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Modelling the On-line Traffic Estimator in OPNET

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Introduction

To support the myriad of envisioned communication products of the future, there is a need to develop a network infrastructure that can provide larger bandwidth, with better control of quality of service (QoS) through proper resource allocation. Allocation techniques are needed to provide these guarantees as efficiently as possible since resources are limited. To cope with this demand, the networks need dynamic and measurement-based resource allocation algorithms. For this task, the choice of appropriately accurate but also practically implementable algorithms is crucial. For network links shared through statistical multiplexing, adaptive bandwidth allocation algorithms based on traffic measurements can achieve important gains.

In this context, it is very important to choose measurement methods that satisfy stringent constraints in terms of both accuracy and complexity.

The measurement time scales have critical effect on the performance. We proposed an approach overcoming this dependency by adjusting the measurement time scale dynamically in accordance to traffic parameter.

The paper covers issue with measured traffic store model with the following parameters estimation.

Measurement time scale

We propose to use correlation interval for determine the measurement time scale. Using information of the traffic correlation interval the overheads of the system related to measurement process will be decreased.

Many research works show that Internet traffic has H parameters varying in the range 0.7<H<0.95.

Fig. 1 presents autocorrelation functions for Poisson traffic where H=0.5, and self-similar traffic with H parameter equals to 0.75 and 0.95.

An interesting feature of self-similar processes is the fact that the autocorrelation function does not degenerate when m→∞. This feature is in contrast to stochastic processes where the autocorrelation function degenerates as m→∞. For the self-similar process the autocorrelation function with the dependence on Hurst parameter can be described as follows:

$$\rho(k) = \frac{1}{2}\left[(k+1)^{2-\beta} - 2k^{2-\beta} + (k-1)^{2-\beta}\right] \quad (1)$$

and is depicted in Fig. 1. Such behaviour of the autocorrelation function corresponds to the Fractal Brownian Motion (fBm) that is a classical example of the self-similar process.

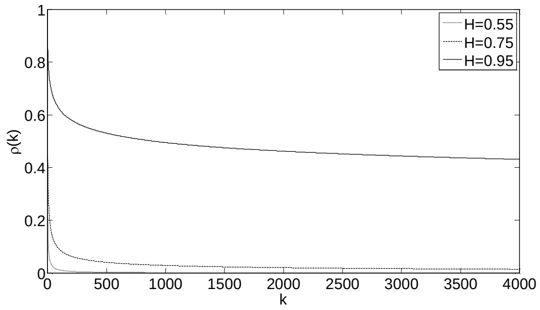

Fig. 1. Autocorrelation function of the self-similar process

Long-range dependent processes are characterized by the autocorrelation function which decays hyperbolically. This implies that the auto-correlation function is non-summable, unlike more conventional short-range dependent processes, which have auto-correlation functions that decay exponentially [4].

The autocorrelation function of the stochastic process can be evaluated in the following way:

$$\rho(\tau) = E[x(t)x(t+\tau)]\,. \quad (2)$$

The autocorrelation of an ergodic process is sometimes defined as equated

$$\rho(\tau) = \frac{1}{N}\sum_{i=0}^{N} x_i x_{\tau+i} \quad (3)$$

or for the finite N number of data

$$\rho(\tau) = \frac{N}{N-k}\sum_{i=1}^{N-k} x_i x_{\tau+i}, \qquad (4)$$

After serious theoretical explorations, experiments with traffic generation and traffic analysis we have found that traffic where interarrival time of the packets has Pareto distribution is not ergodic.

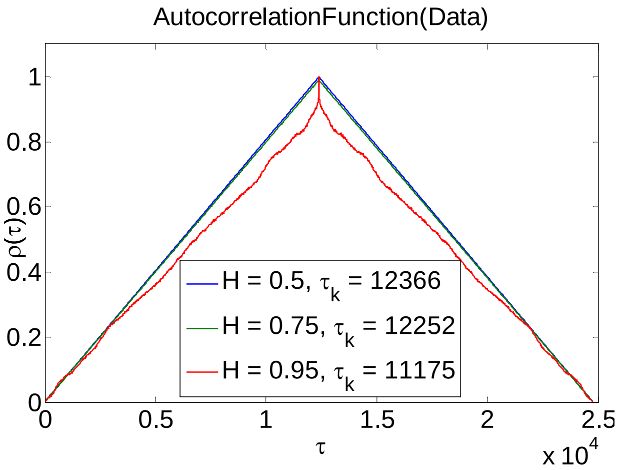

Fig. 2. Autocorrelation function for the ON-OFF modelled self-similar traffic based on 2-parameters Pareto distribution and ρ=0.75

Taking into account non-ergodic property of the self-similar traffic the autocorrelation function has to be used as follows:

$$\rho(\tau) = E[(x(t) - \mu)(x(t+\tau) - \mu)]. \qquad (5)$$

The Eq. (5) should be modified to take into account non-ergodic feature of the traffic and can be presented as follows:

$$\rho(\tau) = \frac{N}{N-k}\sum_{i=1}^{N-k}[x_i - E(x_i)[x_{\tau+i} - E(x_i)]]. \qquad (6)$$

Knowing the autocorrelation function the correlation interval can be evaluated as follows:

$$\tau_k = \frac{S(0)}{\rho(0)}. \qquad (7)$$

The τ_k value approximately shows the time interval where the correlation of a random process is and denotes the time period while the random process keeps the statistical parameters.

Based on the Fig. 1 and above mentioned correlation interval, we can argue that the random process with the high self-similarity degree has the higher correlation ("long memory") and, consequently, correlation interval is higher than the process with low self-similarity property.

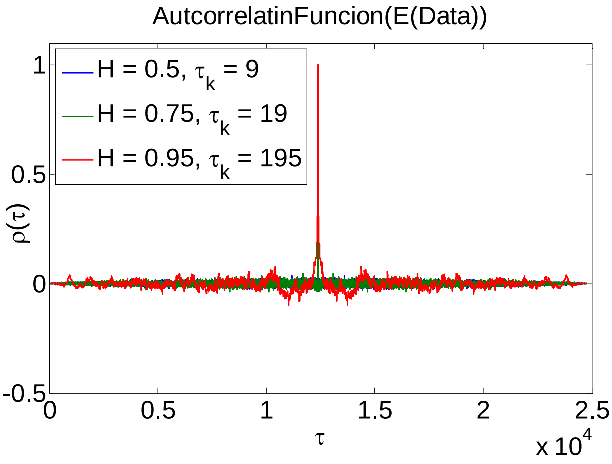

Fig. 3. Autocorrelation function for normalized the ON-OFF modelled self-similar traffic based on 2-parameters Pareto distribution and ρ=0.75

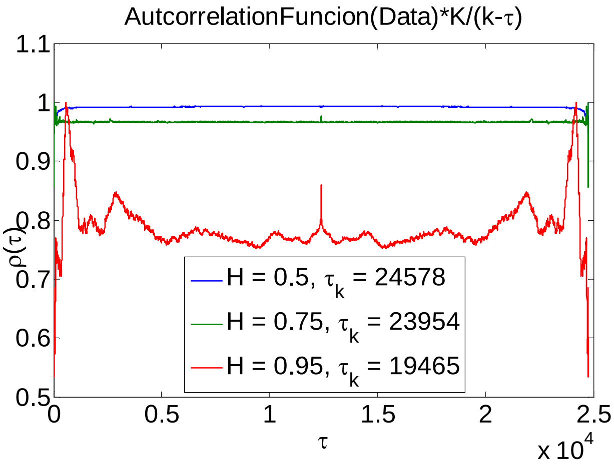

Fig. 4. Scaled by N/N-k autocorrelation function for the ON-OFF modelled self-similar traffic based on 2-parameters Pareto distribution and ρ=0.75

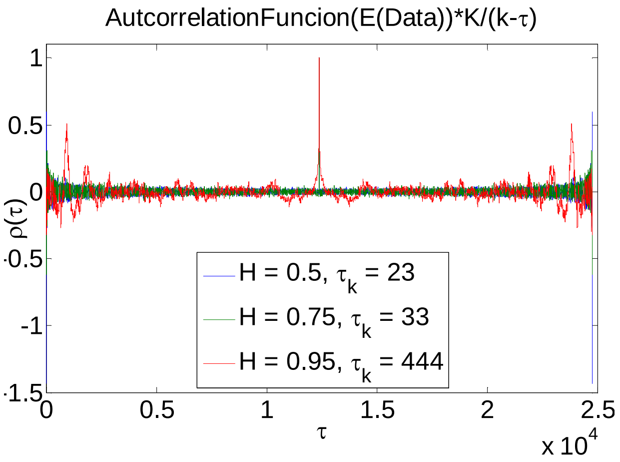

Fig. 5. Scaled by N/N-k autocorrelation function for the normalized ON-OFF modelled self-similar traffic based on 2-parameters Pareto distribution and ρ=0.75

On the Fig. 2–6 you can see autocorrelation functions estimated in various way (4), (5) and (6) respectively. As you can see functions represents completely different values for the different methods.

For the time scale estimation Eq. (6) is going to be used. The [1] shows that correlation interval depends not only on the H parameter but on the traffic intensity as well. The correlation interval increases with the increase of H parameter, and it decreases with the traffic intensity increase. The information of the correlation interval gives opportunity to free measurements system resource within the following correlation interval for other processes.

MBAC DFD Diagram

Measurement-based admission control use statistical service guarantees (Fig. 6). The advantages of statistical service guarantees in the absence of strict performance bounds as deterministic service guarantees do. The deterministic service guarantee management technique uses worst-case analytical bound and it results in low network utilization because the worst-case happens rarely in real networks. In comparison to deterministic service guarantees the measurement-based admission control (MBAC) can achieve higher network utilization.

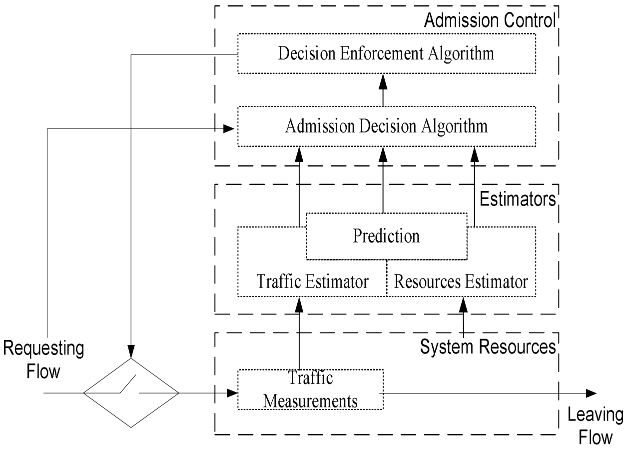

Fig. 6. Structure of MBAC

The decision algorithm of measurement-based admission control uses the a priori traffic characteristics only for newly arrived flows while for already existing in the system flows characteristics are measured.

For the algorithm it is necessary to estimate characteristics of traffic measurement which are it's interarrival peak and average rates and the number of flows in the system. Also, it is needed to estimate the remaining resources in the system. When a new flow requests admission to the system, the MBAC mechanism uses the admission control algorithm to decide if this flow can be admitted. This decision is based on the inputs from the traffic and resource estimators. In addition, the decision relies on input from the requesting flow, which typically includes its quality of service requirement and its traffic description.

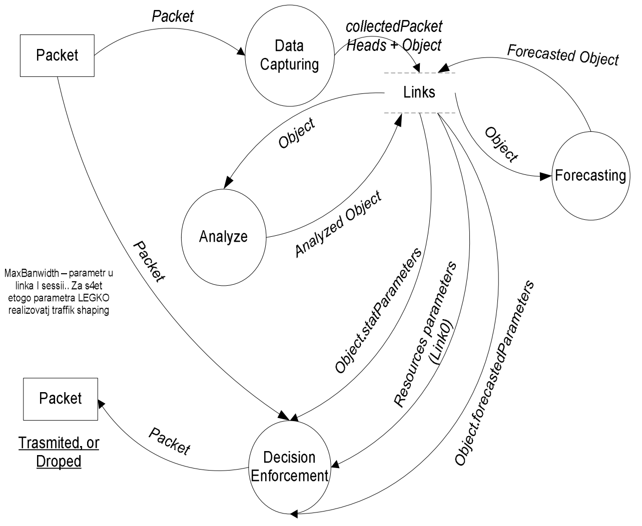

Fig. 7. Data processing DFD

The measured network traffic should be efficient estimated. For that reason the following chapter presents storage model for measurements that provide estimation on the different network control levels: *Time Scale, Packet Scheduling Level, Burst Level, Session Level and Beyond the Session Level.*

This paper presents the model design for the traffic estimator module of MBAC mechanism.

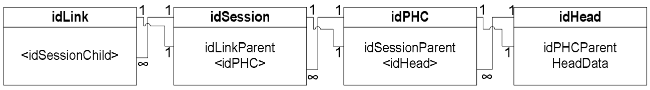

Fig. 8. Data storage

Fig. 7 depicts the major data flow diagram of the data processing. This diagram presents holistic view of the MBAC model. DataCapturing deals with measurement of the established flows. Responsibility of the Analyze is to estimate traffic parameters of the measured traffic. Function Forecasting module is predict network traffic. The DecisionEnforcement module implements admission control functions. Based on the estimated together with forecasted traffic parameters the admission decision is enforced. According to the packet, decision enforcement means whether or not the packet will be transmitted or dropped.

It was mentioned, that proposed model degraded overhead. The noticeable reduction of the overhead applied to *DataCapturing* process for the use correlation interval. The [2] presents model in details.

Traffic storage model

Network packet variety is united into session that is established between source and destination. More than one session can be created between one pair of the traffic source and destination. The session variety is organized into one link.

The network equipment could have more than one link connection. Fig. 8 presents our proposal for the Links storage component.

Packet heads of the same session and on the same correlation interval are collected to the same PHC (*PacketHeadCollection*). Variety of *PacketHeadCollection* with the same *sessionID* fully describes characteristics of a session. And finally, variety of the sessions with the same *linkID* can fully describe link characteristic.

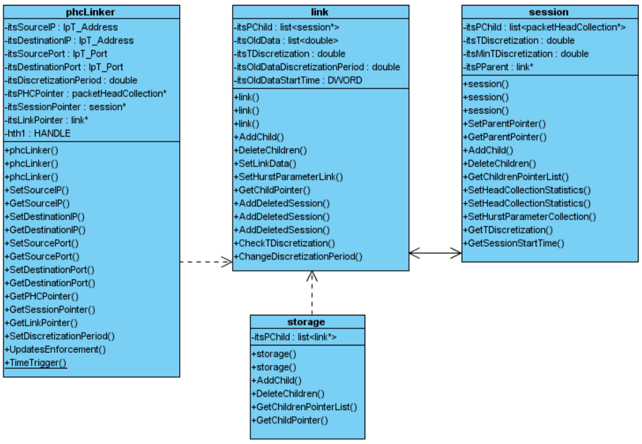

Fig. 9. Link Class Diagram

It is necessary to mention, that cross-reference between objects in the storage element plays important role. The child object could notification to parent object about its changes, and parent object is able to get information from the child object. Our implementation is presented in Fig. 9–11.

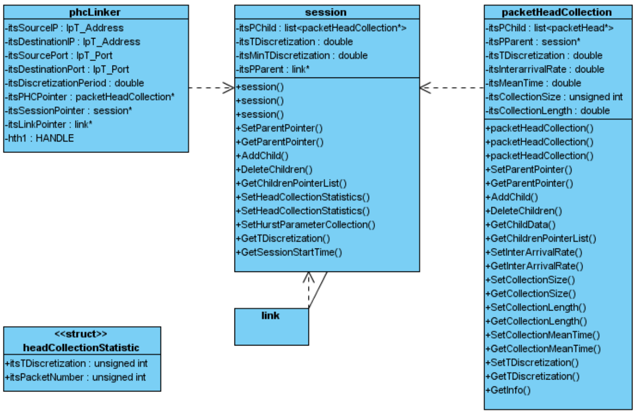

Fig. 10. Session Class Diagram

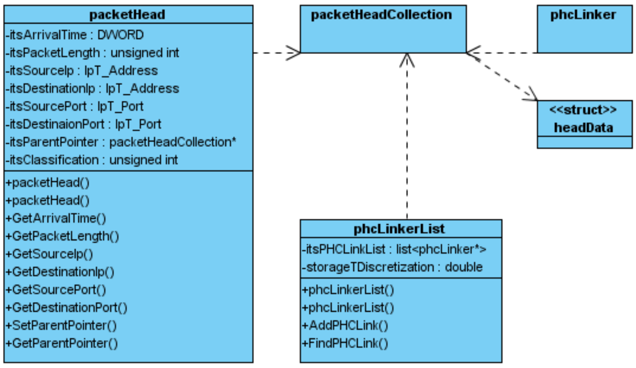

Fig. 11. Packet Head Collection and Packet Head Class Diagram

This way of storage organization provides great flexibility whether it is not the most efficient. We argue that the model is developed for the MBAC algorithm and is going to be implemented in network simulation environment, where the side procedure, like storage element access time, does not influence on the simulated objects. The most important for us is the measurements number, and confidential interval for the estimated parameters.

Conclusions

The correct traffic parameters estimation strictly depends on the time interval between measurements. Traffic estimator module of the MBAC mechanism can estimate the interval using the correlation interval of the data flow.

We propose to decrease overheads of the measurement process by turning it in the idle state within nearest correlation interval while the random process keep the statistical parameters.

In the paper present storage model for measured traffic that could be used for easy traffic estimation on any traffic abstraction level.

The future goal is to implement the storage model and estimation of dynamical measuring time scale and to evaluate proposed algorithm in simulation environment.

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M. Kulikovs, E. Petersons. Modeling the On-line Traffic Estimator in OPNET // Electronics and Electrical Engineering – Kaunas: Technologija, 2009. – No. 7(95). – P. 82–86.

Allocation techniques are needed to provide data services as efficiently as possible since resources are limited. To cope with this demand, the networks need dynamic and measurement-based resource allocation algorithms. For network links shared through statistical multiplexing, adaptive bandwidth allocation algorithms based on traffic measurements can achieve important gains. In this context, it is very important to choose measurement methods that satisfy stringent constraints in terms of both accuracy and complexity. The measurement time scales have critical effect of on the performance. We proposed an approach overcoming this dependency by adjusting the measurement time scale dynamically in accordance to traffic parameter. The paper covers issue with measured traffic store model with the following parameters estimation. Ill. 11, bibl. 5 (in English; summaries in English, Russian and Lithuanian).

М. Куликовс, Э. Петерсонс. Моделирование потока данных интернета в сети OPNET // Электроника и электротехника. – Каунас: Технология, 2009. – № 7(95). – C. 82–86.

Описываются методы распределения ресурсов с учетом динамических параметров измерения. Указывается, что наилучшие результаты можно получить, когда используются адаптивные алгоритмы деления пропускной полосы связи. Найдена зависимость, как исключить влияние процесса измерения на производительность канала связи. Определена возможность оценки динамических искажений. Ил. 11, библ. 5 (на английском языке; рефераты на английском, русском и литовском яз.).

M. Kulikovs, E. Petersons. Interneto duomenų srauto modeliavimas OPNET tinkle // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2009. – Nr. 7(95). – P. 82–86.

Siekiant kuo efektyviau teikti duomenų paslaugas, reikalingi ribotų išteklių paskirstymo metodai. Tinklams reikalingi dinaminiai ir parametrų matavimo rezultatais pagrįsti išteklių paskirstymo algoritmai. Naudos galima gauti statistinio multipleksavimo principu padalytiems tinklo kanalams pritaikius adaptyvius pralaidumo juostos padalijimo algoritmus, kurie įvertina duomenų srauto parametrus. Todėl svarbu pasirinkti tinkamus matavimo metodus, kurie tenkintų griežtus tikslumo ir kompleksiškumo reikalavimus. Matavimo laiko mastelis turi esminę įtaką tinklo našumui. Pasiūlyta šią priklausomybę panaikinti dinamiškai keičiant matavimo laiko mastelį pagal duomenų srauto parametrų vertes. Analizuojamas dinaminio parametrų įvertinimo galimybę turintis tinklo modelis. Il. 11, bibl. 5 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).

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