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ABOUT NETWORK TRAFFIC MODELS

Traffic modeling allows evaluating the performance and capabilities of the network, as well as assessing the requirements presented to them. In the literature, various approaches were proposed for simulating the network traffic. However, there is no a single model that can simulate the traffic of all existing networks. Thus, the analysis of the characteristics of existing network traffic models, the selection of suitable models for certain network architectures, and the correct modeling of traffic is of great importance. This article analyzes some widely used models of network traffic.

Keywords: *network traffic models, Poisson model, Pareto model, Weibull model, Markov model, ON-OFF model, Markov modulated Poisson process, Autoregressive model.*

Introduction

Network Traffic Modeling is crucial for solving the issues, such as the provision of QoS (Quality of Service), to control the performance of computer networks (CN), and so forth.

The control of the performance of CN is aimed at minimizing the network delays and ensuring high reliability. The key factors affecting the performance of CN include: delay, packet loss and release capability. These factors should be analyzed to ensure the high performance. One of the main steps is the network traffic analysis. A network traffic model is used to analyze the network traffic. The model should sufficiently describe the real-time characteristics of the network.

The objective of QoS is to ensure high level performance in line with the requirements of the network users, applications and services. In the networks supporting QoS, a guarantee of QoS is provided under the agreements. For this purpose, QoS is constantly monitored and evaluated. To ensure the QoS, an idea of network traffic should be clarified, in the first place. The network traffic model is used in this regard.

To solve the above mentioned issues, a model, which allows describing and analyzing the actual characteristics of the network, would be developed. The actual characteristics of the network are directly related to the network traffic characteristics. Many different network traffic models have been proposed in literature for their analysis [1-4]. However, there is no a united effective network traffic model for analyzing the traffic characteristics of the networks based on different architectures. Therefore, it is significant to study the characteristics of existing models and to determine which model is more effective for existing CNs.

The article aims to investigate and analyze of the main network traffic models presented in the literature in the specific application context.

Network Traffic Models

The network traffic can be modeled as a sequence of the packets, frames and etc. that are discretely received. There are two different concepts of network traffic modeling, and these concepts are mathematically described as follows [2]:

$\{N(t)\}_{t=0\ldots\infty}$ - the network traffic collection is a continuous and stochastic integer process, where $N(t)$ $(0,\ t]$ refers to the number of packages, frames, and so on received within the time interval.

$\{A_n\}$ - the sequence of time intervals between the receipts of the packages, frames, etc., that is non-negative random sequence, where $A_n = T_n - T_{n-1}$ indicate the time interval between n and $n-1$, and T_n and T_{n-1} are the moments of access of n and $n-1$ respectively. These two processes are interconnected with each other by the following formula:

$$\{N(t) = n\} = \{T_n \le t < T_{n-1}\} = \left\{\sum_{k=1}^{n} A_k \le t < \sum_{k=1}^{n+1} A_k\right\}$$

When the network traffic is complex, i.e., the network traffic consists of the packets or frames series, several packets or frames can be received at the same moment T_n. In this case, the network traffic can be modeled by the non-negative, additionally random sequence $\{B_n\}$, $(n = 1 \dots \infty)$, where B_n is the power of the n -th series.

The following well-known models are used for the network traffic modeling [3]:

– Poisson model;
– Pareto model;
– Weibull model;
– Markov models:
– ON-OFF model;
– Alternate status renewal model;
– Markov modulated Poisson process;
– Autoregressive model;
– etc.

Poisson model

When the network traffic is modeling, the process of packets incoming and occurrence of their combining is considered to be the Poisson process since this process has certain time characteristics. To be analytically simple, the process of the packet and frame entry in the networks is modeled as the Poisson process.

The time between the entries in the Poisson process is exponentially distributed with the intensity λ: $\lambda: P\{A_n \le t\} = 1 - e^{(-\lambda t)}$. The Poisson distribution is practical when the entries come from a large number of independent sources - Poisson sources. The distribution has an average value and dispersion equal to the parameter λ. The Poisson model has two basic assumptions:

– the number of sources is infinite;
– the traffic entry characteristics is random.

The probability distribution and distribution density functions in the model are expressed as follows:

$$F(t) = 1 - e^{-\lambda t};$$
$$f(t) = \lambda e^{-\lambda t}.$$

Some studies show that the time interval between packages is not explicitly distributed. For example, the studies described in [5-8] confirm that the distribution of the time interval between the packet entries in the local and global networks differs from the exponential distribution. Therefore, the statistical “self-similar” processes, which differ from the Poisson process for their network traffic modeling, began to be used [9, 10].

One of the main disadvantages of the Poisson model is that it is not capable to detect the data burstiness that is inherent to the traffic of the data transfer network. This is explained by the fact that the auto-correlation function in the renewable network traffic equals to zero. However, the positive auto-correlation between the different network traffic flows shows the existence of the burstiness in the network traffic, and this burstiness may occur at different times [11, 12].

Pareto model

Pareto distribution [13] implies an unrelated and similar distribution of the time between the entries. In general, if X is a random quantity with Pareto distribution, then the probability that X is greater than the value x is given as follows:

$P(X > x) = (x/x_m)^{-k}$, for all $x \geq x_m$, where k is positive and x_m is the minimum possible value of X_i.

The probability distribution and density functions in the model are expressed as follows:

$$F(t) = 1 - (\alpha/t)^{\beta}$$

Where $\alpha, \beta \geq 0$ və $t \geq \alpha$;

$$f(t) = \beta\alpha^{\beta}t^{-\beta-1}$$

β and α are the form and location components respectively.
Pareto distribution is applied to the modeling of "self-similar" entries in packet traffic. Pareto model is a "heavy-tailed" distribution and might describe extreme burstiness.

Weibull model

Weibull distribution [14, 15] is a "heavy-tailed" process [16]. It can model the unstable intensities during ON and ON/OFF periods while creating the "self-similar" traffic by multiplying the ON/OFF sources. In this case, the distribution and density functions of the Weibull distribution are identified by the following formula respectively:

$$F(t) = 1 - e^{-(t/\beta)\alpha}, t > 0;$$
$$f(t) = \alpha\beta^{-\alpha}t^{\alpha-1}e^{-(t/\beta)\alpha}, t > 0,$$

Where $\beta \geq 0$ and $\alpha > 0$ are the scales and location parameters respectively.

When the Weibull distribution is similar to the normal distribution, and if $\beta \leq 1$, the distribution density is L –shaped, if $\beta > 1$ is bell-shaped. This distribution allows the determination of the intensity of rejections depending on time. Thus, when$\beta \leq 1$, the intensity of rejections decreases depending on the time, while if $\beta = 1$, the intensity of rejections remains constant and the service time is exponentially distributed.

Markov models

The Markov model is used to model the finite number of states of the performance of the traffic source [17, 18, 19]. The accuracy of the model linearly increases depending on the number of states used. In addition, the complexity of the model increases with regard to the number of states.

The important aspect of the Markov model is the Markov property which shows that the next (future) state depends only on the current state.

The set of random numbers corresponding to the various states $\{X_n\}$ is called the *Discrete Markov Chain (DMC).* If the transition of the states of the studied system occurs only at the absolute values $0,1,2,3, \dots, n$, then the *Markov Chain (MC)* will consist of a discrete time sequence and the random X will follow the geometric distribution, otherwise, the random X will be distributed exponentially.

The simple Markov traffic model is constituted upon the transition of each state describes the process of new entry to the network.

The Semi-Markov model is obtained due to the time dependent distribution of probabilities between the time transitions.

ON-OFF model

In early 1990s, the authors of the work [20] argued that the change in the nature of IP-traffic is a scalable process and leads to high burstiness. Ultimately, this has a strong impact on priority and performance.

Enabling the interconnection between the network traffic elements and the scalable nature of the network traffic does not allow them to be modeled as the "simple" updated processes and complicates the introduction of commonly accepted models. The ON-OFF model is used to solve this problem, and this model allows describing the scalable change in the nature of the network traffic. Therefore, the ON-OFF model is used for IP-traffic analysis [21] and for the evaluation of the network and server performance [22].

The ON-OFF model allows accurately describing the network traffic between the channel level and the application level. The ON-OFF model uses only two states - the ON and OFF states. The time spent between the ON and OFF states is called transition time and is distributed under the exponential law.

Figure 1 depicts the commonly used queue/channel between the different ON-OFF sources N. In this case, the sources for the ON-OFF model should be statistically identical and independent. The source serves to the queue at the distance M at the fixed speed C. The source ON-OFF is characterized by the average L number of packets/frames generated in the ON state, the peak frequency S of the source in ON mode and the average speed r of the source. These factors determine the average length of the source's ON and OFF periods. The probability that the source is ON is calculated using the formula $\gamma = r/S$.

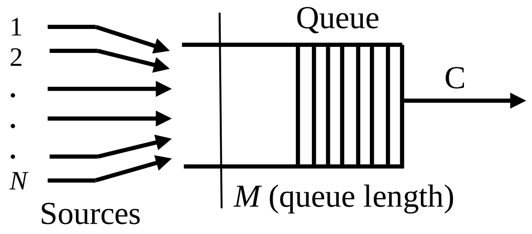

Figure 1. Description of the queue/channel model commonly used between various ON-OFF sources N

The ON-OFF periods are not exponentially distributed and can be modeled using two states of the source MC. The average intensity of the packages/frames generation is probable to be greater than one, then $L \gg 1$. Switching the source ON or OFF (Fig. 2) is calculated as follows:

t_1(switch from OFF to ON): $\gamma S/(L(1-y))$;

t_2(switching from ON to OFF): S/L

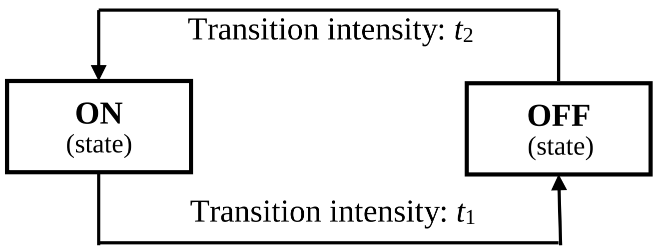

Figure 2. The model of switching the source from ON to OFF state and vice versa

Alternating state renewal model

Although the usual Markov model is mathematically favorable, its capabilities are limited to describe the actual traffic of high-end networks.

On high-end networks the packets are transferred as a successive stream, that is, it is probable that the packet entry will be followed by other's entry. Moreover, continuous packet entry indicates the presence of "heavy tailed" distribution. This situation referred to the *Alternate State Renewal Process (ASRP)* [23].

Alternate state renewal process is also a binary process and used for the network traffic modeling. As with the ON-OFF model, there are also two states $S_1$and S_2, though, there is no random transition between the states. The traffic amplitude equals to 0 in the state S_1 and 1 in the state S_2. The average time required for the transition between the two states is indicated by d_1 and

d_2, respectively. The probability that any of the states $S_1$and S_2 can be calculated with the formulas $P_{S_1} = d_1/(d_1 + d_2)$ and $P_{S_2} = d_2/(d_1 + d_2)$ respectively.

Markov modulated Poisson process

The Markov modulated Poisson process (MMMP) is widely used to analyze the network traffic models [17, 24, 25, 26]. *The Markov Modulated Process (MMP)* uses additional Markov process and its current state monitors the distribution of traffic probabilities. MMPP is one of the Markov modulated processes, and the additional process used is a distributed Poisson process. In other words, MMPP is a bi-stochastic process and the intensity of the Poisson process is determined by the MC's state.

MMPP is classified by the number of states in MC modulator. The MC, which consists of two states of different intensity, is referred to MPP-2 and sometimes called as the SPP (*Switched Poisson Process*). However, when the intensity of MC states is the same, the process is transformed into a typical Poisson process.

Autoregressive model

Autoregressive model [27] is one of the linear prediction solutions, which enables to predict the system output y_n based on previous outputs $\{y_k\}$, $(k < n)$ and inputs $\{x_k\}$, $(k < n)$. Several models have been developed for certain differences in predictive calculation methods. Generally, the model is related to the autoregressive model only when it depends on the previous states of the system.

If the model depends only on the system input, it is assumed to be *Moving Average Model (MAM)* [28]. In the autoregressive-moving average model [29], the current output of the system depends on the previous inputs and outputs. p value autoregressive model is denoted as $AR(p)$and expressed as follows:

$$X_t = R_1 X_{t-1} + R_2 X_{t-2} + \ . \ . \ . + R_p X_{t-p} + W_t,$$

Where W_t is the "white noise", R_i $(i = \overline{1, p})$ - the real number and X_t - the random numbers that determine the correlation.

The auto-correlation function of the process $AR(p)$consists of switching sinusoidal waves depending on the true or imaginary value of the roots of the model solution. The p value *Discrete Autoregressive Model* is denoted as $DAR(p)$and generates the stationary sequence of the discrete random numbers through the distribution of probability, which has the autocorrelation structure of the p value autoregressive model $AR(p)$.

Conclusion

The paper explored the advantages and disadvantages of each network traffic models. The network architecture and the characteristics of the analyzed traffic seriously affect the choice of the network traffic model. The selected network traffic model shall provide an effective description of the real network traffic characteristics. Otherwise, the used model cannot guarantee the correct performance and QoS of the network.

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