International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-2, December, 2019

Quality Assurance of Data Transmission in Queuing Networks

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***Abstract**: With the development of high-speed communication networks, the so-called property of self-similarity of flows has an increasing impact on the quality of service. From a practical point of view, this can be explained by the high variability of traffic intensity and, as a consequence, the high receipt of packets to the network node at a high data rate, which leads, due to the limitation of the buffer, to packet losses. For a long time, it was believed that the traffic of the local network is described by the classical Poisson distribution. Telephone networks were originally built on the principle of channel switching, and computer networks are usually based on the principle of packet switching, but the calculation methods have remained virtually the same. Packets at high speed of their movement on a network arrive on a node not separately, and the whole pack. Traffic in such networks has ripples, which increases the likelihood of congestion in the network nodes, which lead to buffer overflows and cause losses and / or delays. Pulsations lead to differences in the speed of information flows, in which the ratio of the maximum value to the minimum speed is tens of times. At the same time, it turned out that in multiservice networks, the number of events in a given time interval depends on previous, very distant events. This means that at large scales of a multiservice network, traffic has the property of self-similarity, i.e. it looks qualitatively the same at any sufficiently large scales of the time axis.*

***Keywords**: Informatization, traffic parameters, communication networks, packet-switched networks, third-video in real time.*

I. INTRODUCTION

Self-similar traffic has a special structure that persists with multiple scaling, i.e. there are some outliers in the implementation at a relatively small average traffic level. This phenomenon degrades performance when self-similar traffic passes through network nodes [8]. Self-similar models can exhibit the property of long-term dependence, which means the manifestation of dependence between events at sufficiently large intervals [3]. An informally self-similar process is defined as a random process whose statistical characteristics exhibit scaling properties. Unlike Poisson processes, self-similar ones are characterized by the presence of an aftereffect: the probability of the next (next) event depends not only on time, but also on previous events (prehistory). This means that the number of current events may depend on the number of previous events at distant intervals [10].

There are threads in which the probability of the next event occurring depends on the occurrence of events in previous time intervals. A typical example of such threads are threads with limited aftereffect [6]. They are given a finite set of distribution functions for the adjacent intervals TK between the arrival of k events [2]. However, such models take into account only the average values of the characteristics or their confidence limits. Such models are typically used to calculate rough estimates of the required network bandwidth. The same models are useful in cases where accurate and reliable values of the initial values of traffic parameters are not available for some reason [1].

II. LITERATURE REVIEW

However, the recent complication of the nature of subscriber traffic leads to the fact that not taking into account random fluctuations can lead to service interruptions even for large nodes, so we consider various mathematical models of subscriber traffic, using different means of its description. The desire of the user to receive at the same time the services of traditional telephony and data transmission determine the vector of development of communication networks [7]. One of the important statistical properties of the load created by modern applications is the presence of a dependence between its individual parts, which does not disappear when the time scale changes in the direction of enlargement, as it happens with traditional random processes used to describe the load in the theory of teletraffic. For example, for a Poisson process, the corresponding correlation is always zero, and for a Markov process with a finite number of States, it exponentially decreases to zero [4]. Integration in packet-switched networks of traffic of different nature, as well as the features of data transmission technologies used to build communication networks and increased activity of network users, are some of the reasons for the manifestation of the self-similar nature of network traffic or, therefore, its fractal properties [9]. The analysis of modern technologies and information transmission networks shows that it is necessary to consider the vector of subscriber load, consisting of several components, each of which should reflect the traffic properties of some groups of subscribers with the same integral characteristics [5].

Revised Manuscript Received on December 30, 2019.
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Since each of them describes traffic of fundamentally different origin: for example,
one – voice traffic, the second-data traffic, the third-video in real time, etc., we can consider these components statistically independent.

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III. MATERIALS AND METHODS

In this regard the traffic served X should be considered as the sum of several components:

$$X = \sum_{i=1}^{n} X_i = \sum_{i=1}^{n} \left(\lambda_i t + \sqrt{a_i \lambda_i} Z_t^{(i)}\right) = \left(\sum_{i=1}^{n} \lambda_i\right) t + \sum_{i=1}^{n} \sqrt{a_i \lambda_i} Z_t^{(i)}$$

where X_i is some standard process describing the I-th component of the traffic, and the processes Xi are statistically independent; $Z_t^{(i)}$ is a fractal Brownian motion with the parameter value Hearst X_i.

Consequently, incoming traffic consists of a mixture of several processes with different values of the Hurst parameter and is of a complex nature and difficult to investigate its properties. Therefore, the most important is to find out how much its properties depend on the values of the Hurst parameter of its components. With the growth of the Hurst parameter, such statistical properties of the process as predictability, range of values, etc. only deteriorate. Accurate determination of the values of the Hurst exponent is difficult in the case when there is only one component. Therefore, it is impossible to determine by statistical means all the parameters characterizing the mixture, especially if the intensities of the individual components are relatively small. Since the main parameter characterizing the quality of network service is the probability of packet loss and the task of determining the sensitivity of this parameter from the values of the Hurst parameter is important. This means that all traffic components must be considered when designing network devices; because there may be congestion in the network, which will occur much more often than the calculated value obtained during the design and the device will not be able to adequately reflect the real flow of events, as it reveals a long-term dependence (the number of events in a given time interval depends on the number of events received in remote time intervals). The way to measure this dependence for random processes is to determine the correlation function.

Self-similar traffic has a special structure that persists with multiple scaling, that is, there is a certain amount of emissions in the implementation at a relatively small average traffic level.

IV. RESULTS AND DISCUSSIONS

Self-similar processes can be detected by several equivalent features: R(k)=k(2H-2) they have a hyperbolically decaying correlation function of the form. Therefore, the correlation function is not summable and the series formed by the successive values of the correlation function diverges $\sum_{k} R(k) = \infty$. This infinite sum another definition of long-term dependence (DVZ), so all self-similar processes are long-term dependent. The consequences of this are significant, as the cumulative effect over a wide range of delays can be significantly different from that observed in a short-term dependency (CVR) process (e.g. Poisson). The analysis of teletraffic is based on KVZ for which DVZ can cause serious consequences. Because DVZ is the cause of long ripples that exceed the average level of traffic and this can lead to buffer overflow and cause losses, delays; - dispersion of the sample average fades slower than the inverse of the sample size. If we introduce into consideration a new temporal sequence $\{X_i^{(m)};\ i=1,2,\dots\}$ obtained by averaging the original sequence $\{X_i;\ i=1,2,\dots\}$ for disjoint sequential blocks of size m, then self-similar processes are characterized by a slower decrease in dispersion according to the law $\sigma^2\left(X^{(m)}\right) \propto m^{2H-2}$, when m→∞, while for the theory of teletraffic $\sigma^2\left(\left\{X_i^{(m)}; i=1,2,\dots\right\}\right) = \sigma^2 m^{-1}$ that is, decreases inversely proportional to the sample size. This suggests that the statistical characteristics of the sample (mean and variance) will converge especially at H to 1. This is expressed in all measures of self-similar processes;

- when considering a self-similar process in the frequency domain, the manifestation of DVZ leads to a power nature of the spectral density near zero. And processes of KVZ are characterized by the spectral density having positive and final value at w=0.

Self-similar processes are expressed in slow decrease of dispersion, long-term dependence (manifestation of dependence between events through rather big intervals of time) and fluctuation character of a power spectrum of such processes. Self-similar processes in the literature are also often called self-similar.

The easiest way to characterize the long-term dependence of one parameter-the Hurst index N. to assess this parameter, there are many methods.

A value of H=0.5 indicates the absence of self-similarity, and large values of H (close to 1) confirm the presence of long-term dependence.

Among the models designed to simulate fractal traffic, the following can be distinguished [27]:

- models based on "dynamic Markov modeling". These models are finite-state automata represented by state diagrams. The output of the model is a set of probabilities of the appearance of symbols;
- neural network models that allow to solve the problem of approximation of several variables in the sample by immersing the time series in a multidimensional space;
- ON/OFF models. In these models, traffic is seen as a combination of sources that generate it. In so-called Interperiods, they can generate packets of information. The ON period is followed by an OFF period when the source does not generate packets. The size of the ON-and off-Periods is a random variable that must have finite expectation and infinite variance;
- multifractal models reproduce traffic aggregated from multiple sources. Multifractality of traffic manifests itself in changing the statistical properties of traffic implementation when the aggregation scale changes;
- fractal Brownian motion. This model is based on a random process starting at the origin with independent infinitesimal Gaussian increments. To generate fractal Brownian motion random midpoint displacement algorithms or sequential random addition algorithms are used;

- fractal Gaussian noise is a stochastic process with certain parameters and an autocorrelation function of a given kind. This model has an additional Hurst parameter that quantifies the degree of fractal scaling.

The results of the implementation of these models make it possible to get a reliable idea about the behavior of traffic in the network, which is necessary for the design and management of telecommunications networks.

An informally self-similar (fractal) process can be defined as a random one whose statistical characteristics exhibit scaling properties. The self-similar process does not significantly change the view when viewed at different scales on the time scale. In particular, unlike processes that do not have fractal properties, there is no smoothing of the process when averaging on the time scale – the process retains a tendency to bursts.

Let {Xk; k=0,1,2,…} – stationary random process.
Given the stationarity and the assumption of the existence and finiteness of the first two moments, we introduce the notation:

$m = E[X_t]$ – average, or expectation;

$\sigma^2 = E[X_t - m^2]$ – dispersion;

$R(k) = E[(X_{t+k} - m)\cdot(X_t - m)]$ – correlation function;

$r(k) = \frac{R(k)}{R(0)} = \frac{R(k)}{\sigma^2}$ – correlation coefficient.

Time-scale averaging refers to the transition to $\{X^{(m)}\}$, because

$$X_k^{(m)} = \frac{1}{m}\sum_{i=km-m+1}^{km} X_i$$

where $X^{(m)}$ is the highest possible resolution for the process. Subsequent evolutions of the $X^{(m)}$ is a less detailed copy of process X_i. If the statistical properties (mean, variance) are preserved during averaging, then the process is self-similar.
In network traffic modeling, the value X_k is interpreted as the number of packets that entered the channel or network during the k-th time interval. The initial process is already averaged.
A continuous stochastic process X(t) considered to be statistically self-similar with Hurst parameter $H(0{,}5 \le H \le 1)X(t)$, if for any positive number a, the process X(t) and $a^{-H}Z(at)$ will have identical distribution, that is, to have the same statistical properties.
In practice, usually there are not strictly self-similar, but asymptotically self-similar processes.
The process X is strictly self-similar in wide sense (SSS) with Hirst coefficient $H = 1 - \frac{\beta}{2},\ 0<\beta<1$ if the condition is satisfied $r_m(k) = r(k),\ \mathrm{m} \in \{2,3,....\}$
The parameter H is an indicator of the degree of self-similarity of the process, and also indicates the presence of such properties as persistence/variability and long-term memory. For a Markov process (memoryless property) the Hurst coefficient is equal to 0.5. The process is completely random, respectively, the simplest (Poisson) flow is also called " pure randomness flow of the first kind.

At [0; 0.5], the process is characterized by variability: high values of the process follow low values and Vice versa. That is, the probability that at k+1 step the process will deviate from the average in the opposite direction (relative to the deviation at k step) is as high as the parameter H is close to 0. In the case of h [0,5; 1] the process is persistent or with long-term memory: if for some time in the past there was an increase in the parameters of the process, then in the future, on average, their growth will occur. In other words, the probability that in step k+1 the process will deviate from the average in the same direction as in step k is as high as the parameter H is close to 1.

In order to confirm the existence of a self-similarity property for different data streams of a multiservice network, it is necessary to measure some characteristics of different types of network traffic. This requires statistics on streams such as audio, video, and data traffic.

That is, a CSSC process does not change its correlation coefficient after averaging over blocks of length m. Or X a process is a CSSC if the aggregated process X • m • is indistinguishable from the original process X, at least with respect to second-order statistical characteristics.

The property of asymptotically self-similar processes in the broad sense (ACCS) is that form tending to infinity, the process converges to the ACCS process
$r_m(k) \to r(k),\ \mathrm{m} \to \infty$
There are observations that for both classes of self-similar processes the variance of $V_{ar}[X^{(m)}]$ decreases much more slowly than $\frac{1}{m}$ by $m \to \infty$ comparison with stochastic processes where the variance decreases proportional to and approximates 0 at $m \to \infty$.
The most accurate property of self-similar processes is that the autocorrelation function does not degenerate at $m \to \infty$, unlike stochastic processes where at R $R(k, X) \to 0$ at $m \to \infty$.
Example of a fractal-the Koch curve belongs to the class of deterministic fractals, i.e. an object is directly composed of its small copies. In the theory of teletraffics, a class of random (stochastic) fractals is used to describe the behavior of the load value in packet-switched communication networks. In this case, the property of self-similarity (scale invariance) is observed only "on average", i.e. similar are not the signal samples themselves, but its correlation function, or PRV at different time scales.
Self-similar processes have a hyperbolically damped correlation coefficient of the form

$$r(k) = \frac{1}{2}\left((k+1)^{2H} - 2k^{2H} + (k-1)^{2H}\right)$$

or for asymptotically self-similar processes, correlation function

$$R(k) \approx k^{2H-2}L(t)$$

where L(t) is a slowly changing function at infinity (i.e. $\lim \frac{L(tx)}{L(t)} = 1$).
Therefore, the correlation function is non-cumulative-the series formed by successive values of the correlation function diverges. This property characterizes almost all self-similar processes and distinguishes them from processes without long-term dependence,

in which the correlation function decreases according to the exponential law and is summable.

Long-term dependence is the cause of pronounced pulsations of the process, but allows us to talk about some predictability in small time limits. From the point of view of queue theory, an important consequence of flow correlation is the unacceptability of queue parameter estimates based on the assumption of the same and independent distribution of intervals in the incoming stream.

Self-similar processes have a slowly decreasing dispersion. When the process is averaged, the dispersion of the sample average fades more slowly than the inverse of the sample size, according to the law:

$$\sigma^2\left(X^{(m)}\right) \propto m^{2H-2}$$

While for traditional stationary random processes

$$\sigma^2\left(X^{(m)}\right) = \frac{1}{\mathrm{m}}\sigma^2(\mathrm{X}),$$

That is, it decreases inversely to the sample size.

The property of slowly decreasing variance suggests the possibility of significant, not smoothed by averaging, "outliers" in a random process, and associates self-similarity with such a concept as distributions with weighty tails. An important corollary of the property of slowly decaying variance is that in the case of classical statistical tests (e.g. calculation of confidence intervals), the generally accepted standard deviation measure σ is erroneous.

Associated with this property is the "uncharacteristic" behavior of the dispersion index, or scatter index, for process samples (IDC), also called the Fano factor. IDC is defined as the ratio of the variance of the number of events in a given time interval T to the expectation of this value:

$$F(T) = \frac{\mathrm{Var}[\mathrm{N(T)}]}{\mathrm{E}[\mathrm{N(T)}]}$$

where N(T) is the number of events of the investigated flow occurring in the interval (window) T.

For self-similar processes, the logarithm of the scatter index F (T) increases linearly:

$$\ln[F(T)-1] = (2H-1)\ln T + y$$

Self-similar processes have distributions with heavy tails. A random variable Z has a distribution with a heavy tail (RVX) if the probability P[Z>x] ~ CX at $x \to \infty$, i.e. the tail of the distribution attenuates according to the power law. An example of a distribution with a weighty tail is the Pareto distribution. At 0<α<2, Z has infinite variance, and at 0<α<1, the mean is also infinite.

The most significant feature of a random variable with a heavy-tail distribution is its extreme variability. With a probability that is not negligible, a number of "very large" values may be present in the sample.

Such distributions significantly reduce the accuracy of statistical estimates; the finite sample size leads to an underestimation of the mean and variance. The presence of RVC in phenomena external to the processes under consideration is one of the reasons for the emergence of self-similarity in the corresponding stochastic models. Often, when considering self-similar processes, we talk about a complex of interrelated concepts: self-similarity, scaling, long-term dependence, RVC and power laws of statistical characteristics. This set of properties distinguishes processes called self-similar from classical random processes, such as Poisson.

The simplest self-similar objects are fractals. According to the definition given by the Belgian scientist Benoit Mandelbrot: "a fractal is a structure consisting of parts that are in some sense similar to the whole." But from a mathematical point of view, a fractal is, first of all, a set of fractional dimension. Therefore, self-similar processes are often called fractal.

There are several approaches in the formation of a self-similar flow. The best known is the method originally proposed by Mandelbrot.

This method is based on the superposition of several (strictly alternating) independent and having the same distribution OF on/OFF sources, the intervals between the ON and OFF periods of which have the Noah effect. By strictly alternating ON/OFF sources we mean a model where ON and OFF periods are strictly alternating, the durations OF on periods are independent and have the same distribution, the durations of OFF periods are also independent and have the same distribution, and the sequences of durations of ON and OFF periods are independent of each other.

In this case, the duration of the ON and OFF periods may have different distributions.

The Noah effect in the distribution of on/OFF period durations is a major point in self-similar traffic modeling as opposed to models where standard exponential or geometric distributions are used. The Noah effect is synonymous with infinite dispersion syndrome, which has emerged from empirical observations that many natural phenomena can be described by an infinite dispersion distribution.

Mathematically, a Pareto distribution or log-normal distribution, also often called heavy-tailed distributions, can be used to achieve the Noah effect.

A random variable is considered to have a distribution with a heavy tail (RTX or Heavy Tailed) if:

$$1 - F(x) \approx x^{-\alpha}, x \to \infty$$

That is, the tail of the distribution attenuates according to the power law, in contrast to, for example, the Gaussian distribution with exponential tail decrease. The most popular is the Pareto distribution (figure 1).

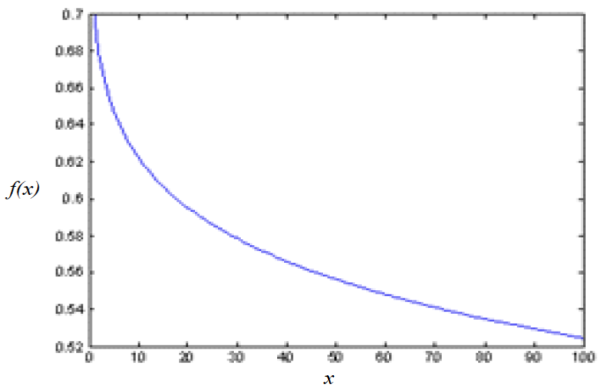

Fig. 1. Example of a heavy-tailed distribution

Retrieval Number: B4667129219/2019©BEIESP
DOI: 10.35940/ijeat.B4667.129219
Journal Website: www.ijeat.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-9 Issue-2, December, 2019

It is believed that network traffic in many cases is best described by heavy-tailed distribution. The Pareto distribution has a distribution function:

$$F(x)=1-\left(\frac{\beta}{x}\right)^{\alpha}$$

where α is the form parameter characterizing whether the distribution will have a finite or infinite mean and variance; • – is the lower bound parameter (the minimum value of the random variable x).

The Pareto distribution density is given by the function:

$$f(x)=1-\frac{\alpha}{\beta}\left(\frac{\beta}{x}\right)^{\alpha+1}, x>\beta, \alpha>0.$$

$$f(x)=F(x)=0, x\leq\beta.$$

The parameter α defines the mean and variance of x as follows: - for $\alpha \leq 1$, the distribution has an infinite mean;
- for $1 \leq \alpha \leq 2$, the distribution has a finite mean and infinite variance;
- for $\alpha \leq 2$, the distribution has infinite variance.

There is also a relation between parameter α and Hurst parameter H:

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

The classical Pareto distribution is used in modeling many objects of the considered process, such as the size of disk files, WEB pages, data ripples, etc., the distinctive feature of which is the presence of the so-called "heavy tail" of the distribution curve (HT, heavy tail of distribution).

Numerous studies of processes in the Internet have shown that statistical characteristics of traffic have the property of time scale invariance (self-similarity).

The simplest self-similar objects are fractals. According to Mandelbrot's definition, " a fractal is a structure made up of parts that are in some sense similar to the whole." An informally self-similar process is defined as a random process whose statistical characteristics exhibit scaling properties.

Strictly self-similar in a broad sense, the process (SSSP) is characterized by invariance of ACF when the level of aggregation changes under the condition of slowly decreasing dependence (MUZ).

Unlike Poisson processes, self-similar ones are characterized by the presence of an aftereffect: the probability of the next (next) event depends not only on time, but also on previous events (prehistory). This means that the number of current events may depend on the number of previous events at distant intervals. Therefore, one of the main properties of self-similar process (self-similar) is MUSE (long range dependence). Therefore, self-similar processes are often called fractal. This is due to the processes of processing network packets, different amounts of data, with the emergence of many new applications, etc. It was noticed that not always the flow of packets in the network can be simulated using the Poisson process. Self-similar process is often explosive (burst) in nature, which is expressed in the possibility of emissions during a relatively low rate of arrival of events.

To represent the property of self-similar flows, models with the following distributions are proposed: log-normal, Weibull (W), Pareto (P). In mathematical modeling, various models of distributions are used, among them mainly the Pareto distribution, which has the following form:

$$w(x)=\frac{\alpha\cdot k^{\alpha}}{x^{\alpha+1}}, \alpha>0, k>0, x>0$$

Where α is the form parameter; k is the parameter that determines the lower bound for a random variable.

The parameter α is related to the Hurst exponent H by the expression:

$$\alpha=3-2H$$

To study and compare the dependencies of the average waiting time in the packet queue on the load, the simulation of the receipt of packets with the distribution of the duration of the intervals between packets according to the Pareto law in the object-oriented program GPSS World was carried out. In this model, the generate block is the source of the Pareto-distributed message flow. Generate (Pareto (1, k, a)) – the parameters of the Pareto law procedure have the following meaning: the first parameter - the number of the built-in generator is used as an argument for the formation of random variables with a given distribution law and the other two parameters directly specify the parameters of the probability distribution. With respect to traffic, self-similarity is expressed in the immutability of behavior when the time scales of observation change and the preservation of the tendency to spikes when averaging on the time scale.

Figure 2 shows the dependence of the average waiting time in the queue on the loading of transactions (packets) distributed according to the Pareto law.

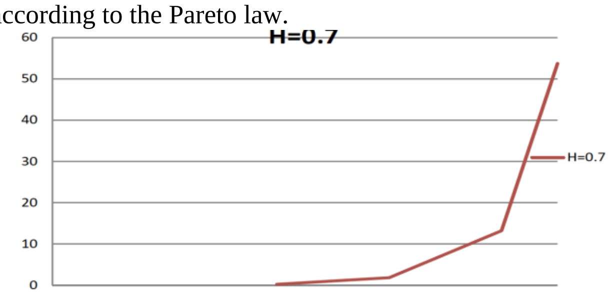

Fig. 2. Dependence of average waiting time on loading

Figure 2 shows that the average waiting time in the queue starts to increase when the load is above 50%, and when the queue is above 90%, the queue increases dramatically.

Figure 3 shows a comparison of the dependence of the average waiting time in the queue on the loading of transactions (packets) distributed exponentially and Pareto's law.

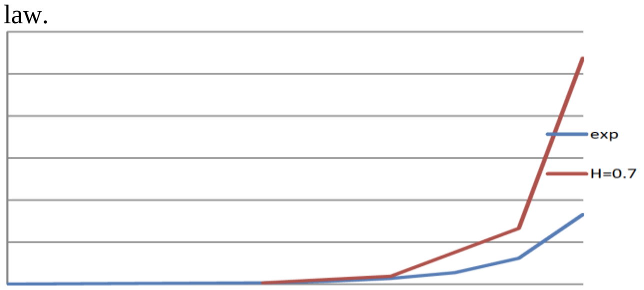

Fig. 3. Dependence of the waiting time in the queue from the load factor of the system

The main property of the Poisson flow, which determines its wide application in modeling, is additivity: the resulting flow of the sum of Poisson flows is also Poisson with total intensity.

In modeling, a Poisson flow can be obtained by multiplexing a set of ON/OFF sources called Markov processes it has Long been believed that the nature of network traffic corresponds to a Poisson process. This meant that the input device receives a Poisson flow of applications, that is, is the simplest-a uniform stationary flow without aftereffects.

Table-I. Output at p=1.6 and H=0.7

load	Ave. cont	Ave.time	Ave. (-0)	load	Ave. cont	Ave. time	Ave. (-0)
0,7	0,273	0,272	1,512	0,9	13,306	13,223	16,285
0,8	1,866	1,854	3,883	0,95	54,02	53,681	57,372

Therefore, until recently, the theoretical basis for the design of information distribution systems was the theory of Queuing. It adequately describes the processes occurring in circuit switching networks. The model of the call flow (data) in this theory is the simplest flow (stationary ordinary flow without aftereffect).

The development of high technology has led to a wide spread of networks with packet data, which gradually began to replace the system with circuit switching, but, as before, they were designed on the basis of the General provisions of the theory of teletraffic.

Flow as a random process is characterized by its statistical properties. The most commonly used are: probability density of data receipt for the period, probability density of intervals between data receipt and autocorrelation function.

V. CONCLUSION

Based on the study of simulation models revealed that the average waiting time of a packet in the queue grows faster with self-similar traffic than with the simplest. It is necessary to take into account the properties of self-similarity in the design and development of network devices. Network device level 3, calculated by mathematical models in accordance with the classical theory of teletraffic reduce the overall quality of service, while the main criteria for the quality of service QoS such as: packet transmission delay and packet loss will have inflated values.

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