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THE INFLUENCE of an SRD STRUCTURE of LRD TRAFFIC on a DROP PROBABILITY[#]

This paper investigates an influence of different SRD structures on a maximum delay value for queued LRD traffic with usage of an envelope analysis. A FARIMA process is used as a traffic model since it can model both SRD and LRD structures independently. A FGN process is used as a reference of LRD traffic due to its relative simplicity. A drop probability is computed as a function of a buffer size that in turn is determined as a maximum delay function. All computations are performed with a support of an envelope process theory. A similarity between theoretical and simulations trends has been shown. An influence of an SRD structure for two different FARIMA models has been analysed for different network parameters.

1. INTRODUCTION

A computer network is built of different devices connected with each other by different technologies. Nevertheless, there is one common problem for all technologies, namely the follow-up effects of implementing some queuing algorithms. The investigation of queue behaviour has a critical impact on enforcing a quality of service (QoS) offered by the network.

Research done by Willinger reveals that network traffic can be described as a self-similar (SS) process [1]. An important property closely connected with SS processes is Long Range Dependence – LRD (in opposite to a Short Range Dependence – SRD) being a slowly decaying correlation structure [2]. SS traffic has long periods with intensity exceeding or remaining below mean source intensity. Surprisingly both effects do not average themselves so a mean queue length for a workload process modelled by a self-similar process is much different than a mean queue length obtained from Markov process analysis [2, 3, 4]. Generally, a maximum queue length obtained for the same drop probability is longer for a workload process with higher Hurst parameter value.

Numerous researches show how vital is to take into consideration a network traffic self-similarity seen exclusively as a LRD [5, 6].

In this paper an influence of both SRD and LRD correlation structures on a maximum queue length has been considered. As a workload process a FARIMA process has been used since a FARIMA process makes possible to model an SRD and an LRD structure separately although simultaneously. A FARIMA process is a generalisation of an ARIMA process described by Box and

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Jankins in [7]. An ARIMA process is flexible in describing numerous different SRD structures; a FARIMA as a generalisation of an ARIMA process can capture both SRD and LRD structures at the same time.

Numerous of different analysis tools support queue parameters computation, one of the widely used is an effective bandwidth describes in [22, 23]. An effective bandwidth is based on logarithmic moment generating function and due to this function properties it supply multiplexing gain and queuing parameters computation. In this paper an envelope process has been use. An envelope process is a function base on quantile lines i.e. a process distribution, details can be found in [17]. An effective bandwidth supports an queue tail distribution computation for long observation period however an envelope process supports computation of a maximum queue length probability.

The paper is organised as follows. Chapter 2 describes shortly LRD processes. Chapter 3 describes FARIMA and FGN processes with their basic properties and corresponding notation. In Chapter 4 an envelope process is presented invoked as a tool for determining selected QoS parameters. Chapter 5 shows results obtained for FARIMA and FGN models. Chapter 6 summarises the paper pointing to most important theoretical results and their implementation options.

2. LONG RANGE DEPENDENCE

For numerous reasons the most important properties of a stochastic process are hidden in an autocorrelation function. Firstly, if a current process value is strongly dependent on its previous values, then we can predict a future process value with high probability and accuracy. Secondly, from autocorrelation decay rate we can conclude how long a process memory is i.e. how many previous process values has a critical influence on current process value.

According to a correlation structure properties stochastic processes can be splitted in two classes [8]. First of those are short range dependence processes (SRD), for which the autocorrelation function is summable, that is

$$\sum_{i=1}^{\infty} \rho_i \leq \infty \quad (1)$$

where ρ_i is an autocorrelation for a lag i . The summability condition (1) can be approved as a some measure of a fast decaying autocorrelation function.

The second class of stochastic processes are long range dependence processes (LRD). The LRD processes pass the opposite condition

$$\sum_{i=1}^{\infty} \rho_i = \infty \quad (2)$$

Note that the series ρ_i is divergent if

$$\rho_i \approx \frac{1}{i^\beta}, \text{ where } \beta \leq 1 \quad (3)$$

For self-similar processes β parameter is connected with a self-similar parameter called Hurst parameter H by equation $\beta = 2 - 2H$. The Hurst parameter is a self-similarity parameter describing similarity of a process observed on different time scales. The Hurst parameter varies in a

range [0.5,1) for telecommunication applications where higher values result in stronger correlation structure.

Additional justification of splitting stochastic processes to SRD and LRD classes is that SRD process behaviour on higher time scales can be modelled by Gaussian process because the SRD processes pass Central Limit Theorem (CLT) assumptions. LRD processes do not pass CLT assumptions [9]; therefore the Gaussian distribution cannot approximate their behaviour on higher time scales. Detailed description of limit properties of self-similar processes and related LRD processes can be found in [10].

The first result of a tail queue distribution with a self-similar workload process was obtained by Norros in [3] and Duffield and Connell in [4]. The most important result coming from the equation derived by Norros is that the queue tail has a Weibullian's distribution instead of an exponential one (obtained for Markov models [11]).

The result obtained by Norros assumes a FGN workload process distribution providing a lower bound of a queue distribution. More results assuming FGN workload process distribution can be found in [4] (a large buffer), [12] (an exact formula), and [13] (an upper bound). These articles are all cited and shortly discussed in [14].

All results based on a FGN workload process do not consider a traffic SRD structure since for a FGN process an SRD structure, according to assumption (3), is fully dependent on β parameter value. A more through insight into an LRD definition[#] shows that the β parameter has to pass assumption (3) only for large lags, i.e. high i values. In other words, both SRD and LRD structures are tied in a close manner. Since an SRD structure impacts a queue length as well as an LRD structure it is important to consider models allowing for an investigation of SRD and an LRD structures separately. Such models provide a comparison of processes with the same LRD structure but with different SRD structures.

Considering LRD and SRD separately have been analysed using MMPP (Markov Modulated Poisson Process) [21]. This paper presents such an analysis made on a basis of an envelope process. The process modelling workload process is a FARIMA process revealing requested properties of integrated capturing both the SRD and LRD [15]. Next section presents a basic description of a FARIMA process and as a necessary reference an exactly self-similar FGN process.

3. FGN AND FARIMA PROCESSES

If Z_t process is a normalized Fractional Brownian Motion (FBM) it follows properties [3]

1. Z_t has stationary increments.
2. $Z_0 = 0$, and for $E\{Z_t\} = 0$ all $t \geq 0$.
3. $E\{Z_t^2\} = t^{2H}$ for all $t \geq 0$.
4. Z_t has continuous paths.
5. Z_t distributions are Gaussian multivariates.

A FGN process composed of FBM increments reveals an LRD feature for $H > 1/2$ as its autocorrelation function has a form [16]

[#] Remind a basic mathematical analysis result that a number series stays divergent no matter how its initial terms behave.

$$\rho_i = \frac{1}{2}((i+1)^{2H} - 2i^{2H} + |i-1|^{2H}) \approx H(2H-1)i^{2H-2}, \text{ where } H > 1/2 \text{ and } i \rightarrow \infty. \quad (4)$$

The Hurst parameter shapes an overall autocorrelation structure comprising of both SRD and LRD so it is not possible to model them separately. The conclusion gains importance if measurement traffic data have a different type of an SDR structure than the behaviour reflected by the LRD structure of a FGN process. This disadvantage disappears for a FARIMA process since it can model an SRD and an LRD structure simultaneously.

A FARIMA process is a generalization of an ARIMA process, which has been proposed by Hosking and described in [16]. A FARIMA(p, d, q) process is characterised by $p+1+q$ parameters and it is given by

$$\Phi(B)(1-B)^d z_n = \Theta(B)a_n, \quad (5)$$

where B is a backshift operator defined as $Bz_n = z_{n-1}$, $\Phi(B)$ and $\Theta(B)$ are polynomials of an order p and q respectively, $d \in [0, 1/2)$, a_n are i.i.d. random variables with a zero mean value, and z_n are process values.

From LRD processes analysis point of view the most important property of a FARIMA process is that for $d \in (0, 1/2)$ an autocorrelation function behaves like [16]

$$\rho_k \approx i^{2d-1}, i \rightarrow \infty. \quad (6)$$

According to equation $\beta = 2 - 2H$ and equation (3) Hurst and d parameters are related by

$$H = d + 1/2. \quad (7)$$

Hence, a FARIMA process makes possible to capture an LRD property and because $\Phi(B)$ and $\Theta(B)$ polynomials influence an autocorrelation function for small lags [7] a FARIMA process can model an LRD and an SRD structure independently.

The limiting behaviour of the autocorrelation function for $k \rightarrow \infty$ is given by equation (6), however, in order to model traffic fluctuations and to obtain some results of interest it is requested to investigate an exact form of the autocorrelation function. In [16] the exact form of an autocorrelation function for three vital and special cases of FARIMA processes is presented. These processes are FARIMA(0, d , 0), FARIMA(1, d , 0) and FARIMA(0, d , 1).

FARIMA(0, d , 0) is described by d parameter only and its SRD structure depends on an LRD structure.

FARIMA(1, d , 0) called FAR(1, d) is described by d (equation (7)) and ϕ parameter which influences an SRD structure only.

FARIMA(0, d , 1) called FMA(d , 1) is described by d (equation (7)) and θ parameter which influences an SRD structure only.

4. ENVELOPE PROCESS

An envelope process [17] is given by

$$\Pr(Z_t > \hat{Z}(t)) = \varepsilon, \quad (8)$$

where Z_t is a stochastic process, $\hat{Z}(t)$ is some deterministic function and ε is an exceed probability. The envelope process poses a deterministic upper bound on stochastic process paths. A concept of an envelope is useful in designing queueing network elements as probabilistic considerations are replaced by deterministic ones [18].

An envelope process can be described as a cumulative distribution function because $\Pr(Z_t > \hat{Z}(t)) = 1 - F_{Z_t}(\hat{Z}(t))$ where $F_{Z_t}(\cdot)$ is a cumulative distribution function of a Z_t process. An envelope process is given by

$$\hat{Z}(t) = F_{Z_t}^{-1}(1 - \varepsilon). \quad (9)$$

Most of results do not depend on the exact form of a process for which the envelope functions are found. On the other hand, an envelope process can be found for any process for which a cumulative distribution function is known or at least it is numerically computable. Therefore, the envelope analysis allows obtaining general results and extending them to some new processes.

Norros has proposed in [3] a model of an accumulated workload process for time interval $(0, t)$ where an FGN process models an autocorrelation; a mean trend value is a and a standard deviation is σ . The total amount of a workload process is given by

$$A_t = at + \sigma Z_t. \quad (10)$$

In [19] a total amount of a workload process with a FARIMA autocorrelation has been proposed. For short, such a process is called a FARIMA model; similarly a total amount of a workload process with an FGN autocorrelation is called a FGN model. In this paper an envelope process is used to compare results obtained for the FGN model and three special cases of FARIMA model.

An envelope process for a FGN model A_t is given by [17]

$$\hat{A}(t) = at + F^{-1}(1 - \varepsilon)\sigma^H. \quad (11)$$

The envelope process for FARIMA models are much more complicated and here only an envelope process of FAR(1, d) process is presented

$$\hat{A}(n) = an + F^{-1}(1 - \varepsilon) \sqrt{\frac{2\Gamma(-1-2d)}{1-\phi^2} \left(\frac{{}_2F_1(1, 1+d; -d; \phi) - 1}{\Gamma^2(-d)} + (-1)^n \frac{{}_1F_1(1, 1+d-n; -d-n; \phi) - {}_2F_1(1, 1+d+n; -d+n; \phi)}{\Gamma(-d-n)\Gamma(-d+n)} \right)}, \quad (12)$$

where ${}_2F_1(a, b; c; z)$ is a hypergeometric function.

Envelope processes of FARIMA(0, d , 0) and FMA(d , 1) are given in [19]. Note that a FARIMA process is discrete in time.

In [19] a queue process for a link capacity c is given by

$$Q_t = A(t) - ct. \quad (13)$$

Equation (13) is valid if during time interval $(0, t)$ a queue process is never empty. Since we are interested in a maximum queue length such an assumption does not pose any considerable restrictions.

The envelope process of a queue process is given by [20]

$$\hat{Q}(t) = \hat{A}(t) - ct. \quad (14)$$

Note that since $\Pr(Q_t > \hat{Q}(t)) = \varepsilon$ then for $\hat{Q}_{\max} = \max_t \hat{Q}(t)$ we have

$$\Pr(Q_t > \hat{Q}_{\max}) \leq \varepsilon. \quad (15)$$

According to equation (15) an upper bound of a drop probability is obtained. For a buffer size $B = \hat{Q}_{\max}$ an exceed probability ε approximates a drop probability p_d .

Note that a buffer size B determines a maximum delay since $D_{\max} = B/c$. Therefore, for $B = \hat{Q}_{\max}$ from envelope analysis a relation between a maximum delay $D_{\max}$ and a drop probability p_d can be found. For a FGN model such a relation is given by

$$D_{\max} = \hat{Q}_{\max} / c = \frac{(a-c)t_{\max} - \sigma F^{-1}(1-p_d)t_{\max}^H}{c}, \quad (16)$$

where $t_{\max}$ is a time instant for which an envelope process takes its maximum value on

$$t_{\max} = \left(\frac{\sigma F^{-1}(1-p_d)H}{c-a} \right)^{\frac{1}{1-H}}, \quad (17)$$

Since a FARIMA model is discrete in time and an envelope process of a FARIMA model is described in terms of the Gamma function it is not possible to find a corresponding $n_{\max}$, however numerical results can be achieved.

5. DROP PROBABILITY COMPARISON

In order to compare an influence of an LRD and an SRD structure on QoS parameters equation (16) has been transformed to obtain a drop probability p_d as a function of traffic parameters for the FGN model $(a, \rho = a/c, \sigma, H)$ and for the FARIMA model $(a, \rho = a/c, \sigma, H, \theta \text{ or } \phi)$ and a maximum delay $D_{\max}$. The obtained equation has a form (for a FGN model)

$$p_d = 1 - F \left(\frac{c-a}{\sigma H} \left(\frac{c H D_{\max}}{(c-a)(1-H)} \right)^{1-H} \right). \quad (18)$$

For the FARIMA model, same as for determining maximum envelope value, the exact form of p_d cannot be found so numerical results have been provided.

In this paper the stress is laid on how an SRD and an LRD structure influence a drop probability so traffic parameters a and σ are chosen from a real traffic trace described in [1] and set to values $a = 138$ bit/ms and $\sigma = 420$ bit/ms.

In Figure 1 a drop probability as a function of a Hurst parameter value is presented. The FGN model has been compared with the FAR(1, d) model obtained for the same Hurst parameter but with two different ϕ values. Figure 2 shows the same comparison where the FMA(1, d) model instead of the FAR(1, d) one is used. It is essential that Figure 1 and 2 are drawn for different FARIMA models and different network parameters as well. For Figure 1 a link utilisation $\rho = 0.8$ and $D_{\max} = 100$ ms whereas for Figure 2 parameters were set to $\rho = 0.9$ and $D_{\max} = 1000$ ms.

The most important conclusion coming from Figures 1 and 2 is that an SRD structure has significant influence on a drop probability value. Note that for both FAR and FMA models the FGN model lies between curves obtained for a negative and a positive SRD structure. What is more, the influence of an SRD structure depends on an SRD model chosen. The FAR model influences more symmetrically as both curves lie within a similar distance to FGN model delivered values. In case of the FMA model a negative correlation has much more influence on a drop probability value than a positive one.

Figure 3 and 4 present a simulation of a drop probability p_d as a function of a Hurst parameter for the same parameters that have been used to plot theoretical values in Figures 1 and 2. Obtained p_d values are shown along with confidence intervals (except the last values of the FAR model that have been removed for a better legibility). The first conclusion is that theoretical values change in a similar way as simulation results i.e. for the FAR model both lines are approximately symmetric around a curve obtained for the FGN model. For the FMA model the curve obtained for a positive SRD correlation structure ($\theta < 0$) is almost the same as a curve obtained for the FGN model. The values obtained for the FMA model and negative SRD structure are essentially smaller than these obtained for the FGN model the same as for theoretical results.

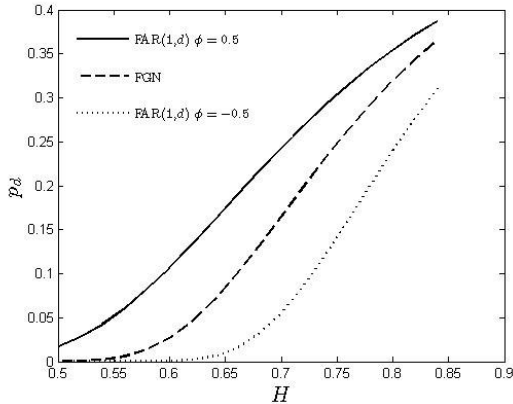


Fig. 1. Drop probability as a function of a H parameter;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $\rho = 0.8$,
 $D_{\max} = 100$ ms.

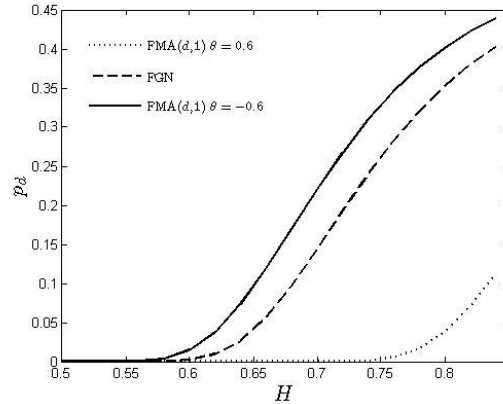


Fig. 2. Drop probability as a function of a H parameter;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $\rho = 0.9$,
 $D_{\max} = 1000$ ms.

Trends of a drop probability as a function of a Hurst parameter are similar for simulations and theoretical results, however the values are essentially different. The reason is that an exceed probability ε is an overestimation of a drop probability p_d given by equation (15).

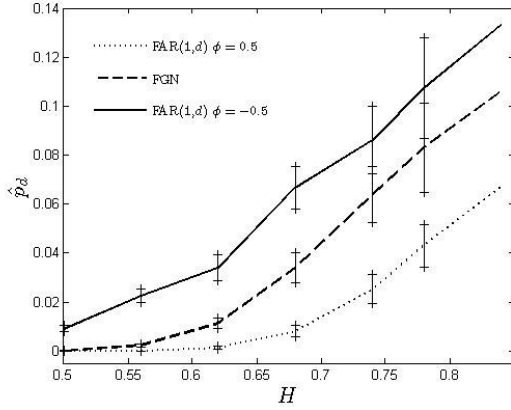


Fig. 3. Drop probability as a function of a H parameter;
simulation results with confidence intervals;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $\rho = 0.8$,
 $D_{\max} = 100$ ms.

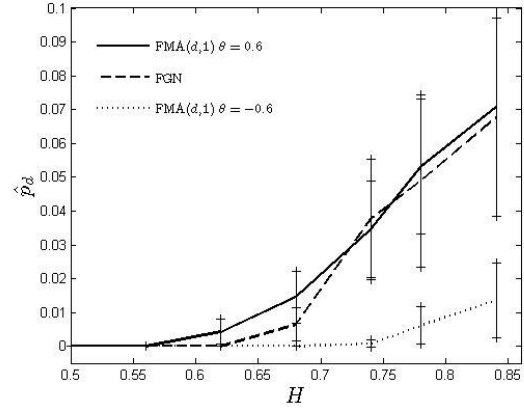


Fig. 4. Drop probability as a function of a H parameter;
simulation results with confidence intervals;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $\rho = 0.9$,
 $D_{\max} = 1000$ ms.

Since trends obtained by simulation study are similar to trends obtained from theoretical equations the rest results is focused on curves obtained by theoretical computations. Note that one should focus on trends and mutually location of obtained curves not the values themselves[#].

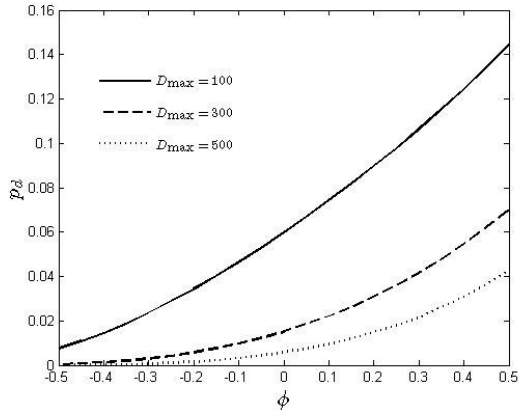


Fig. 5. Drop probability as a function of a ϕ parameter;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $\rho = 0.7$, $H = 0.7$.

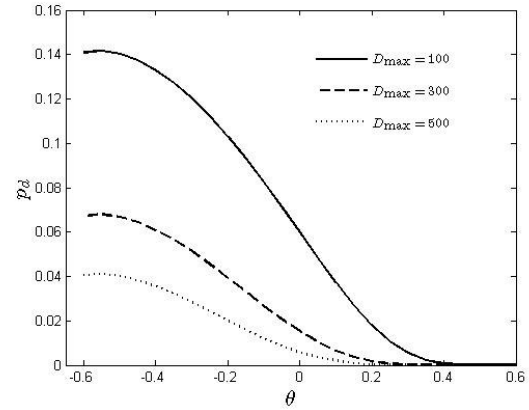


Fig 6. Drop probability as a function of a θ parameter;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $\rho = 0.7$, $H = 0.7$.

Figures 5 and 6 shows an influence of ϕ and θ parameters on a drop probability for different maximum delay values. Values obtained for the FMA model decrease much faster for increasing and positive θ values than the opposite behaviour for the FAR model. This result explains difference between curves obtained for $\theta = -0.6$ and $\theta = 0.6$ presented in Figure 2 and 4.

Note that for the FAR and the FMA models a drop probability value obtained for $\phi = 0$ and $\theta = 0$ respectively is similar to the value obtained for the FGN model [15]. If an SRD structure can be approximated by the FMA model then increasing a θ value has less influence on a drop probability for a small (negative) θ value, but for a negative SRD structure (positive θ) a drop

[#] The differences between theory and simulation results are resulted not only because of overestimation but an approximation of a queue process as well. Since a queue process is difficult to analyse an accuracy of applied in this paper approximation will be more precisely analysed by the authors in the future work.

probability decreases faster than for the FAR model. Therefore, if new technologies like protocols, coding algorithms etc. are to be implemented one should consider which of their parameters are responsible for θ or ϕ values in traffic being generated. For example, a video coding algorithm can send B frames in any order resulting in minimal θ and/or ϕ what ensures ‘optimal’ traffic (i.e. the best from QoS point of view).

The last presented results are shown in Figures 7 and 8.

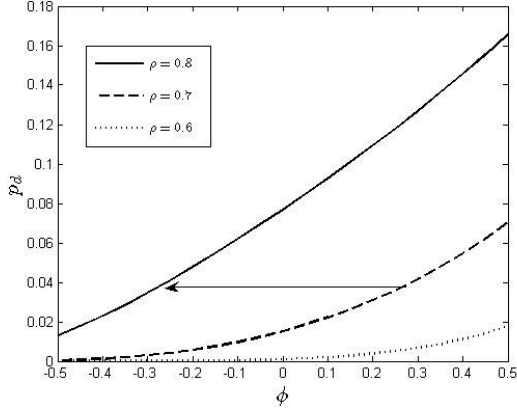


Fig. 7. Drop probability as a function of a ϕ parameter;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $D_{\max} = 300$ ms,
 $H = 0.7$.

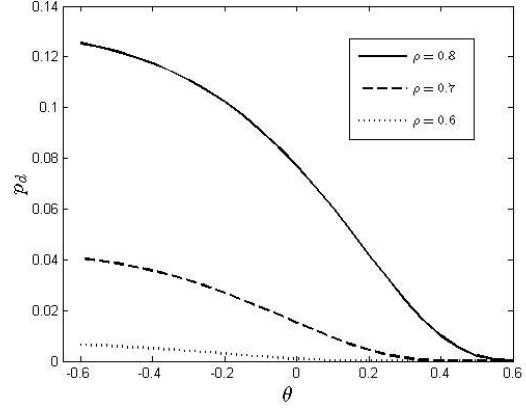


Fig 8. Drop probability as a function of a θ parameter;
 $a = 138$ bit/ms, $\sigma = 420$ bit/ms, $D_{\max} = 300$ ms,
 $H = 0.7$.

In Figure 7 an influence of different link utilisations on a drop probability as a function of a ϕ parameter is shown. Better resource usage can be obtained by decreasing a ϕ value; as an example an arrow is plotted in Figure 7 where changing a ϕ value from 0.25 to -0.25 makes possible to change a ρ value from 0.7 to 0.8.

6. CONCLUSIONS

In the paper an influence of an SRD and an LRD structure on a drop probability has been analysed according to an envelope process analysis. As it has been shown in references a higher Hurst parameter results in increasing a drop probability, however in this paper a SRD structure is considered, too. The presented analysis exploits a concept of an envelope process, which makes possible to compute an overestimate to a drop probability for a drop tail algorithm. Two important properties of the theoretical results have been shown. The first is that simulation results have similar trends as theoretical results. The second is that simulation results provide a smaller drop probability than values obtained by an envelope analysis.

Detail consideration of an influence of an SRD structure on a drop probability for different maximum delay, Hurst parameter and link utilisation values confirms that an SRD structure cannot be omitted in a queuing analysis what confirms results obtained by different than an envelope analysis methods. It is important that for some algorithms, for example video coding algorithms, it is possible to use a traffic shaping algorithm. The results obtained in this paper make possible to predict a trends of influences the SRD and LRD structures.

A future work will focus on comparing obtained results with network measurements and finding an equation or some heuristic function yielding an overestimate to obtained results. An open

question is finding applications that can benefit from traffic shaping based on the results having been presented in this paper.

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