Network traffic model for industrial environment

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Abstract - **In the paper a model of the traffic in the LAN is presented. In the model the most important components influencing the network traffic are taken into account. Namely, the transmission protocols and information buffering, operational systems and queuing algorithms as well as users' behavior working with the network applications are considered. The model is based on an "on-off" function. The network traffic observed at the physical layer is a superposition of many sequential and self-similar "on-off" processes. It has been shown that self-similarity of the traffic measured by Hurst parameter changing from almost 1.0 for very low frequencies to 0.5 for high frequencies. Implications, which are derived from the model, are described in the conclusion.**

Index Terms—**network protocols, traffic model, components traffic**

I. INTRODUCTION

Computer network traffic has a very complex and time depended structure. The layers in network ISO/OSI model perform specific tasks, which are concurrent with other tasks running in the computer system. Information flows between layers sequentially but this flow is not laminar due to buffering and CPU time sharing. In the layer protocol model many competitive tasks are being performed at the same time. This has significant impact on the shape of the network traffic. The signal processed in the physical layer is the superposition of all signals in the remaining layers of the link.

In the first model of the network traffic, proposed by Erlang in 1920s the Poisson process was used in analyzing the traffic in the telecommunication networks [1].

Networks with packet switching properties were developed in 70-ths. At that time most of analytical models of computer networks were based on simplified exponential approximations. In these models both intervals between packets and duration of packets were described by exponential relationships. These models were not capable to represent correlations between neighboring events. These deficiencies were partially eliminated in models based on the Markov processes [2].

Regressive models are also used for the network traffic approximation. They are described by the value of the random variable (or the sequence of random variables), which are defined by the linear combination preceding random variables. Several such models were already described [3, 4]:

- DAR - Discrete Autoregressive model,
- MA - Moving Average model,
- ARMA - Autoregressive Moving Average model,
- ARIMA - Autoregressive Integrated Moving Average model.

A common property of all autoregressive models is that the interval between subsequent events is expressed as a linear combination of previous intervals and randomly introduced values.

The Markov stream and autoregressive streams are distinguished by the inner correlation fading in an exponential way, so they are relatively efficient. The stream occurrences' models are as follows:

- FBM - Fractional Brownian Traffic [5]
- FARIMA - Fractional Autoregressive Integrated Moving Average model [6, 7, 8],
- "on-off" model [9].

With the introduction of Internet properties network traffic has changed significantly. Many modern traffic analysis lead to the conclusion that there is a stronger correlation in stream of events than were earlier observed. These types of processes are known as long-memory processes. At different time scales (milliseconds, seconds, hours) some correlations can be observed which are described by the term of self-similarity.

This paper is organized as follows. In Section II, we give a brief definition of self-similarity and estimation methods of self-similarity from measured data. In Section III, we proposed the network model with the components significantly influencing the network traffic. In Section IV, we presents experimental verification. Finally, we summarize this paper in Section V.

II. BACKGROUND

The self-similarity is defined as:
Stream of events:

$$\{t_n\}_{n=1}^{\infty} = t_1, t_2, \ldots, t_n, \ldots \tag{1}$$

is **self-similar** [3], if

$$\left\{t_n^{(s)}\right\}_{n=1}^{\infty} = \left\{t_1^{(s)}, t_2^{(s)}, \ldots, t_n^{(s)}, \ldots\right\} \tag{2}$$

or

$$\left\{t_n^{(s)}\right\}_{n=1}^{\infty} \underset{d}{\equiv} \{t_n\}_{n=1}^{\infty} \tag{3}$$

and this is valid independently of time scaling

Stream of events (1) is **exactly self-similar** with parameter $0<\beta<1$, if correlation function (2) is fulfilling the following condition

$$\begin{cases} Var\left\{t^{(s)}\right\} = \dfrac{\sigma_t^2}{s^{\beta}} \\ \hat{\rho}_t^{(s)}(k) \equiv \hat{\rho}_t(k) \end{cases} \tag{4}$$

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For every s, k = 1, 2, ..., where s is time scale for subsequent k time intervals between events.

Stream of events (1) **asymptotically self-similar** with parameter $0<\beta<1$, if

$$\begin{cases} Var\{t^{(s)}\} = \dfrac{\sigma_t^2}{s^\beta} \\ \hat{\rho}_t^{(s)}(k) \xrightarrow[s\to\infty]{} \hat{\rho}_t(k) \end{cases} \tag{5}$$

The measure of self-similarity is the Hurst parameter introduced by H. E. Hursta [10].

The Hurst parameter can be evaluated in several ways:

– using rescaled adjusted range plot of R/S s a function of time [3,6,11, 12],

– using variance-time plot of R/S s a function of time [3, 6, 13],

– using periodogram [6],

– using Wittle's estimator [6].

The Hurst parameter for self-similar processes is in the range of $0.5<H<1$. For two identical processes $H=1$. Lower values of Hurst parameter indicates larger differences in processes and for $H=0.5$ processes are not correlated (like white noise)

Simple "on-off" models are commonly used to describe a random nature of the network traffic [13, 14]. The on-off model successfully captures the second-order correlations of traffic, in particular their Long Range Dependence (LRD). The "on" states are interlaced by the "off" states. Source is transmitting the packet in the "on" state while "off" state exists when there is no packet transmission. Therefore, the source works on the principle of the switch between the following active and inactive states.

Let $X(t)$, $t>=0$ is the stationary process in which [9]:

$$X_i(t) = \begin{cases} 1 & \text{for interwal "on"} \\ 0 & \text{for interwal "off"} \end{cases} \quad i = 1,2,3,\ldots, M \tag{6}$$

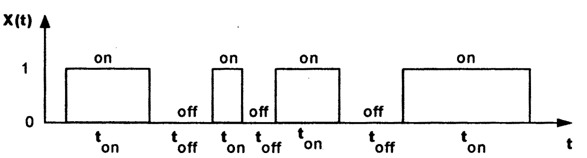

Fig. 1. An example of an "on-off" process.

The distribution of time interval for „on" state is given by:

$$\begin{cases} F(t) = 0 & t \le d \\ 1 - F(t) = \left(\dfrac{d}{t}\right)^\alpha & t > d,\ 1<\alpha<2 \end{cases} \tag{7}$$

d- minimal time interval for „on" state

Average time interval for „on" state for $1<\alpha<2$ is:

$$\bar{t}_{on} = \frac{\alpha d}{\alpha - 1} \tag{8}$$

The time interval for „off" state is described by classical random distribution with the mean value $\bar{t}_{off}$. The probability that the stream is in the "on" state is given by:

$$p = \frac{\bar{t}_{on}}{\bar{t}_{on} + \bar{t}_{off}} \tag{9}$$

The average intensity of streams' components is:

$$E\{X_i(t)\} = p \qquad , i = 1,2,\ldots,M \tag{10}$$

while resultant intensity is:

$$E\left\{\sum_{i=1}^{M} X_i(t)\right\} = Mp \tag{11}$$

In the case when function

$$x(t) = \sum_{i=1}^{M} X_i(t) \tag{12}$$

is asymptotically self-similar (5):

$$\lim_{s\to\infty} \hat{\rho}_t^{(s)}(k) = \hat{\rho}_t(k) = \frac{1}{2}[(k+1)^{3-\alpha} - 2k^{3-\alpha} + (k-1)^{3-\alpha}],\ k>0 \tag{13}$$

and

$$\hat{\rho}_t(-k) = \hat{\rho}_t(k) \quad , k<0 \tag{14}$$

then

$$\lim_{|k|\to\infty} \hat{\rho}_t(k) = \frac{1}{|k|^{\alpha-1}} \tag{15}$$

Assuming that the correlation function decay exponentially

$$\hat{\rho}_t(k) \sim \frac{1}{|k|^\beta},\quad 0<\beta<1 \tag{16}$$

and that:

$$H = 1 - \frac{\beta}{2} \tag{17}$$

then

$$H = \frac{3-\alpha}{2} \tag{18}$$

The typical switching is between 1 and 0 states ("on" and "off" states) is random. This randomness reflects a human's behavior at a computer as well as the applications employing the network services. The traffic "on-off" model is also connected with the client-server model. In the "on" state client sends request to server and server is expecting a request. In the "off" state client waits for the response and server is generating request. Lengths of the "on" and "off" are random process, as well as the length of neighboring, following intervals "on-off".

The superposition of such sources results in the LRD observed in network traffic. This was described in [15] where the "on-off" traffic models were derived as a superposition of a large number of "on-off" sources, with heavy-tailed "on" and/or "off" periods.

In the papers [16, 17] authors presented a new model called "alpha-beta on-off model" which is a composition of two different "on-off" models.

There is a strong tendency for adaptation of TCP/IP protocols for industrial environment [18]. This technology is used in industry dedicated network technologies due to both significant increase of TCP/IP throughput and its easy integration with ERP (Enterprise Resource Planning) systems which need open environment [19]. In industrial environment there is a lot of real time processes and this creates additional constraints on the network protocols. For the more optimal use of network protocols a better understanding of the network traffic and its origin is required. New, better network models would be essential for easier adaptation of

TCP/IP protocols in industry.

III. Proposed Traffic Model

The human behavior has a significant impact on Internet services with an access to remote multimedia information libraries (video and sound), www-pages searching and increasing number of e-business applications (e.g. VoIP). The usage of the network is mainly based on the review of the information resources and on their transfer. The whole process is conveyed to a simple model of "on" (connecting) and "off" (thinking or reviewing and the decision about an eventual collection of existing stock) processes.

It is obvious that relatively intensive network traffic in LAN is generated when the users start their work. At the beginning of the day the most of the internet traffic is related to various e-mail services. Later, other kind of internet traffic like web browsing, ftp file transferring, and remote computer operation become dominant. Another characteristic feature is the tendency to copy the day's schedule, which results frequently from company internal rules and work time set up. In consequence of a wide scale of marketing action or the temporal fashion, it happens that in a very short period of time (even minutes) the number of visitors on one server is growing many times.

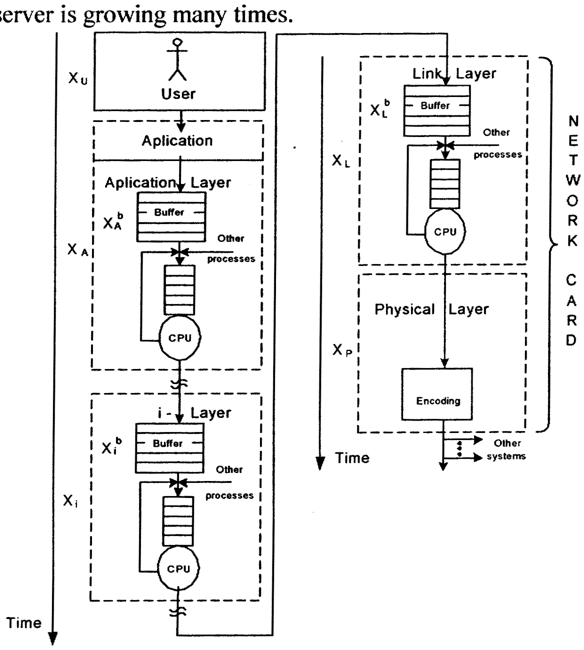

Fig. 2. The network model with the components significantly influencing the network traffic where: X_U, X_A, X_i, X_L, X_P are "on-off" processes depending on the user behavior, the application and application layer, intermediate layers, the link layer and the physical layer respectively.

The traffic burst, for example, can be due to people's preferences caused by an advertisement. Consequently, the human's behaviors are a very important aspect to understand the causality of self-similar phenomenon originated in the network. So, the self-similarity cannot be explained without deep analysis of the way the individuals use the computer network. Self-similarity is not only conditioned by transition protocols and computer systems but also it is strictly connected with such disciplines like psychology and sociology.

In order to better describe the traffic network, the model must take into account all essential factors, which influence that traffic. To achieve a correct description of the network traffic several factors such as: human behavior, the properties of the operational system, the processes scheduling algorithm, and features of transmit protocols have to be analyzed. Most of the network applications use TCP/IP protocol and this has a significant impact on the shape of network traffic. The information between the user's application and the physical layer is sequentially converting (transforming) by several processes like coding, fragmentarization, buffering and the headers and tail adding. Thus, a communication between processes has significant influence on the traffic. The proposed model, as shown in Fig. 2, is based on the ISO-OSI network model, which was enhanced by mentioned above traffic properties.

Individual components of the models represents network traffic generators with different frequency ranges for "on – off" processes. The proposed model will be verified by measuring Hurst parameter for network traffic for different time scale (s) Changing from 10^3s to 10^{-3}s.

The higher frequencies analysis (>10 Hz) shows an influence of used protocol algorithms, operational system and information buffering. E.g. a frequency of ready processes (i.e. processes in run queue) context switches varies from about 10 to 100 Hz. The influence of the particular components on the shape of corresponding function $X(t)$ presents Fig. 3.

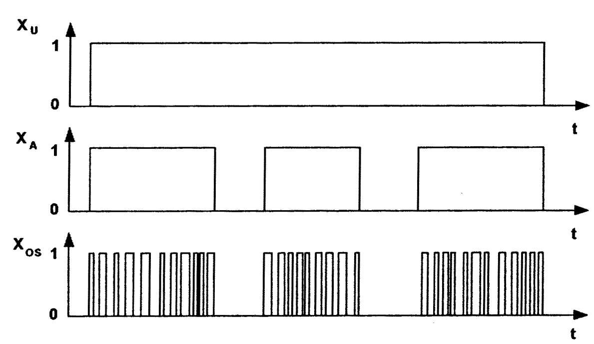

Fig. 3. An example of various "on-off" functions modeling network traffic generators: X_U - the user, X_A – applications and application layer and X_{OS} – operational system respectively.

In the model shown in Fig. 2 the components can be characterized by "on-off" functions, which are switched with different frequencies (f) in following domains:

X_U – human's with $f \lesssim 10^{-2}$ Hz,

X_A – the network processes embedded in network application with $10^{-2} \lesssim f \lesssim 1$ Hz,

X_{OS} – the queuing of the processes to CPU with $10 \lesssim f \lesssim 10^2$ Hz,

X_i - the i-th process realizing information conversion accordingly to network layer protocols with $10 \lesssim f \lesssim 10^3$ Hz,

X_L – link layer with $f \gtrsim 10^3$ Hz

X_P – signal in the physical layer expressed in packets per second.

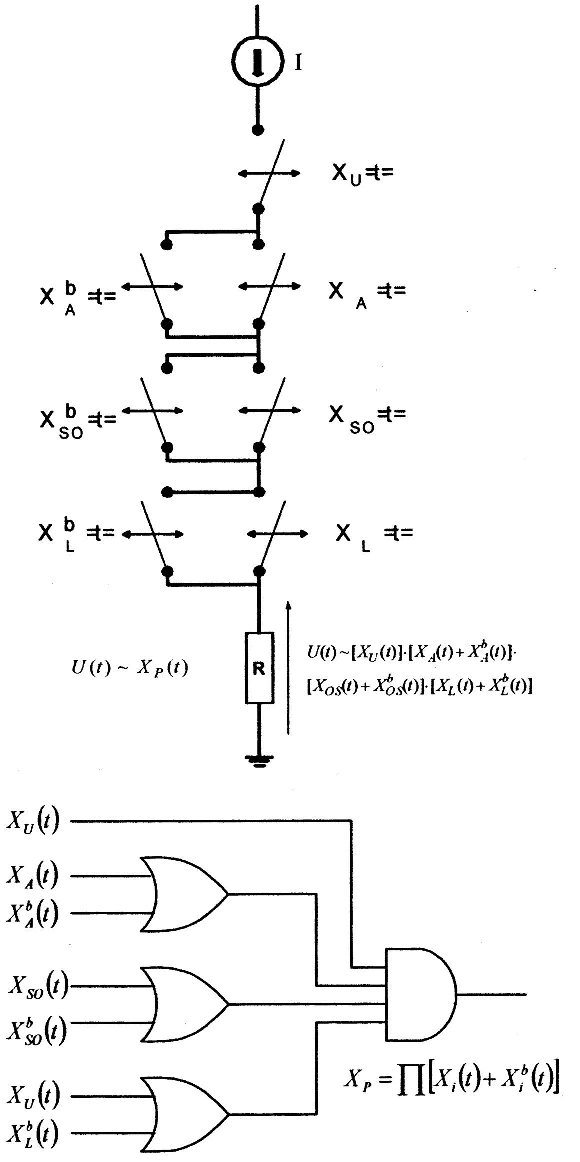

Fig. 4. Electrical equivalents of the model of Fig. 2.

Taking into account that in physical layer observed traffic is a superposition of mentioned above components, we propose the following formula for its description:

$$X_P(t+\Delta t_{ps}) = \prod_{i=1}^{n}[X_i(t+\Delta t_{p_i}) + X_i^b(t+\Delta t_{p_i}^b)] \quad (19)$$

where:

X_i – function describing behavior of *i-th* layer.

X_i^b – function describing behavior of *i-th* bufor.

Δt_{p_i} – time of signal propagation in computer system,

$\Delta t_{p_i}^b$ – time of signal propagation in the buffers.

Since:

$$\Delta t_{pi}, \Delta t_{pi}^b \ll t_{ON}, t_{OFF}, \quad (20)$$

thus from (19):

$$X_P(t) \approx \prod_{i=1}^{n}[X_i(t)+X_i^b(t)] \quad (21)$$

Considering components of the model:

$$X_P(t) \approx [X_U(t)]\cdot[X_A(t)+X_A^b(t)]\cdot [X_{OS}(t)+X_{OS}^b(t)]\cdot[X_L(t)+X_L^b(t)] \quad (22)$$

and assuming that maximum throughput is equal p_{max} one can obtain throughput I from (22) as:

$$I(t) \approx X_P(t)\cdot p_{\max} \quad (23)$$

IV. Experimental verification

Experimental verification of the proposed model was done on the local network of the University of Information Technology and Management in Rzeszow. This network consistes 550 computers PC, 2 routers and 30 servers.

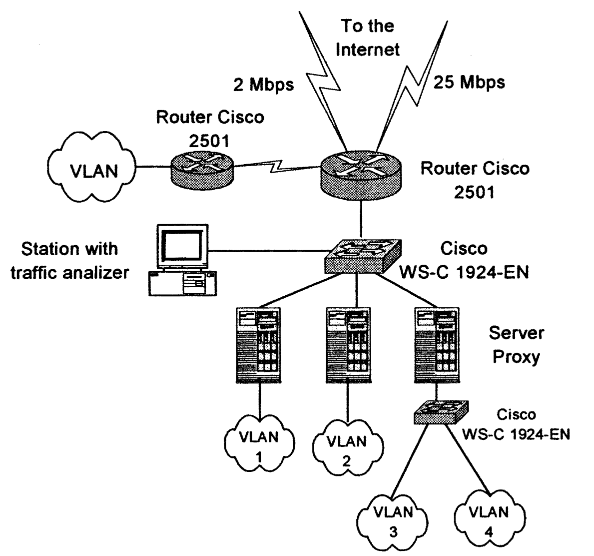

Fig. 5. The configuration LAN University of Information Technology and Management in Rzeszow.

In measurement of the traffic in the LAN network the following equipment was used:

Process snoop – network operational system UNIX Solaris 9,

Link View Classic – the special kart to the analysis network traffic. The LinkView Classic Network Analyzer is a self-contained, software-only LAN analyzer that works with most third party Ethernet or Token Ring Network adapter cards.

Typical shape of the traffic in LAN is shown in Fig. 6, Fig. 7 and Fig. 8.

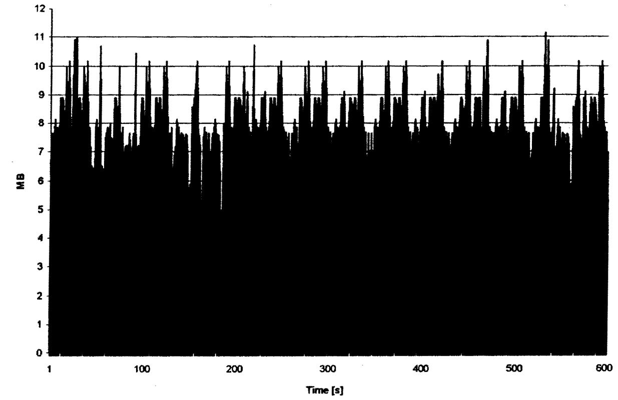

Fig. 6. Real traffic shape in the LAN.

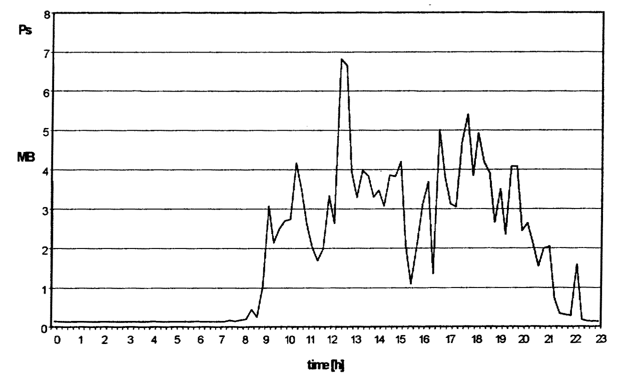

Fig. 7. An example of night and day traffic to selected LAN server.

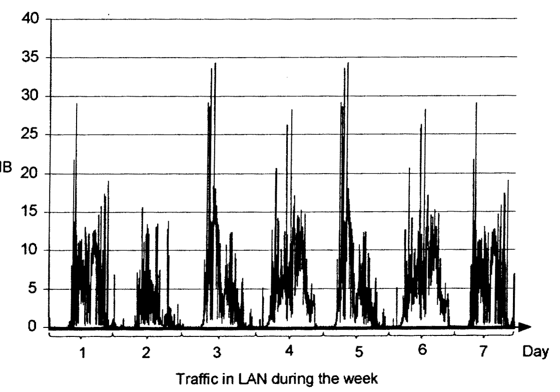

Fig. 8. Real traffic in LAN during the week to the University of Information Technology and Management in Rzeszow. The measurements started Sunday midnight (time gradation $\Delta t = 60s$).

To check the influence of the processor load on the generation traffic in LAN, the measurement of the file (size 150 MB) sending to use FTP protocol, between two computers (Sun Blade 100, processor Spark 400 MHz, memory 256MB, operational system: Unix Solaris 9) was done. These measurements were done in two different conditions:

– station was loaded only by system and transmission processes

– station was additionally loaded with user processes.

It was observed that with the increase of server load originated by uses processes the transmission time of information increases. At the same time the level of traffic slightly decreases. The influence of the processor load on the traffic LAN presents Fig. 9.

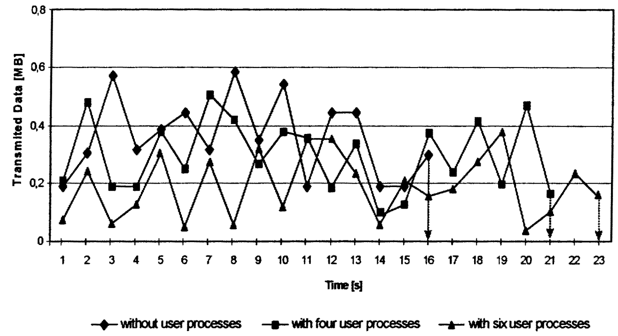

Fig. 9. The dependence of accumulated network traffic (gradation - $\Delta t = 1s$) in time; without user processes in queue to the CPU and with four and six user processes in queue to the CPU.

To investigate the self-similarities of the traffic, the traffic was analyzed under different gradations Δt conditions. The results are shown on Fig. 10.

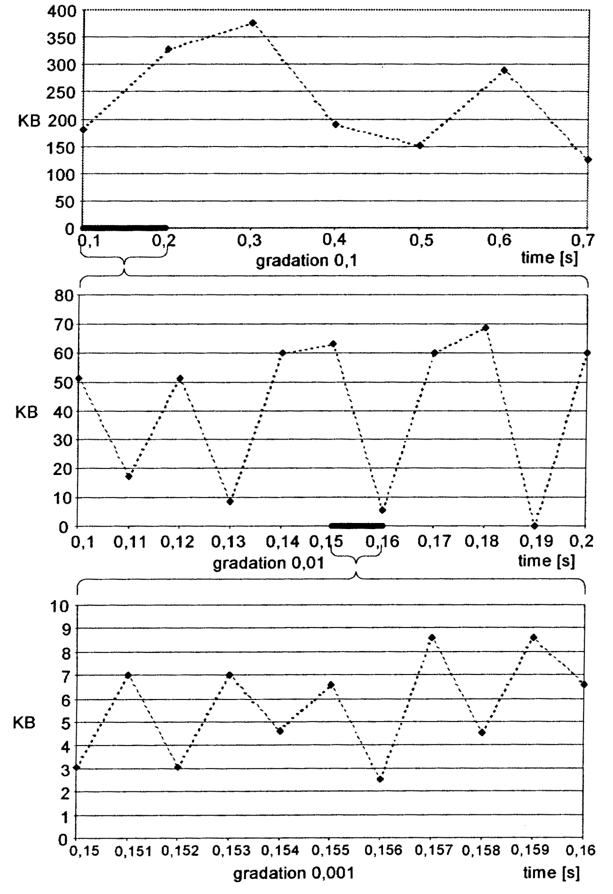

Fig. 10. The total transmitted data for different gradation of the time measurement and traffic accumulation.

The traffic in all these cases is self-similar with the Hurst parameter of 0,5 – 1. Tab. 1 presents the obtained values of the Hurst parameter.

Tab. 1. Hurst parameter as a function of frequency estimated by R/S and Variance Plot analysis for the results of the traffic measurements in LAN.

Sampling frequency [Hz]	R/S analysis	Variance Plot
0.001	0.91	0.89
0.01	0.84	0.86
0.1	0.79	0.78
1	0.69	0.66
10	0.64	0.63
100	0.58	0.57
1000	0.54	0.53

The standard deviation for experimental results is lower than 0.03 for both methods. Since both methods produce a similar values of Hurst parameters H; therefore, one can be consider them as trustful.

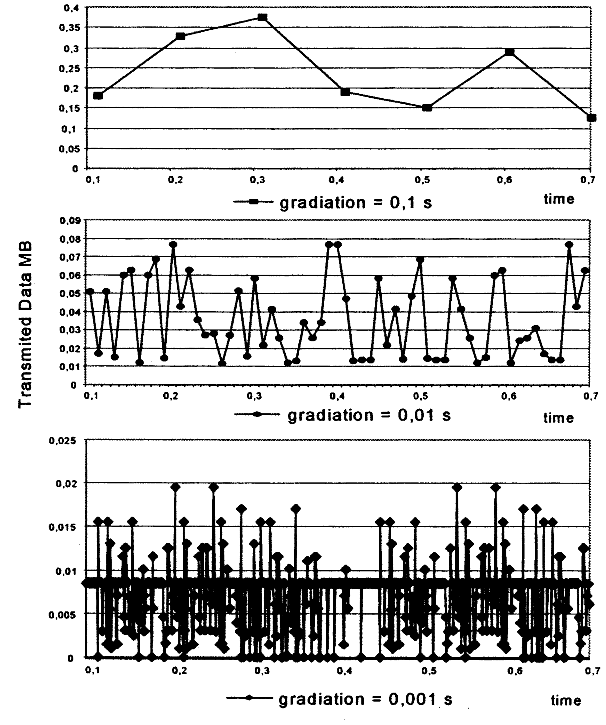

Fig. 11. The graph of transmitted data for different time of averaging.

V. Recapitulation and Conclusions

The traffic of a computer network is a very complex self-similar phenomenon, dependent on many factors and consisting of the component with frequencies in wide spectrum. The highest frequency of the traffic is generated by the link layer but the human is a low frequency component generator. The obtained results show that a major influence on traffic self-similarity is man's behavior as network traffic "generator". This conclusion can be drawn from high values of Hurst parameter for low frequencies (Tab. 1).

Another important factor is the operational system, especially its queuing algorithm of the processes and the performance of the computer system.

Our investigation verified that the model we propose qualitatively agrees with observed traffic and include the most important components – traffic generators. Further research both on human behavior when using the network applications as well as on transmission protocol running under operational system in computer system should give us the possibility to model precisely the *X(t)* function for all considered model components.

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