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# QoS multicast routing using a quantum-behaved particle swarm optimization algorithm ☆

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ABSTRACT

QoS multicast routing in networks is a very important research issue in networks and distributed systems. It is also a challenging and hard problem for high-performance networks of the next generation. Due to its NP-completeness, many heuristic methods have been employed to solve the problem. This paper proposes the modified quantum-behaved particle swarm optimization (QPSO) method for QoS multicast routing. In the proposed method, QoS multicast routing is converted into an integer programming problem with QoS constraints and is solved by the QPSO algorithm combined with loop deletion operation. The QPSO-based routing method, along with the routing algorithms based on particle swarm optimization (PSO) and genetic algorithm (GA), is tested on randomly generated network topologies for the purpose of performance evaluation. The simulation results show the efficiency of the proposed method on QoS the routing problem and its superiority to the methods based on PSO and GA.



## 1. Introduction

The provision of quality-of-service (QoS) guarantees is of utmost importance for the development of the multicast services and have been used by various continuous media applications (Alrabiah and Znati, 2001; Oliveira and Pardalos, 2005). It makes QoS multicast routing become one of the key issues in the areas of networks and distributed systems (Guerin and Orda, 1999; Charikar and Naor, 2004). QoS multicast routing relies on state parameters specifying resource availability at network nodes or links, and uses them to find paths with enough free resources. Its primary goal is to allocate efficiently network resources while the different QoS requirements are satisfied simultaneously. The QoS requirements can be classified into link constraints (e.g., bandwidth), path constraints (e.g., end to end delay) and tree constraints (e.g., delay-jitter). The inter-dependency and confliction among multiple QoS parameters, however, make the problem very difficult. It has been demonstrated that it is NP-complete to find a feasible multicast tree with two independent additive path constraints (Drake and Hougardy, 2004).

Due to the NP-completeness of QoS multicast routing, many heuristic algorithms such as genetic algorithms (GAs) have been employed to solve the problem (Feng et al., 1999; Wang and She, 2001; Haghighata et al., 2003; Liu and Wu, 2003; Zhang et al., 2009). GA reassures a higher chance of reaching a global optimum by starting with multiple random search points and considering several candidate solutions simultaneously. However, it is always complained that GA encounters some faults such as lack of local search ability, premature convergence and slow convergence speed.

During the last decade, the development in optimization theory sees the emergence of swarm intelligence, a category of stochastic search methods for solving global optimization (GO) problems. Ant colony (AC) and particle swarm optimization (PSO) are two paradigms of this kind of methods, and recently have been shown to be efficient tools for solving the multicast routing problem (Liu et al., 2006; Li et al., 2007; Tseng et al., 2008; Huang et al., 2009).

The PSO algorithm was originally proposed by J. Kennedy as a simulation of social behavior of bird flock (Kennedy and Eberhart, 1995). It can be easily implemented and is computationally inexpensive, since its memory and CPU speed requirements are low. PSO has been proved to be an efficient approach for many continuous GO problems and in some cases it does not suffer the difficulties encountered by GA (Angeline, 1998). During the last decades, many researchers have proposed a lot of improvements on the algorithms (Shi and Eberhart, 1998; Clerc, 1999; Kennedy, 2003; Janson and Middendorf, 2005; Parrott and Li, 2006).

Recently, a new variant of PSO, called quantum-behaved particle swarm optimization (QPSO), has been proposed in order

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to improve the global search ability of the original PSO (Sun et al., 2004a, 2004b, 2005). The iterative equation of QPSO is very different from that of PSO and leads QPSO to be global convergent (Fang et al., 2010). Besides, unlike PSO, QPSO needs no velocity vectors for particles and has fewer parameters to adjust, making it easier to implement.

The QPSO algorithm has been shown to successfully solve a wide range of continuous optimization problems (Coelho and Alotto, 2008; Gao, 2008; Omkara et al., 2009). So far, it has rarely been used to solve discrete combinatory optimization problems. In this paper, we will modify the QPSO algorithm to be suitable for QoS multicast routing problem, which is a significant attempt to explore the applicability of QPSO to combinatory optimization problems. By the proposed method, the problem is first converted into a constrained integer programming and then solved by the QPSO algorithm with loop deletion operation. The QPSO-based multicast routing method is tested and its performance is evaluated by comparing to multicast routing methods based on PSO and GA.

The rest of the paper is organized as follows. In Section 2, the network model of QoS multicast routing problem is introduced. The principle of QPSO is described in Section 3. Section 4 presents the proposed QPSO-based QoS multicast routing approach. The experiment results are provided and analyzed in Section 5. The paper is concluded in Section 6.

## 2. Problem statement

A network is usually represented as a weighted digraph $G=(V, E)$, where $V$ denotes the set of nodes and $E$ denotes the set of communication links connecting the nodes. $|V|$ is the numbers of nodes and $|E|$ is the number of links in the network, respectively. Without loss of generality, only digraphs are considered in which there exists at most one link between a pair of ordered nodes.

Let $s\in V$ be source node of a multicast tree, and $M\subseteq\{V-\{s\}\}$ be a set of destination nodes of the multicast tree. Let $R^+$ be the set of all the nonnegative real numbers. For any link $e\in|E|$, we can define the some QoS metrics: delay function $delay(e)$: $E\to R^+$; cost function $cost(e): E\to R^+$; bandwidth function $bandwidth(e)$: $E\to R^+$; and delay jitter function $delay\_jitter(e)$: $E\to R^+$. Similarly, for any node $n\in V$, we can also define some metrics: delay function $delay(n)$: $V\to R^+$; cost function cost: $cost(n): V\to R^+$; delay jitter function $delay\_jitter(n)$: $V\to R^+$; and packet loss function $pactlet\_loss(n)$: $V\to R^+$. We also use $T(s,M)$ to denote a multicast tree, which has the following relations:

$$D((p(s,t))=\sum_{e\in p(s,t)} delay(e)+\sum_{n\in p(s,t)} delay(n) \tag{1}$$

$$C(T(s,M))=\sum_{e\in T(s,M)} cost(e)\sum_{n\in T(s,M)} cost(n) \tag{2}$$

$$B(p(s,t))=\min(bandwidth(e)),\quad e\in p(s,t) \tag{3}$$

$$DJ(p(s,t))=\sum_{e\in p(s,t)} delay\_jitter(e)+\sum_{n\in p(s,t)} delay\_jitter(n) \tag{4}$$

$$PL(p(s,t))=1-\prod_{n\in p(s,t)}(1-packet\_loss(n)) \tag{5}$$

where $p(s, t)$ denotes routing path of multicast tree $T(s, M)$ from source node $s$ to end node $t\in M$. $D(\cdot)\in R^+$ is delay function. $C(\cdot)\in R^+$ is cost function. $B(\cdot)\in R^+$ is bandwidth function. $DJ(\cdot)\in R^+$ is delay jitter function. $PL(\cdot)\in R^+$ is packet loss function. With QoS requirements, a multicast tree $T(s, M)$ must satisfy the following constraints:

a. delay constraint: $D(p(s,T))\le QD$;
b. bandwidth constraint: $B(p(s,T))\ge QB$;
c. delay-jitter constraint: $DJ(p(s,T))\le QDJ$;
d. packet-loss constraint: $PL(p(s,T))\le QPL$;

where $QD$ is delay constraint, $QB$ is bandwidth constraint, $QDJ$ is delay-jitter constraint and $QPL$ is packet-loss constraint.

Therefore, QoS multicast routing problem can be represented as a minimization problem whose goal is to find a multicast tree $T(s, M)$ such that minimizes the cost function $C(T(s,M))$ while satisfying the constraints. That is, the problem can be formulated as following:

$$\text{Minimize}\quad C(T(s,M)) \tag{6}$$

$$s.t.\quad D(p(s,T))\le QD \tag{6a}$$

$$B(p(s,T))\ge QB \tag{6b}$$

$$DJ(p(s,T))\le QDJ \tag{6c}$$

$$PL(p(s,T))\le QPL \tag{6d}$$

## 3. Quantum-behaved particle swarm optimization

In the PSO with $m$ individuals, each individual is treated as a volume-less particle in the $D$-dimensional space, with the current position vector and velocity vector of particle $i$ at the $k$th iteration represented as $X_{i,k}=(X_{i,k}^1,X_{i,k}^2,\cdots,X_{i,k}^D$ and $V_{i,k}=\ V_{i,k}^1,V_{i,k}^2,\cdots,V_{i,k}^D)$. The particle moves according to the following equations:

$$V_{i,k+1}^j=wV_{i,k}^j+c_1r_{i,k}^j(X_{i,k}^j-P_{i,k}^j)+c_2R_{i,k}^j(X_{i,k}^j-G_k^j) \tag{7}$$

$$X_{i,k+1}^j=X_{i,k}^j+V_{i,k+1}^j \tag{8}$$

for $i=1,\ 2,\ldots,m$; $j=1,\ 2,\ldots,D$, where $c_1$ and $c_2$ are called acceleration coefficients. Parameter $w$ is the inertia weight that can be adjusted to balance the exploration and exploitation of PSO. Vector $P_{i,k}=(P_{i,k}^1,P_{i,k}^2,\cdots,P_{i,k}^D)$ is the best previous position (the position giving the best objective function value or fitness value) of particle $i$ called *personal best* (*pbest*) position, and vector $G_k=(G_k^1,G_k^2,\cdots,G_k^D)$ is the position of the best particle among all the particles in the population and called *global best* (*gbest*) position. Without loss of generality, if we consider the following minimization problem:

$$Minimize\quad f(X),\quad s.t.\quad X\in S\subseteq R^D \tag{9}$$

where $f(X)$ is an objective function and $S$ is Tthe feasible space, then $P_{i,k}$ can be updated by

$$P_{i,k}=\begin{cases} X_{i,k} & \text{if}\quad f(X_{i,k})<f(P_{i,k-1}) \\ P_{i,k-1} & \text{if}\quad f(X_{i,k})\ge f(P_{i,k-1}) \end{cases} \tag{10}$$

$G_k$ can be found by $G_k=P_{g,k}$, where $g=\arg\min_{1\le i\le m}[f(P_{i,k})]$. The parameters $r_{i,k}^j$ and $R_{i,k}^j$ are sequences of two different random numbers distributed uniformly within (0, 1), which is denoted by $r_{i,k}^j,R_{i,k}^j\sim U(0,1)$. Generally, the value of $V_{i,k}^j$ is restricted in the interval $[-V_{\max},V_{\max}]$.

Trajectory analysis (Clerc and Kennedy, 2002) demonstrated the fact that convergence of the PSO algorithm may be achieved if each particle converges to its local attractor, $p_{i,k}=(p_{i,k}^1,p_{i,k}^2,\cdots,p_{i,k}^D)$ defined at the coordinates

$$p_{i,k}^j=\varphi_{i,k}^jP_{i,k}^j+(1-\varphi_{i,k}^j)G_k^j \tag{11}$$

where $\varphi_{i,k}^j=c_1r_{i,k}^j/(c_1r_{i,k}^j+c_2R_{i,k}^j)$ with regard to the random numbers $r_{i,k}^j$ and $R_{i,k}^j$ in (7). In PSO, the acceleration coefficients $c_1$ and $c_2$ are generally set to be equal, i.e. $c_1=c_2$, and thus $\varphi_{i,k}^j$ is a