

Now it is obvious that the above can be calculated by the integral of $I_1(x)$.Therefore,

$$\phi(a,b) = \int_0^\infty e^{\left(-\frac{a}{y_1} - by_1\right)} dy_1 = \sqrt{\frac{4a}{b}} I_1\left(\sqrt{4ab}\right)$$

where $a = \gamma_0^2 + \gamma_0$ and $b = 1$. Use the above result, $F_2(\gamma_0)$ can be written as

$$F_2(\gamma_0) = -2e^{-2\gamma_0} \sqrt{\gamma_0^2 + \gamma_0} \times I_1\left(2\sqrt{\gamma_0^2 + \gamma_0}\right) + e^{-2\gamma_0}$$

So

$$\begin{aligned} F_{S,R,D}(\gamma_0) &= F_1(\gamma_0) + F_2(\gamma_0) \\ &= 1 - 2e^{-2\gamma_0} \sqrt{\gamma_0^2 + \gamma_0} \times I_1\left(2\sqrt{\gamma_0^2 + \gamma_0}\right) \end{aligned}$$

For the single relay selection based on SNR, the relay which has the maximum end-to-end SNR is chosen. Therefore, $Y_{\max} = \{Y_1, Y_2, \cdots, Y_R\}$. The CDF of $Y_{\max}$ can be represented as

$$\begin{aligned} F(\gamma) &= \Pr(Y_{\max} \le \gamma_0) \\ &= \Pr(Y_1 \le \gamma_0, \cdots, Y_R \le \gamma_0) \\ &= \prod_{i=1}^{R} \Pr(Y_i \le \gamma_0) \\ &= \left(F_{S,R,D}(\gamma_0)\right)^R \\ &= \left(1 - 2e^{-2\gamma_0} \sqrt{\gamma_0^2 + \gamma_0} \times I_1\left(2\sqrt{\gamma_0^2 + \gamma_0}\right)\right)^R \end{aligned} .$$

Considering theory simulation and Monte-Carlo simulation, the CDF varies with SNR which select one best relay in cooperative relay networks based on SNR is simulated. **Fig. 2** shows the result when the relay number is 1, 5 and 10 respectively. From **Fig. 2**, it is obvious that the CDF obtained by theory has almost the same performance with the CDF obtained by

Monte-Carlo, which demonstrates the accuracy of our derivation.

From **Fig. 2**, we can see that although the diversity gain increases with relay number, however it is rather limited. **Fig. 3** presents the simulation of CDF which consider selecting one relay and multiple relays (the best multi-relay selection is obtained through exhaustive search scheme, where all of the 2^R solutions are calculated and the optimal one is chosen).

From **Fig. 3**, it is obvious that selecting multiple relays has much more diversity compared with selecting one relay. Besides, if only one relay is selected, it is likely to have heavy load problem. In order to explore more diversity of selecting multiple relays, the multi-relay selection problems and schemes are proposed to select a set of relays from the R potential relays. Since the data to transmit is distributed among multiple relays, the multiple relays can overcome the problem of heavy load transmission of the single relay.

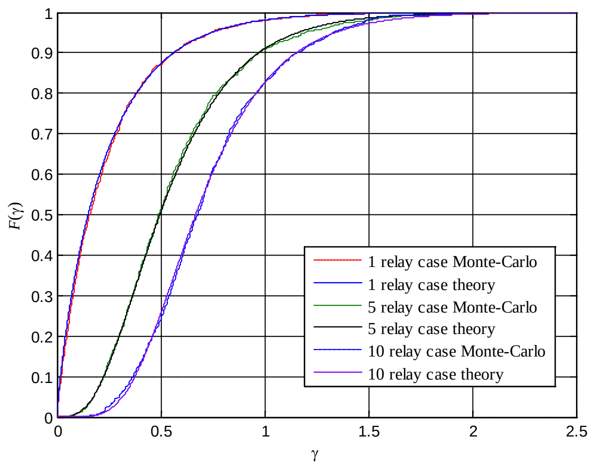


Fig. 2. CDF of single relay selction schemes based on SNR

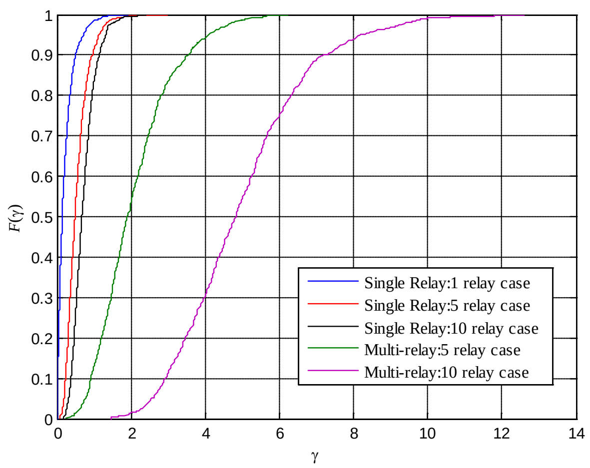


Fig. 3. Comparison of CDF for both single and multi-relay selction schemes

In multi-relay system, the transmitter sends the signal $\sqrt{P}z$ to the i-th relay in the first transmission process, while in the second transmission process, the i-th relay amplifies its signal received from transmitter by $\frac{a_i\sqrt{P_i}\mathrm{e}^{\mathrm{j}\theta_i}}{\sqrt{1+|f_i|^2 P}}$ (therefore the transmission power is $a_i^2 P_i$) and then forwards it, where a_i represents whether the i-th relay is chosen or not. If $a_i = 1$, the i-th relay is chosen , otherwise $a_i = 0$.

Assume that the relays transmit at the same time, that is to say, synchronization problem is not considered. The angle $\theta_i = -(\arg f_i + \arg g_i)$ represents the phase of the signal. The received signal by the i-th relay's is defined as $|f_i|\sqrt{P}s + v_i$ .Thus, the received signal is

$$y = \sqrt{P}\sum_{i=1}^{R}\frac{a_i|f_i g_i|\sqrt{P_i}}{\sqrt{1+|f_i|^2 P}}s + \sum_{i=1}^{R}\frac{a_i|g_i|\sqrt{P_i}}{\sqrt{1+|f_i|^2 P}}u_i + w \tag{5}$$

where w is AWGN at the receiver and $u_i = v_i e^{-\mathrm{j}\arg f_i}$ while v_i is the AWGN at the i-th relay. w and v_i are assumed to be i.i.d. complex Gaussian random variables with zero-mean and unit-variance. It is obvious that u_i and v_i have the same distribution. The average SNR of the communication system is

$$\gamma = P\left(\sum_{i=1}^{R}\frac{a_i|f_i g_i|\sqrt{P_i}}{\sqrt{1+|f_i|^2 P}}\right)^2 \Bigg/ \left(1+\sum_{i=1}^{R}\frac{a_i^2|g_i|^2 P_i}{1+|f_i|^2 P}\right) \tag{6}$$

The single objective multi-relay selection optimization problem considering SNR can be written as

$$\max_{a_1,\cdots,a_R} \gamma \qquad s.t. \qquad a_i \in \{0,1\} \tag{7}$$

In wireless networks, energy expenditure is also an emergency problem, so energy-saving communication are widely researched. It is easy to see that the power of all selected relays, $P_{total} = \sum_{i=1}^{k} P_i$ increases with the selected relays number k. Define the power efficiency as the ratio of γ to all of the transmission powers (the transmitter power and the relay power). The single objective multi-relay selection problem considering power efficiency can be written as

$$\begin{aligned} &\max_{\alpha_1,\cdots,\alpha_R} \eta = \frac{\log_2(1+\gamma)}{P+\sum_{i=1}^{R} a_i^2 P_i} \\ &s.t. \qquad \alpha_i \in \{0,1\} \end{aligned} \tag{8}$$

Assume that the receiver knows all CSI, this problem is equivalent of solving the problem of the SNR or power efficiency maximization, which is like the problem in [24]. But, here the power control problem is not taken into consideration. Instead, each relay has only two choices: to cooperate with full power or not to cooperate at all. Since every relay has two choices, the problems considering SNR or power efficiency are general 0-1 optimization problems. Exhaustive search scheme has the ability to solve the problem, but the complexity increases exponential with relay number. Therefore QBCO is used to solve the multi-relay selection problems to get a better solution, which will be presented in Section 3.

Since the SNR target increases with the power, the SNR target maximization and the power consumption target minimization are contradictive. Considering the SNR and power consumption simultaneously, multi-objective relay selection problem is proposed, which is in the following

$$\begin{cases} \max\limits_{a_1,\cdots,a_R} \gamma \\ \min\limits_{a_1,\cdots,a_R} P_{\text{total}} = P + \sum\limits_{i=1}^{R} a_i^2 P_i \end{cases} \quad s.t. \quad a_i \in \{0,1\} \tag{9}$$

Also, the SNR target increases with the power increasing, while the power efficiency may be decrease with the increased power, the SNR target maximization and the power efficiency target maximization are also contradictive, i.e., they cannot get the largest value with the same relay selection scheme. Considering the SNR and power efficiency simultaneously, another multi-objective multi-relay selection problem is proposed, which is in the following

$$\begin{cases} \max\limits_{a_1,\cdots,a_R} \gamma \\ \max\limits_{a_1,\cdots,a_R} \eta = \dfrac{\log_2(1+\gamma)}{P + \sum\limits_{i=1}^{R} a_i^2 P_i} \end{cases} \quad s.t. \quad a_i \in \{0,1\} \tag{10}$$

Exhaustive search can be used to solve multi-objective multi-relay selection problem (9) and (10), but the complexity is intolerable, that is to say it cannot be used in technology application. In this paper, NSQBCO is proposed to solve the multi-objective multi-relay selection problems, which will be illustrated in Section 4.

3. Single objective multi-relay selection scheme

The relay ordering multi-relay selection schemes proposed in [10] is reviewed and then we propose the single objective multi-relay selection schemes based on QBCO.

The process of relay ordering schemes can be illustrated in the following:

Step1: Order the available relays according to certain functions (Best Worse Channel Selection, which can be written as $\min\{P|f_i|, P_i|g_i|\}$, Best Harmonic Mean Selection, which can be written as $\left(P^{-1}|f_i|^{-2} + P_i^{-1}|g_i|^{-2}\right)^{-1}$, SNR-based Selection, which can be written as $\dfrac{|f_i g_i| P P_i}{1+|f_i|^2 P + |g_i|^2 P_i}$), therefore get an ordering $(x_1, x_2, \cdots, x_R)$ of $(1, 2, \cdots, R)$. That is to say, if $i<j$, then relay x_i is prior to relay x_j. In other words, if relay x_i is not selected, relay x_j should not be selected either.

Step2: Calculate the SNR, $\gamma(x_1), \gamma(x_1, x_2), \cdots, \gamma(x_1, x_2, \cdots, x_R)$.

Step3: The destination finds the x_i such that $\gamma(x_1, x_2, \cdots, x_i)$ is the largest among the $\gamma(x_1)$, $\cdots$, $\gamma(x_1, x_2, \cdots, x_i), \cdots$, $\gamma(x_1, x_2, \cdots, x_R)$. The relays which take part in the cooperative communication can be represented as $(x_1, x_2, \cdots, x_i)$.

For power efficiency problem, [10] modifies the relay ordering schemes, that is instead of selecting the x_i which has the largest value of $\gamma(x_1), \cdots, \gamma(x_1, x_2, \cdots, x_i), \cdots, \gamma(x_1, x_2, \cdots, x_R)$, choose the smallest x_i such that $\gamma(x_1, x_2, \cdots, x_i) > \gamma(x_1, x_2, \cdots, x_{i+1})$. In other words, we examine the following values $\gamma(x_1), \cdots, \gamma(x_1, x_2, \cdots, x_i), \cdots, \gamma(x_1, x_2, \cdots, x_R)$ till the SNR values stop increasing. This makes the "worse" relays are not selected, although some overall SNR may be lost.

It has been proposed in [10] that for wireless communication relay networks which has more than 2 relays, there exists no optimal relay ordering. So the schemes proposed in [10] are not global-optimal, that is to say, only a sub-optimal solution is obtained. So we propose the single objective multi-relay selection schemes based on QBCO.

In this paper QBCO is used to solve multi-relay selection problems, which is referred by social behaviour of quantum bees. Quantum employed bees, quantum onlooker bees and quantum scouts bees consist of the colony of quantum bees. They look for food resources (which are represented by quantum position) in an R dimensions space according to its own and its parteners' historical experiences; where R represents the optimization problem's dimension. In QBCO, quantum coding is used to represent the probabilistic state, and the quantum position can be updated by quantum rotation angle (which is defined by certain quantum bee, its local experiences and the whole quantum colony's experiences), which is similar to the bird's flying process. One quantum position can be written by a pair of numbers (α, β), where $|\alpha|^2 + |\beta|^2 = 1$. The bit position is decided by the quantum position with certain functions, where $|\alpha|^2$ decides the probability that the bit position is in the '0' state and $|\beta|^2$ decides the probability that the bit position is in the '1' state.

The i-th quantum bee's quantum position is

$$\mathbf{v}_i = \begin{bmatrix} \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{iR} \\ \beta_{i1} & \beta_{i2} & \cdots & \beta_{iR} \end{bmatrix} \tag{11}$$

where $|\alpha_{ij}|^2 + |\beta_{ij}|^2 = 1, (j = 1, 2, \cdots, R)$, therefore $\mathbf{v}_i$ can represent 2^R values simultaneously. For efficiency, set α_{ij} and β_{ij} are real numbers and $0 \le \alpha_{ij} \le 1$, $0 \le \beta_{ij} \le 1$. Therefore $\alpha_{ij} = \sqrt{1 - \beta_{ij}^{\ 2}}$, and equation (11) can be simplified as

$$\mathbf{v}_i = \begin{bmatrix} \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{iR} \end{bmatrix} = \begin{bmatrix} v_{i1} & v_{i2} & \cdots & v_{iR} \end{bmatrix} \tag{12}$$

3.1 Evolutionary process of quantum employed bees

The first half of quantum bees in the quantum colony are quantum employed bees. The quantum position is mainly calculated by quantum rotation angle. In QBCO, for simplicity, the i-th $\left(i=1,2,\cdots,h/2\right)$ quantum employed bee's j-th quantum position v_{ij} is updated as

$$v_{ij}^{t+1}=\mathrm{abs}\left(v_{ij}^{t}\times\cos\theta_{ij}^{t+1}-\sqrt{1-(v_{ij}^{t})^{2}}\times\sin\theta_{ij}^{t+1}\right) \tag{13}$$

where superscript t is the number of generations (which is also iterations), $\mathrm{abs}(\cdot)$ represents the absolute function which makes quantum position in the domain[0, 1], and θ_{ij}^{t+1} is the quantum rotation angle calculated through (15) which will be described later.

If $\theta_{ij}^{t+1}=0$, according to (13), $v_{ij}^{t+1}=v_{ij}^{t}$. To keep the diversity of the colony of quantum employed bees, if $\theta_{ij}^{t+1}=0$ the quantum position v_{ij} is updated in certain possibility by

$$v_{ij}^{t+1}=\sqrt{1-(v_{ij}^{t})^{2}} \tag{14}$$

The quantum colony consists of $h/2$ quantum employed bees that flies in a space of R dimensions, $\mathbf{x}_i=\left(x_{i1},x_{i2},\cdots,x_{iR}\right)$ represents the i-th quantum employed bee's bit position in the space. $\mathbf{v}_i=\left(v_{i1},v_{i2},\cdots,v_{iR}\right)=\left[\alpha_{i1}\quad\alpha_{i2}\quad\cdots\quad\alpha_{iR}\right]$ represents the i-th quantum employed bee's quantum position and until now the best bit position (the local optimal bit position) of the i-th quantum employed bee is $\mathbf{p}_i=\left(p_{i1},p_{i2},\cdots,p_{iR}\right)$. The global optimal bit position found by the whole quantum bee colony is $\mathbf{p}_g=\left(p_{g1},p_{g2},\cdots,p_{gR}\right)$. At each iteration, the quantum rotation angle, quantum position and bit position is updated by

$$\theta_{ij}^{t+1}=e_1(p_{ij}^{t}-x_{ij}^{t})+e_2(p_{gj}^{t}-x_{ij}^{t}) \tag{15}$$

$$v_{ij}^{t+1}=\begin{cases}\sqrt{1-(v_{ij}^{t})^{2}}, & \text{if}\quad (p_{ij}^{t}=x_{ij}^{t}=p_{gj}^{t}\ \text{ and }\ r<c_1)\\ \mathrm{abs}(v_{ij}^{t}\times\cos\theta_{ij}^{t+1}-\sqrt{1-(v_{ij}^{t})^{2}}\times\sin\theta_{ij}^{t+1}), & \text{else}\end{cases} \tag{16}$$

$$x_{ij}^{t+1}=\begin{cases}1, & \text{if}\quad \gamma_{ij}^{t+1}>(v_{ij}^{t+1})^{2}\\ 0, & \text{if}\quad \gamma_{ij}^{t+1}\le(v_{ij}^{t+1})^{2}\end{cases} \tag{17}$$

where r is a uniform random number in the real domain[0, 1], c_1 is a constant among $[0,1/R]$, $\gamma_{ij}^{t+1}\in[0,1]$ is uniform random number, $\left(v_{ij}^{t+1}\right)^{2}$ defines the selection probability of bit position state in the $(t+1)$-th generation. The value of e_1 and e_2 represents the relative important degree of $\mathbf{p}_i^t$ and $\mathbf{p}_g^t$.

After updating the quantum and bit position, calculate the fitness of each quantum employed bee based on certain function, that is (7) or (8). If the fitness of $\mathbf{x}_i^{t+1}$ is better than that of $\mathbf{p}_i^t$, then update $\mathbf{p}_i^{t+1}$ as $\mathbf{x}_i^{t+1}$. If the fitness of $\mathbf{p}_i^{t+1}$ is better than that of $\mathbf{p}_g^t$, then update $\mathbf{p}_g^{t+1}$ as $\mathbf{p}_i^{t+1}$.

3.2 Evolutionary process of quantum onlooker bees

The second half of quantum bees in the quantum colony are quantum onlooker bees. The quantum onlooker bees' quantum updating process is based on the selected quantum employed bee's quantum position. The selection possibility of the k-th $\left(k = 1, 2, \cdots, h/2\right)$ quantum employed bee can be calculated by the following equation:

$$p_k^t = U\left(\mathbf{x}_k\right) \Big/ \sum_{i=1}^{h/2} U\left(\mathbf{x}_i\right) \tag{18}$$

where $U\left(\mathbf{x}_k\right)$ represents the fitness of $\mathbf{x}_k$, which is γ in (7) or η in (8).

At each iteration, the quantum rotation angles and velocities of the i-th $\left(i = h/2 + 1, h/2 + 2, \cdots, h\right)$ quantum onlooker bee are updated by the following equations, assume that the k-th quantum employed bee is selected as the guidance of the quantum onlooker bee:

$$\theta_{ij}^{t+1} = e_1 (p_{kj}^t - x_{ij}^t) + e_2 (p_{gj}^t - x_{ij}^t) \tag{19}$$

$$v_{ij}^{t+1} = \begin{cases} \sqrt{1-(v_{ij}^t)^2}, & \text{if} \quad (p_{kj}^t = x_{ij}^t = p_{gj}^t \ \text{ and } \ r < c_1) \\ \text{abs}(v_{ij}^t \times \cos\theta_{ij}^{t+1} - \sqrt{1-(v_{ij}^t)^2} \times \sin\theta_{ij}^{t+1}), & \text{else} \end{cases} \tag{20}$$

$$x_{ij}^{t+1} = \begin{cases} 1, & \text{if} \quad \gamma_{ij}^{t+1} > (v_{ij}^{t+1})^2 \\ 0, & \text{if} \quad \gamma_{ij}^{t+1} \le (v_{ij}^{t+1})^2 \end{cases} \tag{21}$$

After updating the quantum and bit position, calculate the fitness of each quantum onlooker bee based on certain function, that is (7) or (8). If the fitness of $\mathbf{x}_i^{t+1}$ is better than that of $\mathbf{p}_i^t$, then update $\mathbf{p}_i^{t+1}$ as $\mathbf{x}_i^{t+1}$. If the fitness of $\mathbf{p}_i^{t+1}$ is better than that of $\mathbf{p}_g^t$, then update $\mathbf{p}_g^{t+1}$ as $\mathbf{p}_i^{t+1}$.

3.3 Evolutionary process of quantum scout bees

When the fitness of each quantum employed bees and quantum onlooker bees does not change in *limit* times, then it becomes a quantum scout bee, which drops the experiences it has owned and has the ability to find new food resources, thus the quantum position is selected randomly from the R dimensions space, while the bit position is generated according to the quantum position.

3.4 Evolutionary process of QBCO

From what we have discussed above, we can see that the proposed QBCO has the advantage of both quantum computing and bee colony optimization. The processes of quantum bee colony optimization for multi-relay selection are shown below:

Step1: Suppose that the receiver knows the CSI $f_1, f_2, \cdots, f_R$ and $g_1, g_2, \cdots, g_R$.

Step2: Create an initial quantum bee colony randomly based on quantum coding.

Step3: For all quantum bees, calculate the fitness (i.e., γ or η) for each quantum bee.

Step4: Update each quantum bee's quantum position, bit position, the local optimal position and the global optimal position of the whole quantum bee colony through the evolutionary process of quantum employed bee, quantum onlooker bee and quantum scout bee.

Step 5: If the maximum iteration is reached, stop and output the relay selection result; if not, go to step 3.

4. Multi-objective multi-relay selection scheme

Most of the relay selections in the current literatures only consider one objective, i.e., SNR or power efficiency. Considering two objectives simultaneously, i.e., SNR and power consumption (or SNR and power efficiency), we propose NSQBCO to solve the multi-objective multi-relay selection problems. NSQBCO is based on non-dominated sorting, where the entire population is sorted into various non-dominated levels. This provides the means for selecting the individuals in the better fronts, hence providing the necessary selection pressure to push the population towards the Pareto front. To maintain population diversity, the crowding distance methods adopted by NSGA-II [15] is used, which will be described in the following part.

4.1 Non-dominated sorting and crowding distance

If we want to minimize $f_m(\mathbf{x})$ $(m=1,\cdots,M)$, where M is the number of objectives we want to optimize, then for solutions $\mathbf{u}$ and $\mathbf{v}$, if for all $m=1,\cdots,M$, $f_m(\mathbf{u}) \le f_m(\mathbf{v})$, and $\exists m=1,\cdots M$, $f_m(\mathbf{u}) < f_m(\mathbf{v})$, then define $\mathbf{u}$ dominates $\mathbf{v}$, and $\mathbf{u}$ is a non-dominated solution, which means for all objectives, solution $\mathbf{u}$ is not worse than solution $\mathbf{v}$ and at least there exists an objective which solution $\mathbf{u}$ is better than solution $\mathbf{v}$. If for all $m=1,\cdots,M$, $f_m(\mathbf{u}) \ge f_m(\mathbf{v})$, and $\exists m=1,\cdots,M$, $f_m(\mathbf{u}) > f_m(\mathbf{v})$, then define $\mathbf{v}$ dominates $\mathbf{u}$, and $\mathbf{v}$ is a non-dominated solution. Otherwise, $\mathbf{u}$ and $\mathbf{v}$ have no dominating relationship.

The process of non-dominated sorting can be described as follows:

For each solution calculate two entities: 1) domination count n_p, the number of solutions which dominate p; 2) S_p, this set contains all the individuals (each individual is defined as q) that are being dominated by p.

All solutions in the first non-dominated front will have their domination count as zero. Now, for each solution p with $n_p = 0$, we visit each member q of its set S_p and reduce its domination count by one. In doing so, if for any member q the domination count becomes zero, it is put in a separate list Q. These members belong to the second non-dominated front. Now the above procedure is continued with each member of Q and the third front is identified. This process continues until all fronts are identified.

Along with convergence to the Pareto front, it is also desired that the algorithm maintains a good spread of solutions in the obtained set of solutions. We calculate the average distance of two points along each of the objectives. The crowding distance is used to maintain population diversity, and the calculation process will be described in the following.

The crowding-distance computation requires sorting the population according to each objective value in ascending order of magnitude for every front. Therefore, for each objective function, the boundary solutions (solutions with smallest and largest function values) are assigned an infinite distance value. All other intermediate solutions are assigned a distance value equal to the absolute normalized difference in the function values of two adjacent solutions. The calculation is continued with other objective functions. The overall crowding distance value is calculated as the sum of individual distance values corresponding to each objective.

From the description of non-dominated sorting and crowding distance, we can see that the solutions with better front and larger crowding distance are better than others.

4.2 Non-dominated sorting quantum bee colony optimization

The process of NSQBCO uses QBCO proposed in Section 3 as the evolutionary algorithm. The process can be summarized in the following steps:

Step 1: Initialize quantum bee colony $\mathbf{S}$, including the quantum bees' quantum positions and bit positions, then evaluate each quantum bee in the colony. The number of quantum bees in $\mathbf{S}$ is recorded as h.

Step 2: Excute non-dominated sorting to obtain non-dominated solutions in $\mathbf{S}$. Calculate the crowding distance and sort the individuals in each front in a descending order. Choose the first $h/2$ bees as the quantum employed bees, and update the quantum position according to (15)-(17). The global best solution $\mathbf{p}_g$ is chosen from a specified top part (top 5%) of the sorted $\mathbf{S}$ randomly, while the local best solution $\mathbf{p}_j\,(j=1,2,\cdots,h/2)$ is chosen from the sorted $\mathbf{S}$ randomly. Then form a new quantum bee colony $\mathbf{S}'$.

Step 3: Choose the last $h/2$ bees as the quantum onlooker bees, and update the quantum position according to (19)-(21). The global best solution $\mathbf{p}_g$ is chosen from a specified top part (top 5%) of $\mathbf{S}$ randomly, while the selected bee's solution $\mathbf{p}_j$ $(j=h/2+1, h/2+2,\cdots,h)$ is chosen from $\mathbf{S}$ randomly. Then form a new quantum employed bee $\mathbf{S}''$.

Step 4: Combine $\mathbf{S}$, $\mathbf{S}'$ and $\mathbf{S}''$ thus form a new quantum bee colony. Execute non-dominated sorting and crowding-distance computation and choose the best h quantum bees to form a new quantum bee colony $\mathbf{S}$ which will take in the next generation.

Step 5: If it has reached the maximum generation T, then stop and the non-dominated solutions in the $\mathbf{S}$ are the Pareto front solutions. Otherwise, go to Step 2 until it has reached the maximum generation.

From the above, we can select the non-dominated solutions in the current bee colony and the parent bee colony and combine them. Then we reject the dominated solutions in the combined bee colony. Through the iteration of the evolutionary process, we can get the non-dominated solutions nearly to the true Pareto front solutions.

4.3 NSQBCO based multi-objective multi-relay selection scheme

According to the above analysis, the processes of NSQBCO based multi-objective multi-relay selection scheme are shown below:

Step 1: Assume the CSI $f_1, f_2,\cdots, f_R$ and $g_1, g_2,\cdots, g_R$ are obtained at the receiver before the relay selection process.

Step 2: Using NSQBCO (while one objective is γ and the other is power consumption or one objective is γ and the other is power efficiency) to obtain the Pareto front solutions.

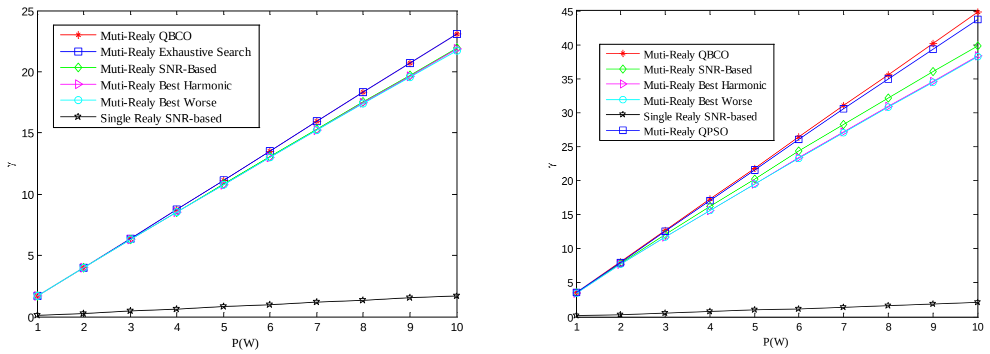
Step 3: The relaying systems choose one solution from the Pareto solutions according to the tradeoff of γ and power consumption or the tradeoff of γ and power efficiency to take part in the cooperative transmission.

5. Simulation results and analysis

In this section, we first show the simulated γ and η of the proposed QBCO based multi-relay selection scheme with relay ordering multi-relay selection schemes, exhaustive search scheme, single relay selection scheme and QPSO scheme proposed in [12]. Then simulation results of NSQBCO based multi-relay selection is presented compared with exhaustive search scheme. In the simulation, all channels and noises at all of the relays and destination are normalized i.i.d. Rayleigh random variables. For QBCO, set the maximal generation to 100, $h = 20, e_1 = 0.06,\ e_2 = 0.03, c_1 = 1/300$.

5.1 QBCO based single-objective multi-relay selection scheme

First, 15 relays are adopted in the simulation and they have the same power value $P_i = 0.1 \cdot P$. **Fig. 4** shows the simulation results which γ varise with P. We can see that SNR increases with the power. From **Fig. 4(a)**, we can also see that the three relay ordering multi-relay selection schemes perform almost the same, and multi Best Worst Channel Selection performs the worst, while the multi SNR-based Selection performs the best among the three relay ordering multi-relay selection schemes, but QBCO performs better than all of the relay ordering multi-relay selection schemes, which is the same as exhaustive search. The gap between QBCO and the other schemes is obvious. Also, it is obvious that multi-relay is much more effective than single-relay.



(a) (b)

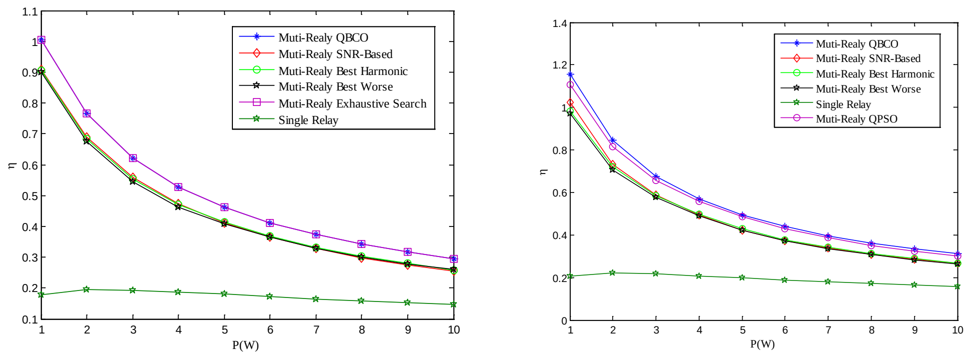
Fig. 4. The comparison of γ for QBCO scheme and relay ordering schemes, QPSO scheme, exhaustive search and single relay scheme

Then set the number of relays to 20, **Fig. 4(b)** shows the simulation results. From **Fig. 4(b)**, we can see that QBCO perform better than the other relay selection schemes including QPSO scheme proposed in [12], and compared with **Fig. 4(a)**, we can see that when the relay number increases, QBCO can find an optimal solution compared with other algorithms.

Now let we consider the power efficiency problem. **Fig. 5** shows the simulation results. **Fig. 5(a)** considers the case when the number of relays is 15, while **Fig. 5(b)** considers the case when relay number is 20. Among the three relay ordering multi-relay selection schemes, the

Best Worst scheme performs the worst, while the SNR-based performs the best, which has similar performance with **Fig. 4**. Our scheme, QBCO, performs better than the other relay selection schemes and has the same performance as exhaustive search when R = 15.

From **Fig. 4** and **Fig. 5**, the differences between the QBCO multi-relay selection scheme and relay ordering multi-relay selection schemes which maximize SNR or power efficiency is obvious. And if the relay number increases, the advantage of the QBCO based multi-relay selection scheme is much more obvious.



(a) (b)

Fig. 5. The comparison of η for QBCO scheme and relay ordering schemes, QPSO scheme, exhaustive search and single relay scheme

.2 NSQBCO based multi-objective multi-relay selection scheme

Next, consider the proposed multi-objective multi-relay selection scheme. For NSQBCO, set $c_1 = 1/R$, the number of quantum bees $h = 20$, e_1 and e_2 are random numbers among $[0,1]$, the predefined maximum generation is 500 (T=500).

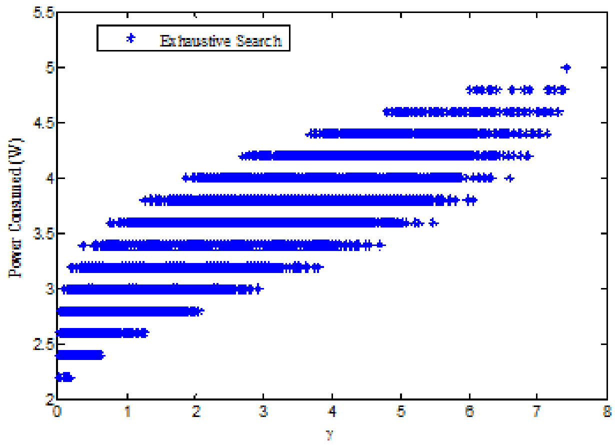


Fig. 6. The performance of all solutions in one multi-relay selcetion case considering γ and power consumption with 15 relays

Set $P = 2\text{W}$ and $P_i = 0.1 \cdot P = 0.2\text{W}$, taking both SNR optimization and power consumed minimization into consideration (9), the performance of all solutions (there are 15 relays in the simulation, so the number of solutions is 2^{15}) which is obtained through exhaustive search are plotted in **Fig. 6**. We can find out that there does not exist one solution which can maximize the SNR while minimize the power consumption simultaneously, that is to say, we have to look for tradeoffs. **Fig. 6** also shows that there are a series of solutions that are non-dominated solutions, which are not inferior to other solutions in both of the two objectives.

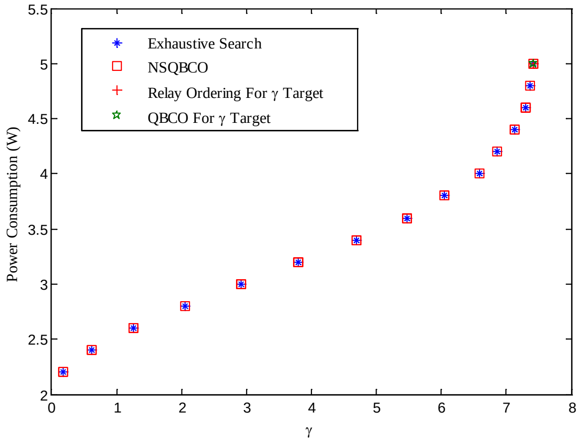


Fig. 7. NSQBCO scheme considering γ and power consumption with 15 relays

Fig. 7 shows the tradeoffs between the SNR and power consumption of NSQBCO based multi-relay selection scheme and non-dominated solutions obtained by the exhaustive search (computed by the non-domination sorting of all the possible solutions in **Fig. 6**). Also, the solutions obtained by the SNR based relay ordering and QBCO scheme for SNR target are presented for comparison. From **Fig. 7**, NSQBCO based multi-relay selection scheme obtains the same solution as the exhaustive search but cost less time when the number of relays is not very large, which shows the effectiveness of NSQBCO scheme. The solutions obtained by QBCO scheme and SNR based relay ordering scheme are non-dominated solutions, which shows the effectiveness of the proposed single objective QBCO based multi-relay selection scheme. Moreover, we can see that the single-objective optimization can only obtain one solution which maximizes SNR value without considering the power consumed. However, as we can see from **Fig. 7**, in high SNR region, the power consumed has little effect on SNR. If the power consumed is larger than 4W, the SNR value remains almost constant. In the design of relay networks, we can decrease the consumed power with the cost of little SNR degradation. The non-dominated solutions contain the solution obtained by single objective optimization, which means the multi-objective multi-relay selection scheme has a much wider application range.

When the number of relays increases, the exhaustive search cannot be used due to algorithm complexity. But NSQBCO can still be used to solve multi-objective multi-relay selection schemes. The non-dominated solutions are presented in **Fig. 8**, in addition to the solutions obtained by QBCO and the SNR based relay ordering schemes. The solution obtained by QBCO scheme for SNR target is still one of the non-dominated solutions, while the solution obtained by the SNR based relay ordering scheme is not, which shows the advantage of the single objective QBCO and the multi-objective NSQBCO relay selection schemes again.

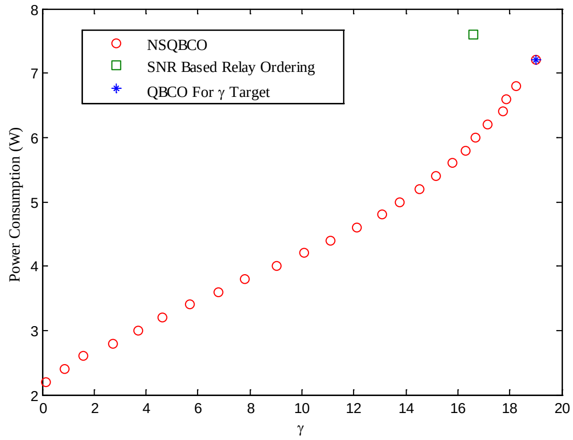


Fig. 8. NSQBCO scheme considering γ and power consumption with 30 relays

Set $P = 4\text{W}$ and $P_i = 0.1 \cdot P = 0.4\text{W}$, considering the SNR and power efficiency simultaneously (10), all solutions (the number of solutions is $2^{15} = 32768$) obtained through exhaustive search are plotted in **Fig. 9**.

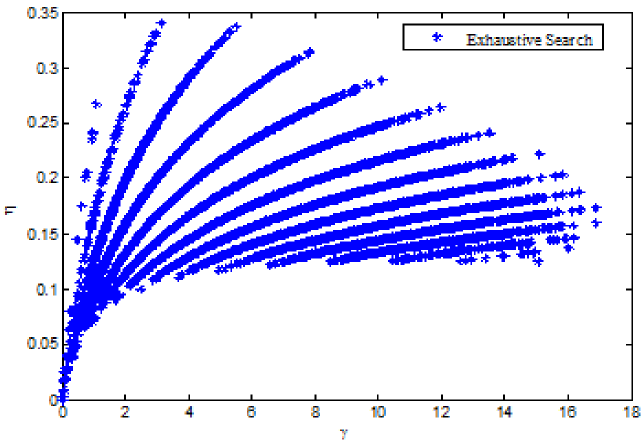


Fig. 9. The performance of all solutions in one multi-relay selcetion case considering γ and η with 15 relays

It is obviously that there also does not exist one solution which can maximize the SNR as well as power efficiency, that is to say, we can only get tradeoffs. **Fig. 9** also shows that there are a series of solutions which are non-dominated solutions. These solutions are not worse than the other solutions in both objectives. The proposed NSQBCO scheme aims to obtain these solutions.

Fig. 10 shows the tradeoffs between SNR and power efficiency optimization of NSQBCO based multi-relay selection scheme, in addition to the performance of non-dominated solutions obtained by the exhaustive search. The solutions obtained by QBCO scheme for SNR and power efficiency target respectively and the solutions obtained by the SNR and power efficiency based relay ordering schemes are also plotted for comparison.

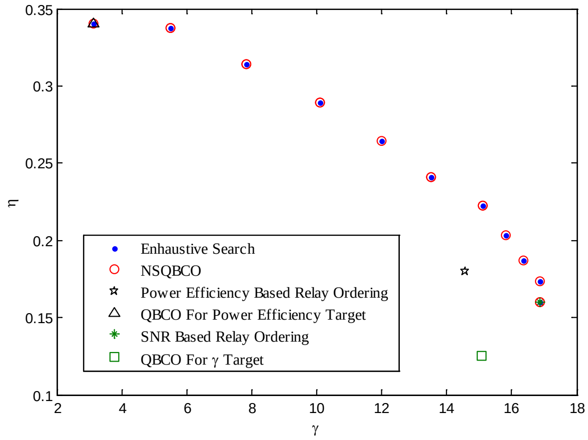


Fig. 10. NSQBCO scheme considering γ and η with 15 relays

The NSQBCO based multi-relay selection scheme obtains the same solution as the exhaustive search but cost less time. The solutions obtained by QBCO scheme for SNR and power efficiency target are among the non-dominated solutions, but the solutions obtained by the relay ordering schemes are really much worse, especially for power efficiency target. Moreover, if we only optimize the power efficiency target, we can only obtain the solution which has the maximum power efficiency value, but the SNR value is rather limited. Such optimization doesn't consider the obtained SNR and data rate. Obviously, such solution can't fulfill the SNR requirement for QoS guarantee in the transmission. In this optimization problem, the optimal power efficiency solution is not "optimal transmission". However, through multi-objective multi-relay selection schemes, we can choose one non-dominated solution which doesn't have the largest power efficiency value but guarantee QoS. This shows the wide application range of multi-objective optimizations.

When the number of relays increases, the exhaustive search cannot be used due to algorithm complexity. But the NSQBCO can still solve this problem efficiently. Simulations are shown in **Fig. 11** when the relay number is 30.

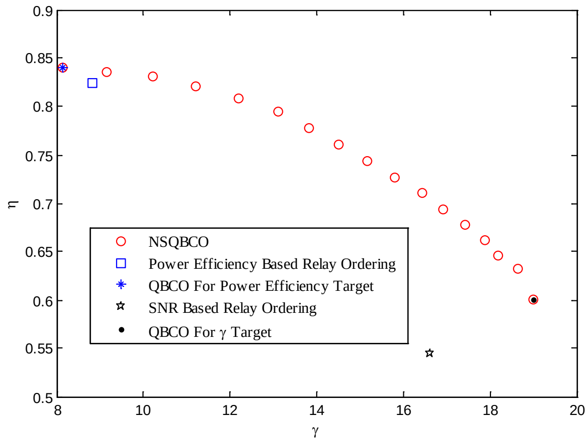


Fig. 11. NSQBCO scheme considering γ and η with 30 relays

From **Fig. 11**, the solutions obtained by QBCO schemes for SNR and power efficiency target respectively and the solutions obtained by the SNR and power efficiency based relay ordering schemes are also presented for comparison. The solutions obtained by QBCO scheme for SNR and power efficiency target are among the non-dominated solutions, but the solutions obtained by the relay ordering schemes are rather poor. This demonstrates that the multi-objective schemes have a wider application field compared with single objective schemes. All these present the advantage of the proposed single objective QBCO based multi-relay selection scheme and the proposed multi-objective NSQBCO based multi-relay selection scheme.

6. Conclusion

This paper has proposed multi-relay selection schemes considering single objective and multi-objective in the cooperative relay networks. Firstly, the single objective optimization problems of the best cooperative relay nodes selection for SNR maximization or power efficiency optimization are solved respectively based on QBCO schemes, and simulation results show that compared with other multi-relay selection schemes in the literature, the proposed schemes have a much better SNR or power efficiency performance. Then, considering SNR maximization and power consumption minimization or SNR maximization and power efficiency maximization simultaneously, this paper has proposed the NSQBCO based multi-objective multi-relay selection schemes, which can obtain the non-dominated solutions. Simulation results show that NSQBCO based multi-relay selection schemes obtain the same Pareto solutions as exhaustive search when the number of relays is not very large. However, when the number of relays is very large, exhaustive search cannot be used due to complexity but NSQBCO based multi-relay selection schemes can still be used to solve the problems. Besides, the solution obtained by QBCO scheme for single objective optimization is included in the non-dominated solutions, which demonstrates the wider application range of NSQBCO based multi-relay selection scheme and the effectiveness of both QBCO and NSQBCO based multi-relay selection schemes.

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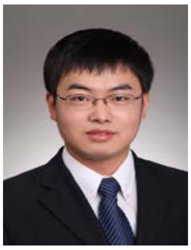

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