Adaptive Method for Estimating Traffic Characteristics in Corporate Multi-Service Communication Networks for Transport Companies

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Abstract. An adaptive method for estimation the traffic characteristics in high-speed corporate multiservice networks based on the methods of preliminary indistinct computer training, functioning in real time mode, is proposed and investigated in this paper. The relevance of the study is due to the fact that many processes of network management in high-speed corporate multiservice communication networks need to be implemented in a mode close to real time. The approach proposed in the paper is based on the concept of conditional nonlinear Pareto-optimal filtering V. C. Pugachev. The essence of this approach consists in the fact that estimation of the traffic parameter is performed in two stages - on the first stage the parameter value prediction is estimated, and on the second stage, when the next parameter observations are received, the parameter values are corrected. In the proposed method and algorithm, predictions of traffic parameter values are made in a small sliding window, and adaptation is implemented based on pseudo-gradient procedures whose parameters are adjusted using the Takagi-Sugeno indistinct logic inference method. The proposed method and algorithm belong to the class of adaptive methods and algorithms with prior learning. The average relative error of the estimated traffic parameters estimation does not exceed 8.2%, which is a sufficient value for the implementation of operational network management tasks.

1 Introduction

Achievements in the development of telecommunications and communication technologies have led to the creation and implementation of the concept of corporate multiservice communication network (CMCN), the basis of which are packet networks based on the

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TCP/IP/MPLS protocol stack, integrating various communication services [1-3]. The explosive growth of dynamics of changes of possible network states, and also growth of speeds of providing communication services in CMCN makes the problem of reliable quality management of provided communication services actual [3, 4].

The traffic in the CMSS consists of multimedia traffic, which is very sensitive to delays, data traffic, signaling information traffic, e-mail traffic and so on. At the same time, the established service quality requirements must be fully met [4 - 6]. At the same time, there are objective difficulties in the construction of CMCN control system, which are caused by the complexity of CMCN structure, its large spatial extent, the need for rapid and qualitative analysis of a large number of different dynamically changing network characteristics [4 - 6].

Consequently, operational continuous assessment of the parameters of high-speed network traffic with a priori unknown, dynamically changing characteristics, with accuracy sufficient for making objective decisions on quality management of communication services provided, is one of the key objectives of CMCN management and represents an urgent scientific problem.

2 Materials and methods

It is noted in [6-8] that traffic for various applications in CMCN can be approximated by means of random sequences (RS), the main probability distributions of which are Poisson, Pareto, Weibull, lognormal and exponential distributions. Traffic in CMCN is non-stationary in nature, and the mathematical models that adequately describe its behaviour are non-linear stochastic models [7-9]. This significantly complicates the development of procedures for estimating the characteristics of network traffic with the required quality [7].

As a rule, recurrence methods and algorithms are used to solve the problem of nonstationary and nonlinear RS parameter estimation, the main of which are linearized Kalman filter (LKF) and extended Kalman filter (EKF) [8, 9].

The peculiarities of these methods include the fact that their resulting accuracy characteristics depend significantly on the values of possible perturbations, as well as on the characteristics of the nonlinearities of the estimated parameters. LKF and EKF are not the optimal algorithms [7, 9].

Application of these algorithms for estimation of traffic parameters in high-speed CMCNs is connected with significant computational costs and necessity of preliminary estimation of algorithm parameters by means of preliminary mathematical modeling, which causes significant difficulties at their technical realization. In addition, the behavior of network traffic can be characterized by both sudden (abrupt) changes in its characteristics and smooth faults of SP characteristics, which also causes great algorithmic difficulties in their technical implementation [7, 9].

Let us note that besides LFK and EFK there are various methods and algorithms of nonlinear filtering [9], which are based on preliminary estimation of conditional RS distribution densities $\{x_n\}$ and on preliminary estimation of current values of conditional covariances of this RS, that also causes large computational difficulties [10].

In [5, 8, 9] it is shown that one of the constructive approaches to the solution of the problem of estimation of the vector parameters of random processes, at nonlinear models of observation, is the method of conditional nonlinear Pareto-optimal filtering. The essence of this method is that the estimation of the unknown parameter is carried out in two stages. At the first stage the function of the current prediction of the parameter values is calculated. At the second stage corrections are made using correction functions and additional a posteriori information about the values of these estimates. The choice of the class and type of current

forecast estimation functions and the class and type of correction functions is quite free and is determined by the specific formulation of the problem to be solved.

3 Results

Let the CMCN traffic intensity observations on a network element (NE) interface be represented as RS $x(i)$, set at discrete points in time $i = \{1, 2, \dots, n, \dots\}$. Let the RS observation $x(i)$ be described by an additive-multiplicative model:

$$x(i) = \beta(i) \cdot F\big(x(i-1)\big) + \xi(i), \tag{1}$$

where $F(*)$ is some random function of the observations, $\beta(i)$ is a random variable, and $\xi(i)$ − observation noise with zero mathematical expectation and finite variance. We suppose also that RS $x(i)$ has a finite mathematical expectation and variance. Let us note that the has a finite mathematical expectation and variance. Note that model (1) and the assumptions made define a non-Gaussian, non-stationary Markov sequence model (1) and the assumptions made define a non-Gaussian, non-stationary Markovian sequence [7-9].

A vector recurrence procedure RS $x(i)$ for estimating expectation values of RS standard deviation and its coefficient of variation according to the minimum mean square error criterion is required, that is:

$$J(i) = M\{\bar{\varepsilon}\} = \begin{Bmatrix} M(m(i) - \widehat{\widehat{m}}(i))^2 \to min,\ M(\sigma(i) - \hat{\hat{\sigma}}(i))^2 \to min, \\ M(Kv(i) - \widehat{\widehat{K}}v(i))^2 \to min \end{Bmatrix}, \tag{2}$$

where $\widehat{\widehat{m}}(i)$, $\hat{\hat{\sigma}}(i)$, $\widehat{\widehat{K}}v(i)$ are the estimates of mathematical expectations, st. dev. and coefficient of variation RS$x(i)$ at step i, and $m(i)$, $\sigma(i)$, $Kv(i)$ are their true values.

The prediction function for the current value of the mathematical expectation RS is defined as:

$$\widehat{m}(i) = \frac{1}{N_1}\sum_{k=1}^{N_1} x(i-k),\ i = 1,2, \dots, n, \dots, \tag{3}$$

where N_1 is the size of the sliding window, which is chosen to be relatively small.

Predictions of st. dev. estimates and RS coefficient of variation at step i are also made in the same sliding window:

$$\hat{\sigma}(i) = \sqrt{\frac{1}{N_1}\sum_{k=1}^{N_1} x^2(i-k) - \left(\frac{1}{N_1}\sum_{k=1}^{N_1} x(i-k)\right)^2}, i = 1,2, \dots, n, \dots, \tag{4}$$

$$\widehat{K}v = \frac{\hat{\sigma}(i)}{\widehat{m}(i)}.$$

Without loss of generality, a further detailed discussion of the construction of the corrective procedure will be carried out for the component of the function's mathematical expectation value (2) $J_m\big(\widehat{m}(i)\big)$, with a generalization to the vector case.

Then, after some simple transformations, the recurrent pseudo-gradient algorithm (PGA) for estimating the current value of the expectation of the RS, taking into account the signs, will be:

$$\widehat{\widehat{m}}(i+1) = \widehat{\widehat{m}}(i) + \lambda_m(i+1)(\widehat{m}(i+1) - \widehat{\widehat{m}}(i)). \tag{5}$$

In order to reduce the average relative error of the expectation of traffic intensity in CMCN, it is proposed that the corrective procedure (5) is based on the mean value of the previous estimates, in the form of:

$$\breve{m}(i) = \frac{1}{N_2}\sum_{k=0}^{N_2-1}\hat{\hat{m}}(i-k), \quad (6)$$

where N_2 - the size of the second sliding window in which the traffic intensity expectation estimates are averaged, and $\breve{m}(i)$ is the average value of the estimates in this sliding window. Then expression (5) will take the form:

$$\hat{\hat{m}}(i+1) = \hat{\hat{m}}(i) + \lambda_m(i+1)(\hat{m}(i+1) - \frac{1}{N_2}\sum_{k=0}^{N_2-1}\hat{\hat{m}}(i-k)). \quad (7)$$

Abbreviated (22) can be written as:

$$\hat{\hat{m}}(i+1) = \hat{\hat{m}}(i) + \lambda_m(i+1)\big(\hat{m}(i+1) - \breve{m}(i)\big). \quad (8)$$

The same approach applies to all vector components$\nabla Q(\xi, \hat{\hat{\varepsilon}}(i))$. A generalisation of the recurrence procedure (8) is a vector PGA of the form:

$$\hat{\hat{G}}(i+1) = \hat{\hat{G}}(i) + R(i+1) \times \nabla Q(i+1), \quad (9)$$

where $\hat{\hat{G}}(i+1)$ is the vector of RS parameter estimates at the step $i+1$:

$$\hat{\hat{G}}(i+1) = [\hat{\hat{m}}(i+1), \hat{\hat{\sigma}}(i+1), \hat{\hat{R}}v(i+1)]^T. \quad (10)$$

Matrix $R(i+1)$ is a diagonal matrix of step coefficients.

It should be noted that the structure of the algorithm does not depend on the statistical properties of RS $x(i)$. This feature of PGA is a consequence of the central limit theorem [7].

For parameter estimation of non-stationary RS the sequence $R(i)$ is bounded from below by constant values. As a consequence of choosing a bounded step factor, the variance of RS parameter estimation will also be bounded from below. Consequently, it is necessary to find a compromise solution between speed and accuracy of RS intensity values estimation [8, 9].

In the developed algorithm it is proposed to take into account the dynamics of the estimated parameters and characteristics of the RS when choosing the vector of step coefficients. Obviously, the gradient moduli of the components of the vector quality functional are proportional to the dynamic properties of the RS. Such dependencies are difficult to be formalized, so it is proposed to automate the procedure of PGA step coefficient adjustment based on Takagi Sugeno's indistinct inference method [10, 11], which has the form:

$$\boldsymbol{IF} < \hat{\hat{m}}(i) \in D1 > AND < \nabla Q(i) \in D2 > AND < \hat{\hat{\sigma}}^2(i) \in D3 >$$
$$\text{TO}R(i+1) = R(k)\ AND\ N_1 = N_1(k)\ AND\ N_2 = N_2(k), \quad (11)$$

where D1, D2 and D3 are the areas of the current values of the mathematical expectation estimate RS, the estimated values of the gradient components in the corrective procedure (8) and the variance estimate RS, N1, and N2 are the dimensions of the corresponding sliding windows in expressions (3) and (7).

To implement these rules, the indistinct logic inference system is pre-trained on experimental data obtained at its design stage, on test RS, with known statistical parameters [8, 9]. Increasing the size of the sliding window, if the need arises, is carried out sequentially, in steps equal to one sliding window cell. This makes it possible to ensure observability of estimated RS parameters.

A feature of this indistinct logic inference system is that training is done during its design phase. Small adjustments to indistinct rule bases and indistinct knowledge bases are possible during the operational phase.

4 Discussion

Mathematical simulations to test the performance of the CMCN traffic intensity estimation algorithm were performed for traffic flows having Poisson distribution, exponential distribution and lognormal distribution. The modulating functions for modelling non-stationary RS were RS autoregressive first order (AR-1) [8, 9] as well as deterministic functions.

Figure 1 shows the surface plot of the step coefficients for the procedure of adjusting the estimates of the mathematical expectation of RS depending on the period of its change and on the possible value of its gradient estimation modulus obtained in the pre-training phase of the indistinct logic inference system. In this case the value λ_m was chosen so that the average relative error of the estimate δ and its st. dev. σ_δ were as low as possible. Then, after pre-training the algorithm to select the values $\{\lambda_m\}$, the rational values for sliding window sizes N_1 and N_2, were determined. The minimum values of the mean relative error of the estimate of the mathematical expectation RS δ% and st. dev. the average relative error of the estimate of the mathematical expectation σ_δ % were achieved. These dependencies are shown in Figure 2 and 3.

The average process value was approximately 312 Mbit/s, the maximum process value was 831 Mbit/s and the minimum process value was 110 Mbit/s.

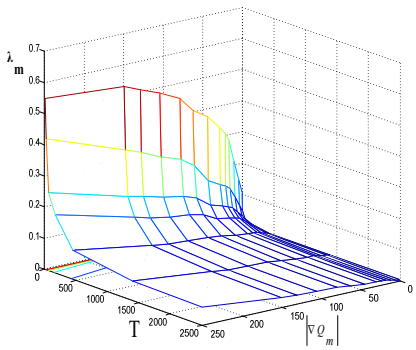
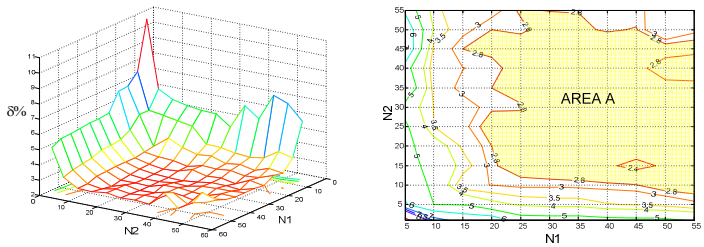


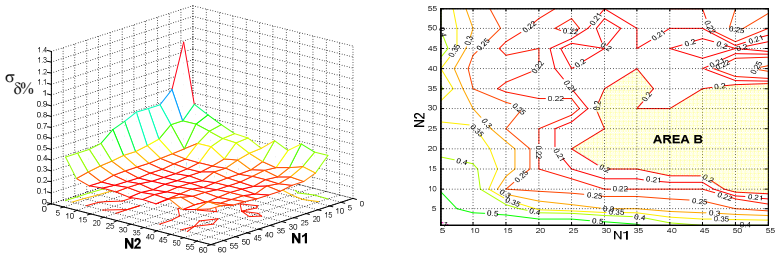
Fig. 1. Dependence of the PGA step coefficient on the period T of the mathematical expectation change and on the value of $|\nabla Qm|$, which achieves the minimum value of the mean relative error of estimation of the mathematical expectation current value RS δ%.



a) three-dimensional surface $\delta = f_1(N_1, N_2)$ %

b) equal level areas $\delta = \psi(N_1, N_2)$ %. Area "AREA A", in which $\delta \leq 2.8$ %.

Fig. 2. Dependence of the average relative error of the mathematical expectation estimate from N1 and N2.



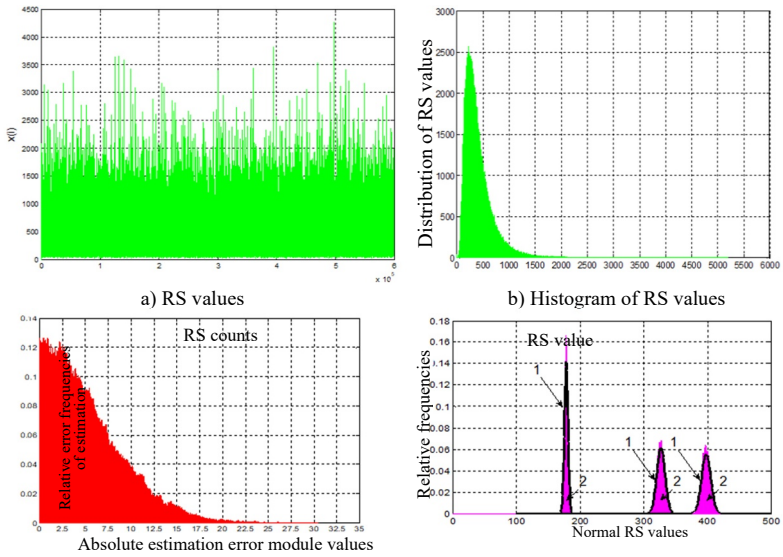
a) three-dimensional surface $\sigma_\delta = f_2(N_1, N_2)$ %

b) equal level areas $\sigma_\delta = \psi_2(N_1, N_2)$ %. Area "AREA B", in which $\sigma_\delta \leq 0.2$ %.

Fig. 3. Dependence of the average relative error st. dev. value of the mathematical expectation estimate from N1 and N2.

The time of change of the expectation value of RS from the minimum to the maximum value was about 300 milliseconds. The mathematical expectation of RS was modelled by the AR-1 process. The analysis of these dependencies shows that the rational values N_1 and N_2 are $N_1 \in [30 - 50]$ and $N_2 \in [25 - 45]$. In this case, the value δ did not exceed 3% and the value σ_δ did not exceed 0.2%. Further increases in the size of the sliding windows led to increases in these values, as there was excessive smoothing of the RS parameters.

Figure 4 shows the results of the test using the criterion χ^2 hypotheses of RS normalisation after applying procedure (6) at finite values of the sliding window size N_1 for a log-normal distribution of RS. Figure 4(a) shows plots of RS sample values and Figure 4(b) shows histograms of their value distributions. Figure 4. c) illustrates a normalized histogram of the distribution of absolute error moduli $m(i)$.



a) RS values

b) Histogram of RS values

c) Normalised histogram of absolute error modules $n(i)$

d) Theoretical distributions and normalised RS histograms for different values $m(i)$, after application of the algorythm (3.22)

Fig. 4. Results of hypothesis test of RS normalisation after procedure (3) by the criterion χ2.

The graph in Figure 4(d) shows a normalised RS histogram obtained after applying procedure (3). In this figure the number 1 indicates the graphs of the theoretical normal density distribution of the values $\hat{m}(i)$, where the parameters are estimates of the expectation and variance of RS following procedure (6), and the number 2 indicates normalised histograms of these distributions for RS with different values of the parameters. The significance level of the criterion χ^2 of the RS normalisation hypothesis was less than $\alpha = 0.01$. Similar results were obtained for RS with Poisson distribution.

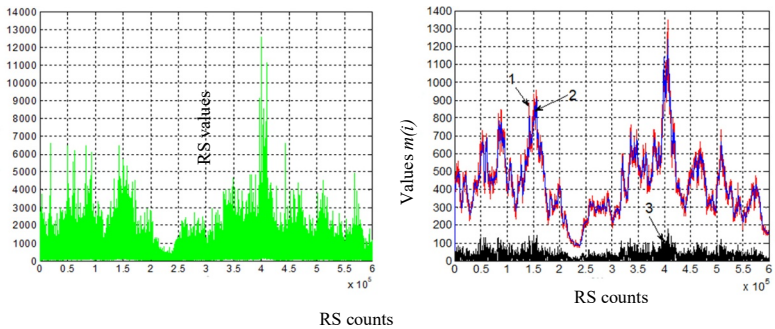
Estimates of the constant expectation of RS with lognormal, exponential and Poisson distributions showed that in all cases the mean relative error of estimation does not exceed the value $\delta \leq 2.24$ %.

Examples of estimates of the expectation value RS for the step modulating function for the lognormal RS distribution are shown in Figure 5. Similarly, for RS with a Poisson distribution, the value is $\delta \leq 0.58$ %.

The results of this numerical experiment showed high dynamic characteristics of the algorithm proposed in the paper. The convergence rate of the algorithm was several tens of counts with high accuracy of mathematical expectation estimation.

This numerical experiment also confirmed the high dynamic and accuracy properties of the developed adaptive algorithm for RS parameter estimation. The maximum value of average relative error was obtained for RS with lognormal distribution $\delta \leq 4.04$ %, which can be considered an acceptable result.

As an example demonstrating high dynamic and accuracy characteristics of the proposed algorithm, Figure 5 shows an example of estimation of mathematical expectation RS with lognormal distribution, in which the modulating function is a first order autoregressive process, in which the correlation coefficient changes by leaps and bounds [8].



a) RS values

b) Estimation of value $m(i)$; 1- true value $m(i)$; 2- estimation $\hat{m}(i)$; 3- absolute error modulus

Fig. 5. Logarithmically normal distribution (δ ≤ 6.28 %).

The following mean relative error of the estimate was obtained: $m(i)$, δ = 3.6% and st. dev. of this error σ_δ = 0.41%. As can be seen from the above graphical results, RS has a high dynamism in its main parameters. RS counts were generated in one microsecond intervals ($10^{-6}s$). Values $N_1$and N_2 were $N_1 = 35$ and $N_2 = 35$.

This study has shown that for stationary RS with a lognormal distribution, if its mathematical expectation varies between 23 and 755 and the process variance between 12.15 and 400 at the same time, the value δ varies from 0.043% to 1.12%, and the value σ_δ varies from 0.043% to 0.096%. Similar traffic parameter values were obtained for other distributions.

The obtained results should be considered acceptable for further analysis and management decision making on quality management of communication services in CMCN, given the fact that PGA operates in real time. Thus, the developed algorithms for CMCN traffic parameter estimation fully satisfy the requirements for timeliness and accuracy.

5 Conclusion

The analysis carried out in this work showed that the practical implementation of existing methods for estimating nonstationary and non-linear traffic in CMCN, such as LFC and RFC, causes significant difficulties, which are due to the need to obtain a priori knowledge of RS models, which in practice is quite difficult to obtain.

The obtained accuracy and dynamic characteristics of the developed method and algorithms provide obtaining estimates of traffic parameters in CMCN with accuracy sufficient for making objective decisions on quality management of communication services.

The most promising is the realization of the algorithm as an intelligent agent for multi-agent intelligent system of operational decision support for quality management of communication services. The hardware basis of such system can be system-on-chip (SoC) and FPGA [9].

References

1. S. Ageev, et al., E3S Web of Conf. **203**, 05017 (2020). DOI:10.1051/e3sconf/202020305017.
2. A. Goldstein, Internet of Things, Smart Spaces, and Next Generation Networks and Syst., 441-454 (2017). DOI: 10.1007/978-3-319-67380-6_40.
3. P.D. Matasaru, L. Scripcariu, F. Diaconu, *On the QoS for Satellite IP networks: a Follow-Up*, International Symposium on Signals, Circuits and Systems (ISSCS), IEEE, 1-3. (2019). DOI:10.1109/ISSCS.2019.8801788.
4. S. Haryadi, The Concept of Telecommunication Network Performance and Quality of Service (2018). DOI:10.31227/osf.io/cq8na.
5. S.A. Ageev, et al., Automation and Remote Control **82**, 7, 1222-1232 (2021). DOI: 10.1134/S0005117921070067.
6. A.H. Hamamoto, et al., Expert Syst. with Applicat. **92,** 390-402 (2018). DOI:10.1016/j.eswa.2017.09.013.
7. D.R. Cox, H.D. Miller, The theory of stochastic processes (Routledge, 2017). DOI: 10.1007/978-3-319-68075-0.
8. S.A. Ageev, et al., J. of Phys.: Conf. Ser. **2176**, 1, 012022 (2022). DOI:10.1088/1742-6596/2176/1/012022.
9. S. Ageev, et al., E3S Web of Conf. **157**, 04027 (2020). DOI: 10.1051/e3sconf/202015704027.
10. T. Takagi, M. Sugeno, IEEE Trans. on System, Man and Cybernet.**15,** 1, 11-132 (1985). DOI: 0.1109/TSMC.1985.6313399.
11. A. Piegat, Physica, **69** (2013). DOI:10.1007/978-3-7908-1824-6.