Paper

Spline-Extrapolation Method in Traffic Forecasting in 5G Networks

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https://doi.org/10.26636/jtit.2019.134719

Abstract—This paper considers the problem of predicting self-similar traffic with a significant number of pulsations and the property of long-term dependence, using various spline functions. The research work focused on the process of modeling self-similar traffic handled in a mobile network. A spline-extrapolation method based on various spline functions (linear, cubic and cubic B-splines) is proposed to predict self-similar traffic outside the period of time in which packet data transmission occurs. Extrapolation of traffic for short- and long-term forecasts is considered. Comparison of the results of the prediction of self-similar traffic using various spline functions has shown that the accuracy of the forecast can be improved through the use of cubic B-splines. The results allow to conclude that it is advisable to use spline extrapolation in predicting self-similar traffic, thereby recommending this method for use in practice in solving traffic prediction-related problems.

Keywords—quality of service, self-similar traffic, spline functions, error of recovery.

1. Introduction

The development of fifth-generation 5G/NR (New Radio) mobile communication networks is associated with the rapid growth in the number of high-speed services offered to users. These include enhanced Mobile Broadband (eMBB) access, massive Machine Type Communications (mMTC) and Ultra-reliable and Low Latency Communications (URLLC), as defined in the recommendations of the 3GPP technical report 38.913 [1], [2]. These services require increased data transmission speeds and quality of service levels, perceived as an optimal combination of packet delay time, packet loss probability and throughput. The main difficulty in solving this problem consists in significant and frequent bursts of intensity, which appear to be statistically similar at different time scales. This property allows us to predict the occurrence of this condition in the future, based on the accumulated statistical data or based on the results of traffic modeling [3]–[6]. In practice, the appearance of a significant number of long-term traffic intensity ripples at arbitrary points in time often leads to a sharp increase in packet delay time, which causes overloading of network nodes and buffer devices and, accordingly, has a significant impact on traffic.

Predicting self-similar traffic will enable to handle the potential peak loads in the network and to manage traffic in an efficient manner, thereby ensuring the required QoS. Given the above facts, the urgency of the problem of predicting self-similar traffic is obvious.

The purpose of the work is to solve the problem of predicting self-similar traffic and choosing the method by which traffic will be restored more precisely beyond the limits of its determining time intervals.

2. Problem Statement

Function extrapolation is a continuation of a function outside its domain of definition, in which the continued function belongs to a given class. Extrapolation is usually performed using formulas that rely on information about the function's behavior at a certain set of points (extrapolation nodes) belonging to its domain of definition [7]. Sometimes, when extrapolating functions, not the entire domain of definition is used. Instead, only a part of it is taken into consideration. In fact, extrapolation of the values of judgment of a given function over a specific portion thereof is performed. In this case, extrapolation formulas give, in particular, the values of the function at the corresponding points of its domain of definition. This method is often used when solving practical problems, when there is no sufficient information available that is necessary to determine the values outside the considered part of the function's domain of definition [7].

A properly selected forecasting method allows to obtain predictions about the availability of the necessary bandwidth and delay time for managing network peak loads. The prediction results will help the operator perform traffic management functions, thereby ensuring the required QoS levels [8].

The prediction problems solved by the authors of the past were based on the extrapolation of random processes, performed using the Lagrange interpolation multi-members, Chebyshev polynomials, etc. Some prediction-related issues are considered in [9]–[11], where numerical methods of Hermite interpolation, as well as trigonometric interpolation and Richardson extrapolation were used. These methods allow solving the forecasting problem with a given level of accuracy. However, the proposed forecasting methods are not universal.

There is no single method for predicting the characteristics of self-similar traffic that would enable real-time prediction of self-similar traffic behaviors, giving the mobile operator the opportunity to take timely measures to prevent network node overloads, and to avoid the corresponding effects of these changes on QoS.

An extrapolation method based on spline functions, which has a number of advantages compared to its already known counterparts, offers the following features [5]:

- splines are more resistant to local perturbations, that is, the behavior of the spline in the vicinity of a point does not affect the behavior of the spline as a whole, as is the case in polynomial interpolation,

- good convergence of spline interpolation in contrast to the polynomial. In particular, for functions with irregular smoothness properties (for example, self-similar traffic) spline interpolation is indisputably high.

Let us consider spline-extrapolation of self-similar traffic, modeled with the use of the Matlab Simulink package for a given set of initial data, using various spline functions (linear, cubic, and B-splines). Spline functions of odd degrees (linear, cubic, cubic B-splines) are used in this paper due to their properties of the minimum norm and the best approximation. This allows to obtain more accurate results in terms of convergence [12].

3. Related Work

A significant number of scientific papers [13]–[19] is devoted to traffic forecasting issues. Their authors propose various forecasting methods. The classical approach to forecasting traffic characteristics is used in [13], where a comparison of various methods, such as the method based on a polynomial extrapolation of Lagrange, Markov chains and the method of automatic and trainees show the feasibility of using an extrapolation method in predicting self-similar traffic. One of the generally accepted traffic prediction mechanisms has the form of linear regression models, such as Autoregressive Integrated Moving Average (ARIMA) and Fractal Autoregressive Integrated Moving Average (FARIMA), as considered in [4]–[16]. These are used only for short-term forecasts, when solving traffic control and network performance problems.

However, their use is based on an accurate estimate of the Hurst parameter which, when predicting traffic in real-time, is fairly difficult to estimate. Therefore, the use of ARIMA and FARIMA models is possible only for traffic with a slight degree of self-similarity.

The neural network prediction method, as discussed in a number of papers, for example in [17], [18], allows to solve a number of practical forecasting problems, such as dynamic bandwidth redistribution, in order to make the optimal use of available network resources and to maintain QoS.

However, it is important to note that the use of the neural network method implies the need for network training. This is a complex and time-consuming process, and even a trained network is not always clearly predictable due to heuristic approaches to training design.

The forecast accuracy in such a network depends on the number of options for its training. The implementation re-quires high computing capabilities. In [19], the results of a comparison of network traffic predictions made using linear regression models and SARIMA neural networks are shown, indicating that in most cases the use of complicated and labor-intensive techniques of neural networks is impractical.

The methods of extrapolation [9]–[11], [13]–[19] are labor-intensive and suffer from considerable errors under conditions of frequent traffic intensity bursts. It should be noted that they are complex when forecasting in real time. Solving the problem of extrapolation by cubic splines or their piece-wise polynomial representation in many cases is a convenient tool, both for solving theoretical problems and for calculating the terms. However, in a number of applications, it is more efficient to represent cubic splines via B-splines.

Therefore, the development of effective methods of prediction of self-similar traffic, reducing the computational complexity and, thus, providing solutions for networks with significant bandwidths, is an important task.

4. Method of Self-Similar Traffic Prediction

Consider self-similar traffic affecting segment $[a;b]$. Let partition Δ: $a = x_0, x_1, \ldots, x_N = b$ be given in interval $[a;b]$. The first-degree spline $S_1(x)$ on grid Δ is a continuous piece-wise linear function. Let Δ grid points be given the values of self-similar traffic $f_i = f(x_i)$, which describes function $f(x)$, defined for interval $[a;b]$. The interpolation spline is defined by [5], [6], [20]:

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

Geometrically, it is a broken line passing through the points (x_i, y_i), where $y_i = f(x_i)$, denoted by $h_i = x_{i+1} - x_i$. Then, according to [20], for $x \in [x_i, x_{i+1}]$, $i = 0, \ldots, N-1$, the linear spline will have the following form:

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

or

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

The authors will also consider a cubic interpolation spline $S_3(x)$, constructed similarly to the 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 [5], [6], [20], for $x \in [x_i, x_{i+1}]$, $i = 0, 1, \ldots, N-1$ the cubic spline is:

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

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

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

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 Eq. (4) in the interval $[a; b]$ [5], [6], [20]:

$$S'(f; a) = f'(a), \quad S'(f; b) = f'(b) \ . \quad (6)$$

For determining a cubic spline type given by Eq. (5), the boundary conditions of the form [5] is used:

$$S''(f; a) = f''(a), \quad S''(f; b) = f''(b) \ . \quad (7)$$

Consider a uniform partition of interval $[a; b]$, then:

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

Let us construct a cubic B-spline, different from zero in the interval (x_{i-2}, x_{i+2}). B-splines of odd degrees are conveniently numbered by the middle node of their carrier intervals. The desired B-spline will be denoted by $B_i(x)$. Setting $y_p = B_i(x_p)$, $M_p = B_i''(x_p)$ for $B_i(x)$ we have [20], [21]:

$$\mu_p M_{p-1} + 2M_p + \lambda_p M_{p+1} = \frac{6}{h_{p-1} + h_p}\left(\frac{y_{p+1} - y_p}{h_p} - \frac{y_p - y_{p-1}}{h_{p-1}}\right) \ , \quad (8)$$

where $p = i-1, i, i+1$, $\mu_i = \frac{h_{i-1}}{h_{i-1}+h_i}$, $\lambda_i = 1 - \mu_i$.

As $B_i(x) = 0$ for $x \notin [x_{i-2}, x_{i+2}]$, then:

$$B_i^{(r)}(x_{i-1}) = B_i^{(r)}(x_{x+2}) = 0 \ , \quad r = 0, 1, 2 \ . \quad (9)$$

Taking into account the fact that the B-spline has a ratio [20], [21]:

$$B_i(x) = y_i(1-t) + y_{i+1}t - \frac{h_i^2}{6}t(1-t) \times \left[(2-t)M_i + (1+t)M_{i+1}\right] \ , \quad (10)$$

where $x \in [x_i, x_{i+1}]$, $t = \frac{x-x_i}{h_i}$, $h_i = x_{i+1} - x_i$, we get:

$$B_i''(x) = \frac{y_{i+1} - y_i}{h_i} - \frac{h_i}{6}\left[(2 - 6t + 3t^2)M_i + (1 - 3t^2)M_{i+1}\right] \ , \quad (11)$$

$$B_i''(x) = M_i(1-t) + M_{i+1}t \ . \quad (12)$$

Then, condition (9), due to Eqs. (10)–(12), may be represented by:

$$\begin{cases} y_{i-2} = y_{i+2} = 0, & M_{i-2} = M_{i+2} = 0, \\ y_{i-1} = \frac{1}{6}h_{i-2}^2 M_{i-1}, & y_{i+1} = \frac{1}{6}h_{i+1}^2 M_{i+1} \end{cases} . \quad (13)$$

The parameters found in Eq. (13) are excluded from Eq. (8), which will lead to [20], [21]:

$$\begin{cases} (h_{i-2} + h_{i-1})(h_{i-2} + 2h_{i-1})M_{i-1} + h_{i-1}^2 M_i = 6y_i, \\ (h_{i-2} + h_{i-1})M_{i-1} + (h_{i-1} + h_i)M_i + (h_i + h_{i+1})M_{i+1} = 0, \\ h_i^2 M_i(h_i + h_{i+1})(2h_i + h_{i+1})M_{i+1} = 6h_i . \end{cases} \quad (14)$$

The result is a system of three equations for finding four parameters: y_i, M_{i-1}, M_i, M_{i+1}.

Assuming:

$$y_i = \frac{h_{i-1}(h_{i-2}+h_{i-1})(2h_i+h_{i+1}) + h_i(h_i+h_{i+1})(h_{i-2}+2h_{i-1})}{(h_{i-1}+h_i)(h_{i-2}+h_{i-1}+h_i)(h_{i-1}+h_i+h_{i+1})} \ , \quad (15)$$

from the Eq. (14) we get:

$$\begin{cases} M_{i-1} = \dfrac{6}{(h_{i-2} + h_{i-1}(h_{i-2} + h_{i-1} + h_i)}, \\ M_i = \dfrac{6\left[(h_{i-2} + h_{i-1} + h_i)^{-1} + (h_{i-1} + h_i + h_{i+1})^{-1}\right]}{h_{i-1} + h_i}, \\ M_{i+1} - \dfrac{6}{(h_i + h_{i+1})(h_{i-1} + h_i + h_{i+1})}. \end{cases} \quad (16)$$

Equations (13), (15), (16) determine the spline $B_i(x)$ in the interval $[x_{i-2}, x_{i+2}]$.

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

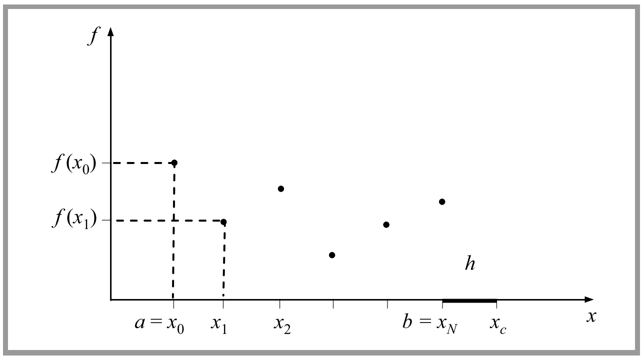

Fig. 1. Extrapolation of self-similar traffic on the interval $[a; b]$R on condition $f(x_c) = f(x_1)$.

Let us now consider short-term and long-term predictions of the characteristics of self-similar traffic using spline extrapolation.

First, a spline function (linear, cubic, or cubic B-spline) on the segment $[b;x_c]$ is constructed with the assumption that $f(x_c) = f(x_1)$. Next, we construct a linear or cubic spline or a cubic B-spline, respectively, on the segment $[b;x_c]$ (Fig. 1). Then, on the segment $[b;x_c]$, a short-term forecast of self-similar traffic is obtained.

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

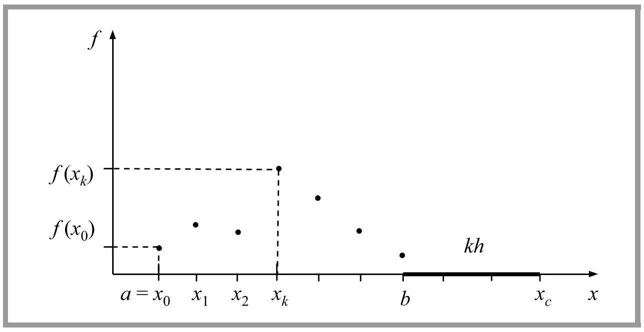

Fig. 2. Extrapolation of self-similar traffic on the interval $[a;b]$ on condition $f(x_{kh}) = f(x_c)$.

According to [20], the error of restoring self-similar traffic on the interval $[b;x_c]$, using the following theorems may be found.

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:

$$\left|S_1(x) - f(x)\right| \leq \omega(\mathrm{f}) \ , \tag{17}$$

where $\omega(\mathrm{f})$ – module of a continuous function of the form.

$$\omega(\mathrm{f}) = \max_{0 \leq i \leq N-1} \omega(\mathrm{f})' = \max_{0 \leq i \leq N-1} \max_{x',x'' \in [x_i,x_{i+1}]} \left|f(x'') - f(x')\right| \ . \tag{18}$$

If the spline cubic $S3(x)$ interpolates the continuous function $f(x)$ on the net Δ and satisfies the boundary conditions (6) or (7), then:

$$\left\|S(x) - f(x)\right\|_{\mathrm{C}} \leq \left(1 + \frac{3}{4}\rho\right)\omega(\mathrm{f}) \ , \tag{19}$$

where:

$\rho = \frac{\max_i h_i}{\min_i h_i}$,

$\left\|f(x)\right\|_{\mathrm{C}} = \max_{x \in [a,b]} |f(x)|$,

$\mathrm{C} = \mathrm{C}[a;b]$ – the function is continuous on the interval $[a;b]$.

Let us find the error of extrapolation of self-similar traffic using cubic B-splines. The interpolation cubic spline $S(x)$ can be found using its B-spline representation [20]:

$$S(x) = \sum_{i=-1}^{N+1} b_i B_i(x) \ . \tag{20}$$

The quality of the interpolation function is characterized as $R(x) = S(x) - f(x)$ and it depends on differential properties of the interpolated function $f(x)$.

Consider a spline satisfying the condition:

$$S(f;x_i) = f_i \, , \quad i = 0, 1, \ldots, N \ , \ . \tag{21}$$

with a boundary:

$$S'(f;a) = f'(a), \ S'(f;b) = f'(b) \ . \tag{22}$$

To determine the coefficients b_i, the system of equations is obtained by [20], [21]:

$$\begin{cases} b_{-1}B'_{-1}(x_0) + b_0 B'_0(x_0) + b_1 B'_1(x_0) - f'_0, \\ b_{i-1}B_{i-1}(x_1) + b_1 B_1(x_1) + b_{i+1}B_{i+1}(x_1) = f_i, \\ b_{N-1}B'_{N-1}(x_N) + b_N B'_N(x_N) + b_{N+1}B'_{N+1}(x_N) = f' \ , \end{cases} \tag{23}$$

where$i = 0, \ldots, N$.

In the periodic case the Eqs. (17) describing the problem of extrapolation, are:

$$b_{i-1}B_{i-1}(x_1) + b_i B_i(x_i) + b_{i+1}B_{i+1}(x_i) = f_i, \quad i = 1, \ldots, N \ . \tag{24}$$

In matrix form, this can be written as:

$$Ab = f \ , \tag{25}$$

where $b = (b_1, \ldots, b_N)^T$, $f = (f_1, \ldots, f_N)^T$ denotes transposition.

The error of extrapolation of self-similar traffic is calculated using Eq. (18)

$$A(b - f) = f - Af \ . \tag{26}$$

Consider the space $C[a;b]$ to be continuous on $[a;b]$, such as:

$$\left\|f(x)\right\|_{C[a,b]} = \max_{x \in [a,b]} |f(x)| \ .$$

On the grid $\Delta : a = x_0 < x_1 < \ldots < x_N = b$, these functions are characterized by their oscillation on segment $[x_i, x_{i+1}]$:

$$\omega_i(f) = \max_{x',x'' \in [x_i,x_{i+1}]} \left|f(x'') - f(x')\right| ,$$

and:

$$\omega(f) = \max_{0 \leq i \leq N-1} \omega_i(f) \ .$$

If the characteristic of the function is independent of the grid Δ, there is the modulus of $\omega(f;h)$, which is defined as [20]:

$$\omega_i(f;h) = \max_{\substack{x',x'' \in [a,b] \\ |x''-x'| \leq h}} \left|f(x'') - f(x')\right|, \quad h \leq b - a \ .$$

If $\overline{h} = \max_i h_i$, then the following inequalities are:

$$\omega_i(f) \leq \omega(f) \leq \omega(f;\overline{h}) \ .$$

Then

$$\left\|f - Af\right\| = \max_i \left|f_i - f_{i-1}B_{i-1}(x_i) - f_i B_i(x_i) - f_{i+1}B_{i+1}(x_i)\right|$$

$$\leq \max_i \left\{B_{i-1}(x_i)\left|f_i - f_{i-1}\right| + B_{i+1}(x_i)\left|f_i - f_{i+1}\right|\right\} \leq \omega(f) \ .$$

Using the property of normalized B-splines $\sum_i B_i(x) = 1$ and the Eq. (19) we have:

$$\|b - f\| \leq \|A^{-1}\| \omega(f) \ , \tag{27}$$

and

$$\|S(x) - f(x)\| = \left| \sum_{i=-1}^{N+1} \left[b_i - f(x) \right] B_i(x) \right|$$
$$\leq \left| \sum_{i=-1}^{N+1} \left[b_i - f_i \right] B_i(x) \right| + \left| \sum_{i=-1}^{N+1} \left[f_i - f(x) \right] B_i(x) \right| \ .$$

Using Eq. (20), the results are obtained by:

$$\left| \sum_{i=-1}^{N+1} \left[b_i - f_i \right] B_i(x) \right| \leq \|b - f\| \leq \|A^{-1}\| \omega(f) \ .$$

In addition, for any $x \in [x_i, x_{i+1}]$, $i = 0, 1, \ldots, N$

$$\left| \sum_{i=-1}^{N+1} \left[f_i - f(x) \right] B_i(x) \right| \leq \sum_{p=i-1}^{i+2} \left| f_p - f(x) \right| b_p(x) \leq 2\omega(f) \ .$$

Finally

$$\left| S(x) - f(x) \right| \leq \left(2 + \|A^{-1}\| \right) \omega(f) \ . \tag{28}$$

According to [20], the matrix A will be ill-conditioned if $\rho \geq \frac{3+\sqrt{5}}{2}$, then it is advisable to use a grid with a partition step for which $\rho < \frac{3+\sqrt{5}}{2}$.

5. Simulations

The spline-extrapolation method described in this paper is used for high-speed video and voice traffic, which are described by the Weibull distribution [3]. The problem concerned may be modeled by other distributions, for example - the Pareto distribution. However, it describes data traffic only.

The authors simulate self-similar traffic for the queuing system (QS) $W_B/M/1/K$ on a 3000–4000 ms segment, where:

- λ is intensity of packet arrival for servicing in the QS, $\lambda = 150$ packet per second,
- μ is packet service duration, $\mu = 125$ packet/s,
  - κ is length of the packet queue, $\kappa = 200$ packets,
  - Hurst parameter H = 0.75,
  - Weibull distribution parameters are $\alpha \approx 0.5$ and $\beta \approx 17.321$.

Self-similar traffic simulation results obtained in the Simulink package of the Matlab environment for specific initial data are shown in Fig. 3, where n is the number of packets, t is time of arrival of packets [5], [6].

According to Fig. 3, it can be seen that for the self-similar traffic obtained on the 3000–4000 ms segment, there is large-scale invariance, a significant amount of "bursts" of traffic intensity and a long-term relationship between the moments of their arrival.

Next, consider the extrapolation of traffic on the interval of [3800; 3850] ms and compare it with the results of modeling self-similar traffic.

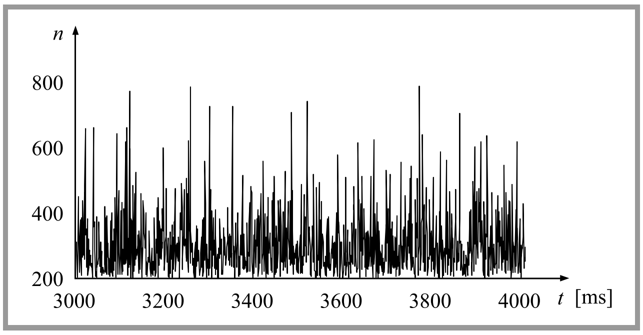

Fig. 3. The results of modeling self-similar traffic.

Using a linear spline for simulated self-similar traffic on the 3800–3850 ms segment, extrapolation of traffic is obtained, which is shown in Fig. 4.

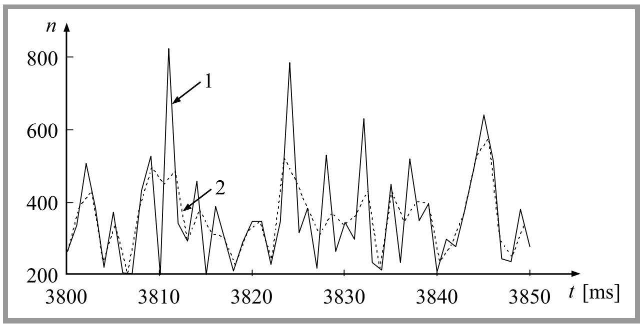

Fig. 4. The results of extrapolating self-similar traffic on the 3800–3850 ms segment using the linear spline function: 1 – self-similar traffic, 2 – extrapolation of self-similar traffic using the linear spline function.

The error in recovering self-similar traffic based on a linear spline will be evaluated according to Eqs. (17)–(18). The calculation results are shown in Table 1.

It is easy to see that the use of linear spline functions is linked with the presence of a significant error, which most often appears on segments where graphs of traffic intensity have periodic "bursts". It should be noted that the studies were conducted using a small segment of 3800–3850 ms, with step $h = 1$. The split step increase will inevitably lead to an increase in the values of extrapolation error. From this, it follows that the use of spline extrapolations based on linear splines to predict self-similar traffic with significant and frequent bursts of intensity is impractical.

However, during the experiment, self-similar traffic with the Hurst coefficient H = 0.75 was used, possibly for self-similar traffic with a lower self-similarity value using linear splines. This assumption will be considered in future work.

Table 1
The error of recovery of self-similar traffic based on a linear spline

Interval	Interval time [ms]	Error value
$[x_0; x_1]$	3800–3801	0.01
$[x_1; x_2]$	3801–3802	2.5
$[x_2; x_3]$	3802–3803	73.3
$[x_3; x_4]$	3803–3804	4.1
...	...	...
$[x_{10}; x_{11}]$	3810–3811	248.2
$[x_{11}; x_{12}]$	3811–3812	335.53
$[x_{12}; x_{13}]$	3812–3813	11.1
$[x_{13}; x_{14}]$	3813–3814	0.1
...	...	...

Using the cubic spline for simulated self-similar traffic on the 3800–3850 ms segment, extrapolation of traffic is obtained, as shown in Fig. 5. The error in recovering self-similar traffic using a cubic spline will be estimated using Eq. (19). The calculation results are summarized in Table 2.

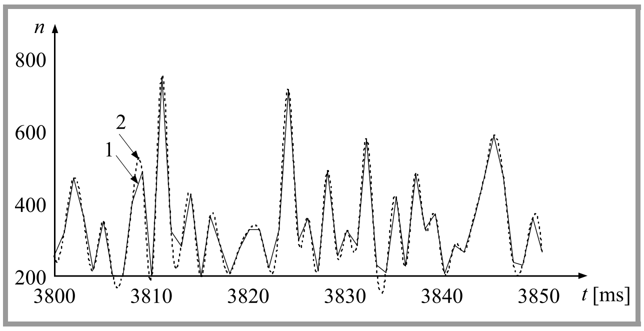

Fig. 5. Extrapolated self-similar traffic on the 3800–3850 ms segment using cubic spline functions: 1 – self-similar traffic, 2 – extrapolation of self-similar traffic using a cubic spline function.

According to the results of the extrapolation of self-similar traffic on the 3800–3850 ms segment using the cubic spline function shown in Fig. 5, the recovery errors are obtained on the segments of the graph, where the traffic intensity has "spikes" at peak points. In general, the use of cubic splines allows you to perform a short-term forecast of traffic parameters and get the predicted "route" of self-similar traffic.

It is possible to increase the accuracy of prediction of traffic characteristics using the spline-extrapolation method based on cubic B-splines. It is known that B-splines have a local character and in their construction several values are used on the considered segments. Therefore, they make it possible to obtain better results compared to cubic splines, the coefficients of which are calculated as a function over the entire domain of the initial function, in this case, at the given interval of 3800–3850 ms.

Table 2
Accuracy of recovery of self-similar traffic based on cubic spline

Interval	Interval time [ms]	Error value
$[x_0; x_1]$	3800–3801	4.6
$[x_1; x_2]$	3801–3802	0.15
$[x_2; x_3]$	3802–3803	2.44
$[x_3; x_4]$	3803–3804	1.46
...	...	...
$[x_{10}; x_{11}]$	3810–3811	0.12
$[x_{11}; x_{12}]$	3811–3812	2.1
$[x_{12}; x_{13}]$	3812–3813	10.6
$[x_{13}; x_{14}]$	3813–3814	70.5
...	...	...

Consider the following spline extrapolation for simulated self-similar traffic on the 3800–3850 ms segment using cubic B-spline (Fig. 6).

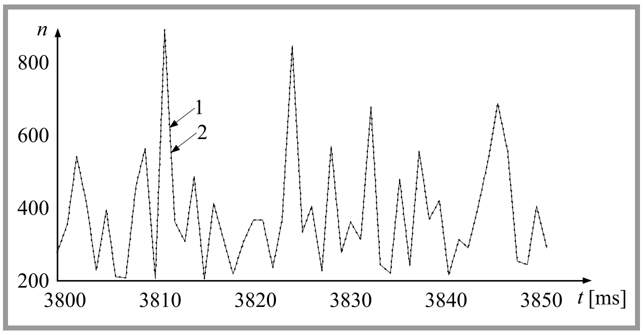

Fig. 6. Extrapolated self-similar traffic on the 3800–3850 ms segment using cubic B-spline functions: 1 – self-similar traffic, 2 – extrapolation of self-similar traffic using a cubic B-spline function.

Let us find the error values of the extrapolation of self–similar traffic using Eq. (21). The calculation results are shown in Table 3.

The use of cubic B-splines allows to reduce the error rate compared with the use of linear and cubic splines. According to the results of extrapolation of self-similar traffic on the 3800–3850 ms segment using the cubic B-splines shown in Fig. 6, the error of extrapolation is even negligible on the segment's "bursts" of traffic intensity.

In general, the use of cubic B-splines allows to perform a short-term forecast of traffic parameters and to almost completely restore the "route" of self-similar traffic.

Let us compare the recovery of self-similar traffic using a linear, cubic, and cubic B-spline, as shown in Fig. 7. The research conducted shows that for the self-similar traffic considered, the use of cubic B-splines is most appropriate. The spline extrapolation method can be used to predict traffic characteristics in real time for short-term forecasts, and long-term forecasts that are based on a large amount of data.

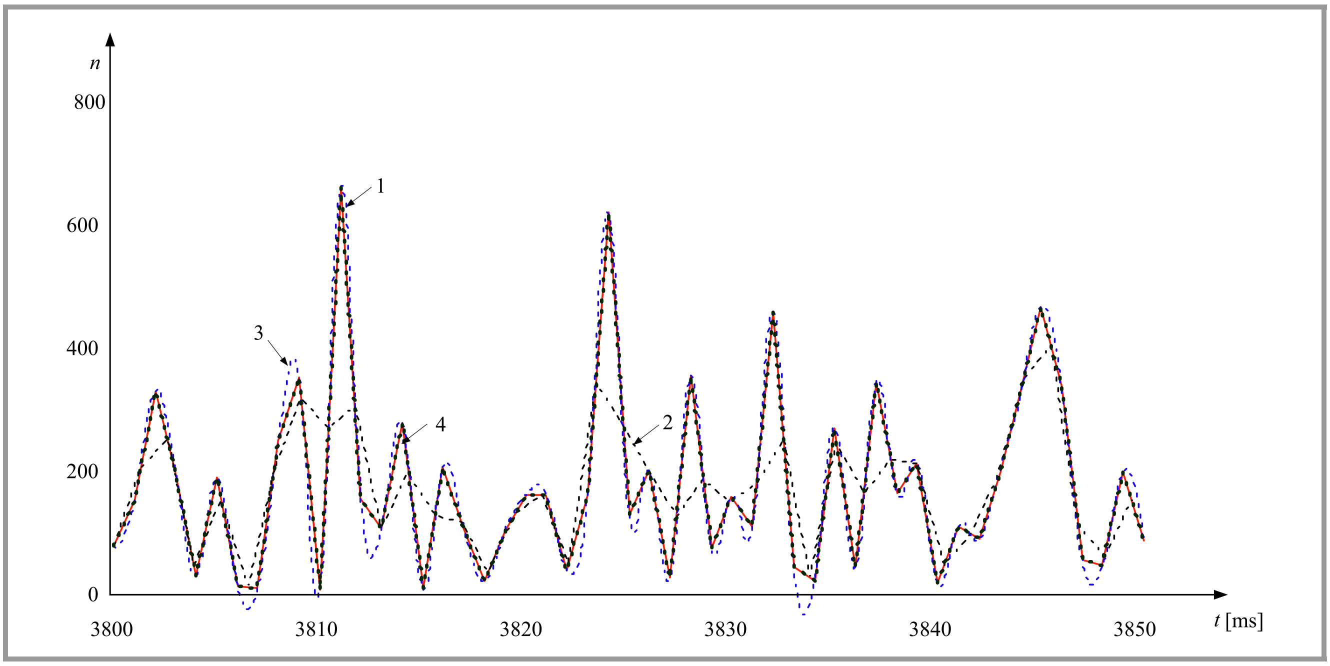

Fig. 7. Comparison of extrapolation results of self-similar traffic using linear, cubic and cubic B-spline on the 3800–3850 ms segment: 1 – self-similar traffic, 2 – extrapolation of self-similar traffic using linear spline function, 3 – extrapolation of self-similar traffic using cubic spline function, 4 – extrapolation of self-similar traffic using cubic B-spline function.

Table 3
The error of recovery of self-similar traffic based on cubic B-spline

Interval	Interval time [ms]	Error value
$[x_0; x_1]$	3800–3801	0.002
$[x_1; x_2]$	3801–3802	0.046
$[x_2; x_3]$	3802–3803	0.551
$[x_3; x_4]$	3803–3804	0.005
...	...	...
$[x_{10}; x_{11}]$	3810–3811	0.016
$[x_{11}; x_{12}]$	3811–3812	0.005
$[x_{12}; x_{13}]$	3812–3813	0.850
$[x_{13}; x_{14}]$	3813–3814	0.006
...	...	...

Short-term traffic forecast is usually associated with the ability to predict traffic characteristics in real time, in order to dynamically allocate network resources depending on traffic behavior, i.e. intensity bursts.

The results of such a forecasting approach allow to improve the network's QoS and to perform the optimal allocation of resources.

The long-term traffic forecast allows to obtain results that are based on a large amount of data, for example to choose the size of the buffer devices on the network nodes and to provide for the length of the packet queue in these devices when designing the network.

6. Conclusions

The proposed extrapolation method based on spline functions, has a number of advantages in comparison with the known methods. It is quite simple to implement, has a low error rate, and can also be used to control traffic in real time.

The practical significance of the results obtained is that the prediction of self-similar traffic will provide for the required amount of buffer devices, thereby avoiding overloads in the network and exceeding the standard QoS values.

Based on the results of traffic forecasting taking into account the maximum workloads of network nodes, practical recommendations can be given on traffic redistribution over IP networks, for example, the operation of TCP/IP protocol. Reduction of the delay, compared with TCP, allows to use a protocol without the guaranteed delivery of User Datagram Protocol (UDP). However, it is rather difficult to provide the required QoS using the UDP/TCP transport protocol only, since the reasons of the delays exist mostly at the network level [22]. Use of the proposed spline extrapolation method allows to perform a prediction of traffic characteristics, balance the load of network elements and improve the efficiency of network equipment.

Future research will need to focus on further improvement of traffic prediction accuracy, by developing the wavelet-extrapolation method based on wavelet functions.

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