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# Active/passive combination-type performance measurement method using change-of-measure framework

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**Abstract**

We propose a new method of performance measurement called the *Change-of-Measure Based Passive/Active Monitoring (CoMPACT Monitor)*, in which estimates of the actual performance seen by users are obtained based on both active and passive measurement data. With this method, the performance experienced by an individual user, organization or application can be estimated from the results of scalable and lightweight measurements. The basic idea of our method is to weight the measurement value of an active-probe packet according to the number of user packets arriving near the active-probe packet. The number of user packets is measured passively. We give a mathematical background that supports the concept of the change-of-measure framework and propose an implementation of the method. Through simulation, we verify that the user performance can be estimated with a high degree of accuracy when the measurement interval is shorter than the mean burst duration. We also examine the accuracy of the method with respect to both the measurement interval and the number of probe packets and show that the accuracy itself can be roughly estimated by using the measured values.
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*Keywords:* Active measurement; Passive measurement; Change-of-measure

## 1. Introduction

The rapid increase in both volumes of traffic and the variety of applications available on the Internet in conjunction with the severe competition among network service providers are making performance measurement increasingly crucial to network management. Providers are being required to provide specific service levels in terms of user performance. This is not simply a matter of managing the network performance; rather the actual performance as experienced by users must be controlled. Recently, many methods of measurement have been developed and their measurement results have also been reported [1–8]. In general, methods of measuring network performance are divided into two types: active and passive.

In active methods, probe packets are sent out and measurement of performance is based on the data (e.g. delay of those packets) [9–11]. There are various active methods for the measurement of such network performance parameters as available bandwidth [12], delay, and loss, and for the estimation of the link-by-link performance [13]. The performance of probe packets sent out periodically is generally used to estimate the performance of users' packets. An active method makes it easy to measure network performance: we simply send out the probe packets and measure the performance data that obtained from the network. Active methods are also easy to deploy, as is seen, for example, in the world-wide deployment of the monitoring hosts for the Internet End-to-end Performance Measurement project [5].

However, active methods have several drawbacks one of which is that, although this is often not recognized, the performance as measured by the probe packets may not be the same as that experienced by users. If we can assume that active monitoring measures the time average of network performance and that the user traffic is Poissonian, then the performance experienced by the users and performance as measured actively will be the same. This well-known

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property is called PASTA (which stands for 'Poisson Arrivals See Time Average') [14]. It is known, however, that current Internet traffic exhibits burstiness and, in general, is not Poissonian [15,16]. More user packets are transmitted during congested periods, so that user packets experience worse performance. The performance experienced by user packets may actually be worse than that indicated by periodic active monitoring. For example, as described in Section 3, delay as measured with active-probe packets was underestimated by 40% in some cases compared to that experienced by user packets. In Ref. [17], we compared the loss rates for user packets and active-probe packets and found that the ratio between the two sometimes becomes two. Thus, using active methods to measure time-average performance is not enough if we are to provide information on network performance for, for example, service-level agreement (SLA) reporting.

In ATM networks, Operation, Administration, and Maintenance (OAM) cells are used for fault and performance management [18]. One such cell is sent per some fixed number of user cells and measure the network performance. Studies of this mechanism in application to IP networks have appeared [19–21]. With this mechanism, the performance statistics obtained by the probe packets agree with those obtained by the users because the number of probe packets is proportional to the number of user packets even during periods of congestion. However, the numbers of probe packets sent by this mechanism grow with the volume of user traffic, so more additional traffic will be injected during congestion periods. In addition, if we need performance statistics for multiple users, we must use a separate series of probe packets for each user.

In passive methods, probe packets are not sent out; rather actual user packets are captured and the data obtained through those packets are used to determine the network performance. For example, we can directly determine the delay on user packets by comparing the time stamps and contents captured by using monitoring devices deployed at the ingress and egress of the network [22,23]. Another representative method is capturing TCP data packets and its ack packets to monitor the round-trip time and loss [24–26]. Passive methods directly measure the actual performance experienced by users. They also have the advantage of not directly creating extra traffic in networks under measurement [27]. However, these methods require the transfer of the captured data for comparison with the other data and the identification of each packet by its header or content, which is hard when the packet volume is huge, as in a high-speed network. This is because the transfer and comparison of huge amounts of data require substantial resources, both network and computational.

In this paper, we propose a new performance measurement method, Change-of-Measure-Based Passive/Active Monitoring (CoMPACT Monitor), for estimating the actual network performance experienced by users. Our method combines both active and passive monitoring using easy-to-measure methods.

The basic procedures of our method are as follows:

(1) measure network performance using active-probe packets; and
(2) convert the network performance to actual performance experienced by user packets by weighting the performance with the number of user packets arriving near the probe packets, which is measured passively.

Therefore, our method overcomes the drawbacks of active and passive monitoring in that it measures the actual performance experienced by users yet only requires simple active and passive monitoring, where the latter only involves counting of the number of user packets. The method can estimate not only the average performance experienced by all users but also the actual performance for individual users, organizations, and applications.

Monitoring of performance as seen by individual users, organizations, and applications is preferable in terms of SLA because network performance varies over time as does user (application)-experienced performance; even on a single network.

The rest of the paper is organized as follows. In Section 2, we give a mathematical description of our method, including use of the change-of-measure framework. In Section 3, as an application of the method, we propose a simple method for estimating the actual delay experienced by users. We also show the validity of the method through simulation. In addition, we extend our method to estimate the performance experienced by an individual user. The accuracy of the estimates in terms of the measurement interval and number of measurements is investigated in Section 4. Finally, we conclude the paper in Section 5.

## 2. Proposed measurement method

In this section, we present a mathematical description of our method using a change-of-measure framework. By change-of-measure framework, we mean a framework in which we can convert a measure of network performance for probe packets to a measure for user packets. We borrow the idea from importance-sampling simulation, where the probability of a rare event is obtained by changing a biased probability to an objective probability [28].

### 2.1. Estimation of user performance

Let $X$ be the measurement objective, e.g. the delay for user packets, whose distribution function is $P$. The distribution of $X$ is written as

$$\Pr(X > a) = \int \mathbf{1}_{\{x>a\}} \mathrm{d}P(x). \tag{1}$$
$$= E_P[\mathbf{1}_{\{X>a\}}],$$

where $\mathbf{1}_{\{\cdot\}}$ denotes the indicator function. Let us consider how to estimate the distribution of $X$. Suppose there are $n$ arrivals in a measurement period, e.g. $n$ packets arrive. $X(i)$ denotes the $i$-th value of $X$. Then an estimator $Z_X(n,a)$ of distribution (1) can be obtained by using $X(i)$ as follows:

$$Z_X(n,a) := \frac{1}{n}\sum_{i=1}^{n}\mathbf{1}_{\{X(i)>a\}}. \tag{2}$$

Actually, if $X(i)$ is ergodic, then $\mathbf{1}_{\{X(i)>a\}}$ is also ergodic for arbitrary $a \in \mathbf{R}$. Thus,

$$\lim_{n\to\infty} Z_X(n,a) = \Pr(X > a) \text{ a.s.} \tag{3}$$

Suppose we have a situation in which it is difficult to measure $X(i)$ directly and an estimator of its distribution cannot be obtained by using Eq. (2). This assumption reflects the statement in Section 1 that direct measurement of the delay of user packets ($X(i)$) requires capture of the user packets at the ingress and egress of the network along with the timestamps of the packets and then comparison of the timestamps, which is more difficult than simply sending probe packets.

Let $V(t)$ be the network performance at time $t$ such that if the $i$-th arrival occurs at $t_i$, then $V(t_i) = X(i)$ (Fig. 1). Also, let $Y$ be the value of $V(t)$ measured independent of the system behavior, and let the distribution function of $Y$ be $Q$. Thus, we can consider $Y$ to be the network performance as measured by active-probe packets. Note that the distributions $P$ and $Q$ may differ from each other because the two types of packets have different transmission timing and the network performance at the time of transmission are also different.

We consider using the distribution of $Y$ to estimate the distribution of $X$. We can rewrite the distribution of $X$ given in Eq. (1) by using a change of measure as follows:[1]

$$\Pr(X > a) = \int \mathbf{1}_{\{y>a\}}\frac{\mathrm{d}P(y)}{\mathrm{d}Q(y)}\mathrm{d}Q(y) = E_Q\left[\mathbf{1}_{\{Y>a\}}\frac{\mathrm{d}P(Y)}{\mathrm{d}Q(Y)}\right]. \tag{5}$$

Now, suppose $m$ active-probe packets are sent and $Y$ is measured $m$ times. Let $Y(j)$ be the $j$-th measurement at $s_j$ such that $Y(j) = V(s_j)$ ($j = 1,2,\ldots,m$). Then an estimator $Z_Y(m,a)$ of $\Pr(X > a)$ can be derived by using $Y(j)$ as follows:

$$Z_Y(m,a) := \frac{1}{m}\sum_{j=1}^{m}\mathbf{1}_{\{Y(j)>a\}}L(j), \tag{6}$$

where

$$L(j) := \frac{\mathrm{d}P(Y(j))}{\mathrm{d}Q(Y(j))}. \tag{7}$$

$L(j)$ is the ratio of the probability between $X$ and $Y$ for the value of $Y(j)$; we refer to it as the likelihood ratio, the term used with the same meaning in the field of importance-sampling simulation [28]. Eq. (3) also holds for $Z_Y(m,a)$ as

$$\lim_{m\to\infty} Z_Y(m,a) = \Pr(X > a) \text{ a.s.} \tag{8}$$

If we can derive $L(j)$, then the estimator of the distribution of $X$ can be derived by using the measured values of $Y$. The fundamental concept of our method is as follows: although estimation of the distribution $\Pr(X > a)$ through direct measurement of $X$ is difficult, values $Y(j)$ and $L(j)$ can easily be measured by active and passive monitoring, respectively, and we can estimate the distribution $\Pr(X > a)$ by using them. Derivation of the likelihood ratio is described in Section 2.2.

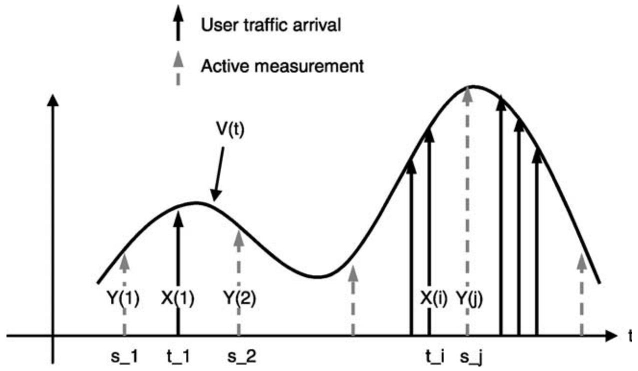

Fig. 1. Relationship between $V(t)$ and $X(i)$, $Y(j)$.

### 2.2. Likelihood ratio

As was stated in Section 2.1, the likelihood ratio $L(j)$ is the ratio between the probabilities of $X$ and $Y$. Here we show how this likelihood ratio can be obtained through passive measurement, in which we simply count the number of user packets arriving close to the probe packet. Let $\rho_X(t,\delta)$ be the traffic volume (i.e. the number of user packets) arriving in an interval $[t, t+\delta(t))$. Let $\rho_Y(t,\delta)$ be the number of measurements in $[t, t+\delta(t))$ (i.e. the number of active-probe packets).

We assume that the interval $\delta(t)$ is short enough compared with the time variance of $V(t)$ that $V(t)$ can be considered almost constant (unchanged) over the period $\delta(t)$. This assumption indicates that a single measurement of

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[1] We assume that, for $a, b \in \mathbf{R}$,

$$P(b) - P(a) > 0 \Rightarrow Q(b) - Q(a) > 0. \tag{4}$$

Since $P$ is the distribution of network performance as seen in packet arrival and $Q$ is the distribution of the measured network performance, this assumption indicates that the network performance that packets experience with a positive probability can be measured with a positive probability. This is natural when the period of measurement is long enough. We can then define $\mathrm{d}P/\mathrm{d}Q$.

$Y$ in the interval $[t, t+\delta(t))$ is equivalent to $\rho_X(t,\delta)/\rho_Y(t,\delta)$ measurements of $X$. Then, for sufficiently small $\delta$, the likelihood ratio $L(j)$ can be approximated by $L(j,\delta)$ which is defined as follows:[2]

$$L(j,\delta) = \frac{\rho_X(s_j,\delta)\Big/\sum_{j=1}^{m}\rho_X(s_j,\delta)}{\rho_Y(s_j,\delta)\Big/\sum_{j=1}^{m}\rho_Y(s_j,\delta)}. \tag{9}$$

Both $\rho_X$ and $\rho_Y$ are the number of packets. The likelihood ratio Eq. (9) can thus be obtained by passive measurement. Combining Eqs. (9) and (6), the distribution of $X$ is estimated as

$$Z_Y(m,a) \simeq \frac{1}{\sum_{j=1}^{m}\rho_Y(s_j)}\sum_{j=1}^{m}\mathbf{1}_{\{Y(j)>a\}}\frac{\rho_X(s_j,\delta)}{\rho_Y(s_j,\delta)} \tag{10}$$

(recall that $\sum_{j=1}^{m}\rho_X(s_j) = m$).

We can also derive an estimator of the mean of $X$, $M_Y(m)$, in a similar way to that for the distribution of $X$. This estimator is

$$M_Y(m) \simeq \frac{1}{\sum_{j=1}^{m}\rho_Y(s_j)}\sum_{j=1}^{m}Y(j)\frac{\rho_X(s_j,\delta)}{\rho_Y(s_j,\delta)}. \tag{11}$$

### 2.3. Advantages of our method

As described so far, our method actively measures network performance, where the number of probe packets is independent of the volume of user traffic, and passively counts the number of user packets. Then, by weighting the number of user packets to the performance of the probe packets, we estimate the user-experienced performance. Therefore, we can expect our method to have the following advantages.

- Since the extra traffic for active probe packets is independent of the volume of user traffic and negligible compared to that for and OAM method [19], it has little effect on the user traffic.
- We have a dependable estimate of QoS/performance measures because our methods can estimate the actual performance as perceived by users.
- As data required to infer the user-experienced performance can be obtained from data measured within the period of measurement in an on-line way, we can obtain the performance data in a timely fashion.
- Since passive measurement is only required for measuring the amount of traffic (counting the number of packets), the passive monitoring devices are simplified.

## 3. Application

### 3.1. Delay estimation

As an application of the method proposed in Section 2.3, we propose a simple method for estimating the actual delay experienced by users. This estimate can be obtained by using statistics on network performance gathered actively and number of user packets measured passively.

#### 3.1.1. Theoretical basis

Let $Y(j)$ $(j = 1,2,\ldots,m)$ be the delay as measured by using probe packets, such as ping, at time $s_j$. The probe-packet interval $s_{j+1} - s_j$ is chosen to be a constant $\tau$, and $\delta(s_j)$ is chosen to be the same interval[3]. Suppose that the number of user packets arriving in $[s_j, s_{j+1})$ is $\rho(j,\tau)$ and the total number of packets arriving in the measurement period is $\sum_{j=1}^{m}\rho(j,\tau) = n$. For the case of delay estimation, $V(t)$ is considered as the virtual waiting time of the network, which is the delay for a packet arriving (virtually) at $t$. If we assume that $\tau$ is short enough compared with the fluctuation of $V(t)$, then we derive the estimator of the packet-delay distribution by applying Eq. (10) for $\rho_X(s_j,\delta) = \rho(j,\tau)$, $\rho_Y(s_j,\delta) = 1$, and $\delta(s_j) = \tau$ as

$$Z_Y(m,\tau,a) = \frac{1}{n}\sum_{j=1}^{m}\mathbf{1}_{\{Y(j)>a\}}\rho(j,\tau). \tag{12}$$

The estimator of the mean user packet delay, $M_Y(m,\tau)$, is also obtained as

$$M_Y(m,\tau) = \frac{1}{n}\sum_{j=1}^{m}Y(j)\rho(j,\tau). \tag{13}$$

As can be seen from Eq. (12), estimating the user delay requires periodical measurement of the network delay by using active probe packets and measuring the number of packets arriving between successive active measurements, which is far easier than directly measuring the delay for user packets by using two monitoring devices deployed at the network edges.

The assumption that $\tau$ is short compared with the fluctuation of $V(t)$ is crucial for the estimation, so, we evaluate the relationship between the measurement interval $\tau$ and the accuracy of estimation in Section 4.

#### 3.1.2. Evaluation for the case of a single bottleneck

To demonstrate the application described above, we used the *ns2* [29] network simulator. Fig. 2 shows the network topology for the simulation. Sources were connected to a bottleneck router via 1.5-Mbps links, and two routers were connected via a 10-Mbps links.

We measured the queuing delay at the bottleneck router, which did not include the service time for the packets

[2] Note that we can always define $\rho_X(s_j,\delta)/\rho_Y(s_j,\delta)$ because at the time $s_j$ of measurement $Y(j)$, we have $\rho_Y(s_j,\delta) > 0$.

[3] To eliminate the influence of periodic network behavior, we can choose an exponential distribution as $\tau$.

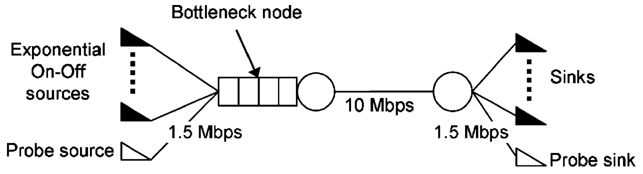


Fig. 2. Network configuration for simulation.

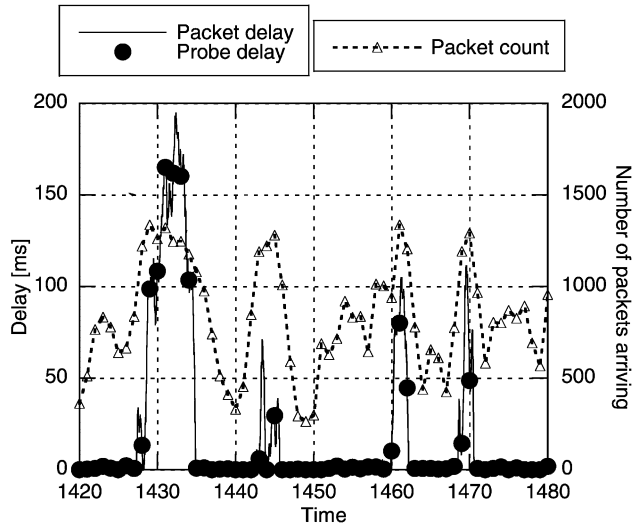


Fig. 3. Sample path for number of packets arriving and delay for user packets and probe packets in simulation.

themselves. The service time is easily calculated from bandwidth and packet length. Other conditions of the simulation were as follows:

- We used exponential On–Off and Pareto On–Off sources as models of traffic generated in the application layer. The mean On duration was 1 s and the mean Off duration was 14 s. The shape parameter for the Pareto distribution was 1.5[4].
- The user packet size was fixed at 1000 bytes.
- The transport protocol for the user packets was TCP.
- The utilization ratio of the bottleneck link was 0.6.
- Simulation lasts 3600 s.
- Probe packets for actively measuring the queuing delay were generated every second. The size of each probe packet was fixed at 64 bytes.

Fig. 3 shows a sample path for the user packet delay, probe packet delay, and number of user packets arriving between probe packets for the case of exponential On–Off sources. We can see that the delay measured with probe packets captures the time variance of delay for the user packets well. However, we can also see a fluctuation in the number of packets arriving between active measurements, which are roughly synchronized with the delay fluctuation.

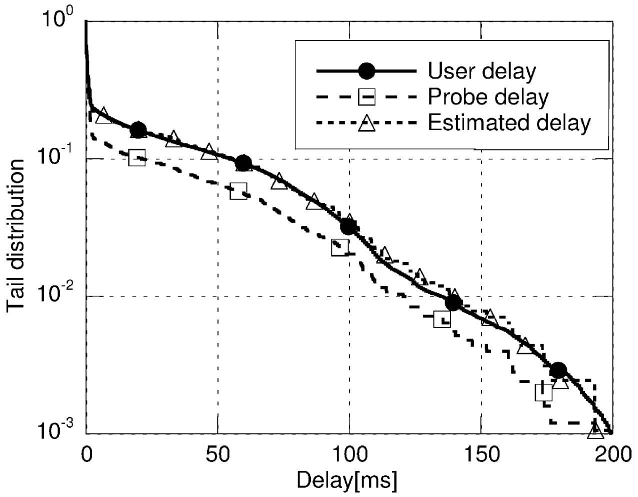


Fig. 4. Distribution of queueing delay for packets generated by exponential On–Off sources and for probe packets and the estimated delay.

This fluctuation causes a discrepancy between the distributions of delay for the bursty user packets and periodic probe packets, because the number of packets with large delay is larger in the case of user packets than in that of probe packets.

Figs. 4 and 5 show the distributions for user and probe packets and the estimated delay. As expected from the sample path, we see a discrepancy between the distribution of delay for user packets and for active-probe packets. By using our proposed method, however, highly accurate estimates of user delay can be obtained from the results of active measurement.

Next, we changed the utilization of the bottleneck link from 0.15 to 0.9 by changing the number of sources. We ran five simulations and took the mean of these results.

Fig. 6 shows the mean and 99% delay experienced by user packets and corresponding estimates. It can be seen that

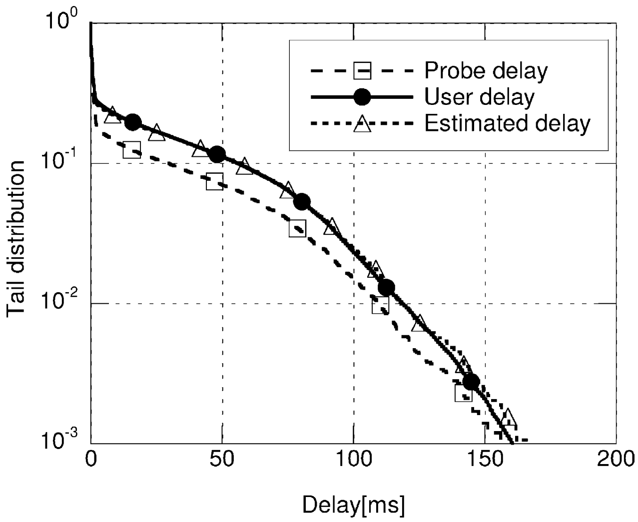


Fig. 5. Distribution of queuing delay for packets generated by Pareto On–Off sources and for probe packets and the estimated delay.

[4] The Pareto distribution function is given by $1-(k/x)^{\alpha}$, where $\alpha$ is the shape parameter.

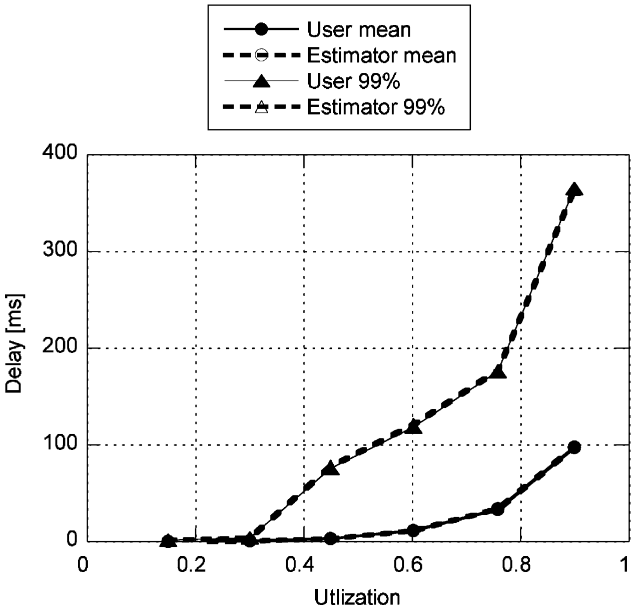


Fig. 6. Delay for users and estimates of delay.

our method accurately estimated the delay of user packets over a range of utilization ratios.

Figs. 7 and 8 show the relative errors of the probe results and the estimated results with respect to the mean and 99% delay cases for user packets. It can be observed that our method accurately estimates the delay of user packets. Although we found estimation errors for the mean under low utilization values of 0.15 and 0.3, the differences were only 0.03 and 0.06 ms, respectively; both values are negligible. On the other hand, consideration of the probe packets alone would underestimate the delay by about 40% (4 ms) for utilization ratios lower than 0.6 in the case of mean delay, and 0.45 in the case of 99% delay.

Under high utilization ratios, the relative errors for both the mean and 99% delays of probe packets are small.

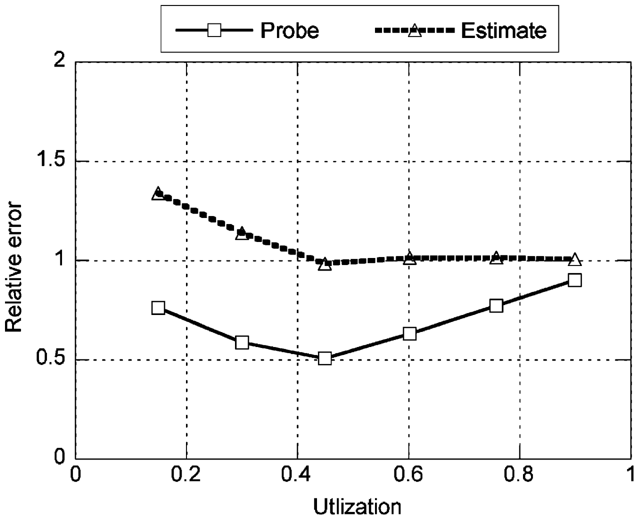


Fig. 7. Relative errors as estimated and probe delay over mean user delay.

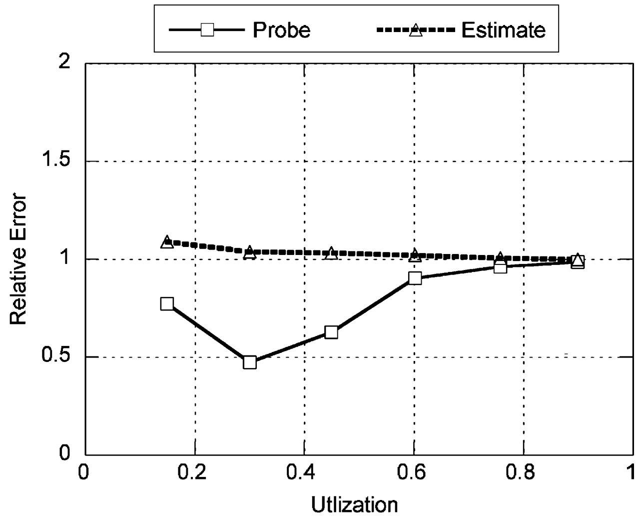


Fig. 8. Relative errors as estimated and probe delay over 99% value of user delay.

### 3.1.3. Evaluation for multiple bottlenecks

We also used a multiple-bottleneck topology to evaluate the method in a more realistic scenario. The topology is illustrated in Fig. 9. Thirty exponential On–Off sources were connected at a router via 1.5 Mbps links and routers are connected via 10 Mbps links. Cross traffic was generated by the sources connected to the intermediate routers. The numbers of intermediate cross-traffic sources for each router were 15, 30, and 60, and the utilization values for the respective intermediate links were 0.45, 0.6, and 0.9, respectively.

Figs. 10–12 show the delay distributions of user packets and probe packets, along with the estimated results. The graphs show that our method provides good estimates of the delays of user packets. In the case of 60 sources (utilization of 0.9), the delay for user and probe packets, and the estimated delay, are agree with each other. This is expected from the results for the single-bottleneck scenario at a high-utilization rate, where the same delays are on the user and probe packets.

## 3.2. Estimation of individual user delay

We describe here an extension of our measurement method, in which estimates are based on the packet delay for

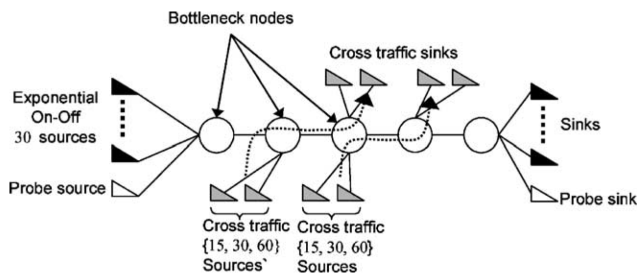


Fig. 9. Network configuration for simulation.

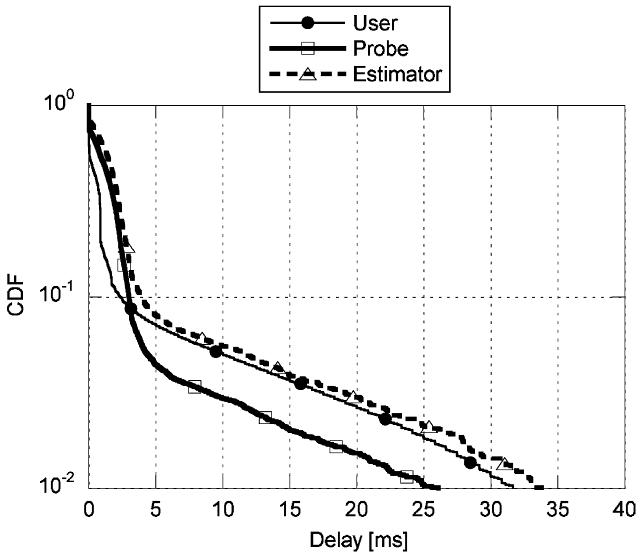


Fig. 10. Distribution of delay for user and probe packets, and estimated delay with the 15 cross-traffic sources.

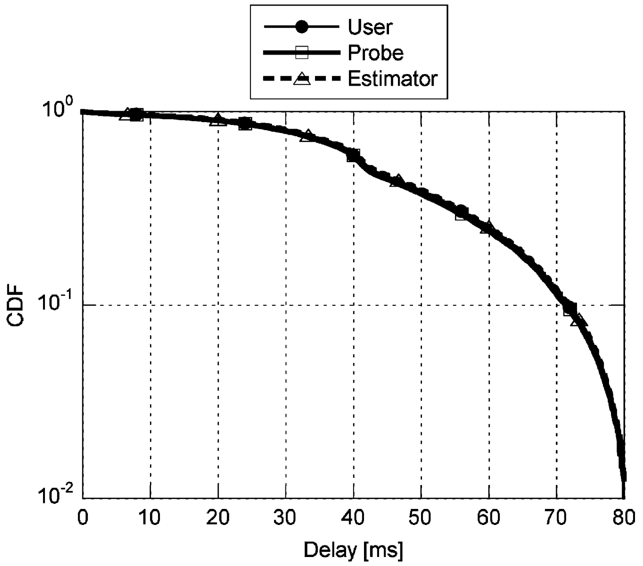


Fig. 12. Distribution of delay for user and probe packets, and estimated delay with the 60 cross-traffic sources.

individual users as obtained in a single series of active measurement and passive measurement of the number of packets for each user.

### 3.2.1. Theoretical basis

Let $X_k$ be the packet delay of user $k$ ($k = 1, 2, \ldots, K$) and $Y(j)$ ($j = 1, 2, \ldots, m$) be the delay as measured by using active packets, e.g. by ping, at time $s_j$. Let the number of packets for user $k$ arriving in $[s_j, s_{j+1})$ be $\rho_k(j, \tau)$ Then, the total number of packets for user $k$ is

$$n_k := \sum_{j=1}^{m} \rho_k(j, \tau). \tag{14}$$

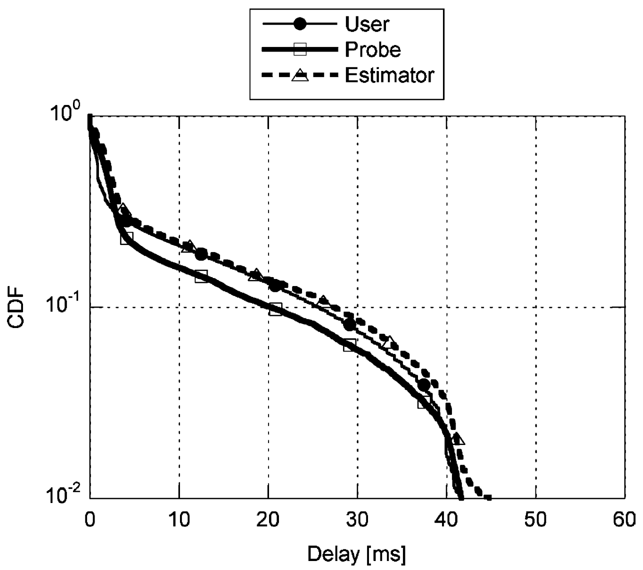


Fig. 11. Distribution of delay for user and probe packets, and estimated delay with the 30 cross-traffic sources.

The likelihood ratio for user $k$ is approximated by $L_k(j, \tau)$, for sufficiently small $\tau$, as

$$L_k(j, \tau) := \rho_k(j, \tau) \frac{m}{n_k}, \tag{15}$$

and we can obtain the estimator as follows:

$$Z_{Yk}(m, \tau, a) = \frac{1}{n_k} \sum_{j=1}^{m} \mathbf{1}_{\{Y(j)>a\}} \rho_k(j, \tau). \tag{16}$$

Thus, by counting the number of packets arriving for each user, we can estimate the delay experienced by individual users.

The classification of traffic is not limited to individual users or groups of users but can be extended to applications. The performance for packets may differ with the application because the traffic pattern will differ with the application. Using our method, we can monitor the performance for each application with one series of active measurements, provided that packets for every class are treated with the same priority in the network.

### 3.2.2. Evaluation

We tested this extension by simulation. The traffic sources were composed of the three classes of users, A, B, and C, as shown in Table 1. The mean rate of transmission from each user in all classes was set to 0.1 Mbps.

Fig. 13 shows the complementary distribution function for the delay of each class under a utilization ratio of 0.6. Figs. 14–16 show the mean and 99% delay for each class of traffic and the respective estimated figures for various link-utilization ratios. While the delay behavior for Class-A users differs from those for Classes B and C, our method accurately estimates the delay for each class of users from a single series of active measurements.

Table 1
Traffic composition

| | Class A | Class B | Class C |
|---|---|---|---|
| Mean On duration (s) | 1 | 5 | 10 |
| Mean Off duration (s) | 14 | 10 | 5 |
| Sending rate in On periods (Mbps) | 1.5 | 0.3 | 0.15 |

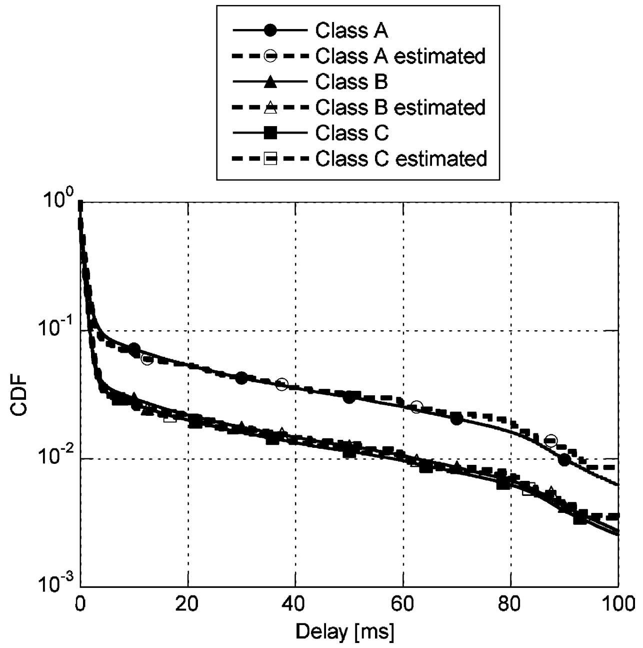


Fig. 13. CDF.

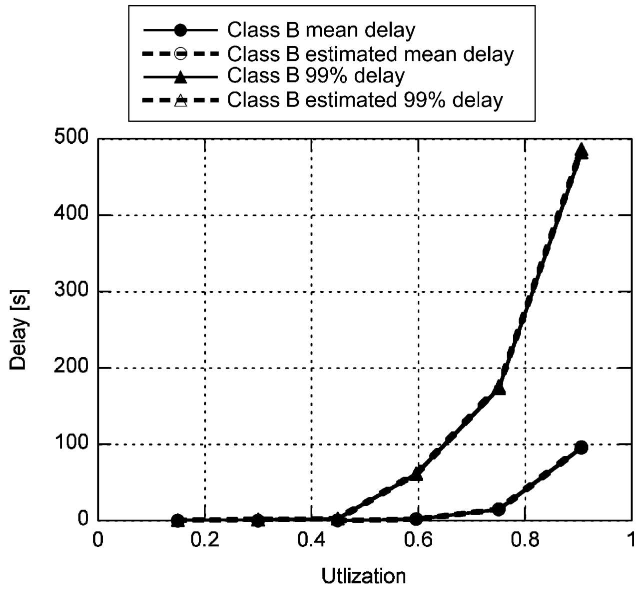


Fig. 15. Delay for Class B.

## 4. Accuracy of estimation

### *4.1. Relationship between accuracy of estimation and probe interval*

Our method of estimation described in Section 3.1.1 is based on the assumption that $V(t)$ can be considered almost constant (unchanged) over the period $\delta(t)$. Hence, the accuracy is expected to decrease with a larger interval for active measurement. However, because a shorter interval means more additional traffic, there is a trade-off between the accuracy of the estimate and the overhead

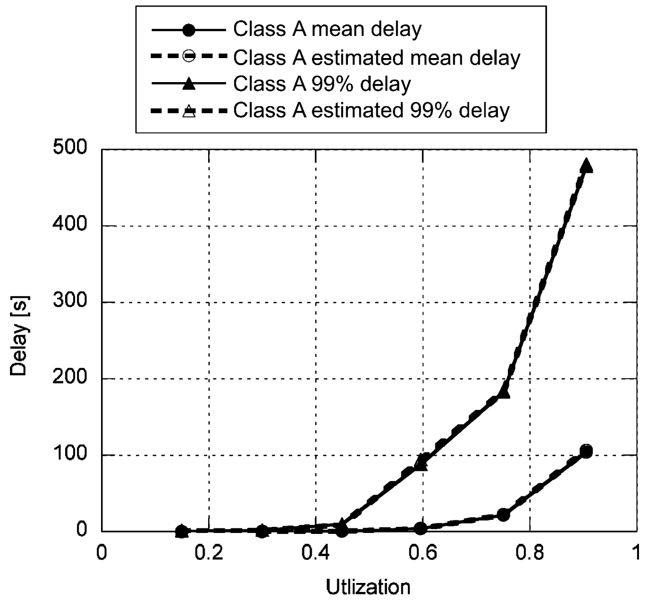


Fig. 14. Delay for Class A.

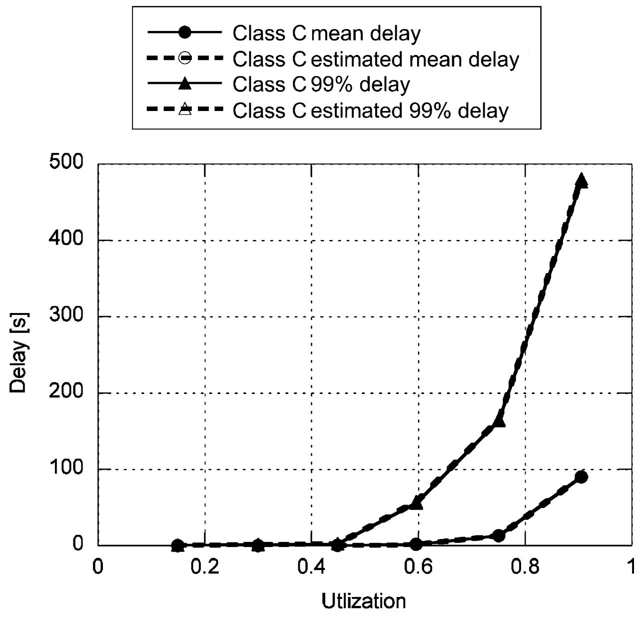


Fig. 16. Delay for Class C.

due to the probe traffic. In this section, we analyze the accuracy of the method, especially in estimating the mean delay.

We ran simulations varying the measurement interval from 62.5 ms to 8 s and observed the changes in the discrepancy between the actual and estimated delays. For each measurement interval, five simulations were performed. Except for the measurement intervals, the conditions of simulation were the same as in Section 3.1.2. We compared the mean delays for user packets and probe packets, and the estimated results.

Fig. 17 shows the results. The mean delay for user packets was about 11 ms, while that for probe packets was around 7 ms. In this case, simple measurement using probe packets underestimated the queuing delay by about 40%. The estimator approximates the user delay with high accuracy when the interval is less than 1 s, which is the same as the mean On duration. As the interval increases, however, so does the error in estimation.

Below, we consider the accuracy of the estimation in terms of the mean and variance of the error in estimation.

### 4.2. Mean of the error

If the system can be assumed to be stationary, then we have

$$E[M_Y(m,\tau)] = \sum_{j=1}^{m} E\left[ Y(j)\frac{\rho_j}{n} \right] \tag{17}$$

$$= mE\left[ Y(1)\frac{\rho_1}{n} \right] \tag{18}$$

$$= E[Y(1)] + \mathrm{Cov}[Y(1), \lambda_\tau(1)], \tag{19}$$

where $\lambda_\tau(j)$ is defined as

$$\lambda_\tau(j) := \frac{m}{n}\rho_j, \tag{20}$$

for which the mean is equal to 1 (hereafter we simply write $E[Y]$ or $\mathrm{Cov}[Y, \lambda_\tau]$ instead of $E[Y(j)]$ or $\mathrm{Cov}[Y(j), \lambda_\tau(j)]$).

We also have

$$E[M_X(n)] = \mathrm{E}[Y] + \lim_{\tau\to 0} \mathrm{Cov}[Y, \lambda_\tau]. \tag{21}$$

if we can assume that the probe packet is small enough.

$E[Y]$ is the mean delay measured with probe packets and is independent of the measurement interval. When $\lim_{\tau\to 0}$ $\mathrm{Cov}[Y, \lambda_\tau]$ is zero, $E[Y]$ agrees with the mean delay of user packets. The estimation error is evaluated from the difference between $[Y, \lambda_\tau]$ and $\lim_{\tau\to 0} \mathrm{Cov}[Y, \lambda_\tau]$, which depends on the measurement interval $\tau$.

Fig. 18 is a plot of the mean of $\mathrm{Cov}[Y, \lambda_\tau]$ and 95% confidence intervals vs. the measurement interval for the five simulations. We can see that the covariance decays as the measurement interval increases. This is natural because the correlation between traffic intensity measured at a fixed interval and the queuing delay decreases as the measurement interval increases.

We cannot obtain the value $\lim_{\tau\to 0} [Y, \lambda_\tau]$ itself, but the graph shows that the covariance converges to on a particular value as the interval approaches zero. Thus, we can roughly estimate the appropriate measurement interval for the required accuracy. For example, if we require 1-ms accuracy and assume $\lim_{\tau\to 0} \mathrm{Cov}[Y, \lambda_\tau]$ is about 5 ms, then measurements every 1 s are sufficient to achieve the required accuracy. Note that, in this estimation, we use only available measurement values such as packet counts and probe delays.

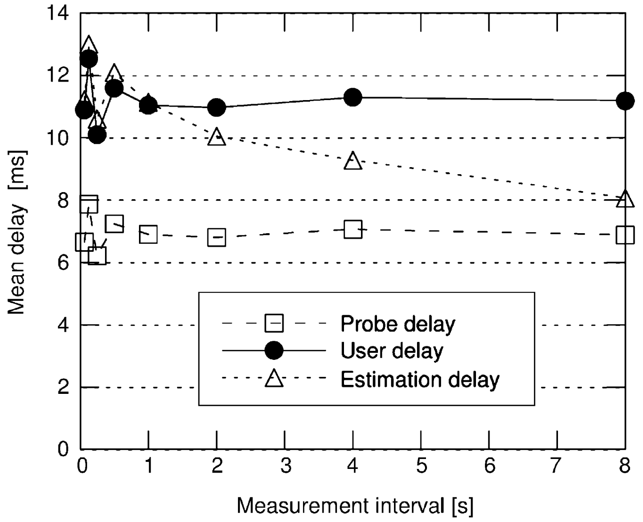


Fig. 17. Measured and estimated mean delay for various measurement intervals.

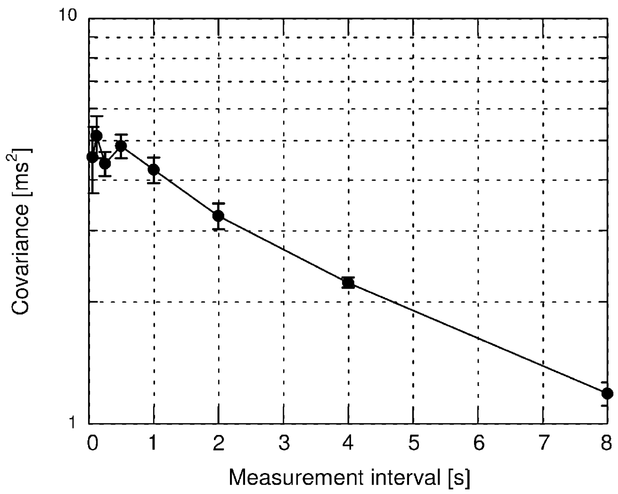


Fig. 18. Covariance between packet count and measured delay.

### 4.3. Variance of the error

The estimation error can be written as

$$M_Y(m,\tau) - M_X(n) = \frac{1}{n}\sum_{j=1}^{m}\left(\sum_{i=1}^{\rho(j)}(Y(j) - X^j(i))\right), \tag{22}$$

where $X^j(i)$ is the delay of the $i$-th user packet arriving in the $j$-th measurement period.

Firstly, we evaluate the variance of the value in the second brackets of Eq. (22). We define the conditional variance of the value for $\rho(j)$,$E_c(\rho(j))$, as

$$E_c(\rho(j)) := \mathrm{Var}\left[\sum_{i=1}^{\rho(j)}(Y(j) - X^j(i))|\rho(j)\right]. \tag{23}$$

We also define the conditional variance and auto-covariance functions of $V(t)$ for $\rho(j)$ as $V_{\rho(j)}(t)$ and $C_{\rho(j)}(t)$, respectively.

For a rough evaluation, we assume that $\rho(j)$ user-packets arrive in the constant intervals between probe packets. Then

$$V_c(\rho(j))Y := \mathrm{Var}\left[\sum_{i=1}^{\rho(j)}\left(V(0) - V\left(\frac{i\tau}{\rho(j)+1}\right)\right)\right] \tag{24}$$

$$\simeq (\rho(j)^2 + \rho(j))\mathrm{Var}[V_{\rho(j)}(0)] - 2\sum_{i=1}^{\rho(j)} iC_{\rho(j)}\left(\frac{i\tau}{\rho(j)+1}\right). \tag{25}$$

(Here we use the stationary condition for $V(t)$ and the equation that $\mathrm{Var}\left[\sum_{i=1}^{s} V(i)\right] = s\mathrm{Var}[V(0)] + 2\sum_{i=1}^{s-1}(s-i)C(i)$.)

Therefore, the unconditional variance of the sum of the errors for one measurement can be calculated with the distribution of the number of user packets $P_k = \Pr[\rho(j) = k]$ as:

$$\mathrm{Var}\left[\sum_{i=1}^{\rho(j)}(Y(j) - X^j(i))\right] \simeq \sum_{k=1}^{\infty} V_c(k)P_k \tag{26}$$

If we can also assume that the sums of the error for different measurements are independent of each other[5], then

$$\mathrm{Var}[M_Y(m,\tau) - M_X(n)] \simeq \frac{m}{n^2}\sum_{k=1}^{\infty} V_c(k)P_k, \tag{27}$$

It may be observed from Eq. (27) that, if the measurement interval is fixed, then the variance of the error is inversely proportional to the number of measurements.

Note that we can obtain the conditional auto-covariance function $C_{\rho(j)}(t)$ and the distribution $P_k$ from the measurements of packet counts and probe delays. Of course, to obtain $C_{\rho(j)}(t)$, we have to measure the delay with a short probe-interval. However, this measurement is only required for the evaluation of the variance of the error. Therefore, we believe that $C_{\rho(j)}(t)$ is available.

[5] We confirm this independence from the auto-correlation function whose values are almost zero for both exponential- and Pareto-distributed On duration.

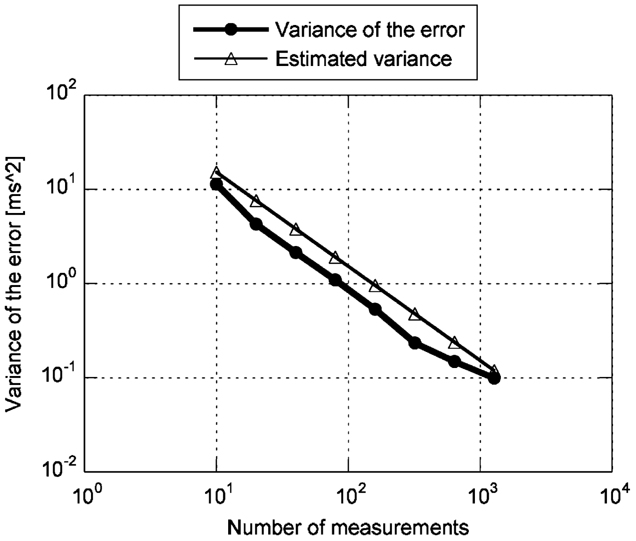


Fig. 19. Variance of the error vs. the number of measurements.

Fig. 19 is a plot of the variance of the error in estimation and the estimated variance of the error in estimation obtained by using Eq. (27) against the number of measurements. The simulation conditions are the same as in 3.1.2, and to obtain $C_{\rho(j)}(t)$, we ran the simulation with probe interval of 100 ms, which is ten times shorter than the normal measurement. We can see that the variance decays as the number of measurements grows and the variance calculated from Eq. (27) estimates the variance of the error fairly well.

We can then roughly evaluate both the mean and variance of the error by using available measurement values. Thus, we are able to determine the appropriate measurement interval and number of measurements to achieve a required level of accuracy in terms of the mean and variance of the error. For example, when we measure the delay with 1000 probe packets and a 1-s measurement interval, then the mean of the error for the estimate is about 1 ms and the variance of the error is approximately 0.1ms$^2$.

## 5. Conclusion

In this paper, we proposed a performance measurement method called *CoMPACT Monitor*, which can estimate user performance in a scalable and lightweight manner. Our method only requires counting of the traffic volume (passive monitoring) and simple measurement of network performance (active monitoring). The method is thus more feasible and tractable than conventional methods. We have applied our change-of-measure method in a simple implementation.

We validated the method by simulation, which showed that it gives a good estimate of the performance as seen by a user. We extended this method to estimate individual user performance, and confirmed the validity of this approach by simulation. We also tested the applicability of the method in terms of accuracy in estimation. We found that the mean of the estimation error depends on the measurement interval and the variance of the error depends on the number of measurements, and that rough estimates of the error can be obtained from the available measurement values.

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