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Batch Quasi-Poisson Models in the Queue Analysis of Packet Telecommunication Traffic

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Abstract—A new type of input flow for queuing systems, a relative of a batch Poisson process, is proposed. As shown below, this flow is a more adequate model of modern traffic than a batch Poisson process when determining the dependence of the mean queue length in a receiving buffer on the load of an outgoing data transmission channel (using H.264 video traffic as an illustrative example). An analytical formula for the mean queue length in a G/D/1 queuing system with such an input flow is derived; therefore, the model's parameters can be estimated to approximate the mean queue length of real traffic using the least squares method. The feasibility of determining the model parameters using a neural network is also demonstrated.

Keywords: non-ordinary input flow, queuing system, telecommunication traffic, simulation modeling, neural network

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1. INTRODUCTION

In the analysis and modeling of telecommunication network traffic, a common problem is to determine the characteristics of the queue created by this traffic in the receiving buffer of a network node. In this case, the coincidence of the statistical characteristics of the model traffic with its real prototype is not as important as the coincidence of the statistical characteristics of the corresponding queues.

For packet-switched data transmission networks, classical Poisson flow models are not adequate. At the same time, the description of complex correlated flows using self-similar processes, which has attracted much attention from the scientific community in the last two decades, allows reflecting the complex correlation properties of the traffic itself, but is inconvenient for analyzing queue characteristics.

A well-proven alternative to this approach is the class of flows governed by a Markov chain and similar models. The development stages of these models were presented in the review [1]. From versatile flows, through Neuts flows (N-flows) [2], they have evolved to Markov Arrival Processes (MAPs) and their generalization known as Batch Markov Arrival Processes (BMAPs); for example, see [3–5].

In this paper, the batch Poisson flow model, which can be considered a relative of BMAP, is generalized to a batch quasi-Poisson flow in which the dependence of the mean queue length in the receiving buffer on the server load, obtained in a simulation experiment, well approximates this dependence for H.264 video traffic.

To determine the parameters of the proposed model, we apply an extension of the Pollaczek–Khinchin formula for a G/D/1 queuing system, obtained by the interval method [6]. For the quasi-Poisson flow proposed, this formula is used to derive a semi-empirical formula for the dependence of the mean queue length in the G/D/1 queuing system on the server load that agrees well with the simulation results.

The feasibility of determining the model parameters using a neural network is also demonstrated.

2. PROBLEM STATEMENT AND BRIEF DESCRIPTION OF PREVIOUS RESULTS

Let us present the previous results that will be utilized below.

Consider a Poisson flow of events with a parameter λ in which each event represents the simultaneous arrival of several requests for service (request packets). The numbers of requests in different packets are independent identically distributed discrete random variables. Such a flow is called a *batch* (*non-ordinary*) *Poisson flow* [7]. It obviously possesses the properties of stationarity and no aftereffect, but does not possess the property of ordinariness.

We denote by B_k the size of the kth request packet. Assume that its distribution is given:

$$Pr\{B_k = n\} = b_n \ \forall k.$$

Consider a random interval of length τ on the time axis. It is required to determine the moments of the random variable $m(\tau)$ that represents the number of requests of the batch Poisson flow arriving in such an interval. To solve this problem, we find the generating function of the random variable $m(\tau)$. If the generating function of the number of requests in a packet is $G_B(z) = \sum_{n=0}^{\infty} b_n z^n$, then for the generating function $G_{m(\tau)}(z)$ we have

$$G_{m(\tau)}(z) = \sum_{k=0}^{\infty} e^{-\lambda\tau} \frac{(\lambda\tau)^k}{k!} \left(G_B(z)\right)^k = e^{\lambda\tau(G_B(z)-1)}.$$

(For details, see [8].) Therefore, the mean and variance of $m(\tau)$ are given by

$$M(m(\tau)) = \lambda\tau\overline{B}, \quad D(m(\tau)) = \lambda\tau\overline{B^2}.$$

In the case of a constant size B of all packets (it will be needed below), we obtain

$$M(m(\tau)) = \lambda\tau B, \quad D(m(\tau)) = \lambda\tau B^2.$$

Let this batch Poisson flow be the input of a G/D/1 queuing system with a service time τ_S of one request. In such a system, the moments of the queue length (in principle, of any order) can be found by the interval method. (The formulas for the first and second moments were derived in [8]; a generalization to the case where the service time of one request in the queuing system is a discrete random variable with a finite number of values was presented in [9].) Here, we need only the expression for the mean under a deterministic service time of one request, which is provided by the generalized Pollaczek–Khinchin formula

$$\overline{Q}(\rho) = \frac{D(m(\tau_S)) + 2R\left(Q_i, m_{i+1}(\tau_S)\right)}{2(1-\rho)} - \frac{\rho}{2} \tag{1}$$

with the following notation: ρ is the server load; $D(m(\tau_S))$ is the variance of the number of requests arriving during the service time of one request; finally, $R\left(Q_i, m_{i+1}(\tau_S)\right)$ is the correlation moment between the queue length at the time of completing the service of a certain request and the number of requests arriving during the next service interval (all values are taken for a given ρ).

In the general case, this formula is difficult to use due to the need to compute $R\left(Q_i, m_{i+1}(\tau_S)\right)$, but for some important special cases it is possible. In particular, for the batch Poisson flow $R\left(Q_i, m_{i+1}(\tau_S)\right) = 0$, due to no aftereffect and the relations

$$M(m(\tau_S)) = \lambda\tau_S B = \rho, \quad D(m(\tau_S)) = \lambda\tau_S B^2 = \rho B$$

for packets of constant size, we obtain

$$\overline{Q}(\rho) = \frac{\rho B}{2(1-\rho)} - \frac{\rho}{2} = \frac{\rho B - \rho(1-\rho)}{2(1-\rho)}. \tag{2}$$

It is easy to see that for $B = 1$, the classical Pollaczek–Khinchin formula for an M/D/1 queuing system arises here.

In [10], the batch Poisson flow was used to approximate the first two statistical moments of the queue length of H.264 video traffic by the least squares method and showed better results than the ordinary Poisson flow. However, this approximation (obtained by the least squares method relative to the packet size as a model parameter) still cannot be considered sufficiently good. Therefore, in this paper, we present a new flow model that will be used for the same purpose.

Consider the following request flow: requests arrive in packets, and the numbers of requests in different packets are independent identically distributed discrete random variables B_k. The intervals between the arrivals of sequential packets are equal to the sum of a certain constant value T and an independent exponentially distributed random variable with a parameter λ. We will call such a flow a *quasi-Poisson flow with identical pauses of duration* T (for brevity, simply a *quasi-Poisson flow*).

The problem is to use this flow as the input of a G/D/1 queuing system to approximate the mean queue length created by real traffic (as mentioned above, H.264 video traffic).

Since we are interested in the dependence of the mean queue length on the server load, and the time scale is not important, the quasi-Poisson flow will be characterized by two parameters: B (the constant packet size) and $\alpha = T\lambda$ (the ratio of the pause between arrivals, i.e., the constant part of the inter-arrival interval, to the mean length of the exponentially distributed part of this interval). These parameters are chosen by minimizing, under the same server load, the difference between the mean queue lengths of the real traffic and the quasi-Poisson flow.

An exact solution of this problem has not been obtained; but in the next section, we present an approximate formula for the mean queue length of such a flow.

3. APPROXIMATION FOR THE MEAN QUEUE LENGTH OF THE QUASI-POISSON FLOW

First of all, note the following empirically established property of a quasi-Poisson flow: for any finite α and constant packet size B, the sample variance of the number of requests arriving in a random interval τ is close to the sample variance of a batch Poisson flow with the same B provided that they create the same server load ρ in a G/D/1 queuing system.

This property was established using a software simulation model of the flows, which was also engaged in other simulation experiments of the work. The model generated a sequence of arrival times for request packets according to the definition of the corresponding flow. In other experiments (see below), that flow of request packets was the input for the simulation model of a G/D/1 queuing system. In the former experiment, for an available flow, it was necessary to determine a constant service time of one request such that the server load would have a given value. (Values from the range [0.1, 0.9], most interesting in practice, were selected.)

In the experiments where the above closeness of sample variances for batch Poisson and quasi-Poisson flows was observed, $\tau = \tau_S$ was taken. In other words, the interval to determine the number of arriving requests was set equal to the service time of one request in the G/D/1 queuing system for a given ρ. These intervals densely covered the entire time axis, and the sample variance $\hat{D}(\rho)$ was computed from the obtained sample of the number of requests arriving in them using the formula

$$\hat{D}(\rho) = \frac{1}{N}\sum_{n=1}^{N} \hat{m}_n^2(\tau_S) - \left(\frac{1}{N}\sum_{n=1}^{N} \hat{m}_n(\tau_S)\right)^2,$$

where the sample element $\hat{m}_n(\tau_S)$, $n = 1, \ldots, N$, is the number of requests arriving in the nth interval τ_S during the simulation run.

As an example, Table provides the sample variances of the number of requests arriving during the service time of one request for batch Poisson and batch quasi-Poisson flows with different α, obtained through simulation modeling.

The sample variances of arrivals for various batch flows. In all cases, $B = 20$

Load	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Poisson	2.00	4.00	6.00	8.00	10.03	12.05	14.05	16.06	17.96
Quasi-Poisson, $\alpha = 0.5$	1.99	3.97	5.91	7.84	9.75	11.64	13.51	15.36	17.19
Quasi-Poisson, $\alpha = 1$	1.99	3.96	5.91	7.84	9.74	11.63	13.50	15.35	17.18
Quasi-Poisson, $\alpha = 2$	1.99	3.96	5.91	7.84	9.749	11.64	13.51	15.36	17.19

The observed closeness can be explained by the following (non-rigorous) reasoning: by the definition of the quasi-Poisson flow, the interval between sequential packet arrivals always exceeds the pause T, and if T is subtracted from each of these intervals, the remainders will be independent exponentially distributed variables. That is, the flow with these remainders as the inter-arrival intervals will be a batch Poisson flow. Let us call it the *embedded flow*. Thus, the original quasi-Poisson flow is obtained from the embedded one by inserting a *pause* (an interval of constant length T during which no requests arrive) after the arrival of each packet.

On any sufficiently large time interval, the embedded Poisson flow will occupy only the $(1/(1+\alpha))$th part of this interval on average, and the rest will be occupied by pauses. Therefore, for the embedded flow to create the same server load over the entire interval as the batch Poisson flow with the same packet size, the rate of packet arrivals in the embedded flow must be proportionally higher.

For a Poisson flow, increasing the rate also means increasing the variance of the number of arriving packets over a certain time interval by the same factor. As the experiment showed, alternating the realization segments of the embedded flow with pause intervals introduces no significant changes in the sample variance.

Based on the closeness of the values of these sample variances, we will consider the theoretical variances of the number of requests arriving during the service interval of one request in the G/D/1 queuing system to be equal for Poisson and quasi-Poisson flows creating the same server load.

Next, let us estimate the mean queue length from the quasi-Poisson flow in the G/D/1 queuing system under low server loads. What is meant by *low load*? Each packet in the quasi-Poisson flow arrives before the start of a pause interval of length T, and the server (if free) begins to serve it in this interval. A load ρ is low if, under it, the service of the packet completely ends within this interval:

$$B\,\tau_S \leqslant T, \tag{3}$$

where τ_S denotes the service time of one request from the packet. The boundary of the interval for low ρ, denoted by ρ_0, can be calculated as follows: by the definition of a quasi-Poisson flow, B requests arrive on average during the time $T + 1/\lambda$ (i.e., one request per $(T + 1/\lambda)/B$ units of time). Under a server load ρ, the service time of one request should accordingly be

$$\tau_S = \rho\,\frac{T + 1/\lambda}{B}. \tag{4}$$

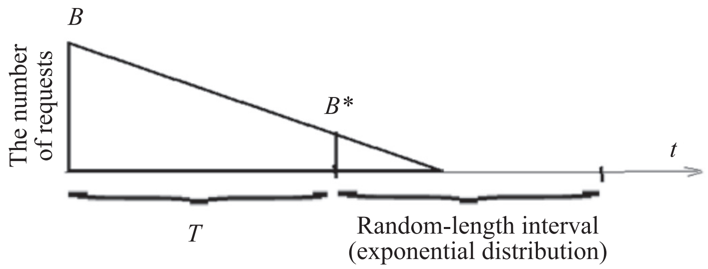

Fig. 1. Change in the number of arrived packet requests during a pause in the system with high load.

In view of (3), we obtain

$$\rho_0 = \frac{T}{T + 1/\lambda} = \frac{\alpha}{\alpha + 1}. \tag{5}$$

Clearly, under low loads, the situation is very similar to the case of a batch deterministic flow (where packets always arrive at equal intervals). Therefore, the generalized Pollaczek–Khinchin formula can be applied to this situation, as to the deterministic flow. (This is another special case where it can be easily done.) Here, we utilize the following consideration:

$$R\left(Q_i, m_{i+1}(\tau_S)\right) = M\left(Q_i\, m_{i+1}(\tau_S)\right) - M\left(Q_i\right)\ M(m_{i+1}(\tau_S)),$$

but Q_i is nonzero only during the pause interval, in which $m_{i+1}(\tau) = 0$, i.e.,

$$R\left(Q_i, m_{i+1}(\tau_S)\right) = -M\left(Q_i\right)\ M(m_{i+1}(\tau_S)) = -\,\overline{Q}(\rho)\ \rho.$$

Substituting this relation into (1) yields

$$\overline{Q}(\rho) = \frac{D(m(\tau)) - 2\overline{Q}(\rho)\rho}{2(1-\rho)} - \frac{\rho}{2}$$

and, after straightforward transformations,

$$\overline{Q}(\rho) = \frac{\rho B - \rho(1-\rho)}{2}. \tag{6}$$

Note that for large B, the dependence of $\overline{Q}$ on ρ is close to linear.

Now consider an approximate estimate of the queue length under high loads ($\rho > \rho_0$).

In this case, $B\tau_S > T$, and at the start of the exponentially distributed part of the inter-arrival interval, the number of packet requests still remaining in the system can be estimated as

$$B^*(\rho) = \left\lceil \frac{B\tau_S - T}{\tau} \right\rceil = \left\lceil B - \frac{T}{\tau_S} \right\rceil = \left\lceil B\left(1 - \frac{\rho_0}{\rho}\right) \right\rceil, \tag{7}$$

where formulas (4) and (5) have been used and the brackets $\lceil \ldots \rceil$ stand for the ceiling of an appropriate number (the smallest integer greater than or equal to this number). For illustration, Fig. 1 shows the dependence of the number of packet requests remaining in the system during the corresponding pause at the start of which this packet has arrived. For a request being served, its currently uncompleted part is taken into account.

In other words, at the end of the pause, the size of the unserved packet will be less than the initial one and will depend on ρ. By removing all pauses from the quasi-Poisson flow ("gluing" the exponentially distributed intervals), we get a batch Poisson flow with the packet size B^*. For estimation, assume that the queue formed by such a Poisson flow will be added to the queue from (6). This additional queue can be found using formula (2), but with ρ replaced by

$$\rho^* = \frac{\rho - \rho_0}{1 - \rho_0}. \tag{8}$$

Indeed, this special batch Poisson flow appears only if $\rho > \rho_0$; for $\rho = 1$, the equality $\rho^* = 1$ must hold for the queue to go to infinity.

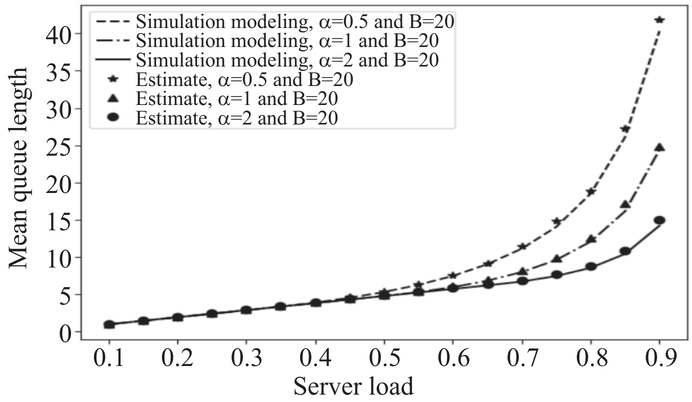

Fig. 2. Comparison of the dependence of the mean queue length on the server load: the simulation experiment vs. formula (9). For all flows, $B = 20$.

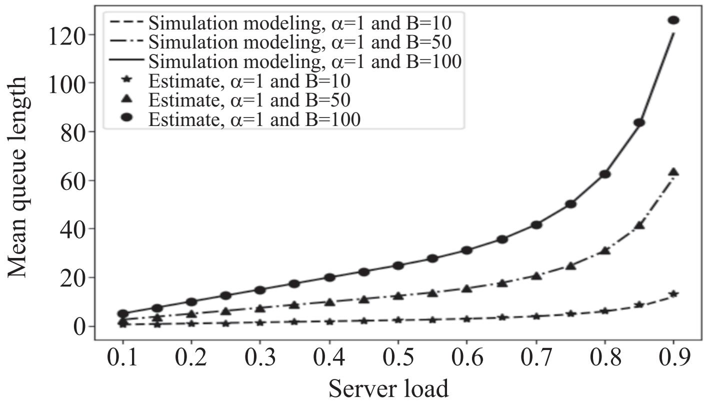

Fig. 3. Comparison of the dependence of the mean queue length on the server load: the simulation experiment vs. formula (9). For all flows, $\alpha = 1$.

In the queue expression, it is also necessary to correct the term related to the segment of the pause T, i.e., the one similar to the expression (6). Now the "tail" of the packet of size B is served beyond the interval T and is accounted for in the expression for the Poisson part of the queue. Therefore, it must be excluded from (6). Since the mean queue length is proportional to the area of the figure in Fig. 1, the correction factor can be found as the ratio of the areas of the trapezoid with bases B and B^* and the triangle with leg B :

$$\frac{S^*}{S} = \frac{\tau(B^2 - (B^*)^2)}{\tau B^2} = 1 - \frac{(B^*)^2}{B^2} \approx 1 - \left(1 - \frac{\rho_0}{\rho}\right)^2 = \left(2 - \frac{\rho_0}{\rho}\right)\frac{\rho_0}{\rho}.$$

Thus, we arrive at the following formula for the queue length:

$$\overline{Q}(\rho) = \begin{cases} \dfrac{\rho B - \rho(1-\rho)}{2}, & \rho \leqslant \rho_0, \\ \dfrac{\rho_0}{\rho}\left(2 - \dfrac{\rho_0}{\rho}\right)\left(\dfrac{\rho B - \rho(1-\rho)}{2}\right) + \dfrac{\rho^* B^* - \rho^*(1-\rho^*)}{2(1-\rho^*)}, & \rho > \rho_0, \end{cases} \tag{9}$$

where B^* and ρ^* are given by (7) and (8), respectively.

Finally, we compare the mean queue length calculated by formula (9) with the results of a simulation experiment on the passage of a quasi-Poisson flow through the G/D/1 queuing system, see Figs. 2 and 3. Here, examples are given for different values of the quasi-Poisson flow parameters: the lines correspond to the simulation results and various markers to the estimates (9). The approximation turns out to be good.

4. APPROXIMATION OF A REAL VIDEO TRAFFIC QUEUE

For experiments, we take traces of H.264 video traffic under different values of the video buffer size used for compressing video frames. In this case, a trace is a sequence of times when information packets exit the video codec, and each such time is considered to be the arrival of a service request in a G/D/1 queuing system. The service time of one request is taken so that the server load ρ under this input flow equals a given value. During the passage of this flow through the queuing system, the empirical time-averaged queue length for a given ρ is calculated.

For each trace of the real traffic, the mean queue lengths were calculated thereby for several values of the server load ρ, denoted by $\hat{Q}(\rho_i),\ i = 1, \dots, N$. They were used to estimate, by the least squares method, the parameters of the quasi-Poisson flow for which the dependence of the mean queue length in the G/D/1 queuing system on ρ approximates the dependence of the mean queue length of the real traffic on ρ found in the above simulation experiment.

The estimates $\hat{\alpha}$ and $\hat{B}$ of the parameters α and B of the approximating quasi-Poisson flow were found as

$$\hat{\alpha}, \hat{B} = \arg\min_{\alpha, B} \sum_{i=1}^{N} \left(\hat{Q}(\rho_i) - \overline{Q}(\rho_i)\right)^2,$$

where $\overline{Q}(\rho_i)$ was calculated by formula (9).

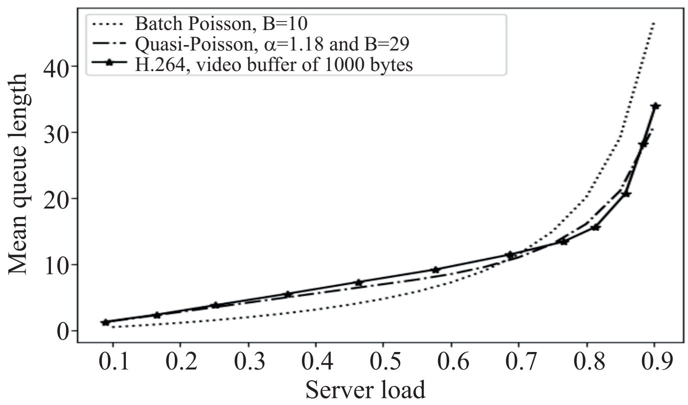

Fig. 4. Approximation of the dependence of the mean queue length on the server load for H.264 video traffic. Video buffer size is 1000 bytes.

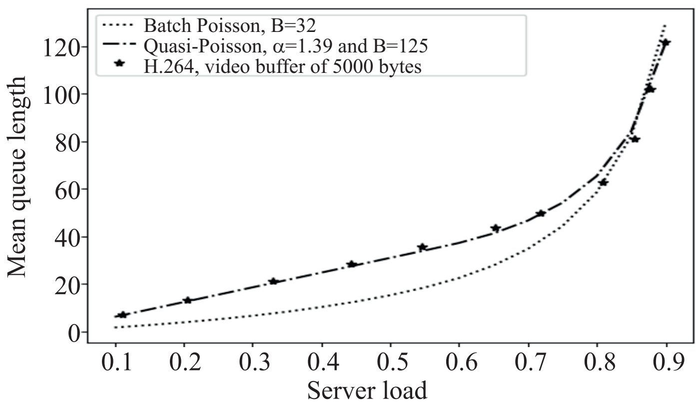

Fig. 5. Approximation of the dependence of the mean queue length on the server load for H.264 video traffic. Video buffer size is 5000 bytes.

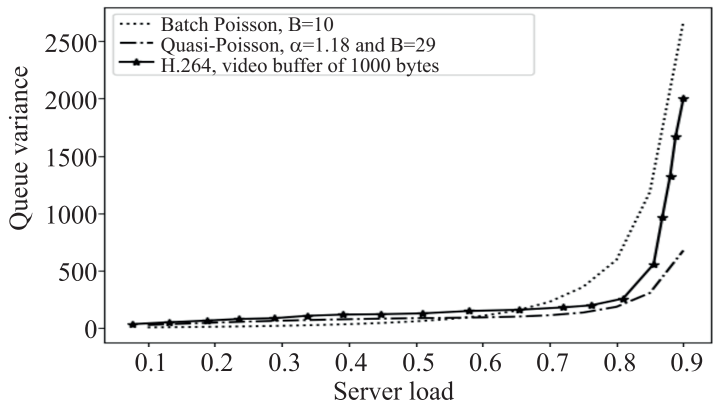

Fig. 6. Approximation of the dependence of the queue variance on the server load for H.264 video traffic. Video buffer size is 1000 bytes.

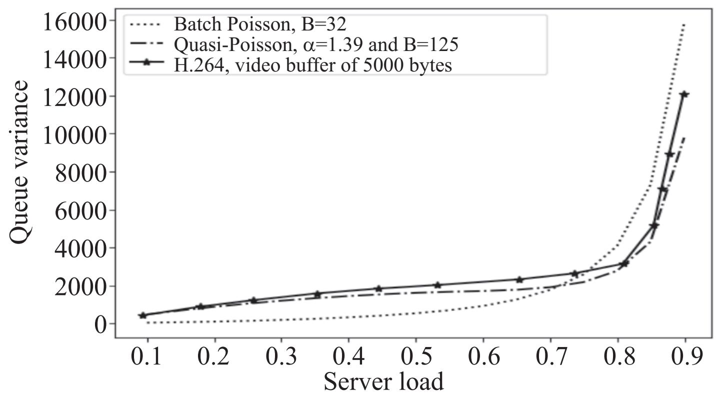

Fig. 7. Approximation of the dependence of the queue variance on the server load for H.264 video traffic. Video buffer size is 5000 bytes.

Figures 4 and 5 show the results, including a similar approximation by a batch Poisson flow for comparison; its packet size was also found by the least squares method. (The real traffic is indicated by the solid line, its quasi-Poisson flow approximation by the dashed line with markers, and its Poisson flow approximation by the dotted line.) Obviously, the quasi-Poisson flow provides a significantly more accurate approximation of the mean queue length of this real traffic.

For a complete picture, it is interesting to see the quality of approximation for the variances of the queue lengths of the real traffic. They are demonstrated in Figs. 6 and 7. Although the difference between the real traffic and the approximating model traffic is greater than for the mean queue length, the quasi-Poisson flow approximation is still good and much better than the batch Poisson flow counterpart.

Note that from a practical viewpoint, the closeness of the first two moments of the distributions of two random variables allows speaking of a considerable closeness of their distributions as well. Therefore, the estimates presented above have practical value.

5. ESTIMATION OF THE PARAMETERS OF THE APPROXIMATING MODEL USING A NEURAL NETWORK

Above, we have derived a good approximating formula for the mean queue length. Here, let us present another way to estimate the traffic model parameters, suitable for the case of no approximating formula. It consists in training a neural network to determine the parameters of the quasi-Poisson flow.

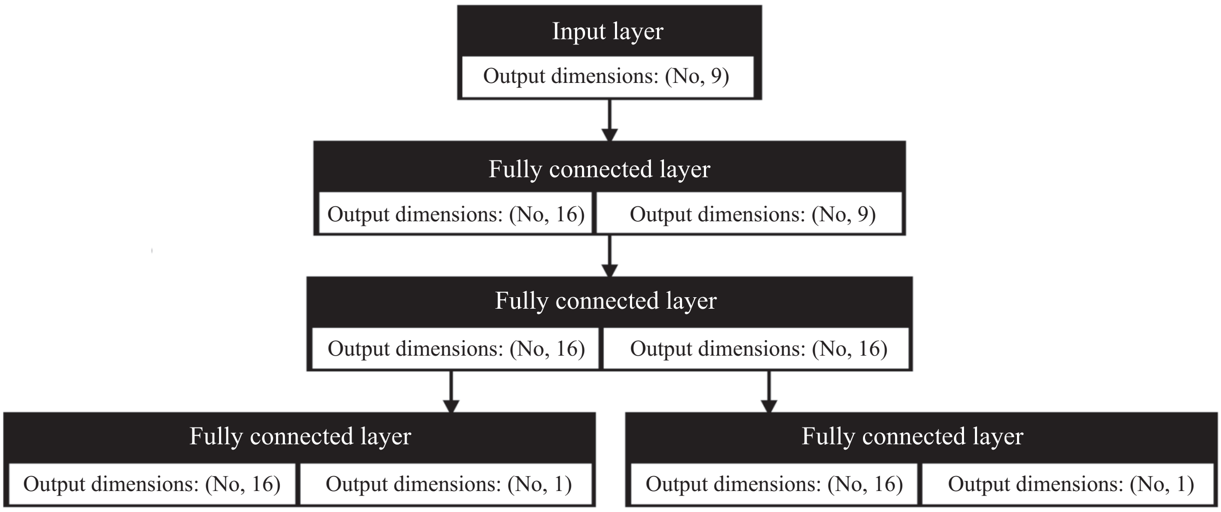

Fig. 8. The neural network architecture (the standard graphical representation in the Keras package of the Python language).

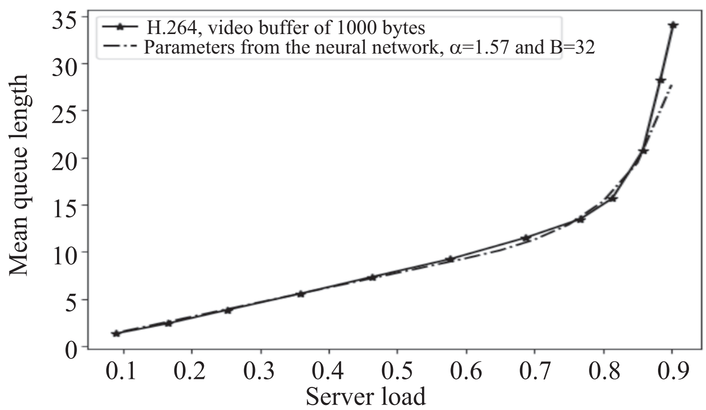

Fig. 9. Approximation of the dependence of the mean queue length on the server load for H.264 video traffic when determining the parameters using a neural network. Video buffer size is 1000 bytes.

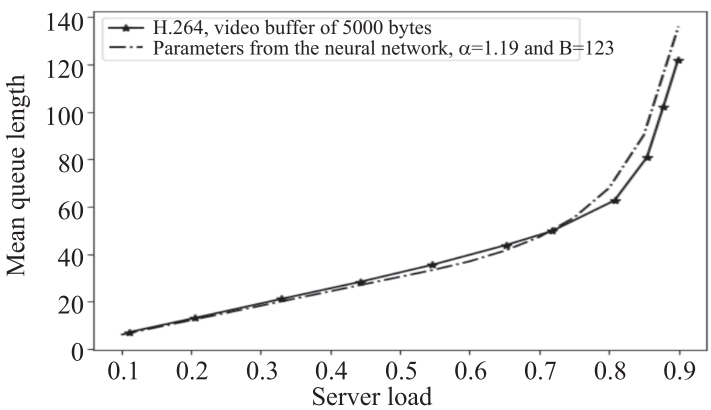

Fig. 10. Approximation of the dependence of the mean queue length on the server load for H.264 video traffic when determining the parameters using a neural network. Video buffer size is 5000 bytes.

The input data for the neural network are a set of mean queue lengths for given server loads. In this work, nine values corresponding to loads from 0.1 to 0.9 with a step of 0.1 were used. There are two output values, namely, the values of the parameters α and B. After supervised training of the neural network, the set of mean queue lengths obtained during the passage of the real traffic through the queuing system under the same loads is supplied as the input parameters for recognition. The output of the neural network is an estimate of the parameters of the quasi-Poisson flow for approximating the real traffic.

Figure 8 shows the architecture of the neural network used. Two neurons, each representing an output layer to estimate one parameter of the quasi-Poisson flow, have no nonlinear element; the others have ReLU. All layers are fully connected.

The training set consisted of 2000 examples, but with a particular sample for each real trace; training examples were generated with parameters from a small range containing the desired estimate. (The graph of the mean queue length of the real traffic lay between the graphs for the boundary values of the parameters of the examples from the training set.)

Figures 9 and 10 demonstrate the results of the experiment: the parameters predicted by the neural network were used for simulation, and the graphs show the mean queue length for both the real and simulated traffic (the solid line and the dashed line with markers, respectively). Clearly, the estimate is also quite good.

6. CONCLUSIONS

This paper has presented a quasi-Poisson flow with identical pauses as a model for approximating the mean queue length of real traffic using the H.264 video traffic as an example.

The analytical formula for estimating the mean queue length, derived in the paper, provides a good approximation to the results of simulation modeling.

The parameters of the flow for approximating the mean queue length of real traffic, obtained using this formula, provide an approximation that is significantly more accurate than the batch Poisson flow approximation.

The feasibility of determining the flow parameters for solving the approximation problem using a neural network has been demonstrated, also giving good results.

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