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# A Cross Traffic Estimate Method for High Speed Networks

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**Abstract.** A cross traffic estimator is proposed based on the loss ratio of probe packets. This method aims to estimate the future networks' available bandwidth such as optical switching networks. In these networks, node's processing time other than tight link becomes the bottleneck. And most popular estimate techniques neglect it. Scheme proposed by paper injects probe packet to networks. Probe traffic intensity and drop ratio are collected and is fitted according to 1st order ordinary least squares algorithm which uses former as dependent variable and latter as independent variable. Then the intercept difference between fitted line and empirical line is just the cross traffic. Simulation shows that our scheme can obtain the bottleneck node cross traffic moderately and outperforms the minimal backlogging algorithm which is also based M/G/1 model.

**Keywords:** Cross traffic; optical burst switching, queuing model; linear fit;

## 1. Introduction

Estimating the cross traffic of a path in network is an important and challenging issue. It can be used in various areas such as QoS providing, network optimization and fault detection. Recently many valuable schemes are proposed to get awareness of path traffic status. Some of them aim to get the available bandwidth of an end-to-end path and others aim to measure the tight link's capacity. In general the cross traffic measurement can be classified into passive [1][2] and active means [3]-[6], [8][12]. Passive method is intrusive but unrealizable because of needs of deploying agent devices into networks core nodes. On the contrary, active method is intrusive but convenient to operators and service providers. If the injected probe packets are lightweight or have less effect on the network users and existing services, the active ones will be more recommendable. So we focus on active method in this paper and will mainly concentrate on the constraint of future networks such as optical burst networks. The rest of paper is organized as follow: related works and our objective are presented in section II. Queuing model based on M/G/1/N is described and some clues are revealed in section III; in section IV, we develop a cross traffic inference algorithm based on the foundation drawn from part III and evaluate its performance through simulation. Finally, conclusion and future works is state in part V.

## 2. Related Works

Current active cross traffic estimating research mainly divided into three kinds. First kind is the packet gap model (PGM) such as IGI/PRT[3], TOPP[4], pathchirp[5] or ASSOLO[6]. These methods usually send packet pair trains at sources and detect the inter-departure time dispersion at destinations. The dispersion value can reflect the bottlenecks cross traffic intensity due to the queuing of the packet pair. IGI investigates how the initial gap of pairs impact the estimated result, and propose a mechanism to find out tuning point at which the estimate result is proper. Other algorithms like TOPP, pathchirp and ASSOLO adopt various schemes to find the tuning point gap (or packet train rate) rapidly and precisely.  This kind of solution can do well in traditional networks such as LAN or internet. But we all know that the backbone network node may be

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consisted of optical switch architecture in the future. Optical burst switch networks (OBS)[7], for example, is considered as a promising solution toward all optical switching network. In optical burst networks, the bottleneck is not the tight link's capacity but the core node's electronic processing time of control burst in control wavelength. OBS core node will reserve wavelength, configure OXC and perform O-E-O conversion when receives an optical control burst. So the control burst's processing time will be large and not deterministic relative to its high speed link. The PGM algorithms mentioned above assume constant and tiny processing time which has no effect on inter-departure time dispersion. The dispersion end host detected is most due to the tight link's insufficient capacity or cross traffic induced with probe pairs. Obviously these algorithms are unsuitable to estimate the optical networks' cross traffic intensity.

The second kind belonged to be queuing model based algorithms. Most of these method use moment estimating method. For example [8], constructs M+M/M/1 and M+M/D/1 model to describe the packets' queuing behavior in bottleneck node. It deduces a series of equation that can relate many QoS metrics moment value to cross traffic. Based on these equations, it propose some cross traffic estimators. Sara proposes a cross traffic inference method based on the MMPP/M/1/N queuing model in [9]. He assumes the network's character can be a mixture status of some discrete states. Network is time variant and switched between these states. This method infers the transition probability matrix of HMM model through the observed drop ratio of probe traffic and estimate cross traffic based on the inferred matrix. Both algorithms mentioned above employ moment based means, so they need much large samples and relatively long period to obtain stabile result and much intrusive. [10] proposes an estimator based on M/G/1 model through a probing means named minimal-backlogging method. This method guarantees at least and only one probe packet in the bottleneck queue to sample delay and drop ratio information from path. It doesn't make any assumption about the router's processing time and is more appropriate for optical networks than the previous two. Nevertheless, it also suffers from the moment based means as above two and at the same time not takes buffer size into account.

The third kind algorithm [11][12] emerged take advantage of either kind of previous. Both have tried to verify that 1st order moment of the loss ratio and delay gap can only be observed through larger samples and higher probing rates which means more intrusive and longer observation period. Square coefficient variance (SCV) of inter-departure time proved by the two works can be a more reasonable metric to infer cross traffic because of their significant linear dependent with probe traffic. The SCV metric is drawn from M+GI/G/1 (or M+M/G/1) and can't be easily observed when buffer capacity is small capered with the probe packet's length. But the capacity of buffer in future optical network will be very small because it is useless to buff a control packet in electronic domain long time while the consequent data's sooner arriving make the control information invalidate.

As discussed above, we aim at find out a proper observation metric of future optical networks, and develop a cross traffic estimate algorithm intrusiveness and simplicity. In section III, we will show that the probe packet's drop ratio will be a nice candidate to be an observation metric.

## 3. Queuing Model of Bottleneck Node

### 3.1. Scenario and assumption

First, we consider a path we concerned has only one bottleneck node in network. This assumption has already been used in various works previously posed and be verified appropriate [9][10]. It can be seen as a series queues connected each other if multiple bottlenecks exist.

Second, the cross traffic pattern this section used is assumed to be Poisson. According to [13], Poisson model is reasonable in merged traffic specifically in future backbone optical burst networks.

Third, we adopt the M/G/1/N model to describe the queuing behavior of bottleneck node. N means buffer size. G means general distribution of the packet's processing time. It is important to emphasize that packet's processing time mainly affected by node architecture, O-E-O latency, wavelength reservation algorithm etc. but not the transmission time of packet ordinary used in previous works. So, in this paper the packet length is ignored in determining cross traffic. At the same time, some notation used in this section is as follow: "L" represents average queue length; "$P_N$" is drop ratio; "W" means average wait time in queue; "  " is the normalized traffic load while "1/  " and "$\sigma$" represent mean and variance of packet processing time in bottleneck nodes.

### 3.2. M/G/1/N queuing model

The analytical solve of the M/G/1/N model is difficult, so we use method from [14] to analysis bottleneck node's queuing behavior approximately. This approximate method is named diffusion, and is appropriate in constraint of moderate size of N. For large number N, the M/G/1 model turns to be a right solution. Diffusion's method is described as follow.

$$\begin{cases} L = \sum_{n=1}^{N-1} nP_n + N*(1-\frac{1-c(1-\rho)}{\rho}) \\ P_n = c*\overline{p}(n) \\ P_N = 1-\frac{1-c(1-\rho)}{\rho} \\ \overline{p}(n) = \rho(1-\overline{\rho})(\overline{\rho})^{n-1} \\ \overline{\rho} = \exp(\frac{2(\rho-1)}{\rho+K_s}) \\ K_s = \sigma^2 u^2 \\ c = \{1-\rho[\rho-\sum_{n=1}^{N-1}\overline{p}(n)]\}^{-1} \end{cases}$$

. .1

And from little theorem, average wait time of a packet is:

$$W = \frac{L}{u*\rho*(1-P_N)}$$

. .

"$K_S$" appears in (1) and (2) is square of the variation coefficient of the packet's processing time.

From (1) and (2), if we know $\rho$ and N in stable condition, “W” and “$P_N$” can be deduced (note as $\rho \to \{W, P_N\}$ ) whereas $\{W, P_N\} \to \rho$ is also possible and thus the cross traffic can be inferred from some observation such as probing delay or drop ratio. Following subsections discuss the quantity dependence of “W”, “$P_N$”," " and "$K_S$" through numerical analysis and computer simulations. Finally make a proper choice of metric from all above as observation metric in order to estimate cross traffic under networks.

### 3.3. Numerial analyse and some clue

From (1) we can see that both “W” and “$P_N$” be influenced by "$K_S$" and " ". In this subsection, we numerically evaluate the quantity relationship of these variables expecting to get some valuable information benefit to $\{W, P_N\} \to \rho$ . Parameter in use is N=6 [14], . . 1.

Fig. 1 shows how “W” and “$P_N$” be dependent with "$K_S$" while stimulated by " ". The four curves rounded by ellipse represent that packet's average wait time in queue has no distinct difference even though the traffic intensity is variant especially when square variance coefficient large than 10. Contrarily, other four curves show “$P_N$” being more distinct when normalized traffic is different. Furthermore, this difference hardly changes no matter what "$K_S$" value is. As discussed above, "$K_S$" is a square variance coefficient which is mainly determined by the node architecture, resource reservation algorithm and O-E-O conversion time. Fig. 1 likely means that drop ratio is less sensitive to the node's parameter and is more reasonable to be observation metric than end-to-end delay.

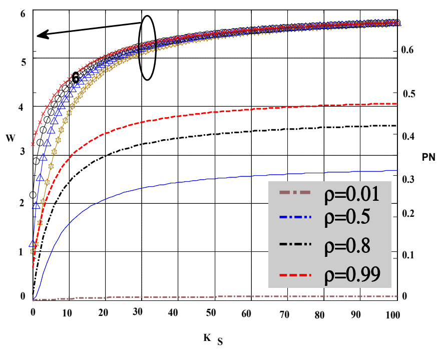


Fig. 1: $\{W, P_N\} \to \rho$ vs. $K_S$

In order to further verify the clue revealed by Fig.1, we plot Fig.2 and Fig.3, both of them contained 101 curves to test $K_S$ range from 0 to 100. A similar conclusion as Fig.1 can be drawn. For most cases "W" is almost constant and "$P_N$" exhibits almost linear dependence with   especially when $K_S >= 5$. This linear characteristic can also be seen by solve (1) and make Taylor series expansion towards "$P_N$". The approximate result is like as (3) and fig. 4 (under $K_S$ =10). We can see the approximation is very precise.

$$\begin{aligned} P_N &= \rho / \exp(10/K_S) + o(\rho) \\ &= \theta * \rho + o(\rho) \end{aligned} \tag{3}$$

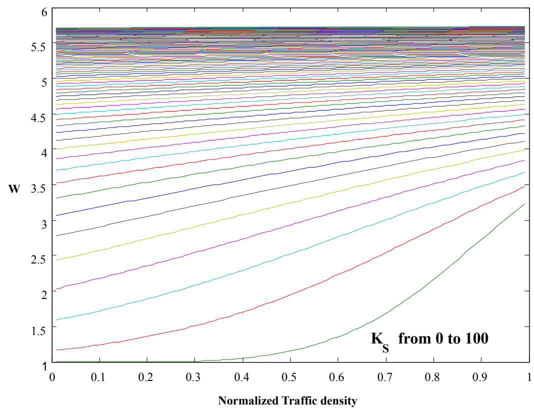


Fig. 2: W vs. $\rho$

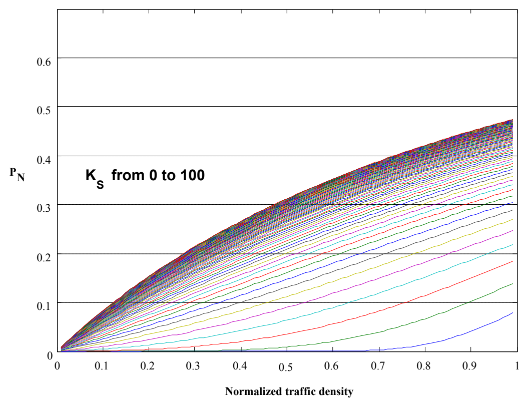


Fig. 3: $P_N$ vs. $\rho$

## 3.4. Simulation of queuing system

From last subsection's numerical analysis, we find out packet's drop ratio being more likely appropriate as observation metric than end-to-end delay. In this subsection, we utilize computer simulation to validate the fact that "$P_N$" is linearly against  and "W" has slight relevant with it in M/G/1/N model.

Simulation scenario is just like Fig.5. Source induces packet to destination with Poisson traffic at speed from 10pkts/s to 100pkts/s and adjusts speed every time with step of 10pkts/s. Switch simulate bottleneck node. The service rate is 100pkts/s i.e. average processing time 0.01s per packet. The processing time obeyed gamma distribution with $K_S$ =10. Of course it can be replaced by any other distribution available. We use gamma distribution just for simulating large variance to reflect the complex factors concerned with future optical networks.

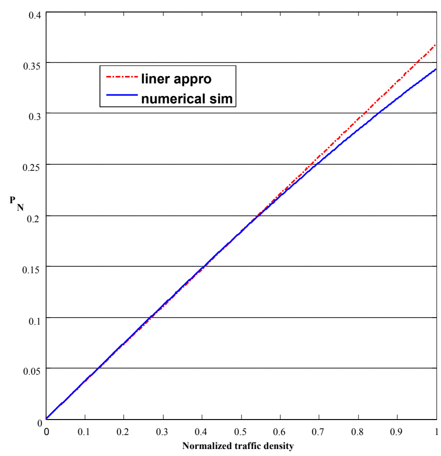


Fig. 4: Linear appro vs, numerical sim

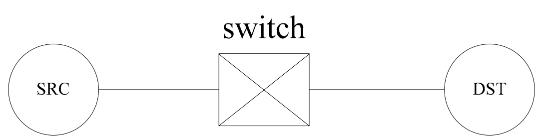


Fig. 5: Simulation scenario

Fig.6 is the moving average result every 500 samples. X-axis in figure represents time series, and y-axis is (no unit), W (times of), $P_N$ (no unit). We can see the traffic intensity is increasing though jitter exists with the simulation time. The shape and trend of $P_N$ curve, as expected is very similar to it of which verifies the III.C result again. Fig.7 enlarges Fig.6 and makes the compare more clarity. Drastic jitter of the curve's tail is due to the lack of sample when toward the end of simulation and doesn't impact the analysis of the overall data.

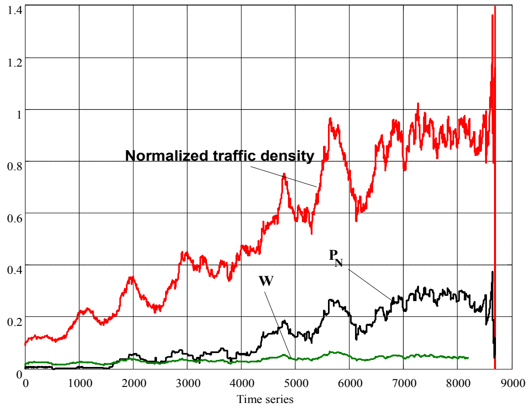


Fig. 6: ρ, $P_N$ && W vs. time series

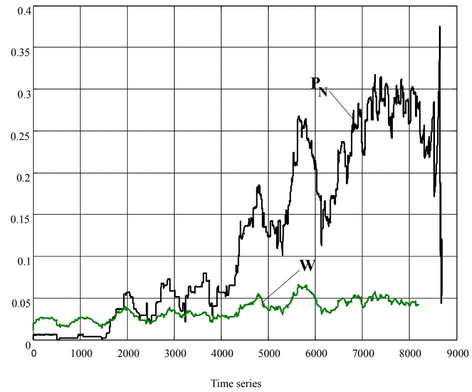


Fig. 7: $P_N$ && W vs. time series

In simulation,we also test the linear characteristic revealed by numerical analysis. Fig.8 shows raw simulation data, segmented average results (about 10 segments) and the OLS fitting result of the raw data. We can see the linearity reappearing and is fitted properly. But the vertical inception of Fig. 8 is not zero as Fig.4 and intercept at about 0.2. When we change the $K_S$ to other values e.g. 5 and 50 as in Fig. 9, the interception is nearly unchanged. So we think when the drop ratio is so low that the end host can hardly detect it or calculate it precisely.

After this subsection's simulation, we can get an aware that the drop ratio detected at end host is linearly dependent with the bottleneck node's traffic intensity. So we can infer the bottleneck node's traffic through the drop ratio observed at destination host. But the slope of this linearity is determined by the $K_S$ (square of variance coefficient of processing time). Unfortunately it is unknown usually. So, we proposed that if we inject some probe traffic at source node while detect and calculate probe traffic density (notified by source) and drop ratio at destination, we can get the inception and slope of the probe traffic by OLS (optimal least square) fitting algorithms like Fig. 8. If cross traffic is stable, the difference between fitted interception and empirical interception will be the cross traffic. Thus the cross traffic can be estimated successfully and of course the fitted slope of probe traffic is got successfully. In the following section IV, we will introduce our estimate algorithm in detail.

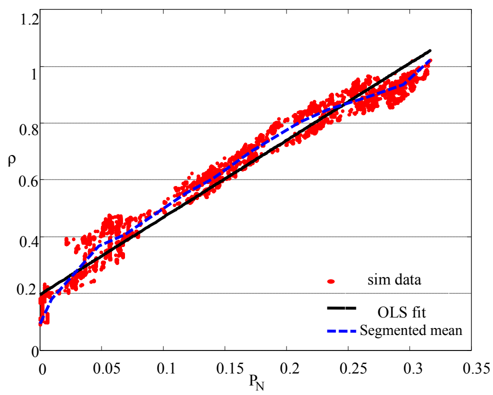


Fig. 8: ρ vs. $P_N$

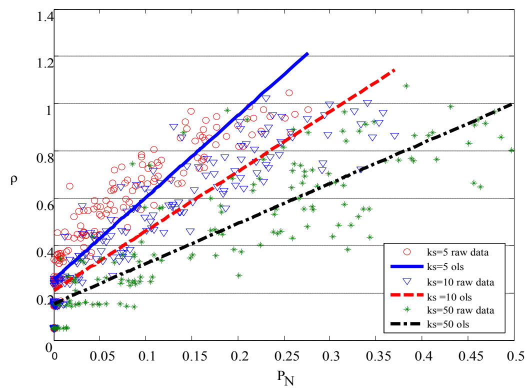


Fig. 9:ρ vs. $P_N$

## 4. Cross Traffic Estimate Algorithm

Our algorithm is focus on the model like Fig.10. SRC and DST is end host pairs be interested in the cross traffic intensity flow through bottleneck queue. SRC injects probe traffic combined with cross traffic. Probe traffic carries some information such as current probe rate and sequence number etc. DST receives probe traffic and calculates drop ratio based on the information carried in probe packet and fitted the sample drop ratio against the probe traffic intensity. When get a stable interception, sub it from empirical interception value (20 proved by section III.D), and thus get the cross traffic. Before describe our algorithm detail, let's take familiar with some notation and first:

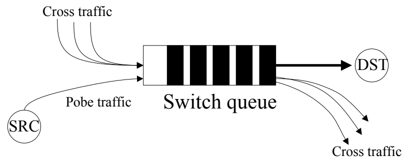


Fig. 10: Network model

*: sample period, minimum time granularity dst observe;*
*$s_i$: number of probe induced at the ith*
*$_i$: probe packet's rate during ith*
*$_c$: cross traffic estimated finally;*
*$y_i$ : sampled drop ratio during ith*
*Avg moving average of unti ith*
*$vgy_i$ moving average of yunti ith*
*$d_p$ : interception of the probe fitted result;*
*$d_e$ : empirical interception (normally setting to 20);*

## 4.1. Pseudo code of algorithm

Pseudo code of algorithm is listed in this subsection. The algorithm consist two main parts. First is init procedure and the second is estimator. We list mainly the destination node's algorithm and ignore the sources node for its simplicity.

```
Process (estimate):
                    Step1(init):
            get(τ), get(Δτ);
            T = M*τ,  i = 0;
            Avgλ = avgy=0;
            d_e = 20;
      end step1;

      step 2(estimator):
            wait until t=i* τ;
            avgλ_t=(1–β)*Avgλ_t + β*λ_t
            avgy_t=(1–β)*Avgy_t + β*y_t

            if(i < M )
                  goto step2;
            else
                  avgλ = [ avgλ_1 avgλ_2 ...... avgλ_i];
                  avgy = [ avgy_1 avgy_2 ...... avgy_i];
                  {θ, d_p} =polyfit(avgλ, avgy);
                  λ_c= d_e - d_p;
            endif

            goto step1;
      end step2;
end process (estimate)
```

In the code, "M" denotes sliding window size, " " represents forgetting factor and "get(.)" means obtain initial value from network operator or network management software.

## 4.2. Simulation and evaluation

In this subsection a series simulations are performed to evaluate the algorithm's performance. Simulation scenario is like Fig.10 and most parameters is set as follow: cross traffic in bottleneck queue is 50 packets/s and obey Poisson distribution; probe traffic rate increase from 10 packets/s to 50 packets/s periodically; sliding window size M=500; forgetting factor =0.75, and other parameters keep the same as section III.D.

Fig.11 and Fig.12 is our estimated result. All the cross traffic samples from bottleneck queue, probe traffic sampled from end host and their segmented mean value are presented in Fig.11. And the estimate line (OLS fitted line) is showed in Fig.12. We can see the fitted interception $d_p$=-22.6, so the estimated cross traffic is $d_e$ - $d_c$ = 20-(-22.6)=42.6. Thus, the estimation error of this test is 6.4 packets/s equivalent to be 6.2/48.8 = 12.7%.

Fig.13 displays the cross traffic, total traffic and probe traffic sampled in this simulation respectively. The probe traffic increases step by step slowly during the whole simulation duration. But under some conditions, we may need short probe period and quickly estimate. We implement the simulation use short period probe and estimate, and the result like Fig.14 and Fig 15. It looks that the estimated cross traffic could be reflected moderately, though suffers from some error.

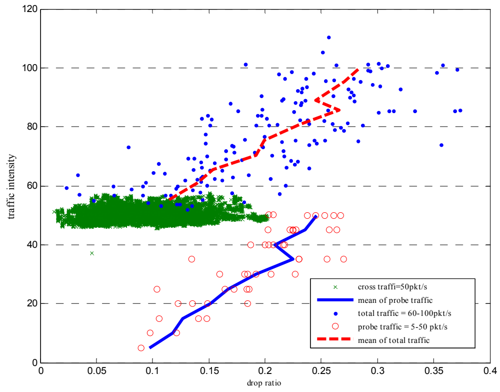


Fig. 11: Cross traffic and probe traffic

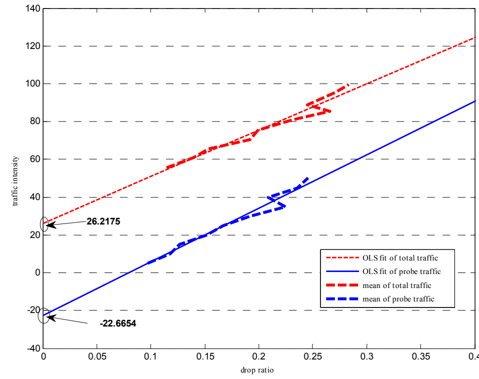


Fig. 12: OLS fit result

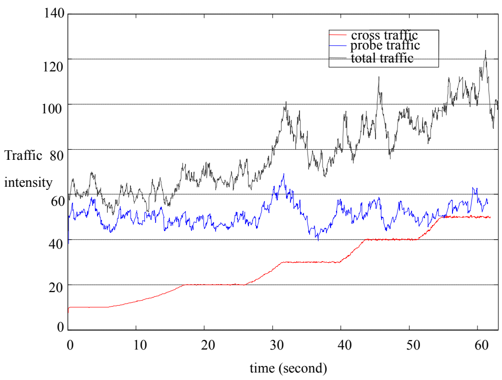


Fig. 13: Probe, total and cross traffic pattern

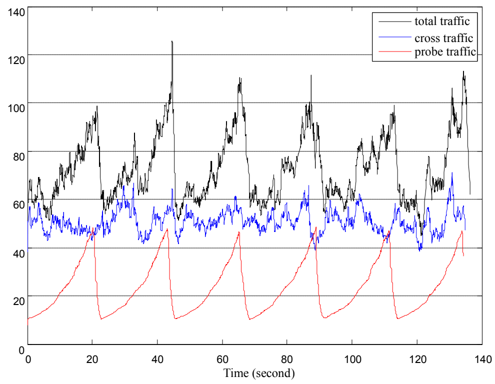


Fig. 14: Short period probe

Minimal backlogging algorithm proposed by[10] is also based on M/G/1 model. Our simulation also implements it in order to show the different between us. From Fig.16 and Fig.17 we can see that at lower cross traffic level, our scheme has similar accuracy as minimal backlogging and an evident advantage against it when network is heavily loaded by cross traffic. This is mainly because of its ignoring of buffer size's effect. And it also exhibits its intrusion (exceed bottleneck capability under almost every conditions) in Fig. 17. The reason lies in its intention to ensure queue with at least one probe packet even when the queue is empty. Our scheme in this simulation maintains the probe traffic lower than 0.2 and decrease probe step to 0.05. So our scheme can keep the probe packet in lower level and intrusive less.

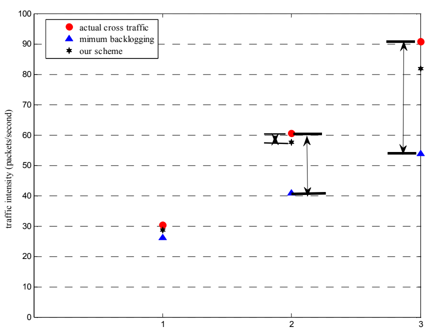


Fig. 15: Quick estimate of short period probe

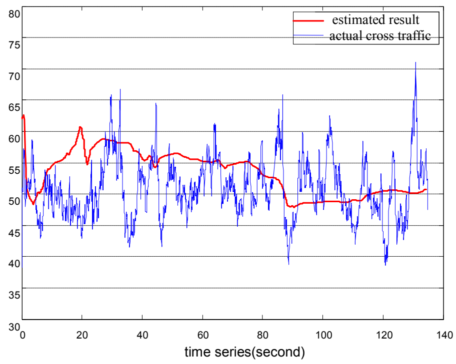


Fig. 16: Minimal backlogging and our scheme

## 5. Conclusion and Future Works

A cross traffic estimate method based on M/G/1/N model is proposed. This method makes the assumption that processing time is bottleneck other than the link capacity. The variance of processing time is considered while deploy inference scheme. The scheme utilizes the linear dependent of drop ratio on the traffic intensity through bottleneck queue. From the difference between probing fitted interception and empirical interception, cross traffic can be inferred. When in simulation, we found it hardly to detect the drop ratio when total traffic is lower than 0.2. In the future, how to infer lower (especially less than 0.2) cross traffic is the main focus of research.

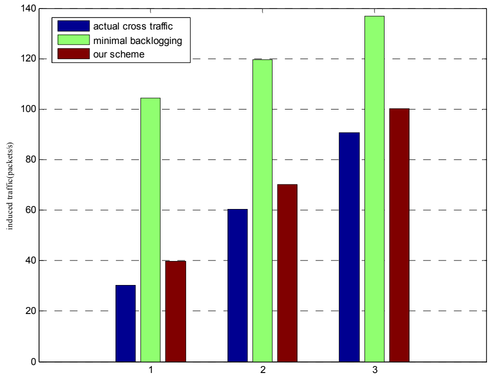


Fig. 17: Minimal backlogging and our scheme's intrusive

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