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Multi-relay selection schemes based on evolutionary algorithm in cooperative relay networks

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SUMMARY

In cooperative relay networks, the selected relay nodes have great impact on the system performance. In this paper, a multi-relay selection schemes that consider both single objective and multi-objective are proposed based on evolutionary algorithms. First, the single-objective optimization problems of the best cooperative relay nodes selection for signal-to-noise ratio (SNR) maximization or power efficiency optimization are solved based on the quantum particle swarm optimization (QPSO). Then the multi-objective optimization problems of the best cooperative relay nodes selection for SNR maximization and power consumption minimization (two contradictive objectives) or SNR maximization and power efficiency optimization (also two contradictive objectives) are solved based on a non-dominated sorting QPSO, which can obtain the Pareto front solutions of the problems considering two contradictive objectives simultaneously. The relay systems can select one solution from the Pareto front solutions according to the trade-off of SNR and power consumption (or the trade-off of SNR and power efficiency) to take part in the cooperative transmission. Simulation results show that the QPSO-based multi-relay selection schemes have the ability to search global optimal solution compared with other multi-relay selection schemes in literature. Simulation results also show that the non-dominated sorting QPSO-based multi-relay selection schemes obtain the same Pareto solutions as exhaustive search, but the proposed schemes have a very low complexity. Copyright © 2013 John Wiley & Sons, Ltd.

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KEY WORDS: cooperative relay; multi-relay selection; evolutionary algorithm; power efficiency

1. INTRODUCTION

Relaying is an emerging and effective technology that can overcome the limitation of cell coverage and cell edge users' throughput and improve the overall system performance of wireless networks [1, 2]. It has been well known that introducing relay nodes in 3GPP long term evolution advanced and the conventional cellular networks can help to enlarge the coverage or increase the cell throughput [3]. Relay nodes also play an important role in the *ad hoc* networks and other wireless networks such as wireless sensor networks for improving the spatial diversity order and increasing the network longevity [4]. In order to exploit the advantage of the relay node deployment in the wireless networks, relay selection, power, and bandwidth allocation for relay nodes have been investigated in the literature [5], in which relay selection is the key issue of the radio resource management in relaying systems.

Generally, relay selection problem can be divided into single-relay selection problem and multi-relay selection problem [6]. Most of the relay selection considers the channel state information (CSI), which can be based on physical distance, path loss, or end-to-end signal-to-noise ratio (SNR) [7]. In the CSI-based relay selection, the assumption is that receiver knows all the CSI

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between the transmitter and the relays and the CSI between the relays and the receiver. Thereafter, chooses one relay that according to certain function of CSI. However, most of the existing single-relay selection schemes may result in imbalance of resource utilization, that is, the selected single relay is likely to have heavy load but other relays may have lightly loaded traffic. Besides, the 'emergence' diversity gain among multiple relays cannot be achieved. Multi-relay cooperation can obtain much more diversity gain compared with single relay, besides, the over load problem of single relay can be solved. Therefore, multi-relay cooperation has been researched widely [8], and a multi-relay selection schemes are studied in [9–12]. It can not only improve the reliability of network, but also maximize the end-to-end capacity. However, the increasing number of relays can cause serious problems of increased interference. Thus, choosing an appropriate number of relays is of great importance. This is special important for networks with simple nodes and complexity constraints. Li [12] gives a closed form solution to the problem of multi-relay selection for maximum destination SNR in a dual-hop amplify-and-forward cooperative relay network, but the basic assumption is that there must be a direct link; besides, it only considers one objective, which is the overall SNR of the whole relay networks. Moreover, green communication has been considered as a key feature in the future networks. Power efficiency should be considered in the radio resource management of wireless networks, such as the relay selection process. In [9], an energy-efficient distributed relay selection scheme is proposed, which takes the energy consumption and residual energy state of candidate relay nodes into consideration. In [10], an energy-efficient relay selection scheme and power allocation scheme are proposed in a two-way relay channel scenario. In [11], a relay ordering-based suboptimal solution that considers the SNR and the power efficiency is proposed; however, it is only a suboptimal solution, as the simulation results in [11] show that the solution has a large gap compared with the optimal solution obtained by exhaustive search.

Because relay selection problem can be seen as an optimization problem, this paper uses intelligence algorithms to solve the multi-relay selection optimization problem, which can obtain the solution nearly to the optimal solution. Intelligence algorithms can also be divided into two categories, single-objective and multi-objective intelligence algorithms. Some single-objective intelligence algorithms are widely studied for application, such as particle swarm optimization (PSO) [13]. Quantum theory is another efficient single-objective optimization algorithm. Quantum genetic algorithm (QGA) combines the quantum computing theory and the genetic algorithm so it has the characteristics of strong searching capability, rapid convergence, short-computing time, and small-population size [14]. Quantum PSO (QPSO) algorithm is an effective swarm intelligence method for single objective multi-relay selection problem [15]. In this paper, we also use the QPSO algorithm to solve single objective multi-relay selection optimization problem considering SNR or power efficiency target. In the current literature, all multi-relay selection problems are formulated for single objective, such as SNR or power efficiency [11, 12]. To our knowledge, no existing research addresses the multi-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. For example, 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. For example, it may give the largest power efficiency when the obtained SNR is very low. 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'. In order to overcome the disadvantage of single objective optimization-based multi-relay selection schemes, we propose the multi-relay selection problems considering multi-objective optimization (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

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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 trade-offs. 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 the 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 non-dominated sorting genetic algorithms (NSGA) [16], NSGA-II [17], strength Pareto evolutionary algorithm [18], and strength Pareto evolutionary algorithm 2 [19]. Sindhya *et al.* [20] proposed 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 application in different fields. Haidine [21] has researched the multi-objective combinatorial optimization in the design of fiber-based distribution networks. In [22], a multi-objective two-nested genetic algorithm is used to solve clustering homogeneous wireless sensor networks. 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 trade-offs 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. We will use this method which will be presented in Section IV. In multi-objective optimization, it is also important to choose the evolutionary method. Because of the effectiveness of the QPSO algorithm [15], we choose QPSO as the evolutionary algorithm. Therefore, we propose the NSQPSO algorithm 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. Section II describes the network model and problem statement. Section III proposes the single objective multi-relay selection schemes based on QPSO and evaluates the performance of QPSO algorithm. Section IV gives the non-dominated sorting QPSO (NSQPSO)-based multi-objective multi-relay selection schemes. Section V presents the simulation results and analysis. Section VI is the conclusions.

2. NETWORK MODEL AND PROBLEM STATEMENT

A cooperative relaying system model is considered [11, 12], which consists of one transmitter for transmission, one receiver for reception, and R candidate relay nodes for cooperation as depicted in Figure 1. 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.

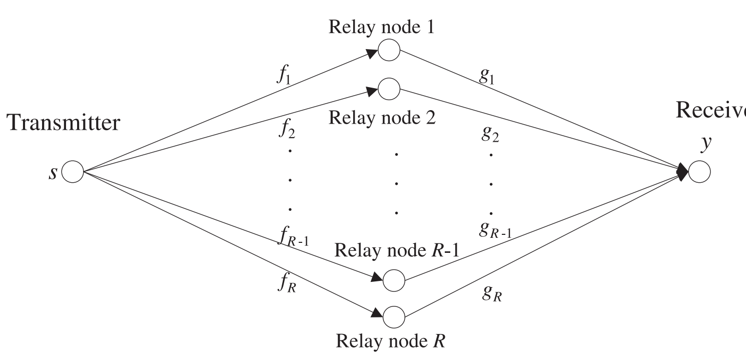

Figure 1. Wireless cooperative relay network.

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It is assumed that each relay has only one antenna which can be used for both transmission and reception. Denote the CSI from the transmitter to the i-th relay as f_i, and the CSI from the i-th relay to the receiver as g_i. Assume that the i-th relay has full knowledge of its own channels f_i and g_i, and the receiver knows all CSI $f_1, f_2, \cdots, f_R$ and $g_1, g_2, \cdots, g_R$. It is also assumed that all channels are normalized independent identical distribution (i.i.d.) Rayleigh random variables with zero-mean and unit-variance. For each transmission, the constant power used at the transmitter and the i-th relay are P and P_i, respectively. Note that in this paper, only short-term power constraint is considered, that is, there is an upper bound on the average transmission power of each node for each transmission. A node cannot save its power to favor transmissions with better channel realizations. When there is a transmission task between the transmitter and the receiver, a relay either cooperates with its full power or does not cooperate at all. A two-step amplify-and-forward protocol is used to send information. In the first step, the transmitter sends $\sqrt{P}s$ to all the other relay nodes, where s is the information transmitted, and if we normalize s as $E|s|^2 = 1$, the average power used at the transmitter is P. In the second step, the i-th relay (if it is selected) scales its received signal and forwards it to the receiver with power P_i.

First, we review existing single-relay selection scheme based on SNR in the literature and derive the CDF function and outage possibility of SNR-based single-relay selection scheme.

Considering a simple scenario of single-source and single-destination assistant with single relay, the signal received at the i-th relay is

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

where v_i is the additive white Gaussian noise (AWGN) with zero-mean and unit-variance at the i-th relay. The relay amplify the received signal and forwards it to the destination, so the signal received at the destination is

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

where w is the AWGN with zero-mean and unit-variance at the receiver. The overall SNR can be written as

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

In the SNR-based single-relay selection, the relay with the maximum SNR will take part in the data forwarding for the source. For simplicity and without generality, set $P = P_i = 1$, and considering the case which selects one relay among R relays, the cumulative distribution function (CDF) function of SNR can be written as

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

The proof is presented in appendix, where γ denotes the instantaneous SNR value of the whole link, and $I_1(\cdot)$ is the first order modified Bessel function of the second kind.

Figure 2 shows the CDF function of SNR for SNR-based single-relay selection schemes in both theory and Monte-Carlo simulations aspects when the number of relays is 1, 5, and 10. From Figure 2, we can see that the CDF function of theory is close to the CDF function of Monte-Carlo simulations thus verifies the correctness of the theory.

Although the SNR-based single-relay selection obtains diversity gain as the number of relays increasing, the diversity gain is rather limited. Figure 3 proposes the comparison of CDF function of SNR for single-relay and multi-relay selection schemes (the best multi-relay selection scheme is obtained by exhaustive search, where we examined all the 2^R possible solutions and choose the best one).

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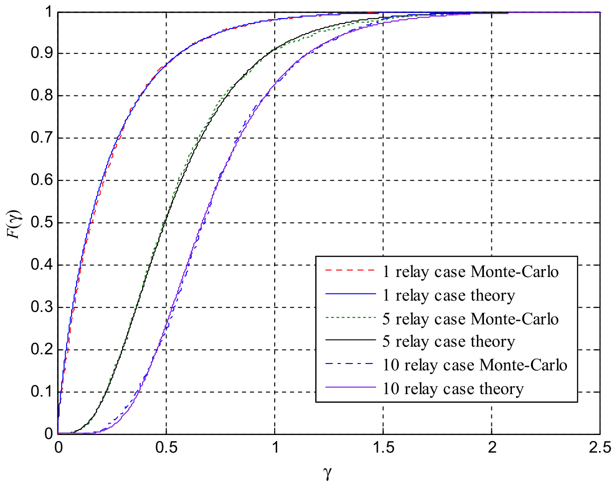

Figure 2. Cumulative distribution function of signal-to-noise ratio-based single relay selction schemes.

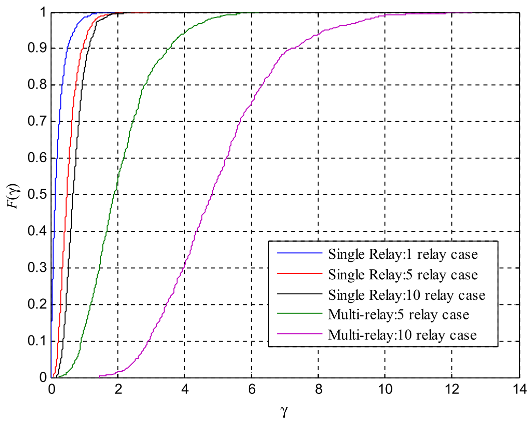

Figure 3. Cumulative distribution function for single relay and multi-relay selction schemes.

From Figure 3, the diversity of multi-relay is much more than in single relay. Besides, the selected single relay is likely to have heavy load but the other relays may have lightly loaded traffic. Therefore, in order to obtain the diversity gain of multi-relay, we propose the multi-relay selection problems and schemes that select a certain number of relays from the R relays to maximize certain objectives. Because traffic load is divided into multiple relays, the multi-relay scenarios can offload traffic from the single relay.

In a multi-relay cooperative communication system, in the first step, the transmitter sends $\sqrt{P}s$ to the i-th relay; whereas in the second step, the i-th relay scales its received signal by $\frac{a_i\sqrt{P_i}e^{j\theta_i}}{\sqrt{1+|f_i|^2P}}$ (so that its transmission power is $a_i^2P_i$) and forwards it to the receiver, where a_i represents whether the i-th relay takes part in the cooperation or not, whereas $a_i=1$ means the i-th relay takes part in the cooperation, otherwise $a_i=0$.

It is assumed that the relays are perfectly synchronized and transmit at the same time. The angle θ_i is used to adjust the phase of the signal. It is obvious that an optimal choice is $\theta_i = -(\arg f_i + \arg g_i)$. The i-th relay received signal can be written as $|f_i|\sqrt{P}s + v_i$. Thus, the receiver gets

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

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

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

The single objective multi-relay selection optimization problem considering SNR is in the following

$$\max_{a_1,\cdots,a_R} \gamma_{general} \quad s.t. \quad a_i \in \{0,1\}. \tag{7}$$

Energy consumption is an important problem in wireless networks, so we consider the relay selection in the view of energy-saving. It is obvious that the total transmission power of the whole network, $P_{\text{total}} = P + \sum_{i=1}^{R} a_i^2 P_i$, increases with the number of cooperating relays $K = \sum_{i=1}^{R} a_i$. The power efficiency is defined as the ratio of network capacity C to total transmission power P_{total}. When the optimization target of cooperative relay selection is to maximize the power efficiency, it is another single objective multi-relay selection problem and the optimization problem can be expressed as

$$\max_{a_1,\cdots,a_R} \frac{C}{P_{\text{total}}} = \frac{\log_2\left(1+\gamma_{\text{general}}\right)}{P + \sum_{i=1}^{R} a_i^2 P_i} \quad s.t. \quad a_i \in \{0,1\}. \tag{8}$$

Because the receiver has full knowledge of all channels, this maximization problem (7) and (8) are equivalent to the maximization of SNR and power efficiency, respectively. This problem formulation is similar to [23]. But, here, the relays are not allowed to adjust their transmission powers arbitrarily. Instead, each relay has only two choices: to cooperate with full power or not to cooperate at all. Because every relay has two choices, cooperate or not cooperate, the optimization problems are general ‘0–1’ programming problems. It is nonlinear programming problem that can only get the optimal solution by exhaustive search. However, the complexity increases exponential with the number of relays. In this paper, we use the QPSO scheme to solve the single objective multi-relay selection optimization problems, which will be presented in Section III.

Because the SNR target increases with the power increasing, 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

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

Because the SNR target increases with the power increasing, whereas the power efficiency may be decrease with the increased power, the SNR target maximization and the power efficiency target maximization are also contradictive, that is, they cannot get the largest value with the same relay

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selection scheme. Considering the SNR and the power efficiency simultaneously, another multi-objective multi-relay selection problem is proposed, which is in the following

$$\begin{cases} \max\limits_{a_1,\cdots,a_R} \gamma_{\text{general}} \\ \max\limits_{a_1,\cdots,a_R} \dfrac{C}{P_{\text{total}}} = \dfrac{\log_2\left(1+\gamma_{\text{general}}\right)}{P+\sum\limits_{i=1}^{R} a_i^2 P_i} \end{cases} \quad s.t. \quad a_i \in \{0,1\}. \tag{10}$$

Exhaustive search can be used to solve multi-objective multi-relay selection problems (9) and (10), but the complexity is also intolerable. In this paper, the NSQPSO algorithm is proposed to solve the multi-objective multi-relay selection problem, which will be illustrated in Section IV.

3. SINGLE OBJECTIVE MULTI-RELAY SELECTION SCHEME

In this section, we first review the relay ordering single objective multi-relay selection schemes and then propose the QPSO-based single objective multi-relay selection schemes which maximize the SNR target and power efficiency target, respectively.

3.1. Relay ordering multi-relay selection scheme

First, we review the SNR-based and power efficiency-based relay ordering multi-relay selection schemes in [11].

The SNR-based relay ordering multi-relay selection schemes can be summarized as follows:

Step 1: Order the relay according to SNR ordering rules (3), therefore, get an ordering $(x_1, x_2, \cdots, x_R)$ of $(1, 2, \cdots, R)$. This means that if $i < i'(i, i' = 1, 2, \cdots, R)$, then relay x_i has a higher priority to relay $x_{i'}$. That is to say, if relay x_i should not do the associated relay cooperation, neither should relay $x_{i'}$ do.

Step 2: Calculate $\gamma(x_1)$, $\gamma(x_1, x_2), \ldots, \gamma(x_1, x_2, \cdots, x_R)$, where $\gamma(x_1, x_2, \cdots, x_i)$ represents the SNR when the relay $x_1, x_2, \cdots, x_i$ takes part in the cooperation.

Step 3: The receiver searches the x_i such that $\gamma(x_1, \cdots, x_i)$ is the largest among the $\gamma(x_1), \ldots, \gamma(x_1, x_2, \cdots, x_i), \ldots, \gamma(x_1, x_2, \cdots, x_R)$. The relays which do the associated relay cooperation can be written as $(x_1, x_2, \cdots, x_i)$.

For power efficiency-based relay ordering scheme, modifies the SNR-based relay ordering scheme, that is instead of choosing the x_i which maximizes the $\gamma(x_1), \ldots, \gamma(x_1, x_2, \cdots, x_i), \ldots, \gamma(x_1, x_2, \cdots, x_R)$, 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 $\gamma(x_1), \ldots, \gamma(x_1, x_2, \cdots, x_i), \ldots, \gamma(x_1, x_2, \cdots, x_R)$ one by one till the SNR values stop increasing. This modification ensures that 'bad' relays do not cooperate, although there may be some overall SNR loss.

In [11], it has proposed that for networks with more than two relays, for the relay cooperation, no optimal relay ordering exists. That is to say, the relay ordering multi-relay selection schemes are not optimal, we can only get a suboptimal solution. Therefore, we propose the QPSO-based multi-relay selection schemes to obtain a nearly to optimal solution.

3.2. Quantum particle swarm optimization

In this paper, QPSO algorithm is used for single objective multi-relay selection. It is based on the consideration of modifying the conventional algorithm to get a better performance, which combines the concept of quantum theory with PSO algorithm effectively [15]. It is a novel multi-agent optimization system inspired by social behavior of agents. Each agent, called quantum particle, flies in an R-dimensional space according to the historical experiences of its own and its colleagues'. It learns from itself and its colleagues' and adjusts its solution. Through a number of iterations, it can get its best solution; therefore, we can get the best solution of the whole quantum swarm. In QPSO

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algorithm, a number of different representations can be used to encode the solutions onto particles. The QPSO uses quantum coding, called a quantum bit or Q-bit, for the probabilistic representation, and a quantum velocity is defined as a string of quantum bits. One quantum bit is defined as the smallest unit of information in the QPSO, which is defined as a pair of composite numbers (α,β), where $|\alpha|^2+|\beta|^2=1$. $|\alpha|^2$ gives the probability that the quantum bit will be found in the '0' state and $|\beta|^2$ gives the probability that the quantum bit will be found in the '1' state. The quantum velocity of the j-th quantum particle is defined as

$$v_j = \begin{bmatrix} \alpha_{j1} & \alpha_{j2} & \cdots & \alpha_{jR} \\ \beta_{j1} & \beta_{j2} & \cdots & \beta_{jR} \end{bmatrix}, \tag{11}$$

where $|\alpha_{ji}|^2+|\beta_{ji}|^2=1, (j=1,2,\cdots,h, i=1,2,\cdots,R)$, h represents the number of quantum particles in the quantum swarm, R represents the dimension of the optimization problem, so the quantum velocity can represent 2^R states simultaneously. In the multi-relay selection algorithm, R represents the number of relays. For simplicity and efficient design of the QPSO algorithm, we define α_{ji} and β_{ji} as real numbers and $0\le\alpha_{ji}\le 1$, $0\le\beta_{ji}\le 1$. Therefore, $\alpha_{ji}=\sqrt{1-\beta_{ji}^2}$, and (11) is simplified as

$$\mathbf{v}_j = \begin{bmatrix} \alpha_{j1} & \alpha_{j2} & \cdots & \alpha_{jR} \end{bmatrix} = \begin{bmatrix} v_{j1} & v_{j2} & \cdots & v_{jR} \end{bmatrix}. \tag{12}$$

In QPSO, the j-th quantum particle's bit position in the space can be represented as $\mathbf{x}_j=[x_{j1}\ x_{j2}\ \cdots\ x_{jR}]$, which is obtained by the evaluation of the j-th particle's quantum velocity $v_j=[v_{j1}\ v_{j2}\ \cdots\ v_{jR}]$ according to

$$x_{ji} = \begin{cases} 1, \text{if} & \gamma_{ji} > (v_{ji})^2 \\ 0, \text{if} & \gamma_{ji} \le (v_{ji})^2 \end{cases}, \tag{13}$$

where $\gamma_{ji}\in[0,1]$ is uniform random number.

Now, we introduce each iteration process of the QPSO algorithm. Until the t-th generation, the best bit position (the local optimal bit position) of the j-th quantum particle is $\mathbf{p}_j^t=\begin{bmatrix} p_{j1}^t & p_{j2}^t & \cdots & p_{jR}^t \end{bmatrix}$. The global optimal bit position discovered by the whole quantum particle population is $\mathbf{p}_g^t=\begin{bmatrix} p_{g1}^t & p_{g2}^t & \cdots & p_{gR}^t \end{bmatrix}$. The evolutionary process of quantum velocity is mainly completed through quantum rotation gate [15]. In the proposed algorithm, for simplicity, the quantum rotation angle θ_{ji}^{t+1} is calculated by

$$\theta_{ji}^{t+1} = e_1\left(p_{ji}^t - x_{ji}^t\right) + e_2\left(p_{gi}^t - x_{ji}^t\right), \tag{14}$$

where e_1 and e_2 express the relative important degree of $\mathbf{p}_j$ and $\mathbf{p}_g$ in the flying process, that is to say, if the local optimal bit position is more important, then e_1 should be larger than e_2. In order to keep the diversity of the quantum swarm, we set $e_1\ge e_2$.

If $\theta_{ji}^{t+1}\neq 0$, the i-th quantum velocity is updated as

$$v_{ji}^{t+1} = \text{abs}\left(v_{ji}^t \times \cos\theta_{ji}^{t+1} - \sqrt{1-\left(v_{ji}^t\right)^2} \times \sin\theta_{ji}^{t+1}\right), \tag{15}$$

where abs(·) is an absolute function that makes quantum velocity in the real domain [0, 1].

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If $\theta_{ji}^{t+1} = 0$, a quantum velocity v_{ji} is updated in a certain small probability by the operator described as

$$v_{ji}^{t+1} = \sqrt{1 - \left(v_{ji}^{t}\right)^2}, \tag{16}$$

which is similar to the concept of mutation operator in genetic algorithm.

Therefore, the updating process of the quantum particle can be written as

$$v_{ji}^{t+1} = \begin{cases} \sqrt{1 - \left(v_{ji}^{t}\right)^2}, & \text{if} \quad \left(p_{ji}^{t} = x_{ji}^{t} = p_{gi}^{t} \text{ and } r < c_1\right) \\ \text{abs}\left(v_{ji}^{t} \times \cos\theta_{ji}^{t+1} - \sqrt{1 - \left(v_{ji}^{t}\right)^2} \times \sin\theta_{ji}^{t+1}\right), & \text{otherwise} \end{cases}, \tag{17}$$

where r is uniform random number between 0 and 1, c_1 is mutation probability that is constant among $[0, 1/R]$.

Then, we update the bit position of each quantum according to

$$x_{ji}^{t+1} = \begin{cases} 1, \text{if} & \gamma_{ji}^{t+1} > \left(v_{ji}^{t+1}\right)^2 \\ 0, \text{if} & \gamma_{ji}^{t+1} \leq \left(v_{ji}^{t+1}\right)^2 \end{cases}. \tag{18}$$

After updating the quantum bit position and bit position of each quantum particle, compute the fitness of each quantum particle according to fitness function. Then the local optimal and global optimal solutions are updated. If the fitness of $\mathbf{x}_j^{t+1}$ is better than that of $\mathbf{p}_j^t$, $\mathbf{p}_j^{t+1}$ is updated as $\mathbf{x}_j^{t+1}$. If the fitness of $\mathbf{p}_j^{t+1}$ is better than that of $\mathbf{p}_g^t$, $\mathbf{p}_g^{t+1}$ is updated as $\mathbf{p}_j^{t+1}$.

Through a number of iterations, the best solution of the problem can be obtained. Always, we set the maximum iteration T, and if the number of iterations reaches the maximum iteration T, output the global optimal bit position $\mathbf{p}_g$ as the optimal solution.

3.3. The performance of quantum particle swarm optimization

We use two benchmark functions to evaluate the convergence of the quantum particle swarm optimization. We set initial population and maximum generation of the four evolutionary algorithms identical. For GA, QGA, PSO, and QPSO, the population size is set to 20. For GA, the crossover probability and the mutation probability are set to 0.8 and 0.02, respectively, and the GA [14] is configured to replace 85% of its population each generation, 17 of every 20 population members. As for QGA, the rotation angle of quantum gates decreases linearly from 0.1 π at the first generation to 0.005 π at the last generation [14]. In PSO, the two acceleration coefficients are equal to 2, and $V_{\max} = 4$. For QPSO, set $h = 20$, $e_1 = 0.06$, $e_2 = 0.03$, $c_1 = 1/300$.

$$F_1(x) = \frac{1}{4000}\left(\sum_{i=1}^{n}(x_i - 100)^2\right) - \left(\prod_{i=1}^{n}\cos\left(\frac{x_i - 100}{\sqrt{i}}\right)\right) + 1$$

$$F_2(\mathbf{x}) = \sum_{i=1}^{n}\left(x_i^2 - 10\cos(2\pi x_i) + 10\right)$$

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In the following simulations, we use binary-encoding, and the length of every variable is 15 bits. We also set $n = 2$ for all benchmark functions, that is, $i = 1, 2$.

The first function is Griewank function. x_i is in the interval of $[-600, 600]$. The global minimum value for this function is $\mathbf{x}_{opt} = (x_1, x_2, \cdots, x_n) = (100, 100, \cdots, 100)$ with the addition of cosine modulation to produce many local minima. Thus, the function is multimodal. The locations of the minima are regularly distributed. The difficulty about finding optimal solution to this function is that an optimization algorithm can easily be trapped in a local optimum on its way toward the global optimum.

The second function is Rastrigin function, which is a well-known classic optimization function. Its' minimum value is 0 at its global minimum solution $\mathbf{x}_{opt} = (x_1, x_2, \cdots, x_n) = (0, 0, \cdots, 0)$. x_i is in the interval of $[-5.12, 5.12]$. It is based on Sphere function with the addition of cosine modulation to produce many local minima. Thus, the function is multimodal. The locations of the minima are regularly distributed. The difficult part about finding optimal solutions to this function is that an optimization algorithm can easily be trapped in a local optimum on its way toward the global optimum.

The simulation results are shown in Figure 4 and Figure 5. From Figure 4, we can see that although classic algorithms have fast convergence rate, but they all trap into local convergence. Our algorithm, however, overcomes the disadvantage of local convergence and has a more accurate convergence value. From Figure 5, we can see that GA and PSO have the similar performance, whereas QGA outperforms GA and PSO. It also presents that our algorithm, QPSO, has a very accurate convergence value compared with the other three algorithms.

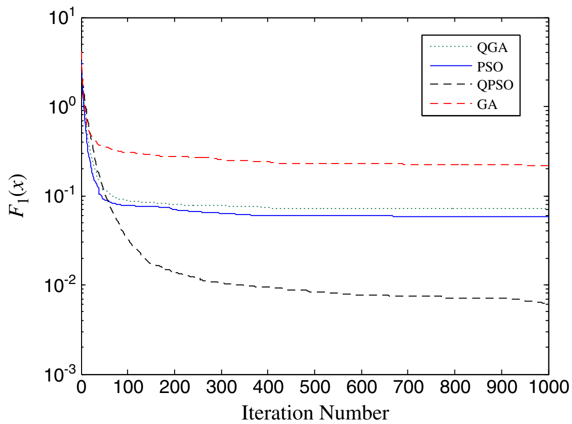

Figure 4. The performance of four algorithms using Griewank function.

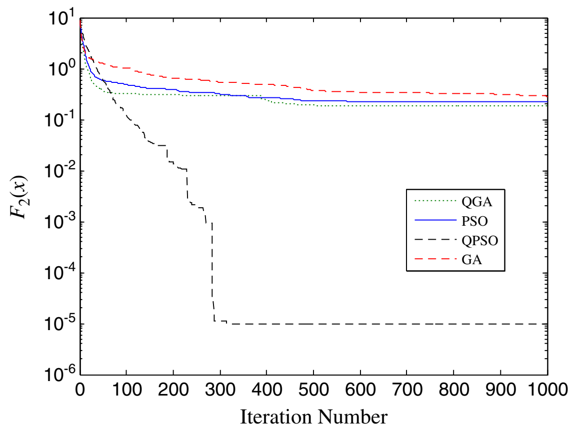

Figure 5. The performance of four algorithms using Rastrigin function.

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3.4. Quantum particle swarm optimization-based single objective multi-relay selection scheme

From the discussion in the previous text, it can be seen that the proposed QPSO algorithm has the advantage of both quantum theory and PSO algorithm. Through Benchmark function evaluation, the QPSO algorithm has more advantage than other classical algorithms. Therefore, it is applied to solve single objective multi-relay selection problems, and the processes are given as in the succeeding text:

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: Randomly generate an initial quantum particle swarm based on binary coding and quantum coding mechanism.
Step 3: For all quantum particle positions, compute the fitness (i.e., γ_{general} or power efficiency) of each quantum particle.
Step 4: Renew each quantum particle's local optimal position; update the global optimal position as evolutionary objective of the whole particle population.
Step 5: Update quantum velocities and bit positions of quantum particles according to (17) and (18).
Step 6: If it reaches the predefined maximum generation T, stop and output outcome $\mathbf{p}_g$ as the relay selection scheme; 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, that is, SNR or power efficiency. Considering two objectives simultaneously, that is, SNR and power consumption (or SNR and power efficiency), we propose the NSQPSO algorithm to solve the multi-objective multi-relay selection problems. The NSQPSO 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 toward the Pareto front. To maintain population diversity, the crowding distance methods adopted by NSGA-II [17] is used, which will be described in the following.

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:

First, for each solution calculate two entities: (i) domination count n_p, the number of solutions which dominate p and (ii) S_p, this set contains all the individuals 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 previous 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.

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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 particle swarm optimization

The process of the NSQPSO uses QPSO proposed in Section III as the evolutionary algorithm. The process can be summarized in the following steps:

Step 1: Initialize quantum particle population **S**, including the quantum particles' quantum velocities and bit positions, then evaluate each quantum particle in the population. The number of quantum particles in **S** is recorded as h.

Step 2: Identify quantum particles that give non-dominated solutions in the **S**. Calculate the crowding distance and sort the individuals in each front in a descending order, then choose the non-dominated solutions and add them into $\hat{\mathbf{S}}$ (an external memory or archive to store non-dominated solutions, the number of non-dominated solutions in this set is no more than $\mathbb{N}$).

Step 3: Generate the new population $\mathbf{S}_{\text{new}}$ through evolutionary algorithm QPSO from **S**. The global best solution $\mathbf{p}_g$ is chosen from a specified top part (top 5%) of the sorted $\hat{\mathbf{S}}$ randomly, whereas the local best solution $\mathbf{p}_j (j = 1, 2, \cdots, h)$ is chosen from the sorted $\hat{\mathbf{S}}$ randomly.

Step 4: Evaluate the quantum particles of the new population. Combine the current population and the parent population and form a new population, and then the new population is sorted according to non-domination. Select non-dominated solutions and add them to $\hat{\mathbf{S}}$.

Step 5: The solutions in $\hat{\mathbf{S}}$ are sorted according to non-domination. Calculate the crowding distance and sort the solutions according to the crowding distance in each front in a descending order. If the size of $\hat{\mathbf{S}}$ is more than $\mathbb{N}$, we select the former $\mathbb{N}$ solutions, and the others are rejected.

Step 6: Update the individuals that will take part in the next iteration step, that is, replace **S** with $\mathbf{S}_{\text{new}}$.

Step 7: If it has reached the maximum generation T, then stop and the solutions in the $\hat{\mathbf{S}}$ are the Pareto front solutions. Otherwise, go to Step 3 until it has reached the maximum generation.

From the previous text, we can select the non-dominated solutions in the current population and the parent population and add them to $\hat{\mathbf{S}}$. Then we reject the dominated solutions in $\hat{\mathbf{S}}$. We keep the number of non-dominated solutions in $\hat{\mathbf{S}}$ is no more than $\mathbb{N}$. Through the iteration of the evolutionary process, we can get the non-dominated solutions nearly to the true Pareto front solutions.

4.3. Non-dominated sorting quantum particle swarm optimization-based muti-objective multi-relay selection scheme

According to the previous analysis, the processes of NSQPSO-based multi-objective multi-relay selection scheme are shown in the succeeding text:

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 NSQPSO algorithm (while one objective is γ_{general} and the other is power consumption or one objective is γ_{general} 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 trade-off of γ_{general} and power consumption or the trade-off of γ_{general} and power efficiency to take part in the cooperative transmission.

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5. SIMULATION RESULTS AND ANALYSIS

In this section, we present the simulation results of both QPSO-based single objective multi-relay selection schemes and NSQPSO-based multi-objective multi-relay selection schemes. In all simulations, all channels are generated as i.i.d. complex Gaussian random variables with zero-mean and unit-variance. The noises at the relays and receiver are also i.i.d. complex Gaussian random variables with zero-mean and unit-variance.

5.1. Quantum particle swarm optimization-based single objective multi-relay selection scheme

First, consider the single objective multi-relay selection schemes that maximize SNR and power efficiency, respectively. Set the number of relays to 20 ($R = 20$) and the power of the i-th relay P_i scales with transmitter power P according to some constant [11], set $P_i = 0.1 \cdot P$. For QPSO, set $e_1 = 0.06, e_2 = 0.03, c_1 = 1/300$, the number of quantum particles $h = 20$ and the predefined maximum generation is 100 ($T = 100$).

The simulation results of the proposed QPSO-based multi-relay selection scheme with single objective (SNR or power efficiency maximization) compared with relay ordering (both SNR-based and power efficiency-based) and exhaustive search multi-relay selection schemes are given in Figure 6 to Figure 8 and Table I to Table II.

Simulation results of the SNR maximization are shown in Figure 6. The γ_{general} increases almost linearly with the power growth, and the QPSO-based multi-relay selection performs better than the SNR-based relay ordering multi-relay selection scheme. With the increased power, the proposed scheme obtains more gain compared with the SNR-based relay ordering multi-relay selection scheme. Moreover, the gap between the SNR-based single-relay selection schemes and multi-relay selection schemes is obvious, which shows the advantage of multi-relay selection schemes; in other words, the multi-relay selection schemes obtain much more diversity gains compared with single-relay selection schemes.

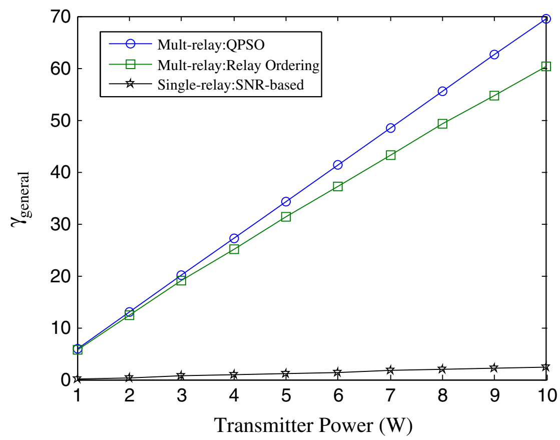

Figure 6. Signal-to-noise ratio performance with signal-to-noise ratio maximization target.

Table I. Signal-to-noise ration performance with signal-to-noise ration maximization compared with exhaustuve search.

	Transmitter power				
Algorithm	$P = 2$ W	$P = 4$ W	$P = 6$ W	$P = 8$ W	$P = 10$ W
Exhaustive search	13.02	27.22	41.34	55.45	69.55
QPSO	13.02	27.22	41.34	55.45	69.55
Relay ordering	12.49	25.18	37.26	49.17	60.38

QPSO, quantum particle swarm optimization

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Table II. Power efficency performance with power efficency maximization compared with exhaustuve search

Algorithm	Transmitter power $P = 2$ W	$P = 4$ W	$P = 6$ W	$P = 8$ W	$P = 10$ W
Exhaustive search	0.8375	0.5640	0.4358	0.3596	0.3085
QPSO	0.8375	0.5640	0.4358	0.3596	0.3085
Relay ordering	0.7227	0.4839	0.3690	0.3051	0.2607

QPSO, quantum particle swarm optimization

Simulation results of the SNR maximization compared with exhaustive search are shown in Table I.

From Table I, it is obvious that the QPSO obtains the same optimal solution as exhaustive search, whereas the SNR-based relay ordering schemes' performances are rather poor, especially, when the power becomes larger ($P = 2$ W, the difference between the SNR-based relay ordering and QPSO scheme is 4%, whereas $P = 10$ W, the difference is 15%).

Simulation results of the power efficiency optimization are shown in Figure 7 and Table II, whereas Figure 8 presents the γ_{general} (the left ordinate) and the power consumption (the right ordinate) performance corresponding to the solutions in Figure 7. Figure 7 shows that the power efficiency decreases with the increased power. With the power efficiency optimization target, the proposed QPSO-based multi-relay selection performs better than the power efficiency-based relay ordering multi-relay selection scheme. From Figure 8, the power efficiency-based relay ordering multi-relay selection scheme outperforms the QPSO scheme in the γ_{general} performance when the target is to optimize the power efficiency, as a result of much more consumed power.

Compared Figure 7 with Figure 8, we can draw the conclusion that a solution which maximize the power efficiency and γ_{general} simultaneously does not exist. Also, the γ_{general} increases with the power consumption, which means that we cannot obtain the best solution that has the largest γ_{general} value as well as the least consumed power. All of these demonstrate the necessity of the proposed multi-objective multi-relay selection schemes.

Simulation results of power efficiency maximization compared with exhaustive search are shown in Table II. From Table II, the QPSO obtains the same optimal solution as exhaustive search, which verifies the effectiveness of the proposed QPSO scheme again, whereas the power efficiency-based relay ordering schemes' performances are really poor ($P = 2$ W, the difference between the SNR-based relay ordering and QPSO is 15%, whereas $P = 10$ W, the difference is 18%).

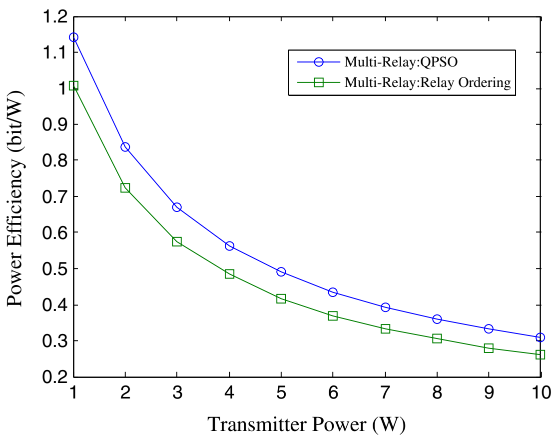

Figure 7. Power efficency performance with power efficiency target.

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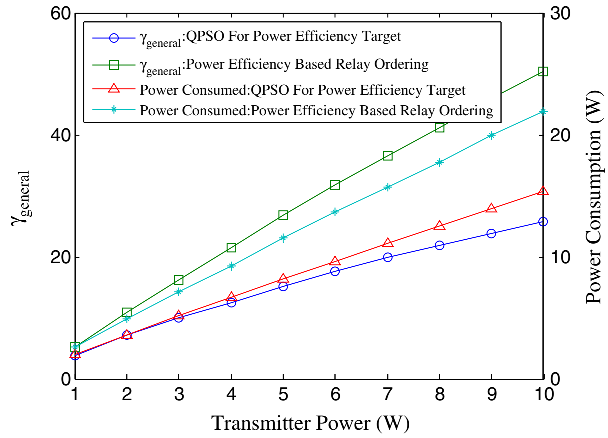

Figure 8. Signal-to-noise ratio and power consumption preformance with power efficiency target.

5.2. Non-dominated sorting quantum particle swarm optimization-based multi-objective multi-relay selection scheme

Next, consider the proposed multi-objective multi-relay selection scheme. For NSQPSO, set $c_1 = 1/R$, the number of quantum particles $h = 20$, $\mathbb{N} = 40$, e_1 and e_2 are random numbers among [0,1], the predefined maximum generation is 500 ($T = 500$).

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 Figure 9. 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 trade-offs. Figure 9 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.

Figure 10 shows the trade-offs between the SNR and the power consumption of NSQPSO-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 Figure 9). Also, the solutions obtained by the SNR-based relay ordering and QPSO scheme for SNR target are presented for comparison.

From Figure 10, the NSQPSO-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

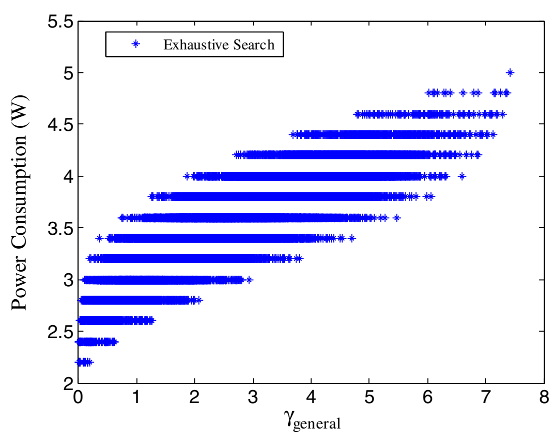

Figure 9. The performance of all solutions in one multi-relay selcetion case considering signal-to-noise ratio and power consumption with 15 relays.

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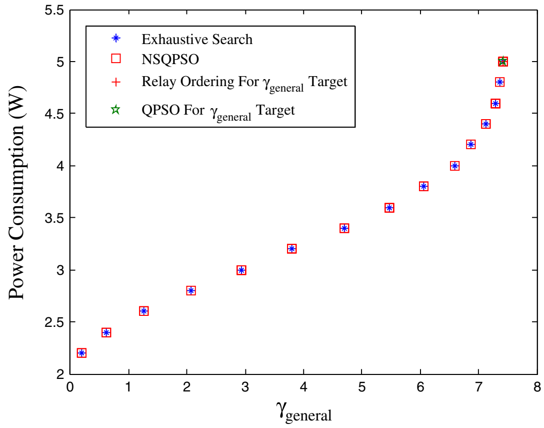

Figure 10. Non-dominated sorting quantum particle swarm optimization-based multi-relay selection scheme considering signal-to-noise ratio and power consumption with 15 relays.

shows the effectiveness of the NSQPSO scheme. The solutions obtained by QPSO-based and SNR-based relay ordering schemes are non-dominated solutions, which show the effectiveness of the proposed single objective QPSO-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 Figure 10, in high SNR region, the power consumed has little effect on SNR. If the power consumed is larger than 4 W, 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 the NSQPSO can still be used to solve multi-objective multi-relay selection schemes. The non-dominated solutions are presented in Figure 11, in addition to the solutions obtained by the QPSO-based and the SNR-based relay ordering schemes. The solution obtained by QPSO scheme for SNR target is still one of the non-dominated solutions, whereas the solution obtained by the SNR-based relay ordering scheme is not, which shows the advantage of the single objective QPSO and the multi-objective NSQPSO relay selection schemes again.

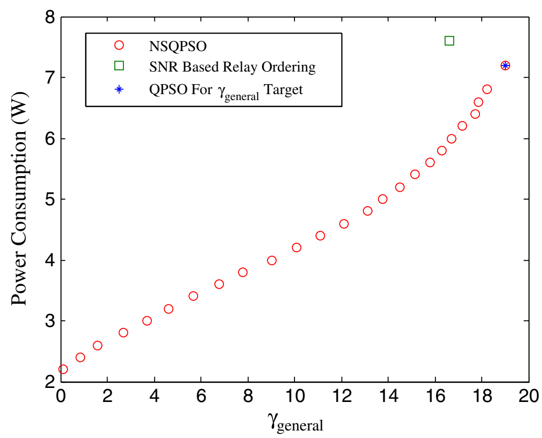

Figure 11. Non-dominated sorting quantum particle swarm optimization-based multi-relay selection scheme considering signal-to-noise ratio and power consumption with 30 relays.

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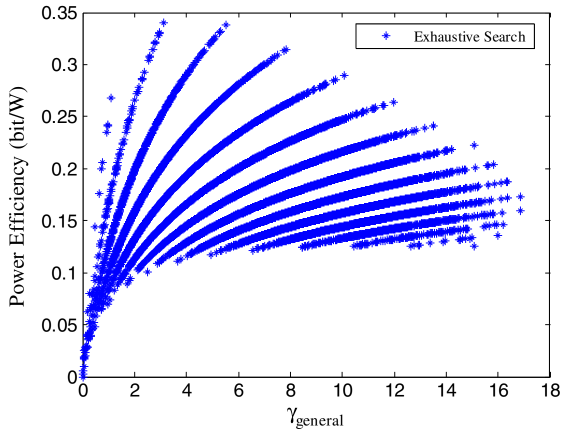

Figure 12. The performance of all solutions in one multi-relay selcetion case considering signal-to-noise ratio and power efficiency with 15 relays.

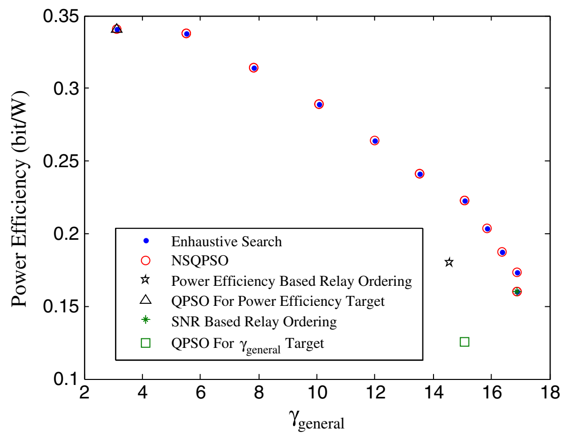

Figure 13. Non-dominated sorting quantum particle swarm optimization-based multi-relay selection scheme considering signal-to-noise ratio and power efficiency with 15 relays.

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 Figure 12. We can see 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 trade-offs. Figure 12 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 NSQPSO algorithm aims to obtain these solutions.

Figure 13 shows the trade-offs between SNR and power efficiency optimization of NSQPSO-based multi-relay selection scheme, in addition to the performance of non-dominated solutions obtained by the exhaustive search. The solutions obtained by the QPSO 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. The NSQPSO-based multi-relay selection scheme obtains the same solution as the exhaustive search but cost less time. The solutions obtained by the QPSO 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

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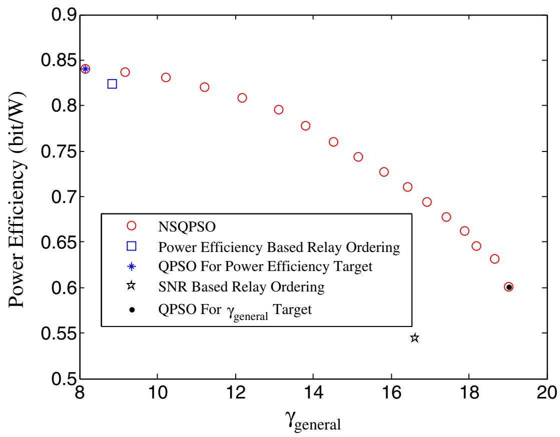

Figure 14. Non-dominated sorting quantum particle swarm optimization-based multi-relay selection scheme considering signal-to-noise ratio and power efficiency with 30 relays.

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 that doesn't have the largest power efficiency value but guarantee QoS. This shows a 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 NSQPSO can still solve this problem efficiently. Simulations are shown in Figure 14 when the relay number is 30. From Figure 14, the solutions obtained by the QPSO schemes for SNR and power efficiency target respectively and the solutions obtained by the SNR-based and power efficiency-based relay ordering schemes are also presented for comparison. The solutions obtained by the QPSO 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 QPSO-based multi-relay selection scheme and the proposed multi-objective NSQPSO-based multi-relay selection scheme.

6. CONCLUSIONS

This paper has proposed multi-relay selection schemes considering single-objective and multi-objective in the cooperative relay networks. First, the single-objective optimization problems of the best cooperative relay nodes selection for SNR maximization or power efficiency optimization are solved respectively based on the QPSO 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 NSQPSO-based multi-objective multi-relay selection schemes, which can obtain the non-dominated solutions. Simulation results show that the NSQPSO-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 NSQPSO-based multi-relay selection schemes can still be used to solve the problems. Besides, the solution obtained by QPSO scheme for single-objective optimization is included in the non-dominated solutions, which demonstrate a wider application range of NSQPSO-based multi-relay selection scheme and the effectiveness of both QPSO-based and NSQPSO-based multi-relay selection schemes.

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APPENDIX A

The CDF of SNR-based single-relay selection algorithm, $F(\gamma)$, can be calculated through single source, single relay, and single destination case, $F_{S,R,D}(\gamma)$. First, we propose the CDF of $F_{S,R,D}(\gamma)$

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

where $X = \Gamma_{S,R} = |f|^2$, which is the SNR of the source to relay link, $Y = \Gamma_{R,D} = |g|^2$, which is the SNR of relay to destination link. Therefore, $\Pr(X \le \gamma) = 1 - \mathrm{e}^{-\gamma}$, $\Pr(Y \le \gamma) = 1 - \mathrm{e}^{-\gamma}$ and the integration region can be divided into two regions, namely, $D_1 = \{X < \gamma\} \cup \{Y < \gamma\}$ and $D_2 = D - D_1$. So the result of the integral can be written as $F_{S,R,D} = F_1 + F_2$.

$$\begin{aligned} F_1(\gamma) = &\ \Pr(X \le \gamma) + \Pr(Y \le \gamma) - \Pr(X \le \gamma, Y \le \gamma) \\ &= 1 - \mathrm{e}^{-\gamma} + 1 - \mathrm{e}^{-\gamma} - (1 - \mathrm{e}^{-\gamma})(1 - \mathrm{e}^{-\gamma}) \\ &= 1 - \mathrm{e}^{-2\gamma}. \end{aligned}$$

Define $X_1 = X - \gamma$, $Y_1 = Y - \gamma$. Because $\frac{XY}{X+Y+1} = \gamma$, we can obtain $X_1 Y_1 = \gamma^2 + \gamma$. Thus,

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

This integral takes the following form:

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

By assuming $z = e^t$ and after some manipulations, we obtain

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

The result is the integral form of fist order modified Bessel function of the second kind $I_1(x)$. Therefore,

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

where $a = \gamma^2 + \gamma$ and $b = 1$. By using this result, we can rewrite $F_2(\gamma)$ as

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

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Then

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

During the SNR-based single-relay schemes, the relay with the best SNR is selected. Therefore, $Y_{\max} = \max\{Y_1, Y_2, \cdots, Y_R\}$. So the CDF function of $Y_{\max}$ can be written as

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

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