Recognition and Modelling of Bursty Period of Flow

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Abstract: This article presents some methods for recognition and modelling of bursty period of event flow. The flow of events represents generally 0/1 bit sequences. We used the Markov modulated Regular process (MMRP) and Bernoulli process (MMBP) for the description of flows with bursty period. We derived probability distribution of spaces of MMRP processes and used it for estimation of unknown parameters of process. Because the uncomfortableness of flows with MMP processes, we used a Effective bandwidth, to gain parameters of MMBP and obtain a process which will over design considered flow.

Key–Words: Burst period, Markov modulated process MMP; Bernoulli process; IPTV traffic; Bit sequences; Effective Bandwidth, LaTeX

1 Introduction

The necessity of a recognition, analysis and modelling of the bursty period of events flows occurs in different informational applications fields. For example in the transmission of speech signal through IP network [KB], when encoding and decoding of add information into the transmitted bit words [JU], in detection and description of transmission errors [PI], in attacks on SIP servers [PS], in simulation technology used for the dealing with crisis situations in transport and society, where the so-called social risk occurs. In the case of simulation and analysis, of different transport - communications networks, it is required to use models of flows, corresponding to real traffic in the field. Using of flows with Burst period permits to analyse model behaviour in sudden peak load. There is for example the congestion of buffer and the lost of quality of service v IP networks, SIP server crash in hackers attack, and the formation of system error in transmission of signal or the formation of complicated situation in transport network in reality.

In our research flows will be represent with real measured IPTV traffic. These measurements are part of our project made with Slovak Telecom [5], one of the largest providers in the Slovak Republic.

There are two main concepts for description of traffic flow. One is based on analysis of random variables τ_i, which describes slots between events (pakets, frames, bits) in traffic. Other way, is description of probability distribution of a number of arrival events in a time interval $\langle a, a+t \rangle$, $A(a, a+t)$.

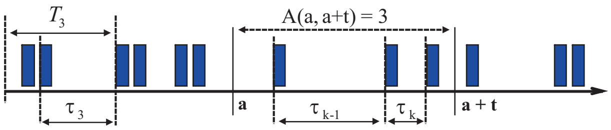

Figure 1: Flow described by variables $A(.)$ and τ_j.

If we consider flow as stationary process, stochastic process $A(a, a+t)$ has the same distribution as process $A(0, t)$ and we can mark it as $A(t)$. Also the random variables τ_i have exactly the same probability distribution. Therefore the traffic source is described by arrival process $A(.)$, the cumulative number of arrivals by the time t, with increments $a(.)$ and the number of arrivals at time t. There holds: $A(t) = \sum_{i=0}^{t} a(i)$.

Next we will consider an occurrence as occurrence number 1, so an investigated flow will represent 0/1 bit sequence and increases of flow in the time t can acquire only values $a(t) = 0$ resp. $a(t) = 1$.

2 Independent arrivals: Bernoulli process

In analyse of an input flow is suitable to verify the independence of even occurrence. The stationary process with independent increments with same probability p is called **Bernoulli process**. Increments of the process $A(t)$ take values 1 and 0 with the probability $\Pr(a(1) = 1) = p$ and $\Pr(a(1) = 0) = 1 - p = q$. Bernoulli process is well-know process. The typical bit sequence with parameter $p = 0.5$:

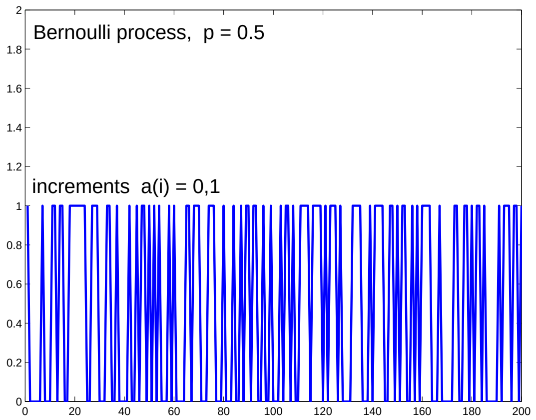

Figure 2: Bernoulli process with $p = 0.5$

There are several ways how to estimate probability p from the data. The easiest way is to divide the number of N_1 by all values N: $\hat{p} = N_1/N$.

The other method is using the knowledge, that variable T describing spaces between events, is a geometrical distribution. The variable coefficient ν_T has a form

$$\nu_T = \frac{\sigma_T}{ET} = \frac{\sqrt{p/q}}{p/q^2} = \frac{1}{\sqrt{1-p}} \quad (1)$$

We can estimate the probability of mean ET and dispersion DT from measured data. We obtain subsequently the estimation of the p from:

$$\hat{p} = 1 - \frac{(ET)^2}{DT} \quad (2)$$

Additionally, this method allows to exclude significantly different flows from Bernoulli processes including probability p does not belong to the interval $\langle 0, 1 \rangle$. Otherwise the necessary condition for p is fulfilled.

Verification of the accuracy of used Bernoulli model with parameter p is simple. We estimate probability distribution of $A(n)$ from the captured data and we compare the result with a binomial distribution:

$$\Pr(A(n) = k) = \binom{n}{k} p^k q^{n-k}, \quad k = 0, .., n \quad (3)$$

Value n determine the number of summed 0/1 slots. Its dimension depends on the dimension of the measurement. We could select n in range from 4 to 8 slots in our experiments.

Bernoulli process is not capable to model the flow with burst periods. If we select average rate for example $\lambda = p = 0.8$ events per time unit, we can expect in during 10 time units the occurrence of 8 events, $EA(10) = 10 \cdot 0.8 = 8$, In that flow there are not changes of burst period (On) and empty period (off). We use the flow with $p = 0.8$ for demonstrating:

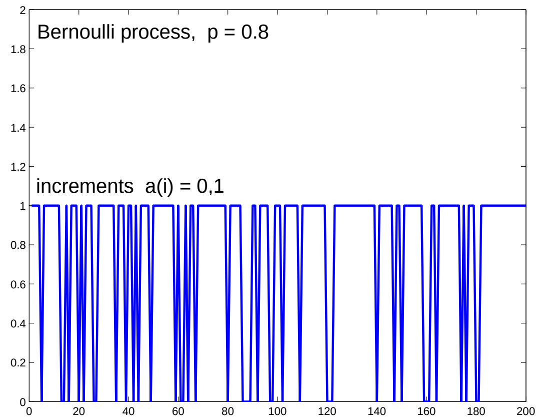

Figure 3: Bernoulli process with $p = 0.8$

We indicate the example with bursty period, but we retain the same average rate per slot 0.8 or $EA(10) = 8$ as in the previous one.

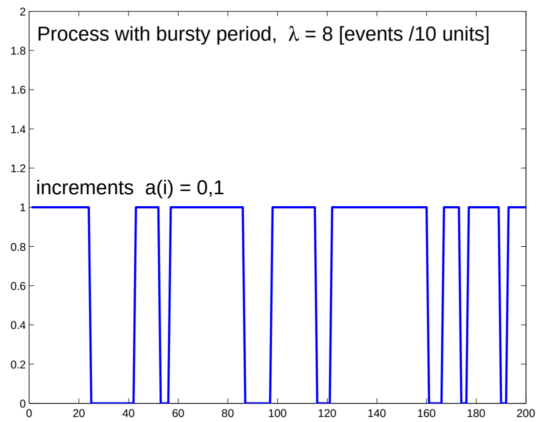

Figure 4: Real process with bursty period

We compare Binomial distribution and empirical distribution of measurement data:

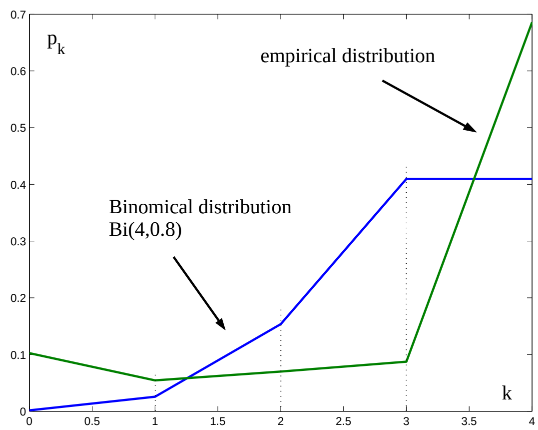

Figure 5: Binomical and empirical distribution

For the comparison we used the sum of four 0/1 bit slots or we compared the distribution of $A(4)$ for Bernoulli process and measurement process. We can see the values of distribution are significantly different. From this reason, we must find the other bit process which be able to model bursty period.

3 Markov Modulated Regular Process

The easiest 0/1 process which is capable to model flow with bursty period is so-called Markov modulated regular process MMRP. This process consists of period On and period Off. If the process is in period On, it produces some events, and if it is in period Off, it means that nothing is transmitted. The simplest situation is when regular (deterministic) flow of ones turned on in period On. Whereas switching between the states On and Off is controlled by Markov chain, MMRP is process with i.i.d. increments $a(i)$, which take values 0 and 1.
First state of the chain describe the period On, second state describe the period Off. Let's designate probability of transitions between states as $p_{1,2} = \alpha$ and $p_{2,1} = \beta$. Let $\pi = (\pi_1, \pi_2)$ be steady-state distribution of Markov chain. Using Queueing theory we compute values of steady-state probabilities (see [6]):

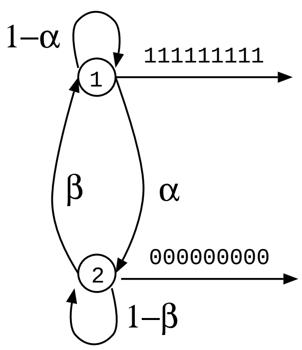

Figure 6: Markov Modulated Regular Process

Let's create a matrix of the probabilities of transitions $\mathbf{P}$ for Markov chain and equations for probabilities of states for stabilized chain π:

$$\mathbf{P} = \begin{pmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{pmatrix}, \qquad \pi \cdot \mathbf{P} = \pi \ \Rightarrow$$

$$\Rightarrow \qquad \pi_1 = \frac{\beta}{\alpha+\beta}, \qquad \pi_2 = \frac{\alpha}{\alpha+\beta} \qquad (4)$$

Arrival process modeled using MMRP is very easy to simulate. If the process is in the first state, then 1 is generated, and if the process is in the second state, 0 is generated. Switching between states is by probability $p_{1,2} = \alpha$ a $p_{2,1} = \beta$.
The following example shows the increments in the first row and the probability of switching between them in the second row. Process starts in $a(1) = 1$, and then process remains in first state (no switching), i.e. probability $P = P(a(2) = 1/a(1)) = 1 - \alpha$, etc.:

$a(i)$	1	1	0	0	0	1	0	1	1
P	1	1-α	α	1-β	1-β	β	α	β	1-α

The easiest method to estimate parameters α and β is by individual pairs 0 a 1 directly in the measurement. The number of pairs occurrence (i, j) we mark $N_{i,j}$:

$$\hat{\alpha} = \frac{N_{1,0}}{N_{1,0} + N_{1,1}}, \qquad \hat{\beta} = \frac{N_{0,1}}{N_{0,1} + N_{0,0}} \qquad (5)$$

It is obvious, it remains to determine, if the measured flow agree with MMRP with estimated parameters.

The other method, which is capable to determine if the measured flow is significantly statistically different from MMRP, is to use the variable τ describing spaces between events. Distribution of variable τ is:

$$\Pr(T = 0) = 1 - \alpha \qquad (6)$$
$$\Pr(T = t) = \alpha(1-\beta)^{t-1}\beta, \quad t = 1, 2, \ldots \qquad (7)$$

There are several examples of probability distribution of variables T for the cases when
$\alpha = \beta = 0.1, 0.3, 0.5, 0.7, 0.9$:

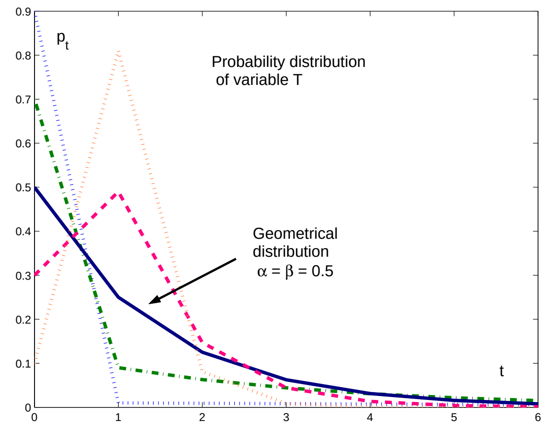

Figure 7: Probability distribution of T, $\alpha = \beta$

We calculate Moment Generation Function (MGF) $\varphi(\theta)$ of random variable T:

$$\varphi(\theta) = \sum_{t=0}^{\infty} e^{\theta t} \Pr(T = t) =$$

$$= 1 - \alpha + \sum_{t=1}^{\infty} e^{\theta t} \alpha (1-\beta)^{t-1} \beta$$

$$\Rightarrow \varphi(\theta) = 1 - \frac{\alpha(1-e^{\theta})}{1-(1-\beta)e^{\theta}} \tag{8}$$

Using derivation of MGF we estimate the first and the second initial moment:

$$ET = \varphi'(\theta)|_0 = \left.\frac{\alpha\beta e^{\theta}}{(1-(1-\beta)e^{\theta})^2}\right|_0 = \frac{\alpha}{\beta}$$

$$ET^2 = \varphi'(\theta)|_0 = \left.\frac{\alpha\beta e^{\theta}(1+(1-\beta)e^{\theta})}{(1-(1-\beta)e^{\theta})^3}\right|_0 \Rightarrow$$

$$\Rightarrow ET^2 = \frac{\alpha}{\beta^2}[2-\beta]$$

We deduced the mean and the dispersion of spaces T:

$$ET = \frac{\alpha}{\beta}, \qquad DT = \frac{\alpha}{\beta^2}[2-(\alpha+\beta)] \tag{9}$$

Variable coeficient of T has a form of:

$$\nu_T = \frac{\sigma_T}{ET} = \sqrt{\frac{2-(\alpha+\beta)}{\alpha}} \tag{10}$$

We can use the following recurrence relations to determine parameters α a β :

$$DT = \frac{\alpha}{\beta^2}[2-(\alpha+\beta)] = ET\left[\frac{2}{\beta}-(ET+1)\right] \Rightarrow$$

$$\Rightarrow \beta = \frac{2ET}{ET^2+ET}, \qquad \alpha = \beta \cdot ET \tag{11}$$

Parameters α and β are transmit probabilities of 2-state Markov chain, therefore if their estimation by recurrence relations is out of range $\langle 0,1\rangle$, the measured processes are significantly different from MMRP. Otherwise if $\alpha,\beta \in \langle 0,1\rangle$, we can consider using of MMRP process.

In the case of Bernoulli process we used classical Binomial distribution for the verification of model, $A(n) \sim Bi(n,p)$. The distribution of $A(n)$ for MMRP is generally an unknown, we derived in [6] the distribution of probability for $n = 2,3,4$.

Probability distribution of variable $A(4)$:

$$\begin{aligned}
p_0 =\ & \pi_2(1-\beta)^3\\
p_1 =\ & (\pi_1\alpha+\pi_2\beta)(1-\beta)^2 + 2\alpha\beta(1-\beta)\pi_2\\
p_2 =\ & (\pi_1\alpha+\pi_2\beta)(1-\alpha)(1-\beta)+\\
& +\alpha\beta(\pi_1\alpha+\pi_2\beta+\pi_1(1-\beta)+\pi_2(1-\alpha))\\
p_3 =\ & (\pi_1\alpha+\pi_2\beta)(1-\alpha)^2 + 2\alpha\beta(1-\alpha)\pi_1\\
p_4 =\ & \pi_1(1-\alpha)^3
\end{aligned}$$

We compare Bernoulli process and MMRP with same parameters ($\alpha = \beta$) with average rate $\lambda_{avg} = 2p/ts$ and peak rate $\lambda_{peak} = 4p/ts$:

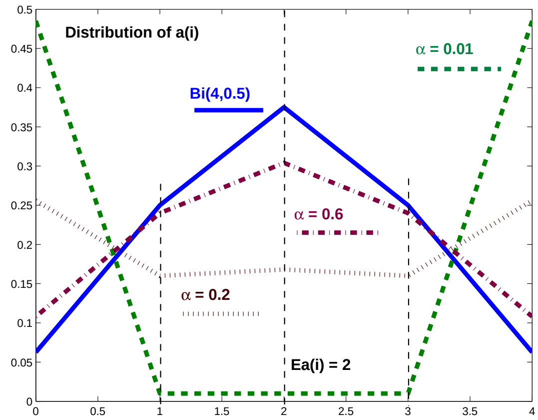

Figure 8: Distribution of $A(4)$ for Bernoulli and MMRP process

We can see, the symetrical distribution $Bi(4,0.5)$ obtains the most frequently value in its average rate, $a(i) = 2$. In the case of appropriate choosing of MMRP, for example $\alpha = \beta = 0.01$ we obtain flow with bursty period, with the increments of flow $a(i) = 0$ and $a(i) = 4$.

Next, we compare Bernoulli process and MMRP process ($3\alpha = \beta$) with average rate $\lambda_{avg} = 3p/ts$ and peak rate $\lambda_{peak} = 4p/ts$:

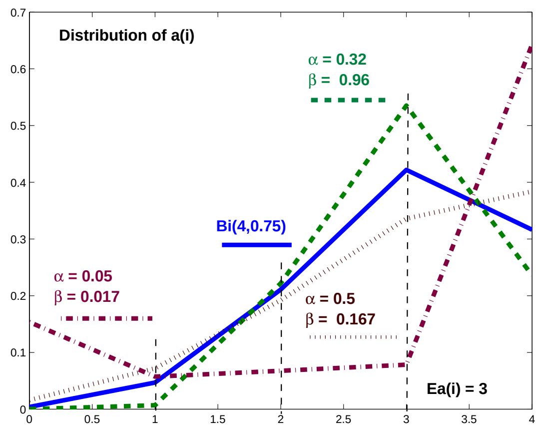

Figure 9: Distribution of $A(4)$ for Bernoulli and MMRP process

We achieve a flow with significant burst periods maintaining the same average rate and peak rate for parameters $\alpha = 0.017$ and $\beta = 0.050$. The mean of bursty period will be approximately three time higher than the mean of Off-period.

Finally, we again compare Bernoulli process and MMRP process with parameters $\alpha = 3\beta$ with average rate $\lambda_{avg} = 2p/ts$ and peak rate $\lambda_{peak} = 4p/ts$. We got a similar picture with the previous only the spins symmetrically:

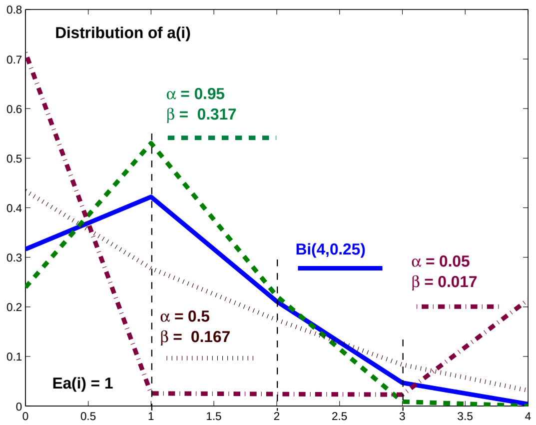

Figure 10: Distribution of $A(4)$ for MMRP process

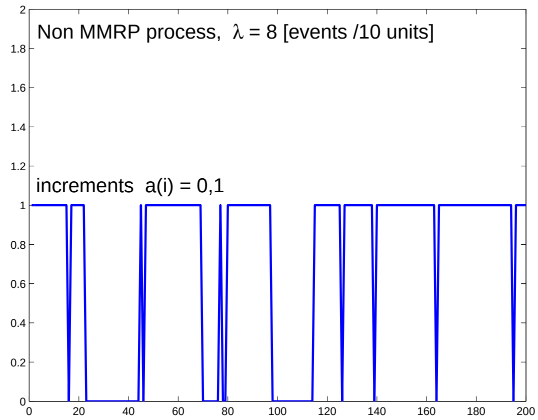

Figure 11: Non MMRP process with $\lambda_{avg} = 8p/ms$

In this case the values of parameter are conversely $\alpha = 0.050$ and $\beta = 0.017$. Mean of bursty period will be approximately three times shorter than the mean of Off-period. But the occurrence of bursty period can cause more problems.

For completeness, we mention the probability distribution of variables $A(3)$ and $A(2)$, although searching the equality with measured process, they showed up insufficient. Distribution of $A(3)$:

$$\begin{aligned} p_0 &= \pi_2(1-\beta)^2 \\ p_1 &= (\pi_1\alpha + \pi_2\beta)(1-\beta) + \alpha\beta\pi_2 \\ p_2 &= (\pi_1\alpha + \pi_2\beta)(1-\alpha) + \alpha\beta\pi_1 \\ p_3 &= \pi_1(1-\alpha)^2 \end{aligned}$$

Probability distribution of variable $A(2)$:

$$p_0 = \pi_2(1-\beta), \quad p_1 = \pi_1\alpha + \pi_2\beta, \quad p_2 = \pi_1(1-\alpha)$$

In our experiments we have met the cases, when the measured flow has characteristics of flow with bursty periods, but the probabilities of transmit between states we have not estimated, or their values have been off unit interval $(0, 1)$. For example see next figure.

From this reason, we were forced to deal with more complicated 3 parameter MMP process.

4 Markov Modulated Bernoulli process

The MMBP is the process modulated by 2-states Mrakov Chain, while in the state On the Bernoulli's process with parameter p is switched, in the state Off zeros are generated. Equations for probabilities of states for stabilized chain π are the same as in MMRP:

$$\pi_1 = \frac{\beta}{\alpha + \beta}, \qquad \pi_2 = \frac{\alpha}{\alpha + \beta} \tag{12}$$

In MMBP the zero can be generated by two different ways,therefore the analysis of probability distribution of its variables is complicated. The distribution of flow increments $a(t) = 0, 1$ has a form of:

$$p_1 = \pi_1 p, \qquad p_0 = \pi_1(1-p) + \pi_2 \tag{13}$$

The following example shows the traffic increments in the first row and the probability of switching between them in the second row. We show two probability sequences describing the same simulation of increments:

$a(i)$	1	1	0	0	0	1	0
P_1	1	(1-α)p	α	1-β	1-β	βp	α
P_2	1	(1-α)p	(1-α)q	α	1-β	βp	(1-α)q

We can see that given sequences of increments can be generated in several different ways. That's why there is a problem to estimate parameters from some measured flow.

We managed only to derive the probability distribution of variables $A(2)$ for the MMBP :

$$\begin{aligned} p_2 &= \pi_1(1\text{-}\alpha)p^2 && (14) \\ p_1 &= 2\pi_1(1\text{-}\alpha)pq + p(\pi_1\alpha + \pi_2\beta) && (15) \\ p_0 &= (1\text{-}\alpha)q^2 + (\pi_1\alpha + \pi_2\beta)q + \pi_2(1-\beta) && (16) \end{aligned}$$

Moments of variable $A(2)$ have the form:,

$$\begin{aligned} EA(2) &= 2\pi_1 p, && (17) \\ DA(2) &= 2\pi_1\pi_2 p\left[1 + (1\text{-}\alpha\text{-}\beta)p + \frac{\beta q}{\alpha}\right] && (18) \end{aligned}$$

The form of variation is complicated and generally it is not suitable for the parameter estimation using moments method. We can notice, in the case, when $\alpha + \beta = 1$ a $p = 1$, we obtain distribution and moments of Bernoulli process, $A(2) \sim Bi(2, \beta)$.

We show some examples of probability distribution of variable $A(8)$ of MMBP process with significant bursty period. We obtained values of distribution using processes simulation.

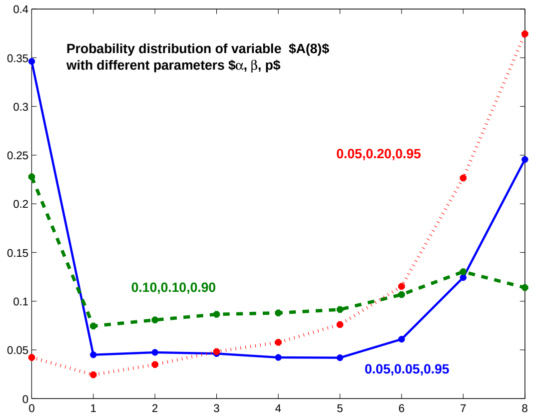

Figure 12: MMBP with bursty period, pdf of $A(8)$

Generally, for variable $A(n)$ $(a(i) = 0, 1, ..., n)$ only mean value and probability of peak rate are known:

$$EA(n) = n\pi_1 p, \quad p_{peak} = \pi_1(1-\alpha)^{n-1}p^n \quad (19)$$

If we estimate average rate $\lambda_{avg} = EA(n)$ and peak probability $p_{peak} = p_n = \Pr(a(i) = n)$, we can use the next relationship for numerical calculation of parameters for MMBP ($\lambda_{peak} = n$):

$$\beta = \frac{\lambda_{avg} \cdot \alpha}{p \cdot n - \lambda_{avg}} \quad (20)$$

$$(1-\alpha)p = \left(p_{peak} \cdot \frac{n}{p \cdot \lambda_{avg}}\right)^{\frac{1}{n-1}} \quad (21)$$

This way is numerically difficult and impractical;therefore we were searching for the other possibilities for the parameters estimation.The advantage of 2-state MMP processes is the existention of analytical form of Effective Bandwidth(EB). For the parameters estimation MMBP we have used the upper limitation for statistical estimation of Effective Bandwidth for measurement flow. Firstly we noticed the basic characteristics of EB.

5 Effective Bandwidth

The concept of effective bandwidth (EB) has gained much attention due to the looming gain for network analysis and design. The effective bandwidth of a general cumulative arrival process has been defined [7] as

$$\alpha(\theta, t) = \frac{1}{\theta t} \sup_{s \geq 0} \ln E\left[e^{\theta(A(s+t)-A(s))}\right] \quad (22)$$

depending upon the space parameter θ and the time parameter t, $0 < \theta, t < \infty$. Theory of Large Deviation Principles provides the tool for link dimension with respect to probability of packet loss (see [8])

$$c = \alpha(\theta, t) \quad \Leftrightarrow \quad P(q > b) \asymp e^{-\theta b} \quad (23)$$

where constant b is size of queue (buffer) and variable q is steady-state length of queue. if we propose the link capacity equal to effective bandwidth, $c = \alpha(\theta, t)$, then the probability of buffer overflow decays ($\asymp$) exponentially with constant θ.

The value of Effective Bandwidth in 0 equals average rate $\alpha(0, t) = \lambda_{avg}$. If process has identical and above bounded increments, $\forall t$, $a(t) \leq \lambda_{peak}$, effective bandwidth is between average rate and peak rate:

$$\forall \theta, t \in R^+, \quad \lambda_{avg} \leq \alpha(\theta, t) \leq \lambda_{peak} \quad (24)$$

Let the process to have independent and identical distribution (i.i.d.) increments $a(t)$. Let $\varphi(\theta) = E\left[e^{\theta a(1)}\right]$ to be the moment generating function (MGF) and function $\lambda(\theta) = \ln \varphi(\theta)$ to be the cumulative generating function (CGF) of increments. Effective bandwidth has form ([8]):

$$\alpha(\theta, t) = \alpha(\theta) = \frac{\lambda(\theta)}{\theta} = \frac{1}{\theta} \ln \varphi(\theta) \quad (25)$$

For example pre Bernoulli process $(a(i) = 0, 1)$ we gain simly form of EB:

$$\alpha(\theta) = \frac{1}{\theta} \ln\left[e^{-a(i)\theta}\right] = \frac{1}{\theta} \ln E\left[q + pe^{-a(i)}\right] \quad (26)$$

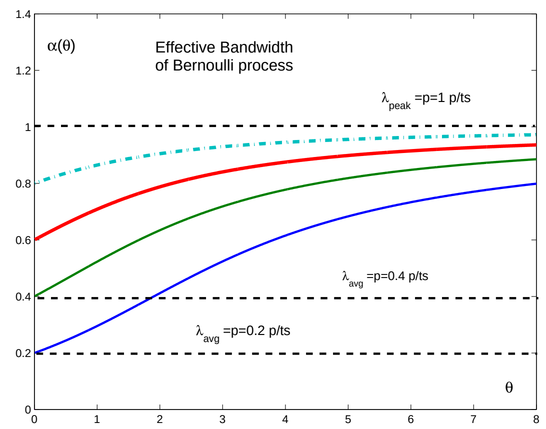

Figure 13: Effective Bandwidth of Bernouilli process

In general ([8]) for any 2-states Markov modulated process holds, that Moment generation function $\varphi(\theta)$ of process equals to spectral radius $sp(.)$ of matrix $\phi(\theta)\mathbf{P}$, where $\phi(\theta)$ is diagonal matrix of moment generation functions $\varphi_i(\theta)$ for the processes based on i's states of Markov chain, $\phi(\theta) = \begin{pmatrix} \varphi_1(\theta) & 0 \\ 0 & \varphi_2(\theta) \end{pmatrix}$ and $\mathbf{P}$ is the matrix of the state transition probabilities, $\mathbf{P} = \begin{pmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{pmatrix}$. Effective Bandwidth for any MMP has the form:

$$\alpha(\theta) = \frac{1}{\theta} \ln \varphi(\theta) = \frac{1}{\theta} \ln sp\left[\phi(\theta)\mathbf{P}\right] \quad (27)$$

To determine the MGF $\varphi(\theta)$, we must calculate maximum eigenvalue of $\phi(\theta)\mathbf{P}$.

In the case of MMBP, there are

$$\varphi_1(\theta) = E\left[e^{\theta \cdot a(t)}\right] = q + pe^{\theta} \quad (28)$$

$$\varphi_2(\theta) = E\left[e^{\theta \cdot 0}\right] = 1 \quad (29)$$

For the estimation of $\varphi(\theta)$ we have calculate the highest eigenvalue of matrix $\phi(\theta)\mathbf{P} = \begin{pmatrix} \varphi_1(1-\alpha) & \varphi_1\alpha \\ \varphi_2\beta & \varphi_2(1-\beta) \end{pmatrix}$. There is analytic solution :

$$\varphi(\theta) = \left[\frac{(q+pe^{\theta})(1\text{-}\alpha) + (1\text{-}\beta) + \sqrt{D}}{2}\right] \quad (30)$$

$$D = (q+pe^{\theta})(1\text{-}\alpha)\text{-}(1\text{-}\beta)]^2 + 4(q+pe^{\theta})\alpha\beta \quad (31)$$

Effective bandwidth for 2-state MMBP is a so-called scale cummulant generation function $\alpha(\theta) = \ln\varphi(\theta)/\theta$

Effective bandwidth uniquely identifies stacionary stochastic process; therefore we can use it searching the parameter processes estimation. At first we calculate statistic Effective Bandwidth from measured data, for the observation process and consequently we estimate the values of process parameters using numerical methods, which EB has an analytical expression, while we can use Mean-square method. The process MMBP has three parameters;therefore its using provides a high flexibility.

In engineering tasks, EB is used for the design of a transport or a telecommunication node capacity, for example,[**?**]. In this case it is not appropriate to use the parameter estimation using Mean-square method, but more efficient is, to create Effective bandwidth, which is the upper limitation of EB estimated by data. If we use so gained process in an analysis or in a simulation of the node, we will achieved the higher capacity as in original flow. We will design the node with a higher safety factor.

6 Numerical Results

We have selected the IPTV process record for the presentation of described approach,expecialy1 channel of Magio. The length of record was 2 minutesy, selecting time slot $ts = 2ms$ we obtained 0/1 packet sequences with average rate $\lambda_{avg} = 0.8647p/ts$ and of course $\lambda_{peak} = 1p/ts$. Next figure shows the short example of the reckord with the length. $1.4s$:

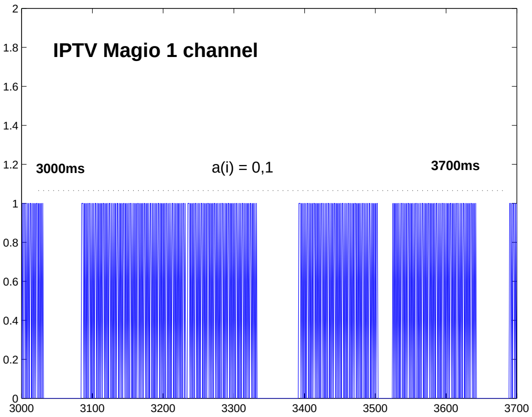

Figure 14: IPTV 0/1 traffic of Maqio channel

The IPTV flow does not correspond to MMRP, estimating parameters α a β we have obtained negative values. We have decided using upper bound of statistical estimate of EB for the determination of MMBP parameters. There are several methods how to estimate EB. We have have decided to estimate probability distribution of increments $p_k = \Pr(a(i) = k)$ where $k = 0, 1, .., 4$ and consequently we changed the scale EB to 0/1 sequences:

$$\hat{\alpha}(\theta) = \frac{1}{\theta} \ln\left[\sum_{k=0}^{4} e^{k\theta}\hat{p}_k\right] \quad (32)$$

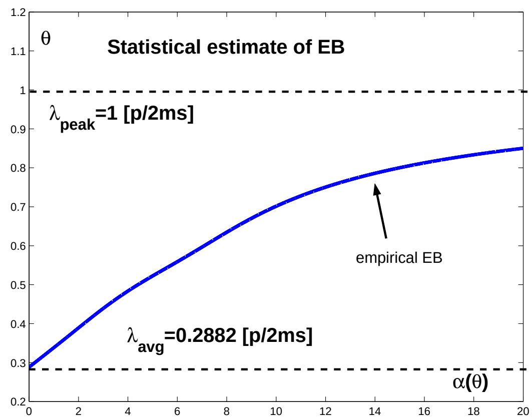

Figure 15: Statistical estimate of EB for IPTV traffic

We use the relation of the mean values equality for the estimation of MMBP parameters:

$$\pi_1 p = \frac{\beta p}{\alpha + \beta} = \lambda_{avg} \Rightarrow \beta = \frac{\lambda_{avg}\alpha}{p - \lambda_{avg}} \tag{33}$$

We use numerical methods for compute the minimum upper bound of Effective Bandwidth of IPTV traffic.

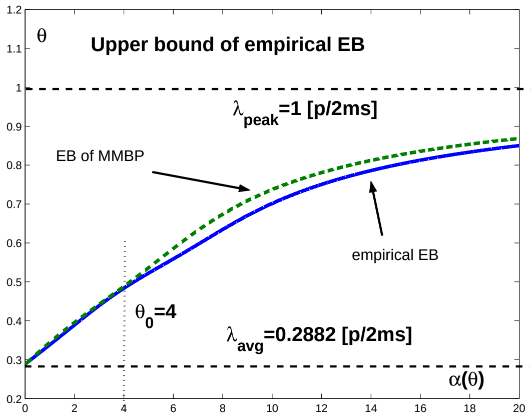

Figure 16: Comparation between IPTV and MMBP

Values of estimated parameters:

$$\alpha = 0.9121, \quad \beta = 0.5115, \quad p = 0.8022 \tag{34}$$

We can see in the figure, after $\theta = 4$ we can consider the equality of analytical form of MMBP EB and statistical estimation of IPTV EB.

Parameter θ is so called space parameter. If we consider the arrival process entering into some single server queue (queueing system with one link), parameter θ is directly depending on a maximum delay d_{max} events waiting in queue, and on probability of lost p_{lost} events in the moment, when queue will fill. If arrival process has EB $\alpha(\theta) = \ln \lambda(\theta)/\theta$, than for θ is valid ([6]):

$$\theta = \lambda^{-1}\left[\frac{\ln p_{lost}}{-d_{max}}\right] \tag{35}$$

For MMBP process:

$$\theta = \ln\left[\frac{p_{lost}^{-1/d_{max}} - 1 + \beta + p_{lost}^{1/d_{max}}(p-1)}{p(1-\alpha) + p(\alpha+\beta-1)p_{lost}^{1/d_{max}}}\right] \tag{36}$$

For normally used values d_{max} a p_{lost} for IPTV does not exceed parameter θ value 2. In this case we can replace examined IPTV traffic by process MMBP.

Generally if we use flow with EB upper limitation of original real flow, in analysis and simulation of a system, we obtain the oversized results depending on tha fact, how close the upper bound original flow of EB we obtained.

7 Conclusion

We have tried to analyse the basic model of 0/1 bit sequences, from Bernoulli's process to Markovov Modulated processes. We have wanted to create the parameters estimation methodology for examined processes. We have used Effective Bandwidth for the estimation of parameters in the case of Markov Modulated Bernoulli process. We have showed, it is possible to obtain relevant results although without the accordance of examined process and MMBP processes using this approach. The main of future research is to identify and analyse complicated MMP process with two Bernoilli's floes or Poisson's processes.

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