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An Ant-based Multipath Routing Algorithm for QoS Aware Mobile Ad-hoc Networks

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Abstract In the wireless ad-hoc network management, Quality of Service (QoS) is an important issue. Along with the QoS ensuring, another desirable property is the network reliability. In data communications, multi-path routing strategy can cope with the problem of traffic overloads while balancing the network resource consumption. In this paper, we propose a new multipath routing algorithm for QoS-sensitive multimedia services. Based on the ant colony optimization technique, the proposed algorithm can establish effective multi-paths to enhance the network reliability. According to the load balancing strategy, data packets are adaptively distributed through the established paths while maintaining an acceptable level of QoS requirement. The most important feature of the proposed approach is its adaptability to current traffic conditions. Simulation results indicate the superior performance of the proposed algorithm, while other schemes cannot offer such an attractive performance balance.

Keywords Multipath routing algorithm · Ant colony optimization · Quality of Service · Mobile ad-hoc networks · Load balancing · Network reliability · Real-time decision

1 Introduction

Recently, Mobile Ad-hoc NETworks (MANETs) is one of the strongest growth areas of communication technology. Especially, explosive growth of new communication services and the widespread proliferation of multimedia data have necessitated to carry diverse multimedia applications; different multimedia services not only require different amounts of bandwidth but also have different Quality of Service (QoS) requirements. Therefore, QoS provisioning is an important issue for the efficient MANET management [1]. In addition, future networks are also expected to support reliable service during the routing operation. Therefore, the

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main challenge in MANETs is to ensure QoS for data routing while providing the network reliability.

For adaptive and efficient network operations, routing is very important; the network performance is strongly related to routing algorithms. Usually, all performance guarantees in MANETs are conditional on effective routing strategies. Therefore, much effort has been made trying to find efficient routing algorithms, which can play a significant role in determining network performance [1–4].

Performance optimization is one of the most important issues in network management. Until now, a lot of network optimization research has been conducted. To get the optimal solution in network operations, multiple objective functions are necessary to take into account conflicting network interactions. However, due to the model complexity, optimal solution approaches are impractical to be implemented for realistic wireless network operations [5–8].

In 1997, Dorigo et al. proposed Ant Colony Optimization (ACO) method inspired by swarm-intelligence [2,3]. The ACO method can explore distributed optimization problems without centralized control or the provision of a global model. In the last few years, ACO-based algorithms have empirically shown their effectiveness in the resolution of several different NP-hard combinatorial optimization problems. The advantages of ACO algorithms are distributing computation, positive feedback, and constructive greed heuristic. These features allow high adaptation to the dynamic topology changes and the adaptive multi-path maintenance in wireless networks [2,3,9,10].

Motivated by the above discussion, we propose a new adaptive routing algorithm based on the ant colony model. The design goal of the proposed algorithm is to satisfy QoS provisioning while increasing network reliability in MANETs. By using the ACO model, the algorithm establishes multiple routing paths, which can provide the required QoS. To enhance network reliability, routing packets are adaptively distributed through the established multiple paths. This multi-path routing mechanism can ease out the heavy traffic load in a specific link to ensure the balanced network resource assumption.

For efficient network management, control decisions in the proposed algorithm are made dynamically by using real-time measurements. Therefore, the proposed QoS-aware routing algorithm is dynamically adaptable to the current network conditions. The important features of the algorithm are (i) ability to maintain energy efficiency as high as possible, (ii) ability to respond to current network conditions with considering real time system information, (iii) reduce constrained resources consumption as much as possible, (iv) ability to achieve load balancing for real network operations, (v) support network reliability and QoS provisioning, and (vi) a well-balanced network performance between contradictory requirements. The principle novelty of the proposed scheme is its adaptability, feasibility and effectiveness in providing energy efficiency and network reliability.

Recently, several ACO algorithms have been introduced to solve the routing problem in MANETs. The *Ant-based Multi-Path Routing* (*AMPR*) scheme in [9] is an ant colony based multi-path routing protocol for wireless networks. To avoid the traffic congestion, the *AMPR* scheme constructs multiple paths for every destination nodes and dynamically allocates the network traffic to the different paths. The *Colony-based Multi-Path Routing* (*CMPR*) scheme [10] adopts the basic concept of load balancing strategy, which is used to extend the network lifetime. In the *CMPR* scheme, the traffic load is distributed over disjoint multiple paths for the network energy equilibrium. All the earlier work has attracted a lot of attention and introduced unique challenges. Compared to these schemes, the proposed scheme attains better performance for wireless network managements.

This paper is organized as follows. Section 2 describes the proposed algorithm in detail. In Sect. 3, performance evaluation results are presented along with comparisons with the schemes proposed in [9] and [10]. Finally, concluding remarks are given in Sect. 4.

2 Proposed Routing Algorithms

In this section, the proposed ant-based routing scheme is explained in detail. Based on the real-time monitoring, the proposed routing algorithm can dynamically adapt to the network changes and approximate an optimal network performance.

2.1 Ant Colony Optimization

The basic idea of the ant colony optimization is taken from the food searching behavior of real ants. When ants search for food, they start to walk toward the food. While walking, ants deposit pheromone, which marks the route taken. Ants are inclined to move toward the places which have the high concentration pheromone. Subsequently, more ants are attracted by these pheromone trails and in turn reinforce them even more. This behavior of the ant can form positive feedback mechanism, which makes ants finally obtain the shortest path [9–12].

In this paper, for the adaptive multipath routing in MANETs, the methodology that we adopt is the ant colony optimization technique. To effectively establish paths, each node maintains a routing table. The ants, seemed as packets, are forwarded randomly from one node to another while putting some amount of pheromone on the links of the path. The next generation ants are attracted by the pheromone to search in the solution space. By using the updating mechanisms, the pheromone amount is dynamically adjusted.

Usually, MANET is represented as a weighted, connected graph $G = (V, E)$, where V denotes the set of network nodes and E denotes the set of full-duplex, bi-directional link. The k^{th} ant selects from its current node i to the node $j (i, j \in V)$ as follows [9–12].

$$j = \begin{cases} \arg\min_{s \in N_i} \{[\tau_{i,s}]^{\gamma} [\eta_{i,s}]^{\delta}\} & \text{if } q \le q_0 \\ p_{i,j}^{k} & \text{otherwise} \end{cases}$$
$$\text{s.t. } p_{i,j}^{k} = \begin{cases} \frac{[\tau_{i,j}]^{\gamma} [\eta_{i,j}]^{\delta}}{\sum_{s \in N_i} [\tau_{i,s}]^{\gamma} [\eta_{i,s}]^{\delta}} & \text{if } j \in N_i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where q is a random number uniformly distributed in [0,1] and q_0 is a constant parameter between 0 and 1. It determines the relative importance of exploitation versus exploration [11,12]. Firstly, q is created randomly. If $q \le q_0$, the best link is chosen according to (1). Otherwise, we choose a new link according to $p_{i,j}^{k}$.N_i is the set of neighbor nodes yet to be visited by ant k, and $\tau_{i,j}$ is the pheromone amount of the link from the node i to the node j [9–12]. In this paper, to evaluate the communication adaptability (η) of each link is defined as an online function.

$$\eta_{i,j} = \frac{1}{\left[(1-\alpha) \times \frac{d_{ij}}{D_M}\right] + \left[\alpha \times \frac{L_j}{ML}\right]} \tag{2}$$

where d_{ij} is distance from the node i to the node j, L_j is the queue length of the node j. D_M and ML are the maximum coverage range and the maximum queue length of each node, respectively. Therefore, the d_{ij} and L_j are normalized by the D_M and ML; the range is varied from 0 to 1. The d_{ij} reflects the energy dissipation rate for wireless communications; the closer a next node, the more attractive for routing due to the less communication cost. The queue length (L) is defined as the amount of traffic buffering. Usually, it is used as a threshold to detect network congestion. If the input data rate exceeds the output data rate in a node, routing packets become congested; a queue length increases. Therefore, based on the queue length condition, it is possible to decide whether packet overflow occurs or not.

To estimate the current link situations, the parameter α controls the relative weights given to distance and remaining energy of corresponding node. Under diverse network environments, a fixed value of α cannot effectively adapt to the changing conditions. In this paper, we treat it as an on-line decision problem and adaptively modify α value. When the queue length of the node j is high, we can put more emphasis on the congestion status of next node j, i.e., on (L_j/ML). In this case, a higher value of α is more suitable. If the buffer space of the node j is enough, the path selection should strongly depend on the energy dissipation for data transmission. In this case, a lower value of α is more suitable for the energy consumption rate, i.e., on d_{ij}/D_M; the distance of two neighbor nodes directly affects the energy consumption rate. In the proposed algorithm, the value of α of the corresponding link (i, j) is dynamically adjusted based on the current queue length ratio of the node $j\,(L_j/ML)$. Therefore, the system can be more responsive to current network conditions by the real-time network monitoring.

After all ants have completed their tours, the pheromone level is updated according to the following formula [9–12]. $\tau_{link(i,j)}$ is the pheromone of the selected link (i, j) by an ant.

$$\tau_{link(i,j)} = (1-\rho_l)\,\tau_{link(i,j)} + \rho_l\Delta\tau_{link(i,j)} \tag{3}$$

where $\rho_l (0 < \rho_l < 1)$ is the pheromone decay parameter. $\Delta\tau_{link(i,j)}$, the increment of pheromone on the link (i, j), is defined as follows.

$$\Delta\tau_{link(i,j)} = \frac{Q_1}{h\_P\,(s,d)} \times \sum_{link \in P(s,d)} \eta_{link} \tag{4}$$

where Q_1 is a constant for rewarding of the pheromone. Based on source node s and destination node d $(s, d \in V)$, let $P(s, d)$ denote the routing path from s to d. The link (i, j) is included in $P(s, d)$, i.e., link$(i, j) \in P(s, d)$. η_{link} is the communication adaptability (η) of each link in $P(s, d)$, i.e., $link \in P(s, d)$, and $h\_P(s, d)$ is the hop number of $P(s, d)$. Therefore, $\Delta\tau_{link(i,j)}$ represents the average link adaptability in $P(s, d)$. Once all ants have finished their tour for one time, there are multiple paths. Based on each path, all the links' pheromone levels are adjusted according to (3).

2.2 Path Setup Algorithm

To make a service admission decision, the proposed scheme finds out routing paths that satisfy the QoS requirement. First, the most adaptable path (*M_Adap*) is selected as follows.

$$M\_Adap = \max_{P(s,d)}\left[\frac{1}{h\_P\,(s,d)} \times \sum_{link(i,j)\in P(s,d)} \tau_{link(i,j)}\right] \tag{5}$$

$$s.t. b\_r\,(S\_A) \le \min[b\,(\text{link}\ \ (i,j))] \text{ and } d\_r\,(S\_A) \le \sum_{link(i,j)\in P(s,d)} [d(\text{link}\ (i,j))]$$

where $b\_r(S\_A)$, $d\_r(S\_A)$ are the bandwidth and delay requirements of service application S_A through $P(s, d)$. $b(link(i, j)), d(link(i, j))$ are the bandwidth and delay of link(i, j), respectively. The selected path is most effective routing route while ensuring the requested QoS conditions. Next step is to find out alternative paths for load balancing. To achieve effective load balancing, we establish multiple routing paths and adaptively distribute data packets. Among the remaining nodes, we attempt to configure the next adaptable path from the source node to the destination node; this path formation process continues repeatedly until all the possible routing paths are established. However, to keep the routing effectiveness, only paths that satisfy the following condition are qualified to actively participate in routing operations.

$$Adap_a \leq \varepsilon \times (M\_Adap) \tag{6}$$

where $Adap_a$ is the adaptability of a selected path and ε is a control factor ($\varepsilon < 1$) for an efficient multiple routing path formation. Usually, the ε value is decided to compromise between load balancing and route efficiency. According to (6), we finally construct multiple routing paths to balance the traffic load.

To estimate the amount of packet distribution, the proposed algorithm estimates a path energy level (P_{e_l}) for each path as follows.

$$P_{e\_l} = [(1-\beta) \times e_{min}] + \left[\beta \times \left(\frac{1}{N} \times \sum_{n \in NP(s,d)} \frac{e_n}{E_M}\right)\right] \tag{7}$$

where $NP(s, d)$ is the set of all nodes in the selected path ($P(s, d)$) and e_{min} is the minimum remaining energy in $NP(s, d)$. N is the total node number in the $P(s, d)$. E_M, e_n, are the initial energy and remaining energy of the node n, respectively. Under diverse network environments, we also adaptively modify β value. When the e_{min} in the path is high, we can put more emphasis on the average remaining energy of the path, i.e., on $(\frac{1}{N} \times \sum_{n \in NP(s,d)} \frac{e_n}{E_M})$. In this case, a higher value of β is more suitable. If the e_{min} in the path is low, the path energy level should strongly depend on the e_{min} to avoid the energy depletion failure. In this case, a lower value of β is more suitable, i.e., on e_{min}. In the proposed algorithm, the value of β is decided as the current e_{min}/E_M value in the selected path. Therefore, β is dynamically adjustable to adapt to current network conditions.

2.3 Routing Packet Distribution

Based on the path adaptability and energy level, the source node can decide the amount of packet distribution for each established path. In the proposed algorithm, the routing adaptability ($R\_A(h)$) of the path h is estimated as follows.

$$R\_A(h) = P_{e\_l}(h) \times Adap_a(h) \tag{8}$$

If the path h is the most adaptable path, $Adap_a(h)$ is the M_Adap. Under dynamically changing MANET environments, the R_A can effectively reflect the path's routing adaptability. Among the selected multiple paths, data packets are adaptively distributed according to the ratio of R_A values; this approach can effectively balance the network resource consumption in MANETs. The data distribution ratio (D_R) for the path h can be estimated as follows.

$$D\_R(h) = R\_A(h) \Bigg/ \sum_{h=1}^{r} R\_A(h) \tag{9}$$

where r is the number of established paths. Based on the feedback mechanism, this value is adjusted periodically in a dynamic online manner.

In this paper, we propose a new multipath routing scheme for QoS aware multimedia services. Based on the adaptive ant-based optimization model, the proposed algorithm gives excellent adaptability and flexibility under widely different and diversified network situations. In addition, control decisions are made in a distributed online fashion; it is practical to be implemented in real network operations. The main steps of the proposed routing algorithm can be described as follows.

Step 1: At the initial time, the position of ants is the source node; each node periodically monitors neighbor nodes to maintain local connectivity.
Step 2: Each ant chose its next step according to (1) and (2).
Step 3: When an ant selects its next link, the pheromone on the link will be modified by using (3) and (4). This ant-moving process is repeated recursively until ants reach the destination node.
Step 4: The most adaptable path (*M_Adap*) that satisfies required QoS conditions is selected according to (5). Based on the *M_Adap*, all available paths are also established by using (6).
Step 5: The path energy level (P_{e_l}) of each selected path is estimated according to (7).
Step 6: Based on the P_{e_l}, the routing adaptability (*R_A*) is estimated according to (8).
Step 7: Based on the *R_A*, the data distribution ratio (*D_R*) can be calculated by using (9). To get the adaptive load balancing, routing packets are adaptively distributed through the established multiple paths based on the *D_R* ratio.
Step 8: Based on the feedback mechanism, the *D_R* value is adjusted periodically in a dynamic online manner. This iterative feedback procedure continues until the end of routing operations.

3 Performance Evaluation

In this paper, the effectiveness of the proposed scheme is validated through simulation; simulation analysis allows more complex realistic modeling for one real-world system. The network simulator ns [13] is used to evaluate the proposed scheme and compare it to other schemes [9] and [10]. With the simulation study, we can confirm the performance superiority of the scheme. The assumptions implemented in the simulation model were as follows.

- 100-nodes are distributed randomly over an area of 500×500 meter square area.
- Each data message is considered CBR traffic (having a different deadline) with the fixed packet size.
- Network performance measures obtained on the basis of 50 simulation runs are plotted as functions of the call requests per second (calls/s).
- Data packets are generated at the source node according to the arrival process for call requests, which is Poisson with rate λ (calls/s).
- The range of offered load (λ) was varied from 0 to 3.0.
- The bandwidth of the wireless link was set to 10 Mb/s.
- The source and destination nodes are randomly selected.
- For simplicity, we assume the absence of noise or physical obstacles in our experiments.
- At the beginning of simulation, all nodes started with an initial energy of 10 joule.
- When studying the fault-tolerance aspects, one node is selected randomly as the faulty node and this occurs at a random time. Faulty nodes can not support any traffic services.
- Three different traffic types were assumed; they were generated with equal probability.

Table 1 Type of traffic and system parameters used in the simulation experiments

Traffic type		Bandwidth requirement	Connection duration (ave./sec)
I		128 Kbps	60 sec (1 min)
II		256 Kbps	120 sec (2 min)
III		512 Kbps	180 sec (3 min)
Parameter	Value	Description	
γ, δ	1,1	Parameters to control the relative importance of trail (γ) versus visibility (δ)	
ε	0.5	Control factor for an efficient multiple routing path formation	
ρ_l	0.5	The pheromone decay parameter	
Q_1	1	Constant factors for the rewarding of pheromone	
q_0	0.5	A parameter to determine the importance of exploitation versus exploration	
m	30	The number of ants	
D_M	10 m	Maximum wireless coverage range of each node	
E_M	10J	Initial assigned energy amount of each node	
Parameter	Initial	Description	Values
α	0	The ratio of remaining and initial energy of node	$0 \sim 1(L_j/ML)$
β	1	A minimum remaining energy among nodes	$0 \sim 1(e_{min})$

Table 1 shows the traffic types and system parameters used in the simulation. Each type of traffic has its own requirements in terms of bandwidth and service time. In order to emulate a real wireless network and for a fair comparison, we used the system parameters for a realistic simulation model [9–12, 14, 15].

In order to effectively control the wireless networks, a number of schemes have been developed. In this section, we compare the performance of the proposed multipath routing scheme with two existing schemes: the *AMPR* scheme [9] and the *CMPR* scheme [10]. These two schemes have been recently published and attracted a lot of attention and introduced unique challenges.

Figure 1 compares the performance of each scheme in terms of the node remaining energy ratio. For the data transmission operation, the energy of each node decreases. In this paper, the average remaining energy amount of nodes is defined as the node remaining-energy ratio. To maximize a wireless network lifetime, the remaining energy is an important performance metric. All the schemes have similar trends. However, the proposed scheme attains much remaining energy; it guarantees a longer node lifetime. Figure 2 shows the comparison of the packet delivery ratio, which is defined as the ratio of data amount received at the destination nodes to the total generated data amount. From low to high network traffic intensities, the proposed scheme can have higher packet delivery ratio than other schemes.

In Fig. 3, the packet loss probabilities are presented. As the offered traffic load increases, wireless nodes will run out of the energy and capacity for data transmissions. Therefore, data packets are likely to be dropped; the packet loss probability increases linearly with the traffic load intensities. Under various traffic load situations, the proposed scheme achieves a lower packet loss rate than other schemes.

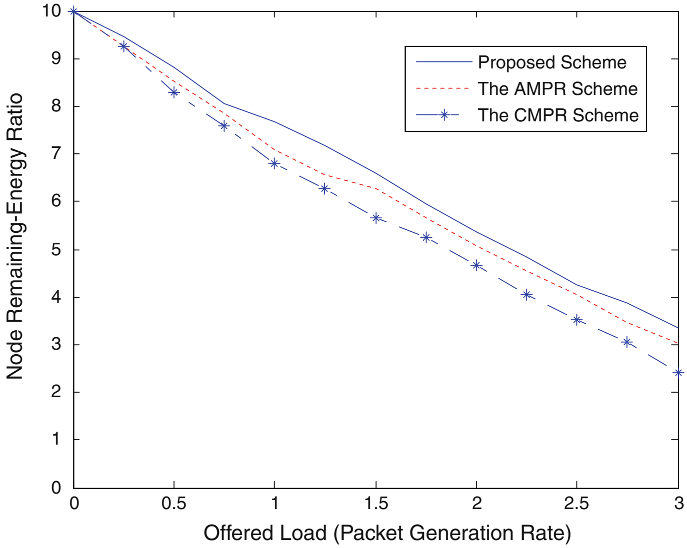

Fig. 1 Node remaining energy ratio per offered load (λ)

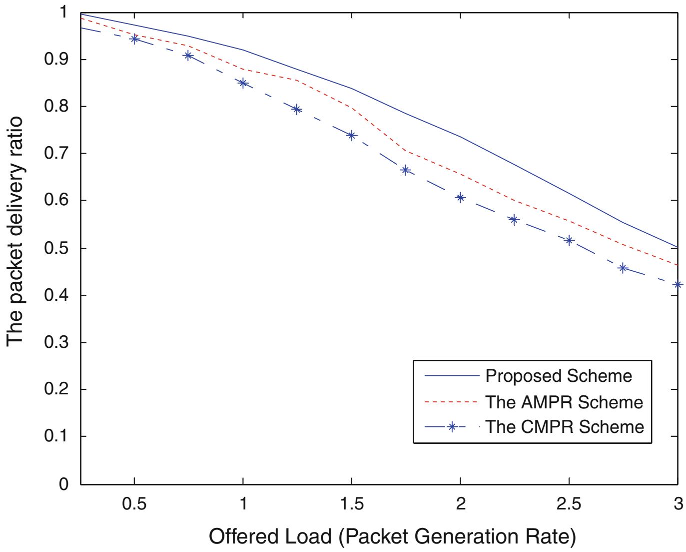

Fig. 2 Packet delivery ratio per offered load (λ)

The curves in Fig. 4 indicate the delay commitment ratio; the delay commitment means that the time requirement is satisfied in data communications. Under various system constraints, the proposed scheme is able to increase the number of routing packets, which meet the time deadline; it ensures the QoS provisioning for packet routing operations.

Figure 5 shows the energy balance among the paths. In this paper, energy balance represents the maximum difference of the minimum remaining energy nodes in the established multiple paths. The proposed scheme can maintain a better energy balance, which is highly desirable property for the network management.

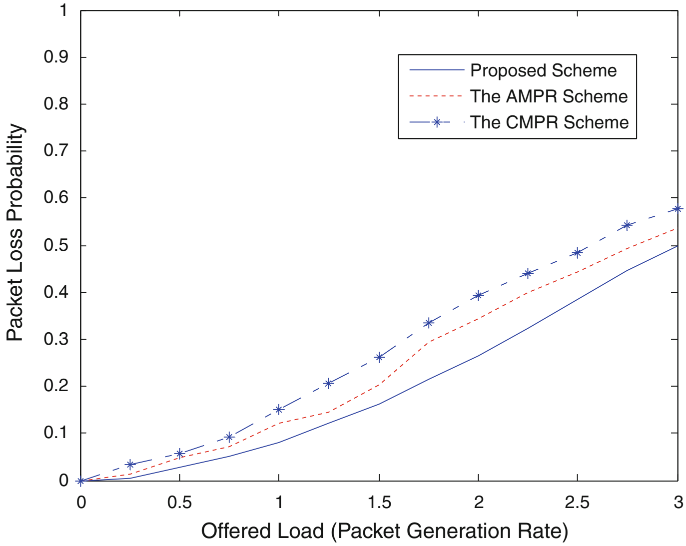

Fig. 3 Packet loss probability per offered load (λ)

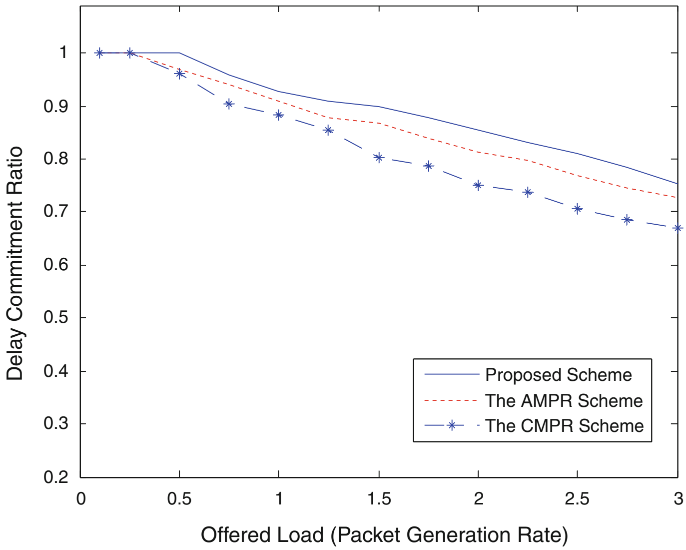

Fig. 4 Delay commitment ratio per offered load (λ)

The simulation results shown in Figs. 1– 5 demonstrate that the proposed multipath routing scheme generally exhibits superior performance compared with other existing schemes. Due to the load balancing strategy, the network resource consumption can be adaptively balanced. In addition, the proposed algorithm constantly monitors the current network conditions and control decisions are made dynamically based on the adaptive online control approach. Through simulation, we confirm that the proposed scheme can balance appropriate network performance while other schemes cannot offer such an attractive network performance.

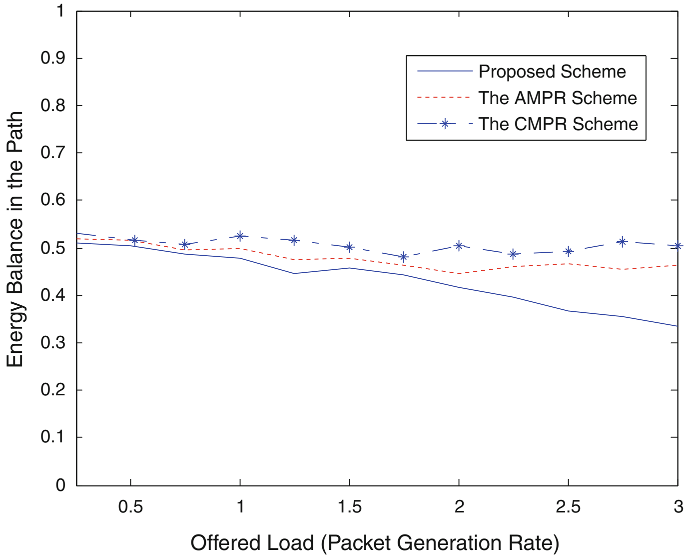

Fig. 5 Energy-balance in the path per offered load (λ)

4 Summary and Conclusions

In recent years, the requirements placed on MANETs have increased dramatically. However, due to dynamic topology changes and limited network resources, the development of efficient MANET routing algorithms is a challenging task. In this paper, a new multipath routing scheme is proposed for QoS sensitive services. Based on the ant colony optimization model and load balancing strategy, the proposed multipath routing scheme can satisfy QoS requirements of traffic services while maximizing network performance. In addition, control parameters are dynamically adjusted by using the dynamic online approach. Therefore, each wireless node is capable of independently adapting its operation and can quickly response to the current network conditions. It is suitable for ultimate practical network implementations in the real world. From simulation results, the proposed scheme significantly outperforms existing schemes in terms of node remaining energy, packet delivery ratio, delay commitment, energy balance and packet loss probability, etc.

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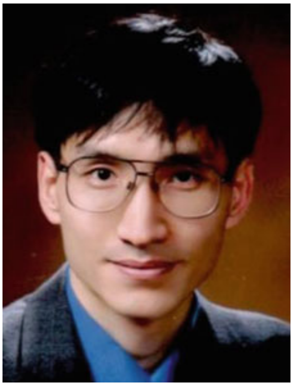
References

1. Yarvis, M. D., & Zorzi, M. (2008). Ad hoc networks: Special issue on energy efficient design in wireless ad hoc and sensor networks. *Ad Hoc Networks, 6*(8), 1183–1184.
2. Attia, R., Rizk, R., & Mariee, M. (2009). A hybrid multi-path ant QoS routing algorithm for MANETs. *International conference on wireless and optical communications networks (WOCN '09)*, pp. 1–5.
3. Shokrani, H., & Jabbehdari, S. (2009). A novel ant-based QoS routing for mobile ad-hoc networks. *International conference on ubiquitous and future networks (ICUFN'09)*, pp. 79–82.

4. Sun, X.-M., & Lv, X.-Y. (2009). Novel dynamic ant genetic algorithm for QoS routing in wireless mesh networks. *International Conference on Wireless Communications, Networking and Mobile Computing (WiCom '09)*, pp. 1–4.
5. Waslander, S.L., Inalhan, G., & Tomlin, C. J. (2004). *Decentralized optimization via Nash bargaining*. Dordrecht: Kluwer.
6. Niyato, D., & Hossain, E. (2006). A cooperative game framework for bandwidth allocation in 4G heterogeneous wireless networks. *IEEE International Conference on Communications*, pp. 4357–4362.
7. Srivastava, V., Neel, J., MacKenzie, A. B., Menon, R., DaSilva, L. A., Hicks, J. E., Reed, J. H., & Gilles, R. P. (2005). Using game theory to analyze wireless ad hoc networks. *IEEE Communications Surveys & Tutorials, 7*(4), 46–56.
8. Xiao, Y., Shan, X., & Ren, Y. (2005). Game theory models for IEEE 802.11 DCF in wireless ad hoc networks. *IEEE Communications Magazine, 43*(3), 22–26.
9. Ling, S., & Wei, W. (2009). Multi-ant-colony based multi-path routing algorithm for overlay network. *Global Congress on Intelligent Systems (GCIS), 1*, 188–192.
10. Yang, J., Lin, Y., Xiong, W., & Xu, B. (2009). Ant colony-based multi-path routing algorithm for wireless sensor networks. *International Workshop on Intelligent Systems and Applications (ISA'09)*, pp. 1–4.
11. Liu, M., Sun, Y., Liu, R., & Huang, X. (2007). An improved ant colony QoS routing algorithm applied to mobile ad hoc networks. *International conference on wireless communications, networking and mobile computing, (WiCom 2007)*, pp. 1641–1644.
12. Dorigo, M., & Gambardella, L. M. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation, 1*(1), 53–66.
13. Network Simulator—ns (2000). [Online]. Available: http://www.isi.edu/vint/nsnam/
14. Kim, S. (2010). Game theoretic multi-objective routing scheme for wireless sensor networks. *Ad-hoc & Sensor Wireless Networks*, 343–359.
15. Kim, S. (2009) Online energy efficient routing approach for QoS-sensitive wireless sensor networks. *International conference on information networking (ICOIN'09)*, pp. 1– 3.

Author Biography



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