Traffic Dynamics Online Estimation Based on Measured Autocorrelation

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Abstract. Estimation of traffic demand is a major requirement in telecommunication network operation and management. As traffic level typically varies with time, online applications such as dynamic routing and dynamic capacity allocation need to accurately estimate traffic in real time to optimize network operations. Traffic mean can be estimated using known filtering methods such as moving averages or exponential smoothing. In this paper, we analyze online traffic estimation based on exponential smoothing, with focus on response and stability. Novel approaches, based on traffic arrivals autocorrelation and cumulative distribution functions, are proposed to adapt estimation parameters to varying traffic trends. Performance of proposed approaches is compared to other adaptive exponential smoothing methods found in the literature. The results show that our approach based on autocorrelation function gives the best combined response-stability performance.

Keywords: Traffic measurement, estimation adaptation, trend detection, exponential smoothing; autocorrelation.

1 Introduction

An important need in network operation and management is the estimation of traffic demand. Depending on the network application, this demand is usually defined by the average arrival rate of data packets or user connections. Depending on the network management function performed, the network provider estimates this average rate using different techniques. Network planning targets a long timescale (months, years), and in this case, arrival rate is estimated in an offline manner based on past traffic statistics and marketing forecasts. Once the network is deployed, call routing and bandwidth allocation occur on a shorter timescale (minutes, hours) and can be classified as online management functions. At this timescale, typical network traffic show diurnal variation in average arrivals corresponding to user activity patterns [1], [2]: daily traffic is non stationary; rather it will go through stationary periods of quiet and busy traffic, joined by transition periods of trend traffic. Static bandwidth allocation based on peak demand would waste network resource in periods of low

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traffic. Conversely, allocation based on the mean demand for the day will cause network congestion and service degradation in high traffic periods. For continued optimal performance, the online network functions must adapt to traffic diurnal variation. It is then crucial for network operators to have a traffic demand estimation method that is simple to be operated online, yet accurate to provide continuous efficient network optimization.

With the advent of adaptive state dependent [3] and revenue-maximizing [4], [5] traffic routing algorithms, traffic demand estimation algorithms such as [6] started to be proposed. Later on, with the possibility of adaptive bandwidth provisioning for network continued optimization (as in MPLS tunnels, virtual and overlay networks), several more online demand measurement and estimation approaches were proposed [7]-[12]. As arrival rate estimation is generally affected by measurement noise, several filtering techniques have been proposed to infer the average rate. In [8], an approach based on the Autoregressive Integrated Moving Average (ARIMA) is used to support bandwidth provisioning. In [9], approximate filtering algorithms based on general birth and death stochastic model were presented. In [10], Kalman filter theory is used in a traffic optimal estimation scheme to forecast link capacity requirements.

Simpler methods well fit for online computation, such as moving averages (MA) [11], weighted average (WA) [12] and exponential smoothing (ES) aka. EWMA (exponentially weighted moving average) [11], [13], [14], [15] have commonly been used to estimate and predict time series average. It was shown in [11] that one can obtain similar estimation accuracy from MA and ES by selecting appropriate controlling parameter values. In this paper, we focus on online estimation of network link traffic demand using modified exponential smoothing methods. We propose two new approaches for improving ES that are based on traffic trend estimation. In one, the trend is estimated based on the traffic arrival process autocorrelation function (acf); in the other, it is based on the process cumulative distribution function (cdf).

The algorithms presented in [16] address a similar problem and the proposed algorithms use an iterative procedure involving an ES scheme. The difference is that we estimate link traffic and use adaptive ES while [16] estimates path traffic and uses fixed ES. The drawback of the path approach is that for large networks the high paths cardinality can overwhelm online path demand estimation. In such networks, a decomposition of network into link processes [5], [11], reduces problem complexity, and link demand estimation can then be used to support online network optimization.

For the performance evaluation of online traffic demand estimation, we propose to use the following two criteria. When demand changes, *estimation responsiveness* criterion measures the lag of the estimated value in reaching the changed average arrival rate. A small lag allows faster reaction to traffic demand changes. Conversely, during periods of stationary demand, *estimation stability* criterion measures the deviation of estimated values from the invariant average arrival rate. In this case, stable estimations avoid unnecessary network operation changes, therefore limiting the volume of signaling messages and unnecessary actions in the network. We will define metrics for these criteria in this paper. Using these metrics, the proposed adaptive ES estimation approaches are compared to static as well as to other previously proposed adaptive ES estimations.

The rest of this paper is organized as follows. In Section 2, we present a traffic model considered in this work. Section 3 summarizes known estimation and forecasting methods that are based on exponential smoothing, and presents our new approaches. In Section 4, we define metrics and evaluate performance of our approaches, by comparing them to existing methods. Section 5 concludes and gives a direction of future research.

2 Model for Traffic Demand and Estimation

Internet traffic patterns and general characteristics were reported by Thompson in [1]. The majority of traffic graphs revealed that both the byte and flow volume follow clear 24-hour patterns that repeat daily over the week. In general, the patterns include two levels of traffic, high during day time and low during night time, showing a difference of as much as 300% - 500%. Transition periods between the levels can last a few hours. Fig. 1 reproduces (from existing literature) real one day traffic trace examples taken at different locations: a) flow volume monitored at a major U.S. East Coast city [1], b) link data traffic collected at University of Missouri-Kansas City [8], c) mean connection arrival rates for various network applications gathered at a Lawrence Berkeley Lab gateway [17]. These and more traces found at the WAND WITS web site [18] confirm the daily pattern.

In this paper, we will estimate traffic demand defined by the average connection arrival rate. Based on the above real traffic patterns, we build a connection arrivals model, shown in Fig. 1d, which we will use for evaluation of the demand estimation. The model presents two stationary periods where average traffic stays around a low and a high level, respectively, and two trend periods where traffic transitions between the mentioned levels. This model simulates the successive stationary and non-stationary periods characterizing the real traffic patterns. Below is the definition of parameters used in the model (expressed at time t):

- $\overline{\lambda}_t$: Average arrival rate (solid line in Fig. 1d). This denotes the theoretic average that should be estimated. This average is invariant in stationary periods, and it follows a linear trend in non-stationary periods.
- $\tilde{\lambda}_t$: Measured arrival rate (dashed line in Fig. 1d).
- e_t : stochastic noise on arrival rates.
- λ'_t : Trend of arrival rate ($\lambda'_t = d\overline{\lambda}_t / dt$).
- λ_t : Estimated arrival rate

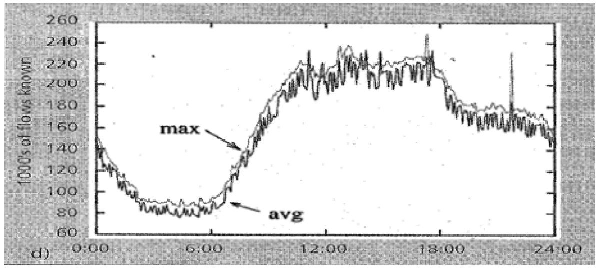
The following set of equations defines the model:

$$\overline{\lambda}_t = \overline{\lambda}_{t_i} + \lambda'_{t_i}(t - t_i) , \tag{1}$$

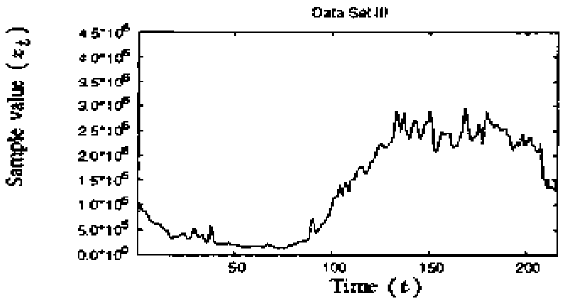
$$\tilde{\lambda}_t = \overline{\lambda}_t + e_t , \tag{2}$$

$$\lambda_t = f_a(\tilde{\boldsymbol{\lambda}}) . \tag{3}$$

where trend λ'_{t_i} is nil in stationary periods and is assumed to be constant during a trend period; and arrival rate estimator f_a is a function of a vector of present and past values of measured arrival rate.



(a)



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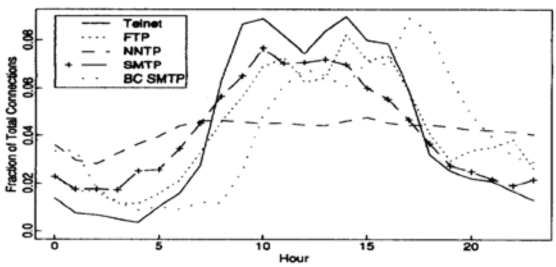

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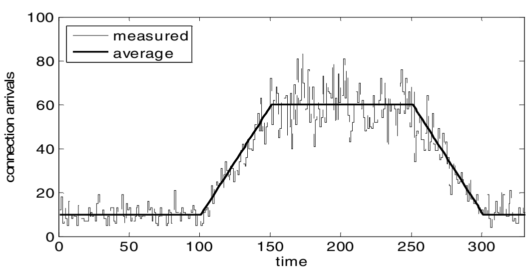

(d)

Fig. 1. One day traces of Internet traffic: a) link flow volume at U.S. East Coast [1], b) link traffic at University of Missouri-Kansas City [8], c) mean connection arrival rates at Lawrence Berkeley Lab gateway [17], d) simulation model of demand (connection arrivals) pattern.

In this model, time and traffic demand are expressed in generic time units, and number of arrivals per time unit, respectively. Average traffic arrival rates $\overline{\lambda}_t$ show the low and high traffic levels with transition periods between them. Arrival rate trends λ_t' and trend period durations form the parameters of the pattern. Arrival rates $\tilde{\lambda}_t$ measured at regular time intervals follow a Poisson distribution with mean corresponding to $\overline{\lambda}_t$. $\overline{\lambda}_t$ and $\tilde{\lambda}_t$ can be generated to realize the patterned demand.

The estimation objective is to achieve values λ_t as close as possible to $\overline{\lambda}_t$. This translates into λ_t being stable (close to invariant $\overline{\lambda}_t$) in stationary demand periods, and responding quickly to changes of $\overline{\lambda}_t$ in transition periods.

3 Demand Estimation by Exponential Smoothing

Average arrival rate estimations are performed at regular time intervals as traffic demand evolves. Exponential smoothing is a well known technique that can be used to produce moving weighted averages of a time series. Different forms of ES have been documented in the literature. Applied to our estimation of average arrival rate, the *Simple ES* (SES) is formulated as follows:

$$\lambda_t = \alpha_t \tilde{\lambda}_t + (1-\alpha_t)\lambda_{t-1} . \tag{4}$$

where α_t is the level smoothing parameter, $0 < \alpha_t < 1$. The *Double ES* (DES) formulation introduces a second equation to account for the trend T_t in the time series, resulting in the set of equations:

$$\lambda_t = \alpha_t \tilde{\lambda}_t + (1-\alpha_t)(\lambda_{t-1} + T_{t-1}) , \tag{5a}$$

$$T_t = \gamma_t(\lambda_t - \lambda_{t-1}) + (1-\gamma_t)T_{t-1} . \tag{5b}$$

where γ_t is the trend smoothing parameter, $0 < \gamma_t < 1$.

Performance of the online estimation, characterized by its stability and responsiveness, depends on the values of the smoothing parameters α_t and γ_t that can be fixed or adaptive. For example in SES, a low α_t will effectively dampen random $\tilde{\lambda}_t$ variations, giving better stability. On the other hand, a high α_t allows ES to better follow changes in traffic demand, improving estimation response [11]. In this section, we first summarize a selection of available methods for assigning α_t and γ_t. Then, we present our proposed approaches for adaptive ES based on the arrival process autocorrelation and cumulative distribution function. Each method will be identified with the convention *ES type-parameter type*, where *ES type* is *SES* or *DES* and *parameter type* denotes the smoothing parameters assignment strategy.

3.1 Literature Review of ES Methods

Currently available methods for choosing parameters α_t and γ_t include fixed and adaptive parameters [13]. A total of 24 ES techniques were reported in 1982 [19]. *Adaptive Extended ES* (AEES [14] and AEES-C [15]) were later developed which provide improved accuracy. For performance comparison with our proposed approaches, we selected two SES methods for its simplicity, and two AEES methods for its improved accuracy.

SES with fixed α_t (SES-fix). In this basic method, parameter α_t is fixed. α_t can be determined by model-fitting using the time series historical data. As mentioned earlier, a tradeoff between estimation stability and responsiveness is dependent on the value chosen for α_t.

SES with adapting α_t (SES-err). In this method, as in following adaptive methods, α_t is adapted at each estimation period as the time series evolves. For its improved accuracy provided, we chose to use the same adaptation formula, based on previous period error that was proposed for AEES:

$$\alpha_t = \left|(\lambda_{t-1} - \tilde{\lambda}_t)/\tilde{\lambda}_t\right|. \tag{6}$$

AEES (DES-err). This method as proposed by Mentzer applies to time series with level, trend and seasonal components [14]. Since seasonal variations are beyond the timescale of online estimation periods, we ignore that component and apply this technique to DES (5a), (5b). α_t is adapted by (6) and γ_t is fixed. Reported AEES tests in general showed better accuracy than previously available ES methods.

AEES-C (DES-derr). This method [15] extended AEES by also adapting trend smoothing parameter γ_t based on previous trend estimation error:

$$\gamma_t = \left|(T_{t-1} - T_{t-2})/T_{t-2}\right|. \tag{7}$$

It was reported that accuracy performance comparisons between AEES-C and AEES were not consistent, but AEES-C was better in 10 of 14 cited test conditions. Given the double error based adaptations of both α_t and γ_t, this method is identified as *DES-derr*.

3.2 New Adaptive ES Approaches

As shown in Fig. 1, traffic demand will go through stationary and trend periods. In stationary periods, changes in arrival rate measurements $\tilde{\lambda}_t$ result solely from noise e_t (2), and use of *SES* with a low α_t as estimator function f_a (3) will provide better stability. In trend periods, the portion of change in $\tilde{\lambda}_t$ due to the trend λ'_t (1) increases with the trend amplitude. To better respond to that change, α_t in *SES* should be increased and therefore should be a function of the trend.

Trend Evaluation. As the trend is a key parameter influencing online estimation by adaptive ES, we need methods to detect and evaluate it. We propose to use the following two measures:

a) Process Autocorrelation Function (acf). The trend of the time series formed by the N successive arrival rate measurements to time t can be indicated by its autocorrelation coefficient at lag one r_t:

$$r_t = \frac{\sum_{n=t-(N-1)}^{t-1} (\tilde{\lambda}_n - \hat{\lambda}_t)(\tilde{\lambda}_{n+1} - \hat{\lambda}_t) \Big/ (N-1)}{\sum_{n=t-(N-1)}^{t} (\tilde{\lambda}_n - \hat{\lambda}_t)^2 \Big/ N} . \tag{8}$$

where $\hat{\lambda}_t = \sum_{n=t-(N-1)}^{t} \tilde{\lambda}_n \Big/ N$ is the mean of the N measurements. With a large N, when the time series is completely random (nil trend), r_t is approximately $N(0, 1/N)$ and is then expected to be within $\pm 2/\sqrt{N}$ in 19 out of 20 instances [20]. When the series has a trend, it can be shown by experimentation that r_t is a function of trend amplitude $|\lambda_t'|$ and N. For given N, r_t increases with $|\lambda_t'|$.

b) Process Cumulative Distribution Function (cdf). In a time series of measurements of random Poisson distributed arrival rates, measured values $\tilde{\lambda}_t$ are concentrated near mean rate $\bar{\lambda}_t$. When a trend is present in the series, it will cause $\tilde{\lambda}_t$ to deviate further from the mean. The probability p_t that the arrival rate random variable x_t is at measured $\tilde{\lambda}_t$ or further from the mean can be obtained with the cdf (we assume that estimated λ_{t-1} approximates $\bar{\lambda}_t$). For the case of $\tilde{\lambda}_t > \lambda_{t-1}$:

$$p_t = \Pr(x_t > \tilde{\lambda}_t \mid \tilde{\lambda}_t > \lambda_{t-1}) = \frac{1 - \Pr(x_t \le \tilde{\lambda}_t)}{1 - \Pr(x_t \le \lambda_{t-1})} = \frac{1 - cdf(\tilde{\lambda}_t)}{1 - cdf(\lambda_{t-1})} . \tag{9}$$

and the case of $\tilde{\lambda}_t \le \lambda_{t-1}$:

$$p_t = \Pr(x_t \le \tilde{\lambda}_t \mid \tilde{\lambda}_t \le \lambda_{t-1}) = cdf(\tilde{\lambda}_t) \big/ cdf(\lambda_{t-1}) . \tag{10}$$

p_t is close to 1 when $\tilde{\lambda}_t$ is close to the mean λ_{t-1}, it decreases as $\tilde{\lambda}_t$ is further away. Therefore, the function p_t (of measured $\tilde{\lambda}_t$) can be used as a stationarity indicator, and its complement $1\text{-}p_t$ as a trend indicator.

The value range for both the *acf* and *cdf* trend indicators is [0..1]. Online measurements of the indicators, applied to our traffic model (Fig. 1d), are shown in Fig. 2. We can see that both indicators move to higher levels when traffic moves from stationary to trend periods.

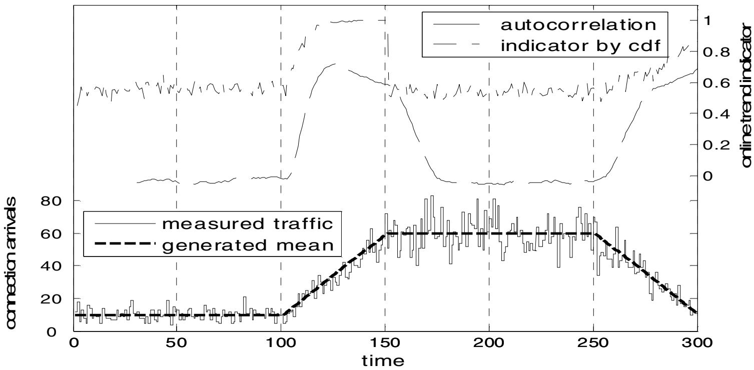

Fig. 2. Trend measurements based on autocorrelation and cdf

Trend Indicator Based Adaptive ES (SES-acf, SES-cdf). In this subsection, we propose two new ES adaptation approaches for dynamic traffic online estimation. The approaches are based on SES (4) and use a function of the trend indicator, r_t (acf approach) or $1\text{-}p_t$ (cdf approach), to adapt parameter α_t in (4). As mentioned, α_t should be low in nil trend traffic to provide stability, and increase when the trend increases to become more responsive to traffic demand changes.

a) Exponential Adaptation Function. Use of a simple exponential function of the trend indicator will limit α_t in stationary traffic and provide good stability. Let I_t denote the trend indicator, representing r_t (acf approach) or $1\text{-}p_t$ (cdf approach). The function can be expressed as:

$$\alpha_t = A_R^{\;1-I_t} \; . \tag{11}$$

where the base, $0 < A_R < 1$, is a constant chosen based on historical traffic data to provide estimation stability in stationary periods traffic. An example of this exponential function of I_t (case of A_R=0.1) is shown in Fig. 3.

b) Logistic Adaptation Function. In the trend indicator range, an exponential function (11) increases slowly with the indicator causing slow estimation response in trend traffic. Given the dual objectives of stability and responsiveness, a steeper change in α_t is needed when traffic transitions between stationary and trend periods. The logistic function fits well with this requirement, and in addition its parameters provide ease of control of the function inflexion point. We propose to use the following logistic based adaptation function:

$$\alpha_t = 0.05 + logistic(I_t) = 0.05 + [0.85/(1 + l_a e^{-l_b I_t})] \; . \tag{12}$$

where l_a and l_b are parameters determining the inflexion point $\left(\frac{\ln(l_a)}{l_b}, 0.05 + \frac{0.85}{2}\right)$. Function (12) presents asymptotes at α_t =0.05 and α_t =0.90, and the inflexion point can be chosen based on historical trend indicator data. For example, logistic based functions used in the case of traffic and trend indicator of Fig. 2 are shown in Fig. 3. When compared to the exponential function, we can see that the logistic functions present distinct α_t levels for low and high trend indicator values, with a much steeper transition between them. Fig. 3 also shows distinct α_t increase start points (obtained by l_a and l_b choices) for the *acf* and the *cdf* indicator cases, corresponding to the respective indicator characteristics from Fig. 2.

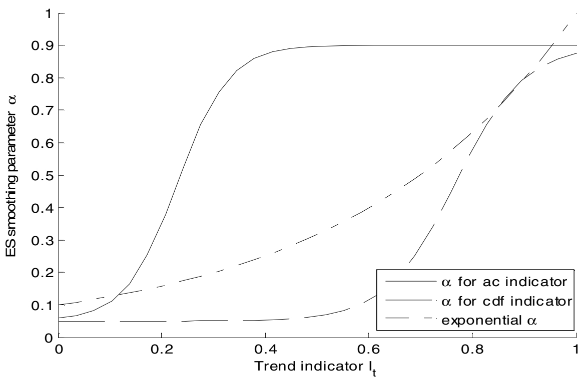

Fig. 3. SES parameter α as exponential and logistic functions of trend

4 Performance Analysis

In this section, performance of our proposed demand estimation methods based on logistic function of the trend indicator, under different traffic levels and trends, is evaluated by comparison with existing methods (Section 3.1). Poisson distributed traffic is generated following the model of Fig. 1d. The methods are compared under the previously mentioned stability and responsiveness criteria, whose metrics are defined below.

4.1 Performance Metrics

Estimation Stability in Stationary Traffic. In stationary traffic periods, a stable estimate of the average arrival rate is advantageous as it avoids unnecessary network routing and capacity allocation changes, therefore limiting the amount of control traffic in the network. We define estimation stability, denoted by σ_S, as the mean absolute deviation of the estimated arrival rate λ_t from the true (generated) average rate $\overline{\lambda}_t$, normalized by the standard deviation of measured arrival rates $\tilde{\lambda}_t$:

$$\sigma_S = \sqrt{\frac{1}{n_S}\sum_{t=1}^{n_s}(\lambda_t - \overline{\lambda}_t)^2} \Bigg/ \sqrt{\frac{1}{n_S}\sum_{t=1}^{n_s}(\tilde{\lambda}_t - \overline{\lambda}_t)^2} = \sqrt{\sum_{t=1}^{n_s}(\lambda_t - \overline{\lambda}_t)^2 \Bigg/ \sum_{t=1}^{n_s}(\tilde{\lambda}_t - \overline{\lambda}_t)^2} . \quad (13)$$

where n_S is the number of samplings in the evaluated stationary traffic period. A smaller σ_S indicates a better stability.

Estimation Responsiveness in Trend Traffic. In trend traffic periods, arrival rate estimates should converge quickly to the true trending $\overline{\lambda}_t$. This is particularly important during increasing demand periods, as slow estimation response will delay network management reaction causing connection or packet losses. The measure of this responsiveness, denoted by σ_C, is defined by the average lag of estimated rates λ_t with respect to $\overline{\lambda}_t$ (a positive lag indicates that $\overline{\lambda}_t > \lambda_t$), normalized by $\overline{\lambda}_t$:

$$\sigma_C = \frac{1}{n_c}\sum_{t=1}^{n_c}(\overline{\lambda}_t - \lambda_t)/\overline{\lambda}_t . \quad (14)$$

where n_C is the number of samplings in the evaluated trend traffic period. Smaller amplitude of lag σ_C indicates a better responsiveness.

4.2 Performance Results

Proposed and existing estimation methods are evaluated under the traffic model shown in Fig. 1d. Arrival rate mean $\overline{\lambda}_t$ (1) are generated for successive periods of stationary and trend traffic. At regular time intervals, arrival rate samples $\tilde{\lambda}_t$ are generated randomly (2) with a Poisson distribution having mean $\overline{\lambda}_t$. In our test traffic, 100 and 50 samplings are included in each stationary and trend period, respectively. Initial stationary rate is set to 10, and trend λ'_t cases of 0.5, 1.0 and 1.5, leading respectively to stationary period rates of 60, 85 and 110, are verified. Coefficients r_t(8) needed in autocorrelation based methods are calculated using a time window of N=30 measurements. Parameters (l_a, l_b), realizing logistic based adaptation function(12), shown in Fig. 3, are (100, 20) for *SES-acf* and (100000, 15) for *SES-cdf.*

Stability and convergence metrics are computed for the arrival rate estimates produced by the different methods and compared. For responsiveness evaluation, we concentrate on the increasing trends as it is in these cases that response is a key in avoiding connection and packet losses. The results for stability and responsiveness are given in Tables 1 and 2, respectively.

Table 1. Demand Estimation Stability Performance

Method	*Traffic estimation stability σ_S (90% confidence)*			
	$\bar{\lambda}$ = 10	$\bar{\lambda}$ = 35	$\bar{\lambda}$ = 60	$\bar{\lambda}$ = 85
SES-fix, α=0.1	0.225 ± 0.009	0.218 ± 0.004	0.218 ± 0.006	0.217 ± 0.006
SES-fix, α=0.5	0.576 ± 0.004	0.570 ± 0.004	0.574 ± 0.006	0.572 ± 0.005
SES-err	0.713 ± 0.008	0.487 ± 0.014	0.399 ± 0.015	0.347 ± 0.013
SES-acf	**0.272 ± 0.010**	**0.261 ± 0.016**	**0.274 ± 0.013**	**0.269 ± 0.021**
SES-cdf	**0.495 ± 0.011**	**0.489 ± 0.012**	**0.494 ± 0.020**	**0.489 ± 0.009**
DES-err	0.753 ± 0.008	0.549 ± 0.015	0.470 ± 0.019	0.421 ± 0.017
DES-derr	1.026 ± 0.014	0.885 ± 0.024	0.832 ± 0.024	0.819 ± 0.027

Table 2. Demand Estimation Response Performance

Method	*Traffic estimation response σ_C (90% confidence)*		
	Trend λ'=0.5	*Trend λ'=1.0*	*Trend λ'=1.5*
SES-fix, α=0.1	0.161 ± 0.005	0.215 ± 0.004	0.247 ± 0.003
SES-fix, α=0.5	0.022 ± 0.006	0.030 ± 0.005	0.037 ± 0.004
SES-err	0.069 ± 0.007	0.083 ± 0.005	0.097 ± 0.004
SES-acf	**0.048 ± 0.007**	**0.031 ± 0.005**	**0.026 ± 0.005**
SES-cdf	**0.031 ± 0.006**	**0.041 ± 0.005**	**0.051 ± 0.006**
DES-err	0.037 ± 0.008	0.030 ± 0.007	0.029 ± 0.005
DES-derr	-0.034 ± 0.007	-0.034 ± 0.007	-0.025 ± 0.008

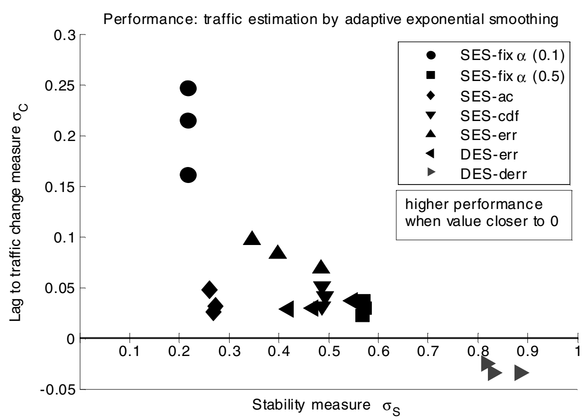

Fig. 4. Demand estimation combined stability-convergence performance. SES-fix, SES-err, DES-err and DES-derr (section 3.1); SES-acf and SES-cdf (section 3.2).

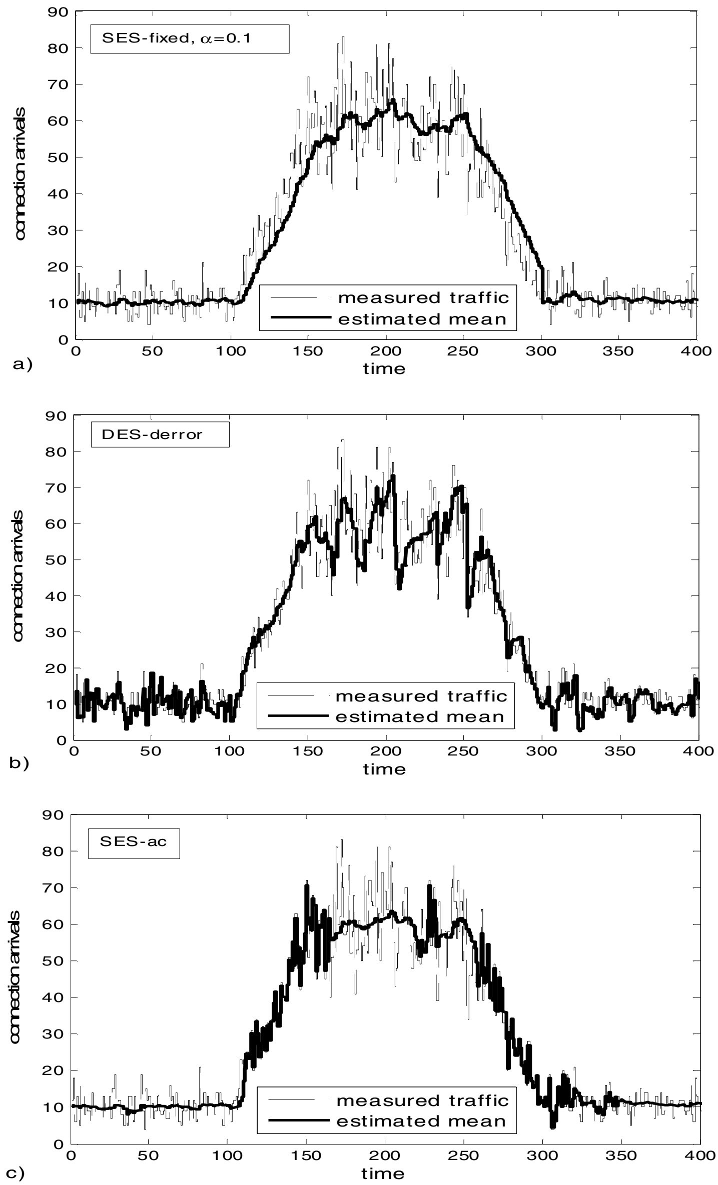

Fig. 5. Arrival rate estimation comparison :
a) *SES-fix with* α*=0.1*, b) *DES-derr*, c) S*ES-acf*

Fig. 4 shows the methods combined stability-responsiveness performance. Each plotted point represents a dynamic traffic case, combining the responsiveness performance corresponding to a given trend λ' and the stability corresponding to the stationary level $\overline{\lambda}$ reached at the end of the trend period. Cases for (λ' , $\overline{\lambda}$) values of (0.5, 35), (1.0, 60) and (1.5, 85) are represented in the figure. For most methods, a performance tradeoff is apparent, as a better stability is shown paired with a poorer responsiveness, and vice-versa. *SES-cdf* provides good responsiveness, although its stability is only average. The proposed *SES-acf* provides the best combined stability-responsiveness performance. For the case of $\lambda' = 0.5$, responsiveness for *SES-acf* is slightly slower. This can be explained by the imprecision of trend detection, caused by the limited number *N* of autocorrelation samples in an environment of low traffic trend to traffic noise ratio. For example, increasing *N* from 30 to 35 improves the method's responsiveness measure from 0.048 to 0.043, while stability performance is maintained (from 0.261 to 0.249).

To visualize online demand estimation performance, Fig. 5 compares estimation responses to real-time measured arrival rates for a) *SES-fix with* α*=0.1*, b) *DES-derr*, c) *SES-acf*. a) shows good stability, however the lag in both increasing and decreasing trends is apparent. b) is very responsive to trends, but stability in stationary traffic is poor. Finally, c) our proposed *SES-acf* is capable of showing both trend responsiveness and reasonable stability.

5 Conclusion

In this paper, we proposed dynamic traffic demand estimation approaches that are simple to function online, yet accurate to allow for efficient network optimization and management. Exponential smoothing is adapted based on traffic trend that is estimated through the use of arrival process acf or cdf. When compared to known adaptive ES methods, proposed *SES-acf,* where adaptation is based on traffic trend evaluated by measured autocorrelation, provided the best combined stability-responsiveness performance. This feature makes it particularly fit for autonomic estimation of time-evolving traffic conditions.

In future research, we will investigate the possibility of online estimation using the Kalman filter, recognized as a general method for signal estimation in the presence of noise, and compare its performance to these proposed approaches.

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