Comparative analysis of algorithms for estimating traffic parameters in corporate multiservice communication networks

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Abstract. Adequate management of modern corporate communication networks is possible if many control procedures function in near real time. In this case, the processed network monitoring data must have accurate characteristics sufficient for making objective management decisions. This fully applies to the data monitoring of network traffic parameters, which determines the relevance of the proposed work. The proposed in the paper algorithm for on-line estimation of traffic parameters in corporate multiservice communication networks is based on the concept of conditional nonlinear Pareto-optimal filtering V. C. Pugachev. Its essence is that the estimation of traffic parameters is performed in two stages - in the first stage, we evaluate the forecast values of parameters, and in the second, with the next observations of random sequences, we make adjustments to their values. Traffic parameter values forecasts are constructed in a small-sized sliding window, and the adjustment is implemented on the basis of pseudo-gradient procedures whose parameters are adjusted using a fuzzy control algorithm based on the Takagi-Sugeno method. The proposed algorithm belongs to the class of adaptive algorithms with prior learning. The maximum value of the average relative error of estimation of traffic parameters was less than 8.2%, which is a sufficient value for the implementation of operational network management tasks. At the same time, the actual scientific and technical task is to analyze the comparison of the characteristics of the developed adaptive algorithm with the characteristics of the optimal algorithms, the characteristics of which are the maximum achievable. Translated with www.DeepL.com/Translator (free version). The results of a comparison of the proposed method with the optimal Coleman filtration (OKF) are presented.

1. Introduction

Modern corporate multiservice communication networks (CMCN), combining various communication services, are created on the principles of packet-based communication networks, the functional basis of which is the protocol stack TCP / IP / MPLS [1 - 3]. The dynamics of changes in network states and rates of provision of communication services in the CMCN makes the problem of reliable operational quality control urgent. To solve it, it is necessary to assess parameters and characteristics of network traffic [2-4].
C McN traffic includes the multimedia traffic, which is very sensitive to delays, data traffic, signaling traffic, e-mail traffic, etc. In this case, the specified requirements for the quality of services must be met [3-7]. This is achieved through the implementation of methods of operational quality control. At the same time, there are objective difficulties in the construction of the C McN control system, the main reasons for which are the large geographical size of the KMSS, the complexity of its functional and technical architectures, the objective need for rapid and qualitative analysis of a large number of dynamically changing network characteristics and parameters [2, 4, 7].

In [4, 7 - 9] it is shown that network traffic can be represented by means of random sequences (RS), which probability distributions are approximated by Poisson, Pareto, Weibull, lognormal and exponential distributions. It should be noted that the mathematical models that adequately describe traffic behavior are nonlinear stochastic models of nonstationary RS [4, 7 - 9].

Thus, continuous estimation of traffic parameters in near-real time with unknown, changing characteristics in advance, with an accuracy sufficient for making objective decisions on managing the quality of communication services provided, is one of the key objectives of the CMCS network management and represents an urgent scientific problem. Comparative properties and characteristics of newly developed adaptive methods and algorithms are also of interest [4, 8, 9].

2. Methods and materials. Analysis of methods for estimating traffic parameters in high-speed C McN

The main characteristics and parameters of multiservice traffic include the values of its maximum and minimum intensity, instantaneous values of mathematical expectation, mean square deviation and coefficient of variation [2, 4, 5, 8, 9].

To estimate the parameters of a non-stationary and non-linear RS, recurrent methods and algorithms are used; the main ones are the linearized Coleman filter and the extended Coleman filter [10-11].

The linearized Coleman filtering. It is necessary to find optimal root-mean-square estimates of the values of the RS \( \{x_n\}, \forall n, \forall n \) satisfying the difference stochastic equation:

\[
x_{n+1} = A_n x_n + B_n \xi_n, n \geq 1, x_0 = \gamma,
\]

where: \( \gamma \sim N(m_\gamma, R_\gamma) \). \( \{\xi_n\} \) – discrete vector Gaussian white noise, \( M\{\xi_n\} = m_\xi(n), \) \( \text{cov}(\xi_n, \xi_n) = D_\xi(n) \); \( \text{cov}(\xi_n, \xi_k) = 0, \) if \( n \neq k \). It is assumed that \( \gamma \) and \( \{\xi_n\} \) - independent random variables (RV). \( \{A_n\} \) and \( \{B_n\} \) – sequences of nonrandom matrices. Taking into account the linearity (1), we can conclude about the Gaussian distribution of RV \( x \). Let the RV observation model \( x_n \) be:

\[
y_n = C_n x_n + v_n, n = 1, 2, \ldots,
\]

where: \( y_n \) - vector of observations at the moment \( n \); \( C_n \) - known nonrandom matrix; \( \{v_n\} \) - Gaussian SD of observation errors. It is assumed that \( \{v_n\} \) - vector discrete white noise; \( M\{v_n\} = m_v(n), \) \( \text{cov}(v_n, v_n) = D_v(n) \), and \( D_v(n) \) - non-degenerate matrix. Let us make the assumption that the RV \( \{v_n\} \) does not depend on RV \( \{\xi_n\} \) and \( \gamma \). As known from [9-10], equations (1) and (2) describe the dynamic model of Coleman observations.

Optimal root mean square estimate \( \hat{x}_n \) for \( x_n \) based on observations \( y_n \) is calculated as in [10-11]:

\[
\hat{x}_n = \tilde{x}_n + \hat{P}_n C_n^T (C_n \hat{P}_n C_n^T + D_v(n))^{-1} (y_n - C_n \tilde{x}_n - m_v(n)), n \geq 1,
\]

\[
\tilde{x}_0 = m_\gamma; \quad \tilde{x}_n = A_n \tilde{x}_{n-1} + B_n m_\xi(n); \quad \hat{P}_n = A_n \hat{P}_{n-1} A_n^T + B_n D_\xi(n) B_n^T.
\]

Matrix \( \hat{P}_n \) is the covariance matrix of the estimation error \( \Delta \hat{x}_n = x_n - \hat{x}_n \), i.e. \( \hat{P}_n = \text{cov}(\Delta \hat{x}_n, \Delta \hat{x}_n) \), which is determined from the difference matrix equation:

\[
\hat{P}_n = \hat{P}_n - \hat{P}_n C_n^T (C_n \hat{P}_n C_n^T + D_v(n))^{-1} C_n \hat{P}_n, n \geq 1, \quad \hat{P}_0 = R_\gamma.
\]

Recurrent equations (3) and (4) are the optimal discrete Coleman filter [10-11].

If we denote \( k_n = \hat{P}_n C_n^T (C_n \hat{P}_n C_n^T + D_v(n))^{-1} \), the Coleman filter will have the form:
\[ \hat{x}_n = \hat{x}_n + k_n \left( y_n - C_n \hat{x}_n - m_y(n) \right), \]  
\[ \hat{p}_n = \left( I - k_n C_n \right) \hat{p}_n, \quad \hat{p}_0 = R_y. \]  
(5)

where: \( I \) - identity matrix, \( \hat{x}_n \) - matrix filter gain.

The transition to the method of linearized Coleman filtering is carried out as follows. The observation model is

\[ x_{n+1} = A_n x_n + U_n + B_n \xi_n, n \geq 1, \quad \hat{x}_0 = m_y; \]
\[ y_n = C_n x_n + W_n + D_n v_n, n = 1, 2, \ldots . \]  
(6)

where \( \{ \xi_n \} \) and \( \{ v_n \} \) - independent standard white Gaussian noise; \( y \sim N(m_y, R_y) \) - vector of initial conditions independent of \( \{ \xi_n \} \) and \( \{ v_n \} \); \( \{ A_n, B_n, C_n, D_n \} \) - known matrices, and the condition \( D_n D_n^T > 0, \forall n \) is met; \( \{ U_n, W_n \} \) - known vectors. In this case, the root-mean-square optimal estimate is calculated as:

\[ \{ \hat{x}_n = \hat{x}_n + k_n (y_n - C_n \hat{x}_n - W_n), \quad \hat{x}_0 = m_y; \]
\[ \hat{x}_n = A_n \hat{x}_{n-1} + U_n \]
\[ k_n = \hat{p}_n C_n (C_n \hat{p}_n C_n + D_n D_n^T)^{-1}, \]
\[ \hat{p}_n = (I - k_n C_n) \hat{p}_n, \quad \hat{p}_0 = R_y \]
\[ \hat{p}_n = A_n \hat{p}_{n-1} A_n^T + B_n B_n^T. \]  
(7)

To construct approximate estimates of the process \( \{ x_n \} \) for a nonlinear difference stochastic observation model [10-11]:

\[ x_{n+1} = a_n(x_n) + u_n + B_n \xi_n, n \geq 1, \quad x_0 = \gamma; \]
\[ y_n = c_n(x_n) + w_n + D_n v_n, \quad n = 1, 2, \ldots . \]  
(8)

where: \( a_n(x) \), \( c_n(x) \) - known nonlinear differentiable functions; \( u_n \), \( w_n \) - known vectors, an assumption is made about the presence of reference path \( \{ x_n^0 \} \), where \( M[|x_n - x_n^0|^2] \ll 1 \). Model (8) is then linearized by expanding nonlinear functions in a Taylor series about the reference value \( x_n^0 \) and discarding terms of the second and higher orders in the form

\[ x_n = a_n(x_n^0) + \frac{\partial a_n}{\partial x} \bigg|_{x_n^0} (x_n - x_n^0) + u_n + B_n \xi_n = \]
\[ = A_n x_n + U_n + B_n \xi_n. \]  
(9)

where: \( A_n = \frac{\partial a_n}{\partial x} \bigg|_{x_n^0} \), \( U_n = a_n(x_n^0) - A_n x_n^0 + u_n \).

Similarly, for the observation process, we have:

\[ y_n = c_n(x_n^0) + \frac{\partial c_n}{\partial x} \bigg|_{x_n^0} (x_n - x_n^0) + w_n + D_n v_n = C_n x_n + W_n + D_n v_n, \]  
(10)

where: \( C_n = \frac{\partial c_n}{\partial x} \bigg|_{x_n^0} \), \( W_n = c_n(x_n^0) - C_n x_n^0 + w_n \).

\( \hat{x}_n \) is calculated from (3.16). Parameters \( \{ A_n, B_n, C_n, D_n \} \) are determined from expressions (7) and (8). This algorithm (7) - (10) is called the first order suboptimal nonlinear filtering algorithm [9-10].

If in (7) the values \( x_n^0 \) are used, this algorithm is called the linearized Coleman filter (LKF) [10-11]. If as \( x_n^0 \) \( \hat{x}_{n-1} \) is selected, this algorithm is called the extended Coleman filter (EKF) [10-11].

The resulting accuracy characteristics depend on possible disturbances and characteristics of the nonlinearities of the estimated parameters [11]. The LKF and the EKF are not optimal algorithms [9].

The use of these algorithms for estimating traffic parameters in high-speed CMCN is associated with significant computational costs, the need for a preliminary assessment of algorithm parameters using the preliminary mathematical modeling method, which causes significant difficulties in their technical implementation. In addition, the behavior of network traffic can be characterized by both a sudden (abrupt) change and smooth variations in the characteristics of the RV, which also causes great algorithmic difficulties [10-11].

There are various methods and algorithms for nonlinear filtering [9], which are based on the preliminary estimation of conditional distribution densities of RV \( \{ x_n \} \) and on the preliminary
estimation of the current values of the conditional covariance of this RV, which also causes great computational difficulties [9].

In [12-13] it is shown that one of the constructive approaches to estimating vector parameters of random processes, with nonlinear observation models, is the method of conditional nonlinear Pareto-optimal filtering. An unknown parameter is estimated in two stages. At the first stage, the function of the current forecast of parameter estimates is calculated. At the second stage, using adjusting functions and the additional information about these estimates, they are adjusted. The choice of the class and type of assessment functions, the class and type of adjusting functions is free and determined by the specific formulation of the problem.

3. Results and discussion. Development of algorithms for estimating traffic parameters in corporate multiservice communication networks

Let us represent the observations of traffic intensity values at an interface of a network element (NE), in the form of RV $x(i)$, given at discrete moments of time $i = \{1, 2, ..., n\}$. Let us assume that RV $x(i)$ observations are described by an additive-multiplicative model [3, 4]:

$$x(i) = \beta(i) \cdot F(x(i - 1)) + \xi(i),$$  \hspace{1cm} (11)

where $F(*)$ – random function from observations, $\beta(i)$ – random variable, $\xi(i)$ – interference of observations with zero mathematical expectation and finite variance. Let us assume that $x(i)$ has finite mathematical expectation and variance. Model (11) and the assumptions determine the non-Gaussian, nonstationary Markov sequence [9].

It is required to develop a vector recurrent algorithm for evaluating the mathematical expectation of $x(i)$, the standard deviation (SD) of the RV and its coefficient of variation according to the criterion of the minimum mean square of the error [3, 4]:

$$J(i) = M[\varepsilon] = \left\{M(m(i) - \hat{m}(i))^2 \to \min, M(\sigma(i) - \hat{\sigma}(i))^2 \to \min, \right\}$$  \hspace{1cm} (12)

where $\hat{m}(i)$, $\hat{\sigma}(i)$, $\hat{\nu}(i)$ – estimates of mathematical expectation, standard deviation and coefficient of variation RV $x(i)$ at step $i$, $m(i)$, $\sigma(i)$, $\nu(i)$ – their values.

The forecast function for the current value of the mathematical expectation RV is determined as [3, 4]:

$$\hat{m}(i) = \frac{1}{N_1} \sum_{k=1}^{N_1} x(i - k), \hspace{1cm} i = 1, 2, ..., n, ..., \hspace{1cm} (13)$$

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

Forecasts of the mathematical estimates of the SD and the coefficient of variation of the RV at step $i$ are also made in the same sliding window [3, 4]:

$$\hat{\sigma}(i) = \sqrt{\frac{1}{N_1} \sum_{k=1}^{N_1} x^2(i - k) - \left(\frac{1}{N_1} \sum_{k=1}^{N_1} x(i - k)\right)^2}, \hspace{0.5cm} i = 1, 2, ..., n, ..., \hspace{1cm} \hat{\nu} = \frac{\hat{\sigma}(i)}{\hat{m}(i)}. \hspace{1cm} (14)$$

Without loss of generality, further development of the adjusting procedure will be carried out for the component of the estimate of the mathematical expectation of functional (12) $J_m(\hat{m}(i))$.

As a rule, the value of functional $J_m(\hat{m}(i))$ is inaccessible to observation, and only a random realization of its gradient with a random error can be observed, that is [3, 4]:

$$\nabla Q(\xi, \hat{m}(i)) = \nabla J_m(\hat{m}(i)) + \xi(i), \hspace{0.5cm} \xi \in R. \hspace{1cm} (15)$$

Where $\xi$ – gradient observation error. It can be assumed that $\xi$ is centered, uncorrelated errors in estimating the gradient of the quality functional. Functional (15) will be minimized using the recurrent algorithm [3, 4, 14-16]:

$$\hat{m}(i + 1) = \hat{m}(i) - \lambda_m(i + 1) \nabla Q(\xi, \hat{m}(i + 1)), \hspace{1cm} (16)$$
where $\nabla Q(\xi, \hat{m}(i + 1)) - \text{random direction of motion in phase space at point } \hat{m}(i + 1)$; $\hat{m}(i) - \text{adjusted estimate of the mathematical expectation}$; $\{\lambda_m\} - \text{sequence of positive numbers, which,}$

for a stationary PN, must satisfy the conditions [13]:

$$\sum_{i=1}^{\infty} \lambda_m(i) = \infty, \quad \sum_{i=1}^{\infty} \lambda_m^2(i) < \infty,$$

(17)

where $\{\lambda_m(i)\} - \text{algorithm step coefficients}$. As is known, the vector $\nabla Q(\xi, \hat{m}(i))$ is called the pseudo-gradient at point $\hat{m}(i)$, if at this point the condition is met [14-15]:

$$\nabla l_m \{\hat{m}(i - 1)\} \cdot M(\nabla Q(\xi, \hat{m}(i))) \geq 0,$$

(18)

where $M(*) - \text{mathematical expectation operation}$.

Implementation of the quality functional at point $\hat{m}(i + 1)$ can be presented as [3, 4, 14-15]:

$$Q(\hat{m}(i + 1)) = (\hat{m}(i + 1) - \hat{m}(i))^2.$$  

(19)

After transformations, the recurrent pseudo-gradient algorithm (PGA) for estimating the current value of the mathematical expectation of the RV, taking into account the signs, is

$$\hat{m}(i + 1) = \hat{m}(i) + \lambda_m(i + 1)(\hat{m}(i + 1) - \hat{m}(i)).$$  

(20)

In order to reduce the average relative error in estimating the mathematical expectation of traffic intensity in the CMCN, it is proposed to develop a corrective procedure (20) based on the average value of previous estimates [3]:

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

(21)

where $N_2 - \text{size of the second sliding window in which the estimates of the mathematical expectation}$

of the traffic intensity are averaged, $\hat{m}(i) - \text{average value of the estimates in this sliding window}$. Then expression (20) takes the form [3]:

$$\hat{m}(i + 1) = \hat{m}(i) + \lambda_m(i + 1)(\hat{m}(i + 1) - \hat{m}(i)).$$

(22)

In reduced form (22) can be written as:

$$\hat{m}(i + 1) = \hat{m}(i) + \lambda_m(i + 1)(\hat{m}(i + 1) - m(i)).$$

(23)

A similar approach is applied for all components of the vector $\nabla Q(\xi, \hat{m}(i))$. The generalization of the recurrent procedure (23) is the vector PGA

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

(24)

where $\hat{g}(i + 1) - \text{vector of estimates of CMCN traffic parameters at the step } i + 1$ [3]:

$$\hat{g}(i + 1) = [\hat{m}(i + 1), \hat{g}(i + 1), \hat{R}(i + 1)]^T.$$  

(25)

Matrix $R(i + 1)$ is the diagonal matrix.

The algorithm structure does not depend on properties and characteristics of RS $x(i)$. This property

of the PGA is a consequence of the central limit theorem. This is a consequence of any probabilistic

characteristics of the network traffic intensity, the structure of the estimation algorithm is constant, and

only its parameters can change.

For estimating the parameters of non-stationary RSs, condition (17) restricts the use of the PGA, since the PGA must track changes in the traffic parameters rather than converge to their certain values [3, 4, 14]. Therefore, the sequence $R(i)$ is limited by constant values. As a consequence of the choice

of the limited step coefficient, the variance of estimation of the RV parameters will also be limited. Therefore, it is necessary to find a compromise between speed and accuracy of RV intensity estimation [7, 14-15].

It is proposed to take into account the dynamics of changes in the estimated parameters and

characteristics of SP when choosing the vector of step coefficients. It follows from expression (24) that

the gradient moduli of the components of the quality vector functional are proportional to the dynamic
properties of RV. Such dependences are difficult to formalize. It is proposed to automate the procedure for adjusting the PGA step coefficients based on the Takagi Sugeno fuzzy inference method in the form [9-10]:

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\[
\begin{align*}
\text{IF } & \langle \hat{m}(i) \in D1 > I < \nabla Q(i) \in D2 > I < \hat{\sigma}^2(i) \in D3 > \\
\text{TOR}(i + 1) = R(k)IN_1 = N_1(k)IN_2 = N_2(k),
\end{align*}
\]

where \(D1, D2, D3\) – the range of current values of the mathematical expectation of the RS, the estimation of gradient components in procedure (23) and the estimation of variance of the RV, \(N_1\) and \(N_2\) – sizes of the corresponding sliding windows in expressions (13) and (22).

To implement these rules, the system of fuzzy inference is preliminarily trained on the basis of experimental data obtained at the design stage, on test JVs with known statistical parameters [3, 4, 9].

The structure of the traffic characteristics assessment algorithm is shown in Figure 1.

Figure 1. The structure of the traffic estimation algorithm

Training is conducted at the design stage. During the operation phase, minor adjustments of fuzzy rule bases and fuzzy knowledge bases are possible.
4. Results of mathematical modeling

Mathematical modeling of the effectiveness of the algorithm for estimating the traffic intensity was carried out for traffic with a normal distribution. The modulating function for modeling non-stationary RVs was chosen by the first-order autoregressive RV (AR-1) \([3, 4]\). The RV and current observations model is as follows:

\[
\begin{align*}
    u(n) &= \rho \cdot u(n-1) + \sigma_x \sqrt{1 - \rho^2} \cdot \xi(n+1); \\
    m(n) &= u(n) + m_x; \\
    y(n) &= x(n) + \theta(n),
\end{align*}
\]

where: \(\rho\) – correlation coefficient AR-1; \(\sigma_x\) – standard deviation (SD) AR-1; \(\xi(n+1)\) - value of the independent random variable at \(n+1\), having distribution \(N(0; 1)\); \(\sigma_x = \sigma \xi / \sqrt{1 - \rho^2}\); \(\rho\) – value of the correlation coefficient of the RV AR-1; \(R_x(k) = \rho^{|k|} = e^{-\alpha |k|}\), where \(\alpha = -\ln \rho; \theta(n)\) – uncorrelated Gaussian RV with zero mean and constant variance \(\sigma^2\); \(m_x\) – value of the constant component of the RV. According to the current values of observations \(y(n)\) it is necessary to build \(\hat{m}(n)\).

In the first numerical experiment, the dynamic properties of the adaptive algorithm were compared with the dynamic properties of the OFC [3, 4]. The criterion was the average relative error in assessing the mathematical expectation of the RS. Figure 2 shows the results obtained using the OFC [10-11]. In this experiment, the mean value of the mathematical expectation changed from race 500 to 1000.

![Figure 2](image)

**Figure 2.** The results of evaluating the mathematical expectation of the network traffic intensity by the Coleman algorithm

SD values are equal \(\sigma_x=100\) and \(\sigma_\theta=100\) respectively. The transient process of the algorithm was about \(100 - 130\) samples, the value of the average relative error was \(\delta = 0.89\%\).

Figure 3 shows the results of estimating \(\hat{m}(n)\) of the RS, obtained using algorithm (22), (26). The statistical parameters of the model were similar to those selected in the first numerical experiment. In this numerical experiment, the transient process of the algorithm was about \(120 - 140\) samples. The value of the average relative error was \(\delta = 1.01\%\). Thus, the obtained value of the loss in \(\hat{m}(n)\) of the algorithm and OFC proves its high dynamic and accuracy characteristics.
Figure 3. Results of estimating the mathematical expectation of the network traffic intensity by algorithm (22), (26).

Figure 4 shows the dependencies $\delta\% = f\left(\frac{\sigma_x^2}{\sigma_\theta^2}\right)$ at constant $\rho = 0.99999$ for the OFK and algorithm (22), (26) for various values of the constant component RS $m_x$.

Figure 4. Dependencies $\delta\% = f\left(\frac{\sigma_x^2}{\sigma_\theta^2}\right)$ at constant $\rho = 0.99999$, for $m_x=1000$ (curves 1 and 2) and $m_x=400$ (curves 3 and 4); curves 1 and 3 – OFK; curves 2 and 4 - adaptive algorithm.

Curves 1 and 3 correspond to the estimates of the average relative error obtained using the OFC, and dependences 2 and 4 - using algorithm (22), (26).

In this experiment, the loss of the mean relative error of algorithm (22), (26) to the optimal Coleman filter was no more than 0.2%, which is a quite acceptable result for its practical application.

Figure 5 shows the dependences $\delta\% = \phi (\rho)$, for different values of the ratio $\frac{\sigma_x^2}{\sigma_\theta^2}$. Curves 1 and 3 correspond to the value of this ratio equal to 100, and curves 2 and 4 - equal to 1.
In this numerical experiment, the loss of algorithm (22), (26) to the optimal Coleman filter was less than 1.83% by the average relative estimation error.

5. Conclusion
The obtained comparative accuracy and dynamic characteristics of the algorithm in comparison with the OFC allows us to assert that its application provides estimates of CMCN traffic parameters with an accuracy sufficient for making objective decisions on communication services quality management.

The use of LFC and EFC requires significant additional efforts in the a priori identification of traffic parameters and construction of an adequate mathematical model, which cannot be realized with the required quality.

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