Multifractal Properties of Traffic Generator Based on Markov Chains

Volodymyr Simakhin [1 [0000-0003-4497-0925]], Serhiy Bondar [1 [0000-0003-4140-7985]], Hanna Drieieva[2[0000-0002-8557-3443]], Oleksandr Kovalenko [2 [0000-0001-9297-0650]], Oleksandr Drieiev [2 [0000-0001-6951-2002]] and Mereke Zhumadilova [[0000-0001-7998-6711]]

[1] International Research and Training Center for Information Technologies and Systems, Ukraine, Kyiv
[2] Central Ukrainian National Technical University, Ukraine, Kropyvnytskyi
[3] Yessenov University, Aktau, Kazakhstan
sima@irtc.org.ua

Abstract. The problems of determining the fractal dimension of a time series obtained using a self-similar traffic generator based on Markov chains with a controlled fractal dimension are stated. Based on numerical experiments to determine the fractal dimension of the generated numerical sequences, statistically significant changes are shown at different scales. The insufficient development of high-performance algorithms and methods for generating self-similar numerical sequences for procedure of traffic simulation in telecommunication systems and networks is indicated. The directions of further research on the management of the multifractality in generators based on Markov chains are proposed.

Keywords: Traffic Modeling, Self-Similar Traffic, Multifractal.

1 Introduction

Mathematical models of a self-similar time series are used to describe telecommunication processes. In the graphs showing the load of the computer's network channel, self-similarity is determined by the presence of outliers, the amount of which exceeds the classical statistical theory predictions (see Fig. 1). The horizontal axis shows time in arbitrary units, and the vertical shows network load to the maximum throughput ratio.

In most cases, analytical expressions for self-similar traffic predicted QoS parameters cannot be formed, or such transformations can be formed for individual specific situations, therefore, analytical calculations are inadvisable. For this reason, to determine the main indicators of QoS, such as jitter, lateness, average number of failures and others, the simulation with self-similar traffic generators is used. This leads to reducing and simplifying the number of calculations for generators of self-similar traffic with controlled fractal properties, which would allow numerical sequences to have properties as close as possible to the properties of the telecommunication network's real traffic, which is being studied.

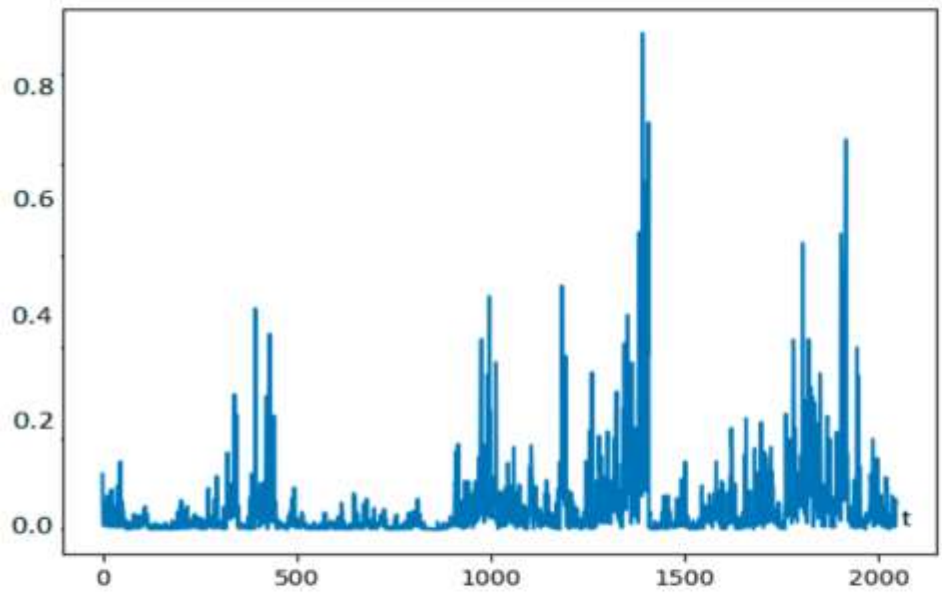

Fig. 1. Self-similar traffic example [3]

Given the relevance of managing the generated traffic's fractal properties, this paper is devoted to determining the dependence of the traffic model's fractal properties on the used scale.

2 Background and related work

The analysis of research and publications on the subject revealed the following. In [1], general methods of fractal and multifractal analysis of time series are considered. Methods for determining the main indicators of numerical sequences usage for traffic analysis in telecommunication systems and networks are described. In [4], basic definitions and concepts of the fractal measurement theory and fractal analysis are also formulated.

Importance of multifractal analysis for information exchange processes in computer networks is described in [2]. An analysis of the Internet traffic, which was collected for more than fourteen years, is shown. The development of a global network, which has changes in fractal properties at all levels of scaling, is described by the authors. The article contains proofs of a different nature self-similarity existence on separate time scales.

In [3], the main attention is devoted to the usage of a trained neural network to automate the classification of traffic according to its fractal and multifractal properties.

Presented in the paper results are successfully used to determine DDoS attacks. This proves the existence of difference in traffic's multifractal metrics for different types of data. The idea of a significant impact on the fractality of traffic is confirmed in [5], where information on the successful use of fractal analysis to identify flows of P2P and gaming traffic, transmission information into the clouds services, scanning of ports or botnet actions is also given.

In [6], multifractal modeling of numerical sequences is used to restore lost fragments of time series. Multifractal interpolation gives better results than random filling and classical interpolation methods. In [8] fractal interpolation is used to restore traffic with known fractal properties on different time scales.

The results obtained in [7] show that the modeling of complex networks becomes possible when hierarchical self-similarity is taken into account in the adjacency matrix. In fact, this approach makes it possible to classify large networks and to carry out modeling. The theory is also applicable for broader content networks, for example, to hierarchical relationships between structural units of different orders or scaling.

Subsequent works [8-17] are related to the modeling of information exchange processes in computer networks aiming to recover lost data, to the simulate telecommunications network at different scales and with various data types, to analyze network traffic for several applications. All these tasks require a simulated source of multifractal traffic with controlled properties. The number of publications [17-23] describing simulating the multifractal traffic emphasize the relevance of the development and improving both the accuracy of reproducing given properties and reducing the computational complexity of multifractal traffic generators. Developing of such methods and algorithms will make it possible to increase the speed or potential complexity of process modeling without using systems that are more expensive in telecommunication networks [24-26].

3 Problem statement

The main task of the paper is to analyze the properties of a binary numerical series, which is obtained using a generator based on a graph model of states and the transitions' probability between them. Such a traffic generator is a typical Markov chains based generator (see Fig. 2).

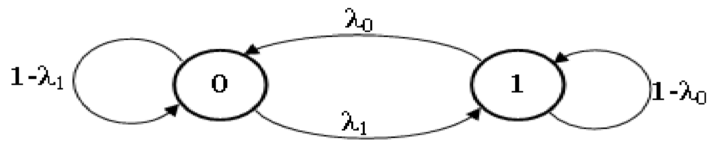

Fig. 2. Fractal Traffic Generator Model

The model contains a number of states that set the initial generated value. The next value is obtained by random transitions, where λ_0 and λ_1 are the probabilities of changing the state to the next time quantum, and the probabilities $1 - \lambda_0$ and $1 -$

$\lambda_1$define chance of staying in the current state. The specified generator does not use heavy-tail distributions and does not require complex calculations. Any standard verified pseudorandom number generators in the interval [0; 1) with uniform distributioncan be used. Reduced number of operations for calculation is a significant advantage for practical application in simulation modeling systems of telecommunication networks and allows saving computation time for traffic formation [27-30].

The fractal dimension of a numerical series can be described by various metrics, which can lead to getting different misleading values. Using a separate metrics on the model and real data also allows comparing their fractal properties. Therefore, for a generator model that is shown in Fig. 2, a separate numerical series metric is constructed. The coverage width is considered unitary if all n consecutive values are not equal, and zero if all n consecutive values are equal to 1 or 0. It is easy to obtain an analytical form for calculating the probability of encountering a zero-span segment with n elements, which is equal:$\lambda_1(1-\lambda_0)^n+\lambda_0(1-\lambda_1)^n$.

Based on statistical modeling of generator's operation, the expected value of the random walk's magnitude with n steps is obtained, which allows determining the fractal dimension of the series analytically. Moreover, the fractal dimension depends on the resulting numerical sequence length $n$as given by (1).

$$d(n,\lambda_0,\lambda_1)=2+\frac{\lambda_1(1-\lambda_0)^n\ln(1-\lambda_0)+\lambda_0(1-\lambda_1)^n\ln(1-\lambda_1)}{\lambda_0+\lambda_1-\lambda_1(1-\lambda_0)^n-\lambda_0(1-\lambda_1)^n} \tag{1}$$

For the transition probability values $\lambda_0=\lambda_1=0.5$, which corresponds to the classical random process, a graph of the fractal dimension Ddependence on the generated series number of elements n obtained by formula (1) is shown in Fig. 3.

The presence of different values of fractal dimension in mathematical objects at different scaling levels is called multifractality. The presence of multifractality in the traffic of computer networks is shown in [3].

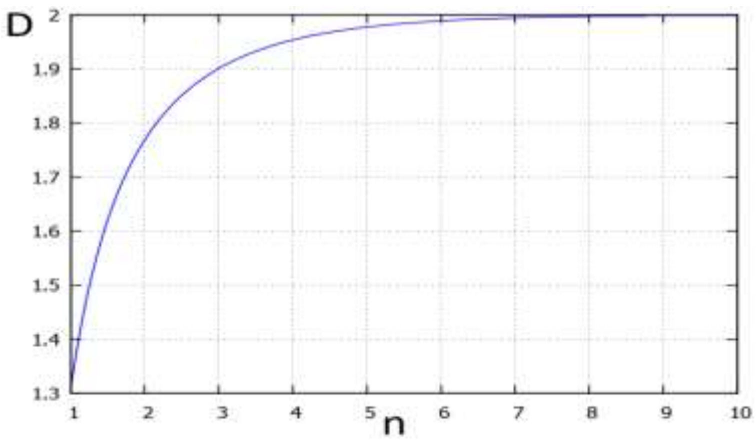

Fig.3. Theoretically determined fractal dimension $D(n)$ with the probability of state change$\lambda_0 = \lambda_1 = 0.5$.

Additional research is needed to use the time series fractal analysis methods based on the Minkowski–Bouligand dimension or R/S analysis.

4 Methods of calculating fractal dimension

The definition in Minkowski's interpretation can be used to determine the fractal dimension [4], as shown by (2).

$$D = \lim_{s \to 0} \frac{\ln(N)}{-\ln(\varepsilon)} \tag{2}$$

where ε – size or diameter of the subset, that is covering the set which dimension is being determined;

N – the minimum number of subsetsε, that should be used to cover the whole set, which dimension is being determined.

It is not possible to directly apply (2) to a discrete set because a minimum ε exists. Therefore, fixed values of ε should be used.

Let coverings with sizes ε and $k\varepsilon$be used to cover the main set (k - for a discrete system is a given natural number; ε is an unknown coefficient characterizing the selected discrete system). Then, according to the selected subsets, the number of such subsets to cover is$N(\varepsilon)$and $N(k\varepsilon)$. The method for calculating the metric $N(k\varepsilon)$ is quite arbitrary, and is selected according to the values studied in a particular process. For a discrete system, if the definition of the limit is rejected,(3) is obtained from equation (2).

$$-D\ln(k) - C = \ln\big(n(k\varepsilon)\big), C = D\ln(\varepsilon) \tag{3}$$

where $\ln(k), \ln(N(k\varepsilon))$ are calculated for several values of k; $D$and C are obtained as a result of applying linear regression to the points $(\ln(k), \ln(N(k\varepsilon)))$.

Given the randomness of the numerical series, $N(k\varepsilon)$is also a random variable, with a certain expected value and dispersion. Hence, the obtained points $(\ln(k), \ln(N(k\varepsilon)))$will approach the line, but not necessarily belong to it.

In order to reduce additional calculations and transformations, the process of generating "0"is changed to generate "-1".As a result, for $\lambda_0 = \lambda_1$, the expected value of the generated sequence becomes 0 and the standard deviation equals 1. In addition, the created sequence $\{a_1, a_2, \dots, a_n\}$ is replaced by a cumulative series corresponding to a random walk $\{b_1, b_2, \dots, b_n | b_i = a_1 + a_2 + \dots + a_i\}$. For such series, the covering width $N(k\varepsilon)$ for a segment with length of k discrete elements can be calculated by (4):

$$N(k\varepsilon) = \sum_{i=0}^{n/k-1} (\max\big(b_{i\cdot k+1} \dots b_{i\cdot(k+1)}\big) - \min\big(b_{i\cdot k+1} \dots b_{i\cdot(k+1)}\big)) \tag{4}$$

We propose using the power of two as n, because then k can also be doubled when constructing reference points for linear approximation. The indicated process for $k = 8,16,32,64,128$ made it possible to construct five points for which a linear approximation determines the Hurst exponent of the test sequence at 0.53 as the inclination angle of the straight line (see Fig. 4):

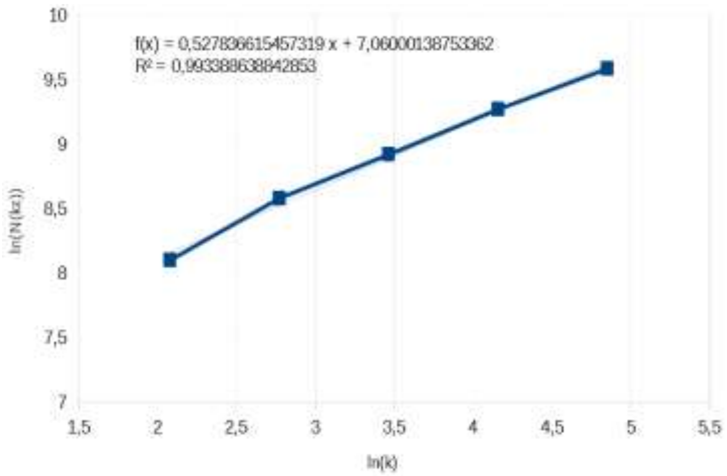

Fig. 4. Diagram for Hurst exponent$H = 0.53$ with corresponding fractal dimension $D = 1.47$ and probabilities to change state$\lambda_0 = \lambda_1 = 0.5$.

Theoretical calculations for a random sequence shows that the values should be $H = 0.5$with$D = 1.5$. This is close to the obtained results.

Classical theory states that for curves on the plane the covering width $N(k\varepsilon)$ should be expressed by the number of squares with sidesize equals$k\varepsilon$, which cover the whole random walk curve. However, the adopted measure (4) is asymptotically equal to the Minkowski–Bouligand dimension. Moreover, with the same values being chosen for$k$, the Hurst exponent matches with the one obtained using R/S analysis, for which the relation to the fractal dimension is already known.

5 Impact analysis of scale selection to the fractal dimension

For the purpose of experimental confirmation eleven generated sequences containing 1024 samples ("-1" and "1", as described in previous paragraph) were used to show the dependence of the numerical series' fractal dimension on the selected scale. For each of those, the Hurst exponent was calculated forsets of k ues:$\{1024, 512, 256, 128, 64\}; \{512, \dots, 32\}; \{256, \dots, 16\}; \{128, \dots, 8\}$. The results of these experiments are shown in Tables 1-3.

An independent measurement of the Hurst exponent on an appropriate scale is formed for each of the generation modes, which allows evaluating the statistical processing of the result. The mean of the Hurst exponent and the standard deviation σ of that mean, which is inversely proportional to the root of the sample length, are found for that result. Based on the standard deviation, a confidence interval of 99% reliability is calculated, which is provided for deviations from the mean $\pm 3\sigma$. The boundaries of the calculated reliability interval are respectively shown in the table columns $-3\sigma$and $+3\sigma$.

The results from all three tables indicate a change in the Hurst exponent while shifting the scale, which confirms the assumption made in the previous paragraph based on the analytical formula (1) for a simplified metric for calculating fractal dimension.

Table 1. Hurst exponents for generating a sequence with $\lambda_0 = \lambda_1 = 0.95$

k	1	2	3	4	5	6	7	8	9	10	11	Mean	-3σ	+3σ
1024..64	0.38	0.23	0.48	0.44	0.34	0.29	0.42	0.46	0.40	0.26	0.40	0.37	0.30	0.45
512..32	0.40	0.33	0.52	0.50	0.34	0.38	0.45	0.44	0.41	0.31	0.48	0.41	0.35	0.48
256..16	0.42	0.35	0.53	0.48	0.38	0.41	0.41	0.45	0.45	0.39	0.47	0.43	0.38	0.48
128..8	0.42	0.35	0.46	0.40	0.40	0.39	0.41	0.42	0.43	0.41	0.43	0.41	0.39	0.44

Table 1 shows that, with a high probability of changing the previous state value to the opposite, traffic modulation occurs almost constantly, which leads to a significantly lower probability of outliers. This is reflected in the Hurst exponent values, which differs from 0.37 to 0.41 for various scales. Fig. 5 shows the signal generated with such parameters.

As a result of random walk based on the obtained sequence, the distance from the beginning of the movement will change much slower, because for each step to the side there will be a significantly higher probability of getting the opposite direction in the next time quantum.

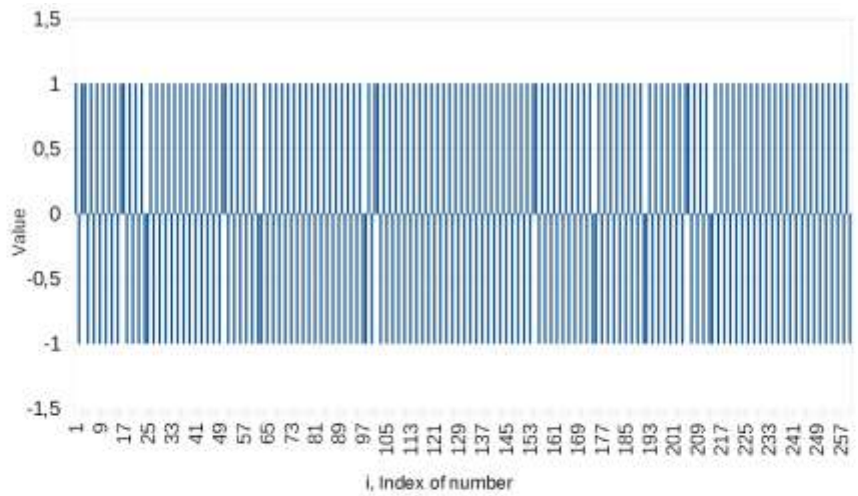

Fig. 5. Histogram of the signal obtained by generator with $\lambda_0 = \lambda_1 = 0.95$.

The following Table 2 contains results of a numerical experiment with the generator being set to keep or change the current state with an equal probability $\lambda_0 = \lambda_1 = 0.50$. In this mode the generator must correspond to the classical random process with the Hurst exponent$H = 0.5$.

Table 2. Hurst exponents for generating a sequence with $\lambda_0 = \lambda_1 = 0.50$

k	1	2	3	4	5	6	7	8	9	10	11	Mean	-3σ	+3σ
1024..64	0.41	0.46	0.39	0.41	0.50	0.37	0.40	0.54	0.35	0.41	0.42	0.42	0.37	0.47
512..32	0.48	0.48	0.53	0.47	0.54	0.48	0.45	0.60	0.47	0.52	0.46	0.50	0.46	0.54
256..16	0.52	0.55	0.58	0.52	0.52	0.55	0.52	0.56	0.56	0.59	0.55	0.55	0.52	0.57
128..8	0.55	0.59	0.61	0.57	0.57	0.57	0.56	0.59	0.60	0.66	0.59	0.59	0.56	0.61

It is noted from Table 2 that four times change of the parameter $k$gives estimated values of the Hurst exponent with a reliability of 99%. Which is equal to the numerical series on 1024 samples giving lower values for the Hurst exponent than on 256 samples with a reliability of 99%. This indicates the difference in the fractal properties of the numerical sequence at different scales. Using the fact, the appropriate queue length of the service system for which the Hurst exponent will have a value close to 0.5can be chosen and the theory of random Poisson flow can be used without taking into account self-similarity using classical statistics to determine the characteristics of such a service system.

Fig. 6 shows a fragment of the obtained sequence with the generation parameters $\lambda_0 = \lambda_1 = 0.50$.

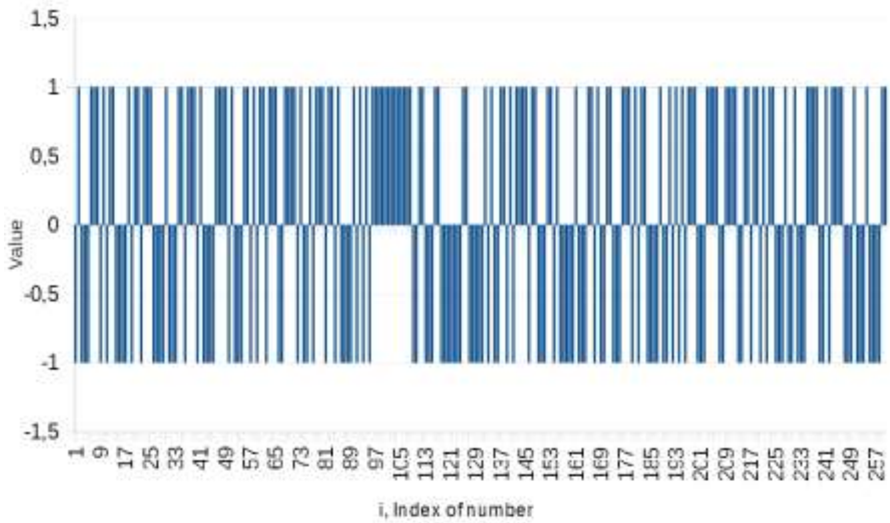

Fig. 6. Histogram of the signal obtained by generator with $\lambda_0 = \lambda_1 = 0.50$.

The results of the last experiment with the state change probabilities $\lambda_0 = \lambda_1 = 0.05$ are shown in Table 3. From the obtained results, it can be concluded that the numerical series has low probability of changing the trends.

Table 3. Hurst exponents for generating a sequence with $\lambda_0 = \lambda_1 = 0.05$

k	1	2	3	4	5	6	7	8	9	10	11	Mean	-3σ	+3σ
1024..64	0.48	0.58	0.45	0.54	0.61	0.58	0.51	0.37	0.64	0.39	0.64	0.53	0.44	0.61
512..32	0.52	0.63	0.56	0.60	0.66	0.61	0.58	0.49	0.69	0.45	0.69	0.59	0.52	0.66
256..16	0.66	0.77	0.72	0.77	0.67	0.69	0.62	0.65	0.79	0.58	0.76	0.70	0.64	0.76
128..8	0.78	0.83	0.83	0.84	0.73	0.82	0.73	0.79	0.86	0.73	0.80	0.80	0.75	0.84

The numerical sequence is persistent and is able to store trends for some time. However, at the same time, the observed mean value of the Hurst exponent is close to $H = 0.5$ at intervals of 1024 samples. This means that at large distance, the range of the cumulative series does not differ from the classical random sequence, where the difference between the maximum and minimum values increases on average in proportion to the root of the number of steps taken.

At short distances, the Hurst exponent is very different, and reaches mean value of $H = 0.8$. In accordance with this, there is a scale for which self-similar traffic, as in the previous case, will have the properties of a classical random process. A fragment of the obtained signal is shown in Fig. 7.

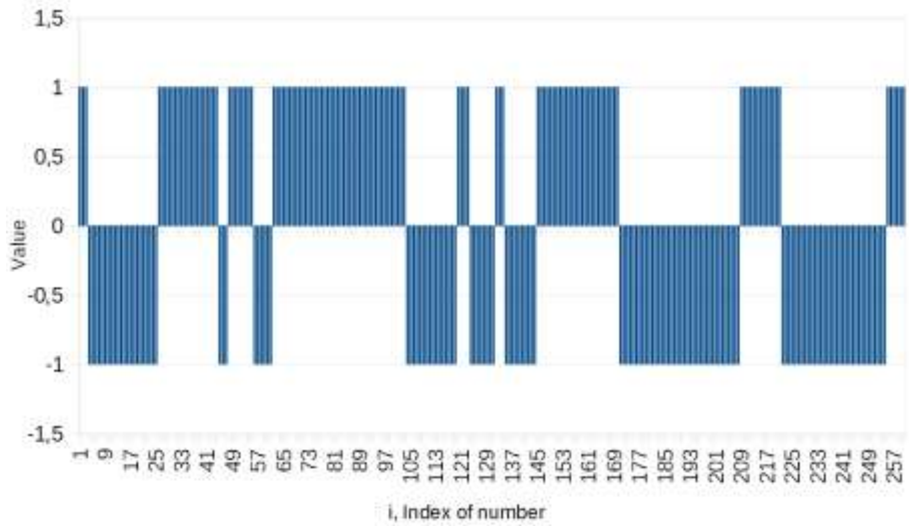

Fig. 7. Histogram of the signal obtained by generator with $\lambda_0 = \lambda_1 = 0.05$.

6 Conclusion and further work

This paper presented self-similar traffic generators using Markov chains, which differ from their analogues in lower computational power requirements for simulation systems, which makes it possible to increase the performance of information movement modeling in telecommunication systems and computer networks. Further development and study of such systems is relevant.

Based on the simplified metric $N(k\varepsilon)$, an analytical expression is formed for calculating the fractal dimension of the generated binary numerical series based on the Markov chain. The dependence of the fractal dimension on the length of the interval on which it is calculated is noted and the assumption is made that the multifractality properties are repeated on classical metrics, such as numerical dimensions based on R/S analysis or Minkowski-Bouligand dimension.

In order to verify the assumption, an experiment part was carried out which confirmed the assumption of a multifractal numerical sequence obtained by generators on Markov chains with a reliability over than 99%.

Potential future work includes developing methods for controlling multifractality parameters, or opposite task of eliminating the appearance of multifractality.

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