

# Fairness and high-throughput scheduling for multihop wireless ad hoc networks<sup>☆</sup>



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## ABSTRACT

In multihop wireless ad hoc networks, it is important to maintain the outcome fairness of throughput and to maximize the throughput. In this paper, we propose a novel opportunistic scheduling framework by considering outcome fairness and throughput simultaneously. Since the data rate fluctuates intensively due to channel errors, we first devise a data rate estimation method with an adaptive sliding window to accurately and adaptively estimate the data rate. Then, we present a framework together with two mechanisms. The first proposed mechanism is ROSA-WOM, with the weighted objective function method to configure the data rate. The other one is ROSA-MGCF, and it is a maximum total goodput method under a constrained fairness index. The proposed mechanisms are able to schedule the flows fairly even when the data rate of all flows is more than the channel capacity. We establish a testbed to evaluate these two mechanisms. The experiment results show that our proposed mechanisms can not only trade off with different fairness and throughput requirements, but also effectively provide robust service isolation, outcome fairness, and high throughput in the presence of channel errors.

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## 1. Introduction

A wireless ad hoc network consists of a number of nodes communicating with each other on wireless links without infrastructure support. A multihop ad hoc network is an ad hoc network in which the packets of a traffic flow are relayed by one or more intermediate nodes before they reach the destination. To support different types of multimedia and real-time applications, providing various Quality of Service (QoS) guarantees for multihop flows is an important issue in wireless ad hoc networks. In this paper, we focus on providing robust service isolation, outcome fairness of goodput and high throughput via opportunistic packet scheduling.

In the rest of this section, we first survey the related work on scheduling in multihop ad hoc networks. Then, we describe the problems encountered and our major contributions on resolving them.

### 1.1. Related work

Considering the different services, channel fading and channel capacity, packet scheduling in ad hoc networks may pursue maximizing the total throughput, maximizing the fairness, minimizing the schedule length, minimizing the delay or optimizing multiple objectives at the same time [1]. We discuss the related work according to these aspects.

From the aspect of network utilization, maximizing the total throughput is an important goal. RBAR [2] is proposed to account for channel errors, and it performs efficient channel quality estimation to gain higher overall throughput for multihop wireless networks. In [3], with reference to the difficulties to achieve network-wide instantaneous information, a low-complexity scheduling algorithm and a back-pressure-like scheduling algorithm are developed to perform throughput optimization. In [4], another method is proposed for improving the total throughput by maximizing the minimum throughput among all flows.

Outcome fairness is another significant issue in multihop wireless ad hoc networks. In [5], based on successive interference cancellation at the physical layer, a greedy algorithm is developed for achieving fair scheduling in polynomial time. In [6], in order to achieve packet fairness rather than flow fairness, a scheduling algorithm is presented by establishing an analogy with the ranked election problem. Transmission Scheduler Algorithm (TSA) [7] is

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proposed for overcoming bandwidth starvation for the nodes with longer distances to the gateway, and it assigns the weight for each node according to its location and traffic load. The Hop Based Multi Queue (HBMQ) scheduler [8] accounts for multiple data rates over multiple data flows in ad hoc networks, and optimizes traffic based on the hop count of packets, for providing fairness to different flows.

In ad hoc networks, minimizing the schedule length would minimize the total time required for a set of flows to transmit their data packets. In [9], since it is considered difficult to determine the interference region, a transmission is assumed to be sent successfully when the channel quality is above a certain signal-to-interference-plus-noise threshold. A column-generation method is proposed and yielded theoretical guarantees of optimality. In [10], an optimal solution based on a graph-theoretic model is proposed. It solves the minimum schedule length problem by finding a shortest path on a single source directed acyclic graph. In [11], considering time-varying wireless networks through joint scheduling and rate control decisions, the minimum length scheduling problem is formulated as a stochastic shortest path problem and an optimal policy by employing principles of dynamic programming is proposed. In [12], taking into account the Signal-to-Interference-plus-Noise Ratio (SINR) constraints with Rayleigh fading, an algorithm based on a column-generation approach is proposed. In [13], considering finding a minimum-length schedule of a power-controlled wireless network subject to traffic demands and SINR constraints, a column-generation based algorithm is proposed that finds the optimal schedules and transmit powers. In [14], considering the transmission of packets of arbitrary sizes in time slots of arbitrary lengths, a heuristic algorithm based on the column-generation method is proposed to achieve minimum length scheduling.

Delay minimization is an important problem in ad hoc networks. In [15], combining wireless link scheduling algorithms with a Coordinated Earliest Deadline First packet scheduler, centralized and distributed schedulers are presented to get the approximate expression of end-to-end delay. Block-based Weighted Fair Queuing [16] is proposed based on weighted fair queuing. It dynamically collects packets in advance and performs scheduling in units of block and priority level, to satisfy the delay upper bound for each session. Based on credit assignment, Credit-based Low Latency Packet Scheduling [17] maintains low and steady queueing delay for real-time flows. In [18], a delay-optimal user selection and power allocation solution is proposed.

In some cases, optimizing multiple objectives is desired. In [19], considering power efficiency and end-to-end bandwidth guarantees, two heuristic cross-layer algorithms, top-down and bottom-up are proposed based on graph theory. In [20], to save energy and reduce computing time, a time division multiple access scheduling scheme is proposed based on genetic algorithm and particle swarm optimization. Fractional Service Buffer [21] is a packet queueing engine based on fractional service buffers and a configurable flow scheduler, and satisfies fair throughputs and differentiated delay guarantees. In [22], considering data rate, SNR and queue size, a fuzzy logic based packet scheduling algorithm is presented for optimizing end-to-end delay, throughput and packet delivery ratio. Highthroughput Twin Fair scheduler [23] is a low latency, low energy consumption and high throughput scheduler based on a modular architecture, and it can combine existing schedulers to provide guarantees for quality of service.

## 1.2. Our contributions and organization of the paper

To the best of our knowledge, none of the previous work took channel error compensation, link status estimation and fair and high-throughput scheduling into consideration simultaneously for distributed scheduling in multihop ad hoc networks. In this work,

we extend our earlier work in [24] to more general situations by proposing two new mechanisms to account for fairness and throughput simultaneously. One is named Robust Opportunistic Scheduling for Ad Hoc networks with Weighted Objective Method (ROSA-WOM), and it considers fairness and throughput at the same time with a weighted objective to configure the data rate of the flow. The other is named Robust Opportunistic Scheduling for Ad Hoc networks with Maximum total Goodput method under Constrained Fairness index (ROSA-MGCF), and it first satisfies the outcome fairness of goodput and then maximizes the total goodput. We also propose a data rate estimation method with adaptive sliding window. In addition, we have constructed a wireless network testbed on which we deploy and evaluate the performance of our proposed mechanisms.

The rest of the paper is organized as follows. Section 2 describes the system model and the assumptions used throughout the paper. Section 3 presents the problem and our strategy. Section 4 describes the data rate estimation method with adaptive sliding window. Section 5 describes the revised framework, and the proposed ROSA-WOM and ROSA-MGCF mechanisms in details. Section 6 presents the experiment scenarios and performance evaluation results in our wireless network testbed. We conclude in Section 7.

## 2. System model and assumptions

We consider a multihop wireless ad hoc network. Nodes communicate over the same channel. A node cannot transmit and receive packets simultaneously. A collision happens when a receiver is in the transmission ranges of multiple transmitters. Wireless links are error-prone and the occurrences of channel errors are not negligible.

Instead of using static flow weights, the QoS requirement of an end-to-end flow specifies the desired service rate. An admission control mechanism is used to grant the desired QoS requirements. The desired service rate is propagated to all the intermediate nodes along the path. This may be accomplished by piggy-backing the desired rate on each packet of the flow.

For ease of presentation, we assume that a contention-based MAC scheme is used, although this is not a requirement of the ROSA framework. Since the packet transmission schedule is computed at each node locally based on incomplete and possibly conflicting network information, collisions are inevitable. However, with the admission control mechanism no flow shall offer a traffic load above the admitted service rate. We assume that the collision rates are statistically stable and predictable [25].

The state of a wireless link is estimated to be either good or bad. A packet sent on a good link has a much higher probability of success than that on a bad link. The link conditions are independent of each other. Unsuccessful transmissions are due to either channel errors or packet collisions. The transmitter has no means to know the cause of an unsuccessful transmission. Lastly, we assume all flows are properly routed. We do not consider routing issues in this paper.

## 3. Problem and strategy

As stated in Section 1.2, the goal of our mechanisms is to gain outcome fairness of goodput and high throughput in multihop ad hoc networks simultaneously. There are several problems that we must conquer.

### 3.1. MAC layer blocking problem and solution

First, the MAC layer blocking problem in ad hoc networks must have to be resolved. Take IEEE 802.11 as an example. When the

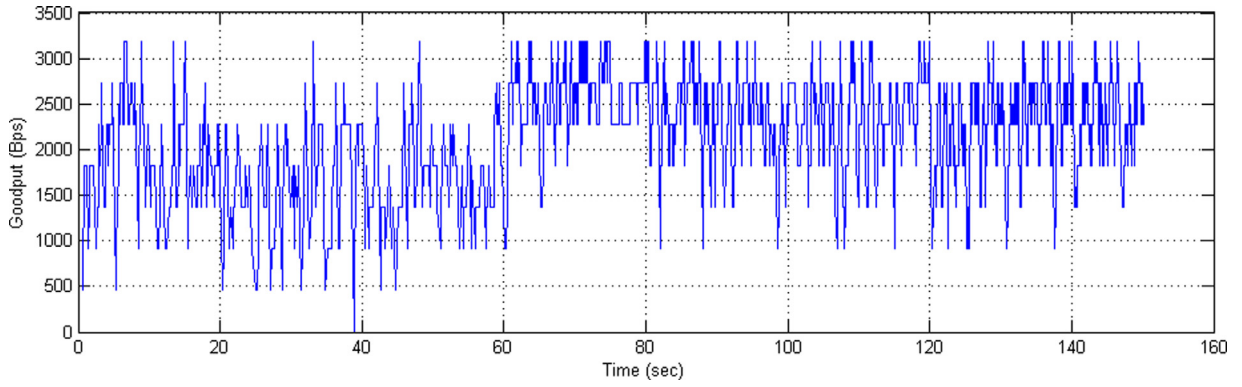


Fig. 1. Direct measurement of goodput.

scheduler gives the Medium Access Control (MAC) layer a packet to transmit, the RTS-CTS-DATA-ACK protocol may fail either on RTS or on DATA at the transmitter when the corresponding CTS or ACK is not received. In any case, IEEE 802.11 will backoff for a random period of time and try to retransmit that packet again. This retry process continues repeatedly until the packet is successfully transmitted or it is dropped as the retry limit is exceeded. Then, the scheduler selects the next packet and passes it to the MAC layer for transmission.

The problem with this model is that, one failed packet in the MAC layer will block the scheduler from scheduling other flows. We term this phenomenon the MAC layer blocking problem. The problem becomes severe when a link becomes bad, since packets transmitted on that link is highly likely to be retransmitted until it is dropped. This further blocks other packets, which may potentially be transmitted on good links, for a relatively long time.

To address this problem, the proposed framework requires that the MAC mechanism does not make any retransmissions automatically, but it reports the result of each transmission to the scheduler. Through this design, all scheduling decisions are made solely by the scheduler. Load control inter-frame space (LIFS) is the interspace from the end of the last frame to the beginning of the current frame, and LIFS is used to implement MAC load control.

### 3.2. Fairness and throughput tradeoff and solution

From the global network view, normally we will attempt to maximize the global network throughput. From the point of each node, fair goodput is important. Unfortunately, fairness for each node and the global throughput normally conflict.

In this paper, to obtain a good tradeoff and optimization between fairness and throughput, we propose two methods. One is ROSA-WOM, based on the weighted objective method to configure the data rate of a flow by taking into account fairness and throughput concurrently. The other is ROSA-MGCF, and it first satisfies the outcome fairness of goodput and then maximizes the total goodput.

## 4. Data rate estimation with adaptive sliding window

There are several key decisions for scheduling multiple flows in ad hoc networks, including which flow to transmit and the data rate. In general, data rate control is based on the measured goodput, target goodput data rate and current data rate. Therefore, the measured goodput plays an important role. However, it is hard to get an accurate goodput due to packetized transmission, link fading, noise, and so on.

Fig. 1 is an example of direct measurement of goodput. We find it very difficult to get the exact value of goodput because of

violent fluctuations of goodput with time. We thus devise an adaptive sliding window filter to get the precise goodput.

We assume a goodput signal given by:

$$D(t) = g(t) + n(t) \quad (1)$$

where  $D(t)$ ,  $g(t)$ , and  $n(t)$  are the measured goodput, accurate goodput and noise, respectively.  $D(t)$  and  $g(t)$  are the time average goodput over a duration from  $t - \tau$  to  $t$ , where  $\tau$  is the length of duration. We assume that noise  $n(t)$  is a Gaussian process with zero mean. Therefore, the mean of  $D(t)$  is an unbiased estimate for the accurate goodput  $g(t)$ . Since the accurate goodput  $g(t)$  is time-varying and different window lengths of the filter will obtain different results, we develop adaptive window length filters that attempt to provide sufficient noise rejection, as well as fast response to rapidly changing goodput data rates.

We seek the minimum Mean-Squared Error (MSE) of the measured goodput to obtain accurate goodput values with respect to different window lengths. The MSE of measured goodput  $D(t)$  is:

$$MSE(D(t)) = E[(D(t) - g(t))^2] \quad (2)$$

Considering a variance component and a bias component, we have:

$$MSE(D(t)) = var(D(t)) + [bias(D(t))]^2 \quad (3)$$

where  $var(D(t))$  is the variance of  $D(t)$ , and  $bias(D(t)) = E[D(t)] - g(t)$ . Since the noise  $n(t)$  is a zero-mean Gaussian process, there is:

$$MSE(D(t)) = var(D(t)) \quad (4)$$

Under different window lengths, different means of measured goodput affect the reliability of this estimate. According to Eq. (4),  $MSE(D(t))$  is comparable with the square of the mean for the measured goodput, we define MSE Factor (MSEF) to evaluate the sliding window filter under a certain window length as below:

$$MSEF = \frac{MSE(D(t))}{\{E[D(t)]\}^2} \quad (5)$$

It is rather computationally intensive to evaluate the optimal window length in Eq. (5). If the maximum length of the sliding window is  $N$ , the time complexity of the adaptive sliding window filter is  $O(N^2)$ . It is necessary to find an efficient way to fulfill the optimization. By Eqs. (4) and (5), we have:

$$MSEF = \frac{var(D(t))}{\{E[D(t)]\}^2} \quad (6)$$

Since  $var(D(t)) = E[D(t)^2] - \{E[D(t)]\}^2$ , there is:

$$MSEF = \frac{E[D(t)^2]}{\{E[D(t)]\}^2} - 1 \quad (7)$$

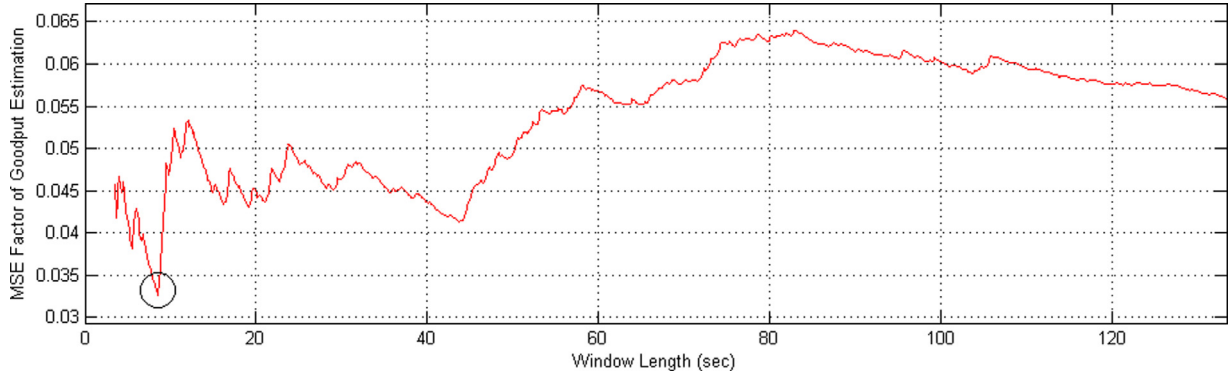


Fig. 2. MSE factor of measured goodput.

We consider a sequence of measured goodput values according to each time slot as follows:

$$\{d_i : i = 1, 2, \dots, n\} \quad (8)$$

Therefore, we have:

$$MSEF = \frac{\frac{1}{n} \sum_{i=1}^n (d_i^2)}{\frac{1}{n^2} (\sum_{i=1}^n d_i)^2} - 1 \quad (9)$$

When we utilize a sliding window filter to the measured goodput data rate with different window lengths, we will find the mean-squared error factor of the goodput is varying according to certain regular pattern owing to noise and changing goodput data rate. Generally, the noise term in Eq. (1) changes more rapidly than the accurate goodput data rate. When we observe the MSEF with different window length filters, MSEF will gradually decrease mainly under the noise effects when the window length rises at first. On the other hand, when the window length increases further, MSEF will increase mainly under the relatively slowly changing effect of the goodput. An MSEF curve which is calculated from experiment data (as shown in Fig. 1) is presented as Fig. 2. From this figure we can select the window length with minimum MSEF (circle marked in Fig. 2) to calculate the goodput. Therefore the adaptive sliding window filter with this window length gives the optimal estimation of the goodput, since the sliding window filters the noise variation and effectively tracks the goodput.

To simplify the calculation of MSEF, we can calculate  $d_i^2$  first with respect to each different time slot  $i$ , then get the result by an iterative process as follows:

$$\begin{cases} \sum_{i=1}^k (d_i^2) = \sum_{i=1}^{k-1} (d_i^2) + d_k^2 \\ \sum_{i=1}^k d_i = \sum_{i=1}^{k-1} d_i + d_k \end{cases} \quad (10)$$

Therefore, the time complexity of the adaptive sliding window filter becomes  $O(N)$ . This will reduce the cost of MSEF calculation significantly.

## 5. The proposed framework and mechanisms

Based on our previous work of the ROSA framework [32], the proposed framework includes four modules as shown in Fig. 3. They include a wireless link state estimator, a data rate control module, a load control medium access control module, and a flow scheduler. Both link state estimation and data rate control are based on our proposed data rate estimation method with adaptive sliding window filter.

### 5.1. Link state estimation

Link state estimation is an important element of opportunistic scheduling in ad hoc networks as it provides the necessary information for the scheduler to exploit multiuser diversity. We base our link state estimation mechanism on the transmission history of each link. A link state estimator (LSE) is employed to monitor each packet transmission and record the last  $L$  transmission results for each wireless link. Each record entry is marked either as “Success” or “Failure”. A link varies between three states: “GOOD”, “BAD”, or “PENDING”. LSE estimates the link state based on the packet success rate,  $P_s$ , which is defined as the fraction of the number of successful transmissions over the most recent  $L$  transmissions, and a threshold  $Th$ , where  $0 < Th < 1$ . All records are initialized as successful and the link state is initialized as GOOD. The link state remains to be GOOD when  $P_s \geq Th$ . It transits from GOOD to BAD when  $P_s < Th$ . When a link goes BAD, it stays in the BAD state for a time period  $T_{bad}$  before it transits to the PENDING state. The transmission records are not updated in the BAD state and the PENDING state. In the PENDING state, LSE estimates the channel status by transmitting  $L'$  packets. If the successful rate  $P'_s$  is above the threshold  $Th'$ , the link status transits to the GOOD state. Otherwise, it goes back to the BAD state and waits for another  $T_{bad}$ .

Note that GOOD, BAD and PENDING are internal states within LSE. When the scheduler consults LSE for the link status, LSE responds good if the link's internal state is GOOD or PENDING, or BAD if the link's internal state is BAD.

### 5.2. Flow scheduling

In this work, the flow scheduler performs opportunistic scheduling algorithm for wireless ad hoc networks. It aims to provide delay and bandwidth guarantees for flows with an error-free link. Taking into account the delay of a packet, the deadline of Packet  $p+1$  for Flow  $i$  can be derived from the deadline of Packet  $p$  for Flow  $i$  as:

$$d_i(p+1) = d_i(p) + \frac{L}{R_i} \quad (11)$$

where  $L$  and  $R_i$  are the packet size and the target rate for Flow  $i$ , respectively. Therefore, the scheduler only needs to maintain one deadline for each Flow  $i$ ,  $d_i$ , by which the head of the packet queue should be served.

To determine how much Flow  $i$  is leading and lagging its target rate, the scheduler keeps track of a parameter  $G_i$ , called normalized goodput gap, which is defined as [26]:

$$G_i(t) = \frac{g_i(t) - R_i \cdot t}{R_i \cdot t} \quad (12)$$

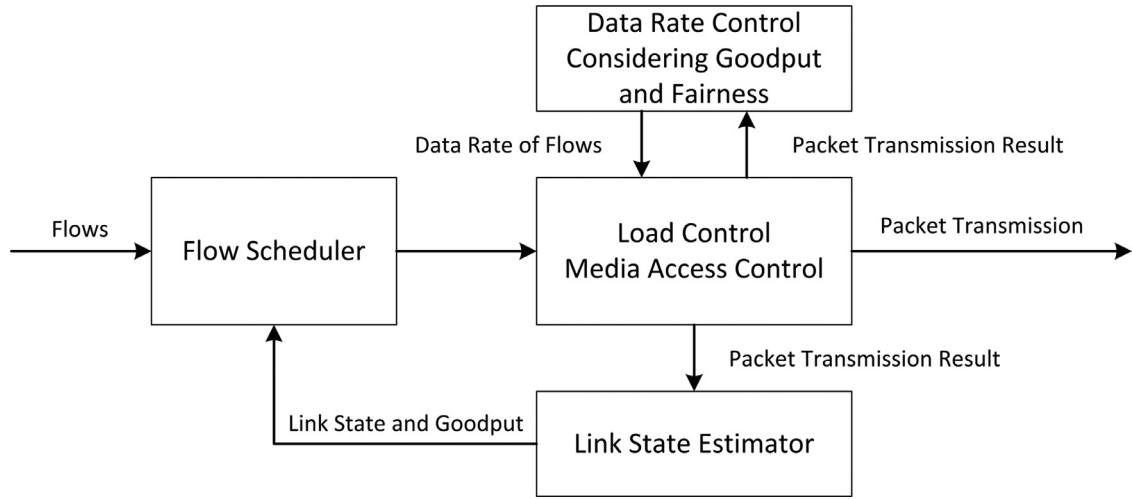


Fig. 3. The proposed framework.

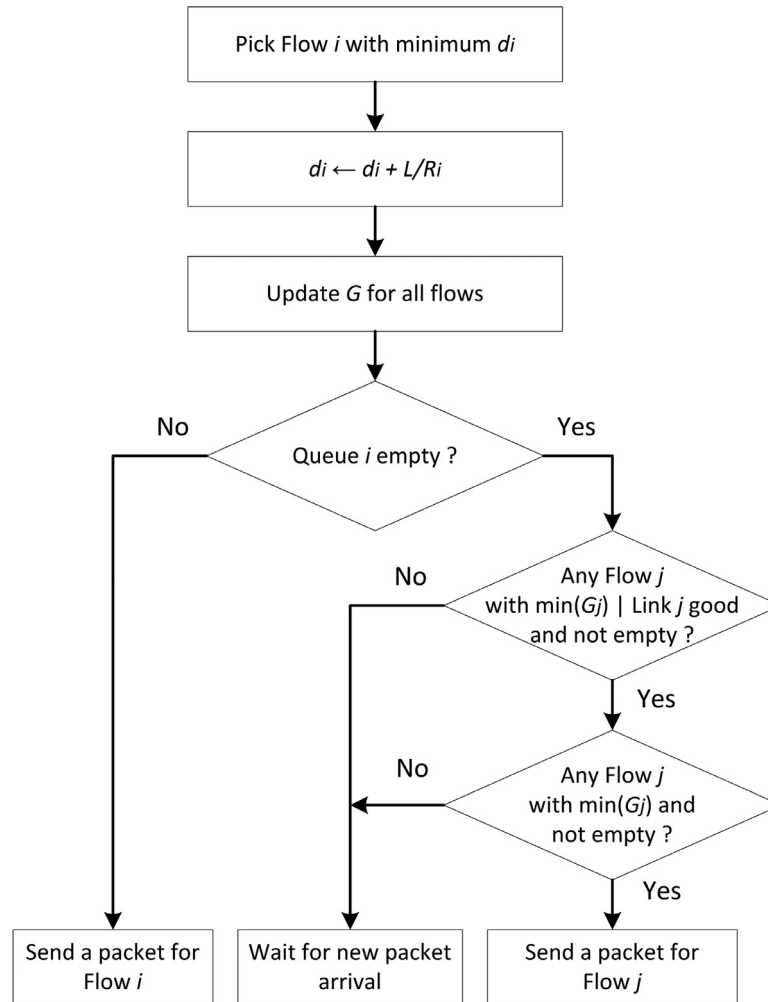


Fig. 4. The flow scheduler.

where  $g_i(t)$  is the amount of data of Flow  $i$  transmitted successfully up to time  $t$  within its current backlog period.

The proposed flow scheduler is shown as Fig. 4. First, the scheduler selects the Flow  $i$  which owns the earliest deadline. Then, it updates the deadline of this flow and  $G_i$  for all flows. After that, Flow  $i$  is checked to see if it is empty or not, and if Flow  $i$  is not

empty, the scheduler will transmit a packet from this flow. Otherwise, the scheduler selects another flow which has minimum  $G_i$ , Link  $j$  is good and its buffer is not empty to transmit a packet. If not, the scheduler selects another flow which has minimum  $G_j$  and its buffer is not empty to transmit a packet. Otherwise, the scheduler waits for new packet arrival.



### 5.3. Medium access control for load control

Medium access control mainly fulfills load control. In our proposed framework, the data rate of each flow is determined by the data rate control module. As a result, the main task of load control focuses on transmitting according to the designated data rate.

Therefore, the inter-frame space for load control is defined as:

$$LIFS = \frac{L}{Rd_i} - \frac{L}{R_C} \quad s.t. \quad Rd_i \leq R_C \quad (13)$$

where  $L$  is the packet size, and  $Rd_i$  and  $R_C$  are the data rate to feed packets to transmit for Flow  $i$  and the capacity of the wireless channel, respectively.  $Rd_i$  is provided by the data rate control module. Since  $R_C$  is the capacity of the wireless channel,  $Rd_i$  should be less than  $R_C$  to make sure that LIFS is not negative.

### 5.4. ROSA-WOM mechanism for data rate control

The objective of this data rate control is to maximize both the total goodput and outcome fairness. However, since maximizing the outcome fairness means minimizing the deviation of the goodputs, we consider to devise an objective function which is the weighted sum of both total goodput and outcome fairness. Our proposed mechanism is ROSA-WOM, and it configures the data rate with the weighted objective method.

First, we consider the maximum goodput. We define the variable of transmission efficiency of Flow  $i$ :

$$\eta_i(t) = \frac{g_i(t)}{Rd_i(t)} \quad (14)$$

where,  $g_i(t)$  is the goodput during period  $t$  of Flow  $i$ , and  $Rd_i(t)$  is the data rate to feed packets to transmit for Flow  $i$  during period  $t$ .

Then, we get the total goodput:

$$G = \sum_{i=1}^N R_i \cdot \eta_i(t) \quad s.t. \quad \sum_{i=1}^N Rd_i(t) < \alpha R_C \quad (15)$$

where we assume there are  $N$  flows on this node,  $R_i$  is the target data rate of Flow  $i$ ,  $R_C$  is the capacity of the wireless channel, and  $0 < \alpha < 1$ , because the offered data rate of the wireless channel can be significantly smaller than  $R_C$ .

For the maximum total goodput, we can select the flows which own maximum transmission efficiency, and configure  $Rg_i(t)$  to make the goodput of this flow  $g_i(t)$  equal to  $R_i(t)$ , where  $Rg_i(t)$  is the data rate to transmit for this case of maximum total goodput. The selection is limited by  $\sum_{i=1}^N Rd_i(t) < \alpha R_C$ .

Fairness is often quantified using Jain's fairness index [27]. Given a number of samples  $K$ , the fairness index is defined by the first and second moments as:

$$f = \frac{E[K]^2}{E[K^2]} \quad (16)$$

Considering the relative fairness, we define normalized goodput as follows:

$$p_i = \frac{g_i(t)}{R_i} \quad (17)$$

We seek the same  $p_i$  for all flows under the condition  $\sum_{i=1}^N Rf_i(t) < \alpha R_C$  by trial and error, and select the case of maximum  $p_i$ , where  $Rf_i(t)$  is the data rate to transmit for this case of maximum fairness.

We assume that the weight of the maximum goodput is  $w_g$ , and the weight of the maximum fairness is  $w_f$ , so we have the data rate of Flow  $i$  is:

$$Rd_i(t) = w_g \cdot Rg_i(t) + w_f \cdot Rf_i(t) \quad (18)$$

where  $w_g + w_f = 1$ .

The pseudo code of ROSA-WOM is shown as Algorithm 1.

### Algorithm 1 ROSA-WOM.

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```

1: Update the current packet transmission state as Success or Failure
2: Calculate  $g_i(t)$  of each flow and  $\eta_i(t)$  of each flow
3: Order the flows by  $\eta_i(t)$ 
4: for each Flow  $i$  of this node in descending order of  $\eta_i(t)$  do
5:   if  $\sum Rd_i(t) > \alpha R_C$  then
6:     Record  $Rg_i(t)$  for the selected flows;  $Rg_i(t)$  of the remaining flows
       is set to zero; Break
7:   end if
8: end for
9: Calculate  $p_i$  of each flow and order the flows by  $p_i$ 
10: for each Flow  $i$  of this node in descending order of  $p_i$  do
11:   Calculate  $Rf_i(t)$  for each flow according to this selected  $p_i$ 
12:   if  $\sum Rf_i(t) < \alpha R_C$  then
13:     Record  $Rf_i(t)$  for the selected flows; Break
14:   end if
15: end for
16: Calculate the data rate to feed packets to transmit  $Rd_i(t) = w_g \cdot Rg_i(t) + w_f \cdot Rf_i(t)$ 

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### 5.5. ROSA-MGCF mechanism for data rate control

In this section, we propose another mechanism, namely, the ROSA-MGCF to maximize the total goodput under the constrained fairness index.

For the maximum total goodput, as mentioned in the last section, we select the flows which own maximum transmission efficiency one by one, and configure the  $Rd_i(t)$  to make  $g_i(t)$  equal to  $R_i$  with constraint by  $\sum_{i=1}^N Rd_i(t) < \alpha R_C$ . The maximum total goodput is denoted as  $G_{max}$ .

After the first step, the framework can obtain the maximum total goodput configuration. However, on the other hand, the fairness index may not satisfy the constrained fairness index. For all of flows, the maximum and minimum of normalized goodput is defined:

$$p_{min} \leq p_i \leq p_{max} \quad i = 1, 2, \dots, N \quad \text{and} \quad p_{min} > 0 \quad (19)$$

Next, we define:

$$K = \frac{p_{max}}{p_{min}} \quad (20)$$

The fairness index can be guaranteed as follows [27]:

$$f_{index} \geq \frac{4K}{(K+1)^2} \quad (21)$$

From (21), when we have a minimum fairness index requirement  $f_{min}$ , we obtain the maximum value of  $K$ . When we use the smallest measured  $p_i$  as  $p_{min}$ , we can obtain  $p_{max}$  from Eq. (20). Therefore, we can reduce the maximum normalized goodput to  $p_{max}$  to satisfy the minimum fairness index requirement. Therefore, we have:

$$gr_i(t) = p_{max} \cdot R_i \quad \text{when} \quad p_i > p_{max} \quad (22)$$

where  $gr_i(t)$  is the data rate of the required goodput for Flow  $i$ .

After that, the total goodput is reduced and becomes less than the maximum total goodput  $G_{max}$ . Hence, we select the flows which own the maximum transmission efficiency one by one to increase the total goodput following  $gr_i(t)$  and the total data rate to transmit follows  $\sum Rd_i(t) \leq \alpha R_C$ . So, we have:

$$Rd_i(t) = \frac{gr_i(t)}{\eta_i(t)} \quad (23)$$

At last, we get the  $Rd_i(t)$  configuration to achieve the maximum goodput with constrained fairness index.

The pseudo code of ROSA-MGCF is shown as Algorithm 2.

## 6. Performance evaluation in wireless network testbed

In this section, we are going to demonstrate the performance of the proposed scheduling framework by considering a performance

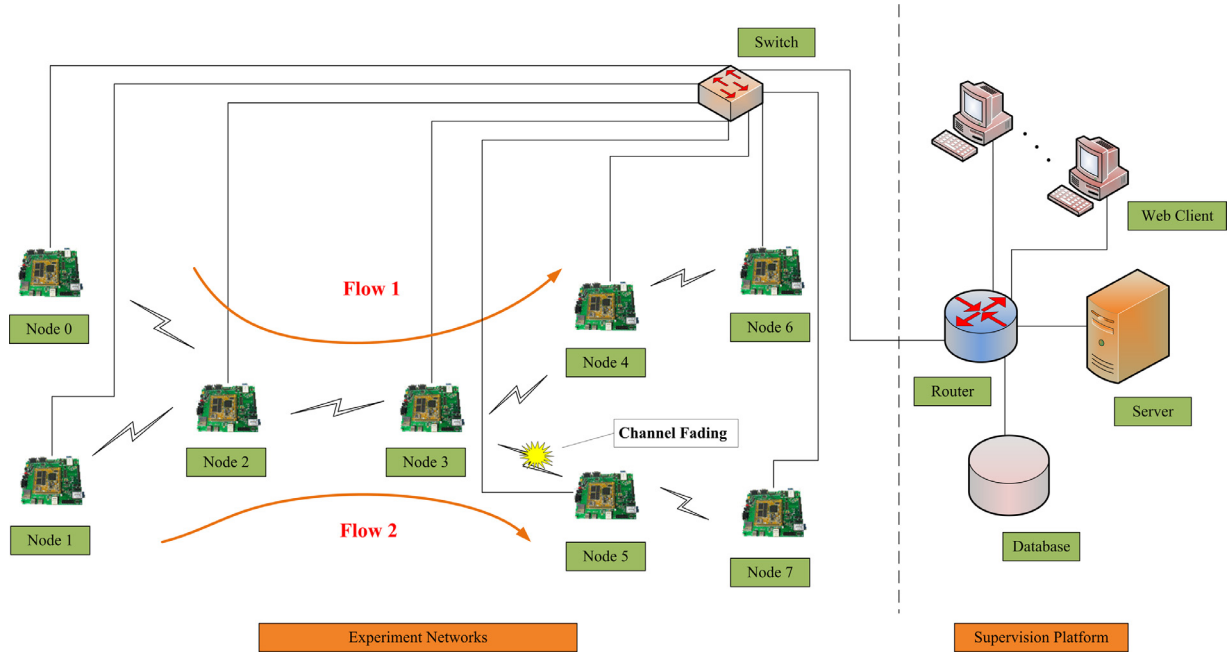


Fig. 5. Testbed architecture for experiments.

**Algorithm 2** ROSA-MGCF.

```

1: Update the current packet transmission state to Success or Failure
2: Calculate  $g_i(t)$  and  $\eta_i(t)$  for each flow
3: for each Flow  $i$  of this node in descending order of  $\eta_i(t)$  do
4:   Calculate  $Rd_i(t) = \frac{R_i}{\eta_i(t)}$ 
5:   if  $\sum Rd_i(t) > \alpha R_C$  then
6:     Record  $Rd_i(t)$  for the selected flows;  $Rd_i(t)$  of the remaining flows
       is set to zero; Break
7:   end if
8: end for
9: Calculate  $p_i$  of each flow and order the flows by  $p_i$ ; Calculate  $K$  with  $f_{min}$ 
10: Select the smallest measured  $p_i$  as the  $p_{min}$ , calculate  $p_{max}$  by  $K$ 
11: for each Flow  $i$  in this node do
12:   if  $p_i > p_{max}$  then
13:     Calculate  $gr_i(t) = p_{max} \cdot R_i$ 
14:   else
15:      $gr_i(t) = R_i$ 
16:   end if
17: end for
18: Order the flows by transmission efficiency
19: for each Flow  $i$  of this node in descending order of transmission effi-
    ciency do
20:   Calculate  $Rd_i(t) = \frac{gr_i(t)}{\eta_i(t)}$ 
21:   if  $\sum Rd_i(t) \leq \alpha R_C$  then
22:     Record  $Rd_i(t)$ 
23:   else
24:     Break
25:   end if
26: end for

```

evaluation in a wireless network testbed. Considering the random and complex characteristics of noise and fading in the wireless environment, a computer simulation may not be able to account for all such wireless characteristics. Therefore, we construct a testbed with wireless nodes and perform experiments to evaluate the performance of the proposed mechanisms in the real wireless environment.

This testbed composes two parts. One is the experiment networks and the other is the supervision platform. For testing our mechanisms, the experiment network consists of eight specially designed wireless nodes in indoor environment, the distance between nodes is about five meters and the error rate of wireless communications occurred during the experiments is generally less

than 2%. Fig. 5 shows the network topology used in the experiments. Two multihop Constant Bit Rate (CBR) flows, namely Flow 1 and Flow 2 are sent from Node 0 to Node 6 and from Node 1 to Node 7, respectively. The bandwidth of wireless channel is set as 32 kbps. The experiments last for about 300 seconds. During the time period from 120th second to 170th second, the link from Node 3 to Node 5 suffers link errors due to channel fading, and about 50% of the packets are discarded. To investigate the performance under different scenarios, we consider two kinds of data rate. The normal scenario is when the sum of data rates for all flows is less than the channel bandwidth. The overload scenario is when the sum is more than the channel bandwidth. The main parameters for experiments are shown as Table 1. After the experiments, we calculate the statistical results for goodput and fairness and analyze them.

In the experiments, we compare ROSA-WOM, ROSA-MGCF with WiFi and ROSA. According to different scenarios and parameters, we perform three groups of experiments. In Experiment A, we compare ROSA-WOM, ROSA-MGCF under maximum fairness with ROSA and WiFi according to the normal and overload scenarios, respectively. Experiment B measures the performance of ROSA-WOM with different weighted coefficients to configure the data rate under the overload scenario. Experiment C compares the performance of ROSA-MGCF according to different fairness indices under the overload scenario.

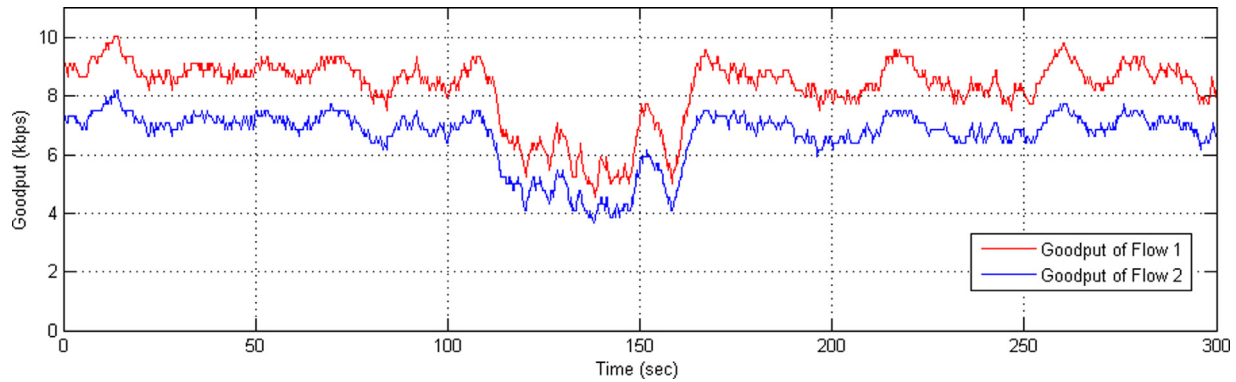
### 6.1. ROSA-WOM And ROSA-MGCF under maximum fairness

To test the performance of ROSA-WOM and ROSA-MGCF under maximum fairness, we perform Experiment A under the normal and overload scenarios as described in Table 1, and compare with ROSA and WiFi at the same time. Since ROSA and WiFi pursue goodput fairness, so the weight of maximum fairness is set as 100% and the weight of maximum goodput is set as 0% for ROSA-WOM. The fairness index is set as 1.0 for ROSA-MGCF.

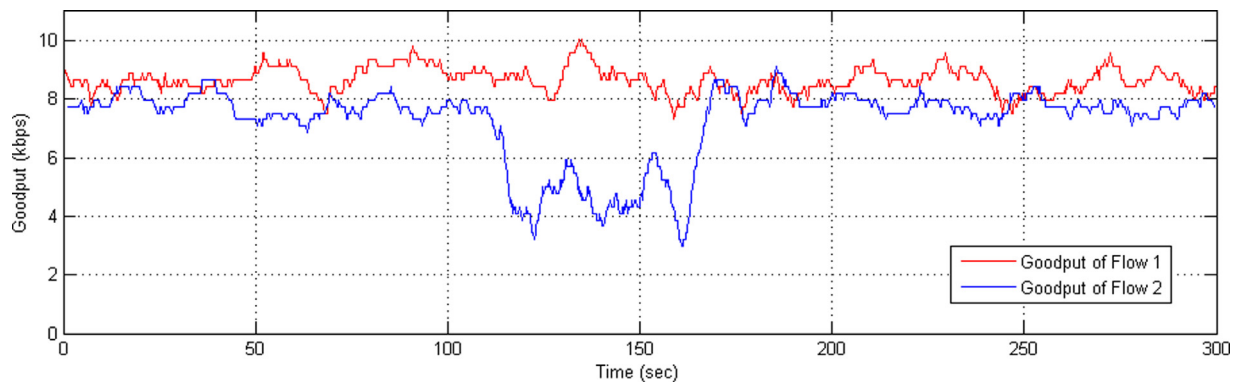
Fig. 6 shows the goodput of two flows for the WiFi mechanism. During the channel fading for Flow 2, the goodput of Flow 2 decreases significantly, and that of Flow 1 also drops at the same time. This is caused by the WiFi MAC blocking problem described

**Table 1**  
Main parameters for experiments.

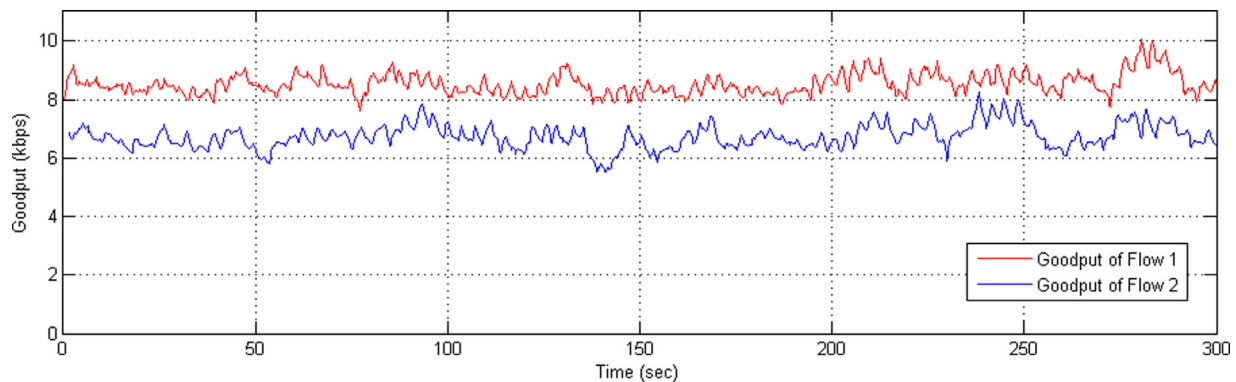
Symbol	$Th$	$Th'$	$T_{bad}$	WiFi channel	Flow 1 Target data rate	Flow 2 Target data rate
Normal scenario	0.75	0.90	30 ms	14	8 kbps	6.4 kbps
Overload scenario	0.75	0.90	30 ms	14	19.2 kbps	16 kbps



**Fig. 6.** Goodput of WiFi in normal scenario for Experiment A.



**Fig. 7.** Goodput of ROSA in normal scenario for Experiment A.



**Fig. 8.** Goodput of ROSA-WOM under maximum fairness in normal scenario for Experiment A.

earlier. The goodput performance for ROSA is shown in Fig. 7. Here, the goodput of Flow 1 is more or less the same and not affected by the channel fading of Flow 2. Figs. 8 and 9 present the goodput of two flows for ROSA-WOM and ROSA-MGCF. We find these two mechanisms can help maintain the goodput for Flows 1 and 2 even when there is a channel fading over the path traversed by.

Next, we analyze the goodput performance as shown in Table 2. The goodput of WiFi fluctuates more severely than the others. During the period without channel fading, the average goodput of Flow 1 for WiFi is 8.68 kbps, and during the fading period it is

6.02 kbps. This implies the blockage of Flow 1 due to the channel fading of Flow 2. However, for ROSA, the average goodput of Flow 1 is 8.66 kbps and not affected by the fading of Flow 2. Flow 1 and total goodput of ROSA fluctuate more lightly than WiFi. ROSA-WOM and ROSA-MGCF present excellent goodputs in the normal scenario, and the goodputs fluctuate less than WiFi and ROSA. ROSA-MGCF yields the least fluctuation among these four mechanisms.

The fairness index directly shows the outcome fairness in goodput among flows. Table 3 presents the fairness index in normal



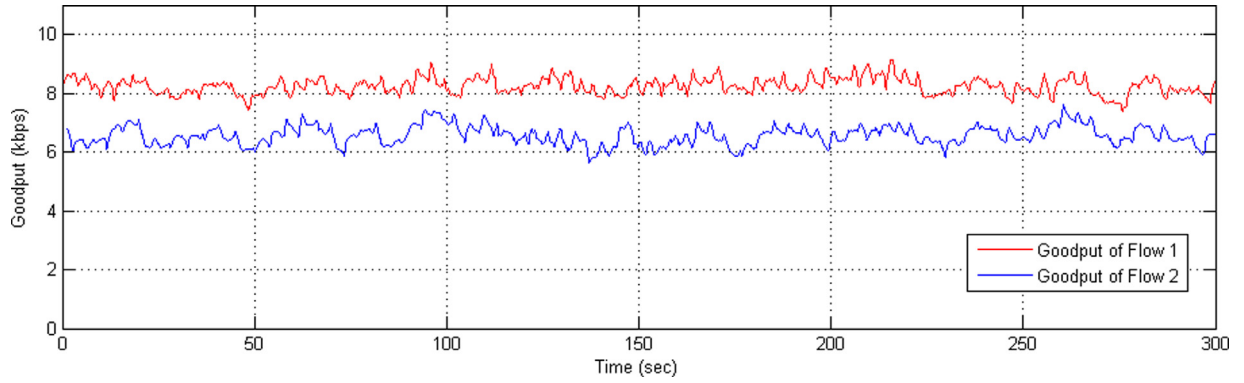


Fig. 9. Goodput of ROSA-MGCF under maximum fairness in normal scenario for Experiment A.

**Table 2**  
Goodput in normal scenario for experiment A.

Case	WiFi (kbps)	ROSA (kbps)	ROSA-WOM (kbps)	ROSA-MGCF (kbps)
No-fading Flow 1	8.68 ± 0.47	8.65 ± 0.41	8.56 ± 0.35	8.22 ± 0.28
Fading Flow 1	6.02 ± 0.74	8.76 ± 0.52	8.34 ± 0.31	8.23 ± 0.23
Total Flow 1	8.38 ± 1.00	8.66 ± 0.43	8.51 ± 0.35	8.23 ± 0.28
No-fading Flow 2	7.00 ± 0.38	7.80 ± 0.37	6.76 ± 0.38	6.58 ± 0.32
Fading Flow 2	4.73 ± 0.58	4.69 ± 0.66	6.35 ± 0.39	6.28 ± 0.27
Total Flow 2	6.57 ± 0.99	7.20 ± 1.32	6.65 ± 0.42	6.52 ± 0.33
Total Flow 1&2	15.13 ± 1.82	15.92 ± 1.31	15.26 ± 0.62	14.80 ± 0.47

**Table 3**  
Fairness index in normal scenario for experiment A.

Case	WiFi	ROSA	ROSA-WOM	ROSA-MGCF
$F_{Index}$	0.999	0.988	0.999	0.999
No-fading $F_{Index}$	0.999	0.995	0.999	0.999
Fading $F_{Index}$	0.999	0.957	0.998	0.998

**Table 4**  
Goodput in overload scenario for experiment A.

Case	WiFi (kbps)	ROSA (kbps)	ROSA-WOM (kbps)	ROSA-MGCF (kbps)
No-fading Flow 1	13.10 ± 0.68	14.77 ± 0.87	13.83 ± 0.79	14.31 ± 0.55
Fading Flow 1	10.66 ± 0.81	13.57 ± 1.13	12.58 ± 1.00	11.52 ± 1.32
Total Flow 1	12.70 ± 1.09	14.52 ± 1.05	13.67 ± 0.93	13.92 ± 1.18
No-fading Flow 2	10.41 ± 0.55	12.14 ± 0.94	12.86 ± 0.66	12.58 ± 0.61
Fading Flow 2	8.27 ± 0.68	7.85 ± 0.76	9.07 ± 0.71	8.66 ± 0.99
Total Flow 2	9.85 ± 1.06	11.24 ± 1.99	11.97 ± 1.70	11.78 ± 1.69
Total Flow 1&2	22.77 ± 1.98	26.06 ± 2.18	26.19 ± 2.18	26.02 ± 2.55

scenario for Experiment A.  $F_{Index}$  presents the total fairness index among Flow 1 and Flow 2, and no-fading  $F_{Index}$  and fading  $F_{Index}$  indicate the fairness indices during the period without channel fading period and with fading period, respectively. From Table 3, WiFi, ROSA-WOM and ROSA-MGCF all present better fairness than ROSA. ROSA also shows inferior fairness during the period without channel fading and fading period than others.

In the normal scenario, ROSA-WOM and ROSA-MGCF can utilize the spare bandwidth to keep the goodput and fairness. In the overload scenario, we still want to keep the outcome fairness even when the sum of all flow data rates is more than the available channel bandwidth.

Table 4 shows the values of goodput in overload scenario for Experiment A. Flow 1, Flow 2 and total goodput of ROSA, ROSA-WOM and ROSA-MGCF are all more than WiFi. Although the sum of target data rates of all flows is 35.2 kbps, for all four cases, total goodput is obviously less than 35.2 kbps.

**Table 5**  
Fairness index in overload scenario for experiment A.

Case	WiFi	ROSA	ROSA-WOM	ROSA-MGCF
$F_{Index}$	0.999	0.992	0.997	0.999
No-fading $F_{Index}$	0.999	0.997	0.998	0.999
Fading $F_{Index}$	0.999	0.974	0.995	0.998

**Table 6**  
Total goodput in overload scenario of ROSA-WOM.

Weight of fairness	0%	20%	40%	60%	80%	100%
Total(kbps)	28.56	28.11	27.56	26.66	26.34	26.19
No-fading(kbps)	28.72	28.63	28.01	27.08	26.52	26.33
Fading(kbps)	26.66	26.12	25.00	24.54	24.27	23.74

Table 5 presents the fairness index in overload scenario for Experiment A. WiFi, ROSA-WOM and ROSA-MGCF all present better fairness than ROSA. ROSA also shows inferior fairness during the period without channel fading and fading period than others. This means that ROSA-WOM and ROSA-MGCF have better fairness property than ROSA.

## 6.2. ROSA-WOM with different weighted coefficient

Considering both fairness and total goodput at the same time, ROSA-WOM configures the data rate with the different weighted objective for the flows. This is evaluated as Experiment B.

According to the results of Experiments A, Table 6 presents the goodput of ROSA-WOM with weighted coefficient of fairness from 0% to 100%. The results show that ROSA-WOM gains more total goodput during the whole period when weight of fairness is less. Table 7 presents the fairness index in Experiment C. ROSA-WOM shows better fairness when the weight of fairness is higher during the whole period.

The total goodput and fairness index vary with the weight of fairness for ROSA-WOM as shown in Fig. 10. When the weight of fairness becomes higher, the fairness index is better. On the other

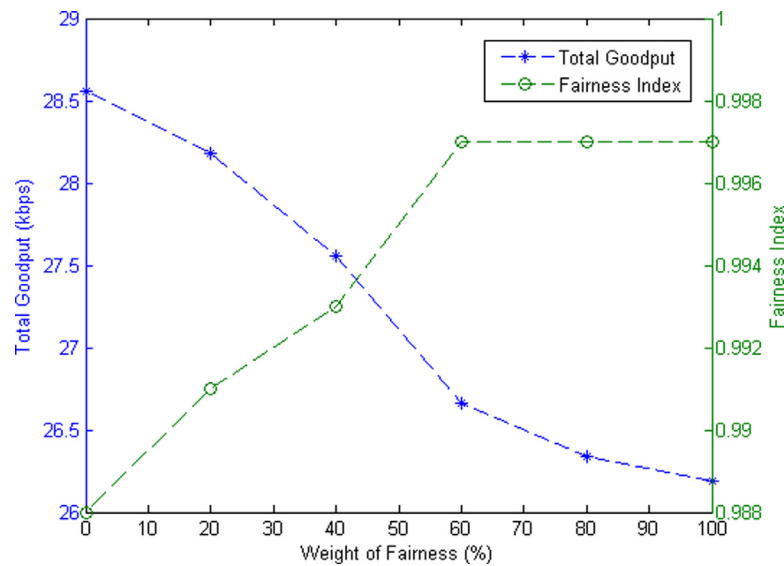


Fig. 10. Goodput and fairness index of ROSA-WOM.

Table 7

Fairness index in overload scenario of ROSA-WOM.

Weight of fairness	0%	20%	40%	60%	80%	100%
$F_{Index}$	0.988	0.991	0.993	0.997	0.997	0.997
No-fading $F_{Index}$	0.993	0.996	0.995	0.998	0.998	0.998
Fading $F_{Index}$	0.961	0.966	0.978	0.993	0.995	0.995

Table 9

Fairness index in overload scenario for experiment C.

Fairness index	0	0.2	0.4	0.6	0.8	1.0
$F_{Index}$	0.986	0.989	0.990	0.989	0.990	0.999
No-fading $F_{Index}$	0.991	0.993	0.995	0.990	0.992	0.999
Fading $F_{Index}$	0.963	0.964	0.964	0.982	0.986	0.998

Table 8

Total goodput in overload scenario for experiment C.

Lower bound of fairness index	0	0.2	0.4	0.6	0.8	1.0
Total(kbps)	28.83	27.98	27.12	26.67	26.33	26.02
No-fading(kbps)	29.34	28.28	27.58	27.16	26.77	26.96
Fading(kbps)	26.54	26.12	24.41	24.30	24.14	20.35

### 6.3. ROSA-MGCF with different lower bounds of fairness index

To optimize the fairness and goodput simultaneously, ROSA-MGCF schedules the flows with maximum total goodput under constrained fairness index. This is evaluated as Experiment C.

According to the results of Experiments A, Table 8 presents the goodput of ROSA-MGCF with lower bound of fairness from 0 to 1.0. The results show that ROSA-MGCF can gain more total goodput when the lower bound of fairness index is smaller. Moreover, goodputs obtained during the period without channel fading and the fading period are similar to the total goodput. Table 9 presents

hand, when the weight of fairness becomes lower, the total goodput gains more. This means ROSA-WOM may control the fairness and total goodput by the weight of fairness.

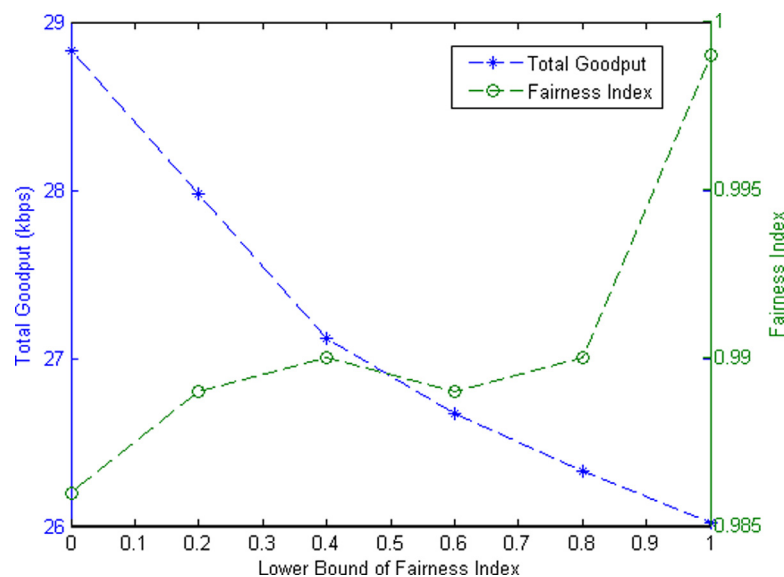


Fig. 11. Goodput and fairness index of ROSA-MGCF.

the fairness index in Experiment C. ROSA-MGCF yields a better fairness when the lower bound of the fairness index is larger during the whole period. The fairness indices during the period without channel fading and the fading period are similar during the whole period.

The total goodput and fairness indices vary with the lower bound of the fairness index for ROSA-MGCF as shown in Fig. 11. When the lower bound of the fairness index becomes bigger, the fairness index in general gets better, and meanwhile, the total goodput gains more. This means ROSA-MGCF may control the fairness and total goodput by the lower bound of fairness index.

## 7. Conclusion

In this paper, we present a proposed framework for distributed opportunistic scheduling in multihop wireless ad hoc networks. First, to obtain an accurate goodput estimate under violent data rate fluctuations, we propose an adaptive sliding window filter for tracking the minimum mean-squared error factor. We then present a novel framework, which includes a wireless link state estimation mechanism, a data rate control scheme considering outcome fairness and total throughput simultaneously, a load control medium access control (MAC) mechanism and an opportunistic bandwidth guaranteed scheduler. To optimize outcome fairness and total throughput at the same time, ROSA-WOM and ROSA-MGCF are thus proposed. A wireless testbed was set up to deploy and to evaluate the performance of the proposed mechanisms. From the experiment results on the testbed, these two mechanisms both solve the MAC layer blocking problem and provide robust service isolation. The results also show ROSA-WOM and ROSA-MGCF can shift smoothly between outcome fairness and high throughput. Under maximum fairness, ROSA-WOM can gain more goodput than ROSA-MGCF in both normal and overload scenarios, and ROSA-MGCF may obtain superior fairness than ROSA-WOM in the overload scenario.

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