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Models of WWW-Traffic:

a Comparison of Pareto and Logarithmic Histogram Models

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Abstract

In this paper we present results from measurements of WWW-traffic, the analysis of the data measured, and derive two simple models that could be used to describe WWW-traffic for performance assessment purposes. We analyze client WWW-sessions that are characterized by the size of the response and inter-response intervals. The samples of both categories are found to exhibit heavy-tailed properties. Thus, we represent WWW-traffic by two models: an independent Pareto model and a logarithmic histogram model. The models are evaluated by simulating the transmission of traffic generated by the models over an ATM link using the VBR service category. We show that the histogram model is able to represent the properties of WWW-traffic with higher accuracy while the Pareto model is able to resume the characteristics of WWW-traffic with fewer parameters.

1 Introduction

In the last five years, an exponential growth of the Internet is observed (c.f. [9]). Most of the traffic volume is originated by data transfers in the WWW (World-Wide Web). Further growing bandwidth demand for WWW-applications is expected due to high resolution graphics workstations, multimedia applications and network computers. Therefore, WWW-traffic is considered to be an important traffic source for future ATM based B-ISDNs.

The characterization and modeling of WWW-traffic gained a lot of attention in the last years. Numerous studies address inquiries of accumulated traffic streams. Either the data-rates of Ethernet-traffic [5] or WWW-traffic [1, 2, 6, 7, 8] are considered as traffic sources. The main result of these investigations is the evidence of self-similarity. Other publications deal with modeling WWW-request traffic [3] and the locality of WWW-references [4], which is an important measure for the performance of proxy-servers.

In this study we concentrate on traffic characteristics of single client WWW-sessions. We derive typical characteristics from measurement of WWW-traffic in a local ethernet segment at the Computing Center of the University of Würzburg. Currently, all WWW-traffic is influenced by the TCP/IP protocol stack and slow ethernet links but this impact is expected to be of less importance in future networks. Abstract and simple models of single WWW-sessions are presented, based on measured data. The models can be applied for the evaluation of connection technologies that cover the last mile to the user, e.g. HFC (hybrid fiber coax) systems or ADSL (asymmetric digital subscriber line) modems [10]. Another interesting application of the models is evaluating the efficiency of potential ATM service categories for the transport of WWW-traffic.

The paper is organized as follows: In Section 2 we describe the components of WWW-traffic, the measurement of WWW-traffic and the analysis of the measured data. Typical characteristics of WWW-sessions and WWW-pages are derived. Section 3 describes the Pareto and the logarithmic histogram model of the measured WWW-traffic. In the last section, both models are evaluated in comparison to measured data by simulating the transmission over an ATM link utilizing the VBR service category. The paper concludes with a summary.

2 WWW-Traffic

Commonly the term WWW-traffic refers to the description of data transmitted in a communication network using the HTTP-protocol [11]. In the following the structure of WWW-traffic on different protocol layers is outlined and the elements relevant for modeling WWW-traffic are identified. We describe the measurement of WWW-traffic, the analysis of the measured traces and the traffic characteristics that are important for traffic modeling.

2.1 Hierarchical Components of WWW-Traffic

On topmost protocol layer WWW-traffic is distinguished in WWW-sessions, that represent the activities of single users. Figure 1 depicts the hierarchical components of a WWW-session. A WWW-session is the period beginning at the time a user launches his WWW-browser and ending when the user quits from the WWW-browser. Therefore, the traffic sources of a single WWW-session include a single client and eventually a large number of WWW-servers. Since the launching and quitting of a WWW-browser causes no traffic and our measurement method, c.f. Section 2.2, is based on the recording of transmitted data, we introduce the concept of sub-sessions. A sub-session is defined as the interval in which a users creates WWW-traffic without being silent for more then a period referred to as time-out. In most cases it can be assumed that both session and sub-session are identical.

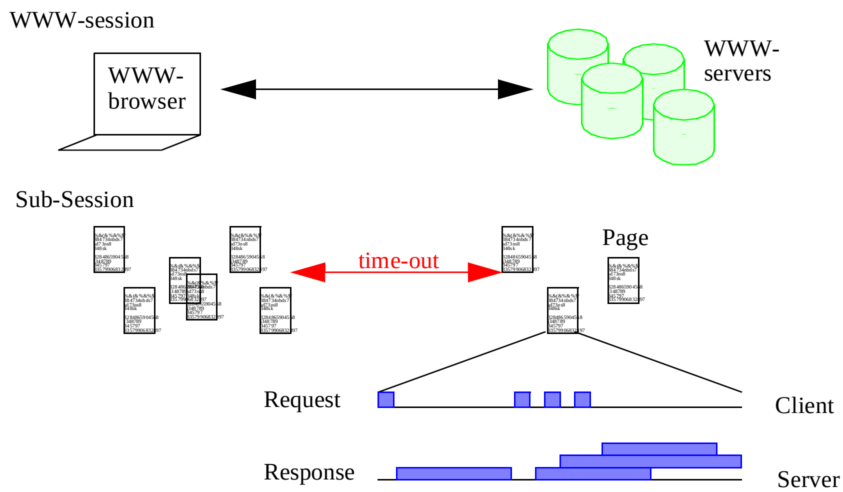

Figure 1: Hierarchical components of WWW-sessions.

A sub-session consists of WWW-pages, that correspond to the data a user requests with a single mouse click. A page might induce several TCP-connections to and from a server. We define the response-size as the sum of all IP-packets sent from the server to the client in order to display a single WWW-page. For modeling the data-flow from the server to the client, the amount of data and the exact instant of the transport is relevant. Thus, we denote the interval lasting from the beginning of a response to the beginning of the succeeding response by inter-response time.

2.2 Measurement of WWW-Traffic

The investigations presented in this paper are based on the measurement of WWW-traffic in an ethernet segment of the Computing Center at the University of Würzburg. About 45 workstations are connected to this segment. The equipment is used by students from all faculties as public terminals. During the measurement period of one week the terminals were highly utilized, enabling us to collect statistically sufficient data.

Technically, the measurement was carried out with the TCPDUMP software [12] on a LINUX workstation. This tool logs the headers of IP-packets. The logged information includes the source address and port, destination address and port, the instant of transmission and the size of the packet. Further flags indicating the initialization and termination of TCP-connections and the TCP-window size are recorded. Options of TCPDUMP allow to filter traffic with respect to the ports used. Since the well-known port number of WWW-servers is 80 packets carrying WWW-traffic can be logged separately.

In the following we describe the analysis of the trace recorded and point out the characteristics of the sub-sessions and responses.

2.3 Characteristics of WWW-Traffic

All packets recorded in our measurement correspond to the transmission of 2.6GB of data. About 10% of the traffic was directed from the clients to WWW-servers (the requests) while the main part of the traffic was caused by responses to these requests.

We divide the whole trace into single sub-sessions and extract the start time and the size of the responses in the order requested by the user. We concentrate on client sub-sessions, taking into account only data requested by local clients. Data requested from outside does not represent complete WWW-sessions and is ignored therefore.

2.3.1 Sub-Sessions

To detect sub-sessions in the trace we assume that a single WWW-browser is launched at most on a workstation. Since all workstations operate under a single-user operating-system it is not possible to use browsers remotely. We can not exclude the case that some users might open several WWW-sessions at a time. The data belonging to these WWW-sessions is therefore assumed to belong to a single sub-session.

The following algorithm is employed for the detection of sub-sessions in the trace: The beginning of a sub-session is given by the transmission of the first IP-packet from a workstation – called the client – to a WWW-server. All subsequent packets sent from the client to the server and packets sent from the server to the client are assumed to belong to the same sub-session. The sub-session is assumed to end if packet transmission stops for a certain time. This time-out is chosen to cover the interval a user might spend reading a document without requesting a new document, but has be short enough to detect the start of new sub-sessions.

The sub-session detection algorithm shows high insensitivity with regard to the choice of the parameter time-out. For time-outs ranging from 15 to 45 minutes, the same 1194 sub-sessions have been detected in our trace. The average sub-session has a size of 2.4MB with a coefficient of variation is 3.2. The mean sub-session duration is 32 minutes with a coefficient of variation of 3.0.

2.3.2 Response Sizes and Inter-Response Times

According to the current HTTP/1.0 standard [11] WWW-pages are typically downloaded on several TCP/IP connections. For each inline graphic or object a separate connection is opened. A similar algorithm as for detecting WWW-sessions can be used in order to extract the download-time and size of WWW-pages. The start-time of a WWW-page is initialized by the first IP-packet of a new connection. All subsequent packets of connections between the same pair of host and client are assumed to belong to the WWW-page if the time between the connections is less than a time-out of 3 seconds. This selection of the time-out interval showed the best performance for the distinction of WWW-pages. During the 5 day measurement a total of 48500 WWW-pages have been downloaded. We define the size of a response onto a WWW-request as the sum of the sizes of all packets that are down-loaded from a WWW-server to the client upon a request. On average a response contains 3.5 separate files comprising the actual WWW-page and inline objects. Furthermore, 40.8 WWW-pages are down-loaded on average in a single sub-session.

On the left-hand side of Figure 2 the histogram showing the response sizes gathered in 1kB bins is illustrated. The average response size is 42kB with a coefficient of variation equal to 10.

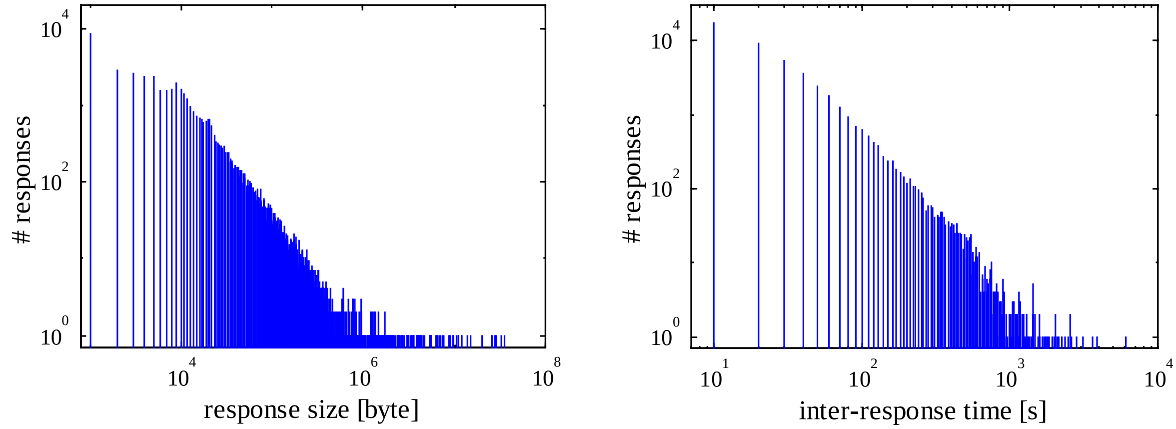

Figure 2: Response size and inter-response time histogram.

The graph on the right-hand side of Figure 2 shows the histogram of the inter-response times gathered in 10s bins. For the computation, intervals between successive sub-sessions are not taken into account. The mean inter-response time is 43.5s and the coefficient of variation of the inter-response times is 2.5. Both the incidence of response sizes and inter-request times – plotted on double logarithmic axes – exhibit a linear decay. This is an evidence that the samples show a heavy-tailed characteristic. Clearly this property has to be taken into account for the modeling of WWW-traffic.

The density of the scatter points in Figure 3 depicts the dependence between the time to the next response and the size of the current response. The more scatter points are in a region, the darker is the region marked. Again, only intervals within sub-sessions have been considered. The area covered by the pairs of inter-response time and current response size is quite large. Consequently, the axes are scaled logarithmically. From Figure 3 we can conclude a week relation between large response sizes and long inter-response times as well as small response sizes and small inter-response times. Furthermore, the correlation coefficient of the samples is 0.15. Both properties indicate a weak correlation between the response-size and inter-response time. An explanation for these findings can be given by looking at user behavior and WWW characteristics. On the one hand, users often utilize large WWW-pages as starting point without really reading these pages, which explains the missing relation of large responses and inter-

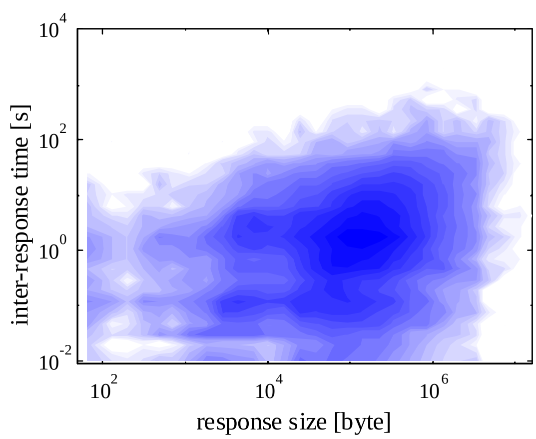

Figure 3: Correlation between response size and inter-response time.

response times. On the other hand, the combination of large inter-response times and small WWW-pages is likely to be caused by congested WWW-servers and Internet links.

3 Modeling WWW-Traffic

To model the data-flow caused by the activities of a single user, we have to take into account the response sizes, that is the amount of data transferred towards the user, and the inter-response times. Both measures exhibit a heavy-tailed behavior as shown in the previous section. Thus, these characteristics are taken into account for the representation of the response size and inter-response time. A model of WWW-traffic consists of the combination of these two quantities.

3.1 Pareto Model

The well-known Pareto-distribution exhibits heavy-tailed behavior and has no maximum value and infinite variance. In difference, our samples from the measured data are bounded by finite minimum and maximum values and exhibit a high but also finite variance. Thus, we introduce a modified Pareto-distribution matching these properties. In detail the Pareto-distribution is normalized to cover values from a minimum k to a maximum m. The gradient of the distribution is given by a parameter α.

We obtain the following equation for the probability density function of the modified Pareto-distribution:

$$f(x) = \frac{1}{1-\left(\frac{k}{m}\right)^{\alpha}} \alpha k^{\alpha} x^{-\alpha-x}, \qquad \alpha, k > 0, k \le x \le m, \tag{1}$$

and by summation the corresponding probability distribution function:

$$F(x) = \frac{1}{1-\left(\frac{k}{m}\right)^{\alpha}} \left(1-\left(\frac{k}{x}\right)^{\alpha}\right), \qquad \alpha, k > 0, k \le x \le m. \tag{2}$$

Figure 4 shows the complementary distribution function of the inter-response time (right) and the response size (left) for measured and modeled data. The dashed lines indicate the empirical distribution functions while the solid lines depict the fitted modified Pareto-distribution functions. The gradient parameters of the distributions were determined by a least-square optimization and the minimum and maximum were chosen to approximate the expectation and variance of the empirical distributions. The selection of parameters allows a high degree of freedom. The estimation of the gradient strongly depends on the choice of the minimum of the distribution.

We used for the distribution of the response size the parameters $\alpha = 0.62$, $k = 520$, and $m = 1.5 \cdot 10^7$ to obtain a expectation of $4.12 \cdot 10^4$ and a coefficient of variation of 10. For the distribution of the inter-response time we used the parameter set $\alpha = 0.9$, $k = 6$, and $m = 2.0 \cdot 10^3$. The expectation of the modeled distribution is 42.7 and the coefficient of variation is equal to 2.9.

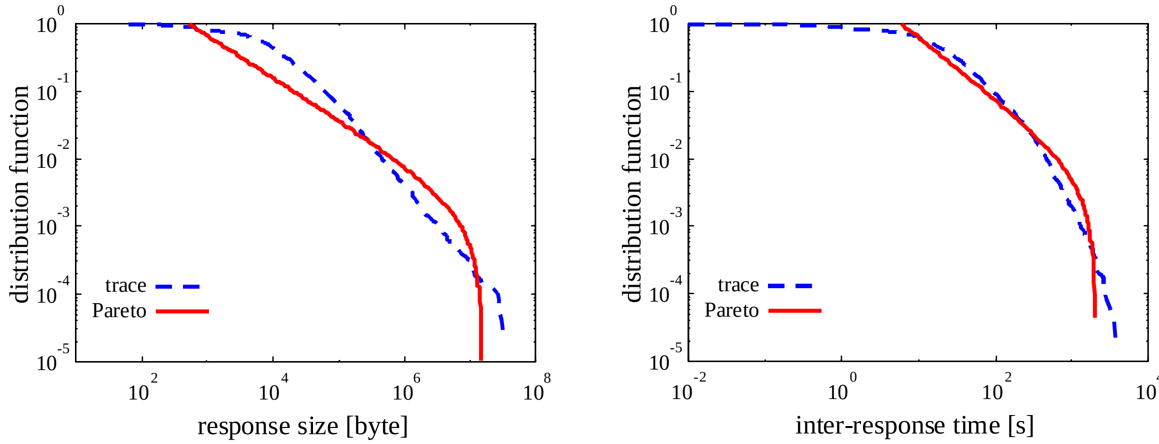

Figure 4: Response size and inter-response time fitting with the pareto model.

Since an optimal selection of the parameters is equivocal to the mean and variance of the distribution, we decide to use a histogram model for further investigations. This model is presented in the following section.

3.2 Logarithmic Histogram Model

Since the original data of the measured WWW-traffic trace covers several orders of magnitude, it is obvious that a simple linear histogram model is not capable to represent the characteristics of the trace efficiently. Thus, a logarithmic histogram model is introduced.

Let $x(i)$ denote sample number i and $min(x)$ the minimum and $max(x)$ the maximum of the samples.

The granularity of the histogram model is determined by the number N of intervals over the range of the distribution. In contradiction to a linear histogram model, the length of the intervals in our model are growing exponential. The boundaries $I(n)$ of the intervals are given by the following equation:

$$I(n) = \exp\left(\frac{n(\log max(x)) - \log(min(x)))}{N} + \log(min(x))\right), \quad n = 0, \ldots, N. \tag{3}$$

We calculate the weight-vector $W(n)$ that represents the expectation of the elements in an interval as follows:

$$W(n) = \frac{\sum_{x(i) \in [I(n-1), I(n)]} x(i)}{\#\{x(i) \in [I(n-1), I(n)]\}}, \quad n = 1, \ldots, N, \tag{4}$$

and the distribution vector $D(n)$ that represents the empirical density of the elements in an interval by:

$$D(n) = \frac{\#\{x(i) \in [I(n-1), I(n)]\}}{\#\{x(i)\}}, \quad n = 1, \ldots, N. \tag{5}$$

Results from applying the logarithmic histogram model to the trace are shown in Figure 6. The empirical distribution functions of the response size (left) and inter-response time (right) are represented by the dashed lines. In both cases the distributions are approximated by a histogram comprising of 10 intervals. The solid step-function shows the resulting distribution function. Even for the low granularity chosen the curves fit well, but the correlation of response size and inter-response time is not modeled.

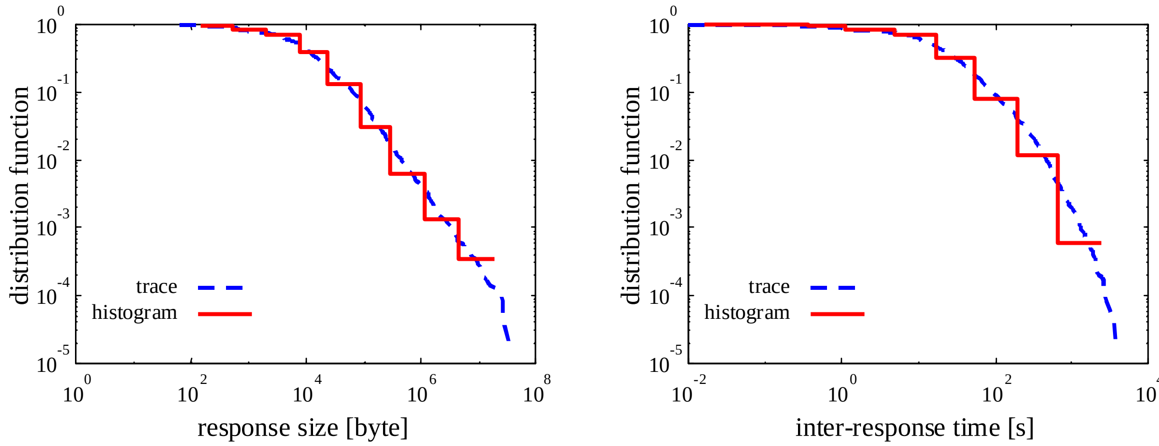

Figure 5: Response size and inter-response time fitting with the histogram model.

3.3 Conditional Logarithmic Histogram Model

.In order to represent the correlation structure of the response size and inter-response time data, we introduce a conditional logarithmic histogram model. For each interval modeled by the global response size distribution, c.f. Figure 5 (left), a separate conditional distribution is derived according to corresponding the samples of inter-response times. Figure 6 shows the conditional inter-response time distribution functions corresponding to the intervals $[I(n-1), I(n)],\ n \in \{1, 3, 6, 8, 10\}$ of the response size histogram. As indicated by the covariance, the distributions are different for each interval. If we apply this kind of modeling technique then we have to take into account that the total number of elements in some of the intervals is quite low. Thus, the statistical relevance of the conditional distributions can be of less significance. The practical effect of modeling the correlation structure as defined above is outlined in the next section

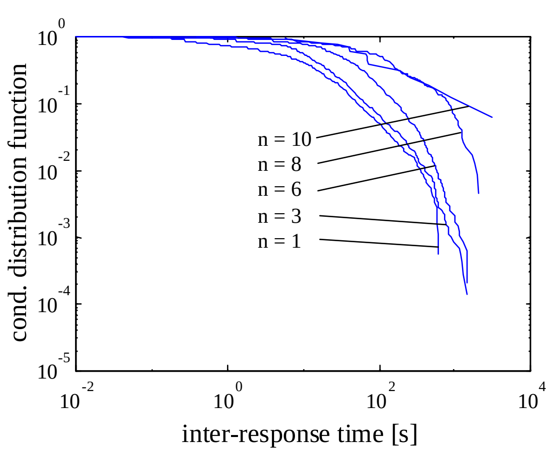

Figure 6: Conditional inter-response time distribution functions.

4 Model Evaluation

To asses the accuracy of the models, we simulate the transmission process of both modeled and measured WWW-pages over an ATM-link using the VBR service category. The number of cells each page comprises is determined and submitted to the link with a PCR equal to the link cell rate. A maximum of BT cells are buffered in a queue. The cells are served with speed SCR and cells that can not be stored in the queue are assumed to be lost. The average data rate of the samples is less than 9kbps. We consider two different transmission speeds: first we observe a link served with 1Mbps and second a link which is served with 10kbps.

Figure 7 presents the cell loss probabilities for a SCR of 1Mbps. The dashed lines indicate the blocking probabilities of the measured response sizes and inter-response times. For small values of the BT, the Pareto model – depicted with the dash-dotted lines – exposes higher blocking probability than the measured traffic, while for large values of the BT the blocking probabilities of the Pareto modeled traffic decays faster than the blocking probabilities of the original traffic. The histogram model – depicted with dotted lines on the left hand side – and the conditional histogram model – shown with bold lines on the right hand side – approximate the blocking probability of the measured time series well. For very large buffers the blocking probability is underestimated. Increasing the granularity of the histogram model from 10 to 20 increases the accuracy of the results. If the granularity is increased over a certain limit, the number of samples in some intervals gets to low for statistical evaluation and the accuracy can not be further increased. Due to the comparatively high transmission rate the correlation structure of response size and inter-response time does not effect the results.

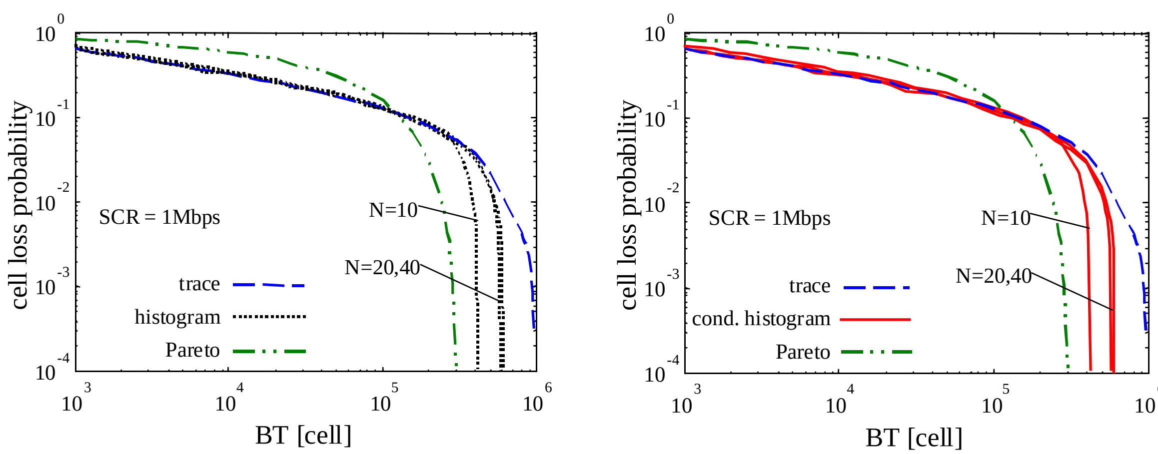

Figure 7: Simulation of WWW-traffic over a VBR connection for model validation.

For a SCR of 10kbps, which is close to the average rate of the samples, the results are depicted in Figure 8. Since for small buffers the results are of the same quality as in the previous figure, we concentrate on large buffers by scaling the x-axes linear. In this scenario the conditional histogram model (dotted lines, right side) clearly outperforms the independent histogram model (dotted lines, left side) and the Pareto model (dash-dotted lines). In this scenario the exact modeling of the inter-response times in dependence of the response size plays an important role, since it is very likely that the buffer is not empty upon the arrival of the next response. In the presented example the conditional histogram with 10 intervals shows the most accurate results. The model with 20 intervals underestimates the blocking probability of the measured samples, while the histogram with 40 intervals overestimates the results of the trace.

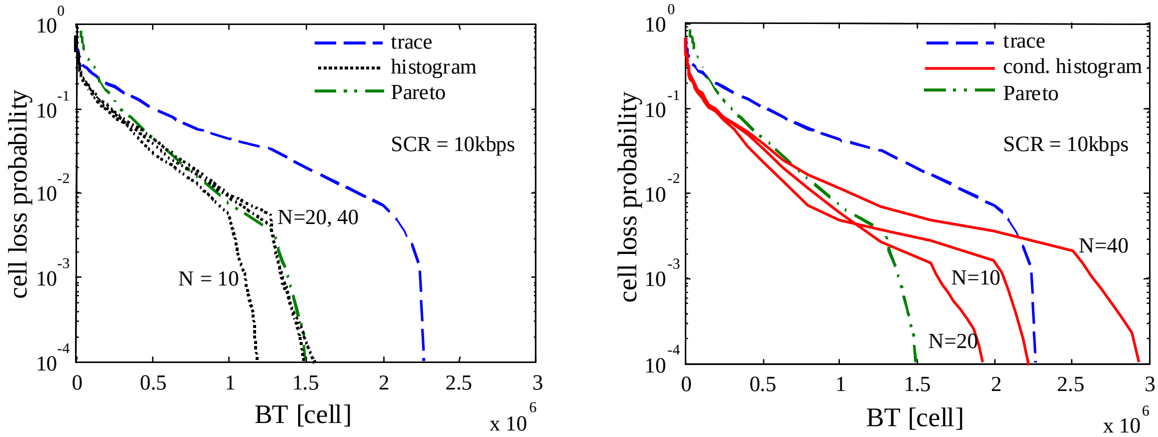

Figure 8: Simulation of WWW-traffic over a VBR connection for model validation.

The presented models for client based WWW-traffic show different properties. The Pareto model is capable to represent WWW-traffic with 6 parameters. The optimal estimation of these parameters is a demanding task and the result is not unequivocally. In difference the parameter estimation for the logarithmic histogram model is a straightforward algorithmic task, that depends on the granularity N of the model. The number of parameters is equal to $4 \cdot N$, to represent the distribution- and weight-vector of the response size and inter-response time distribution. Evaluated with regard to the queueing behavior the logarithmic histogram model – with adequate chosen granularity – approximates the properties of WWW-traffic better than the Pareto model.

Both models are not capable to represent the correlation structure of the response size and inter-response time. Thus, the conditional logarithmic histogram model – an enhancement of the logarithmic histogram model – is introduced. For every interval of the response size distribution a conditional distribution of the corresponding inter-response times is derived. Consequently, the number of parameters is $2 \cdot (N+N^2)$, assuming the same modeling granularity for the response-size and conditional inter-response time distributions. In the case of high load the queueing behavior of the measured trace is approximated more accurate by the conditional histogram model than by the models, that do not represent the correlation structure of response size and inter-response time.

5 Conclusion

In the future it is expected that WWW-communications will be major traffic source for emerging broadband networks. Thus, modeling this kind of traffic is required to evaluate the applicability of different ATM service categories for the transmission of WWW-traffic.

In the investigation presented in this paper we have measured WWW-traffic in the local Ethernet segment of the Computing Center of the University of Würzburg. The measured data was analyzed and characteristics of WWW-traffic were derived. The inter-response time and the response size proof to be the most important characteristics of WWW-traffic for the modeling of client-based WWW-sessions.

The distributions of samples of the response size and the inter-response time show a heavy-tailed characteristic. Thus, we model the inter-response time and response size as independent and normalized Pareto-distributions. Since the parameter fitting for the Pareto model has no optimal solution we introduce a logarithmic histogram model. An extension of this model, the conditional logarithmic histogram model is introduced. It is able to represent the correlation structure of response size and inter-response time.

The models are validated by simulating the transmission of data over an ATM-link utilizing the VBR service category. The Pareto model is capable to describe certain aspects of WWW-traffic with 6 parameters but in general the histogram model performs better than the Pareto model. For some applications it is appropriate to model the dependence of the response sizes and inter-response times but the granularity of the model has to be considered carefully. Due to the goal of high transmission rates in a common ATM scenario the logarithmic histogram model is most adequate for the evaluation of the efficiency of different service categories for the transmission of WWW-traffic.

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