Queuing Modeling for Delay Analysis in Many-to-One Wireless Networks under the Protocol Interference Model

Bowu Zhang
Department of Mathematics and Computer Systems
Mercyhurst University
Erie, PA, USA
bowuzh@gwmail.gwu.edu

Wei Cheng
Department of Computer Science
Virginia Commonwealth University
Richmond, VA, USA
wcheng1979@gmail.com

Limin Sun
Institute of Information Engineering
Chinese Academy of Sciences
Beijing, China 100093
sunlimin@iie.ac.cn

Xiuzhen Cheng
Department of Computer Science
The George Washington University
Washington DC, 20052, USA
cheng@gwu.edu

Taieb Znati
Department of Computer Science
University of Pittsburgh
Pittsburgh, PA, USA
znati@cs.pitt.edu

Mznah A. Al-Rodhaan
Abdullah Al-Dhelaan
Information Technology
King Saud University
Riyadh, Saudi Arabia
{rodhaan,dhelaan}@ksu.edu.sa

ABSTRACT

The success and increasing deployment of mission-oriented sensor networks has required sensors to collaboratively accomplish many complex real time tasks. In this paper, we focus on many-to-one mission-oriented sensor networks, where data are collected from multiple resources to one data sink. A critical component in realizing real-time services over such a network is the estimation of end-to-end delay. This problem has been widely investigated for wireless sensor networks under various assumptions such as Poisson packet arrivals or infinite queue length. In this work, we consider a more practical network setting in which the packets need to be forwarded to a data sink along multi-hop communications, the packet arrival rate and service rate are both generally distributed, and the queue length is finite. Our analytical expressions of the G/G/1/K queuing model under the popular protocol interference model when CSMA/CA is adopted for MAC control are carefully derived. An extensive simulation study is carried out and the results indicate that the proposed G/G/1/K queueing model outperforms M/M/1/K and G/G/1 under a high network load while it provides competitive results when the network is lightly loaded.

Categories and Subject Descriptors

C.2.1 [**Computer Communication Networks**]: Network Architecture and Design—*Network communication, Wireless communication, Sensor Networks*

MiSeNet'13, October 4, 2013, Miami, Florida, USA

http://dx.doi.org/10.1145/2509338.2509345 .

Keywords

Mission-oriented wireless sensor networks; End-to-end delay analysis; Queueing theory; Queuing delay; Protocol Interference model

1. INTRODUCTION

The advance of wireless sensor networking has inspired a wide range of mission-oriented sensor network applications in military, civil, scientific, and commercial industries for monitoring and control. This type of applications typically requires sensors to collect data in real time from multiple resources through multi-hop communications along a routing tree rooted at a data sink. A major challenge of such a many-to-one mission-oriented sensor network is to estimate the end-to-end delay, as it may significantly impact on the performance of real-time applications. Additionally, accurate end-to-end delay modeling in wireless sensor networks has long been an area of interest because of its critical role in routing protocol design and QoS provisioning, and its complexity compared to the wired networks due to the continuous wireless channel interferences. Queuing theory has been widely adopted for wireless sensor network delay analysis, assuming that either the packet arrival rate or the service rate or both are Poisson distributed, or the queue length is infinite though the arrival rate and/or service rate is generally distributed [1, 4, 5, 8, 12, 24]. These assumptions, however, are impractical for real-world wireless settings due to the omnipresent interference that may cause congestion at any sensor. The objective of this paper is to relax such assumptions and propose an analytical model for the end-to-end delay in many-to-one mission-oriented sensor networks.

Queueing models such as M/M/1/K and G/G/1 have been commonly employed to investigate end-to-end delay in sensor networks [1, 4, 5, 22], where "M" and "G" represent the Poisson distribution and the General distribution, respectively. A queue is represented as A/B/m/K following Kendall's notation, with "A" and "B" denoting the distributions of the arrival rate and the service rate, respectively, "m" representing the number of servers, and "K" being the queue size. An omitted "K" implies that the queue does not have a finite maximum size. In this paper, we propose a G/G/1/K queueing model to analyze the end-to-end delay of many-to-one wireless sensor networks. We consider wireless interference in addition to the inherent networking constraints for delay analysis. The protocol interference model, in which two sensors interfere with each other when their physical distance is less than a given threshold, is adopted to model the wireless interference ([21, 11, 13]), and the CSMA/CA MAC protocol is employed for the MAC control (similar to [15, 25, 6]). To the best of our knowledge, this is the first work that jointly considers wireless interference and the CSMA/CA MAC protocol for delay analysis with a queuing model having a finite queue size and Generally distributed packet arrive/service rate.

The major contributions of the paper are stated as follows:

- A many-to-one wireless sensor network is modeled as a queueing network, in which each wireless sensor is treated as an independent queue such that all sensors can be analyzed separately [2].
- A G/G/1/K queueing model is proposed and its closed-form expressions under the protocol interference model when the CSMA/CA MAC protocol is adopted are derived.
- An extensive comparison-based simulation study is performed to validate the proposed G/G/1/K queuing model. Our results indicate that the proposed G/G/1/K model outperforms the existing ones when the network is congested, and provides competitive results when the network is lightly loaded.

The rest of the paper is organized as follows: Section 2 summarizes the most related work in end-to-end delay analysis for wireless sensor networks. Our network model and the basic preliminary knowledge on queueing theory are introduced in Section 3. Section 4 details the G/G/1/K queueing model under the protocol interference model and the CSMA/CA MAC protocol. Simulation results are reported in Section 5. Finally, the paper is concluded in Section 6.

2. RELATED WORK

A considerable amount of effort has been made on delay analysis in wireless sensor networks. Generally speaking, one can classify the technical approaches for wireless sensor network delay analysis into two categories: queueing-theory based and non-queueing-theory based.

Queueing theory has been widely adopted for delay analysis in wireless sensor networks [7, 1, 12, 4, 5, 17, 8, 24]. Research by [7] represents one of the early effort in applying queueing theory in network delay analysis, where the authors argue that an M/M/1 queue model is more accurate in real network environments than an M/D/1 model. In [1, 12], the link delay is modeled by a queue with an infinite length, and the end-to-end delay is approximated by multiplying the one-hop delay with the path length. A G/G/1 queueing model is introduced in [1] to evaluate the end-to-end delay of a wireless ad hoc network under a protocol interference model, where the packets are randomly absorbed by any sensor with a fixed probability. This work also assumes that the maximum window size W_{max} is a constant during the backoff stage of the CSMA/CA MAC protocol. In [12], the end-to-end delay is analyzed by employing an M/G/1 queuing model under athe physical interference model, assuming that the CSMA/CA MAC channel state process follows a regenerative stochastic process such that its moments can be utilized to calculate the packet service time. Recently, [4, 5] propose a simple mixed queueing network model of mobility with infinite (./G/∞) queues to predict various performance measures. They model the wireless sensor network as a mixed network of infinite queues, and examine the system performance such as network capacity and average end-to-end delay through the analysis of queueing behaviors. Finite queueing models have been considered by [17, 8, 24]. In [17], the expected end-to-end delay in a 802.11 multihop wireless sensor network is estimated by modeling each sensor as a M/M/1/K queue to derive the service time and combining it with an accurate evaluation of each link's collision probability. In [8], the end-to-end delay of the contention-based enhanced distributed channel access (EDCA) in a non-saturated wireless local area network is considered by modeling each access category as a M/G/1/K queue. In [24], two queueing models of finite buffers are considered in wireless cellular networks, and the end-to-end delay from the joint distribution of Markov arriving process and phase-type serving process are derived.

Non-queueing theory based methods mainly focus on examining the end-to-end delay of different scheduling algorithms. In [15], the relationship between delay and collision probability is studied by modeling the exponential backoff process in the MAC control as a Markov chain. This analysis ignores the queueing delay, making the proposed approach inapplicable for congested networks. Recent works [10, 14, 9, 16] tackling priority-based scheduling mainly report the upper bounds of the end-to-end delay by analyzing the delay at the worst case. In [10], the end-to-end delay bound is derived in single-channel cluster-tree sensor networks with a mobile sink under the time division cluster scheduling. This work models each router in tree networks as a buffered FIFO queue, and provides a deterministic analysis based on the min-plus algebra. The end-to-end delay in a multihop wireless backhaul network is investigated in [14], where links are grouped into two categories and are active at alternate times. It is proved that the proposed odd-even scheduling regime has approximately twice the delay of the corresponding wireline topology, because a wireless link which has the same capacity as in the wireline system is only activated half of the time. The authors in [9] study the upper bound of the end-to-end delay under a rate-based scheduling algorithm in multihop wireless sensor networks by modeling the evolution of the queue length as a Markov Chain. Research by [16] maps the real-time transmission scheduling in WirelessHART networks to real-time multiprocessor scheduling and analyzes the end-to-end delay using the results of the delay analysis for multiprocessor scheduling. However, this work does not consider transmission failures and retransmissions, which can lead to an underestimation of the delay when retransmissions are allowed.

The objective of this work is to better integrate the features of mission-oriented sensor networks for a more accurate delay estimation. We first model the many-to-one wireless sensor network as an open steady queueing network, in which the behavior of each sensor can be examined independently. By assuming that both the service rate and the arrival rate of the queue can be General, which is more practical in wireless sensor networks, a G/G/1/K queueing model is then derived to analyze the delay of each sensor under the protocol interference model when the random Binary Exponential Backoff algorithm is adopted for MAC control. The end-to-end delay is finally calculated by summing the delay of each sensor on the path.

Our work differs from the most related ones mainly in two aspects. (i) We consider a more practical network setting, where the packet arrival rate and departure rate at each network sensor could be General, especially when the network becomes congested. A significant amount of effort is made to derive the analytical expressions for the G/G/1/K queuing model. (ii) We adopt a Binary Exponential Backoff procedure that is close to the one in the 802.11 standard MAC protocol; thus our model can more accurately capture the delay feature of a 802.11 wireless sensor network, which is verified by our simulation study.

3. NETWORK MODEL AND PRELIMINARIES

The problem of real-time data transmission in the context of mission-oriented sensor networks requires accurate end-to-end delay estimation. In this section, we start from the network model and the basic preliminary knowledge on queueing theory for delay analysis in many-to-one mission-oriented sensor networks.

3.1 Network Model and Assumptions

We consider a many-to-one mission-oriented wireless sensor network in which there exist n sensors being connected to a public distributed system (e.g. Internet) via a gateway. Assume that the upstream traffic to the gateway and the downstream traffic from the gateway both employ shortest path routing. Therefore the routing topology is a line or a tree rooted at the gateway. Note that other traffic flow patterns are not considered in this study. Also note that our analysis focuses on the upstream traffic.

Each sensor works as a data source, which generates packets following a Poisson process with the parameter λ_0 (packets per second). Each sensor also works as a relay, which forwards packets for its downstream neighbors. Let λ_i be the *packet arrival rate* at sensor i. Since a packet is either generated locally, or relayed for other sensors, λ_i is the summation of λ_0 and the packet reception rate for packet relaying.

Let K (packets) be the maximum length of the send queue at each sensor. Once a queue is full, newly arriving packets are dropped. The packets in the queue are served based on the FIFO (First In First Out) policy. Since our work focuses on the delay analysis for a network with finite queues, we assume that packet transmission is free of errors to emphasize the impact of packet drops due to congested queues. But our results can be easily generalized to the case when this ideal transmission model is not applicable. Let μ_i be the average packet service rate of sensor i at which a packet is sent out by the MAC layer. It can be seen that the service rate μ_i is determined by the interference experienced at sensor i and the MAC protocol. Let T_{s_i} be the average service time of a packet at sensor i, we have

$$\mu_i = \frac{1}{T_{s_i}} \tag{1}$$

T_{s_i} is affected by the experienced interference at sensor i and the underlying MAC protocol. For simplicity, we adopt the protocol interference model and the popular CSMA/CA MAC protocol in this study. On the other hand, since the queuing behavior of each sensor characterizes its transmission behavior, it is reasonable to model a sensor by a queue. As a result, the network becomes a *queuing network*, with each sensor being modeled by a single-server finite FIFO queue.

An example linear network together with its queuing network representation is illustrated in Figure 1. For the first sensor, $\lambda_1 = \lambda_0$. All its packets are transmitted to sensor 2 at the service rate μ_1. Since we assume that no random error is introduced during the transmissions, sensor 2 receives the packets from sensor 1 at the rate μ_1. Then, we have $\lambda_2 = \mu_1(1 - \pi_{0_1}) + \lambda_0$, where π_{0_1} is the probability at which sensor 1 has an empty queue. Similarly, we obtain

$$\lambda_i = \lambda_0 + \mu_{i-1}(1 - \pi_{0_{i-1}}) \tag{2}$$

where $i = 1, 2, \cdots, n$, $\mu_0 = 0$, and $\pi_{0_{i-1}}$ is the probability at which the sensor $i-1$ has an empty queue.

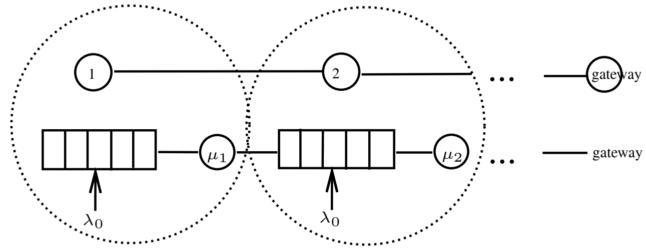

Figure 1: An example linear queuing network model.

Table 1: Notations and Semantic Meanings of the Parameters Characterizing a Queue.

Name	Definition
λ_0	The packet generation rate
λ_i	The arrival rate of sensor i
μ_i	The service rate of sensor i
K	The finite queue length
π_k	The probability of k packets existing in the queue
$\overline{L}$	The expected queue length
$\overline{D_s}$	The expected time a packet resides in a queue
T_{s_i}	The average service time of a packet at sensor i
C_A^2	The squared coefficients of the variances of the inter-arrival time
C_B^2	The squared coefficients of the variances of the packet service time

For a tree queuing network with n sensors, let C_i be the set of child sensors of sensor i. Then, we have

$$\lambda_i = (\lambda_0 + \sum_{j \in C_i} \mu_j (1 - \pi_{0_j})) \tag{3}$$

where $i = 1, 2, \cdots, n$.

Note that both the linear and the tree queueing networks under our consideration are stable since we assume that the queue length is finite. According to queueing theory, each sensor in a stable queuing network can be examined in isolation from the rest of the network [2]. In other words, we can partition the network into separated sensors, and consider each sensor independently as long as the network is stable. According to this principle, we present the delay representations in the next subsection.

3.2 Queuing Delay Representations

In our network model presented in section 3.1, each sensor is modeled by a FIFO queue. The most significant parameters characterizing a queue are defined in Table 1. Based on queuing theory [2], the expected time a packet resides in the queue i, denoted by $\overline{D_{s_i}}$, can be computed by

$$\overline{D_{s_i}} = \frac{\overline{L_i}}{\lambda_i (1 - \pi_{K_i})} \tag{4}$$

where $\overline{L_i}$ and π_{K_i} are the expected queue length and the packet blocking probability, respectively.

For a linear network with n sensors sequentially numbed from 1 to n and the nth sensor connected to the gateway, the end-to-end delay DL_{linear} is the summation of the system delays of all queues along the line. Thus we have

$$DL_{linear} = \sum_{i=1}^{n} E[D_s] = \sum_{i=1}^{n} \overline{D_{s_i}} \tag{5}$$

where $\overline{D_{s_i}}$ is calculated according to (4).

The end-to-end delay DL_{tree} of a tree network is defined to be the delay experienced by the longest path to the gateway in the tree.

3.3 Queuing Models

In this subsection, we discuss possible queuing models that can be employed to represent the queues in our study.

As mentioned in Section 3.1, a sensor's packet arrival rate λ_i is a linear combination of the sensor's local packet generation rate λ_0 and the packet service rates of the downstream sensors. These two components come from independent random processes. Therefore, the packet arrival rate should follow the same distribution as that of the packet service rate when λ_0 is sufficiently small, which is the case under our consideration.

When the collision probability is low, a packet would be processed and transmitted as soon as it arrives at the sensor. If the packet generation is a Poisson process, the packet service rate of the first sensor along any path would also follow a Poisson distribution. Consequently, the packet arrival rate of the next sensor would follow a Poisson distribution. The same inference can be applied to other sensors along the paths to the gateway. Thus a M/M/1/K model can be applied in such a case. On the other hand, when the packet collision probability is high, the packets would be stalled at a sensor for various length of time dependent on the traffic conditions. Thus neither the packet arrival rate nor the package generation rate follows a Poisson process, even though λ_0 is Poisson distributed. Therefore a General distribution is adopted and a G/G/1/K queueing model is employed. General distributions are wildly used in queueing systems to represent the rate distribution [1], which can be achieved by merging several statistical distributions [18].

4. QUEUING MODELING UNDER THE PROTOCOL INTERFERENCE MODEL AND THE CSMA/CA MAC PROTOCOL

In this section, we first present the well-known results in G/G/1 and M/M/1/K models [2], based on which we propose a novel G/G/1/K queuing model. Next, we jointly consider the protocol interference model and the CSMA/CA MAC protocol and derive the model parameters for the G/G/1/K queue in Section 4.4. Note that in this section we consider the queuing behavior of a general sensor in the network and therefore all subscripts i are excluded in our notations.

4.1 G/G/1 queue

The well-known results on the G/G/1 queue with no restrictions on the queue size are approximated by the Allen Cunneen formula [2], which is based on the embedded Markov model. The approximate expression for the probability that there are k packets in a G/G/1 queue is given by:

$$\pi'_k = \begin{cases} 1-\rho, & k=0 \\ \frac{\rho}{1-\rho}(1-\sigma)\sigma^{k-1}\pi'_0, & k>0 \end{cases} \tag{6}$$

where

$$\sigma = \exp(-\frac{2(1-\rho)}{\rho c_A^2 + c_B^2}) \tag{7}$$

and c_A^2, c_B^2 are the squared coefficients of the variances of the inter-arrival time and the service time, respectively.

The expected number of packets for a G/G/1 queue is given as follows:

$$\overline{L} \approx \frac{\rho^2}{1-\rho} \times \frac{c_A^2 + c_B^2}{2} \tag{8}$$

4.2 M/M/1/K queue

The M/M/1/K queue has been studied in [2], which derives the following equations for the state variables π_k and the expected queue length $\overline{L}$:

$$\pi_k = \begin{cases} \frac{(1-\rho)\rho^k}{1-\rho^{K+1}}, & o \le k \le K \\ 0, & k > K \end{cases} \tag{9}$$

where ρ denotes the *traffic density*, which is defined to be the ratio of the packet arrival rate λ and the service rate μ. That is,

$$\rho = \lambda/\mu \tag{10}$$

The expected number of packets for a M/M/1/K queue is given by:

$$\overline{L} = \begin{cases} \frac{\rho}{1-\rho} - \frac{K+1}{1-\rho^{K+1}} \times \rho^{K+1}, & \rho \ne 1 \\ \frac{K}{2}, & \rho = 1 \end{cases} \tag{11}$$

4.3 G/G/1/K queue

To our best knowledge, there is no analytical results for the G/G/1/K queue. In this subsection, we derive the approximate equations of the state variables of G/G/1/K based on the existent results of G/G/1, which is summarized by the following two theorems.

THEOREM 4.1. *In a G/G/1/K queue, the probability that there are k packets in the queue is:*

$$\pi_k = \begin{cases} \frac{1-\rho}{1-\rho+\rho\times(1-\sigma^K)}, & k=0 \\ \pi_k = \frac{\rho(1-\sigma)\sigma^{k-1}}{1-\rho+\rho\times(1-\sigma^K)}, & 0<k\le K \end{cases} \tag{12}$$

PROOF. Let $A(t)$ and $B(t)$ be the distributions of the packet inter-arrival time and the service time, respectively. Denote by $a_k = P(Y=k)$ the probability of k arrivals during a service time interval T_s. According to [2], a G/G/1 queue is approximated by an embedded Discrete-Time Markov Chain (DTMC) $X = \{X(t)|X(t) \in \{0,1,\cdots,\}\}$, where t represents the tth service time interval and $X(t)$ is the state at interval t. Then the transition matrix of a G/G/1 queue can be represented by:

$$P' = \begin{pmatrix} a_0 & a_1 & a_2 & \dots \\ a_0 & a_1 & a_2 & \dots \\ 0 & a_0 & a_1 & \dots \\ 0 & 0 & a_0 & \dots \\ \vdots & \vdots & \vdots & \vdots \end{pmatrix} \tag{13}$$

where an entry p'_{ij} in P' represents the transition probability from state i to state j. The global balance equations of G/G/1 queue are represented by

$$\pi'_k = \pi'_0 a_k + \sum_{i=1}^{k+1} \pi'_i a_{k-i+1}, k \ge 0 \tag{14}$$

For G/G/1/K, we still employ the Markov birth-death process for approximation, though neither G/G/1 nor G/G/1/K is a Markovian queue. Then the inter-arrival and service behaviors of a G/G/1/K queue is modeled by an embedded DTMC $X = \{X(t)|X(t) \in$

$\{0, 1, \cdots, K\}\}$. Let the random variable Y describe the number of arrivals during a service time interval. Then:

$$X(t+1) = \begin{cases} X(t) + Y - 1, & X(t) > 0 \\ Y, & X(t) = 0 \end{cases} \quad (15)$$

Accordingly, the transition probabilities of G/G/1/K are given by:

$$P[X(t+1) = j | X(t) = i] = \begin{cases} a_{j-i+1}, & i > 0, j \geq i-1 \\ a_j, & i = 0, j \geq 0 \end{cases} \quad (16)$$

Then the transition probability matrix P is represented by:

$$P = \begin{pmatrix} a_0 & a_1 & a_2 & \dots & 1 - \sum_{i=0}^{K-1} a_i \\ a_0 & a_1 & a_2 & \dots & 1 - \sum_{i=0}^{K-1} a_i \\ 0 & a_0 & a_1 & \dots & 1 - \sum_{i=0}^{K-2} a_i \\ 0 & 0 & a_0 & \dots & 1 - \sum_{i=0}^{K-3} a_i \\ \vdots & \vdots & \vdots & \vdots & \\ 0 & 0 & 0 & \dots & 1 - a_0 \end{pmatrix} \quad (17)$$

Note that P can be easily created if the distributions of the packet inter-arrival time $A(t)$ and service time $B(t)$ are known.

Based on the transition matrix, we obtain the global balance equations for G/G/1/K according to the embedded DTMC:

$$\pi_k = \pi_0 a_k + \sum_{i=1}^{k+1} \pi_i a_{k-i+1}, k = 0, 1, 2, \dots, K-1 \quad (18)$$

$$\pi_k = 1 - \sum_{i=0}^{K-1} \pi_i, k = K \quad (19)$$

Observe that (14) for G/G/1 is identical to (18) for G/G/1/K when $k = 0, 1, \cdots, K-1$. Then π_k and π'_k must be proportional for $i \leq K-1$, i.e., $\pi_k = C\pi'_k$. Since $\sum_{i=0}^{K} \pi_i = 1$, we have $C = 1/\sum_{i=0}^{K} \pi'_i$. Therefore

$$\pi_k = \begin{cases} \frac{1-\rho}{1-\rho+\rho\times(1-\sigma^K)}, & k = 0 \\ \frac{\rho(1-\sigma)\sigma^{k-1}}{1-\rho+\rho\times(1-\sigma^K)}, & 0 < k \leq K \end{cases} \quad (20)$$

□

Since the expected number of packets in the queue can be computed by

$$\overline{L} = \sum_{k=0}^{K} k \times \pi_k \quad (21)$$

$\overline{L}$ for G/G/1/K can be derived by (22).

THEOREM 4.2. *The expected number of packets in a G/G/1/K queue is:*

$$\overline{L} \approx \begin{cases} \frac{\rho\times(1-\sigma^K-(1-\sigma)\times K\sigma^K)}{(1-\rho+\rho\times(1-\sigma^K))\times(1-\sigma)} \times \sigma^K, & \rho \neq 1 \\ K/2, & \rho = 1 \end{cases} \quad (22)$$

4.4 Parameter Derivation under CSMA/CA

From (20) and (22), we notice that the state variables of G/G/1/K are functions of ρ and σ, which are defined by λ and μ, and C_A^2 and C_B^2, respectively. In this subsection, we derive these parameters under the CSMA/CA MAC protocol. For simplicity we adopt a simple random exponential backoff procedure, which is described in Section 4.4.1. A similar backoff procedure is also employed by the mainstream research on throughput and delay analysis such as in [3]. The average service time is investigated in Section 4.4.2. The squared coefficients of the variances of the packet service time and the inter-arrival time, i.e., C_B^2 and C_A^2, are derived in Sections 4.4.3 and 4.4.4, respectively.

4.4.1 *The Backoff Procedure and the Collision Probability*

The CSMA/CA MAC protocol under our consideration adopts a simple exponential random backoff algorithm to schedule the transmissions with collisions. Let TX_{max} be the maximum allowable number of transmissions (the initial transmission plus $TX_{max} - 1$ retransmissions) for any packet, and CW_{min} be the minimum contention window size. We denote the backoff window size for the ith transmission by W_i, where $W_i = 2^{i-1} \times CW_{min}$, and $i = 1, \cdots, TX_{max}$.

For simplicity, we assume that time is divided into fixed-length slots. At the beginning of the ith transmission, a sensor randomly selects a value B_i from $[0, W_i - 1]$ as the initial value of its backoff timer. In a time slot, the timer is decreased by one if the channel is idle; otherwise the timer is frozen. A sensor can try to transmit the packet at the next time slot after its timer reaches zero. This backoff procedure is illustrated in Figure 2.

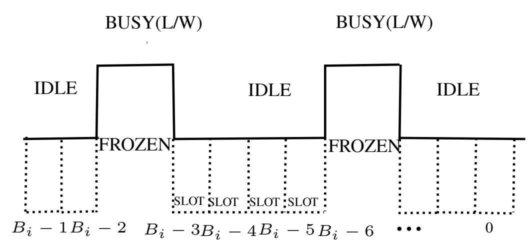

Figure 2: The backoff procedure of the i_{th} transmission.

Let P_c be the collision probability when all the sensors are greedy [20], which means that they always have packets to transmit. The overall expected backoff window size $\overline{W}$ can be derived as follows:

$$\begin{aligned} \overline{W} &= \eta \times [\frac{W_1 - 1}{2} + P_c(\frac{W_2 - 1}{2}) + P_c^2(\frac{W_3 - 1}{2}) \\ &\quad + \cdots + P_c^{TX_{max}-1}(\frac{W_{TX_{max}} - 1}{2})] \end{aligned}$$

where $\eta = \frac{1-P_c}{1-P_c^{TX_{max}}}$ is the normalization term to make sure that the sum of the probabilities of all the backoff stages is 1. Since $W_i = 2^{i-1} \times CW_{min}$, we obtain

$$\overline{W} = \frac{CW_{min}[1 - (2P_c)^{TX_{max}}](1 - P_c)}{2(1 - 2P_c)(1 - P_c^{TX_{max}})} - \frac{1}{2} \quad (23)$$

Given $\overline{W}$, P_c can be presented by

$$P_c = 1 - (1 - \frac{1}{\overline{W}})^n \quad (24)$$

where n is the number of interfering sensors based on the underlying interference model.

Let P_{idle} be the probability with which the channel is idle in a time slot. Then we have

$$P_{idle} = (1 - \frac{1}{\overline{W}})^{n+1} \quad (25)$$

Note that (23) is an approximation of the real $\overline{W}$ because it is based on the following two assumptions: (i) TX_{max} is the maximum number of transmissions for any packet. (ii) P_c is derived when the network is saturated.

4.4.2 The Service Time

According to CSMA/CA, the service time T_s consists of two components: (i) the time consumed in the backoff stage, denoted by T_b; and (ii) the transmission delay T_{tr}.

$$T_s = T_{tr} + T_b \tag{26}$$

Given the packet length L and the transmission rate R, we have $T_{tr} = L/R + T_o$, where T_o is the overhead time incurred for a successful transmission (e.g., DIFS).

We adopt the backoff procedure described in subsection 4.4.1. Let T_i be the time consumed by the ith transmission in the ith backoff stage, and B_i be the corresponding initial backoff timer value, where $i = 1, \cdots, TX_{max}$. Let D_j be the time between the j_{th} and $(j+1)_{th}$ timer decrement, where $j = 0, 1, \cdots, B_i - 1$. We have

$$E[D_j] = \delta + T_{tr} \times (1 - P_{idle}) \tag{27}$$

where δ is the slot duration time, and P_{idle} is the channel idle probability as defined in subsection 4.4.1. Denote by $\overline{D} = E[D_j]$ the expected time between two adjacent decrements. Since B_i is a discrete random variable uniformly distributed in $[0, 2^{i-1} \times CW_{min} - 1]$, we have

$$P(B_i = b) = \frac{1}{2^{i-1}CW_{min} - 1} \tag{28}$$

where $b \in [0, 2^{i-1} \times CW_{min} - 1]$. Then, the expected time consumed by the ith transmission can be depicted as:

$$\begin{aligned} E[T_i] &= E[E[\sum_{j=0}^{B_i-1} D_j | B_i = b]] \\ &= 2^{i-2}CW_{min} \times \overline{D} \end{aligned} \tag{29}$$

Let TX be a random variable denoting the total number of transmissions. We have

$$P(TX = t) = (1 - Pc) \times P_c^{t-1} \tag{30}$$

where $t = 1, 2, \cdots, TX_{max}$. Then, the expected number of transmissions can be computed by

$$\begin{aligned} E[TX] &= \sum_{t=1}^{TX_{max}} t \times P(TX = t) \\ &= \frac{1 - P_c^{TX_{max}}}{1 - P_c} - TX_{max}P_c^{TX_{max}} \end{aligned} \tag{31}$$

Consequently, we obtain the expected time spent in the whole backoff process, denoted by $E[T_b]$, as follows:

$$\begin{aligned} E[T_b] &= \frac{CW_{min}\overline{D}(1 - P_c)}{2} \times \\ &\quad (1 + \frac{4P_c(1 - (2P_c)^{TX_{max}-1})}{1 - 2P_c} \\ &\quad - \frac{P_c(1 - P_c^{TX_{max}-1})}{1 - P_c}) \end{aligned} \tag{32}$$

Then, the mean of the service time $E[T_s]$ is presented by

$$E[T_s] = T_{tr} + E[T_b] \tag{33}$$

Accordingly, we obtain the mean service rate μ:

$$\mu = 1/E[T_s] \tag{34}$$

4.4.3 The Derivation of C_B^2

According to the definition,

$$C_B^2 = (E[T_s^2] - E[T_s]^2)/E[T_s]^2 \tag{35}$$

The mean service time $E[T_s]$ has been derived in (33). According to (26), we obtain

$$\begin{aligned} E[T_s^2] &= E[(T_{tr} + T_b)^2] \\ &= T_{tr}^2 + 2T_{tr}E[T_b] + E[T_b^2] \end{aligned} \tag{36}$$

$E[T_b]$ has been derived in (32). Thus we have

$$\begin{aligned} E[T_b^2] &= \sum_{t=1}^{TX_{max}} P(TX = t) \\ &\quad \times (\sum_{i=1}^{t} E[T_i^2] + \sum_{i,j=1,i\neq j}^{t} E[T_i]E[T_j]) \end{aligned} \tag{37}$$

The last equality holds because, when $TX = t$ is given, T_i and T_j are independent of each other as B_i and B_j are randomly and independently selected from the backoff windows at the ith and jth backoff stages, respectively. Since $T_i = \sum_{j=0}^{B_i-1} D_j$, where D_j is the time consumed between the jth and $(j+1)$th timer decrement, we have

$$\begin{aligned} E[T_i^2] &= E[E[\sum_{j=0}^{B_i-1} D_j^2 | B_i = b]] \\ &+ E[E[\sum_{k,j=0,k\neq j}^{B_i-1} D_k D_j | B_i = b]] \end{aligned} \tag{38}$$

As D_j and D_k are independent of each other, we obtain

$$\begin{aligned} E[\sum_{k,j=0,k\neq j}^{B_i-1} D_k D_j | B_i = b] &= \sum_{k,j=0,k\neq j}^{b-1} E[D_k]E[D_j] \\ &= b(b-1)\overline{D}^2 \end{aligned} \tag{39}$$

According to (27), D_j follows a Bernoulli distribution. Therefore

$$E[D_j^2] = \delta^2 P_{idle} + T_{tr}^2(1 - P_{idle}) \tag{40}$$

Note that $E[D_j^2]$ is a constant for all j. Thus, we can denote $\overline{D^2} = E[D_j^2]$ and get $E[\sum_{j=0}^{B_i-1} D_j^2 | B_i = b] = b \times \overline{D^2}$.

Based on (28), (39), and (40), we obtain

$$\begin{aligned} E[T_i^2] &= 2^{i-2}CW_{min}(\overline{D^2} - \overline{D}^2) \\ &\quad + \frac{\overline{D}^2}{2^{i-1}CW_{min} - 1} \sum_{b=0}^{2^{i-1}CW_{min}-1} b^2 \end{aligned} \tag{41}$$

4.4.4 The Derivation of C_A^2

In this subsection, we study a linear queuing network first. Let T_{linear_i} be the expected packet arrival time following the General distribution. According to the definition of $C_{A_i}^2$,

$$C_{A_i}^2 = (E[T_{linear_i}^2] - E[T_{linear_i}]^2)/E[T_{linear_i}]^2 \tag{42}$$

T_{linear_i} can be presented as follows,

$$T_{linear_i} = \begin{cases} \frac{1}{\frac{1-\pi_{0_{i-1}}}{T_{s_{i-1}}} + \frac{1}{T_{\lambda_0}}}, & \text{Queue lengh } < K \\ T_{s_i}, & \text{Queue lengh } = K \end{cases} \tag{43}$$

where $T_{s_{i-1}}$ and T_{s_i} are the service times of the $(i-1)$th and ith sensor, respectively, and T_{λ_0} is the average packet inter-generation time at the ith sensor.

The means and second moments of $T_{s_{i-1}}$ and T_{s_i} have been derived in Section 4.4.3. The mean and second moment of T_{λ_0} can be obtained since it follows a Poisson distribution. According to (43) and by employing the bivariate Taylor series expansion at the mean, we can derive the estimations of the mean and the second moment of T_{linear_i}.

This philosophy can also be applied to the tree network. Let C_i be the set of child sensors of i. Then

$$T_{tree_i} = \begin{cases} \dfrac{1}{\sum_{j \in C_i} \frac{\frac{1}{1-\pi_{0_j}}}{T_{s_j}} + \frac{1}{T_{\lambda_0}}}, & \text{Queue lengh } < K \\ T_{s_i}, & \text{Queue lengh } = K \end{cases} \quad (44)$$

Based on multivariate Taylor expansion, we can derive the estimations of the mean and the second moment of T_{tree_i} accordingly. Then, $C^2_{A_i}$ for a sensor in a tree network can be derived as follows:

$$C^2_{A_i} = (E[T^2_{tree_i}] - E[T_{tree_i}]^2)/E[T_{tree_i}]^2 \quad (45)$$

5. SIMULATION STUDY

In this section, we validate the proposed G/G/1/K model under various network settings and compare its performance with those of M/M/1/K and G/G/1 in many-to-one wireless sensor networks. The simulation results are obtained through Qualnet 5.0.2, and the numerical results are computed via MATLAB R2009a.

5.1 Simulation Set-up

The performance of the proposed G/G/1/K model is evaluated for both linear and tree networks. For the linear network scenario, $N \in \{10, 50, 100, 200, 400\}$ sensors are deployed in a line, with the distance between any two sensors being fixed to $100m$. In tree networks, 100 sensors are randomly deployed in a $1000 \times 1000m^2$ area. Two sensors can mutually communicate with each other when their distance is less than $150m$. A shortest path tree rooted at the gateway (also known as the root) is adopted as the routing tree. The gateway is placed in the center of the network area. For both types of networks, packets are generated by each sensor following a Poisson process with an arrival rate λ_0 varying from 0.1 to 1.5 packets per second. All the packets are routed to one endpoint in the linear network and to the gateway in the tree network.

The simulation settings are summarized as follows. According to the Qualnet settings adopted by [23] and [19], we set the queue size $K = 30$ packets, the time slot duration $\delta = 9\mu s$, $SIFS = 16\mu s$, $DIFS = 34\mu s$, the packet size $L = 1K$ bits, the transmission rate $R = 2Mbps$, and the sensor's transmission range $TR = 150m$. Based on the IEEE 802.11 standard, the interference range is usually about twice of the transmission range. Thus, the interference range IR is selected from $\{200m, 300m, 400m\}$. The generated traffic can be UDP or TCP, and the employed MAC protocol is CSMA/CA. The simulation time is fixed to 1000 seconds. Each result is an average of the corresponding measurements in 50 runs.

The network delay is the summation of the delays experienced by all the sensors along the longest routing path. In other words, it is the sum of the delays of all the sensors in a linear network, or the sum of the delays of all the sensors along the longest path from the leaf sensor to the root in a tree network. In our numerical analysis, the delay and other queuing parameters are computed based on the derivations provided in Section 4.4.

5.2 The Performance of the G/G/1/K Queueing Model

The end-to-end delay of UDP traffic in a linear network *vs.* the network size is reported in Figure 3. The number of sensors varies from 10 to 400, the interference range is fixed to $300m$, and the packet generation rate λ_0 is chosen from $\{0.3, 0.7, 1.0\}$.

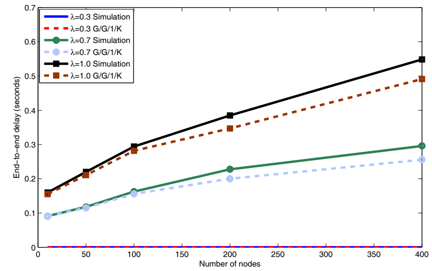

Figure 3: The delay of UDP traffic $vs.$ the network size in linear networks, with $IR = 300m$ and $\lambda \in \{0.3, 0.7, 1\}$.

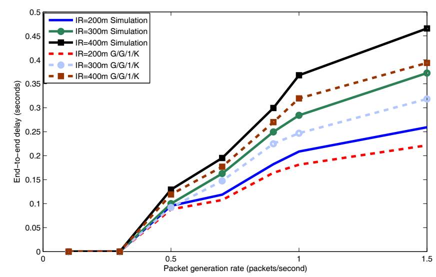

Figure 4: The delay of UDP traffic $vs.$ the packet generation rate λ_0 in linear networks, with $IR \in \{200m, 300m, 400m\}$, and the network size being fixed to 100 sensors.

From Figure 3, we obtain the following observations:

1. The network delay increases with the increase of the network size.
2. The network delay increases with the increase of λ_0.
3. The difference between the simulation results and the G/G/1/K numerical results (computed from Eq. (5)) slightly increases as the network size or λ_0 increases.
4. When λ_0 is small ($\lambda = 0.3$), the end-to-end delay is negligible.

The first observation indicates that a larger linear network has a larger aggregated delay; therefore it is more likely to have congested sensors. The second observation can be trivially justified as follows: since each sensor has a higher packet generation rate, the network becomes more congested and therefore its delay increases. The third observation indicates that it is more difficult to model its delay when the network becomes congested; as a result, larger accumulated errors in delay modeling can be expected. The last observation indicates that when the packet generation rate is low, the network has a light load, yielding a short end-to-end delay resulted from the packet transmission time (no queuing delay); while when the network load is high, the queuing delay plays a dominate role, producing a non-negligible end-to-end delay that is significantly affected by the MAC coordination.

The end-to-end delay of UDP traffic in a linear network *vs.* the packet generation rate λ_0 is reported in Figure 4. For this scenario, the network size is fixed to 100 sensors, and the interference range varies among $\{200m, 300m, 400m\}$.

Figure 4 exhibits the following observations, with three of them (1, 2, and 4) consistent with those in Figure 3:

1. The delay increases with the increase of the packet generation rate λ_0.
2. The delay increases with the increase of the interference range IR.
3. The difference between the simulation results and the G/G/1/K numerical results (computed from Eq. (5)) grows with the packet generation rate λ_0 and the interference range IR.
4. When λ_0 is small (≤ 0.3), the end-to-end delay is negligible.

The similar observations as those in Figure 3 will not be further discussed here. The new observation (the third one) in Figure 4 indicates that the network delay increases with the increase of the interference range as the network becomes more congested when more sensors interfere each other.

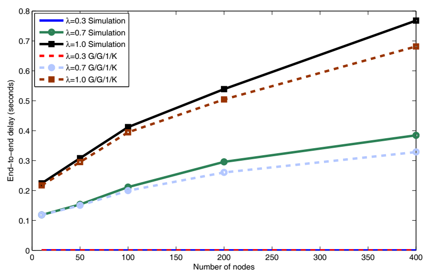

Figure 5: The delay of TCP traffic $vs.$ the network size in linear networks, with $IR = 300m$ and $\lambda \in \{0.3, 0.7, 1.0\}$.

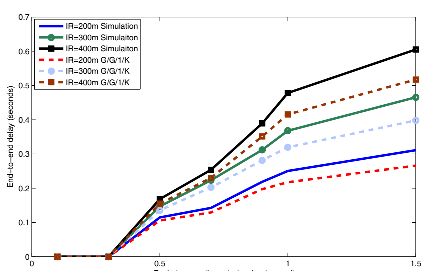

Figure 6: The delay of TCP traffic $vs.$ the packet generation rate in linear networks, with $IR \in \{200m, 300m, 400m\}$ and the network size being fixed to 100 sensors.

We also carry out a similar study on the delay of TCP traffic in linear networks under the same sets of parameter settings and report the results in Figure 5 and Figure 6. Notice that the performance of TCP traffic is similar to that of UDP traffic, except that in general TCP traffic suffers a longer delay because of its connection-oriented retransmission scheme, which may make the congestion even worse. However, our G/G/1/K model provides quite close estimations under various settings for TCP traffic, though its accuracy decreases as the network congestion increases.

The performance of our G/G/1/K model in the tree network is reported in Figures 7 and 8. The interference range varies among $\{200m, 300m, 400m\}$. The average length of the longest path for

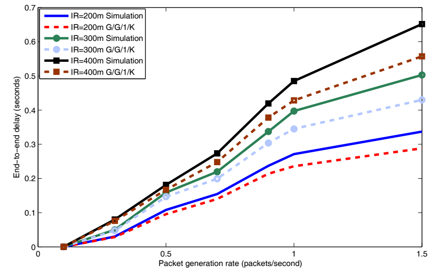

Figure 7: The delay of UDP traffic $vs.$ packet generation rate in the tree network, with $IR \in \{200m, 300m, 400m\}$ and the network size being fixed to 100 sensors.

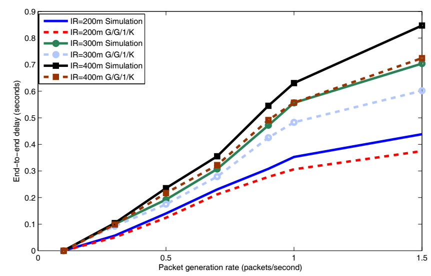

Figure 8: The delay of TCP traffic $vs.$ packet generation rate in the tree network, with $IR \in \{200m, 300m, 400m\}$ and the network size being fixed to 100 sensors.

the 50 random topologies is about 10.94 hops. Comparing to the results shown in Figures 4 and 6, we observe that the end-to-end network delay in the tree network is larger than that in the linear network for the same interference range and even shorter path length. This is reasonable as a non-leaf sensor in the tree network usually has more neighbors than an intermediate sensor in the linear network; thus experiencing more interference and yielding a longer delay. However, the performance of the G/G/1/K model has been shown to be consistent with that in the linear network.

5.3 Comparison Study

We compare the performance of three queuing models: G/G/1/K, M/M/1/K, and G/G/1, in terms of end-to-end delay under different packet generation rates and different network sizes.

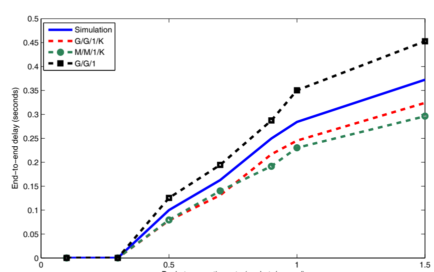

Figure 9: The delay of UDP traffic $vs.$ packet generation rate in a linear network, with $IR = 300m$ and the network size being fixed to 100 sensors.

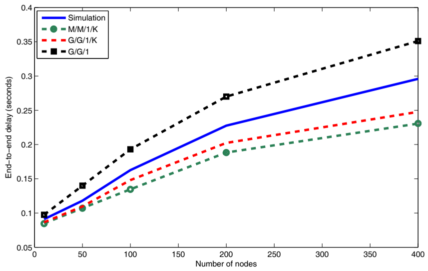

Figure 10: The delay of UDP traffic $vs.$ network size in linear networks, with $IR = 300m$ and the packet generation rate being fixe to 0.7.

The estimated delays of these three models for UDP traffic in linear networks under different packet generation rates are reported in Figure 9. The network size is fixed to 100 sensors and the interference range is set to $300m$. From Figure 9, we observe that our G/G/1/K model provides the best delay estimation compared to the simulation study when λ_0 is high. When the packet generation rate is low (less than 0.7 packets/second), the M/M/1/K model gives the closest estimation and the G/G/1/K model provides competitive results. This observation is reasonable as the service rate is more likely to follow the packet generation distribution (Poisson distribution) when the packet collision probability is small, while it is more likely to follow a General distribution in the case of long queueing delays, as elaborated in Section 3.3. Note that the delay estimation accuracy of G/G/1/K decreases as λ increases. This is because in the G/G/1/K model, a queue of length K indicates that when there are K packets in the queue waiting for their chances of transmissions, the packets arriving after the K_{th} one are dropped. Thus the π_K in the G/G/1/K model should include the possibilities that a queue would have grown to the lengths of $K+1, K+2, \cdots$, but has packets dropped due to limited capacity. In our G/G/1/K model, we "borrow" those possibilities and distribute the sum of them to every $\pi_k, k \in 0, 1, \ldots, K$ proportionally (see the proof of theorem 4.1), which serves as an approximation of the real probability distribution, leading to a difference between simulation and numerical results.

Figure 10 reports the performance of the three models in linear networks when the network size varies. The packet generation rate $\lambda_0 = 0.7$ and the interference range is $300m$. It is obvious that under a heavy network load, the G/G/1/K model outperforms the other two models for delay estimation.

The performances of the three models for TCP traffic in linear networks, and those of both UDP and TCP traffic in the 100-sensor tree network, are very similar, which will not be reported to avoid redundancy.

In summary, the G/G/1/K model proposed in this paper outperforms M/M/1/K and G/G/1 for end-to-end delay estimation when the network load is heavy, and provides competitive results in lightly-loaded linear/tree networks. Moreover, compared to the simulation study, the G/G/1/K model and the M/M/1/K model both underestimate the network congestion while G/G/1 results in an overestimation in congested networks as it keeps all incoming packets in the queue.

6. CONCLUSION AND FUTURE RESEARCH

End-to-end delay estimation is an important step towards enabling real-time applications over mission-oriented sensor networks. In this paper, we investigate the end-to-end delay problem in a many-to-one wireless sensor network and outline its challenges. The analytical expressions of a G/G/1/K queueing model are derived under the protocol interference model when the CSMA/CA MAC protocol is adopted. Our numerical analysis and simulation study reveal that the proposed G/G/1/K model is more accurate for delay analysis compared to the existing queueing models when the network load increases. As a future research, we will extend our analysis to the physical interference model and other MAC protocols. Moreover, we will extend our analysis to the cases where certain missions have a higher priority than other missions. In addition, we will investigate the impact of various mission-related factors (e.g., energy management, event priority, etc.) on the end-to-end delay of more general sensor network settings.

Acknowledgment

The research was partially supported by the US National Science Foundation under grants CNS-0852673, CNS-0963957, and CNS-1017662.

7. REFERENCES

[1] N. Bisnik and A. Abouzeid. Queuing network models for delay analysis of multihop wireless ad hoc networks. In *Proceedings of the 2006 international conference on Wireless communications and mobile computing*, IWCMC '06, pages 773–778, 2006.

[2] G. Bolch, S. Greiner, Hermann, and Kishor. *Queueing Networks and Markov Chains*. John Wiley and Sons,Inc., 2nd edition, 2005.

[3] H. Chang, V. Misra, and D. Rubenstein. A general model and analysis of physical layer capture in 802.11 networks. In *INFOCOM 2006. 25th IEEE International Conference on Computer Communications. Proceedings*, pages 1–12, 2006.

[4] Y.-C. Chen, J. Kurose, and D. Towsley. A simple queueing network model of mobility in a campus wireless network. In *Proceedings of the 3rd ACM workshop on Wireless of the students, by the students, for the students*, pages 5–8. ACM, 2011.

[5] Y.-C. Chen, J. Kurose, and D. Towsley. A mixed queueing network model of mobility in a campus wireless network. In *INFOCOM, 2012 Proceedings IEEE*, pages 2656–2660. IEEE, 2012.

[6] Z.-K. Chong, H. Ohsaki, B.-M. Goi, H.-T. Ewe, and C.-K. B. Ng. Performance analysis of fountain-based protocol in csma/ca wireless networks. In *Applications and the Internet (SAINT), 2012 IEEE/IPSJ 12th International Symposium on*, pages 184–189. IEEE, 2012.

[7] M. Harchol-Balter and D. Wolfe. In network of queues, M/M/1 can outperform M/D/1. Technical report, EECS Department, University of California, Berkeley, 1994.

[8] J. Hu, G. Min, M. E. Woodward, and W. Jia. Analytical modelling of ieee 802.11 e enhanced distributed channel access protocol in wireless lans. In *Performance Models and Risk Management in Communications Systems*, pages 173–190. Springer, 2011.

[9] P.-K. Huang and X. Lin. The end-to-end delay performance of a class of wireless scheduling algorithms. In *Communication, Control, and Computing (Allerton), 2010 48th Annual Allerton Conference on*, pages 951 –952, 2010.

[10] P. Jurcik, R. Severino, A. Koubaa, M. Alves, and E. Tovar. Real-time communications over cluster-tree sensor networks

with mobile sink behaviour. In *Embedded and Real-Time Computing Systems and Applications, 2008. RTCSA '08. 14th IEEE International Conference on*, pages 401–412, 2008.

[11] G. Kang, Y. Taniguchi, G. Hasegawa, and H. Nakano. Extending the protocol interference model considering sinr for wireless mesh networks. In *AICT 2011, The Seventh Advanced International Conference on Telecommunications*, pages 26–31, 2011.

[12] R. Khalaf, I. Rubin, and J. Hsu. Throughput and delay analysis of multihop IEEE 802.11 networks with capture. *IEEE International Conference on Communications, 2007. ICC '07.*, pages 3787 – 3792, 2007.

[13] H. Li, C. Wu, Q.-S. Hua, and F. Lau. Latency-minimizing data aggregation in wireless sensor networks under physical interference model. *Ad Hoc Networks*, 2011.

[14] G. Narlikar, G. Wilfong, and L. Zhang. Designing multihop wireless backhaul networks with delay guarantees. *Wirel. Netw.*, 16(1):237–254, 2010.

[15] P. Park, P. Di Marco, P. Soldati, C. Fischione, and K. H. Johansson. A generalized markov model for effective analysis of slotted ieee 802.15.4. In *IEEE 6th International Conference on Mobile Ad-hoc and Sensor Systems 2009 (IEEE MASS 09)*, pages 130– 139, 2009.

[16] A. Saifullah, Y. Xu, C. Lu, and Y. Chen. End-to-end delay analysis for fixed priority scheduling in wirelessHART networks. *Real-Time and Embedded Technology and Applications Symposium, IEEE*, 0:13–22, 2011.

[17] C. Sarr and I. Guérin-Lassous. Estimating Average End-to-End Delays in IEEE 802.11 Multihop Wireless Networks. Technical Report RR-6259, INRIA, 2007.

[18] R. Srivastava, L. K. Singh, and J. Hsu. Memory estimation of Internet server using queuing theory: Comparative study between M/G/1, G/M/1 and G/G/1 queuing model. *World Academy of Science, Engineering and Technology*, 33, 2007.

[19] K. Sungoh and N. B. Shroff. Paradox of shortest path routing for large multi-hop wireless networks. In *INFOCOM 2007. 26th IEEE International Conference on Computer Communications. IEEE*, pages 1001–1009, 2007.

[20] H. Vu and T. Sakurai. Collision probability in saturated IEEE 802.11 networks. In *Australian Telecommunication Networks and Application Conference 2006*, pages 21–25, 2006.

[21] P.-J. Wan, O. Frieder, X. Jia, F. Yao, X. Xu, and S. Tang. Wireless link scheduling under physical interference model. In *INFOCOM, 2011 Proceedings IEEE*, pages 838–845. IEEE, 2011.

[22] Q. Wang and P. Fan. On the throughput-delay tradeoff in the diamond relay networks. In *Wireless Communications and Mobile Computing Conference, 2008. IWCMC '08. International*, pages 183–188, 2008.

[23] Y. Yang, Y. Liu, and L. Ni. Level the buffer wall: Fair channel assignment in wireless sensor networks. In *Mobile Adhoc and Sensor Systems, 2009. MASS '09. IEEE 6th International Conference on*, pages 208–216, 2009.

[24] Z. Zhou and Y. Zhu. Computational analysis of (map1, map2)/(ph1, ph2)/n queues with finite buffer in wireless cellular networks. *Systems Engineering and Electronics, Journal of*, 22(5):739–748, 2011.

[25] J. Zhu, Z. Tao, and C. Lv. Delay analysis for ieee 802.15. 4 csma/ca scheme with heterogeneous buffered traffic. In *Measuring Technology and Mechatronics Automation (ICMTMA), 2011 Third International Conference on* volume 1, pages 835–845. IEEE, 2011.

,