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Different Extrapolation Methods in Problems of Forecasting

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Abstract. The task of forecasting characteristics of self-similar traffic in IoT network objects with a significant number of pulsations and the property of long-term dependence is considered, which makes it difficult to forecast in practice. Using the different extrapolation method of spline-extrapolation based on linear, cubic and B-cubic spline function and wavelet-extrapolation based on Haar-wavelet, the results of forecasting of self-similar traffic are obtained. The comparison made allowed the results of traffic forecasting based on the Haar-wavelet and the linear, cubic and B-cubic spline-function using wavelet- and spline-extrapolation. This will allow you to choose one or another extrapolation method to improve the accuracy of the forecast, while ensuring scalability and the ability to use it for various IoT applications to prevent network overloads.

Keywords: Self-similar traffic · Internet of Things · Forecasting · Extrapolation · Spline-function · Wavelet-function

1 Introduction

The development of IoT (Internet of things) networks based on Machine-to-Machine Communication (M2M) is associated with the rapid introduction of a high-speed services nomenclature. These are Video Surviliance video services, Smart-TV, IoT-cameras, smart-M2M objects services, IoT-telematra telemetry services, IoT-telemedicine telemedicine services, Smart house systems, smart parking, Smart parking lots, Smart grids and, in perspective, holographic TV, virtual VR (Virtual reality) and augmented reality (AR) services. Implementing IoT applications uses Wi-Fi radio access technologies (IEEE 802.11n/ac/ad standards), ZigBee and Bluetooth (IEEE 802.15 standards), as well as the LoRaWan (Low-power Wide-area Network) and NB-IoT mobile communication network (Narrow Band) fourth generation 4G/LTE and fifth generation NR (New Radio) technology 5G. A feature of the IoT network architecture is the use of AdHoc/Mash architectures, which are based on self-organization and the use of virtualization technologies, including cloud [1, 2].

The traffic that is generated by IoT network objects is quite heterogeneous, has different characteristics depending on the type of service. Sometimes this is a low-speed data transmission by IoT sensors, and sometimes, real-time HD-video transmission.

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It is known [3, 4] that the high-speed data traffic that is generated by the IoT network objects is self-similar. This is determined by the long-term relationship between traffic values at different periods of time, significant and frequent bursts of intensity, which are statistically similar for different time scales. Thus, the IoT network in one and the same application may generate traffic using different M2M and D2D devices. Therefore, it is rather difficult to predict the impact of traffic of individual M2M and D2D devices on the network infrastructure of IoT. From the operator's point of view, this does not allow for accurate analysis and evaluation of network performance and, accordingly, dynamic optimization of IoT network resources. In addition, according to [1], the IoT network architecture will be horizontal and will combine various open platforms and systems, but how this affects the traffic characteristics is not known yet.

Solving the problem of forecasting self-similar IoT network traffic, both short-term and long-term, will allow you to get the traffic characteristics of various applications and M2M, D2D network devices. This will allow them to provide the necessary performance and the possibility of using for various IoT applications in order to prevent overloads and maintain the required quality of service QoE (Quality of Equipment).

The issues of forecasting self-similar traffic in the IoT network are considered in the works by the authors [5–17]. The proposed solutions are not universal prediction, but allow solving many problems associated with forecasting. In [5], the authors considered the prediction of "IoT traffic paths" in real time and compared four prediction methods, such as the classical Fourier time series, artificial neural networks, and the double exponential smoothing method. This paper focuses not only on the accuracy of the comparison, but also on other factors: such as - the cost of solutions and energy consumption. On the contrary, in [6] IoT traffic prediction based on a recurrent neural network was proposed. In practice, it is rather difficult to forecast dynamic network update in real time using a neural network.

An alternative to the considered methods is the "deep intelligent network study method" based on the prediction of traffic load channels of IoT devices [7]. In this case, the method allows avoiding overloads in the network and achieving optimization of network resources, but it requires specific "training" for each considered IoT network architecture. The results of traffic prediction using ARIMA/FARIMA models were obtained in [8].

However, these models do not allow for different types of traffic to obtain an accurate prediction of characteristics outside the considered interval. This is due to the fact that it is quite difficult to obtain the corresponding trend of a specific type of traffic M2M of IoT network device. Previously, the authors of the work obtained the results of short-term prediction of self-similar traffic using the spline-extrapolation method [9–13]. The use of cubic and cubic B-splines showed the advantage of using the latter, especially for real-time forecasting.

The authors in [14–17] considered the use of wavelet functions for forecasting the characteristics of networks that are different in construction and operation. In each of the cases considered the use of the corresponding wavelets significantly improved the results obtained.

Therefore, in this paper, it is proposed to use the wavelet-extrapolation method to forecast the traffic of IoT network objects. This will improve the accuracy of the forecasting, ensure its scalability and use for various IoT applications.

The goal of the work is to solve the problem of forecasting the characteristics of self-similar traffic of IoT network objects using wavelet extrapolation and to conduct a comparative analysis of this method with the previously considered spline-extrapolation method.

2 Prediction of the Self-similar Traffic Based on the Spline-Extrapolation

To forecast the self-similar traffic, we use the extrapolation method. The research task is as follows [11]:

1) forecast the traffic beyond the considered time period, where the transmission of packet data is considered;
2) choose an approximating device, with the help of which it is possible to perform a more accurate prediction of self-similar traffic;
3) determine the error in restoring self-traffic outside the gap.

Earlier, problem solving extrapolation of random processes was based on the use of Lagrange interpolation polynomials, Chebyshev polynomials, etc. As an approximating apparatus for forecasting the applicable "spline-extrapolation" when extrapolation is performed using spline-functions.

The task of forecasting self-similar traffic is solved by the "spline-extrapolation" method, that is, the recovery of self-similar traffic outside the considered time interval based on spline functions (for example, linear, cubic, etc.).

Considering that self-similar traffic is characterized by the presence of "bursts" packets, it is possible to use extrapolation based on wavelet-functions to improve the accuracy of prediction.

Let us dwell on the method of "spline-extrapolation." The term "spline-extrapolation" we mean an extrapolation based on the use of spline functions.

Consider self-similar traffic on the segment $[a; b]$. Let at the interval $[a; b]$ is given a partition Δ: $a = x_0 < x_1 < \ldots < x_N = b$. The first-degree spline $S_1(x)$ on the grid Δ - is a continuous piecewise linear function. Let Δ grid points are given the values of self-similar traffic $f_i = f(x_i)$, which describes a function $f(x)$, defined on the interval $[a; b]$. The interpolation spline is defined by the following conditions:

$$S_1(x_i) = f_i, i = 0, \ldots, N. \tag{1}$$

Geometrically, it is a broken line passing through the points (x_i, y_i), where $y_i = f(x_i)$. We denote by $h_i = x_{i+1} - x_i$. Then, according to [18], for $x \in [x_i, x_{i+1}]$, $i = 0, \ldots, N - 1$, the linear spline will have the form:

$$S_1(x) = f_i \frac{x_{i+1} - x}{h_i} + f_{i+1} \frac{x - x_i}{h_i}. \tag{2}$$

or

$$S_1(x) = f_i + \frac{x - x_i}{h_i}(f_{i+1} - f_i). \tag{3}$$

We will also consider a cubic interpolation spline $S_3(x)$, constructed similarly to a linear spline, with the only difference being that this is a cubic function on each interval $[x_i, x_{i+1}]$, $i = 1, \ldots, N - 1$. According to [18], for $x \in [x_i, x_{i+1}]$, $i = 0, 1, \ldots, N - 1$ the cubic spline has the form:

$$S_3(x) = f_i(1 - t)^2(1 + 2t) + f_{i+1}t^2(3 - 2t) + m_i h_i t(1 - t)^2 - m_{i+1} h_i t^2(1 - t), \tag{4}$$

where $t = (x - x_i)/h_i$, $S_3(x_i) = f_i$, $S_3(x_{i+1}) = f_{i+1}$, $m_i = S'(f; x_i)$

or

$$S_3(x) = f_i(1 - t) + f_{i+1}t - \frac{h_i^2}{6}t(1 - t)[(2 - t)M_i + (1 + t)M_{i+1}] \tag{5}$$

where $S''(x_i) = M_i$, $S''(x_{i+1}) = M_{i+1}$.

The boundary conditions are used to determine the cubic spline of the form (4) on the interval $[a; b]$ [18]:

$$S'(f; a) = f'(a), S'(f; b) = f'(b). \tag{6}$$

For determining a cubic spline type (5) using the boundary conditions of the form [18]:

$$S''(f; a) = f''(a), S''(f; b) = f''(b). \tag{7}$$

We consider a uniform partition of the interval $[a; b]$, that is:

$$h_i = h = \frac{b - a}{N}, i = 0, 1, \ldots N - 1.$$

It is necessary to restore the self-similar traffic outside the interval $[a; b]$, namely, the right of the point b. For definiteness, let this be a point x_c, $x_c > x_N = b$, $x_c - b = h$,

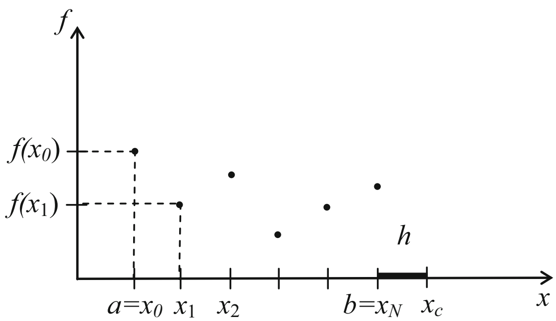

Fig. 1. The extrapolation of self-similar traffic on the interval $[a; b]$ on condition $f(x_c) = f(x_1)$.

where h - is a step partition of the interval $[a; b]$. Construct on the interval $[b; x_c]$ spline function (linear or cubic).

Let's consider two variants. In the first case, we assume that $f(x_c) = f(x_1)$ and construct a linear or cubic spline, respectively, on the interval $[b; x_c]$ (Fig. 1).

In the second case (Fig. 2) we set $f(x_k) = f(x_c)$, where $x_k = x_0 + kh$, where k is natural. If $kh \neq x_c - b$, then for $f(x_c)$ we take the value of the function $f(x)$ which are closest to the point x_k.

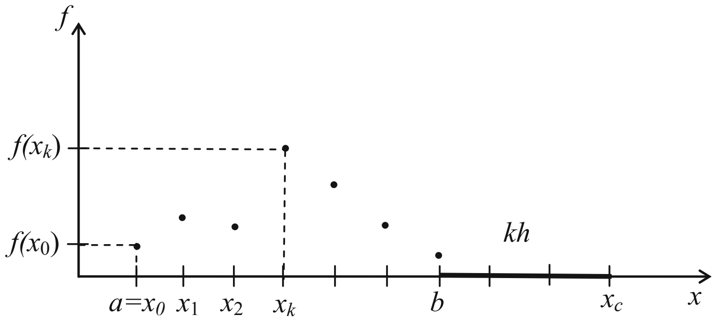

Fig. 2. The extrapolation of self-similar traffic on the interval $[a; b]$ on condition $f(x_{kh}) = f(x_c)$.

According to [18], it is not difficult to find the error of restoring self-similar traffic on the interval $[b; x_c]$, using the following theorems:

Theorem 1 [18]. If a spline of the first degree $S_1(x)$ interpolates a continuous function $f(x)$ on the grid Δ, then the estimation of the error is valid:

$$|S_1(x) - f(x)| \leq \omega(f), \tag{8}$$

where $\omega(f)$ - module of a continuous function of the form

$$\omega(f) = \max_{0 \leq i \leq N-1} \omega_i(f) = \max_{0 \leq i \leq N-1x'}, \max_{x'' \in [x_i, x_i+1]} \left| f(x'') - f(x') \right|. \tag{9}$$

Theorem 2 [18]. If the spline cubic $S_3(x)$ interpolates the continuous function $f(x)$ on the net Δ and satisfies the boundary conditions (6) or (7), then

$$\|S(x) - f(x)\|_C \leq (1 + \frac{3}{4}\rho)\omega(f), \tag{10}$$

where $\rho = \max_i h_i / \min_i h_i$, $\|f(x)\|_C = \max_{x \in [a;b]} |f(x)|$, $C = C[a; b]$ - this process is continuous on the interval $[a; b]$ of the function.

3 Prediction of the Self-similar Traffic Based on the Wavelet-Extrapolation

To predict self-similar traffic, we use the extrapolation method. The authors of [11–13] used an extrapolation method. When forecasting self-similar traffic, similarly to [11–13], we use the extrapolation method based on wavelet functions, since:

1) the use of *wavelet functions* allows to obtain information about the nature of changes in the parameters of the function under study, which is especially important when studying non-stationary traffic characteristics;
2) *wavelet functions* are able to identify local features of the studied self-similar traffic (break points, intensity bursts, sharp drops and self-similarity), which are often overlooked by other extrapolation methods, which allows to reproduce the most important characteristics of the traffic in question;
3) The use of *wavelet functions* allows independent analysis of the function at different scales of its change, because each traffic component is additionally described by a scaling function, which allows determining the point in time at which one or another traffic characteristic changed.

The problem of forecasting self-similar traffic is solved by the wavelet-extrapolation method, that is, the recovery of self-similar traffic outside the considered time interval based on wavelet functions (for example, Haar-wavelet, Daubechies-wavelet, Morlet-wavelet, etc.) [19].

Let us dwell on the method of "wavelet-extrapolation." By "wavelet-extrapolation" we mean extrapolation based on the use of wavelet functions.

In work [20–23], wavelet transform allows to perform the signals restoration both in the temporary parameters with the basic wavelet function $\psi(x)$, and in the frequency parameters with the scaling function $\varphi(x)$:

$$\psi(x) = \sqrt{2}\sum_k g_k \varphi(2x-k),\ \ \varphi(x) = \sqrt{2}\sum_k h_k \varphi(2x-k), \tag{11}$$

where $h_k = \sqrt{2}\int \varphi(x)\overline{\varphi}(2x-k)dx$, $g_k = (-1)^k h_{(N-1)-k-1}$ is expansion coefficient, k, N is natural numbers.

With a special choice of the coefficients h_k, we obtain mother wavelets of a particular type, which form an orthonormal basis.

All the wavelets are obtained from the basic wavelet with the scaled transformation $1/2^k$ and shifts $j/2^k$ [21, 22]:

$$\psi_{j,k} = 2^{j/2}\psi(2^j x - k),\ \ \varphi_{j,k} = 2^{j/2}\varphi(2^j x - k). \tag{12}$$

Then, according to [20–23], any function $f(x)$ from Hilbertian space $L^2(R)$ can be expressed in the series of the form:

$$f(x) = \sum_k s_{j_n,k}\varphi_{j_n,k}(x) + \sum_{j\geq j_n,k} d_{j,k}\psi_{j,k}(x), \tag{13}$$

where $f(x)$ is temporary function of the original signal, $\varphi_{j,k}(x)$ is scaling-function (father wavelet), $\psi_{j,k}(x)$ is basic wavelet function (mother wavelet), $s_{j,k}$ and $d_{j,k}$ is wavelet coefficients, j_n is scaling level, k, j, j_n is natural numbers.

Wavelet coefficients $s_{j,k}$ and $d_{j,k}$ for the expression (3) are calculated as follows [20–23]:

$$s_{j-1,k} = \sum_m h_m s_{j,2k+m},\ \ d_{j-1,k} = \sum_m g_m s_{j,2k+m}, \tag{14}$$

where h_m, g_m is approximation and expansion coefficients.

On the most detailed level of scaling $j_n = j_{max}$ there left only s coefficients and the signal is given by the scaling function [18–21]:

$$f(x) = \sum_k s_{j_{\max},k}\, \varphi_{j_{\max},k}(x). \tag{15}$$

Similar to [20], we consider the extrapolation of self-similar traffic using the simplest Haar-wavelet functions. It is known [14] that the Haar-wavelet is a short square wave on the interval [0, 1], which has a long ‘tail’ in the frequency domain and can be used for traffic. For self-similar traffic of IoT objects, we use Haar-wavelet, for which the basic wavelet function $\psi(x)$ and scaling function $\varphi(x)$ have the following form (Fig. 3,a) and (Fig. 3,b) respectively:

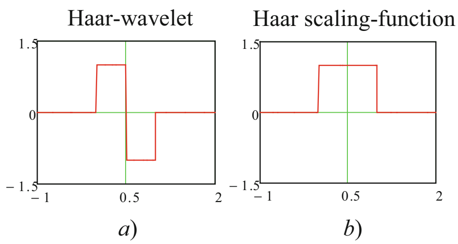

Fig. 3. Mother Haar-wavelet $\psi(x)$ *a*) Haar-wavelet, *b*) scaling function $\varphi(x)$.

For a Haar wavelet, according to [20–23], the analytical record for its basic $\psi(x)$ and scaling function $\varphi(x)$ has the form:

$$\psi(t) = \begin{cases} 1, & 0 \le t < 1/2, \\ -1, & 1/2 \le t < 1, \\ 0, & t < 0,\ t \ge 1. \end{cases} \tag{16}$$

$$\varphi(t) = \begin{cases} 1, & 0 \le t < 1, \\ 0, & t < 0,\ t \ge 1. \end{cases} \tag{17}$$

The mother wavelet $\psi(x)$ and the scaling function $\varphi(x)$ refer to orthogonal subspaces of the hibert space $L^2(R)$, which corresponds to the fulfillment of the condition [20–23]:

$$\sum_k h_k g_{k+2M} = 0. \tag{18}$$

From the formula (18) you can determine the dependence between the coefficients h_k and g_k of the Haar-wavelet values [20–23]:

$$g_k = (-1)^k h_{2M-1-k}. \tag{19}$$

The resulting h_k and g_k coefficients determine the Haar-wavelet. To perform the wavelet transform, the Haar calculation of the wavelet coefficients of the function in question is performed according to formulas (14), we obtain the formulas for the direct [20–23]

$$s_{j-1,k} = \frac{1}{\sqrt{2}}\left[s_{j,2k} + s_{j,2k+1}\right],\ d_{j-1,k} = \frac{1}{\sqrt{2}}\left[s_{j,2k} + s_{j,2k+1}\right], \tag{20}$$

and inverse transform

$$s_{j,2k} = \frac{1}{\sqrt{2}}\left[s_{j-1,k} + d_{j-1,k}\right],\ s_{j,2k+1} = \frac{1}{\sqrt{2}}\left[s_{j-1,k} - d_{j-1,k}\right]. \tag{21}$$

Thus, the calculated values of the coefficients of the Haar-wavelet values h_k, g_k and the values of the wavelet transform coefficients $s_{j,k}$, $d_{j,k}$ make it possible to obtain an extrapolation based on the Haar-wavelet.

4 Solution of the Problem of Forecasting Self-similar Traffic Using the Method of Wavelet-Extrapolation

Consider a "wavelet-extrapolation" using a specific example. Simulate self-similar traffic queuing system (QS) W_B/M/1/K with the following parameters:

- λ is an intensity admission packages for service in the QS, $\lambda = 150$ pack/s,
- μ is a duration of the service packs, $\mu = 100$ pack/s,
- K is a packet queue length, $K = 1000$ packages,
- Hurst parameter $H = 0{,}65$,
- Weibull distribution parameters $\alpha \approx 0{,}6$ and $\beta \approx 2{,}58$.

The simulation results for the self-similar traffic in the Simulink package in the area of Matlab for the given source data that are shown in Fig. 4, where N is the number of packets, t is the packet arrival time [9–13].

The received traffic in the [2100; 2500] ms segment, according to [9–13], is self-similar, has large-scale invariance, the presence of "bursts" of packet intensity and a long-term relation between the moments of their arrival. Consider self-similar traffic on the segment [2075; 2115] ms.

Let self-similar traffic be described by some function $f(x)$, defined on the considered segment. Consider the extrapolation of the self-similar traffic $f(x)$, using the Haar-wavelet function (Fig. 4) defined by its base function (mother wavelet) $\psi(x)$ and scaling function $\varphi(x)$ by formulas (16–17).

A necessary condition for extrapolation using wavelet functions is its definition by the number of samples equal to $N = 2^{j_n}$, where $j_n \geq 1$ determines the maximum possible number of scaling levels [20].

In our case, $j_n = j_{max} = 4$, $N = 2^4 = 16$. In the Table 1 shows the calculated values of the coefficients $s_{j,k}$ and $d_{j,k,}$ obtained according to (20), while the coefficients $s_{0,k}$ are the values of the function $f_k = f(x_k)$ at the interpolation nodes.

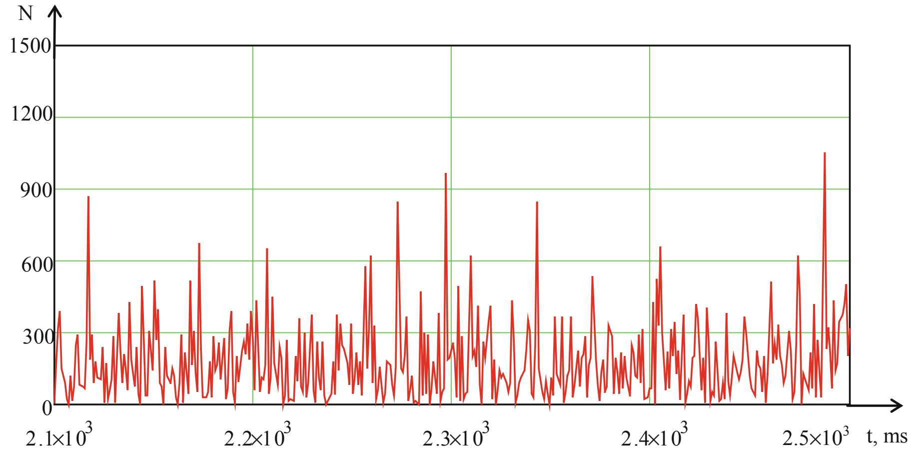

Fig. 4. The simulation results of self-similar traffic for QS type W_B/M/1/K.

Table 1. Calculated values of coefficients $s_{j,k}$ and $d_{j,k}$.

j=1	*k*	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
	$s_{j,k}$	31,5	124,5	42,3	3,78	24,6	57,5	66,6	25,6
	$d_{j,k}$	-29,7	-12,5	10,8	3,0	18,7	-29,8	36,9	1,4
		j=2			*k*	*0*	*1*	*2*	*3*
					$s_{j,k}$	110,3	32,6	58,1	65,2
					$d_{j,k}$	-65,7	27,3	-23,3	29,0
			j=3				*k*	*0*	*1*
							$s_{j,k}$	0,1	87,2
							$d_{j,k}$	54,9	-5,0
				j=4				*k*	*0*
								$s_{j,k}$	-0,1
								$d_{j,k}$	5,0

Perform an extrapolation of self-similar traffic using formula (14) [20], using the Haar-wavelet, for simulated self-similar traffic in the [2100; 2115] ms segment, the mother wavelet $\psi(x)$ and the scaling function $\varphi(x)$ are defined by the formulas (16–17).

The extrapolation results using the Haar wavelet were obtained in Mathcad 15 and are presented in Fig. 5.

Using the original data, according to issue 3, we obtain an extrapolation of self-similar traffic on the [2100; 2115] ms segment using a cubic spline (Fig. 5).

In general, the proposed method of extrapolation based on wavelet functions, according to the authors, has a number of advantages in comparison with known methods. It is quite easy to implement, it has a low resource consumption and error, and it can also be used to control traffic in real time.

As can be seen from Fig. 6, the use of Haar-wavelet functions to extrapolate self-similar traffic, characterized by bursts of intensity and sharp increases in function, leads to a global smoothing of the signal. Local “bursts” at the time of sudden changes in traffic intensity have an extrapolation error of about 5%. Similar results are provided

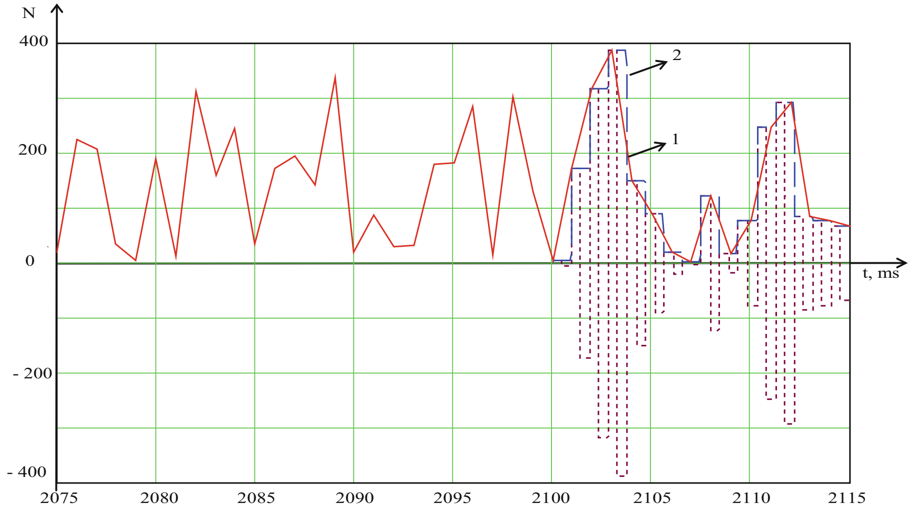

Fig. 5. The results of the extrapolation of self-similar traffic on the interval [2100; 2115] ms, 1) simulated self-similar traffic, 2) extrapolation of self-similar traffic using Haar-wavelet.

by the use of a cubic spline, which has an extrapolation error of about 10%. However, applying the wavelet transform does not interfere with the recovery of these peaks due to the scalability property.

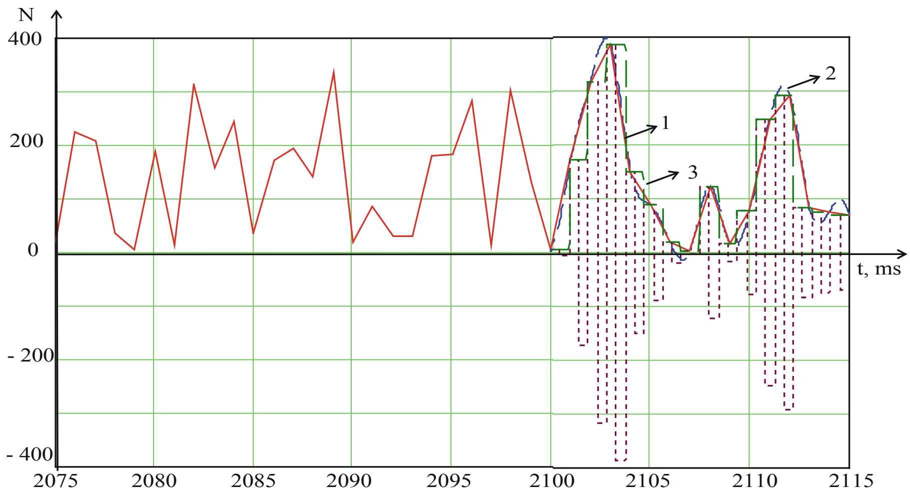

Fig. 6. The results of the extrapolation of self-similar traffic on the interval [2100; 2115] ms 1) simulated self-similar traffic, 2) extrapolation of self-similar traffic using cubic spline function, 3) extrapolation of self-similar traffic using Haar-wavelet

Based on the results of traffic prediction, taking into account the maximum values of the workloads of IoT network objects, practical recommendations can be given on the redistribution of traffic in the network and the use of various IoT applications to prevent network overload. This will balance the load on IoT network objects and increase the efficiency of using M2M and D2D network devices.

5 Conclusions

1. The solution of the problem of forecasting self-similar IoT traffic, obtained using the Simulink software package in Matlab, is considered.
2. The use of the wavelet extrapolation method for forecasting the characteristics of self-similar traffic is proposed.
3. A comparative analysis of the spline and wavelet extrapolations on a specific example. The results showed that the use of spline extrapolation is appropriate for self-similar traffic, which is characterized by smooth changes in intensity. On the contrary, for traffic that is characterized by the presence of frequent and rapid changes in intensity, it is advisable to use wavelet extrapolation.
4. The proposed wavelet extrapolation method has several advantages compared to other known methods, first of all, it is sufficient simplicity in implementation, low resource consumption and forecast accuracy, which can be improved through the use of various wavelet functions.
5. A comparison of the results of forecasting the characteristics of IoT traffic based on the extrapolation method using the Haar-wavelet and the cubic spline functions confirmed the feasibility of using wavelet functions.
6. The results of the prediction of self-similar traffic of IoT network objects and M2M devices make it possible to improve the forecast accuracy, ensure its scalability and use for various IoT applications, thereby avoiding network overloads and exceeding the standard values of QoE characteristics.

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