An Adaptive Proportional Integral Active Queue Management Algorithm based on Self-Similar Traffic Rate Estimation in WSN

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Abstract

Wireless Sensor Network (WSN) is made up of a number of sensor nodes and base stations. Traffic flow in WSN appears self-similar due to its data delivery process, and this impacts queue length greatly and makes queuing delay worse. Active queue management can be designed to improve QoS performance for WSN. In this paper, we propose self-similar traffic rate estimating algorithm named Power-Law Moving Averaging (PLMA) to regulate packet marking probability. This algorithm improves the availability of the rate estimation algorithm under the self-similar traffic condition. Then, we propose an adaptive Proportional Integral algorithm (SSPI) based on the estimation of the Self-Similar traffic rate by PLMA. Simulation results show that SSPI can achieve lower queue length jitter and smaller setting time than PI.

Keywords: Self-similar, QoS, traffic rate estimation, active queue management, WSN

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1. Introduction

Sensor networks are distributed networks made up of small sensing devices equipped with processors, memory, and short-range wireless communication. They differ from conventional computer networks in that they have redundant low-rate data, and a plethora of information flows.

QoS requirements in traditional data networks mainly result from the rising popularity of end-to-end bandwidth-hungry multimedia applications. QoS requirements generated by the applications of WSNs may be very different from traditional network. Sensor nodes have the capability of collecting data about an ambient condition and sending data reports to a sink node. Since there exist many envisioned applications in WSNs and their QoS requirements may be very different, it is impossible for us to analyze them individually. Also, it is unlikely that there will be a "one-size-fits-all" QoS support solution for each application [1].

We focus on self-similar traffic feature in WSN and the Active Queue Management (AQM) algorithm for QoS control. It is useful for nodes in WSN to estimate the congestion and avoid the congestion by means of dropping or marking packets depending on the policy of AQM.

2. Related Work

Dazhi Chen et al. in [1] have discussed QoS support in WSNs, and analyzed the QoS requirements imposed by the main applications of WSNs. The applications are classified to three types: event-driven, query-driven and continuous model. In many applications, the data delivery models may coexist and form a hybrid model.

A QoS-aware protocol is proposed for WSNs in [2]. Real-time traffic is generated by imaging or video sensors. The proposed protocol finds a least cost and energy efficient path that meets certain end-to-end delay requirement during the connection. In addition, a class-based queueing model is employed to support both best effort and real-time traffic simultaneously.

Y. Sankarasubramaniam et al. in [3] propose a new reliable transport scheme (ESRT) for WSNs. ESRT is a novel transport solution developed to achieve reliable event detection in WSN with minimum energy expenditure. More importantly, their solution is based on a non-end-to-end concept. The solution includes a congestion control component that serves the dual purpose of achieving reliability and conserving energy, and the reliability of event detection is controlled by the sink which has more power than sensors. However, their solution only resides in an individual transport layer. Further, it does not consider other important QoS factors.

From these researched, we know that solutions based on the concept of end-to-end applications may not be necessarily used in WSNs. Next, the mechanisms in some protocols are too complex and costly for resource constrained sensors. Finally, how to support the QoS under self-similar traffic should be considered since it is much more feasible for them to be implemented in WSNs.

3. Impact of Self-similar Traffic on Network QoS Performance

3.1 Self-similarity of traffic flow

In the area of traffic characterization, a number of empirical researches of network traffic have demonstrated that network traffic is self-similar or long-range dependent (LRD) in nature. This implies the traffic properties at present time contain a significant amount of information about the traffic properties in the future. The correlation structure at large time scale of LRD can be exploited to estimate future traffic rate and calculate packet marking probability.

Performance evaluation of WSN protocols requires realistic data traffic models since most of WSNs are application specific [4]. The traffic load can be categorized as event-driven or periodic data generation. Periodic data generation such as in [5][6] can be modelled as CBR or Poisson. On the contrary, the event-driven scenarios such as target detection and tracking generate burst traffic which cannot be modelled as either CBR or Poisson. Event-driven traffic is somehow self-similar [7][8].

1) Definitions of self-similarity

Assuming $x = \{x(i), i = 0,1,2,...\}$ to be a wide-sense stationary stochastic process with constant mean μ, finite variance σ^2 and autocorrelation function $r(k), k \geq 0$, let $x^m(i) = [x(i) + x(i+1) + ... + x(i+m-1)]/m, (i = 0,1,2...)$, for every m, define $x^m(i)$ as a covariance stationary stochastic process and $r^m(k)$ as the autocorrelation function of x^m.

If for every m, the covariance stationary stochastic of x is as follow:

$$r^m(k) = r(k) \sim k^{-l} (0 < l < 1) \tag{1}$$

$x(i)$ is exactly self-similar with parameter $H = 1-(l/2)$.

While, if for every *m*, the covariance stationary stochastic of *x* is as follows:

$$r^m(k) \sim r(k), \qquad m \to \infty \tag{2}$$

$x(i)$ is asymptotically self-similar with parameter $H = 1-(l/2)$ [7].

Self-similarity parameter *H* (Hurst parameter), reflects the second order statistic property of data. $0 < H < 1/2$ shows the short-range dependence; $H = 1/2$ means there is no correlation; $1/2 < H < 1$ presents the process has long-range dependence. And the larger *H* is, the more significant degree of self-similarity is.

2) On/Off model and self-similar traffic generation

The self-similarity shown in network traffic has brought exciting challenge into modeling the self-similar network traffic. Many self-similar traffic simulating methods have been put forward including fractional Gaussian noise (FGN), fractional Brownian motion (FBM), fractional autoregressive integrated moving average (FARIMA) and On/Off processes, etc [8]. Because parameters calculation of fractional model is tedious and the process is complicated, it is not a common choice. On/Off process model is an extended traditional model. Since it is simple, practical, easy to control and can reflect self-similarity properly, we generate the self-similar traffic based on it.

The self-similar traffic generated from On/Off process model is a superposition of several single sources. It assumes every single source has two states—on and off. In the on state, the source sends packets at a constant rate; and in the off state, the source doesn't generate any data, just waiting for the next on state. According to actual observations and theoretical analysis, we find that the self-similarity of the traffic depends on durations of on and off states—the heavy-tailed distribution in microscopic scales causes the self-similarity in macroscopic scales.

In recent years, numerous ways of assessing the self-similarity has been proposed, such as Variance Time Method, Higuchi Method, R/S Method, etc. They are all based on the H parameter and the main idea is estimating the value of H to assess the self-similarity. The most popular and simple one is Variance Time (V-T) Method. The principle is:

Equation (1) is equivalent to $Var[x^{(m)}] \sim \alpha m^{-l}, m \to \infty$.

If we draw $(\log m, \log Var[x^{(m)}])$ in logarithmic coordinates, and use least square method to get a fitted line with the slope equals $-l$. And according to the equation $H = 1-(l/2)$, we will get H and assess the self-similarity of a process through its value.

Set the H=0.8 with On/Off model and analyze generated traffic by V-T method. We get $-l = -0.4146$ and H=0.7927. Compared with the parameter we set, the traffic generated by this model is almost accurate. It can be used in further research.

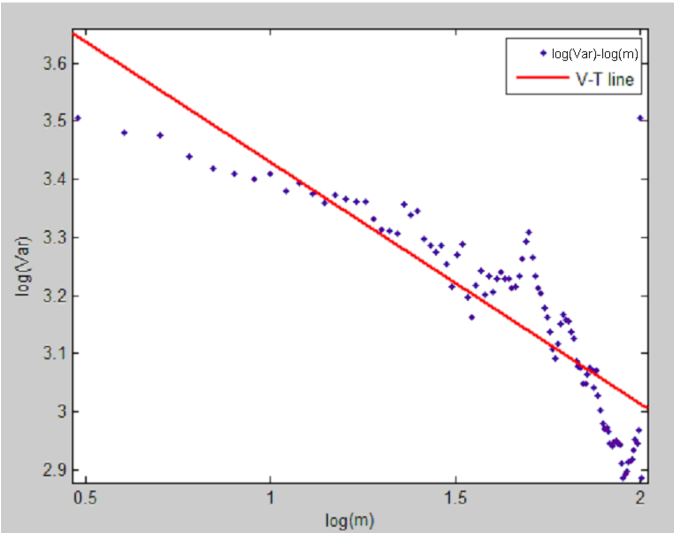


Fig. 1. The Variance Time (V-T) line

3.2 Impact of self-similar traffic on network

Fig. 2 and **Fig. 3** show that the negative effect that self-similar traffic brings to the network. Queuing delay increases quickly and dropped packets are jittering drastically in transmission. So it is necessary to develop an efficient approach to reduce this influence.

The self-similar traffic occupies more buffer than poisson traffic does. This is the main reason for the rising of queuing delay and packets loss. The self-similar and multi-fractal nature of traffic can cause a number of undesirable effects like high buffer overflow rates, which leads large delays and persistent periods of congestion [10][11][12][13].

4. Active Queue Management Algorithm for WSN

Active Queue Management (AQM) is a key technique in the WSN QoS area, that consists in dropping or marking packets before queue is overflow. In this paper, we use the term “marking” to refer to any operation taken by the WSN router node to notify the source of incipient congestion. To address the problems of random early detection (RED), a robust

AQM scheme should take into account traffic rate and require very little manual tuning of parameters. In [9], authors linearize a non-linear dynamic model for TCP/AQM. Based on that, [14] provides the simplified TCP/AQM closed-loop feedback system model as following:

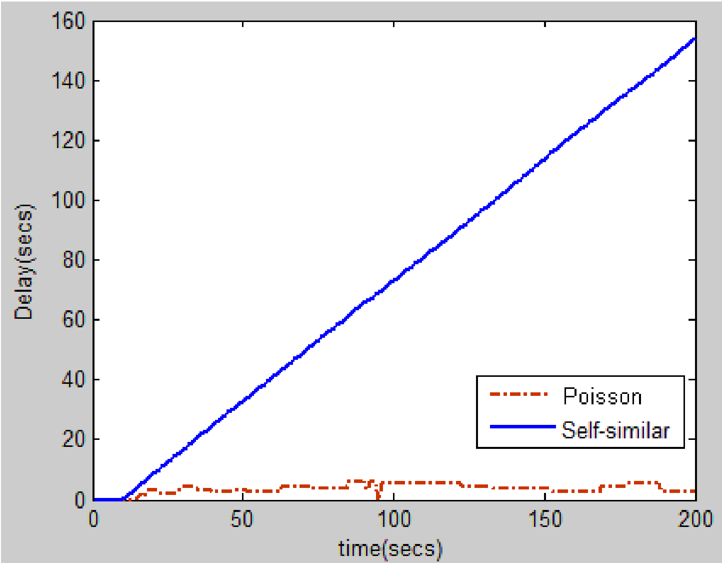


Fig. 2. Comparison of queuing delay under self-similar traffic and poisson traffic model

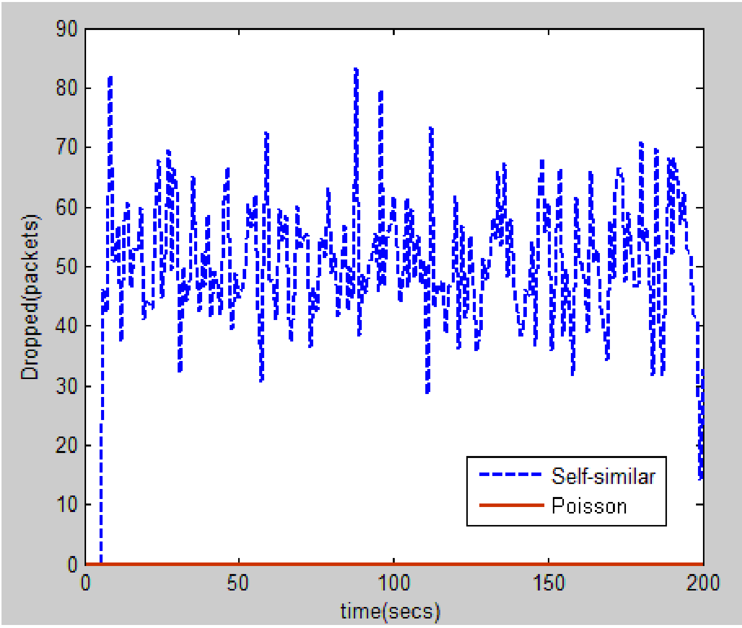


Fig. 3. Comparison of dropped packets under self-similar traffic and poisson traffic model.

$$\begin{cases} \dot{W}(t) = \dfrac{1}{R(t)} - \dfrac{W(t)W(t-R(t))}{2R(t-R(t))} p(t-R(t)) \\ \dot{q}(t) = \dfrac{W(t)}{R(t)} N(t) - C \end{cases} \tag{3}$$

Where C is link capacity of WSN, $W(t)$ is window size of TCP connection, $q(t)$ is queue length, $p(t)$ is dropping or marking probability, $N(t)$ is the number of active connections, $R(t)$ is transmission delay including queuing delay. Plugging TCP linear model into the AQM control model, the dynamic model could be described as following,

$$G_p(s) = \frac{\frac{C^2}{2N} e^{-sR_0}}{(s + \frac{2N}{R_0^2 C})(s + \frac{1}{R_0})} \tag{4}$$

Block diafram of TCP/AQM control system is is depicted in **Fig. 4**,

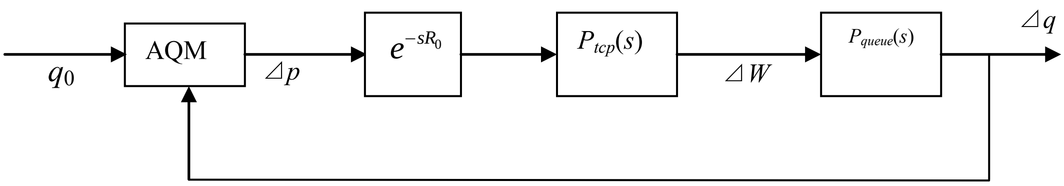


Fig. 4. Block diagram of TCP/AQM control system

Where q_0 is target queue length, $P_{tcp}(s)$ is the transfer-function between the increment of marking porpability and the increment of TCP window, $P_{queue}(s)$ is the transfer-function between the increment of TCP window and the increment of queue length. From the viewpoint of cybernatic theory, the compensator or controller should be inserted to WSN congestion control system to improve system performace. AQM module is one kind of compensator. So, the essence of AQM design is to select and determine compensator correctly.

Although the performance of proportional integral (PI) controller in [14] is superior to that of RED and Tail-drop, it dose not take self-similarity of traffic into account. In this section, we firstly propose self-similar traffic rate estimating algorithm PLMA for AQM scheme to regulate packet marking probability. This algorithm improves the availability of the rate estimation algorithm under the self-similar traffic condition. To solve the problem in PI algorithm, proportional integral based on self-similar traffic (SSPI) algorithm is proposed by combining the advantage of self-similar traffic rate estimation and PI controller.

4.1. Traffic Rate Estimation

One of most widely used methods in rate estimation is Exponentially Weighted Moving Averages (EWMA)[15]. For the EWMA, the decision depends on the EWMA statistic, which is an exponentially weighted average of all prior data, including the most recent measurement. The rate estimated for the next sampling (measurement interval) is given by:

$$R(t+1) = (1 - e^{-T_s/K})\frac{l}{T_s} + e^{-T_s/K} R(t) \tag{5}$$

where R $(t+1)$, R (t) represents the rate estimated at times $t+1$ and t respectively, l is the observation of packet length at time t, K is a constant that determines the depth of memory of the EWMA. Measurement interval T_s is a trade-off between the estimation accuracy and computational overhead. EWMA may be a reasonable solution to the traffic rate estimation if the packet interarrivals assume to be exponentially-distributed. However, as aforementioned, in many cases the widely used exponential assumption is not adequate for characterizing network traffic, but heavy-tailed (also called power-law) distributions can be used as a plausible model nevertheless. Heavy-tailed distributions have properties that are qualitatively different to the exponential distribution. Rate estimation under such exponentially distribution assumptions may be misleading or incorrect in the presence of heavy-tailed distributions. So, we are finding more effective algorithm to estimate self-similar traffic rate accurately. This paper presents a new rate estimation algorithm called Power Law Moving Averaging (PLMA) achieving good performance in the self-similar traffic context.

Heavy-tailed distributions have been observed in many natural phenomena. A distribution is said to have a heavy-tail if:

$$P[X > x] \sim x^{-\alpha} \quad \text{as } x \to \infty,\ 0<\alpha<2 \tag{6}$$

where 0< α <2 , as α decreases, a large portion of the probability mass is present in the tail of the distribution. The relationship between file sizes and self-similar traffic has shown that self-similarity in traffic might arise due to the heavy-tailed distribution of file sizes. A quantitative measure of self-similarity is obtained by using H parameters. A time series with LRD has an autocorrelation function of the form

$$r(x) \sim x^{2H-2} \quad \text{as } x \to \infty \tag{7}$$

As $H\to 1$, the degree of LRD increases. The H Parameter is related to α via $H = (3-\alpha)/2$. Traffic rate estimation of communication systems with heavy-tailed date traffic is defined by

$$R(t+1) = (1-T_s^{-\alpha})\frac{l}{T_s} + T_s^{-\alpha}R(t) \tag{8}$$

As the heavy-tailed distribution decays via a power of x which is much slower than exponential- type distribution. So, in PLMA, rate estimated at times t has much more influence on the rate estimated at times t+1 than EWMA. Plugging $H = (3-\alpha)/2$ into eq.(8), we have

$$R(t+1) = (1-T_s^{2H-3})\frac{l}{T_s} + T_s^{2H-3}R(t) \tag{9}$$

There are several methods for estimating self-similarity. For the space limitation, the detailed discuss was not present here.

4.2. SSPI Algorithm

In this section, we will explain the SSPI algorithm in detail. In SSPI, we estimate the congestion by using estimated WSN traffic rate in the future and measured instantaneous queue length. The traffic rate estimated by the PLMA is used to adjust the packet marking probability in the next interval.

Let $Q(k)$ denote the queue length at the end of the k-th interval, then the function of the queue length is

$$Q(k+1) = Q(k) + \hat{R}(k+1)T_s - D(k+1)T_s - C$$

where $\hat{R}(k+1)$ is the arrival rate at k+1-th interval and can be estimated by PLMA, $D(k+1)$ is the packet marking rate at k+1-th interval, $C = V*T$ is the number of packets transmitted on the outgoing link and V is the capacity of the outgoing link. Marking probability p for the k+1-th interval is denoted by $p = D(k+1) / R(k+1)$.

Due to expected queue length is Q_{opt}, so we have:

$$\begin{aligned}
&Q(k) + \hat{R}(k+1)T_s - D(k+1)T_s - C = Q_{opt} \\
&\Rightarrow Q(k) + \hat{R}(k+1)T_s(1-p(k+1)) - C = Q_{opt} \\
&\Rightarrow p(k+1) = \begin{cases} 0, & Q(k) < C + Q_{opt} - R(k+1)T_s, \\ \dfrac{R(k+1)T_s - Q_{opt} - C + Q(k)}{R(k+1)T_s}, & C + Q_{opt} - R(k+1)T < Q(k) < C + Q_{opt}, \\ 1, & Q(k) > C + Q_{opt}. \end{cases}
\end{aligned} \tag{10}$$

The goal of SSPI is to converge the queue length to given expected value Q_{opt} and minimize the error of queue length.

$$e(k) = Q(k) - Q_{opt} \tag{11}$$

The stable queue length could bring many benefits, such as highly resource utilization, expectable max queue delay and network performance without the impact of the traffic load. If parameters of SSPI could be adjusted based on WSN dynamic state, it could take on better queue performance. If *N*, *R* are given, marking probability *p* could be deduced. The theroretical basis for parameter adjustment of SSPI is discussed as following.

Proposition 1. Let $\frac{2N}{R^2C} << \frac{1}{R}$, denote estimated traffic rate as $\hat{R}(t)$, denote current queue length as $Q(t)$, denote system load as *N*, denote round trip time in WSN as *R*, $p(k+1)$ is given by eq.(10), let $\xi = \max(p(k+1), 0.1)$, if $\omega_g = \frac{\xi}{\sqrt{T_1T_2}}$, $\frac{k_I}{k_P} = \frac{\omega_g}{10}$, $k_P \le \frac{1+\xi^2}{K_m}$, then the whole system is stable.

Proof: The open loop transfer-function for TCP/AQM system is $G(s) = \frac{k_I + k_P s}{s} \frac{K_m e^{-sR}}{T_1T_2s^2 + (T_1+T_2)s + 1}$, then the amplitude-frequency characteristic of system is

$$\left|G(j\omega)\right| = \frac{\sqrt{k_I^2 + k_P^2\omega^2}}{\omega} \frac{K_m}{\sqrt{\left(1 - T_1T_2\omega^2\right)^2 + \left(T_1+T_2\right)^2\omega^2}},$$

$$\left|G(j\omega_g)\right| = \frac{\sqrt{k_I^2 + k_P^2\omega_g^2}}{\omega_g} \frac{K_m}{\sqrt{\left(1 - T_1T_2\omega_g^2\right)^2 + \left(T_1+T_2\right)^2\omega_g^2}}$$

Since $\frac{k_I}{k_P} = \frac{\omega_g}{10} << \omega_g$, so $\frac{\sqrt{k_I^2 + k_P^2\omega_g^2}}{\omega_g} = \frac{k_P\sqrt{\frac{k_I^2}{k_P^2} + \omega_g^2}}{\omega_g} \approx k_P$, we get

$$\begin{aligned}
\left|G(j\omega_g)\right| &= \frac{\sqrt{k_I^2 + k_P^2\omega_g^2}}{\omega_g} \frac{K_m}{\sqrt{\left(1 - T_1T_2\omega_g^2\right)^2 + \left(T_1+T_2\right)^2\omega_g^2}} \\
&\approx \frac{k_PK_m}{\sqrt{\left(1 - T_1T_2\omega_g^2\right)^2 + \left(T_1+T_2\right)^2\omega_g^2}} \\
&= \frac{k_PK_m}{\sqrt{\left(1 - \xi^2\right)^2 + \left(T_1+T_2\right)^2\omega_g^2}} \\
&\le \frac{k_PK_m}{\sqrt{\left(1 - \xi^2\right)^2 + 4\xi^2}} \\
&= \frac{k_PK_m}{1+\beta^2}
\end{aligned}$$

Since $k_P \le \frac{1+\xi^2}{K_m}$, so $\left|G(j\omega_g)\right| \le 1$, the phase-frequency characteristic of system is:

$$\varphi(\omega_g) = -90^\circ + \mathrm{arctg}\left(\frac{\omega_g}{k_I / k_P}\right) - \mathrm{acrtg}\frac{(T_1+T_2)\omega_g}{1 - T_1T_2\omega_g^2} - \omega_g R$$

From $\frac{2N}{R^2C} \le \frac{1}{R}$, we have $\frac{2N}{RC} \le 1$, $\omega_g R = \frac{\xi R}{\sqrt{T_1 T_2}} = \xi\sqrt{\frac{2N}{RC}} \le 1$, so

$$\begin{aligned}\varphi(\omega_g) &\ge -90^\circ + arctg(10) - 90^\circ - 1 \\ &\ge -90^\circ + 84^\circ - 90^\circ - 58^\circ = -154^\circ \\ &\ge -180^\circ\end{aligned}$$

We can determine the system is stable according to the Nyquist stability criterion. Therefore, SSPI could adjust packet marking probability adaptively based on instantaneous queue length. The key feature of SSPI algorithm is to calculate the packet marking probability based on the instantaneous queue length and estimated rate. This feature enables the algorithm to achieve promptly response to dynamic traffic while maintain the queue length stability. This stability can reduce delay jitter.

5. Simulation and Results

In this section, we used OPNET as our simulation tool and evaluated performance of PLMA and SSPI.

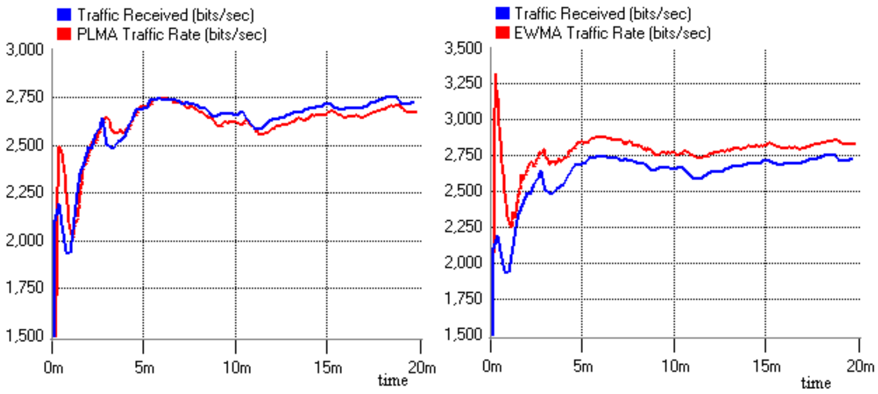
5.1 Simulation of PLMA

The first problem needed to be addressed is whether the PLMA can estimate the traffic rate accurately. The Raw Packet Generator (RPG) model is a traffic source model used to generate self-similar traffic in OPNET. In the RPG model, several fractal point processes have been implemented to generate packet-based and flow-based traffic. Based on the RPG model, we compare the performance of PLMA and EWMA in the context of self-similar traffic.

The parameters of RPG model are listed in **Table 1**. The similarity of PLMA and EWMA is that, traffic received which is closer to current time will be of more contribution to the rate estimation. But the changing regularity of this impact is not same. As time goes on, the impact of the former traffic rate to the succedent estimation decreases exponentially in EWMA, yet this is power-law in PLMA. **Fig. 5** shows traffic rate estimated by PLMA and by EWMA comparing with actual taffic in time average seperately in **Fig. 5-(a)** and **Fig. 5-(b)**. From this, we found that average estimated rate by PLMA converges to the actual traffic rate more quickly than that of EWMA and the PLMA is able to estimate the traffic rate to a reasonably accuracy. EWMA has greater steady-state error than PLMA does. The reason is that PLMA exploits self-similar traffic characteristics while EWMA does not.

Table 1. Parameters of the RPG model

Parameters	Value
Average Arrival Rate (pkts-flows/sec)	25
Hurst Parameter	0.85
Fractal Onset Time Scale	0.1
packet size (bytes)	Constant(100)
k	1
T_s (seconds)	1.175



(a) **(b)**

Fig. 5. Convergence performance Comparison of PLMA and EWMA

5.2 Transient and steady state performance of SSPI

This experiment focuses on the transient and steady performance of SSPI and PI. During simulation, self-similar traffic generated by RPG model starts from 10s. As **Fig. 6** shows, the queue length rises rapidly from zero to 477 and then converges to the target length 200 by the control of PI, and the adjusting time is 151.2 seconds. Besides, the queue length fluctuates greatly in simulation period under PI algorithm and mean-square variance gets 42.534 packets. By contrast, the overshoot of the queue length is only 256 under SSPI algorithm and adjusting time is 32.4 seconds, which is much smaller than that of PI. The queue length of SSPI, whose mean-square variance is 7.895 packets, is also more stable than that of PI. The jitter of queuing delay due to queue length variation is 9.658 seconds of PI and 6.229 seconds of SSPI. Some statistics are shown in **Table 2**. The simulation results show that the transient and steady performance of SSPI is better than that of PI.

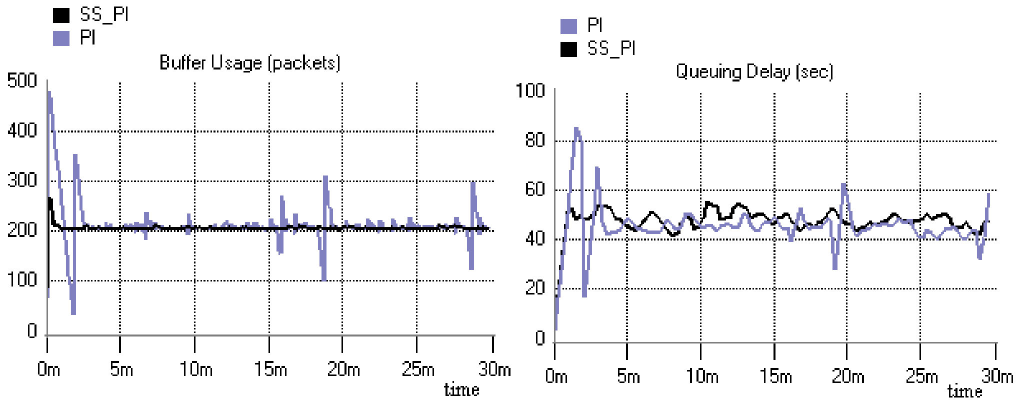


Fig. 6. Performance Comparison of SSPI and PI

Table 2. Comparison of SSPI and PI

Metrics	**SSPI**	**PI**
Overshoot (packets)	256	477
Adjusting time(seconds)	32.4	151.2
mean-square variance of queue length (packets)	7.895	42.534
jitter of queuing delay (seconds)	6.229	9.658

5.3 Robustness of SSPI

In this experiment we evaluate the performance of SSPI under variable traffic. There is another self-similar traffic flow which starts from 900s. Its parameters list in **Table 3**. Simulation results show that when there is interference traffic and traffic flow changes dynamically, SSPI has better robustness and a smaller jitter of queue length. By contrast, PI is affected obviously by variable traffic flow. **Fig. 7** shows queuing delay and its jitter. Some statistics are shown in **Table 4**. SSPI is much more suitable for those applications sensitive to jitter of delay.

Table 3. Parameters of new self-similar traffic

Parameters	Value
Average Arrival Rate (pkts-flows/sec)	100
Hurst Parameter	0.7
Fractal Onset Time Scale	1
packet size (bytes)	exponential(1024)

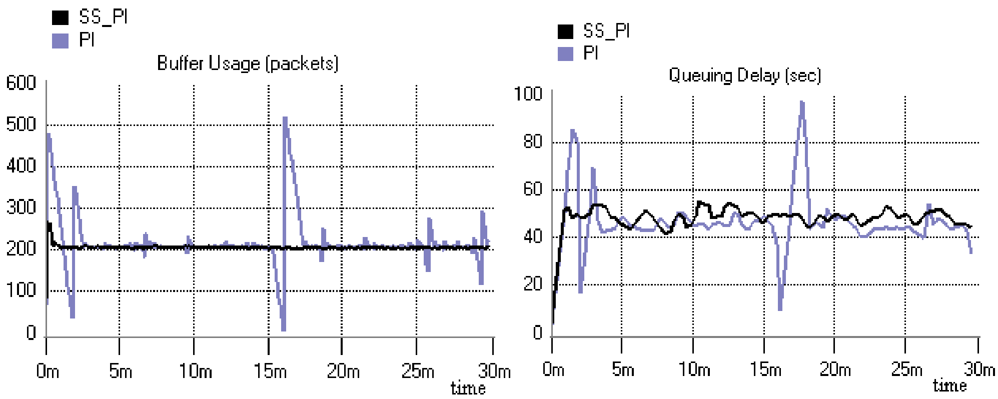


Fig. 7. Robustness Comparison of SSPI and PI

Table 4. Comparison of SSPI and PI

Metrics	SSPI	PI
mean-square variance of queue length (packets)	7.895	59.726
mean-square variance of jitter of queuing delay (seconds)	6.219	12.530

From the experiments above, we can find that compared with PI, our algorithm SSPI has better stable performance of queue length including faster convergence speed and smaller jitter of queue length under self-similar traffic flow.

6. Conclusion

Recent studies have revealed that self-similar nature consists in most kind of network traffic including traffic in WSN. At present, self-similar traffic has been widely considered in traffic modeling and performance analysis of queuing systems. The self-similar trends were also found in wireless ad hoc networks based on network measurements and simulations in some conditions [16][17].

In this paper, we proposed self-similar traffic rate estimating algorithm PLMA for active queue management scheme to regulate packet marking probability. Then, we design a robust

AQM mechanism SSPI based on rate estimated by the PLMA. All parameters used in SSPI can be adjusted by using measured and estimated value. This feature enables SSPI algorithm to be more responsive to rate fluctuation and maintain higher throughput with lower packet loss ratio. The simulation results show the validity of the proposed algorithms including PLMA and SSPI. The future work will implement the algorithm in WSN testbed.

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