

# MOEAQ: A QoS-Aware Multicast Routing algorithm for MANET

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## ABSTRACT

Multicast routing is regarded as a critical component in networks especially the real-time applications become increasingly popular in recent years. This paper proposes a novel fast multi-objective evolutionary algorithm called MOEAQ for solving multicast routing problem (MRP) in MANET. The strengths and limitations of the well-known multicast model are analyzed firstly in this work. Specifically, the “Greedy” and “family competition” approach are integrated into MOEAQ to speed up the convergence and to maintain the diversity of population. The theoretical validations for the proposed method are presented to show its efficiency. After that, a CBT-based improved protocol is then proposed to simplify the MRP, and finally, the performance of MANET scaled from 20 to 200 nodes with different types of service is evaluated by OPNET, experimental results show that the proposed method is capable of achieving faster convergence and more preferable for multicast routing in MANET compared with other GA-based protocol well-known in the literature.

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## 1. Introduction

Multicast routing has drawn a lot of attention in recent years, since it enables a source to send messages to multiple destinations concurrently. The wireless communication technologies and mobile devices have realized the important and useful applications of mobile ad hoc network (MANET) with greatly advancement. Multicast routing plays a critical role in the transmission of information, such as video and other streaming data. Nevertheless, the main difficulty in designing a routing protocol for mobile ad hoc networks is the dynamical topology which results from the random movement of mobile nodes within the source's transmission range. MANET, which is fundamentally different from conventional infrastructure-based networks, is self-configuring and formed directly by a set of mobile nodes. In MANET, the heterogeneity of networks and destinations makes it difficult to improve bandwidth utilization and service flexibility. Therefore, mobility of hosts (nodes) makes the design of multimedia distribution jobs greatly challenging.

Up to now, various works involved focus on design multicast routing algorithm. An early summary of problems and general technical solution related to multicast communication were given by Diot, Dabbous, and Crowcroft (1997). Hanzo and Tafazolli (2007) and Chen and Heinzelman (2007) present a survey of multicast routing under certain QoS constraints solutions for MANET. As an NP-Complete problem, to develop different types of heuristic algorithm for calculating near-optimum paths with multiple QoS

constraints is a research focus. For example, Wang, Cao, Cheng, and Huang (2006) investigate three representative intelligent computational methods (genetic algorithm, simulated annealing and Tabu search) to construct the QoS multicast trees to support multimedia group communication separately; the proposed algorithms consider both the end-to-end delay constraint and network resource requirement; the simulation evaluates the performance of three heuristics on a small-scale real-world multimedia communication network and a randomly generated large-scale network, and then concludes that genetic algorithm shows the best performance in terms of the solution quality. In 2008, Qu, Zhao, Zhao, Zhang, and Shu (2008) propose a set of node-based rate constraints to model the interference relationship among nodes in a wireless ad hoc network and to provide rate constraints for its QoS flows, they demonstrate that, the algorithm can always admit the feasible flows as well as make full use of the bandwidth resource. Zahrani, Loomes, Malcolm, and Albrecht (2006, 2008) import logarithmic simulated annealing (LSA) as pre-processing of GA; the algorithm utilizes the partially crossover operation (PMX) under the elitist model and the landscape analysis is presented to estimate the depth of the deepest local minimal in the landscape generated by the routing tasks and the objective function; experimental results show that the algorithm is effective on the randomly generated networks. Yang, Xu, Li, and Liu (2004) and Ikeda et al. (2006) focus on creating a robust path to find solution for specified networks; the genetic algorithm is proposed and, respectively, the individuals of the population are represented by trees, algorithm uses the single point crossover and a mutation operation where the “tree junctions” are chosen randomly, the algorithm employs the elitist

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model where the individual with the highest fitness value in a population is left unchanged in the next generation, the simulation results show that the algorithm is reasonably fast on small and medium size networks. Differ from the above network architecture, Rango, Tropea, Santamaria, and Marano (2007) and Mala and Swlvakumar (2006) refer a scheme called Core Based Tree (CBT) with genetic algorithm which provides a new way for realizing multicast routing protocol in wireless networks, however, it needs much running time.

The remainder of the paper is organized as follows. In Section 2 we state some basic conceptions of multi-objective optimization and give the mathematical description for problem. A QoS-Aware Multicast Routing architecture is given in Section 3. We outline the design of proposed algorithm in Section 4. Section 5 analyses the properties of our method. Section 6 implements the proposed method into a QoS-Aware multicast protocol. The simulation results and performance evaluation are shown in Section 6 and the last section presents our conclusion.

## 2. Notations and problem formulation

To begin with we will introduce some basic conceptions of multi-objective optimization before we describe the problem that would help us know the model thoroughly.

### 2.1. Basic conceptions

**Definition 1** (Multi-objective optimization problem, MOP). The MOP consists of  $n$  decision parameters,  $k$  objective functions and  $m$  constraints, without loss of generality

$$\begin{aligned} \text{Maximize } y &= f(x) = (f_1(x), f_2(x), \dots, f_k(x)) \\ \text{Subject to } e(x) &= (e_1(x), e_2(x), \dots, e_m(x)) \leq 0 \end{aligned}$$

where  $\mathbf{x} = (x_1, x_2, \dots, x_m) \in \Omega$ ,  $\mathbf{y} = (y_1, y_2, \dots, y_n) \in \Phi$ .  $\mathbf{x}$  is decision vector,  $\mathbf{y}$  is objective vector,  $\Omega$  denotes the decision space formed by  $\mathbf{x}$ ,  $\Phi$  denotes the objective space formed by  $\mathbf{y}$ .

**Definition 2** (Pareto Dominance). A vector  $\mathbf{a} = (a_1, a_2, \dots, a_n)$  is said to dominate  $\mathbf{b} = (b_1, b_2, \dots, b_n)$  if and only if  $\mathbf{a}$  is partially less than  $\mathbf{b}$ , i.e.

$$\forall i \in \{1, 2, \dots, n\}, a_i \leq b_i \wedge \exists j \in \{1, 2, \dots, n\}, a_j < b_j.$$

**Definition 3** (Pareto Optimal). A decision vector  $\mathbf{x}_b$  is said to be Pareto Optimal if and only if there is no  $\mathbf{x}_a \in \Omega$  where  $F(\mathbf{x}_a) = \mathbf{a} = (a_1, a_2, \dots, a_n)$  dominates (use Definition 2's scheme)  $F(\mathbf{x}_b) = \mathbf{b} = (b_1, b_2, \dots, b_n)$ .

**Definition 4** (Pareto Front). The set of all Pareto Optimal decision vectors is called the Pareto Optimal set of the problem and the corresponding set of objective vectors is called Pareto Front.

As we know, most of problems in the world are known as non-linear problems. In a linear problem, each component is independent, so that any improvement to any one part will lead to an improvement of the entire system. But few real-world problems like this, while most of real world problems are nonlinear, one component changing may have ripple effects on the entire system, and thus we should treat the problem as a multi-objective optimization model.

### 2.2. Problem formulation

A network can be modeled as an undirected graph  $G = (V, E)$ , where  $V$  is the set of nodes that represent routers and  $E$  is the set of arcs (arcs represent path between nodes). Each link between

two nodes is bi-directional, it means that if there is a link  $e = (u, v)$ , the link  $e' = (v, u)$  also exists. We employ the metrics of  $bandwidth(e)$ ,  $delay(e)$ ,  $packet\ loss(e)$  ratio and  $delay\ jitter(e)$ , which could describe the QoS request of most services from our previous study, to evaluate each link  $e$  (Liu, Tang, Wang, & Sun, 2005). Let  $p(s, d)$  be a path from the source node  $s$  to the destination  $d$ , the total bandwidth of the path  $p(s, d)$  is the minimum of bandwidth of all links along  $p(s, d)$  and it is denoted as  $Bandwidth(p(s, d))$

$$Bandwidth(p(s, d)) = \min_{e \in p(s, d)} [bandwidth(e)] \quad (1)$$

$$Delay(p(s, d)) = \sum_{e \in p(s, d)} delay(e) \quad (2)$$

$$Loss(p(s, d)) = 1 - \prod_{e \in p(s, d)} (1 - loss(e)) \quad (3)$$

$$Jitter(p(s, d)) = \max[Delay(p(s, d))] - \min[Delay(p(s, d))] \quad (4)$$

QoS multicast routing problem can be defined as follows

$$\min F = \min\{-F_1, F_2, F_3, F_4\} \quad (5)$$

where

$$\begin{cases} F_1 = \min_{e \in p(s, d)} [Bandwidth(e)] \\ F_2 = \sum_{e \in p(s, d)} Delay(e) \\ F_3 = 1 - \prod_{e \in p(s, d)} (1 - (Loss(e))) \\ F_4 = \max[Delay(p(s, d))] - \min[Delay(p(s, d))] \end{cases} \quad (6)$$

In contrast, this model imports a scalarization scheme to depict the problem rather than to aggregate the multi-metric into a single value. Ikeda et al. (2006) describe the relationship between Pareto solution and the solution space (see Fig. 1). Fig. 1 indicates that solutions obtained by GA are rare in the Pareto solution space. It can be predicted that we will get no solution in the Pareto solution space if the coefficients are not appropriate. Due to contradiction among metrics, GA will make only one of them prone to optimum.

Accordingly, it is improper to aggregate the multi-metric into a single value among multi-objective problem, and thus our definition for solving multicast problem is more preferable.

## 3. QoS-Aware Multicast Routing architecture

Fig. 2 illustrates the change of topology of MANET. It is more complex to construct a Steiner tree for the group with dynamic

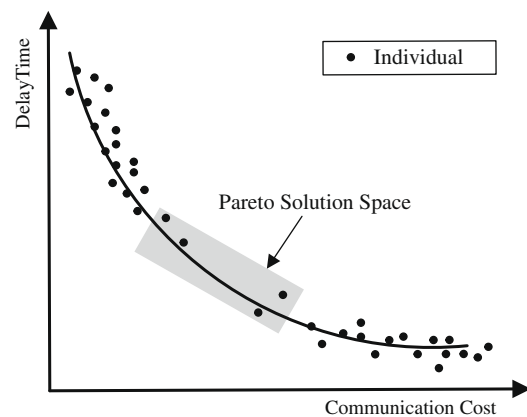


Fig. 1. Relationship between Pareto solution and solution space.

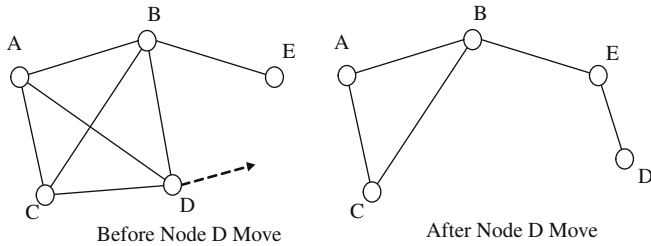


Fig. 2. Dynamic topology of MANET.

change in group members. Thus the CBT technique is chosen, and one node will be regarded as the Rendezvous Point (RP). Rango et al. (2007) shows details that how the CBT protocol works when nodes are allowed to join and leave the multicast group dynamically. We focus on the RP (core) selection herein rather than address the details again. Nevertheless, as a key point of CBT, it adopts link costs for the core selection, namely, it aims at only one component of the problem instead of all.

In order to overcome the difficulty of selecting core, we redefine the  $cost(p(s, d))$ :

$$\begin{cases} cost(p(s, d)) = \omega_1 \cdot Bandwidth(p(s, d)) + \omega_2 \cdot Delay(p(s, d)) \\ + \omega_3 \cdot Loss(p(s, d)) + \omega_4 \cdot Jitter(p(s, d)) \\ \prod_{i=1}^4 \omega_i = 1 \end{cases} \quad (7)$$

Let  $r(p(s, d))$  be the sum of cost, the mean cost associated to core node  $c$  can be expressed as follows:

$$cost(c) = \frac{1}{|V_{MG}|} \sum_{x \in V_{MG}} r(p(c, x)) \quad (8)$$

where  $|V_{MG}|$  is the amount of members in multicast group.

The multicast routing architecture can be described as Fig. 3. We divide the multicast routing problem into two segments: one is formed by the multicast group and the core via improved CBT protocol that uses new policy in selecting core showed in formula (7) and (8); the other is the combination of the source and the core, using the proposed method (we will show it in the next section) to find the optimum path from the source to the core. It means that the MRP is divided into “Unicast” segment and “Multicast” segment (see Fig. 3).

**Proposition 1.** The II-segments division of MRP does not change its property of NP-Complete.

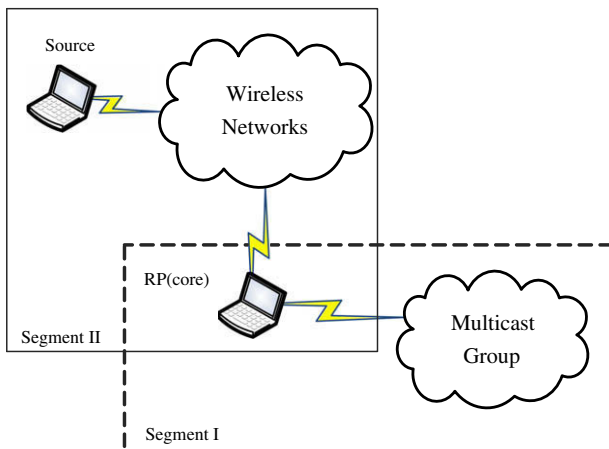


Fig. 3. II-segments architecture of multicast routing.

**Proof.** Wang and Crowcroft (1996) has proved that two or more additive and multiplicative metrics in any possible combination is NP-Complete. In our architecture, the delay is an additive metric and the loss is multiplicative, therefore, it is still an NPC problem after division of MRP in MANET.  $\square$

## 4. Design of MOEAQ

### 4.1. Multi-objective evolutionary algorithm

EAs have been recognized to be possibly well-suited to multi-objective optimization since early in their development. Multiple individuals can search for multiple solutions in parallel, eventually taking advantage of any available similarities in the family of possible solutions to the problem. The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations, reinforces the potential effectiveness of EA in multi-objective search and optimization, which perhaps is a problem area where Evolutionary Computation distinguishes itself from other multi-objective algorithms (see Fig. 4).

More stuff about multi-objective evolutionary algorithm (e.g. NSGA-II, SPEA2) can be found in Deb's book (Deb, 2001).

### 4.2. MOEAQ for MANET

Throughout this paper,  $\bar{X}(n)$  denotes the  $n$ th generation population,  $\bar{X}$  denotes the current population.  $X_i$  is the individual in  $\bar{X}$ . Probabilities for crossover and mutation are denoted by  $p_c$  and  $p_m$ .  $T_s(\cdot)$ ,  $T_c(\cdot)$  and  $T_m(\cdot)$  stand for the selection, crossover and mutation for population respectively.

#### 4.2.1. Coding

Chromosome coding, the chief matter and key issue when applying the evolutionary algorithm, affects not only the methods of decoding and fitness evaluation, but also the realization of selection, crossover and mutation procedures. There are many works focusing on coding. Zhou, Gen, and Wu (1996) summarize three normal coding approaches and conclude that Prüfer coding is more feasible because of lower complexity. However, for the specificity of MRP in MANET, coding methods can be divided into two categories: one is that the individual is represented by a tree (Ikeda et al.,

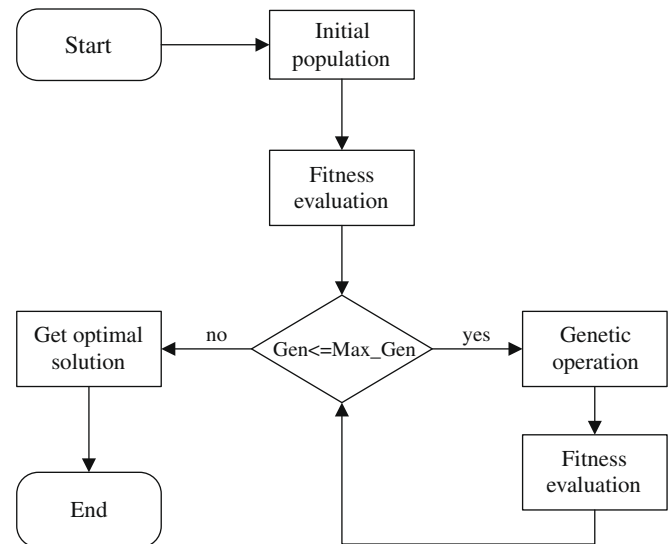


Fig. 4. Framework of EA.

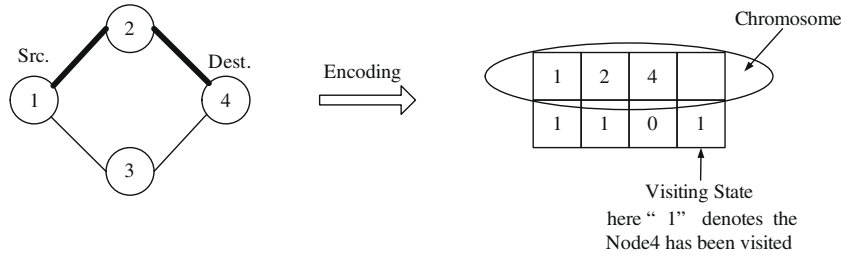


Fig. 5. An example of encoding.

2006), however, whether this method could traverse the whole state space or not needs to be proven despite it can eliminate cycles and invalid paths after genetic operations; the other is path coding, which utilizes the visiting sequence of nodes as the coding principle that conforms to Dejong's block assumption.

In this paper, we adopt path coding and attach a visiting vector to each chromosome. It is simple and doable; moreover, it does not generate invalid paths after genetic operation (see Fig. 5).

#### 4.2.2. Fitness function

The algorithm sorts all the chromosomes according to Pareto Dominance relationship between two individuals when evaluating each individual's fitness; i.e. it defines the first batch of Pareto Dominant individuals' fitness, which is called "Pareto Rank", equal to 1, and then removes these individuals from the population. In the residual population, the second batch of Pareto Dominant individual's fitness is defined as 2, and the rest may be similarly deduced till all individuals are defined.

#### 4.2.3. Selection

By means of individual's fitness evaluation, we can conclude that individuals in the same Pareto Dominant have the same Pareto rank. So, the selection can be described as

$$P\{T_s(\vec{X}) = X_i\} = \frac{f(X_i)}{\sum_{k=1}^n f(X_k)} \quad (9)$$

#### 4.2.4. Crossover

We first define the "adaptive back-off selection probability" as

$$p = \frac{|N| - |M_{weight\_k}|}{|N|} \quad (10)$$

where  $|N|$  is the number of individuals, and  $|M_{weight\_k}|$  stands for the number of individuals whose Pareto rank equals to  $k$ . Because adaptive back-off selection is an ideal way to implement "family competition", it can avoid two potentially negative effects – the loss of population diversity and trapping at a local optimal.

Hence, when one individual is chosen randomly, the other one that participates in crossover could be selected by:

$$P\{T_s(\vec{X}) = X_j\} = \begin{cases} \frac{f(X_j)}{\sum_{k=1}^n f(X_k)} \cdot p & X_j \in M_{weight\_k} \\ \frac{f(X_j)}{\sum_{k=1}^n f(X_k)} \cdot (1 - p) & X_j \notin M_{weight\_k} \end{cases} \quad (11)$$

where  $\vec{X}(n)$  is the  $n$ th generation population,  $\vec{X}$  stands for the current population and  $X_i$  is the individual in  $\vec{X}$ .

To speed up convergence of MOEAQ, greedy algorithm is imported. Greedy, a useful and powerful means in many optimization problems (Liu & Huang, 2007, 2008; Zahrani et al., 2006), converges very quickly but it is liable to trap at a local optimal. That is the reason why we employed "family competition". So, the crossover operation can be described as follows:

**Step 1:** Select  $N$  individuals independently from the group  $\vec{X}(n)$  so as to get the population of  $\vec{X}(n) = (X_1, X_2, \dots, X_N)$ .

**Step 2:** Select two individuals according to "family competition":

$$X_i(n) = (v_1, v_2, \dots, v_n) \quad (12)$$

$$X_j(n) = (v_1, v'_2, \dots, v_n) \quad (13)$$

**Step 3:** Let  $v_1$  be the first gene of  $X_i(n+1)$ , find the next gene of  $v_1$  in (12) and (13), evaluating their Pareto Dominant Relationship, then choose one (such as  $v_2$ ) that dominates the other as the second gene of  $X_i(n+1)$  and set the corresponding unit of its visiting vector to 1.

**Step 4:** Find the position  $v_2$  in (12) and (13), compare their tail gene to confirm which is better, then choose it as the next gene of  $X_i(n+1)$  and set its corresponding unit of visiting vector to 1 analogously.

**Step 5:** Repeat the above steps, till  $X_i(n+1)$  is formatted.  $X_j(n+1)$  can be generated similarly, just with the difference of getting the next gene from the reversed direction. Then crossover can be described as follows:

$$P\{T_c(X_i, X_j)\} = \begin{cases} (l_1 + l_2)p_c & X_i \neq X_j \\ 1 - p_c & X_i = X_j \end{cases} \quad (14)$$

where  $l_1$  and  $l_2$  is the length of chromosome  $X_i$  and  $X_j$ ,  $p_c$  is the probability of crossover.

#### 4.2.5. Mutation

The single point mutation is adopted in MOEAQ

$$P\{T_m(\vec{X}) = Y\} = p_m^{d(X,Y)} (1 - p_m)^{l-d(X,Y)} \quad (15)$$

where  $p_m$  is the probability of mutation, and  $d(X, Y)$  represents the number of gene pairs that the corresponding gene in  $X$  and  $Y$  is different with each other.

## 5. Analysis of MOEAQ

We assumed that  $|V|$  is the number of nodes in networks;  $c \cdot |V|$  is the size of population,  $c$  is a constant;  $|\text{Gen.}|$  denotes iterative times of MOEAQ, the pseudo-code of MOEAQ is shown as Fig. 6.

### 5.1. Time complexity

Firstly, for population initialization that takes  $O(c \cdot |V| \cdot (|V| - 1))$ ; secondly, the algorithm needs to sort all of the individuals when evaluating fitness, which takes  $O(c^2 \cdot |V|^2)$ ; moreover, operations selection, crossover (it contains "family competition" selection for crossover) and mutation take  $O(c \cdot |V|)$ ,  $O(c \cdot |V| + c \cdot |V|^3)$  and  $O(c \cdot |V|)$  respectively. Therefore, the one time of evolutionary operation takes  $O(c \cdot |V| \cdot (|V| - 1) + c \cdot |V| + c \cdot |V| + c \cdot |V|^3 + c \cdot |V|)$ . So, the time complexity of MOEAQ is

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```

1. Void Main
2. {
3.   set generation=0;
4.   While (generation <= |Gen.|)
5.   {
6.     Initialization;
7.     Fitness evaluation;
8.     Selection;
9.     Select two individuals by “family competition”;
10.    Crossover;
11.    Mutation;
12.  }
13. }

```

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Fig. 6. Pseudo-code for MOEAQ.

$$\begin{aligned}
T_{\text{MOEAQ}} &= O(|\text{Gen.}| \cdot (c \cdot |V| \cdot (|V| - 1) + c \cdot |V| + c \cdot |V| + c \\
&\quad \cdot |V|^3 + c \cdot |V|)) \\
&= O(|\text{Gen.}| \cdot |V|^3)
\end{aligned} \quad (16)$$

GAQ, which proposed by Liu and Chen (2006), takes  $O(c \cdot |V| \cdot (|V| - 1))$  for population initialization;  $O(c \cdot |V|^2)$  for fitness evaluation;  $O(c \cdot |V|)$ ,  $O(c \cdot |V|^2)$  and  $O(c \cdot |V|)$  for selection, crossover and mutation respectively, besides, it eliminates the circle and invalid path that needs  $O(c \cdot |V|^3)$ , therefore, the time complexity of GAQ is

$$\begin{aligned}
T_{\text{GAQ}} &= O(|\text{Gen.}|' \cdot (c \cdot |V| \cdot (|V| - 1) + c \cdot |V| + c \cdot |V|^2 + c \cdot |V| \\
&\quad + c \cdot |V|^3)) \\
&= O(|\text{Gen.}|' \cdot |V|^3)
\end{aligned} \quad (17)$$

where  $|\text{Gen.}|'$  denotes the iterative times of GAQ.

Based on our previous research in traveling salesman problem (TSP) [], we can conclude that  $|\text{Gen.}|' \gg |\text{Gen.}|$ . So, theoretically, MOEAQ can converge much faster than GAQ.

## 5.2. Convergence analysis of MOEAQ

To validate the convergence of MOEAQ, two definitions are required as follows:

**Definition 5** (Satisfactory Population Value).  $F(\vec{X}) = \max\{f(X_i); i \leq N\}$  is the satisfactory population value of  $\vec{X} = \{X_1, X_2, \dots, X_N\}$ .

**Definition 6** (Satisfactory Population Set).  $M^* = \{\vec{X}; F(\vec{X}) = \max\{f(X); X \in S\}\}$  is satisfactory population set.

**Lemma 1.** Utilizing formula (7) to depict fitness is the sufficient condition of Pareto rank in MOEAQ.

**Proof.** It is obvious that, the individual who with the lowest Pareto rank in the population is definitely to be with the highest fitness depicted by Eq. (7), i.e. the former is the sufficient condition of the latter.  $\square$

According to the above two definitions and the Lemma we assumed that QEA uses formula (7) to evaluate fitness and the same genetic operators mentioned in Section 4, then we have:

**Theorem 1.** Assume that  $\{\vec{X}(n); n \geq 0\}$  is the initial population generated by QEA then  $\{\vec{X}(n); n \geq 0\}$  is a homogeneous Markov chain.

**Proof.** Firstly, QEA is a Markov chain for the reason that there is no following effect after genetic operations; secondly, we know that  $P\{\vec{X}(n+1) = \vec{Y} / \vec{X}(n) = \vec{X}\}$  is independent of  $n$ , so it is homogeneous. In summary,  $\{\vec{X}(n); n \geq 0\}$  is a homogeneous Markov chain.  $\square$

**Theorem 2.**  $\{\vec{X}(n); n \geq 0\}$  converges to  $M_0^* = \{\vec{Y} = (Y_1, Y_2, \dots, Y_N)\}$  with probability one.

**Proof.** In terms of formula (9), (11), (14) and (15), if  $\vec{X}, \vec{Y} \in M_0^*$ ; then crossover operator can guarantee that  $P_n(\vec{X}, \vec{Y}) > 0$  and  $P_n(\vec{Y}, \vec{X}) > 0$ , i.e.  $\vec{X} \leftrightarrow \vec{Y}$ ; if  $\vec{X} \in M_0^*, \vec{Y} \notin M_0^*$ ; we have  $P_n(\vec{X}, \vec{Y}) = 0$ , i.e.  $\vec{X}$  could not arrive  $\vec{Y}$  and there must exist a stationary distribution  $\pi$  which makes that:

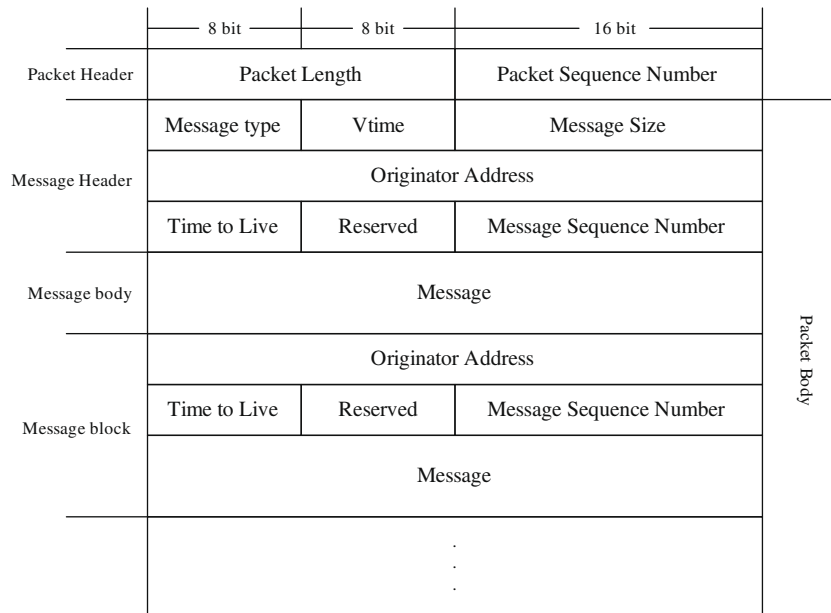


Fig. 7. Packet Format for MOEAQ.



$$\lim_{n \rightarrow \infty} P\{\vec{X}(n) = \vec{Y}/\vec{X}(0) = X_0\} = \begin{cases} \pi(\vec{Y}), & Y \in M_0^* \\ 0, & Y \notin M_0^* \end{cases} \quad (17)$$

Obviously,  $P(\infty)$  has a unique, irreducible, non-periodic, and positive recurrence class  $M_0^*$ , and  $S/M_0^*$  is a non-recurrence class, so  $\{\vec{X}(n); n \geq 0\}$  is strongly ergodic, to an arbitrary initial state  $\vec{X}(0) = X_0$ , we have

$$\begin{cases} \lim_{n \rightarrow \infty} P\{\vec{X}(n) = \vec{Y}/\vec{X}(0) = X_0\} = \pi(\vec{Y}) \\ \sum_{\vec{Y} \in M} \pi(\vec{Y}) = 1 \end{cases} \quad (18)$$

Therefore, we get:

$$\lim_{n \rightarrow \infty} P\{\vec{X}(n) = \vec{Y}/\vec{X}(0) = X_0\} = \sum_{\vec{Y} \in M} \pi(\vec{Y}) = 1 \quad (19)$$

From the validation of [Theorems 1 and 2](#), we know that QEA can achieve convergence. According to the *lemma*, utilizing formula (7) to depict fitness is the sufficient condition of Pareto rank in MOEAQ, and we have that MOEAQ can achieve convergence too.  $\square$

## 6. MOEAQ-based QoS multicast routing protocol

As mentioned in Section 3, MRP was divided into two segments, one is formed by the multicast group and the core via improved CBT protocol; the other is the combination of the source and the core, using the proposed method to find the optimum path from

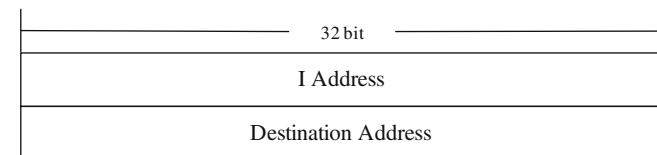


Fig. 8. Packet Format of RREQ.

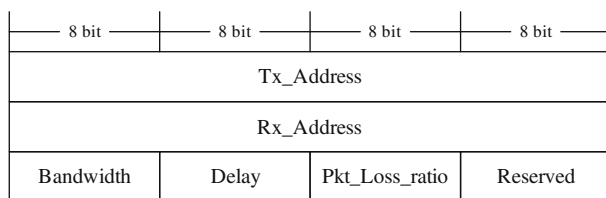


Fig. 9. Routing Table for MOEAQ.

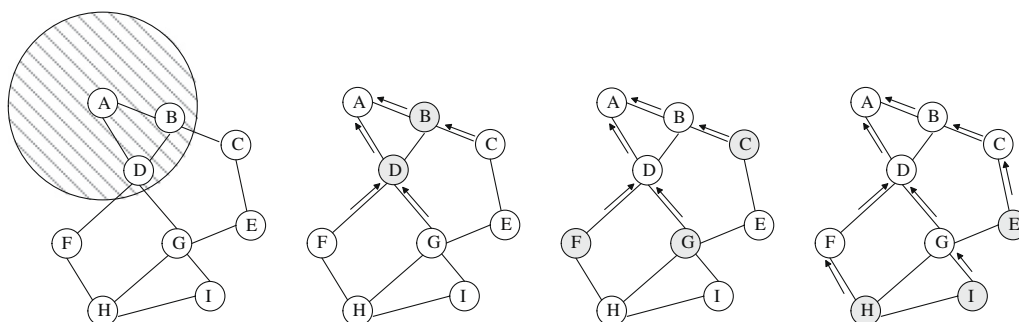


Fig. 10. Route Finding in MOEAQ.

the source to the core. We now give a protocol based on MOEAQ for the “Unicast” segment.

### 6.1. Message format

The given protocol communicates using a unified packet format (showing in [Fig. 7](#)) for all data related to the protocol. The purpose of this is to facilitate extensibility of the protocol without breaking backwards compatibility. This also provides an easy way of piggy-backing different “types” of information into a single transmission, and thus for a given implementation to optimize towards utilizing the maximal frame-size, provided by the network. These packets are embedded in UDP datagrams for transmission over the network.

Each packet encapsulates one or more messages. The messages share a common header format, which enables nodes to correctly accept and (if applicable) retransmit messages of an unknown type.

[Fig. 8](#) gives the packet format of Routing RREQ.

[Fig. 9](#) presents the routing table.

The meaning of each field in the packet format and routing table were explained in [Huang et al. \(2009\)](#).

### 6.2. Operations

[Fig. 10](#) shows the route finding of the protocol. We assume that node A is the source, node I is the destination. In the initial time, A floods a RREQ, node B and D then receive the RREQ which comes from A. B and D reply a message RREQ-Ack respectively, after A receive the RREQ-Ack messages, A can compute the for QoS parameters according the round-trip time and reserved them as route entries. In the similar way, node B will have a route entry about C, D will have route entries about F and G. A short period later, the routing information converged, that means each node will know the neighbor node, in this time, each node transmit their routing table to the node A, and then A know the topology of the entire network, now A can use the MOEAQ to obtain a optimum QoS-aware path.

## 7. Simulations and performance evaluation

The main concern of this section is to test the efficiency of MOEAQ in providing multicast users with QoS and satisfying the service requirements of multimedia applications. We focus on quantitative aspects of efficiency such as throughput, delivery delay, media access delay and packet loss ratio. The simulations are conducted using OPNET Modeler 14.0 Educational Version and Wireless Module. The results are aggregated for a multicasting scenario with typical two QoS classes. The simulation parameters are defined in [Table 1](#).

**Table 1**

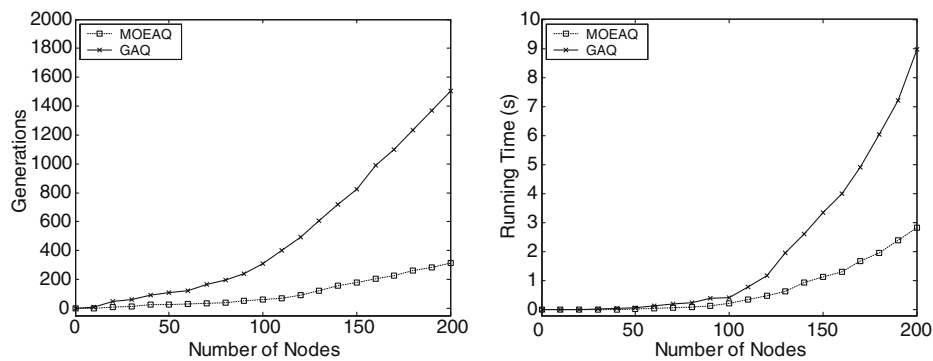
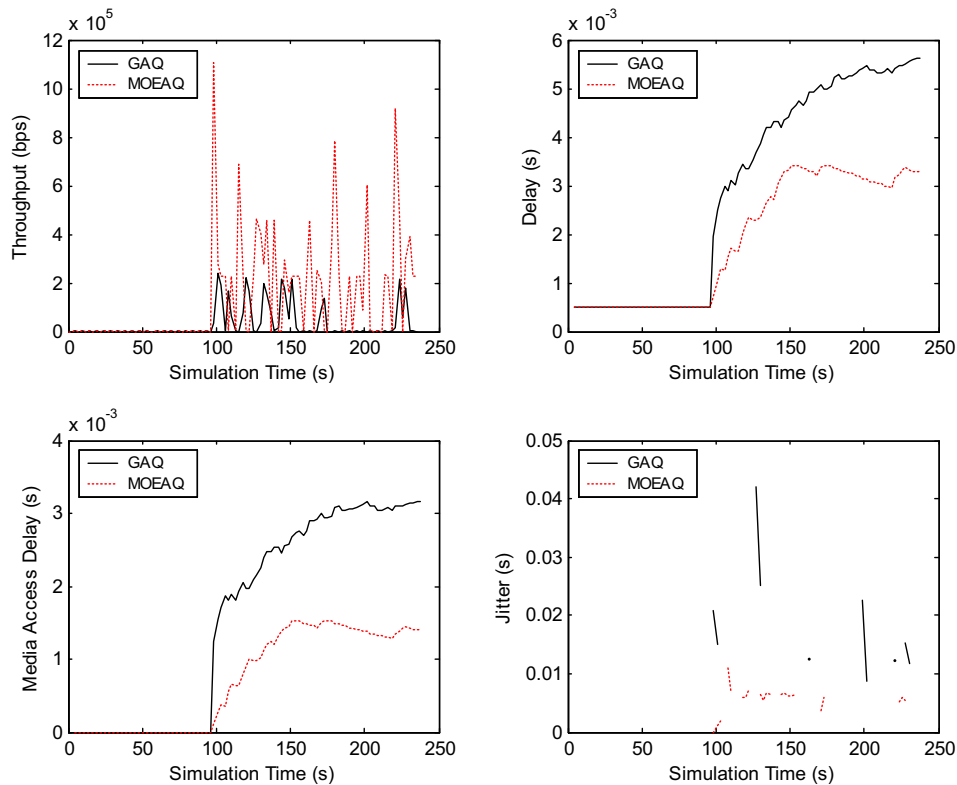
Simulation parameters for MANET.

|                       |                            |
|-----------------------|----------------------------|
| Number of nodes       | 200                        |
| Type of node          | Mobile terminal            |
| Area                  | 1000 × 1000 m <sup>2</sup> |
| Transmission protocol | TCP, UDP                   |
| Type of service       | FTP, Video Conferencing    |
| Simulation time       | 240 s                      |
| Service start time    | 100 s                      |

Fig. 11 compares the iteration times and running time of MOEAQ and GAQ. As we have discussed in our previous study (Liu & Huang, 2008), we set the crossover and mutation probability for MOEAQ are 0.45 and 0.1 respectively, while for GAQ they are set to 0.6 and 0.05. From the figure, we can see that with respect to the iteration times (generation) and running time, GAQ needs

more than three times as much as MOEAQ. This result follows the analysis in Section 5 that MOEAQ can converge much faster than GAQ. As the nodes increase, MOEAQ acts more effectively. MOEAQ, integrating greedy and “family competition” approach, can not only stabilize the search behaviors, but also yield solutions of higher quality and cost less running time. In summary, MOEAQ is a promising method for MANET multicast routing within reasonable time.

Fig. 12 is the comparison of performance between MOEAQ and GAQ with FTP service. The data drop curve is not given herein because FTP uses TCP to transmit data to ensure the number of data drop to be zero. The graph indicates that the system throughput of MOEAQ is higher than GAQ, but the delay, media access delay and delay jitter are lower than GAQ, i.e. MOEAQ has better system performance than GAQ.

**Fig. 11.** Comparison of two algorithms in generation (iteration times) and running time.**Fig. 12.** Performance comparison of two methods with FTP services.

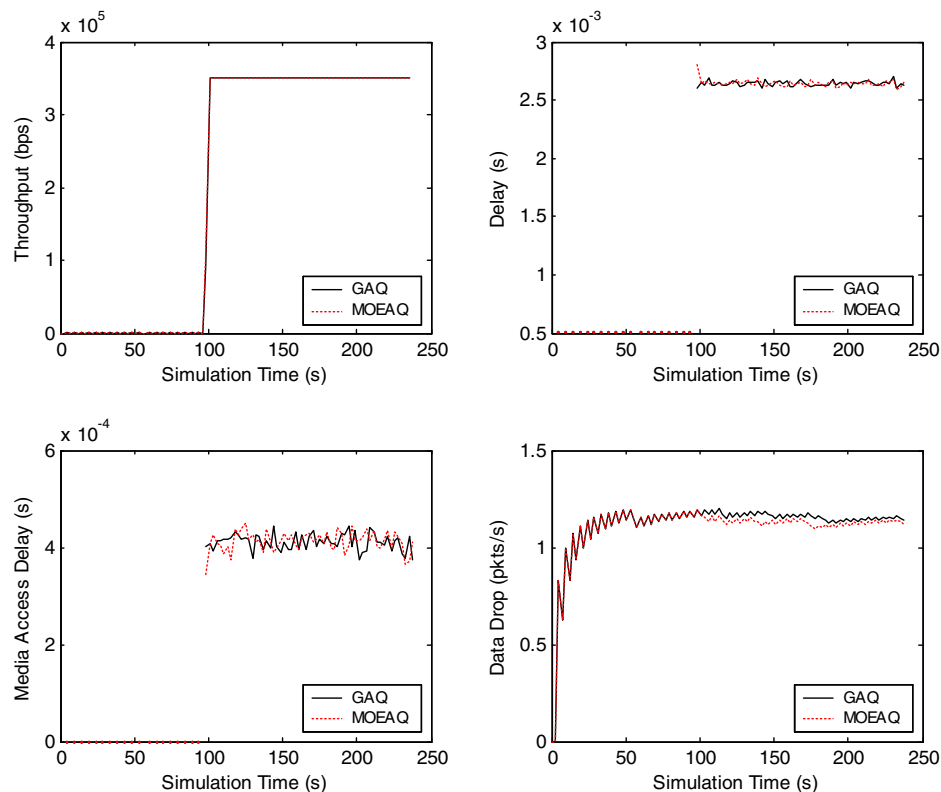


Fig. 13. Performance comparison of two methods with Video Conferencing services.

Fig. 13 is the comparison of performance between two algorithms with Video Conferencing service. It is quite obvious that the MOEAQ and GAQ have almost the same throughput, delay and media access delay. However, MOEAQ's data drop ratio is lower than GAQ. Consequently, MOEAQ not only has better performance than GAQ but also can deal with multi-objective problem effectively, moreover, it is more preferable for the dynamic topology of MANET since it can get a Pareto set rather than one "optimal" solution acquired from GAQ.

## 8. Conclusions

In this work, we analyzed strengths and limitations of the well-known multicast model firstly, and then an improved CBT protocol was proposed to simplify the QoS multicast routing problem in MANET; Based on the protocol, we came up with a novel fast multi-objective evolutionary algorithm to overcome the defection of slow convergence and liable to "premature" of conventional GA. The algorithm absorbs the "greedy" and "family competition" approaches which can speed up the convergence of algorithm and maintain the diversity of population; Apart from those traits, the proposed algorithm also can synthesize multi-objective effectively. Through the theoretical analysis, we obtained conclusions that (1). MOEAQ needs less running time than typical method GAQ; (2). MOEAQ can achieve convergence. The simulation results validate the correctness of these conclusions. Finally, the performance evaluation of two methods (GAQ & MOEAQ) are given, experimental results show that MOEAQ has better performance than that of GAQ.

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