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The choice of optimal 3-rd order polynomial packet dropping function for NLRED in the presence of self-similar traffic

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Abstract. Algorithms of queue management in IP routers determine which packet should be deleted when necessary. The article investigates the influence of the self-similarity on the optimal packet rejection probability function in a special case of NLRED queues. This paper describes another approach to the non-linear packet dropping function. We propose to use the solutions based on the polynomials with degree equals to 3. The process of obtaining the optimal dropping packets function has been presented. Our researches were carried out using the Discrete Event Simulator OMNET++. The AQM model was early verified using the discrete-time Markov chain. The obtained results show that the traffic characteristic has the great impact on the network node behavior, but self-similarity of network traffic has no influence on the choosing of the optimal dropping packet function.

Key words: self-similarity, Active Queue Management, non-linear RED, dropping packets.

1. Introduction

The necessity of computer modeling appears in many areas of computer networks design and exploitation. The computer networks modeling helps developers:

- to predict the behaviour of a proposed network,
- to compare different topologies,
- to locate overloaded nodes,
- to characterize a network load,
- to determine the number and type of necessary components.

For the proper evaluation of the computer network performance it is necessary to create not only appropriate models of network mechanisms, but also the realistic packet traffic model.

In the traditional queuing models it is assumed that the input stream of customers (packets, frames, cells . . .) is characterized by the interarrival time distribution. The interarrival times are independent and represent the values of the same random variable, hence the generated traffic was characterized by the short-term dependencies. However, network traffic measurements have shown that these dependencies are long-term. This feature is associated with the self-similarity of the stochastic processes [1]. The problem of self-similarity has been described in Sec. 2.

The Internet has evolved from a limited size data transfer network into enormous public net offering various services where the quality of service – determined by transfer time, jitter and loss probability – becomes an important issue. Algorithms of queue management in IP routers determine which packet should be deleted when necessary. The Active Queue Management, recommended by IETF (Internet Engineering Task Force) [2], enhances the efficiency of transfers and cooperates with a TCP congestion window mechanism in adapting flow intensity to a network congestion.

There are many kinds of AQM algorithms. One of them – the RED (Random Early Detection) algorithm was first described by Sally Floyd and Van Jacobson [3]. Its idea is based on a dropping function yielding probability that a packet is rejected. There are many researches concerning improvement of the RED efficiency [4–10]. The existing varieties of the RED algorithm mostly differ in the way of defining the packet dropping probability functions [11–14]. Sometimes they differ in a choice of the packet dropping strategy [15]. One of these modifications is NLRED (non-linear RED) [13]. In NLRED, the linear packet dropping function is replaced by a quadratic function. This paper describes another approach to packed dropping function used in NLRED. We reconsider the problem of non-linear packet loss probability function based on sum of linearly independent polynomials. Our conference paper [16] has presented the first steps in the research associated with the use of polynomial packet dropping function $p(x)$. In the paper [17] we have also considered the polynomial function $p(x)$, but our study concerned only the Poisson type of traffic sources. We have considered a minimal index of quality built on several traffic parameters. In this article we use the self-similar traffic source and for such type of traffic we look for the optimal form of function $p(x)$.

Section 3 provides the basic notions for the active queue management mechanisms and the description of the proposed modification of the NLRED packet dropping function. Section 4 describes the full algorithm of obtaining the optimal packets dropping function. This algorithm lets us to obtain the optimal set of NLRED parameters (see Sec. 5). Section 5 demonstrates also how much NLRED performance is influenced by

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self-similarity of incoming traffic and therefore advocates the necessity of considering the self-similar processes in studies of congestion-control mechanisms. Some conclusions are presented in Sec. 6.

2. Self-similarity of network traffic

Traditionally, the traffic intensity, has been treated as a stochastic process, was represented in queuing models by short term dependencies [18]. However, the analysis of measurements shows that the traffic possesses also long-terms dependencies and has a self-similar character. It was observed on various protocol layers and in different network structures [19–24].

The term "*self-similar*" was introduced by Mandelbrot [25] in description of processes in the field of hydrology and geophysics. It means that a change of a time scale does not influence statistical properties of the process. A stochastic process X_t is self-similar with Hurst parameter H $(0.5 \leq H \leq 1)$ if for a positive factor g the process $g^{-H}X_{gt}$ has the same distribution as the original process X_t, [1]. Mathematically, the difference between short-range dependent processes and long-range ones (self-similar) is as follows [26]:

For a short-range dependent process:

- $\sum_{r=0}^{\infty} \mathrm{Cov}(X_t, X_{t+\tau})$ is convergent,
- spectrum at $\omega = 0$ is finite,
- for large m, Var $(X_k^{(m)})$ is asymptotically of the form Var $(X)/m$,
- the aggregated process $X_k^{(m)}$ tends to the second order pure noise as $m \to \infty$;

For a long-range dependent process:

- $\sum_{r=0}^{\infty} \mathrm{Cov}(X_t, X_{t+\tau})$ is divergent,
- spectrum at $\omega = 0$ is singular,
- for large m, Var $(X_k^{(m)})$ is asymptotically of the form Var $(X)m^{-\beta}$,
- the aggregated process $X_k^{(m)}$ does not tend to the second order pure noise as $m \to \infty$,

where the spectrum of the process is the Fourier transformation of the autocorrelation function and the aggregated process $X_k^{(m)}$ is the average of X_t on the interval m:

$$X_k^{(m)} = \frac{1}{m}(X_{km-m+1} + ... + X_{km}) \qquad k \geq 1.$$

Self-similarity of a process means that a change of a time scale does not affect statistical characteristics of the process. It results in long-range dependence and makes the occurrence of very long periods of high (or low) traffic intensity possible. These features have a great impact on a network performance. They enlarge mean queue lengths at buffers and increase packet loss probability, reducing this way the quality of services provided by a network [27]. TCP/IP traffic has been characterized by burstiness and long-term correlation as well [28]. Its features are additionally influenced by the performance of congestion avoidance and congestion management mechanisms, [21, 29]. According to Stallings [27], "Self-similarity is such an important concept that, in a way, it is surprising that it has only recently been applied to data communications traffic analysis". As mentioned above, many empirical and theoretical studies have shown the self similar characteristics of the network traffic. That is why it is necessary to take into account this feature when you want to create a realistic model of traffic sources [30].

To represent the self-similar traffic we use here a SMPP (Special Semi-Markov Process) model introduced by S. Robert [31, 32]. The time of the model is discrete and divided into unit length slots. Discrete-time models can be more complex to analyze than equivalent continuous-time ones, but computer networks operate on the basis of time-slotting and such discrete representation seems natural. Only one packet can arrive during each time-slot. In the case of memoryless, geometrical source, the packet comes into system with fixed probability α. In the case of self-similar traffic, packet arrivals are determined by a n-state discrete time Markov chain called modulator. It was assumed that modulator has $n = 5$ states $(i = 0, 1, \ldots 4)$ and packets arrive only when the modulator is in state $i = 0$. The elements of the modulator transition probability matrix depend only on two parameters: q and a – therefore only two parameters should be fitted to match the mean value and Hurst parameter of the process. If p_{ij} denotes the modulator transition probability from state i to state j, then it was assumed that $p_{0j} = 1/a^j$, $p_{j0} = (q/a)^j$, $p_{jj} = 1-(q/a)^j$ where $j = 1, \ldots, 4$, $p_{00} = 1-1/a-\ldots-1/a^4$, and remaining probabilities are equal to zero. The passages from the state 0 to one of other states determine the process behavior on one time scale, hence the number of these states corresponds to the number of time-scales where the process may be considered as self-similar. Figure 1 presents the normalized variance of the aggregated series of SSMP traffic as a function of time scale in log-log coordinates. For comparison, the same plot is also drawn for the Poisson process. The SSMP model enable us to represent a network traffic which is self-similar over several time-scales.

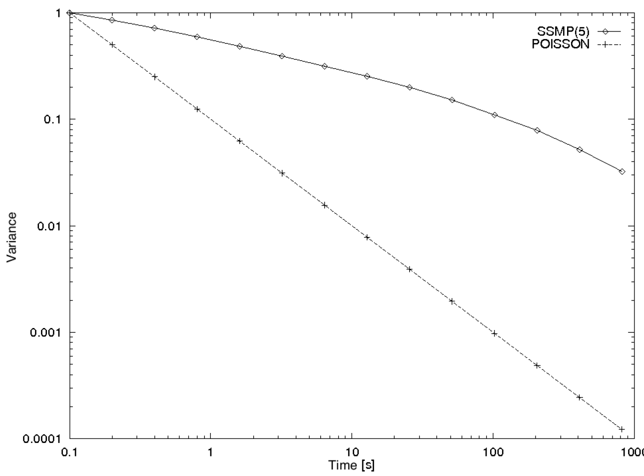

Fig. 1. Log-log variance-time plot for SSMP(5) model

3. Active queue management

In *passive* queue management, packets coming to a buffer are rejected only if there is no space in the buffer to store them, hence the senders have no earlier warning on the danger of growing congestion. In this case all packets coming during saturation of the buffer are lost. The existing schemes may differ on the choice of packet to be deleted (end of the tail, head of the tail, random). During a saturation period all connections are affected and all react in the same way, hence they become synchronized. To enhance the throughput and fairness of the link sharing, also to eliminate the synchronization, the Internet Engineering Task Force (IETF) recommends *active* algorithms of buffer management. They incorporate mechanisms of preventive packet dropping when there is still place to store some packets, to advertise that the queue is growing and the danger of congestion is ahead. The probability of packet rejection is growing together with the level of congestion. The packets are dropped randomly, hence only chosen users are notified and the global synchronization of connections is avoided. A detailed discussion of the active queue management goals may be found in [2]. The RED (Random Early Detection) algorithm has been proposed by IETF to enhance the transmission via IP routers. It was primarily described by Sally Floyd and Van Jacobson in [3]. Its idea is based on a drop function giving probability that a packet is rejected. The argument *avg* of this function is a weighted moving average queue length, acting as a low-pass filter (Fig. 2) and calculated at the arrival of each packet as

$$avg = (1-w)avg' + wq, \tag{1}$$

where avg' is the previous value of avg, q is the current queue length and w is a weight determining the importance of the instantaneous queue length, typically $w \ll 1$. If w is too small, the reaction on arising congestion would be too slow, if w is too large, the algorithm would be too sensitive on ephemeral changes of the queue (noise). Articles [3, 33] recommend $w = 0.001$ or $w = 0.002$, and [34] shows the efficiency of $w = 0.05$ and $w = 0.07$. Article [35] analyses the influence of w on queuing time fluctuations, obviously the larger w, the higher fluctuations. The RED drop function has two thresholds Min_{th} and Max_{th}. If $avg < Min_{th}$ all packets are admitted, if $Min_{th} < avg < Max_{th}$ then dropping probability p is growing linearly from 0 to $P_{\max}$:

$$p(avg) = P_{\max}\frac{avg - Min_{th}}{Max_{th} - Min_{th}} \tag{2}$$

and if $avg > Max_{th}$ then all packets are dropped. The value of $P_{\max}$ has also a strong influence on the RED performance: if it is too large, the overall throughput would be unnecessarily choked and if it's too small the danger of synchronization arises; [33] recommends $P_{\max} = 0.1$. The problem of the choice of parameters is still being discussed, see e.g. [34, 36, 37]. The mean avg may be also determined in other way, see [38] for discussion. Despite evident highlights, RED has also such drawbacks as low throughput, unfair bandwidth sharing, introduction of variable latency, deterioration of network stability. Therefore numerous propositions of basic algorithms improvements appear, their comparison may be found e.g. in [39].

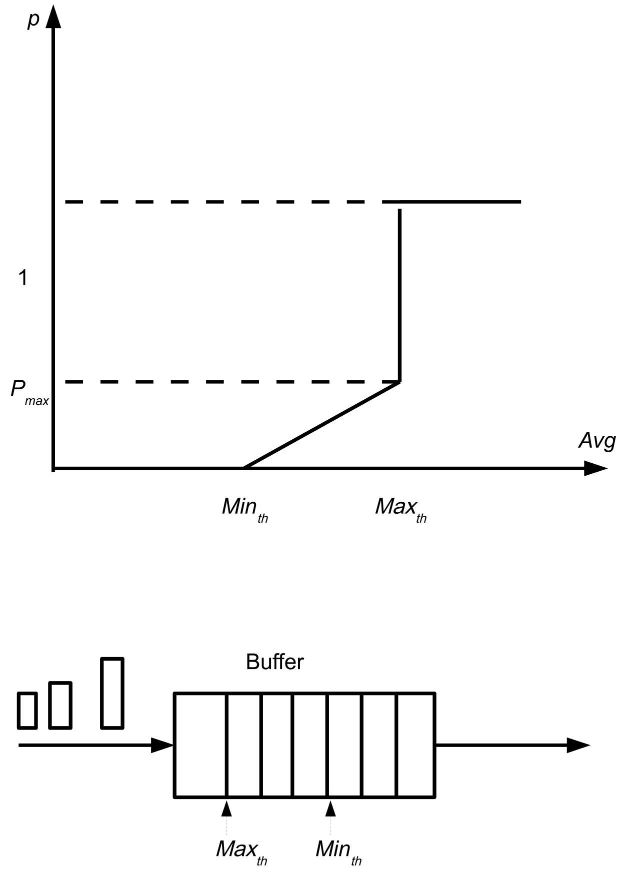

Fig. 2. Dropping functions for RED algorithm

One of these modifications is NLRED (non-linear RED) [13]. In NLRED, the linear packet dropping function is replaced by a quadratic function. For this solution dropping probability p is growing non-linearly as follows:

$$p(x) = \begin{cases} 0 & \text{for } x < Min_{th} \\ \left(\dfrac{x - Min_{th}}{Max_{th} - Min_{th}}\right)^2 P_{\max} & \text{for } Min_{th} \le x \le Max_{th} \\ 1 & \text{for } x > Max_{th} \end{cases} \tag{3}$$

where x is an average queue size. Figure 3 shows dropping functions for RED and NLRED.

This paper describes another approach to a non-linear packet dropping function. Instead of the well-known quadratic function we propose to use the solutions based on the third degree polynomials. This solution seems to be more flexible and allows to choose the optimal shape of dropping packet function.

Any continuous function $f(x)$ with domain $[0, l]$ can be approximated by $\widehat{f}(x)$ as a finite linear combination of basic functions:

$$\widehat{f}(x) = \sum_{i=1}^{N} a_j \Phi_j(x), \tag{4}$$

where a_j are undetermined parameters and basis functions $\{\Phi_j\}$ is a set of linearly independent polynomials:

$$\Phi_j = x^{j-1}(l - x). \tag{5}$$

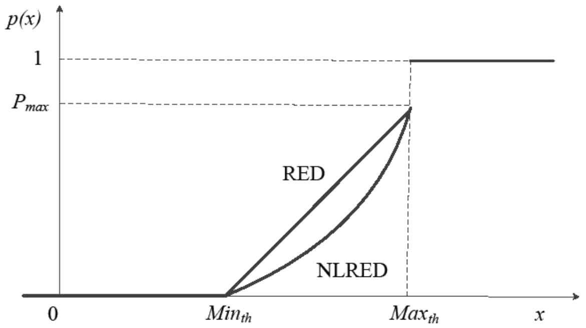

Fig. 3. Dropping functions for RED and NLRED

Optimal values of a_j can be numerically obtained by finding minimum of some functional J implicitly defined on f. In the real application only a few elements Φ_j are required to obtain accurate approximation of f.

Using approach described above (Eq. (4) and (5)) we propose to define the probability of packet dropping function as follows:

$$p(x, a_1, a_2, P_{\max}) = \begin{cases} 0 \quad \text{for } x < Min_{th} \\ \varphi_0(x) + a_1\varphi_1(x) + a_2\varphi_2(x) \\ \quad \text{for } Min_{th} \leq x \leq Max_{th} \\ 1 \quad \text{for } x > Max_{th} \end{cases} \tag{6}$$

where set of basis function is defined as follows:

$$\varphi_0(x) = P_{\max}\frac{x - Min_{th}}{Max_{th} - Min_{th}}, \tag{7}$$

$$\varphi_1(x) = (x - Min_{th})(Max_{th} - x), \tag{8}$$

$$\varphi_2(x) = (x - Min_{th})^2(Max_{th} - x). \tag{9}$$

Sample packet dropping functions for set of exemplary parameters $(a_1, a_2, P_{\max})$ are shown in Fig. 4.

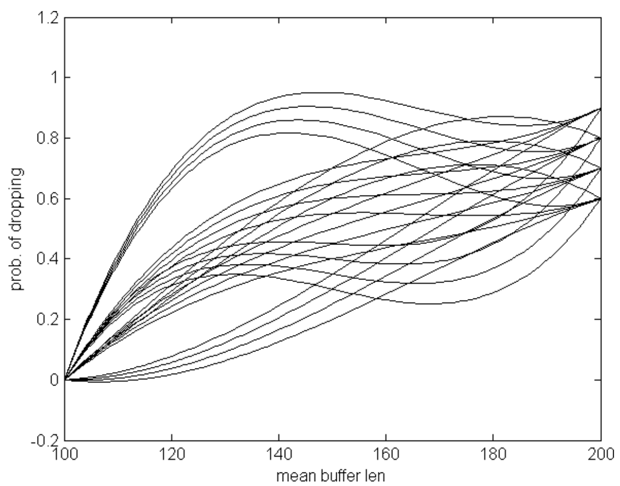

Fig. 4. Sample functions of probability of packed dropping for some a_1, a_2 and given values $Min_{th} = 100$, $Max_{th} = 200$, $P_{\max} = 0.6, 0.7, 0.8, 0.9$

4. The method

In this section we describe the process of obtaining the optimal packets dropping function for our NLRED modification (see Sec. 3). This issue may be considered as a problem in a 5 dimensional space. The first dimension affects type network traffic source (nts). Two type of sources are taken into account: the geometric source and the self-similar one. The second one is μ – probability of the end of service within a current time-slot. The values of parameter μ changes from 0.05 to 0.5 step 0.15. Due to the changes of μ, different traffic loads (very low, low, medium, and high) were considered. Remaining three dimensions affect parameters $P_{\max}, a_1, a_2$ of the polynomial function (Eq. (4)) of dropping packets.

Finding the best values of $P_{\max}$, a_1, a_2 for the given type of traffic source may be considered as optimization problem in 3 dimensional space. An evaluation functional J should have a minimal value for the optimal parameters ($P_{\max}$, a_1, a_2).

Many types of functional were considered (e.g. mean waiting time, mean queue length, number of dropped packets, probability of dropping packet by RED mechanism, etc.) but most of them are correlated. This is the reason why only the mean waiting time is used as the score functional J.

Determining of the domain of J i.e. such subspace of $A_1 \times A_2 \times P_{\max}$ where $0 \leq p(x) \leq 1$ is not trivial task. We propose simple necessary conditions for domain of J (which allows to limit the domain). They are based on the first two derivates of p respect to x. Obviously, values of p-function in a local extrema and an inflection point should be included in [0, 1].

The local extrema and the inflection point can be easily found by solving the following equations:

$$\frac{dp}{dx} = 0, \tag{10}$$

$$\frac{d^2p}{dx^2} = 0. \tag{11}$$

The Eq. (10) is equivalent to:

$$\begin{aligned} &a_1(Max_{th} - Min_{th})(Max_{th} + Min_{th} - 2x) \\ &+a_2(Max_{th} - Min_{th})(x - Min_{th}) \\ &\cdot (2Max_{th} + Min_{th} - 3x) + P_{\max} = 0. \end{aligned} \tag{12}$$

When the discriminant of Eq. (12) is greater than 0 it lets to find roots x_1 and x_2. This allows to set conditions as follows:

$$\text{for} \quad i = 1, 2 : Min_{th} < x_i < Max_{th} \wedge 0 \leq p(x_i) \leq 1. \tag{13}$$

Regions of $A_1 \times A_2$ satisfying some selected conditions for ($P_{\max} = 0.8$, $Min_{th} = 100$, $Max_{th} = 200$) are shown in Fig. 5, i.e. Fig. 5a ($x_1 \geq Min_{th}$) and Fig. 5b ($p(x_1) \leq 1$).

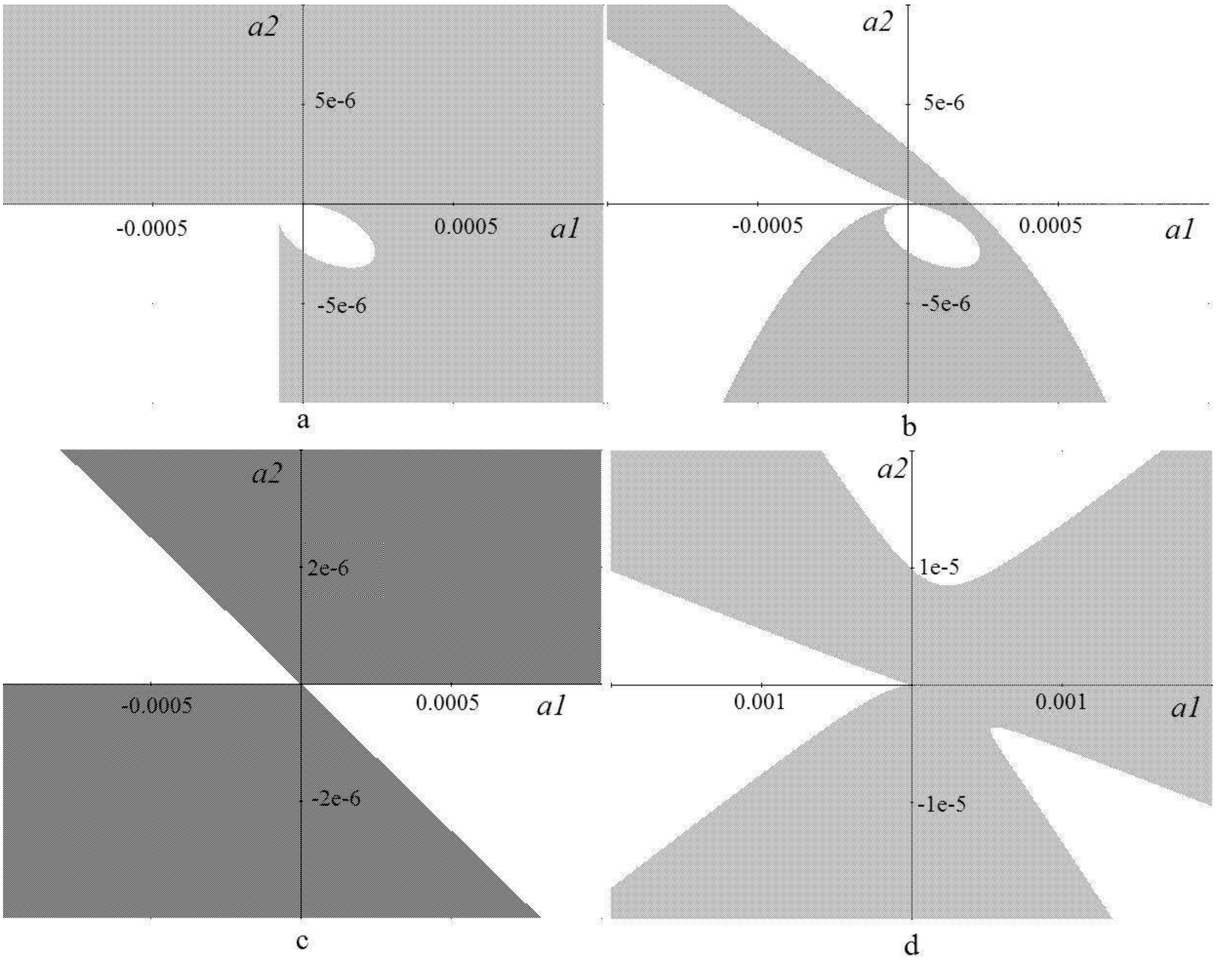

Fig. 5. Regions of $A_1 \times A_2$ (gray colour) for some selected conditions: a) $x_1 \geq Min_{th}$, b) $p(x_1) \leq 1$, c) $x_0 \leq Max_{th}$, d) $p(x_0) \leq 1$

Equation (11) is equivalent to:

$$(a_1 - a_2(Max_{th} - 2Min_{th} - 3x))(Min_{th} - Max_{th}) = 0 \quad (14)$$

and lets to find root x_0. This allows to set conditions as follows:

$$Min_{th} < x_0 < Max_{th} \wedge 0 \leq p(x_0) \leq 1. \quad (15)$$

Regions of $A_1 \times A_2$ satisfying selected conditions for ($P_{\max} = 0.8$, $Min_{th} = 100$, $Max_{th} = 200$) are shown in Fig. 5, i.e. Fig. 5c ($x_0 \leq Max_{th}$) and Fig. 5d ($p(x_0) \leq 1$).

The final domain for ($P_{\max} = 0.8$, $Min_{th} = 100$, $Max_{th} = 200$) based on the logical product of all conditions (Eq. (13) and (14)). The domain is an intersection of all obtained regions (inter alia those ones from Fig. 5).

This assignment of the domain $A_1 \times A_2$ allows to set constraints for a method of searching minimum of functional J. In this solution the Hooke-Jeves method was applied [40].

The full algorithm of obtaining the optimal packet dropping function may be described in a pseudocode as follows:

1. For a type of network traffic source (*nts* = geometric or self-similar)
2. For a source frequency (μ from 0.05 to 0.5 step 0.15)
3. For a parameter $P_{\max}$ of p-function ($P_{\max}$ from 0.55 to 0.95 step 0.05)
4. Assign domain for space $A_1 \times A_2$
5. Find *JValue* – minimum of bivariate functional J $(a1, a2)$ using Hooke-Jeeves method.
6. Store results $(nts, \mu, P_{\max}, a_1, a_2, JValue)$

5. Experimental results

The algorithm described in the previous section allows to obtain results presented in Table 1. For given accuracy of J ($\Delta J = 0.1$) the optimal values of parameters a_1 and a_2 were obtained (for given nts and μ). Obtained acuracy values of a_1 and a_2 are equal $\Delta a_1 = 0.00002$ and $\Delta a_2 = 0.0000002$. Value of $P_{\max}$ accuracy ($\Delta P_{\max}$) equals 0.05.

The experimental results show the existence of one optimal set of values of parameters of p (a_1, a_2, $P_{\max}$) independently on type of network traffic source and traffic load for given score functional J, i.e. the mean waiting time.

The set of optimal parameters is ($P_{\max}$, a_1, a_2) = (0.855, 0.00042, -0.0000038). The shape of p-function for optimal values of parameters has been shown in Fig. 6.

Table 1
Selected simulation results for the mean waiting time used as the score functional J

nts	μ	$P_{\max}$	a_1	a_2	Δa_1	Δa_2	JValue
Geo	0.5	0.855	0.00042	−0.0000038	0.00002	0.0000002	52.2
Geo	0.35	0.855	0.00042	−0.0000038	0.00002	0.0000002	72.1
Geo	0.20	0.855	0.00042	−0.0000038	0.00002	0.0000002	78.9
Geo	0.05	0.855	0.00042	−0.0000038	0.00002	0.0000002	109.1
...	...	...	...	...	...	...	...
Self	0.5	0.855	0.00042	−0.0000038	0.00002	0.0000002	75.0
Self	0.35	0.855	0.00042	−0.0000038	0.00002	0.0000002	91.4
Self	0.20	0.855	0.00042	−0.0000038	0.00002	0.0000002	101.0
Self	0.05	0.855	0.00042	−0.0000038	0.00002	0.0000002	126.4
...	...	...	...	...	...	...	...

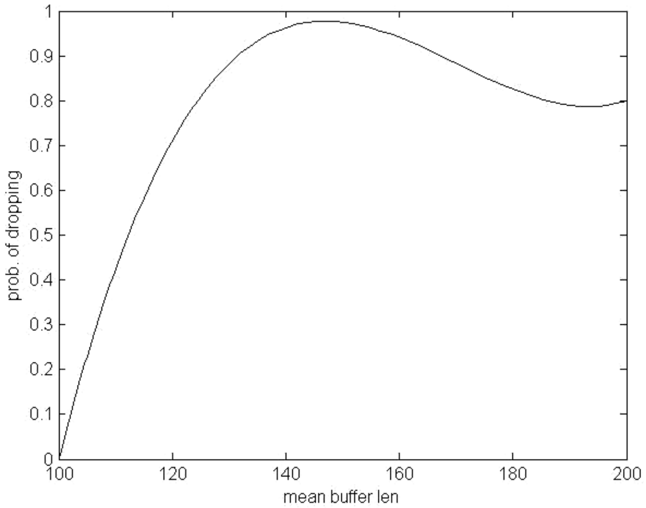

Fig. 6. The shape of optimal packet dropping function for parameters ($P_{\max}$, a_1, a_2) = (0.855, 0.00042, −0.0000038)

We have analyzed the NLRED queues behaviour for the described above parameters. The NLRED queue mechanisms are represented by a single-server model. The service time represents the time of a packet treatment and dispatching. Its distribution is geometric. For modelling incoming traffic, time is divided into slots and at each slot at most one packet may come. In case of a geometric interarrival time distribution (which corresponds to Poisson traffic in case of continuous time models) the probability α of a packet arrival is constant. In case of self-similar traffic this probability is determined by a 5-state independent Markov chain (modulator) and follows the model proposed in [31] and described in Sec. 2. For both geometrical traffic and self-similar one the considered traffic intensities are the same. A detailed discussion of the choice of SSMP model parameters has been also presented in [41].

Our NLRED analysis was carried out in the OMNeT++ simulation environment [42, 43]. OMNeT++ is a public-source, component-based, modular, and open-architecture Discrete Event Simulator. It is free for academic and non-profit use; commercial users should obtain a license. Our AQM simulation model was early validate using the discrete-time Markov chain [15].

Figures 7–10 show the influence of the input traffic characteristics on the NLRED queue distributions and queuing times. Input traffic intensity (for geometric and self-similar traffic) was chosen as $\alpha = 0.5$, and due to the modulator characteristics, the Hurst parameter of self-similar traffic was fixed to $H = 0.85$.

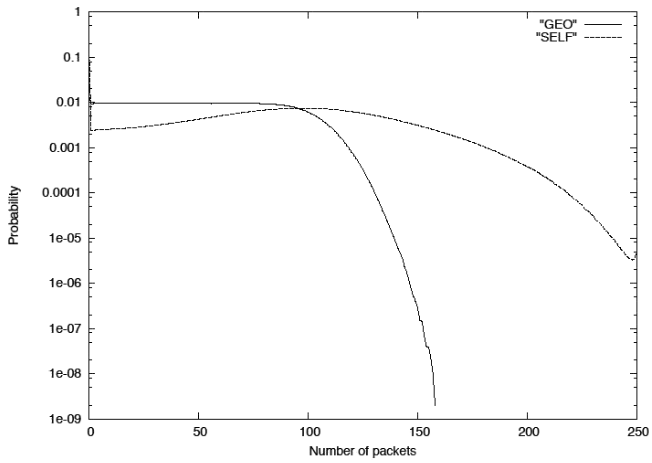

Fig. 7. Queue length distribution for NLRED: geometric and self-similar sources, $\alpha = 0.5$, $\mu = 0.5$

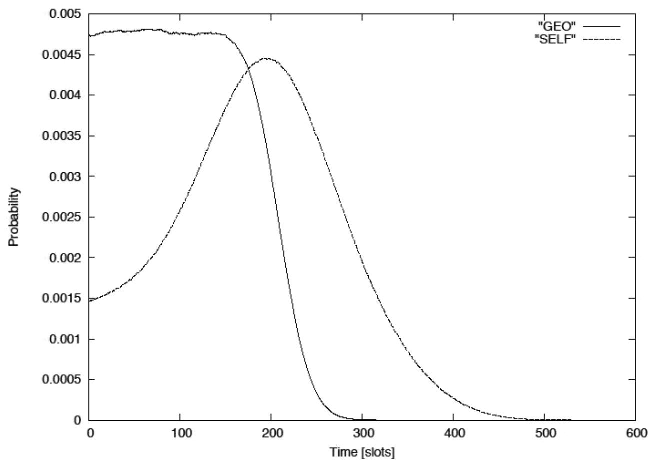

Fig. 8. Waiting time distribution for NLRED: geometric and self-similar sources, $\alpha = 0.5$, $\mu = 0.5$

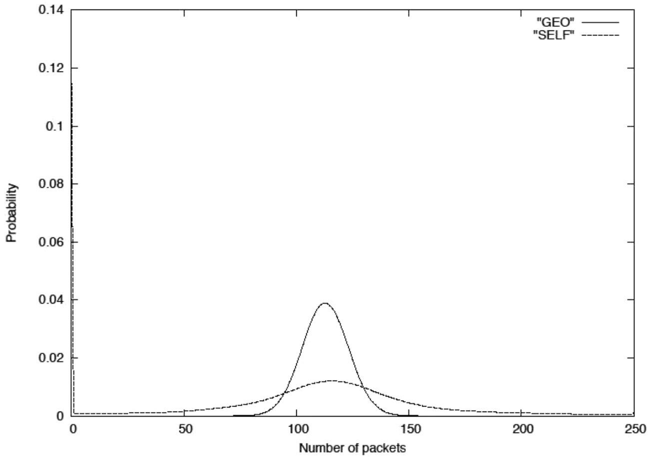

Fig. 9. Queue distribution for NLRED: geometric and self-similar sources, $\alpha = 0.5$, $\mu = 0.25$

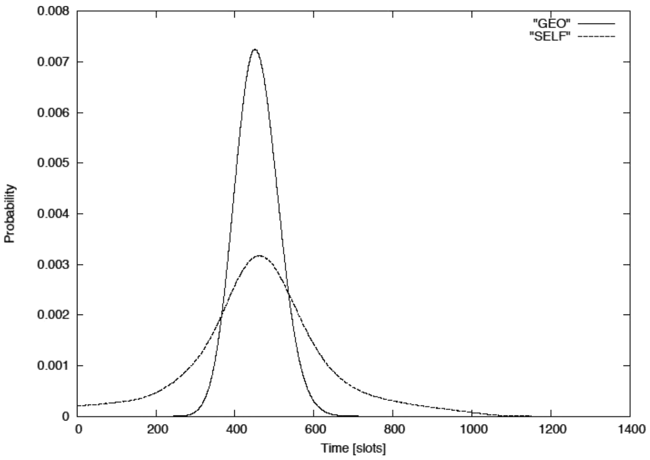

Fig. 10. Waiting time distribution for NLRED: geometric and self-similar sources, $\alpha = 0.5$, $\mu = 0.25$

It is clearly visible that the buffer content is much greater in case of self-similar traffic, especially for a light load. Similarly as for queue sizes, traffic self-similarity also makes the waiting time substantially longer for a light traffic. These results confirm that the NLRED performance is influenced by self-similarity of incoming traffic and therefore advocates the necessity of considering self-similar processes in studies of congestion control mechanisms.

6. Summary

In this paper we have presented the problem of packet loss probability function and its influence on the behavior of the AQM queue. We have also considered the problem of choosing the optimal shape of dropping packet function for NLRED algorithm. We have focused our attention on obtaining the minimum packet waiting time. We have based our solution on polynomials with degree equals 3. The process of obtaining the optimal packet dropping function has been presented.

During the tests we analyzed the following parameters of the transmission with AQM: the length of the queue, the number of rejected packets and waiting times in queues. The waiting time in queues parameter was chosen for optimization. This minimization is done at the expense of increasing the number of rejected packets. This is useful only for multimedia applications. Depending on a particular criterion of optimization a proper form of non-linear function may be found. Our researches were carried out using the Discrete Event Simulator OMNET++. The RED model was early verified using the discrete-time Markov chain.

In the studies we have also reconsidered the problem of a non linear packet loss probability function in presence of self-similar traffic. The obtained results show that the traffic characteristic has the great impact on the network node behavior, but the the optimal values of parameters of p-function (a_1, a_2, $P_{\max}$) are independent on type of network traffic source (self-similarity, geometrical) and the network node load (for given score functional J based on mean waiting time). The authors think that this is due to the rapid grow of the packet dropping function. The values of this function grow very quickly from the first moment of exceeding the Min_{th} parameter. It's very likely that the optimal packet dropping function will not have the same shape for self-similar and not self-similar traffic in the case of choice two optimization parameters: the number of rejected packets and the waiting time in queues. Our future works will focus on obtaining such a packet dropping function.

We have studied the models of AQM in IP routers in open-loop scenario because of the difficulty in analyzing AQM mathematically [15, 44]. Our future works will also focus on using the fluid flow approximation technique to model the interaction between the set of TCP/UDP flows and AQM.

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