Multifractal Analysis of Outgoing Signals from the Statistical Multiplexer with Neural Network Control

Marija Zajeganović-Ivančić[1], Irini S. Reljin[2], Branimir D. Reljin[3]

Abstract – **The paper considers simulation model of statistical multiplexer controlled by modified self-organizing neural network. The modifications are derived in order to avoid the packet loss, even in case of bursty traffic. In scheduling mechanism the priority of input streams are considered as well. Proposed model was tested over real input signals with multimedia content and outgoing signal was analyzed from the multifractal point of view.**

Keywords – **Statistical multiplexer, buffer overflow, priority control, neural network, Kohonen learning law, multifractals.**

I. Introduction

The multimedia traffic is predominant in modern telecommunications. Information is discretized and transmitted in the form of units: packets of variable length (number of bytes), depending on the content (as in Ethernet traffic), fixed-length packets called "cells" (as in asynchronous transfer mode (ATM) technique), or frames (the whole slide), slices (1/30 of frame) and blocks (8x8 pixels), as in video transmission [1]. Such traffic is characterized by burstiness and fractal nature (self-similar shape in different scales), which is illustrated in Fig. 1, where the traces (number of ATM cells per frame and per slice) [2], taken from the motion JPEG (MJPEG) version of the movie "Star Wars" [3] is depicted.

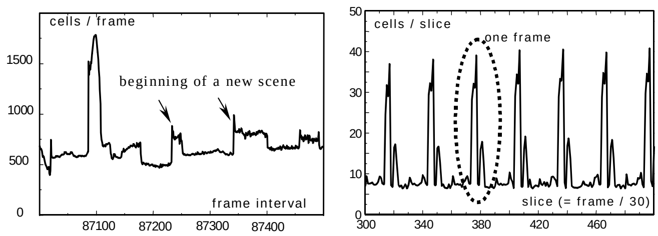

Fig. 1. Video traces for MJPEG version of "Star Wars" movie.

The burstiness of incoming traffic may produce the packet loss, if the input node is overloaded. By introducing input buffers the traffic flow may be smoothed. Very good results are obtained with statistical multiplexer, as in Fig. 2. Depending on the scheduling policy, only one of input buffers is connected to output, transferring its content to a line. The simplest scheduling policy is known as a "Round Robin" (RR) method: in this method the inputs are successively connected to the output, in fixed order, transferring predetermined amount of packets, say k_d, irrespective of actual occupancy of input buffer. Although such a method suffers from packet loss (when some input is highly active) this is still very popular, due to its simplicity. From general model as in Fig. 2, a variety of different control mechanisms are suggested, targeted mainly to the cell loss reduction.

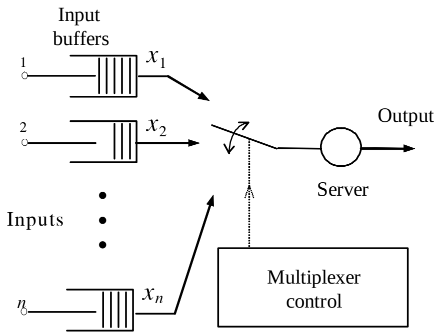

Fig 2. Model of statistical multiplexer.

Statistical multiplexer may be controlled in different ways. Certainly, an efficient scheduling algorithm is possible if the traffic characteristics are known. Unfortunately, modern multimedia communications are characterized by high complexity and unpredictable variability, producing very difficult (and almost impossible) modeling of such traffic. Consequently, the multiplexer control is very complex. In many cases we only know what will be good output, but input parameters, traffic conditions, algorithms, and the procedure for traffic flow control are unknown. For such kind of problem(s) the artificial neural networks (ANNs) may give the answer. The ANNs are (in many cases) very efficient in solving different over- or under-determined problems, with weak and/or unknown relations between parameters. The ANN may be trained to resolve given problem according to "positive" and "negative" examples presented to a network, but without exact algorithm for such resolving. Since modern multimedia traffic belongs just to this class of problems, we decided to use the ANN in controlling the statistical multiplexer with multiple inputs and one output, as in Fig. 2.

In this paper the multifractal (MF) analysis of outgoing signals from the statistical multiplexer, controlled by an algorithm based on the self-organizing neural network, is considered. The basic goal of the NN control was to avoid, as much as possible, the cell loss in real bursty traffic. Neural network decides which input will be connected to the output in each time slot, taking into account several parameters depending on the input traffic: the input buffers occupancy

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(static parameter), input traffic dynamics (the rate of incoming packets), and the history of packet scheduling (measured as number of packets transferred to the output from given input). Also, the algorithm takes into account the priority of inputs, depending on the prescribed conditions.

The paper is organized as follows. In Section II the modified Kohonen NN learning law, targeted to avoiding the cell loss in statistical multiplexer, is presented. In section III the multifractal analysis of output signals, under different scheduling policies, is described, while in Section IV some concluding remarks are derived.

II. MODIFIED COMPETITIVE NEURAL NETWORK FOR INPUT PRIORITIES CONTROL

The Kohonen learning law (KLL) [4] is suitable for tracking the changes in input signal. The essence of the KLL is based on comparing the inputs, described by an appropriate vector $\mathbf{x} = [x_1, x_2, ..., x_n]^T$, with neuron states described by a weight matrix $\mathbf{w} = [\mathbf{w}_1\ \mathbf{w}_2\ ...\ \mathbf{w}_N]^T$. (Note that the number of inputs, n, and the number of neurons, N, may differ, but usually the same number is assumed.) The intensity, I_j, of each neuron j=1,2,…,N, is calculated as the distance between jth weight and inputs

$$I_j = D(\mathbf{w}_j, \mathbf{x}) \tag{1}$$

The neuron with minimal intensity is declared as the winning neuron. Then the outputs of Kohonen layer take the values

$$z_j = \begin{cases} 1, \text{for the winner} \\ 0, \text{otherwise} \end{cases}, \tag{2}$$

and the neuron weights are updated according to the relation

$$\mathbf{w}_j^{new} = \mathbf{w}_j^{old} + a(\mathbf{x} - \mathbf{w}_j^{old}) z_j, \quad 0 < a \leq 1, \tag{3}$$

known as the Kohonen learning law. The constant a controls the learning rate and is determined empirically.

Although the KLL may be very efficient in many cases, it suffers from at least one drawback known as the „once-winner-always-winner” effect. Namely, since only the winning neuron adapts its weights, it is most reliable that this neuron will be closest to inputs in further time steps, so, it will be a winner in future. For minimizing this drawback, several modifications in KLL have been suggested. For instance, Duane DeSieno [5] introduced the „conscience” term, c_j, and instead of (1) the modified intensity is suggested

$$I_j = D(\mathbf{w}_j, \mathbf{x}) - c_j \tag{4}$$

The term c_j enables the fairness in winning. In [5] this term was given by

$$c_j = g(1/N - f_j) \tag{5}$$

where N is the number of neurons, g is an empirical constant (typical value is g=10), and f_j is a function describing the contribution of jth neuron in winning

$$f_j^{new} = f_j^{old} + b(z_j - f_j^{old}), \quad 0 < b < 1. \tag{6}$$

The idea of this modification is to monitor the neuron's history of success in the competition. Since the number of neurons in Kohonen layer is N, each will have the oportunity of 1/N wins in fair competition. From (4) to (6) follows that if the neuron j wins more often than 1/N of the time, the term f_j increases and c_j decreases, becoming even negative, leading to higher value of its intensity, I_j. Consequently, its chance for winning decreases, while other neurons take a chance for winning.

The idea of Duane DeSieno was further improved and applied to the input packet scheduler [6]. The conscience term of the form

$$c_j = c_j(k) = g\left(\frac{1}{N} - f_j(k) + q_{lj} \cdot \varphi(x_j(k))\right) \tag{7}$$

was suggested. The term k denotes the processing time slot, while the term $\varphi_j(x_j(k))$ takes into account the actual state of jth buffer, given by a number of packets in this input buffer (static parameter), and the trend (first derivative) of incoming packets (dynamic parameter). In this way an adaptive node control is obtained, avoiding the cell loss, even in highly burst traffic. According to [6] the term f_j may be expressed as

$$f_j(k) = 1 - (1-b)^{k-1}, \quad 0 < b < 1 \tag{8}$$

where

$$b = 1 - b_o^{N_k} = 1 - (1 - 1/N)^{N_k} \tag{9a}$$

with exponent N_k given by

$$N_k = \frac{1}{k_d q_{ei} - 1}. \tag{9b}$$

By adjusting terms q_{lj} and q_{ej}, the input priorities may be adjusted. If $q_{lj} = q_{ej} = 1$, there is no priority control, as already used in [6]. When changing q_{lj} the priority is changed with linear term in (7), while q_{ej} controls the priority by exponential term in (9). If coefficients q_{lj} and/or q_{ej} increase, the bias term c_j is increasing as well, leading to decreasing of the intensity I_j, according to (4), enabling jth element to have better chance to win. (Note that the bias term c_j may have fixed value, if some inputs are expected to have guaranteed quality of service (QoS), but also may be adaptive, depending on traffic conditions.) In this paper we will consider adaptive bias term depending on the buffer occupancy. From intensive simulations we decided that if input buffer is loaded over 60% of its capacity, its priority term(s) has to be increased by 40%.

III. MULTIFRACTAL ANALYSIS OF OUTGOING SIGNALS

Priority control, in general, may be consedered in different ways. When outgoing capacity (bandwidth) is less than input flow, the input(s) may be overloaded producing the cell loss. In this case the scheduling discipline has to be introduced for avoiding the cell loss and decreasing the delay, particularly for packets with hard demands, such as in real-time services. Priorities may be introduced from several reasons: for avoiding the input overflow and packet loss, but also for obtaining predetermined QoS or guaranteed traffic flow, etc. From these reasons the input priorities have sense.

The analysis of outgoing signal of statistical multiplexer may be derived in different ways. In [7] the statistical analysis was derived, while in this paper the multifractal analysis is performed, because such analysis may be very useful for describing complex signals and phenomena [8]. Simulations were derived under the assumption of different scenarios, and here only a small portion of our research will be exposed. We analyzed the MJPEG version of the „Star Wars“ movie: the movie content was described by corresponding video traces (the number of bytes per slices). The whole movie was splitted into 60 sequences. Only several sequencies (5 in presented simulation) was selected randomly and connected to input buffers. Buffers are identical with the capacity of C_b=100 packets. We defined the maximal number of successive outgoing packets from each input, in one time slot, of k_d = 5. Several characteristic results, related only to one of inputs (input 1) and its outgoing packets, are presented in Figs. 3-8. In Fig. 3 the multifractal spectrum of interarrival times is depicted. This spectrum has two significant regions: one is characterized by Holder exponent alpha between 0.7 and 0.8, and the second, for alpha greater than 0.9. Such bimodal spectrum indicates to the highly additive characteristic of the input process (due to the combination of natural scenes and artificially generated objects in this movie), as noticed in [2].

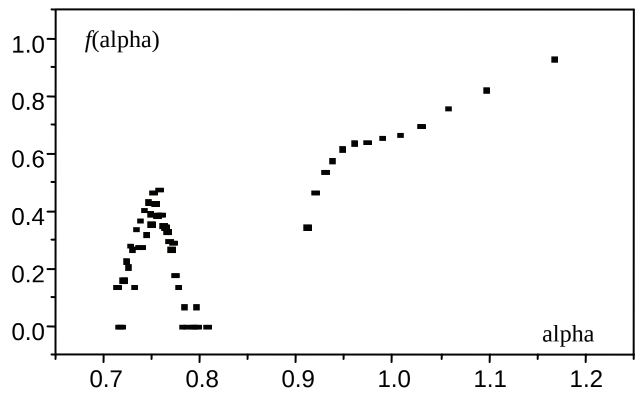


Fig. 3. Multifractal spectrum of interarrival times for input 1. MJPEG version of „Star Wars“ movie is assumed.

Two scheduling policies were assumed: classical RR and proposed NN control, with three scenarios of input priorities: fixed priority, given by the predetermined number of successive wins k_d (for RR policy), and with adaptive priority, depending on the buffer occupancy (in NN control): the influence of linear and exponential terms, q_{lj} and q_{ej}, describing priority control, as explained in (7)-(9), are considered separately.

The diagrams of interdeparture times (outgoing signals), t_d, versus time, for packetsl loaded at input 1, are depicted in Fig. 4, assuming RR and NN control mechanism, respectively. As it is evident, the interdeparture times decrease when NN control is applied (a horizontal line at t_d=70 is placed as a reference), indicating to better adaptivity of this method according to actual buffers' occupancies.

When applying the scheduling control, outgoing signal become smoother, which is recognized from corresponding multifractal spectra, as in Figs. 5-7. In both scheduling policies, particularly with NN, Figs 6-7, the bimodal shape of the multifractal spectrum becomes less expressed indicating to better eqalization of outgoing streams. Note that linear (Fig. 6) and exponential (Fig. 7) priority control produce almost the same effect on the MF spectra.

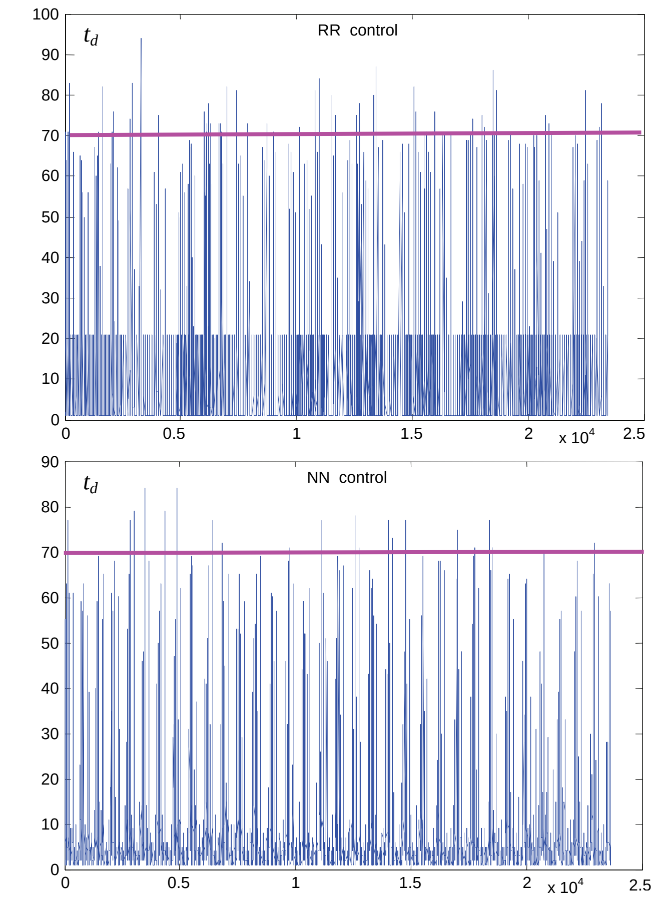


Fig. 4. Interdeparture times (sequence 1). MJPEG version of „Star Wars“ movie. RR (top) and NN (down) control is applied.

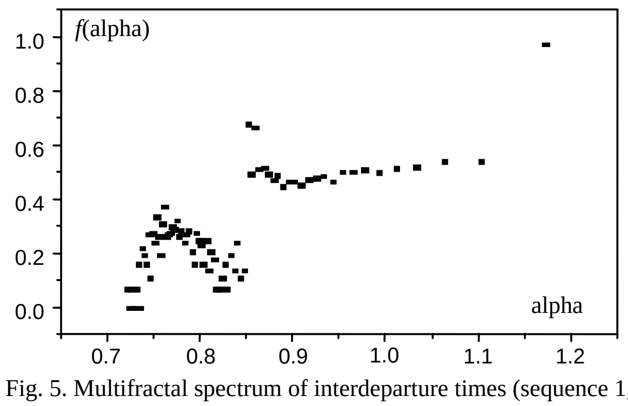


Fig. 5. Multifractal spectrum of interdeparture times (sequence 1, MJPEG version of "Star Wars" movie) for RR priority control.

Note also that the NN control decreases t_d, compared to the RR, which is illustrated in Fig. 8. Our previously derived program [9] permits to extract samples from input signal, having particular value of Holder exponent, alpha, and/or the magnitude of MF spectrum, *f*(alpha). By appplying this program we extracted samples characterized by parameter alpha within limits: 0.92<alpha=< 0.93 (top diagrams) and 0.71< alpha =< 0.72 (down), for RR (left) and NN control (right).

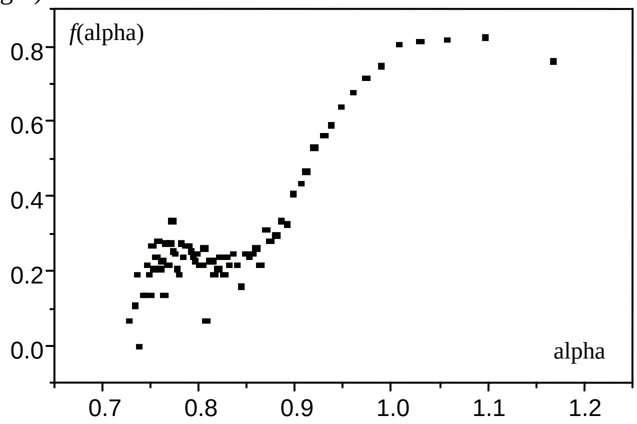


Fig. 6. Multifractal spectrum of interdeparture times (sequence 1, MJPEG version of "Star Wars" movie) for NN linear priority control.

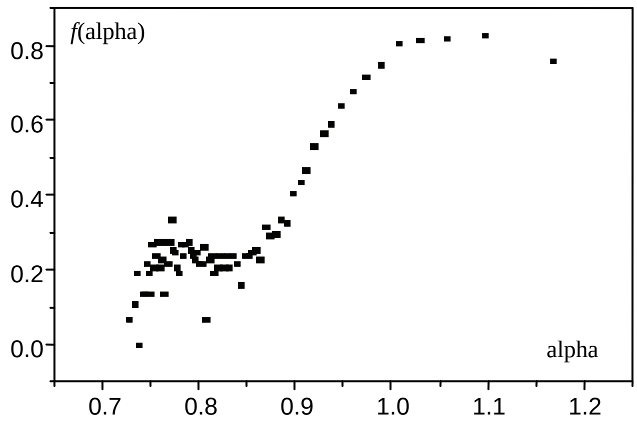
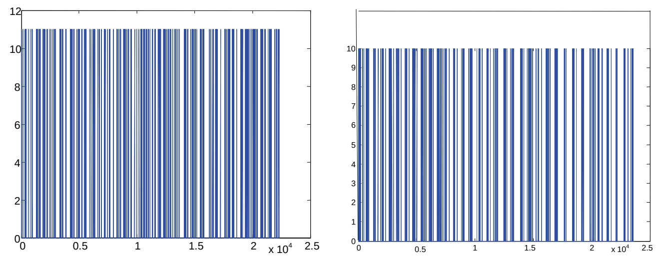
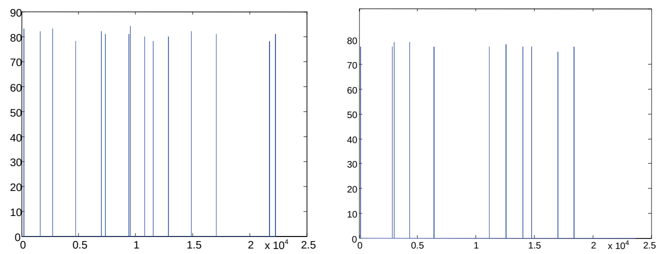


Fig. 7. Multifractal spectrum of interdeparture times (sequence 1, MJPEG version of "Star Wars") for NN exponential priority control.



0.92 < alpha =< 0.93



0.71 < alpha =< 0.72

Fig. 8. Extracted samples from outgoing sequence 1, characterized by particular value of holder exponent, for rr (left) and nn control (right).

IV. Conclusions

In this paper the statistical multiplexer with scheduling control was considered. Two scheduling policies were assumed: classical RR method and the NN control, and the analysis of the influence input priorities on cell loss was performed, as well. NN control takes into account the actual buffer occupancy and the trend of input traffic flow, as in [6], while priorities depend on the input activities. By monitoring the buffer occupancy we decided to increase by 40% the term(s) controling the priority of given input, if its buffer is loaded over 60% of its capacity. In this way the priorities are changed dynamically, depending on the actual input traffic, and the cell loss is avoided even in the case of bursty traffic. Intensive simulations confirm the efficiency of such scheduling policy.

After scheduling, the outgoing traffic becomes smooth enough, which was already described by statistical analysis [7]. Here, the multifractal analysis is used for describing the nature of outgoing traffic. It was confirmed that the NN control was better than RR control, as expected, and already approved in case of equal-priority control [6].

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