A New CAC Method Using Queuing Theory

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Abstract. *The CAC (Connection Admission Control) method plays an important role in the ATM (Asynchronous Transfer Mode) network environment. The CAC is the first step in the prevention of congested states in the network topology, and conducts to the optimal network resources utilization.*

The paper is aimed to propose an enhancement for a convolution method that is one of the statistical CAC methods used in ATM. The convolution method uses a buffer-less assumption in the estimation of the cell loss. Using formulas for the G/M/1 queuing system, the cell loss can be estimated as the buffer overflow probability.

In this paper, the proposed CAC method is compared with other three statistical CAC methods, and conclusions regarding the exploitation of the CAC method are presented.

Keywords

Connection Admission Control (CAC), Asynchronous Transfer Mode (ATM), convolution method.

1. Introduction

In recent years, a huge amount of various CAC methods was deployed. The connection admission is used to determine whether the connection can be admitted into the network with respect to the desired quality of service (QoS) without violating the existing QoS guarantees other connections. The proposition and the field of the exploitation for the CAC method belong to the most important tasks for many researches. The CAC method design consists of the description of two processes, and their mutual interconnection: a traffic process and an ATM node switching and a queuing process. There is much knowledge about the traffic process, but in most cases, the interconnection between the traffic and ATM node models is a very complicated matter. Moreover, the CAC method should be simple and easy to implement because of the real time employment.

The convolution method, the diffusion approximation method and the effective bandwidth method are widely used statistical CAC methods. The convolution method uses a buffer-less assumption, and calculates the cell loss as the output link capacity overflow. Traffic sources are described with a multi-state bandwidth model. This model represents the probability distribution of an aggregated cell rate. Remaining two methods use the stationary approach assuming that the aggregated bandwidth is Gaussian in order to obtain its mean and variance. This is only true if the sufficiently large number of connections is multiplexed together. On the other hand, they use the conventional approach that the cell loss is given by the buffer overflow probability (except of the buffer less Gaussian approach used in the case of the effective bandwidth method for the small buffer size).

The presented research was aimed to enhance the convolution method. Since the buffer size is a weighty system parameter influencing the cell loss, it is desirable to replace the buffer-less assumption with a more precise approach. Exploiting knowledge from the queuing theory for a G/M/1 system, we are able to enhance the convolution method in the matter of the cell loss estimation as the buffer overflow probability instead the buffer-less assumption.

Our efforts can be summarized into the following points:

- The design and the mathematical definition of the enhanced convolution method.
- The methodology of the mutual comparison of selected CAC methods, the designation of the exploitation for the enhanced convolution method in a network environment.

2. Convolution Method: Implementation Issues

In ATM, the rate is stated in specific units, namely in ATM cells per second (cells.s^{-1}). The bit rate can be easily converted into the cell rate and vice-versa:

$$R_{cell} = \left\lceil \frac{R_{bit}}{48 \cdot 8} \right\rceil . \quad (1)$$

Here, R_{cell} is the cell rate (cells.s^{-1}) and R_{bit} is the bit rate (bits.s^{-1}). For computing simplicity, insertions from upper layers regime are ignored.

The traffic process generated by a given source can be described by the discrete probability distribution:

$$(\lambda_1, a_1); (\lambda_2, a_2); (\lambda_3, a_3); \ldots ; (\lambda_k, a_k) \tag{2}$$

where

$$0 \le a_i \le 1 \text{ and } \sum_{i=1}^{k} a_i = 1 \ .$$

In (2), a_i is the probability, that the source is transmitting at the normalized rate λ_i (cells.s^{-1}). This approach is useful, if there are no specific assumptions about the probability distribution (Gaussian, Poisson, Pareto, etc.). In the case that the connection is characterized by the peak cell rate (PCR) and the sustainable cell rate (SCR) [9], we can use:

$$(0, a_1); (PCR, a_2) \tag{3}$$

where

$$a_1 = 1 - \frac{SCR}{PCR} \text{ and } a_2 = \frac{SCR}{PCR} \ .$$

The connection aggregation and the removal is done by the discrete convolution process. Since the convolution is very time consuming, possible states in the aggregated process have to be merged or quantized. This is the way of making the CAC algorithm tunable and determining the relation between the accuracy and the processing power. Inspiring examples and the convolution algorithm could be found in [4], [5].

3. Model with General Arrival and Exponential Service Times

In this section, the arrival-point steady-state system-size probabilities for G/M/1 are analyzed and derived. We assume a queuing situation where service times are exponential and no specific assumption is made concerning the arrival pattern other that successive inter-arrival times are independent and identically distributed (IID) [3]. We focus only on main ideas and formulas cited from [3], for more detailed derivation see [3].

First, we examine a single server with the mean service rate μ and the exponential service times. The mean arrival rate is λ and arrivals come singly, and the successive inter-arrival times are IID. The cumulative distribution function (CDF) is denoted by $A(t)$, and the density function by $a(t)$.

For the probability b_n that there are n services during an inter-arrival time, we introduce the following simplifying notation:

$$b_n = \int_0^\infty \frac{e^{-\mu t}(\mu t)^n}{n!} dA(t) \tag{4}$$

so that we can obtain the imbedded, single-step transition probability matrix:

$$\mathbf{P} = \{p_{ij}\} = \begin{pmatrix} 1-b_0 & b_0 & 0 & 0 & 0 & \cdots \\ 1-\sum_{k=0}^{1} b_k & b_1 & b_0 & 0 & 0 & \cdots \\ 1-\sum_{k=0}^{2} b_k & b_2 & b_1 & b_0 & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix} \tag{5}$$

where p_{ij} is the probability that the system size after a departure is j and the system size after the previous departure was i.

Assuming that the steady-state solution exists and denoting the probability vector that an arrival finds n in the system by $\mathbf{q} = \{q_n\}$, $n = 0, 1, 2, \ldots$, we have the usual stationary equations:

$$\mathbf{qP} = \mathbf{q} \quad \text{and} \quad \mathbf{qe} = \mathbf{1} \tag{6}$$

for $\mathbf{e}$ a column vector with all elements equal to one. This equations yield:

$$q_i = \begin{cases} \sum_{k=0}^{\infty} q_{i+k-1} b_k & \text{for } i \ge 1 \\ \sum_{j=0}^{\infty} q_j \left(1 - \sum_{k=0}^{j} b_k\right) & \text{for } i = 0 \end{cases} \tag{7}$$

Letting $D\, q_i = q_{i+1}$, for $i \ge 1$ eqn. (7) can be written as:

$$q_i - (q_{i-1}b_0 + q_i b_1 + q_{i+1} b_2 + \ldots) = 0 \ , \tag{8}$$

so that

$$q_{i-1}(D - b_0 - Db_1 - D^2 b_2 - D^3 b_3 - \ldots) = 0 \tag{9}$$

for a nontrivial solution

$$D = \sum_{n=0}^{\infty} b_n D^n \ . \tag{10}$$

Since b_n is a probability, the second term on the left is merely the probability generating function of the $\{b_n\}$; we will call it $\beta(z)$. Eqn. (10) becomes

$$\beta(z) = z \ . \tag{11}$$

Now, we can easily show that

$$\begin{aligned} \beta(z) &= \int_0^\infty e^{-\mu t} \sum_{n=0}^{\infty} \frac{(\mu t z)^n}{n!} dA(t) = \\ &= \int_0^\infty e^{-\mu t(1-z)} dA(t) = \\ &= A^*[\mu(1-z)] \end{aligned} \tag{12}$$

where $A^*(z)$ is the Laplace-Stieltjes transform of the inter-arrival time CDF. Eqn. (11) can be also written as

$$z = A^*[\mu(1-z)] \ . \tag{13}$$

There is a short proof in [3] that (13) has only a single root with absolute value less than 1 (must be real and positive).

Denoting this root by r_0, we can write that the steady-state arrival-point distribution is given by

$$q_n = (1 - r_0) r_0^n \qquad (n \geq 0, \rho < 1) \ . \tag{14}$$

4. Enhanced Convolution Method

We suppose a single-server queuing situation with the unlimited queue size and the exponential service time with the mean $\mu = C$ [cells.s^{-1}]. The input traffic is determined by k-point probability distribution for inter-arrival times, so that

$$\Pr\{\text{inter - arrival time} = t_i\} = a(t_i) = a_i \qquad (1 \leq i \leq k) . \tag{15}$$

We have to determine the root r_0 from (11). Before that, (11) has to be transformed to the discrete form. For the continuous case, we solve

$$z = \int_0^\infty e^{-\mu t(1-z)} dA(t) = A^*[\mu(1-z)] = \beta(z) \tag{16}$$

where $A(t)$ is the cumulative distribution function of the inter-arrival time. Rewriting (16) for k-point probability distribution yields

$$\beta(z) = \int_0^\infty e^{-\mu t(1-z)} dA(t) = \int_0^\infty a(t) e^{-\mu t(1-z)} dt \\ \Rightarrow \sum_{i=1}^{k} a(t_i) e^{-\mu t_i(1-z)} = \sum_{i=1}^{k} a_i e^{-\mu t_i(1-z)} \tag{17}$$

where $a(t)$ is the probability density of the inter-arrival time. For the discrete case, we solve

$$z = \sum_{i=1}^{k} a_i e^{-\mu t_i(1-z)} \ . \tag{18}$$

Since (18) does not have any analytical solution, we shall use the numerical method of the successive substitution, beginning from $z^{(0)} = 0.5$

$$z^{(k+1)} = \beta\left(z^{(k)}\right) \quad k = 0,1,2,\ldots, \quad 0 < z^{(0)} < 1 \ . \tag{19}$$

Since the service times are exponential, $\beta(z)$ is strictly convex and takes a few iterations to converge (see [3], eight iterations to converge to three decimal places). The steady-state solution exists only if

$$\rho = \frac{\lambda}{\mu} < 1 \ . \tag{20}$$

There is only one root r_0 of (18) lying between 0 and 1.

Supposing the buffer size B [cells], we are able to write the formula for CLR given by the buffer overflow probability

$$CLR = 1 - \sum_{n=0}^{B} q_n \ , \tag{21}$$

where q_n is the probability that the arrival finds another n arrivals in the system obtained from (14).

5. ATM Node Model

Functionality of the ATM node is often approximated with a simplified queuing model, as shown on Fig. 1. This approximation is sufficient in both the simulations and the CAC method design. The ATM node model consists of the set of input links, the buffer with a limited capacity B (cells) and the service server with the service rate C (cells.s^{-1}).

The buffer has to be related to the output link. In this case, the CAC method runs independently on each output link. Other positioning is inappropriate for the CAC method decision. Besides other facts it is extremely hard to find out the relation of the concrete cell in buffer to the output link.

If the input traffic is modeled with the Poisson process, we can use equations from queuing theory to approximate the interconnected traffic and ATM node models. This queuing system is marked as M/D/1 [3]. Inter-arrival times in input traffic are given by the Poisson process, the service time is deterministic. Because of the Poisson process, the mean rate of the super-positioned input traffic is λ (cells.s^{-1}), and can be easily obtained as

$$\lambda = \sum_{i=1}^{N} \lambda_i \tag{22}$$

where λ_i is the mean rate of i-th connection. The super-positioned traffic consists of N connections. Capacity or intensity of the output link is $C = \mu$ (cells.s^{-1}). The queuing system has a stability condition

$$\rho < 1 \text{ where } \rho = \frac{\lambda}{\mu} \ . \tag{23}$$

The probability p_n that n cells are in the buffer is given by

$$p_n = \begin{cases} 1-\rho & \text{for } n = 0 \\ (1-\rho)(e^{\rho} - 1) & \text{for } n = 1 \\ (1-\rho) \sum_{k=1}^{n} e^{k\rho} (-1)^{n-k} \dfrac{(k\rho)^{n-k}}{(n-k)!} + \\ + (1-\rho) \sum_{k=1}^{n-1} e^{k\rho} (-1)^{n-k-1} \dfrac{(k\rho)^{n-k-1}}{(n-k-1)!} & \text{for } n > 1 \end{cases} \tag{24}$$

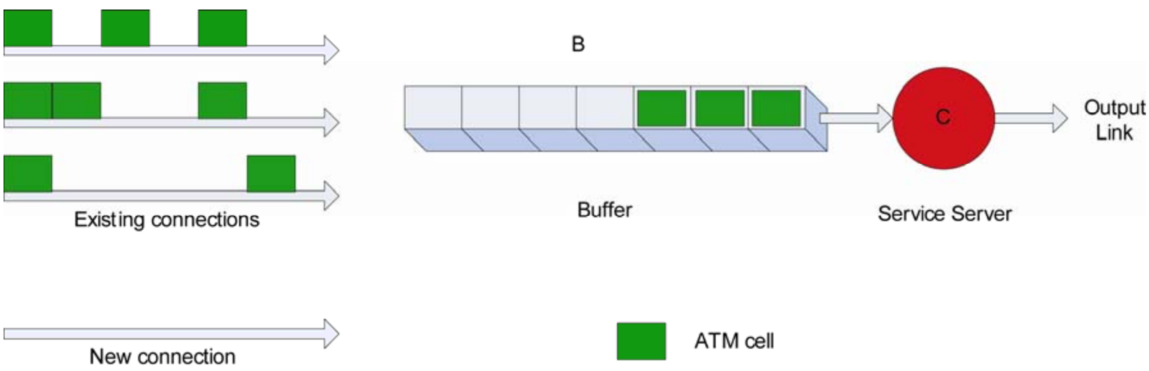

Fig. 1. The ATM node model.

If all the probabilities are known, the CLR parameter for the buffer size B (cells) can be approximated by

$$CLR = 1 - \sum_{n=0}^{B} p_n \ . \tag{25}$$

The mean number of cells in the buffer is given by

$$L = \rho + \frac{\rho^2}{2(1-\rho)} \ . \tag{26}$$

The simplification of input traffic properties is the disadvantage of this abstraction. Some services and applications generate the traffic that can not be modeled with the Poisson process (e.g. video and data). Therefore, we construct discrete traffic models on the cell scale and the rate scale.

6. Traffic Models

For simulation purposes, two traffic models on the cell and rate scale were created. The model at the cell scale was inspired by the typical transmission of the single layer MPEG video source [7]. Some properties have to be ignored in order to obtain the general traffic source with minimum correlations in the transmission (scene and frame pattern correlations). Correlations present in the video transmission have a serious impact on cell losses in the case of the aggregation of homogeneous connections, especially. In order to avoid this situation, GoP pattern is ignored, and other properties are preserved. In order to describe the single layer MPEG cell stream produced by an ATM adaptor, the following is assumed:

- The ATM adaptor and the transmission link have the same capacity.
- The ATM adaptor transmits the cells with the given inter-cell distance.
- The first cell of a frame is transmitted at the beginning of the frame.

This means that one frame at a time will arrive at the ATM layer the packetization takes place and the ATM cells are transmitted with the maximum rate of the adaptor taking into account the given spacing distance. Preserving the frame structure and the mentioned transmission seems to be the realistic assumption for the general connection with the variable rate traffic.

The modeled cell stream can be described by the following parameters:

- *Maximum frame size bind to output channel capacity and frame rate D*, which is measured in cells and can be calculated by $D = R/r_f$, where R [cells.s^{-1}] denotes the maximum output rate of the ATM adaptor and r_f [frame.s^{-1}] denotes the frame rate of the video sequence. The typical frame rate (25 frames per second) for MPEG was preserved. Of course, the maximum frame size of the video sequence always has to be smaller than D cells.
- *Inter-cell distance d_{cell}*, i.e., each used slot is followed with $d_{cell} - 1$ empty slots. If $d_{cell} = 1$, the cells are transmitted back-to-back. The maximum value of d_{cell} is $[D/x_{max}]$, where x_{max} is the number of cells of the largest frame.

Fig. 2. Traffic model at cell scale.

- *Frame size sequence* x_i, $i = 1, 2, \ldots, N$, where N is the number of frames in video data. For sequence generation, a simple Markov chain was used [7]. Hence, inter-frame correlations were partially preserved in the generated sequence.

In Fig. 2, the cell stream for one sample from the sequence is shown as an example. Frame duration D lasts 1 second for simplicity, the transmitting link capacity is set to 26 cells per second. The peak cell rate R of the connection is 8 cells per second resulting into 2 empty slots between successive cell arrivals. As shown in Fig. 2, instantaneous frame size x is 3 cells. For the next frame size from the sequence, the whole situation repeats but the condition must be hold that the maximum frame size must be less or equal to 8 cells.

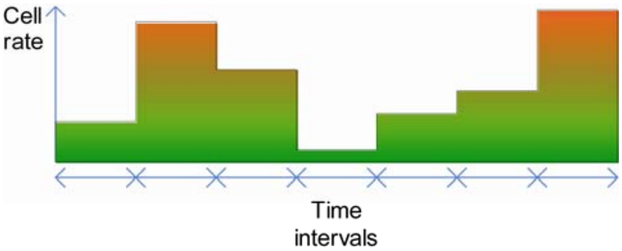

Fig. 3. Traffic model at rate scale.

Our second model at the rate scale is a simplified fluid flow model. We assume that during the relatively long time period T (in our case the frame duration), the cell rate is constant and the traffic character is not markedly changing. The principle for this simplified assumption is shown in Fig. 3.

	R [Mbit/s]	λ [Mbit/s]	b [cells]
Class 1	10	1.0	340
Class 2	2	0.1	2 600
Class 3	5	1.2	2 600

Tab. 1. Traffic parameters for three classes.

Obviously, the frame size is the random variable in this case too. The frame size sequence in this model is generated by the method based at the histogram approach [7].

7. Performance Evaluation

In this section we provide a graphical comparison among the following CAC schemes: the proposed enhanced convolution method, the convolution method, the method of the diffusion approximation and the method of the effective bandwidth. These statistical schemes use the same set (or subset) of traffic descriptors, namely the peak bit rate, the mean bit rate and the mean burst length of a connection (R, λ, b).

Our evaluation assumes an ATM node with the finite buffer capacity B. This buffer is served by a server (the output link) of capacity C. The connections handled by this queuing situation are classified into M classes. We specify three connection classes, their traffic descriptors are shown in Table 1. All connections in the same class i have the same traffic descriptor (R_i, λ, b_i).

7.1 Admission Region

The admission region is a set of all values (n_1, n_2, …, n_i, …, n_M) for which the cell loss probability is less than a specified value ε, where n_i is the number of the allocated class i connections. In the graphs given below, we obtain the outermost boundary of the region. All the points enclosed between axes and boundary represent combinations of connections from each class which lie within the admission region, and thus, the cell loss probability will be in compliance with the requested CLR.

In our simulation, connections of class 1 and class 3 were used. Output link capacity was set to 155.52 Mbit/s. The buffer capacity was set to 1 (compound graph marked with (a)), 5 (b), 1000 (c) and 200 000 ATM cells (d). In the first case (see Fig. 4), the CLR target was set to 10^{-3}.

The convolution method (CV – magenta) has approximately the same admission region as the method of the diffusion approximation (DA – blue) in a region of the relatively small buffer size (in our case approximately 1000 cells). After this point, the convolution method becomes very pessimistic in this comparison. On the other hand, CLR will be ensured at the expense of the effective bandwidth usage.

The admission region in the case of the enhanced convolution method (ECV – red) is very conservative in the case of a small buffer size (in our case less than 5 cells). After this point, the admission region grows very rapidly and, what is very interesting, it overestimates the admission region boundary set with SCR parameters. Due to the fact that the enhanced convolution method is proposed at the cell scale, this approach is thus suitable for small buffer sizes.

The method of the effective bandwidth (EFB – green) is also very conservatively for relatively small buffer sizes (in our case to 1000 cells). In this area, the effective bandwidth method uses the Gaussian buffer, less approximation and estimation is very conservative. If larger buffer size is used (200 000 cells), the admission region is approximately the same as in the case of the method of the diffusion approximation (DA).

In our second case, all connections requested higher CLR target, namely 10^{-9}. It seems that the situation looks quite like before, but there are some interesting circumstances. As we can see, the enhanced convolution method is very sensitive on CLR, especially in the region with the small buffer size. The admission region is the smallest of all in this case. But with growing buffer size, admission region grows very fast and becomes very optimistic.

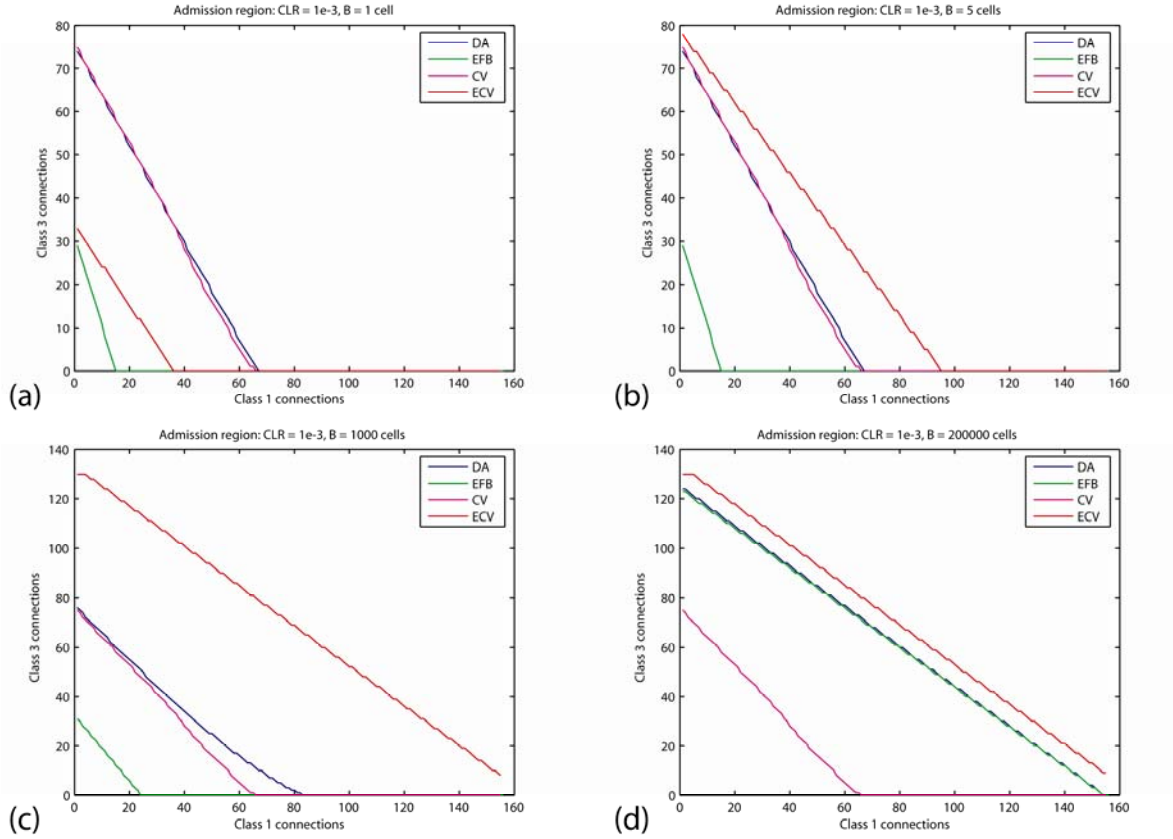

Fig. 4. Admission region for various buffer sizes (four cases), CLR target 10^{-3}.

7.2 Buffer Size and CLR Dependence

CLR is one of the most important quality indicators in transmission. Request on CLR has a remarkable impact on the number of admitted connections. Simulation in this section focuses on the CLR area of interest covering the interval from 10^{-2} to 10^{-12}.

The buffer size has a significant impact on cell losses. This enables the protection in short terming congested states or simultaneous cell arrivals. If congested states are long terming or permanent, the buffer of any size is not able to ensure the protection from cell losses. Moreover, the very high dimension of the buffer size has an unacceptable impact on cell delay variations. In the case of network dimensioning, a buffer capacity planning is a serious matter. Simulation in this section covers a wide range of the buffer capacity from one cell to 10^6 cells.

The traffic consists of connection classes 1 and 2. The link capacity is set to 155.52 Mbit/s. In the first simulation, the effect of the CLR request is examined.

Fig. 6 shows that the enhanced convolution method (ECV) is the most sensitive on the CLR request and on the buffer size too. If compared with other methods, it is very soon too optimistic in dependence on the increasing buffer size. Last two charts show that the effect of the CLR request is dimmed with the buffer size effect. The convolution method (CV) is also sensitive on the CLR request but the buffer-less effect is also visible. On the other hand, the estimation is comparable to the diffusion approximation method (DA) and the effective bandwidth method (EFB) up to the relatively high buffer capacity 1000 cells. If we compare the method of the diffusion approximation and the effective bandwidth method, their dependency on the CLR is almost equivalent. The difference in admitted connections is visible in the region circa 1000 cells. Due to the two components approach in equations for the effective bandwidth method, there is not such a smooth change as in the behavior of the diffusion approximation method. We will discuss this behavior in second simulation.

The enhanced convolution method is strongly dependent on the buffer size. It looks very pessimistic in the case of the small buffer size but then it rises very rapidly. Due to the cell scale approach, this method is exact for small buffer sizes as shown in section 7.3. The convolution method uses the buffer-less assumption, the admission does not depend on this factor. The diffusion approximation method and the effective bandwidth method have almost the same behavior except of the region between 1 000 and 100 000 cells. The effective bandwidth method has two components. The first component uses the Gaussian buffer-less assumption, and is clearly visible as the straight line independent on the buffer size. The component dependent on the buffer size uses original formulas for calculating the effective bandwidth.

7.3 Verification with Traffic Models

Previous simulation results show that the enhanced convolution method is suitable for ATM nodes with the small buffer size. In this section, we verify this conclusion with our traffic models and the ATM node model. The principles of the ATM node and traffic models are given in sections 5 and 6.

In our first simulation, we use the traffic model at the cell scale. The random variable in this case is a frame size in a video sequence. First, we need to derive parameters for the discrete Markov chain – the transition matrix and the state vector. Two original sequences from video [8] trace were used; two traffic source classes were the results. Frame sequences observed in connections from one traffic source class were not the same in time, but they have the same statistical parameters, the mean and the variance. It must be noted that the GoP structure was ignored in this model, our aim was to ignore its contribution to cell losses.

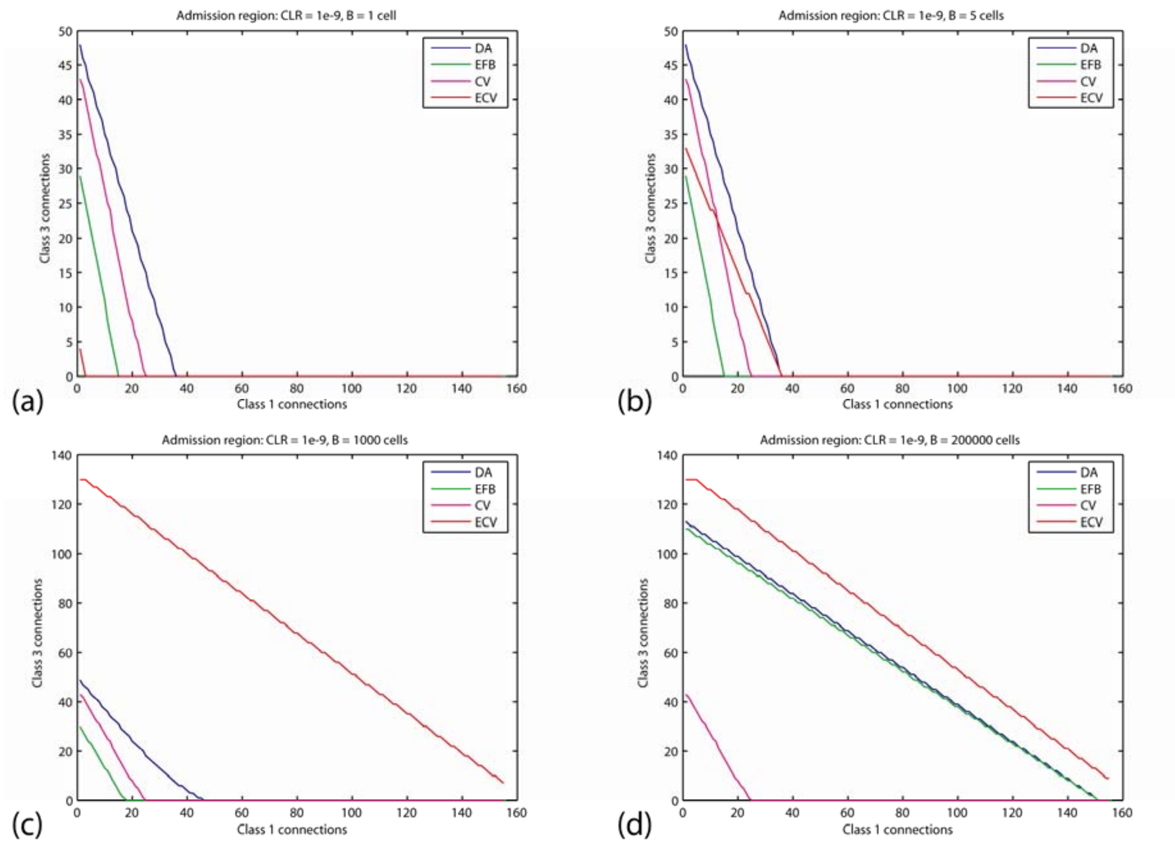

Fig. 5. Admission region for various buffer sizes (four cases), CLR target 10^{-9}.

The parameters used for the simulation were the consequent: the link capacity was set to 622.08 Mbit/s (i.e. 1 620 000 ATM cells per second). A single FIFO buffer was used with the capacity 1, 3, 5, 8, 10, 15, 20, 30, 50, 80, 100, 200 and 500 ATM cells (i.e. 53 B to 26.5 kB). For the traffic generation, two video frames sequences were used from movies *Die Another Day* and *Silence Of The Lambs*. This means that there were two traffic classes with the transition matrix (the dimension 160 × 160) and the state vector (the dimension 1 × 160) describing the size of the video frame. The traffic was generated with help of these transition matrices and state vectors. The contribution of the GOP structure was ignored, but the contribution of the correlations of the start time and the concurrent cell arrivals was well-preserved. Model parameters were consequent: for first class, the maximum bit rate was 5.74 Mbit/s and the mean bit rate was 1.021 Mbit/s. For the second traffic source class, the maximum bit rate was 4.761 Mbit/s and the mean bit rate 0.922 Mbit/s. It seems that traffic classes have the same parameters, but there are differences in scene dynamics. The first video source is an action movie with lot of scene changes in the contrast with the relative smooth scene changes in a psychological movie with lot of “talking” scenes. The Markov model is suitable because it is able to catch these scene changes in the movie.

There were both the source classes in the multiplex and their number was equal for simplicity. The minimum traffic intensity consists of 50 sources of both source classes; the maximum traffic intensity was achieved with 320 sources of both classes. The number of sources was increased in steps of 10 source classes resulting into 28 measurements. This implies that the resulting load at the ATM node ranged from 15.617% to 99.949%. The cell loss obtained from the model at the cell scale is figured on the first graph (see Fig. 8). Note that the second graph is in the logarithmical scale. The simulation time was set to 500 seconds. Fluctuations in cell losses were inducted by start times of sources transmission. The starting point in time was common for all connections but there was a random offset for the starting time for each connection. The maximum value for the offset time was equal to the transmission time of one frame (1/25 second) and was uniformly distributed with mean equal to 1/50 second. As we can see on Fig.8, these correlations in starting times have a strong influence at cell losses.

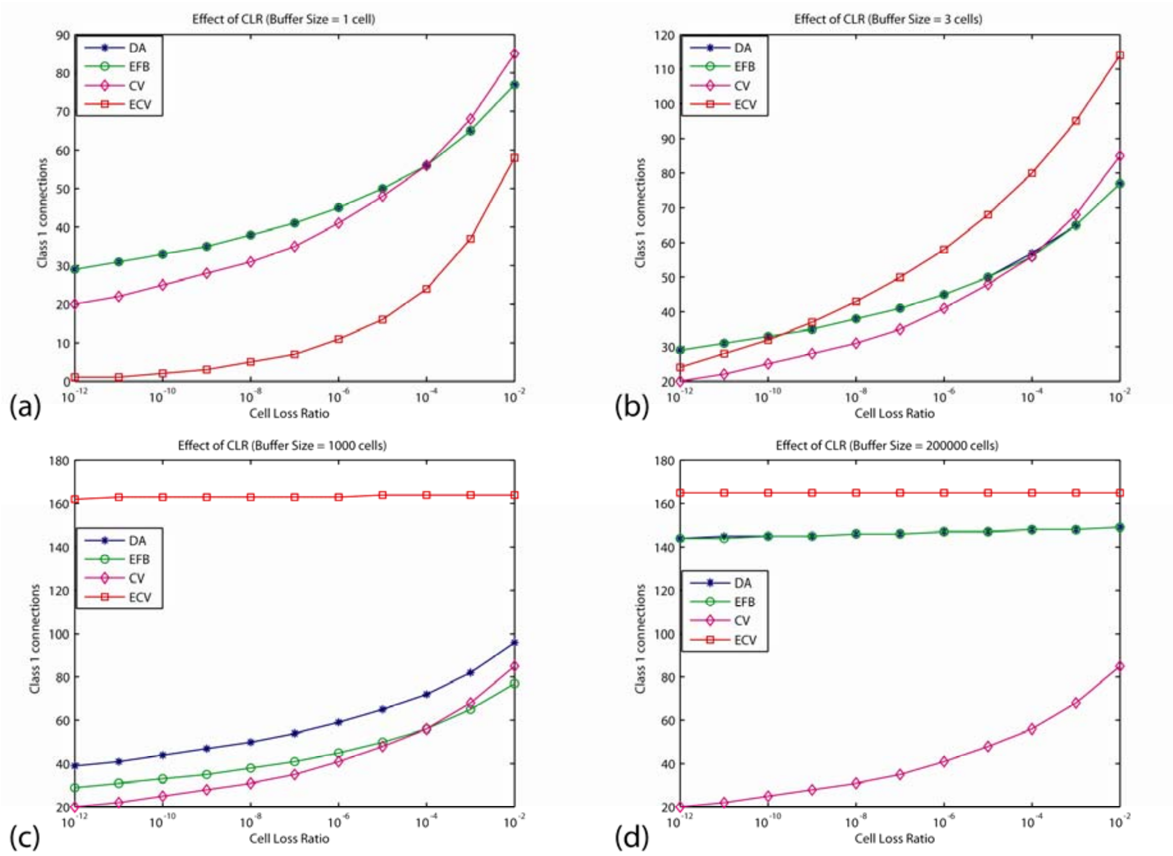

Fig. 6. Effect of Cell Loss Ratio request on admission (four cases of buffer size).

Fig. 9 and Fig. 10 show cell losses estimated by the enhanced convolution method and the convolution method. Regarding real conditions, connections are characterized only with PCR and SCR parameters.

Fig. 9 and Fig. 10 show that the enhanced convolution method is also dependent on the buffer size in contrast with the simple convolution method.

Interesting result is shown both in Fig. 11 and Fig. 12. We can see here the surface of the difference for cell losses obtained from the model at the cell scale and the enhanced convolution method, and the convolution method, respectively. Note that graphs for the enhanced convolution method are contradictory oriented for the buffer size in order to achieve better visualization.

Comparison of these two surfaces of difference shows that the enhanced convolution method gives the perfect estimation for cell losses in the region of small buffer sizes. The difference in this case is not higher than 10%.

There is a small area (Fig. 11) in a relatively low utilization. For a small buffer size, the difference is very high. This difference is a matter of high correlations in starting times of connections transmissions. Due to the correlations and a very small buffer size, cell losses in the traffic model are very high, but according to the low utilization, the cell loss predicted by the enhanced convolution method is very optimistic. There is the second area of the high difference for the high load and the large buffer size. In this case, the system is too close to the stability condition. Moreover, for such a high load, cell losses are out of the range of interest (range 10^{-3} to 10^{-12}). Since the traffic model is discrete, we assume that in real conditions, the contribution of correlation in starting times will not be so high. For higher loads, the result is very encouraging.

In the case of the convolution method, the estimation for cell losses in the area of the small buffer size is very optimistic, resulting into the high difference between the model and the method estimation.

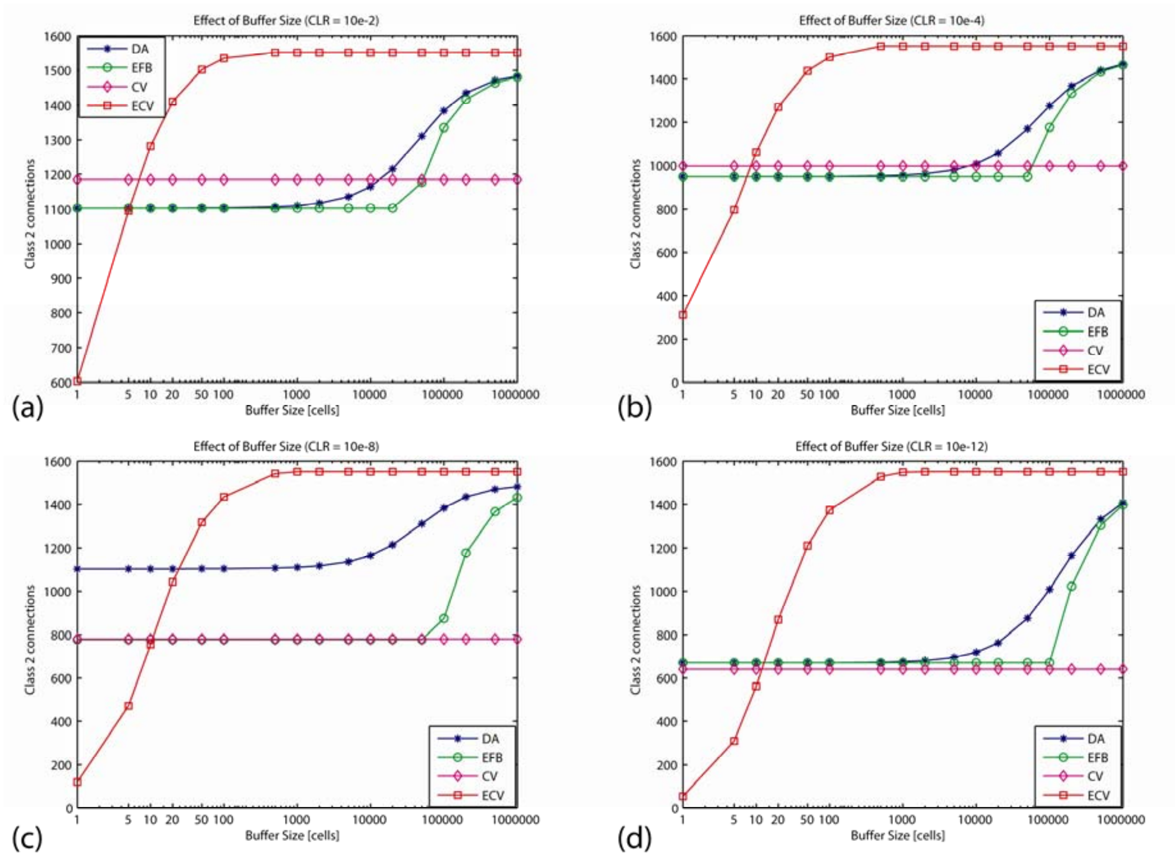

Fig. 7. Effect of buffer size on admission (four cases of CLR request).

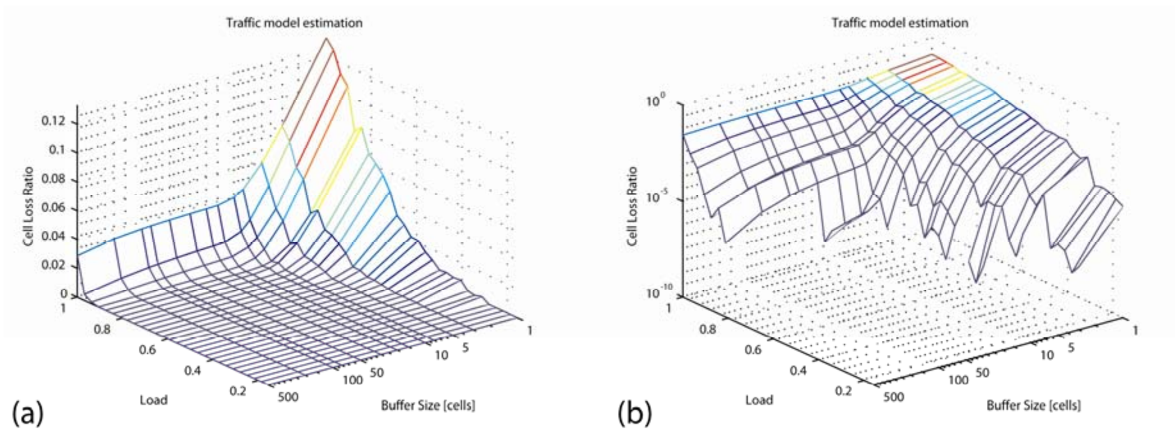

Fig. 8. Cell losses obtained from simulation at cell rate.

If all the results are put together, we can suggest the enhanced convolution method for policing ATM nodes with very small buffer sizes (including the buffer-less systems).

A question if the optimistic admission region in the case of the very large buffer size is acceptable must be solved in the case of the enhanced convolution method. In order to find an answer, we proposed the model at the rate scale. The frame size is the random variable. In this case, this is modeled with the histogram approach. The result and the answer to our question is shown on Fig. 13.

Fig. 13 shows the cell loss obtained with the model at the rate scale (CR model), the cell loss estimated with the enhanced convolution method (ECV) and the convolution method (CV). Results in the cell loss are interesting only in the reduced interval (from 10^{-2} to 10^{-12}). Thus, the model at the rate scale recorded the substantial cell loss only at the higher loads (above 85%). The situation clearly demonstrates the theory about the cell loss curve in dependence on the buffer size. After a certain point of the concrete buffer size value, the enhanced convolution method becomes very optimistic in the cell loss estimation. We can clearly see that this value is dependent on the load (higher the load, higher the break value). This value must be set by the simulation with the concrete traffic input because of the load dependence. The traffic characterization due to the wide scale of services is so variable that it is impossible to set a concrete universal value for all cases of traffic load.

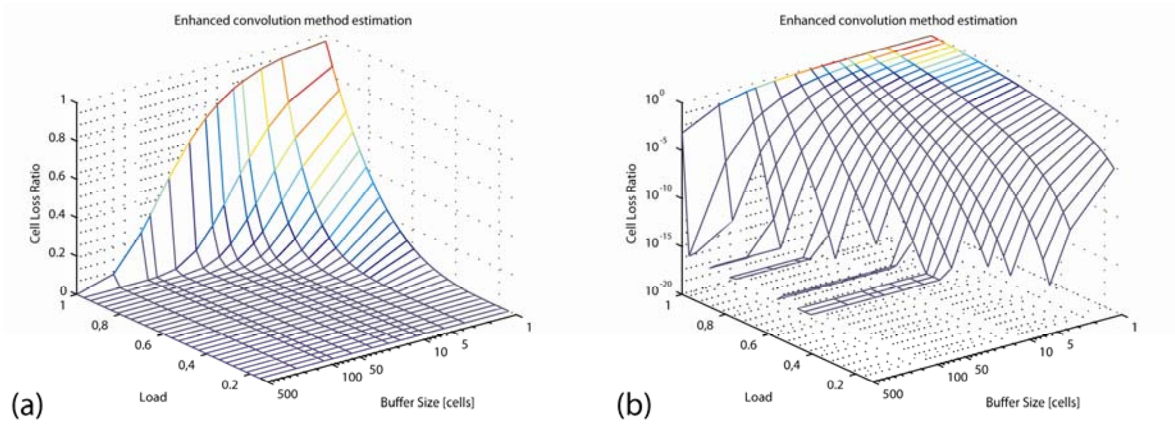

Fig. 9. Cell losses estimated by enhanced convolution method.

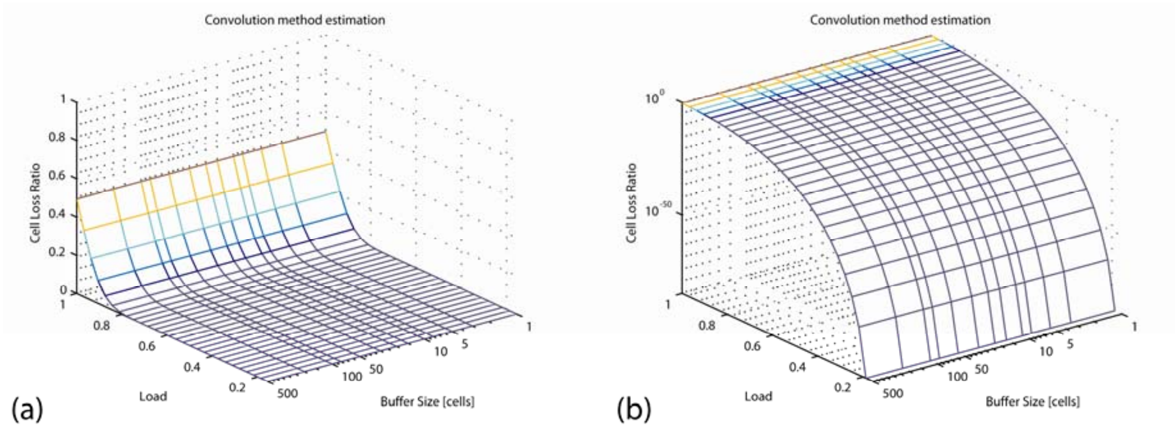

Fig. 10. Cell losses estimated by convolution method.

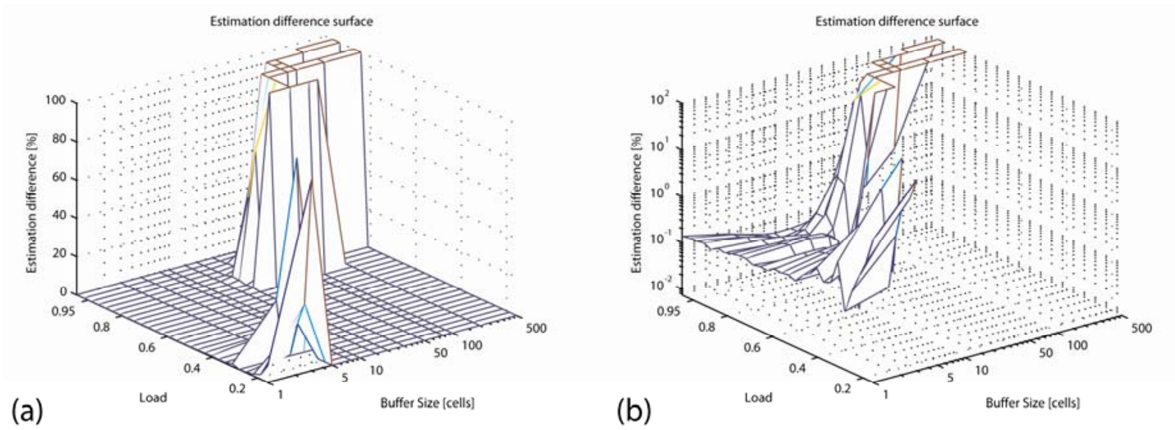

Fig. 11. Surface of estimation difference between model at cell scale and enhanced convolution method.

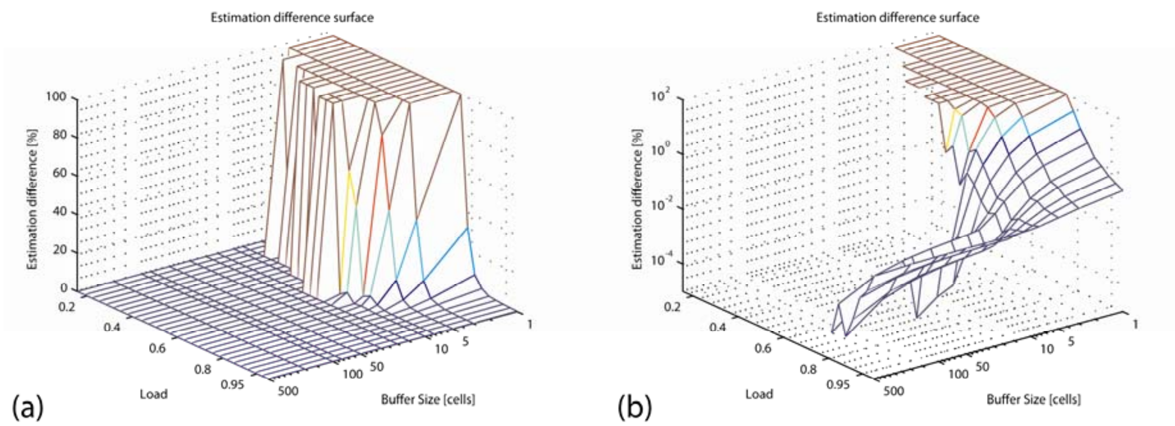

Fig. 12. Surface of estimation difference between model at cell scale and convolution method.

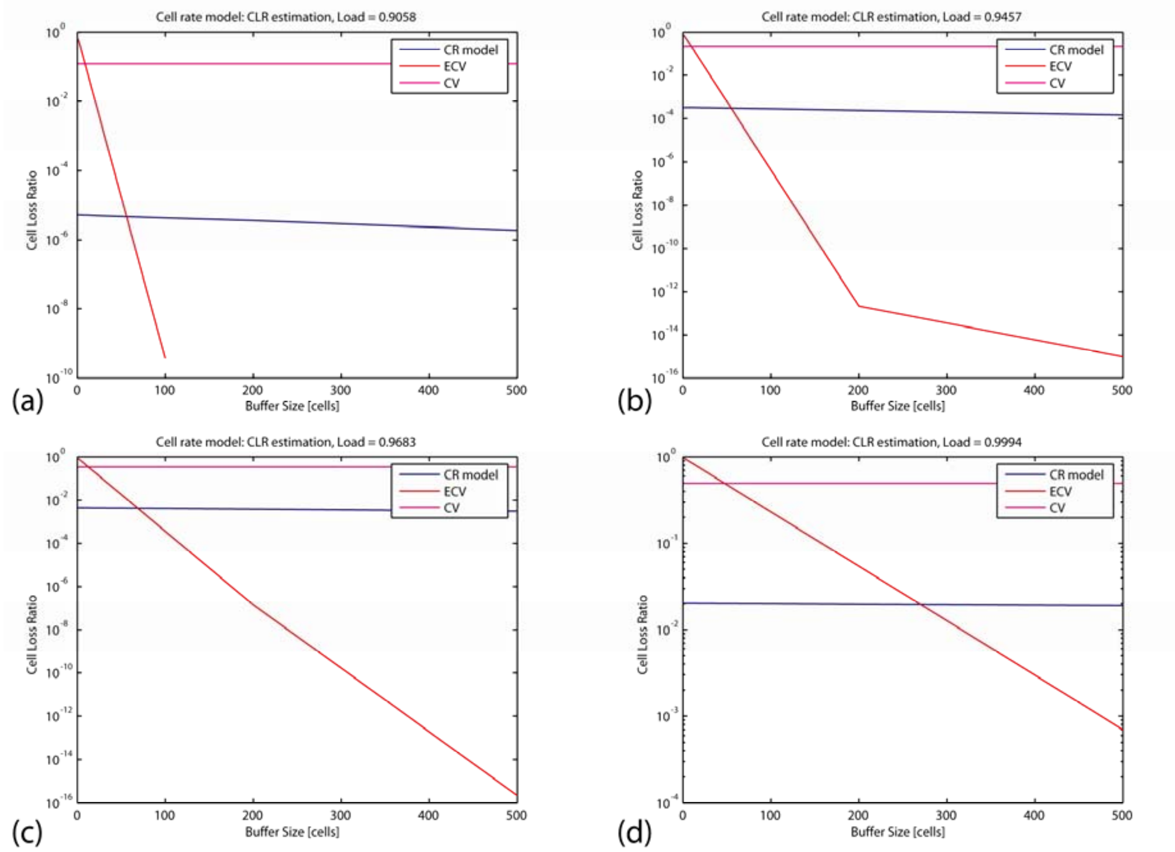

Fig. 13. Cell losses from simulation at rate scale compared with CAC methods estimations.

To set the breakpoint value, the consequent approximation is possible: the cell loss estimation in the dependence on the buffer size for both the enhanced convolution and the convolution method are made. The buffer size breakpoint value is set as a point, where cell loss curves meet (see Fig. 13). Since we already know the buffer capacity in the system, the question which method is suitable is solved. We can clearly see that this value is an upper bound. The result is that the cell loss for all connections in the multiplex is satisfied at the expense of the bandwidth usage.

8. Discussion

Designating the region of the exploitation for the proposed enhanced convolution method is the main idea of this work. The new CAC method was compared with three other statistical CAC methods: the diffusion approximation method, the method of the effective bandwidth and the convolution method. The effect of the system and QoS parameters on CAC methods cell loss estimations was investigated. For better illustration and results acknowledgement, the cell loss estimates obtained from the enhanced convolution method were compared with simulation results. In simulations, interconnections between the ATM node model and two traffic models at the cell and rate scale were created. Since there was no possibility to obtain experimental results, these simulations approximate cell losses from the real system structure.

The proposed enhanced convolution method can be easily implemented into systems where the connection admission is controlled by the convolution method. It exploits the discrete probability distribution of the cell rate, which is a product from the convolution process. If possible, the input traffic can be described by the discrete probability distribution of the cell rate. Alternatively, a characterization with only PCR and SCR parameters is possible too.

The convolution is very time consuming operation, but a lot of work was done in this area. Therefore, this paper does not deal with this task in detail. The advantage for this approach lies in the exact statistical characterization of the input traffic process since there is no concrete probability distribution used (e.g. Gaussian, Pareto, etc.). This implies that this method is suitable as the control for fewer connections in the multiplex which is impossible in case of the Gaussian approximation (the large number of connections has to in the multiplex because their aggregated probability distribution is close to the Gaussian probability density function). Of course, in case of the enhanced convolution method, we basically assume that cell arrivals are independent and the arrival process is stationary. In other words, cell arrivals are non-overlapping and their statistical parameters (e.g., the mean and the variance) are constant as long as the connection is active. Generally speaking, this is a common assumption for the statistical CAC method.

The disadvantage is typical for Markov chains: the service time is approximated by the Poisson process. In our case, the deterministic service time is more appropriate, but is not feasible in theoretical approach due to so called memory less property of the Poisson process. Concerning a relative small variance of the Poisson process, we assume that this approximation does not bring a substantial inaccuracy into our approach.

The convolution method, the method of the diffusion approximation and the effective bandwidth method are very well reviewed [4], [5], [6]. Thus, comparing the newly developed CAC method with these three statistical CAC methods is promising.

Simulations presented above show that the enhanced convolution method clearly covers the region at the cell scale. Moreover, the enhanced convolution method is very sensitive to the required CLR, but larger buffer sizes repress this sensitivity very quickly. The buffer size is the system parameter which significantly determines the exploitation of the CAC method. The cell scale component reflects the small queues which occur due to the asynchronous arrival of cells from distinct connections. The enhanced convolution method is thus suitable for ATM nodes with relative small buffer sizes. Since the cell loss estimation is very pessimistic (the most pessimistic admission region from all the examined methods), the enhanced convolution method is applicable as the admission control for connections extremely sensitive to cell losses. This goes at the expense of gain from the statistical multiplexing and the effective bandwidth usage. On the other hand, the required QoS will be satisfied.

9. Scientific Resume

For the *universal telecommunication network*, the mechanism for the traffic control is necessary because of the effective transmission for the wide scale of services and applications. This mechanism is an inseparable part of the convergent transmission technology. The preventive mechanism of the connection admission control was a part of the ATM design since the beginning. That is why the ATM network guarantees the compliance of the traffic and QoS parameters during the active time duration of the connection. The effective usage of network resources is another advantage. Years of the research and the evolution bring new knowledge on one hand and new challenges on the other hand.

The most important and original contributions of this paper can be summed up into the following points:

- The design and the mathematical definition of the new connection admission control method: the enhanced convolution method.
- The design and the mathematical description of the interconnection between two models (the model of the ATM node and the input traffic) was proposed. The description is based on M/D/1 equations. For simulation purposes, two traffic models were designed: the model based on the cell and the rate scale.
- The implementation in MATLAB referring to the interconnection between the model of the ATM node and the traffic model. The verification of the designed CAC method in the connection admission control was the purpose.
- The design of the mutual comparison and the MATLAB implementation of four statistical CAC methods: the convolution method, the enhanced convolution method, the diffusion approximation method and the method of the effective bandwidth. The optimization in the selection of the applicable CAC method based on simulation results was designed.

10. Conclusion

This paper introduced an idea of enhancing the existing CAC method with knowledge from the queuing theory. The resultant enhanced convolution method showed a high accuracy for the network systems with a relatively small buffer and also for the buffer-less systems. The quality of service guaranties for each connection is satisfied, but the enhanced convolution method maintains relatively low link utilization. On the other hand, this arrangement is negligible to avoid conflicts in sudden cells arrivals especially in the case if the buffer size is very small.

The CAC method is very easy to implement and is tunable using the state reduction. Due to the small probability values, the state reduction technique is necessary. Connections can be characterized by PCR and SCR parameters or, if possible, by the discrete probability distribution of the cell rate.

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References

[1] KAVACKÝ, M., BAROŇÁK, I. Practical use of traffic control simulations for education purposes. In *Proceedings of the 4th International Conference ICETA 2007*. Stará Lesná (Slovakia), 2007.

[2] CHROMÝ, E., BAROŇÁK, I. Contribution of call centre to regional development. In *Proceedings of the 5th EURASIP Conference Focused on Speech and Image Processing, Multimedia Communications and Services*. Smolenice (Slovakia), 2005, p. 212–215.

[3] GROSS, D., HARRIS, C. M. *Fundamentals of Queuing Theory*. 3rd ed. New York: J. Wiley and Sons, 1998.

[4] ENGEL, R. *Design and Implementation of a New Connection Admission Control Algorithm Using a Multi-state Traffic Source Model*. Diploma Thesis. St. Louis (USA): Department of Computer Science, Washington University, 1996. Available at:
www.seas.wustl.edu/Research/FileDownload.asp?58.

[5] MARZO I LAZARO, J. L. *Enhanced Convolution Approach for CAC in ATM Networks: An Analytical Study and Implementation*. Girona (Italy): University of Girona, 1996. Available at:
http://www.tdx.cesca.es/TDX-1003101-155128/

[6] KOUVATSOS, D., et al. *Performance Evaluation and Applications of ATM Networks*. Kluwer International Series in Engineering and Computer Science. Boston (USA): Kluwer Academic Publishers, 2002.

[7] ROSE, O. *Traffic Modeling of Variable Bit Rate MPEG Video and its Impacts on ATM Networks*. Ph.D. Dissertation. Wurzburg (Germany): Bayerische Julius-Maximilians-Universität, 1997.

[8] *Video Traces for Network Performance Evaluation*. Available at: http://trace.eas.asu.edu/tracemain.html

[9] The ATM Forum: *Traffic Management Specification Version 4.0*, af-95-0013R13, Letter Ballot, April 1996.

[10] MATLAB and Simulink User's Guide. Natick (USA): The MathWorks, Inc. Available at:
http://www.mathworks.com/