Alcom-FT Technical Report Series
ALCOMFT-TR-01-179

A MARKOVIAN ANALYSIS OF AIMD ALGORITHMS

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ABSTRACT. The Additive-Increase Multiplicative-Decrease (AIMD) schemes designed to control congestion in communication networks are investigated from a probabilistic point of view. Functional limit theorems for a general class of Markov processes that describe these algorithms are obtained. The asymptotic behavior of the corresponding invariant measures is described in terms of the limiting Markov processes. For some special important cases, including TCP congestion avoidance, an important ARMA property is proved. As a consequence, the explicit expression of the related invariant probabilities is derived. The transient behavior of these algorithms is also analyzed.

CONTENTS

1. INTRODUCTION

This paper investigates the mathematical structure underlying the so-called additive increase multiplicative decrease (AIMD) window based flow control schemes used in data transmission. With the emergence of TCP (Transmission Control Protocol) as the ubiquitous data transfer protocol, the study of these algorithms is crucial to understand the complex behavior of modern communication networks. Keeping in mind that TCP is one of the AIMD algorithms, using the language of communication networks, these algorithms can be described as follows. When a packet is sent, it is acknowledged by the destination when received; if no acknowledgement is received after some time, the packet is considered as lost. To simplify the description, we shall assume that the round trip time (RTT) between the source and the destination is constant. The source maintains a variable W referred to as the congestion window size which controls the emission of packets over an RTT interval. When W packets are sent to the destination during an RTT interval, the

Date: September 26, 2001.
1991 *Mathematics Subject Classification.* Primary 60K30, 90B18; Secondary 68M12.
Key words and phrases. TCP. Convergence of invariant probabilities. ARMA Processes. Hitting times. Network protocols.
* Partially supported by the contract 00-1B320 with France Telecom and the IST Programme of the EU under contract number IST-1999-14186 (ALCOM-FT).

source detects if one of them has been lost. If there is a loss, the variable W is changed to $\lfloor \delta W \rfloor$ for the next RTT interval, $\delta \in]0,1[$ is the multiplicative constant which decrements the window size; in this case the number of packets sent during the next cycle is drastically reduced. If all the packets are successfully transmitted, W is just incremented by some value $\beta > 0$ if it does not exceed some maximal value $w_{\max}$, the maximal congestion window size. This is of course a simplification of the real algorithms involved, but the basic mechanism of reducing the congestion (called congestion avoidance) is captured by this model. See Jacobson [14], Allman *et al.* [2] and Stevens [20] for more details.

Roughly speaking, the motivation of this algorithm can be described as follows: the loss of packets in the network is mainly due to buffer overflow in the nodes of the network. If the congestion window of many sources in the network is large, these sources will send many packets at approximately the same time and, very likely, they will create more and more overflow if their respective window sizes are not reduced very quickly. Multiplicative decrease is a way of rapidly cooling down congestion. The additive increase can be seen as a very progressive test of the congestion of the network.

A Markovian representation

The model considered in the paper describes the exchange of packets between the source and the destination. Each packet has some probability of being lost and the probability that packets are lost are independent. (In section 2 we consider a more general loss model.) The influence of the network is described through this loss process. With this assumption, the sizes of the congestion windows over the successive RTT intervals is a Markov chain (W_n).

The transitions of the Markov chain (W_n) are described by: if $W_0 = x \geq 1$,

$$W_1 = \begin{cases} \min\left(\lfloor x+\beta \rfloor, w_{\max}\right) & \text{with probability } \exp(-\alpha x) \\ \max\left(\lfloor \delta x \rfloor, 1\right) & \text{otherwise,} \end{cases} \tag{1}$$

where $\beta > 0$, $0 < \delta < 1$ and $\alpha > 0$; $\lfloor x \rfloor$ is the integer part of x. The quantity $\exp(-\alpha)$ is the probability that a packet is not lost in the network and, assuming independence of the losses, $\exp(-\alpha x)$ is the probability that all the x packets of the window are successfully transmitted. In this model the interaction between the network and the data transfer is represented only through losses of packets. The constant $w_{\max}$ is the maximal congestion window size, only determined by the destination.

When W_0 is very large, the drift $\mathbb{E}(W_1 - W_0)$ of the Markov chain is equivalent to $-(1-\delta)W_0$; it implies that the Markov chain cannot travel very far from the origin, in particular it is ergodic. (See the details below.) Thus, the long term behavior of the source is mainly driven by the invariant measure (π_n) of (W_n). For a fixed α, very little is known about this invariant probability, Dumas *et al.* [8] gives stochastic bounds for (π_n) which are accurate when the loss rate is not small.

In practice, hopefully, the loss rate will be small in the network. This suggests to look at the limiting behavior of this Markov chain when α tends to 0. This is the main topic of this paper. Most of earlier papers on the subject (see below) give a partial view of the limiting properties of the various Markov processes involved in this model: asymptotics for the throughput, or for some invariant measures. In particular they do not prove the convergence of the invariant probabilities when the loss rate converges to 0. As we shall see, it is possible to get a fairly complete description of the Markovian setting of these AIMD schemes. This approach allows us to get some information on the transient behavior of these algorithms; on the distribution of the duration of time necessary to reach the maximal congestion window size for example (Section 5).

Related work.

Floyd [12], Floyd *et al.* [13] and Madhavi and Floyd [15] analyze the impact of AIMD algorithms through simulations and some approximated models.

Altman *et al.* [3] gives a description of the evolution of the size of the congestion window in terms of an ARMA process. At equilibrium it implies that the tail distribution of the size of the window is exponential. (This is not the case for the model we consider.) Baccelli and Hong [6] consider an algebraic setting describing precisely TCP when the input is deterministic or periodic.

Padhye *et al.* [18] considers a detailed model of the evolution of TCP. Using a finite Markov chain they express some of the stationary characteristics of the protocol.

Finally, Ott *et al.* [17] analyzes the evolution of the size of the congestion window as the perturbation of a deterministic differential equation by a Poisson process when the loss rate is small. In this setting they are able to give a detailed description of the invariant measure when α tends to 0. Altman *et al.* [4] extended some of these results to study the case of a finite maximal congestion window. The model considered by Ott *et al.* [17] can be seen as an approximation of the model considered here but at a different time scale (or, more accurately, packet granularity). It is not clear for us how one could justify the approximation of the invariant probabilities in this setting (see Section 4). Along the same lines of investigations, Adjih *et al.* [1] give an asymptotic expression of the invariant measure of the size of the congestion window.

The results of the paper

Two Markov chains are considered in this paper (W_n^α) describing the evolution of congestion window size over the successive RTT intervals and (V_n^α) which is the embedded Markov chain of (W_n^α) observed when a packet is lost. In a quite general framework we prove the convergence in distribution of their invariant probability measures properly rescaled when the loss rate α goes to 0, i.e. the following convergences in distribution $\lim_{\alpha\to 0}\sqrt{\alpha}W_\infty^\alpha = \overline{W}_\infty$ and $\lim_{\alpha\to 0}\sqrt{\alpha}V_\infty^\alpha = \overline{V}_\infty$ (Theorem 9 and Theorem 10).

When the loss probability per packet is constant, an interesting ARMA (Autoregressive Moving Average) property of the Markov chain $\left((V_n^\alpha)^2\right)$ holds when α is close to 0. This result and the convergence results give the key to most of the explicit calculations of distributions: the distribution of $\overline{V}_\infty$ (Propositions 13 and 18), of $\overline{W}_\infty$ (Proposition 16) and the asymptotic throughput of the algorithm (Propositions 15 and 19).

This ARMA property does not seem to have been earlier identified in the literature. This is a real benefit of the approach of this paper to consider the convergence of the complete dynamics of the system rather than analyzing only the convergence of the invariant probability distribution when α tends to 0. In most of the studies of TCP, the ARMA property is generally *assumed* (i.e. not proved) not for $((V_n)^2)$ but for (V_n). It implies that the probability of a loss during an RTT interval does not depend on the number of packets sent during that time. In our case it does depend, the more it is sent consecutively, the more likely there will be a loss. It turns out that this assumption seems to lead a different constant for the throughput, 1.22 instead of the constant derived here 1.3098, already observed by Floyd *et al.* More important, when the maximum congestion window is infinite, the equilibrium has an exponential tail distribution instead of quadratic exponential in our case (i.e. $\sim \exp(-Cx^2)$), the number of large congestion windows is thus significantly smaller for the model considered here.

To our knowledge the transient behavior of AIMD algorithms has not been investigated through analytical models. For example, the time to reach the maximal congestion window is clearly an important characteristic. For the moment it has not received much attention in the stochastic models. Some results in this domain are derived with our approach.

Organization

In Section 2 we prove the main convergence results of this paper: convergence in finite time of the Markov processes. More important, convergence of the corresponding invariant distributions is shown in Section 3. In Section 4 the explicit expression of the corresponding invariant distributions is derived. The formulas for the asymptotic throughput are obtained and discussed. Section 5 gives some results concerning the transient behavior of TCP, in particular the hitting time of the maximal congestion window size is investigated.

2. A generalized Markovian model

In this section, with the terminology of communication networks, we consider the sequence (W_n^α) describing the size of the congestion window over the successive RTT intervals. It is assumed that the round trip time is large and the state of the network evolves sufficiently rapidly so that the packet loss events in one RTT interval do not depend on the contiguous RTT intervals. The sequence (W_n^α) is described as a Markov chain with the following transitions: if $W_0^\alpha = n \geq 1$,

$$\begin{cases} W_1^\alpha = \min(n+1, w_{\max}^\alpha), \text{ with probability } \prod_{i=1}^n \exp(-h_i^\alpha), \\ W_1^\alpha = \max\left(\lfloor \delta n \rfloor, 1\right), \text{ otherwise .} \end{cases} \tag{2}$$

The quantity $\exp(-h_i^\alpha)$ is the probability that during an RTT interval the ith packet is not lost when $i-1$ packets have been successfully transmitted. We shall assume that for $i \in \mathbb{N}$,

$$h_i^\alpha = \alpha \overline{h}\left(i\sqrt{\alpha}\right), \tag{3}$$

where $\overline{h}$ is a non identically 0, continuous function on $\mathbb{R}_+$. In particular, for $x \geq 0$,

$$\lim_{\alpha \to 0} \frac{h^\alpha_{\lfloor x/\sqrt{\alpha} \rfloor}}{\alpha} = \overline{h}(x).$$

The parameter α controls the loss rate of the algorithm. With this model, it is implicitly assumed that the probability of loss of a packet is non decreasing with respect to its index in the current window. (As the number of packets in the network grows, the more likely they will be lost). The original model (1) corresponds to the case where $\overline{h}$ is constant equal to 1.

The constant $w_{\max}^\alpha \in \mathbb{N} \cup \{+\infty\}$ is the maximal window size, it is assumed that it satisfies the following scaling relation with α,

$$\lim_{\alpha \to 0} \sqrt{\alpha}\, w_{\max}^\alpha = \overline{w}_{\max}. \tag{4}$$

Without loss of generality for the asymptotic results we are considering, the additive constant β of the transitions (1) can be taken equal to 1.

The embedded Markov chain

It is natural to consider the state of the Markov chain (W_n^α) just after a loss. The associated process is denoted by (V_n^α), this is clearly a Markov chain whose transitions are given by, if $V_0^\alpha = n \geq 1$

$$V_1^\alpha = \lfloor \delta \min\left(n + G_n^\alpha, w_{\max}^\alpha\right) \rfloor \vee 1 \tag{5}$$

where $x \vee 1 = \max(x, 1)$ and the random variable G_n^α is defined by

$$\mathbb{P}(G_n^\alpha \geq m) = \prod_{k=n}^{n+m-1} \prod_{j=1}^{k} \exp(-h_j^\alpha),$$

for $m \geq 1$ and $n \geq 1$, recall that $\prod_{j=1}^k \exp(-h_j^\alpha)$ is the probability that a congestion window of k packets is successfully transmitted over an RTT interval. The quantity G_n^α is the number of congestion windows sent successfully when the initial window size is n.

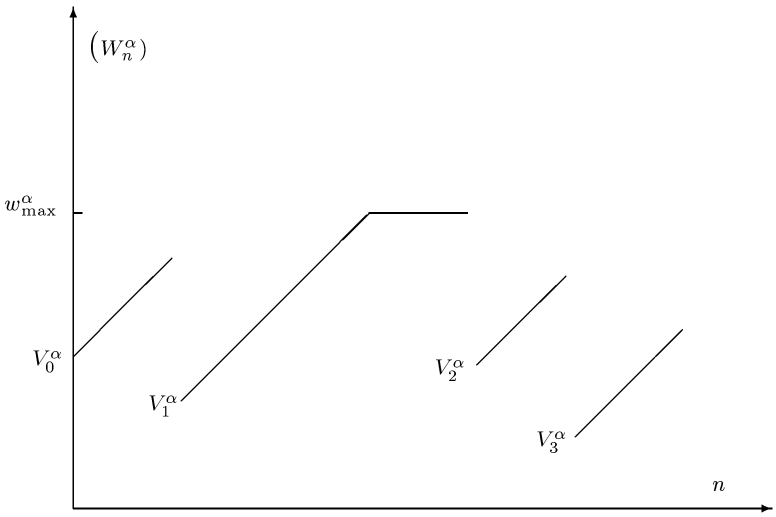

FIGURE 1. Evolution of the congestion window size

Convergence to a Markov process in finite time. We now show that the Markov chains described above are of the order $1/\sqrt{\alpha}$ when α tends to 0. The next proposition shows that $\sqrt{\alpha}$ is indeed the right scaling for the embedded Markov chain.

Proposition 1. *For $x > 0$, as α goes to 0, the random variable $\sqrt{\alpha}\, G^\alpha_{\lfloor x/\sqrt{\alpha} \rfloor}$ converges in distribution to a non negative random variable $\overline{G}_x$ such that for $y \geq 0$,*

$$\mathbb{P}\left(\overline{G}_x \geq y\right) = \exp\left(-\int_x^{x+y} \overline{H}(u)\, du\right), \tag{6}$$

with $\overline{H}(u)=\int_0^u \overline{h}(v)\,dv$, *and for* $K>0$,

$$\lim_{\alpha\to 0}\sup_{\sqrt{\alpha}\le x,y\le K}\left|\mathbb{P}\left(\overline{G}_x\ge y\right)-\mathbb{P}\left(\sqrt{\alpha}\,G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}\ge y\right)\right|=0. \tag{7}$$

Moreover, there exists $\lambda_0>0$ *such that for* $\lambda<\lambda_0$,

$$\sup_{0<\alpha<1}\sup_{x\ge\sqrt{\alpha}}\mathbb{E}\left(e^{\lambda\sqrt{\alpha}\,G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}}\right)<+\infty \tag{8}$$

Proof. For x, $y\ge\sqrt{\alpha}$ and $\alpha\in]0,1[$, we have

$$\mathbb{P}\left(\sqrt{\alpha}\,G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}>y\right)=\mathbb{P}\left(G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}>\lfloor y/\sqrt{\alpha}\,\rfloor\right)=\prod_{k=\lfloor x/\sqrt{\alpha}\rfloor}^{\lfloor x/\sqrt{\alpha}\rfloor+\lfloor y/\sqrt{\alpha}\rfloor}\prod_{j=1}^{k}\exp(-h_j^\alpha),$$

therefore

$$\begin{aligned}\log\mathbb{P}\left(\sqrt{\alpha}G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}>y\right)&=-\sum_{k=\lfloor x/\sqrt{\alpha}\rfloor}^{\lfloor x/\sqrt{\alpha}\rfloor+\lfloor y/\sqrt{\alpha}\rfloor}\sum_{j=1}^{k}\alpha\overline{h}(j\sqrt{\alpha}\,)\\&=-\sum_{k=\lfloor x/\sqrt{\alpha}\rfloor}^{\lfloor x/\sqrt{\alpha}\rfloor+\lfloor y/\sqrt{\alpha}\rfloor}\sqrt{\alpha}\int_0^{k\sqrt{\alpha}}\overline{h}(\sqrt{\alpha}\lceil v/\sqrt{\alpha}\,\rceil)\,dv\\&=-\int_x^{\sqrt{\alpha}(\lfloor x/\sqrt{\alpha}\rfloor+\lfloor y/\sqrt{\alpha}\rfloor)}\int_0^{\sqrt{\alpha}\,\lfloor u/\sqrt{\alpha}\rfloor}\overline{h}(\sqrt{\alpha}\lceil v/\sqrt{\alpha}\,\rceil)\,dv\,du.\end{aligned}$$

The uniform continuity of $\overline{h}$ over compact intervals implies that $\overline{h}(\sqrt{\alpha}\lceil\cdot/\sqrt{\alpha}\rceil)$ converges uniformly on $[0,K]$ to $\overline{h}$ as α tends to 0. The uniform convergence (7) is then easily obtained.

The above identity shows that for $x\ge 0$, $K>0$ and $y\ge 1$,

$$\log\mathbb{P}\left(\sqrt{\alpha}G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}>y\right)\le-\int_1^{y-1}\int_0^{K\wedge\sqrt{\alpha}\,\lfloor u/\sqrt{\alpha}\rfloor}\overline{h}(\sqrt{\alpha}\lceil v/\sqrt{\alpha}\,\rceil)\,dv\,du.$$

If λ_0 is the integral of $\overline{h}$ on $\mathbb{R}_+$, then for $\lambda<\lambda_0$ there exists $K>0$ such that

$$\lambda<\int_0^K\overline{h}(u)\,du,$$

using again the uniform convergence of $\overline{h}(\sqrt{\alpha}\lceil\cdot/\sqrt{\alpha}\rceil)$ on the interval $[0,K]$, one gets the relation

$$\limsup_{y\to+\infty}\sup_{0<\alpha<1}\sup_{x\ge 0}\frac{1}{y}\log\mathbb{P}\left(\sqrt{\alpha}G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}>y\right)\le-\int_0^K\overline{h}(v)\,dv$$

consequently,

$$\sup_{0<\alpha<1}\sup_{x\ge 0}\int_2^{+\infty}e^{\lambda y}\mathbb{P}\left(\sqrt{\alpha}G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}>y\right)\,dy<+\infty,$$

using Fubini's Theorem, this yields

$$\sup_{0<\alpha<1}\sup_{x\ge 0}\int_2^{+\infty}\mathbb{E}\left(e^{\lambda\sqrt{\alpha}G^\alpha_{\lfloor x/\sqrt{\alpha}\rfloor}}\right)<+\infty.$$

The proposition is proved. □

Notice that the scaling $\sqrt{\alpha}$ does not depend on the particular choice of $\overline{h}$. The scaling of $\overline{h}$ in $h_i^\alpha = \alpha\overline{h}\,(i\sqrt{\alpha})$ determines the correct profile for the space dependence of the loss probability. One can introduce the following Markov chain, as we shall see, this is the asymptotic embedded Markov chain when α tends 0.

Definition 2. *The sequence $(\overline{V}_n)$ denotes a Markov chain whose transitions are given by*

$$\overline{V}_1 = \delta \min\left(\overline{V}_0 + \overline{G}_{\overline{V}_0}, \overline{w}_{max}\right), \tag{9}$$

where $\left(\overline{G}_x;\, x > 0\right)$ is a family of random variables independent of V_0 such that, for $x > 0$, the distribution of $\overline{G}_x$ is given by the relation (6).

Proposition 3. *For any continuous function f on $\mathbb{R}_+$ with compact support, the following convergence holds,*

$$\lim_{\alpha\to 0} \sup_{x\geq\sqrt{\alpha}} \left|\mathbb{E}\left(f\left(\sqrt{\alpha}\, G_{\lfloor x/\sqrt{\alpha}\rfloor}\right)\right) - \mathbb{E}\left(f(\overline{G}_x)\right)\right| = 0. \tag{10}$$

If for $x > 0$, $\mathbb{P}_x$ denotes the probability such that $V_0^\alpha = \lfloor x/\sqrt{\alpha}\rfloor$ for all $\alpha > 0$ and $\overline{V}_0 = x$, then for $n \in \mathbb{N}$ and $a_1, \ldots a_n \in \mathbb{R}_+$,

$$\lim_{\alpha\to 0} \sup_{x} \left|\mathbb{P}_x\left(\sqrt{\alpha}V_1^\alpha \leq a_1, \ldots, \sqrt{\alpha}V_n^\alpha \leq a_n\right) - \mathbb{P}_x\left(\overline{V}_1 \leq a_1, \ldots, \overline{V}_n \leq a_n\right)\right| = 0$$

Proof. If f is a C^1 function on $\mathbb{R}_+$ with support in $[0, K]$, $k > 0$, the identities

$$\sum_{k=2}^{\lceil K/\sqrt{\alpha}\rceil} (f(k\sqrt{\alpha}) - f((k-1)\sqrt{\alpha}))\mathbb{P}(Y \geq k\sqrt{\alpha}) = \mathbb{E}\left(f(Y) - f(\sqrt{\alpha})\right),$$

for $Y = \sqrt{\alpha}\, G_{\lfloor x/\sqrt{\alpha}\rfloor}$ and $Y = \overline{G}_x$ are easily verified. The uniform continuity of f' on $\mathbb{R}_+$ and the estimate (7) give the desired convergence (10). If f is a continuous function on $\mathbb{R}_+$, it can be approximated uniformly by C^1 functions. The first part of the proposition is proved.

We shall prove the last part of the proposition for $n = 2$, i.e.

$$\lim_{\alpha\to 0} \sup_{x} \left|\mathbb{P}_x\left(\sqrt{\alpha}V_1^\alpha \leq a_1, \sqrt{\alpha}V_2^\alpha \leq a_2\right) - \mathbb{P}_x\left(\overline{V}_1 \leq a_1, \overline{V}_2 \leq a_2\right)\right| = 0.$$

Because of the transitions of the Markov chains, it is sufficient to show that for any a_1, $a_2 \leq \overline{w}_{\max}$, the following convergence holds

$$\lim_{\alpha\to 0} \sup_{x} \left|\mathbb{P}_x\left(\sqrt{\alpha}V_1^\alpha \leq a_1, \sqrt{\alpha}V_1^\alpha + \sqrt{\alpha}G_{V_1^\alpha}^\alpha \leq a_2\right)\right.$$
$$\left. - \mathbb{P}_x\left(\overline{V}_1 \leq a_1, \overline{V}_1 + \overline{G}_{\overline{V}_1} \leq a_2\right)\right| = 0.$$

Since

$$\mathbb{P}_x\left(\sqrt{\alpha}V_1^\alpha \leq a_1, \sqrt{\alpha}V_1^\alpha + \sqrt{\alpha}G_{V_1^\alpha}^\alpha \leq a_2\right)$$
$$= \int_0^{a_1} \mathbb{P}\left(y + \sqrt{\alpha}G_{\lfloor y/\sqrt{\alpha}\rfloor}^\alpha \leq a_2\right)\mathbb{P}_x(\sqrt{\alpha}V_1^\alpha \in dy),$$

since the quantity under the integrand is uniformly close to $f(y) = \mathbb{P}(y + \overline{G}_y \leq a_2)$ with respect to $y \in [0, a_1]$, one has to verify that $|\mathbb{E}_x(f(\sqrt{\alpha}V_1^\alpha)) - \mathbb{E}_x(f(\overline{V}_1))|$ is uniformly small, but this is precisely a consequence of what has just been proved. The proof for an arbitrary n is done by induction. This completes the proof. $\square$

Corollary 4. *If* $\lim_{\alpha\to 0}\sqrt{\alpha}V_0^\alpha = \overline{v}$, *then, as* α *tends to* 0, *the Markov chain* $(\sqrt{\alpha}V_n^\alpha)$ *converges in distribution to the Markov chain* $(\overline{V}_n)$ *(See Definition 2).*

Proof. Since one has to prove the convergence of the finite dimensional distributions, the corollary is a direct consequence of Proposition 3 and Relation (5). ☐

Proposition 5. *If* $\lim_{\alpha\to 0}\sqrt{\alpha}W_0^\alpha = \overline{w}$, *then the Markov process*

$$(W^\alpha(t)) = \left(\sqrt{\alpha}W^\alpha_{\lfloor t/\sqrt{\alpha}\rfloor}\right)$$

converges in distribution to the Markov process $\left(\overline{W}(t)\right)$ *on* $[0, \overline{w}_{max}]$ *such that* $\overline{W}(0) = \overline{w}$ *and with the infinitesimal generator given by*

$$\Omega(f)(x) = f'(x)1_{\{x<\overline{w}_{max}\}} + \int_0^x \overline{h}(u)\,du\,\left(f(\delta x) - f(x)\right), \tag{11}$$

for any C^1 *function* f *on* $\mathbb{R}_+$.

The Markov process $(W^\alpha(t))$ is right continuous with left limits everywhere. The convergence mentioned in this proposition is the convergence of probability distributions on the space of right continuous functions on $\mathbb{R}_+$ with left limits endowed with Skorohod topology. (See Billingsley [7] or Ethier and Kurtz [11] for the definitions and results concerning this topology).

The distributions of the variables $(\overline{G}_x,\, x \geq 0)$ have the following remarkable property that for $x,\, y \geq 0$,

$$\mathbb{P}(\overline{G}_x \geq y) = \frac{\mathbb{P}(\overline{G}_0 \geq x + y)}{\mathbb{P}(\overline{G}_0 \geq x)}.$$

(See Definition (6).) This property can be also seen as a consequence of the Markov property of the asymptotic Markov process $\left(\overline{W}(t)\right)$ when the maximum window size is infinite.

Proof. We shall assume that $\overline{w}_{\max}$ is infinite, the proof is analogous (even simpler) when this quantity is finite. Basically we shall prove that the infinitesimal generators converge to the appropriate infinitesimal generator. If this gives an indication of the kind of results one might expect, to prove the convergence rigorously some uniform convergence has to be established. We shall use the criterion given by Corollary 8.9 page 233 of Ethier and Kurtz [11].

We denote and by $\mathcal{C}$ the set of C^2-functions f on $\mathbb{R}_+$ such that the convergence

$$\lim_{x\to+\infty}(1 + \overline{H}(x)^2)\sup_{u\geq x-1}|g(u)| = 0,$$

($\overline{H}$ is defined in Proposition 1), is true for $g = f,\ f',\ f''$ and $g(x) = f(\delta x)$; $\mathcal{C}$ is an algebra that strongly separates the points, i.e. if $x \in \mathbb{R}_+$ and $\delta > 0$ then there exists $f \in \mathcal{C}$ such that

$$\inf(|f(y) - f(x)| : |y - x| \geq \delta) > 0.$$

If P^α is the transition matrix of the Markov chain $(\sqrt{\alpha}W_n^\alpha)$ and

$$A_\alpha = (P^\alpha - I)/\sqrt{\alpha},$$

where I is the identity; we have to prove that for any $f \in \mathcal{C}$,

$$\lim_{\alpha\to 0}\|A_\alpha(f) - \Omega(f)\|_\infty = \lim_{\alpha\to 0}\sup_{x\geq 0}|A_\alpha(f)(x) - \Omega(f)(x)| = 0. \tag{12}$$

For $x \geq 0$ and $f \in \mathcal{C}$,

$$A_\alpha(f)(x) = \frac{1}{\sqrt{\alpha}}(f(x+\sqrt{\alpha}) - f(x))\mathbb{P}\left(G_x^\alpha \geq 1\right) \\ + \left(f\left(\sqrt{\alpha}\lfloor \delta x/\sqrt{\alpha}\rfloor\right) - f(x)\right)\frac{1-\mathbb{P}\left(G_x^\alpha \geq 1\right)}{\sqrt{\alpha}}.$$

For $x \geq 0$ the difference $|A_\alpha(f)(x) - \Omega(f)(x)|$ can be bounded by the quantity $\Delta_1(x) + \Delta_2(x)$, with

$$\Delta_1(x) = \left|\frac{1}{\sqrt{\alpha}}(f(x+\sqrt{\alpha}) - f(x)) - f'(x)\right| \\ + |f'(x)|\left|1 - \exp\left(-\sqrt{\alpha}\int_0^x \overline{h}(\lfloor u/\sqrt{\alpha}\rfloor\sqrt{\alpha})\,du\right)\right|$$

and

$$\Delta_2(x) = \left|f\left(\sqrt{\alpha}\lfloor \delta x/\sqrt{\alpha}\rfloor\right) - f(\delta x)\right|\int_0^x \overline{h}(u)\,du \\ + (|f(\delta x)| + |f(x)|)\left|\frac{1-\exp\left(-\sqrt{\alpha}\int_0^x \overline{h}(\lfloor u/\sqrt{\alpha}\rfloor\sqrt{\alpha})\right)\,du}{\sqrt{\alpha}} - \int_0^x \overline{h}(u)\,du\right|.$$

Taylor's formulas for f and $x \to \exp(-x)$, the fact that f is in $\mathcal{C}$ and straightforward calculations give the desired uniform convergence (12). The proposition is proved. □

The limiting Markov process grows deterministically at rate 1 and jumps from x to δx with intensity $\int_0^x \overline{h}(u)\,du$. It is easy to check that, starting from $x > 0$, the duration of time to jump downwards has the same distribution as $\overline{G}_x$.

3. Convergence of the invariant measures

We are now interested by the equilibrium behavior of the AIMD algorithm. Up to now, a closed form expression for the invariant probabilities of the Markov chains (W_n^α) and (V_n^α) is not known, see Dumas *et al.* [8] for stochastic bounds in some special cases. The main results of this part concern the convergence in distribution of these invariant probability measures when α tends to 0. As we shall see in Section 4, the limiting probabilities have an explicit expression in some cases of practical interest. For the moment we study the behavior of the embedded Markov chain (V_n^α).

Definition 6. *If $K \geq 0$, T_K^α [resp. T_K] is the hitting time of the interval $[0, K]$ by the Markov chain $(\sqrt{\alpha}\,V_n^\alpha)$ [resp. $(\overline{V}_n)$],*

$$T_K^\alpha = \inf\left\{n \geq 1 : \sqrt{\alpha}\,V_n^\alpha \leq K\right\} \text{ and } \overline{T}_K = \inf\left\{n \geq 1 : \overline{V}_n \leq K\right\}.$$

Proposition 7. *For $\alpha > 0$, the Markov chain (V_n^α) is ergodic. When $\overline{w}_{max}^\alpha = +\infty$, there exist K, ξ and $\lambda > 0$ such that for $0 < \alpha < 1$,*

$$\mathbb{E}\left(e^{\xi T_K^\alpha - \lambda\sqrt{\alpha}V_0^\alpha}\,\middle|\,\sqrt{\alpha}V_0^\alpha > K\right) \leq 1. \tag{13}$$

Proof. The Markov chain (V_n^α) is clearly irreducible and aperiodic on $\mathbb{N}-\{0\}$. For $\lambda > 0$ and $n \in \mathbb{N}$, define $Z_n = \exp(\lambda\sqrt{\alpha}V_n^\alpha)$. For $K > 0$, the inequality

$$\mathbb{E}(Z_{n+1} - Z_n | \sqrt{\alpha}V_n^\alpha > K) \leq Z_n \mathbb{E}\left(e^{\lambda(\delta-1)K+\lambda\delta\sqrt{\alpha}G^\alpha_{V_n^\alpha}} - 1\right),$$

holds, therefore if $\alpha < 1$,

$$\mathbb{E}(Z_{n+1} - Z_n | \sqrt{\alpha}V_n^\alpha > K) \leq Z_n \left(e^{\lambda(\delta-1)K} \sup_{\substack{0<\alpha<1 \\ y\geq 0}} \mathbb{E}\left(e^{\lambda G^\alpha_{\lfloor y/\sqrt{\alpha}\rfloor}}\right) - 1\right);$$

According to Proposition 1, we can fix $\lambda < \lambda_0$ so that there exists a constant C satisfying

$$\mathbb{E}(Z_{n+1} - Z_n | \sqrt{\alpha}V_n^\alpha > K) \leq Z_n \left(Ce^{\lambda(\delta-1)K} - 1\right),$$

for all $\alpha \in]0, 1[$. Consequently, there exist some $K > 0$ and $\eta < 1$ such that

$$\mathbb{E}(Z_{n+1} | \sqrt{\alpha}V_n^\alpha > K) \leq \eta Z_n, \tag{14}$$

for $x \geq K$. If $(\mathcal{F}_n^\alpha)$ is the natural filtration generated by the Markov chain (V_n^α), the inequality (14) implies that if $\sqrt{\alpha}V_0^\alpha > K$, the sequence

$$(U_n) = \left(\eta^{-n\wedge T_K^\alpha} Z_{n\wedge T_K^\alpha}\right)$$

is a super-martingale with respect to $(\mathcal{F}_n^\alpha)$. Hence for $n \geq 0$,

$$\mathbb{E}\left(\eta^{-n\wedge T_K^\alpha} \middle| \mathcal{F}_0^\alpha\right) \leq \mathbb{E}\left(\eta^{-n\wedge T_K^\alpha} Z_{n\wedge T_K^\alpha} \middle| \mathcal{F}_0^\alpha\right) = \mathbb{E}(U_n | \mathcal{F}_0^\alpha) \leq U_0 = e^{\lambda\sqrt{\alpha}V_0^\alpha}.$$

By letting n go to infinity we get the inequality

$$\mathbb{E}\left(\eta^{-T_K^\alpha} \middle| \mathcal{F}_0^\alpha\right) \leq e^{\lambda\sqrt{\alpha}V_0^\alpha}.$$

The proposition is proved. □

Proposition 8. *The continuous state space Markov chain $(\overline{V}_n)$ is Harris ergodic. If $\overline{V}_\infty$ is some random variable distributed as the invariant probability of $(\overline{V}_n)$, it satisfies the following identity*

$$\overline{V}_\infty \overset{dist.}{=} \delta \min\left(\overline{V}_\infty + \overline{G}_{\overline{V}_\infty}, \overline{w}_{max}\right) \tag{15}$$

where $(\overline{G}_x;\, x \geq 0)$ are random variables independent of $\overline{V}_\infty$ whose distributions are given by the relation (6).

For the general definitions and results concerning Markov processes with a continuous state space, see Nummelin [16].

Proof. Since the transition of the Markov chain has a continuous density, it is a Harris chain (See Durrett [9] page 326). It is easily seen that for any $x \geq 0$, then $\mathbb{P}(\overline{G}_0 \geq y) \leq \mathbb{P}(\overline{G}_x \geq y)$ for $y \geq 0$; $\overline{G}_x$ is stochastically bounded by $\overline{G}_0$. Thus we can construct a sequence (Z_n) and an i.i.d sequence $(\overline{G}_{0,n})$ with the same distribution as $\overline{G}_0$ such that $Z_0 = \overline{V}_0$,

$$Z_{n+1} = \delta(Z_n + \overline{G}_{0,n}) \text{ and } \overline{V}_n \leq Z_n,$$

for all $n \in \mathbb{N}$. The sequence (Z_n) is an ARMA process (Autoregressive Moving Average) which is Harris ergodic (see Durrett [*ibid*]). Thus we get that the sequence of probability distributions

$$\left(\frac{1}{n}\sum_{k=1}^{n}\mathbb{P}\left(\overline{V}_k \in \cdot\right)\right)$$

is tight; clearly any limit of this sequence is an invariant probability distribution for the Markov chain $(\overline{V}_n)$. To conclude, an Harris Markov chain with an invariant probability distribution is necessarily ergodic. (See Durrett [9] Exercise 6.11 page 330.)

According to the definition (9) of the transitions of the Markov chain $(\overline{V}_n)$, its invariant distribution satisfies the relation (15). □

Theorem 9. *When α tends to 0 the invariant distribution of the Markov chain $(\sqrt{\alpha}V_n^\alpha)$ converges to the invariant distribution of the Markov chain $(\overline{V}_n)$. Consequently, the following diagram commutes,*

$$\begin{array}{ccc}
(\sqrt{\alpha}V_n^\alpha) & \xrightarrow{n\to+\infty} & \sqrt{\alpha}V_\infty^\alpha \\
{\scriptstyle \alpha\to 0}\Big\downarrow & & \Big\downarrow \\
(\overline{V}_n) & \longrightarrow & \overline{V}_\infty .
\end{array}$$

Proof. We denote by π^α the invariant probability of $(\sqrt{\alpha}V_n^\alpha)$ and (Z_n^α) is the sequence of the successive elements of $[0,K]$ visited by this Markov chain. In the rest of the proof, for variables with index α, the notation $\mathbb{E}_\mu(\cdot)$ and $\mathbb{P}_\mu(\cdot)$ refer to the Markov chain $(\sqrt{\alpha}V_n^\alpha)$ when the distribution of $\sqrt{\alpha}V_0^\alpha$ is μ.

Notice that if $\sqrt{\alpha}V_0^\alpha \le K$, then $Z_0^\alpha = \sqrt{\alpha}V_0^\alpha$ and $Z_1^\alpha = \sqrt{\alpha}V_{T_K^\alpha}^\alpha$. With the same argument as in the proof of Proposition 8 it easily seen that (Z_n^α) is a Harris ergodic Markov chain; π_K^α denotes its invariant probability, in particular $\pi_K^\alpha[0,K]=1$. The probability π^α can be represented as

$$\mathbb{E}_{\pi^\alpha}(f) \stackrel{\text{def}}{=} \int_{\mathbb{R}+} f\,d\pi^\alpha = \frac{1}{\mathbb{E}_{\pi_K^\alpha}\left(T_K^\alpha\right)}\mathbb{E}_{\pi_K^\alpha}\left(\sum_{k=0}^{T_K^\alpha-1} f\left(\sqrt{\alpha}V_k^\alpha\right)\right), \tag{16}$$

for any bounded measurable function f on $\mathbb{R}_+$ (see Asmussen [5] for example). For the asymptotic Markov chain, with the corresponding notations ($\overline{\pi}$ is the invariant probability of $(\overline{V}_n)$), the following identity holds,

$$\mathbb{E}_{\overline{\pi}}(f) = \frac{1}{\mathbb{E}_{\overline{\pi}_K}\left(\overline{T}_K\right)}\mathbb{E}_{\overline{\pi}_K}\left(\sum_{k=0}^{\overline{T}_K-1} f(\overline{V}_k)\right), \tag{17}$$

where $\overline{\pi}_K$ is the invariant probability of $(\overline{Z}_n)$ which is the embedded Markov chain of the visits of $(\overline{V}_n)$ in the set K.

The proof of the Theorem consists in showing that, for some $K>0$, the left hand side of (16) converges to the left hand side of (17) when α tends to 0. To prove this convergence, the inequality (13) is used to truncate the sum under the expectation and the remaining terms are shown to converge with the help of relation (10).

The set of probability measures $\{\pi_K^\alpha;\, \alpha>0\}$ is obviously tight. Consequently, there exists a probability π_K on $[0,K]$ and a sequence (α_n) converging to 0 such that $(\pi_K^{\alpha_n})$ converges to π_K.

The probability π_K is invariant for $\left(\overline{Z}_n\right)$.
For $n \in \mathbb{N}$ and a, $x \leq K$,

$$\mathbb{P}(T_K^\alpha = n, Z_1^\alpha \leq a) = \mathbb{P}\left(V_1^\alpha > K, \dots, V_{n-1}^\alpha > K, V_n^\alpha \leq a\right)$$

According to Proposition 3, when α goes to 0 this last quantity is converging to

$$\mathbb{P}\left(\overline{V}_1 > K, \dots, \overline{V}_{n-1} > K, \overline{V}_n \leq a\right) = \mathbb{P}(\overline{T}_K = n, \overline{Z}_1 \leq a)$$

uniformly on $\sqrt{\alpha}V_0^\alpha \in [0, K]$. In particular the variables $(T_K^{\alpha_n})$ [resp. $(Z_1^{\alpha_n})$] converge in distribution to the variable $\overline{T}_K$ [resp. $\overline{Z}_1$]. By invariance, for $\alpha > 0$,

$$\pi_K^{\alpha_n}([a, +\infty[) = \mathbb{P}_{\pi_K^{\alpha_n}}(Z_0^{\alpha_n} \leq a) = \mathbb{P}_{\pi_K^{\alpha_n}}(Z_1^{\alpha_n} \leq a),$$

the uniform convergence gives the identity

$$\pi_K([a, +\infty[) = \lim_{n \to +\infty} \mathbb{P}_{\pi_K^{\alpha_n}}(Z_1^{\alpha_n} \leq a) = \mathbb{P}_{\pi_K}(\overline{Z}_1 \leq a)$$

The probability π_K is therefore an invariant probability measure for the Markov chain $\left(\overline{Z}_n\right)$; by uniqueness this implies that $\pi_K = \overline{\pi}_K$. Thus, we have shown that the probabilities $(\pi_K^\alpha; \alpha > 0)$ converge to $\overline{\pi}_K$ as α tends to 0.

Proposition 7 shows that there exist constants K, ξ, $\lambda > 0$ such that

$$\mathbb{E}\left(e^{\xi T_K^\alpha - \lambda\sqrt{\alpha}V_0^\alpha} \,\middle|\, \sqrt{\alpha}V_0^\alpha \geq K\right) \leq 1.$$

The Markov property gives the relation

$$\begin{aligned} e^{-\xi}\mathbb{E}_{\pi_K^\alpha}\left(e^{\xi T_K^\alpha}\right) &\leq 1 + \mathbb{E}_{\pi_K^\alpha}\left(e^{\lambda\sqrt{\alpha}V_1^\alpha}\, \mathbb{E}_{\sqrt{\alpha}V_1^\alpha}\left(e^{\xi T_K^\alpha - \lambda\sqrt{\alpha}V_1^\alpha} \,\middle|\, \sqrt{\alpha}V_1^\alpha > K\right)\right) \\ &\leq 1 + \mathbb{E}_{\pi_K^\alpha}\left(e^{\lambda\sqrt{\alpha}V_1^\alpha}\right) \leq 1 + \mathbb{E}_{\pi_K^\alpha}\left(e^{\lambda\delta\sqrt{\alpha}V_0^\alpha + \delta\lambda\sqrt{\alpha}G_{V_0^\alpha}^\alpha}\right) \end{aligned}$$

since $\sqrt{\alpha}V_0^\alpha \leq K$ for the probability measure $\mathbb{P}_{\pi_K^\alpha}$,

$$e^{-\xi}\mathbb{E}_{\pi_K^\alpha}\left(e^{\xi T_K^\alpha}\right) \leq 1 + e^{\lambda\delta K}\mathbb{E}_{\pi_K^\alpha}\left(e^{\lambda\sqrt{\alpha}G_{V_0^\alpha}^\alpha}\right),$$

and this quantity is bounded for $0 < \alpha < 1$, according to the inequality (8) (by choosing λ sufficiently small). With the initial distributions (π_K^α), the variables $(T_K^\alpha; \alpha < 1)$ are therefore uniformly integrable, in particular

$$\lim_{\alpha \to 0} \mathbb{E}_{\pi_K^\alpha}(T_K^\alpha) = \mathbb{E}_{\pi_K}(\overline{T}_K),$$

and for $\varepsilon > 0$ there exists $C > 0$ such that

$$\mathbb{E}_{\pi_K}\left(\overline{T}_K 1_{\left\{\overline{T}_K \geq C\right\}}\right) \leq \varepsilon \quad \text{and} \quad \mathbb{E}_{\pi_K^\alpha}\left(T_K^\alpha 1_{\left\{T_K^\alpha \geq C\right\}}\right) \leq \varepsilon,$$

for $0 < \alpha < 1$. From these estimates and the uniform convergence of Proposition 3, for a bounded measurable function f, we deduce that

$$\lim_{\alpha \to 0} \mathbb{E}_{\pi_K^\alpha}\left(\sum_{k=0}^{T_K^\alpha - 1} f(V_k^\alpha)\right) = \mathbb{E}_{\overline{\pi}_K}\left(\sum_{k=0}^{\overline{T}_K - 1} f(\overline{V}_k)\right),$$

as α goes to 0, hence according to the identities (16) and (17), the probabilities $(\pi^\alpha; \alpha > 0)$ converge to $\overline{\pi}$ as α tends to 0. The theorem is proved. □

Theorem 10. *When α tends to 0 the invariant distribution of the Markov chain $(\sqrt{\alpha}W_n^\alpha)$ converges to the invariant distribution of the Markov process $(\overline{W}(t))$,*

$$\begin{array}{ccc} \left(\sqrt{\alpha}W^\alpha_{\lfloor t/\sqrt{\alpha}\rfloor}\right) & \xrightarrow{t\to+\infty} & \sqrt{\alpha}W^\alpha_\infty \\ {\scriptstyle \alpha\to 0}\downarrow & & \downarrow \\ \left(\overline{W}(t)\right) & \longrightarrow & \overline{W}(\infty). \end{array}$$

Proof. The proof is similar to the proof of Theorem 9. Basically the sums in (16) and (17) have to be replaced by integrals. □

4. The representation of the limiting invariant measures

In this section we shall consider the case when $\overline{h} \equiv 1$; the loss probability is a constant for all packets. In this case, for $x \geq 0$, the distribution of $\overline{G}_x$ is given by

$$\mathbb{P}(\overline{G}_x \geq y) = e^{-xy-y^2/2}, \tag{18}$$

for $y \geq 0$. The infinitesimal generator Ω given by (11) of the asymptotic Markov process is given by

$$\Omega(f)(x) = f'(x)1_{\{x<\overline{w}_{\max}\}} + x(f(\delta x) - f(x)). \tag{19}$$

The following simple proposition is crucial to get the stationary behavior of AIMD algorithms analyzed in this section.

Proposition 11. *For $x > 0$, if the distribution of a random variable $\overline{G}_x$ is given by (18), the following identity holds*

$$\left(x + \overline{G}_x\right)^2 \stackrel{dist.}{=} 2E_1 + x^2, \tag{20}$$

where E_1 an exponentially distributed random variable with parameter 1.

Proof. For $y \geq 0$, the relation (18) gives

$$\mathbb{P}((x + \overline{G}_x)^2 \geq y + x^2) = e^{-y/2},$$

and the result follows. □

We first study the case of the infinite maximum window size. The characteristics of the system at equilibrium (invariant probability, throughput) have rather simple closed form expressions. The corresponding expressions for the finite maximum window size case are still explicit but more intricate.

4.1. Infinite maximum window size.

The embedded Markov chain. The following proposition gives a probabilistic representation of $\overline{V}_\infty$ when the maximum window size is infinite. Its analytic counterpart is the proposition 13 below. It shows that the square of the limiting embedded Markov chain is an ARMA process. To our knowledge, this crucial property does not seem to have been remarked previously. The ARMA property is the key characteristic of the AIMD control scheme. Usually, the ARMA property is assumed, a priory, for the Markov chain itself but not related to the intrinsic behavior of the control algorithm (see Altman *et al.* [3] for example). As we shall see later the ARMA property has important consequences on the qualitative behavior of TCP. In particular it implies that the tail distribution of the size of the congestion window decays as $\exp(-\beta x^2)$ instead of $\exp(-\beta x)$ for some constant β as x gets large.

Proposition 12. *When the maximum window size is infinite, $\overline{w}_{max} = +\infty$, the square of the Markov chain $(\overline{V}_n)$ is an ARMA process with the following representation: for $n \in \mathbb{N}$,*

$$\overline{V}_{n+1}^2 = \delta\left(\overline{V}_n^2 + 2E_n\right)$$

where (E_n) is an i.i.d. sequence of exponentially distributed random variables with parameter 1.

Its invariant probability can represented by the random variable $\overline{V}_\infty$ satisfying relation (15)

$$\overline{V}_\infty \stackrel{dist.}{=} \sqrt{2\sum_{n=1}^{+\infty} \delta^{2n} E_n}. \tag{21}$$

Proof. From relation (9) we get

$$\overline{V}_{n+1} \stackrel{\text{dist.}}{=} \delta\left(\overline{V}_n + \overline{G}_{\overline{V}_n}\right),$$

where the variables $(\overline{G}_g;\, x > 0)$ are independent of $\overline{V}_n$. Therefore Proposition 11 gives the identity

$$\overline{V}_{n+1}^2 \stackrel{\text{dist.}}{=} \delta^2\left(\overline{V}_n^2 + 2E_n\right),$$

where E_n is an exponential variable with parameter 1. The ARMA property is proved. At equilibrium, using relation(15), the corresponding equation is

$$\overline{V}_\infty^2 \stackrel{\text{dist.}}{=} \delta^2\left(\overline{V}_\infty^2 + 2E_1\right).$$

If this relation is iterated, one gets identity (21) (the residual term $\delta^{2n}\overline{V}_\infty^2$ converges in distribution to 0). ☐

From the above proposition one can derive the density of the limiting random variable $\overline{V}_\infty$.

Proposition 13. *The density function of $\overline{V}_\infty$ when the maximum window size is infinite is given by, for $x \geq 0$,*

$$h_\delta(x) = \frac{1}{\prod_{n=1}^{+\infty}(1-\delta^{2n})} \sum_{n=1}^{+\infty} \frac{1}{\prod_{k=1}^{n-1}(1-\delta^{-2k})} \delta^{-2n} x e^{-\delta^{-2n}x^2/2}. \tag{22}$$

Proof. Let $\widetilde{V}_\infty$ denote the Laplace transform of the random variable $\overline{V}_\infty^2/2$, which is defined for $\xi \in \mathbb{C}$ with $\Re(\xi) \geq 0$ by

$$\widetilde{V}_\infty(\xi) = \mathbb{E}\left(e^{-\xi \overline{V}_\infty^2/2}\right).$$

A direct consequence of the independence of the exponential random variables (E_n) in equation (21) is that

$$\widetilde{V}_\infty(\xi) = \prod_{k=1}^{\infty} \frac{1}{(1+\delta^{2k}\xi)}.$$

The Laplace transform $\widetilde{V}_\infty$ has simple poles located at the points $\{-1/\delta^{2n},\, n \geq 1\}$. For $n \geq 1$, the residue of $\widetilde{V}_\infty$ at $-1/\delta^{2n}$ is given by

$$\frac{1}{\delta^{2n}} \prod_{k=1}^{n-1} \frac{1}{(1-\delta^{2k}/\delta^{2n})} \prod_{k=n+1}^{\infty} \frac{1}{(1-\delta^{2k}/\delta^{2n})} = \frac{\delta^{-2n}}{\prod_{k=1}^{n-1}(1-\delta^{-2k})} \frac{1}{\prod_{k=1}^{\infty}(1-\delta^{2k})}.$$

It follows that

$$\widetilde{V}_\infty(\xi) = \frac{1}{\prod_{k=1}^{\infty}(1-\delta^{2k})} \sum_{n=1}^{+\infty} \frac{1}{\prod_{k=1}^{n-1}(1-\delta^{-2k})} \frac{\delta^{-2n}}{\xi+\delta^{-2n}},$$

hence the density of $\overline{V}_\infty^2/2$ is given by, for $x \geq 0$,

$$\frac{1}{\prod_{k=1}^{\infty}(1-\delta^{2k})} \sum_{n=1}^{+\infty} \frac{1}{\prod_{k=1}^{n-1}(1-\delta^{-2k})} \delta^{-2n} e^{-\delta^{-2n}x}.$$

This completes the proof of the proposition. □

As shown by the picture below the distribution of $\overline{V}_\infty$ is sharply concentrated near the origin. Its tail distribution is equivalent to $Cx\exp(-\delta^2 x^2/2)$ as x gets large.

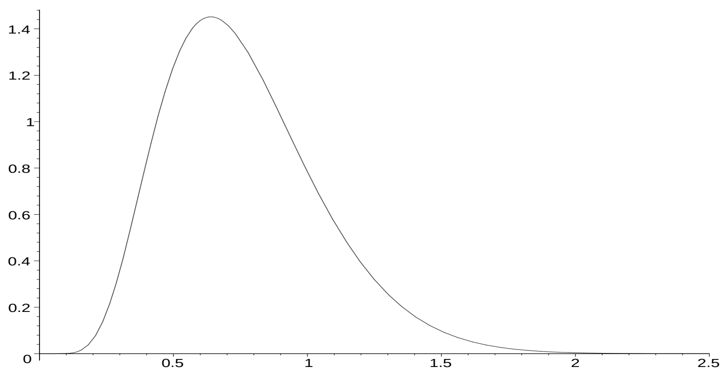

FIGURE 2. The density of $\overline{V}_\infty$ for $\delta = 1/2$

The throughput.

Definition 14. *For $\alpha > 0$, the throughput of the algorithm is defined as the limit*

$$\rho^\alpha(\delta) = \lim_{n\to+\infty} \frac{1}{n} \sum_{i=1}^{n} W_k^\alpha.$$

This definition assumes that the round trip time (RTT) is taken equal to 1. Thus, up to this factor, this is the definition of the literature. The ergodic theorem for the Markov chain (W_n^α) gives that $\rho^\alpha(\delta) = \mathbb{E}(W_\infty^\alpha)$. Using the embedded Markov chain (V_n^α) it is easily seen that the throughput can also be written as

$$\rho^\alpha(\delta) = \lim_{n\to+\infty} \frac{1}{\sum_1^n G_{V_i^\alpha}^\alpha} \sum_{i=1}^{n} \sum_{k=0}^{G_{V_i^\alpha}^\alpha - 1} (V_i + k).$$

From the ergodic theorem applied to the Markov chain (V_n^α), we get finally

$$\rho^\alpha(\delta) = \frac{\mathbb{E}\left(\sum_{k=0}^{G^\alpha_{V^\alpha_\infty}-1}(V^\alpha_\infty + k)\right)}{\mathbb{E}\left(G^\alpha_{V^\alpha_\infty}\right)} = \frac{\mathbb{E}\left(2G^\alpha_{V^\alpha_\infty}V^\alpha_\infty + \left(G^\alpha_{V^\alpha_\infty}\right)^2\right)}{2\mathbb{E}\left(G^\alpha_{V^\alpha_\infty}\right)} - 1/2. \tag{23}$$

Proposition 15. *The asymptotic throughput of an AIMD algorithm with multiplicative decrease factor δ is given by*

$$\overline{\rho}(\delta) \stackrel{def}{=} \lim_{\alpha\to 0}\sqrt{\alpha}\rho^\alpha(\delta) = \frac{\delta}{(1-\delta)\mathbb{E}\left(\overline{V}_\infty\right)} = \sqrt{\frac{2}{\pi}}\,\frac{\prod_{n=1}^{+\infty}\left(1-\delta^{2n}\right)}{\prod_{n=0}^{+\infty}\left(1-\delta^{2n+1}\right)}. \tag{24}$$

Proof. By definition of the throughput, we have

$$\rho^\alpha(\delta) = -1/2 + \mathbb{E}\left(\left(V^\alpha_\infty + G^\alpha_{V^\alpha_\infty}\right)^2 - (V^\alpha_\infty)^2\right)\Big/\, 2\mathbb{E}\left(G^\alpha_{V^\alpha_\infty}\right).$$

Identity (15) shows that

$$\begin{aligned}\rho^\alpha(\delta) &= -1/2 + \mathbb{E}\left((V^\alpha_\infty)^2(1/\delta^2 - 1)\right)/\,2\mathbb{E}\left(G^\alpha_{V^\alpha_\infty}\right)\\ &= \frac{(1+\delta)\mathbb{E}((V^\alpha_\infty)^2)}{2\delta(1-\delta)\mathbb{E}(V^\alpha_\infty)} - 1/2.\end{aligned}$$

According to Theorem 9, the following convergence holds

$$\lim_{\alpha\to 0}\sqrt{\alpha}\rho^\alpha(\delta) = \frac{(1+\delta)\mathbb{E}\left(\overline{V}^2_\infty\right)}{2\delta(1-\delta)\mathbb{E}(\overline{V}_\infty)} = \frac{\delta}{(1-\delta)\mathbb{E}(\overline{V}_\infty)},$$

where the last relation is a consequence of representation (21). The quantity $\mathbb{E}(\overline{V}_\infty)$ is obtained with expression (22) of the density h_δ. The relation

$$\int_0^{+\infty}\delta^{-2n}x^2\exp(-\delta^{-2n}x^2/2)\,dx = \sqrt{\frac{\pi}{2}}\,\delta^n,$$

for $n \geq 1$ and Euler's identity (see Erdelyi [10] formula (25) page 261),

$$\sum_{n=0}^{+\infty}\frac{x^{n(n+1)/2}t^n}{\prod_{l=1}^n(1-x^l)} = \prod_{l=1}^{+\infty}\left(1+tx^l\right) \tag{25}$$

applied for $x = \delta^2$ and $t = -\delta$ give the final formula for the throughput. □

Note that Ott *et al.* [17] obtained expressions similar to (22) and (24) for a continuous system, described as the solution of a deterministic differential equation perturbated at the points of a Poisson process. For the finite time behavior, this system can be considered as a limit of the original model. If we observe the system at the level of the packets instead of the successive congestion windows, the points of the Poisson process are the instants, properly renormalized, when packets are lost. At equilibrium there is no convergence result for the invariant distributions supporting the fact that this system may be seen as a limit of the original model. Technically, the trouble comes from the deterministic differential equation

$$x'(t) = a/x(t)$$

considered in that paper. It has a singularity when $x(0)$ is close to 0. In finite time, this singularity can be controlled; for the equilibrium, i.e. at $t = +\infty$, it is less clear how one can prove that the invariant probability distributions converge to the invariant probability measure of the perturbated differential equation.

REMARKS.

a) *For the case of TCP, $\delta = 1/2$, the throughput is* ~ 1.3098 *which is the value observed in earlier simulations and experiments (see Floyd* [12], *Floyd* et al. [13] *and Madhavi and Floyd* [15]*).*

b) *Trite manipulations with the expression* (24) *of* $\overline{\rho}(\delta)$ *show that*

$$\overline{\rho}(\delta) \sim \sqrt{\frac{2}{\pi(1-\delta)}}$$

when $\delta \nearrow 1$. *This does not mean that, in practice, the throughput really increases with* δ. *Indeed, the loss process is in fact also related to* δ. *The model we consider does not take into account this relation.*

The continuous time process. The above results on the invariant distribution of the embedded Markov chain give the expression of the density of the invariant distribution of the continuous time process $(\overline{W}(t))$.

Proposition 16. *When the maximum window size is infinite, the rescaled asymptotic density function of the congestion window size at equilibrium* $\overline{W}_\infty$ *is given by, for* $x \geq 0$,

$$H_\delta(x) = \frac{\sqrt{2/\pi}}{\prod_{n=0}^{+\infty}(1-\delta^{2n+1})} \sum_{n=0}^{+\infty} \frac{\delta^{-2n}}{\prod_{k=1}^{n}(1-\delta^{-2k})} e^{-\delta^{-2n}x^2/2}. \tag{26}$$

Proof. The classical representation of the invariant measure of the continuous time process $(\overline{W}(t))$ with the invariant probability of $(\overline{V}_n)$ is given by

$$\mathbb{E}\left(f\left(\overline{W}_\infty\right)\right) = \frac{1}{\mathbb{E}\left(\overline{G}_{\overline{V}_\infty}\right)} \mathbb{E}\left(\int_0^{\overline{G}_{\overline{V}_\infty}} f\left(\overline{V}_\infty + s\right)\, ds\right), \tag{27}$$

for any non negative measurable function f on $\mathbb{R}_+$. The invariance relation (15) (with $\overline{w}_{\max} = +\infty$) gives the identity

$$\mathbb{E}\left(\overline{G}_{\overline{V}_\infty}\right) = \frac{1-\delta}{\delta}\mathbb{E}\left(\overline{V}_\infty\right),$$

the right hand side is precisely the inverse of the asymptotic throughput according relation (24). If we take $f(x) = \exp(-\lambda x)$ for x in identity (27) and $\lambda \geq 0$, the Laplace transform of $\overline{W}_\infty$ is given by

$$\begin{aligned}
\mathbb{E}\left(\exp\left(-\lambda \overline{W}_\infty\right)\right) &= \overline{\rho}(\delta)\, \mathbb{E}\left(\int_0^{\overline{G}_{\overline{V}_\infty}} \exp\left(-\lambda\left(\overline{V}_\infty + s\right)\right) ds\right) \\
&= \frac{\overline{\rho}(\delta)}{\lambda}\left(\mathbb{E}\left(\exp(-\lambda \overline{V}_\infty) - \exp\left(-\lambda\left(\overline{V}_\infty + \overline{G}_{\overline{V}_\infty}\right)\right)\right)\right).
\end{aligned}$$

Relation (15) shows that this last expression is

$$\begin{aligned}
\mathbb{E}\left(\exp\left(-\lambda \overline{W}_\infty\right)\right) &= \frac{\overline{\rho}(\delta)}{\lambda}\left(\mathbb{E}\left(\exp(-\lambda \overline{V}_\infty)\right) - \mathbb{E}\left(\exp\left(-\lambda \overline{V}_\infty/\delta\right)\right)\right.\\
&= \overline{\rho}(\delta)\,\mathbb{E}\left(\int_{\overline{V}_\infty}^{\overline{V}_\infty/\delta} e^{-\lambda s}\, ds\right)\\
&= \int_0^{+\infty} e^{-\lambda s}\mathbb{P}\left(\overline{V}_\infty \le s \le \overline{V}_\infty/\delta\right)\, ds.
\end{aligned}$$

From relation (27) we get that the density of $\overline{W}_\infty$ is given by

$$H_\delta(x) = \overline{\rho}(\delta)\,\mathbb{P}\left(\overline{V}_\infty \le x \le \overline{V}_\infty/\delta\right) = \overline{\rho}(\delta)\,\mathbb{P}\left(\delta x \le \overline{V}_\infty \le x\right),$$

for $x \ge 0$. The expression (22) of the density of $\overline{V}_\infty$ is used to conclude the proof. □

4.2. **Finite maximum window size.**

The embedded Markov chain. In this section, we assume that the rescaled maximum window size $\overline{w}_{\max}$ is finite. As we shall see, by using equation (15), it is also possible to explicitly compute the distribution of the limiting random variable $\overline{V}_\infty$. The following proposition is the analogue of Proposition 12, it gives an explicit probabilistic representation of $\overline{V}_\infty$.

Proposition 17. *If (E_i) is an i.i.d. sequence of exponential random variables with parameter 1, the invariant probability measure of the limiting Markov chain can be represented as follows,*

$$\overline{V}_\infty \stackrel{dist.}{=} \sqrt{\inf_{n\ge 0}\left(\delta^{2n}\overline{w}_{max} + 2\sum_{i=1}^{n}\delta^{2i}E_i\right)}, \tag{28}$$

where (E_n) is an i.i.d. sequence of exponentially distributed random variables with parameter 1.

Proof. From the identity (20) and Equation (15), we get that

$$\overline{V}_\infty^2 \stackrel{\text{dist.}}{=} \delta^2 \min\left(\overline{w}_{\max}^2, 2E_1 + \overline{V}_\infty^2\right), \tag{29}$$

where E_1 is an exponential random variable with unit mean, independent of $\overline{V}_\infty$. If we iterate this equation, by induction we obtain that for $N \ge 1$,

$$\overline{V}_\infty^2 \stackrel{\text{dist.}}{=} \min_{0\le n\le N-1}\left(\delta^{2n}\overline{w}_{\max}^2 + 2\sum_{i=1}^{n}\delta^{2i}E_i\right) \wedge \left(\delta^{2N}\overline{V}_\infty^2 + 2\sum_{i=1}^{N}\delta^{2i}E_i\right).$$

The proposition follows by letting N go to infinity. □

Notice that when $\overline{w}_{\max}$ goes to infinity, the representation (28) converges to the expression (21) obtained for the infinite window size. We now give the explicit representation of the distribution of $\overline{V}_\infty$. The equation (29) shows that this variable has a mass at $\delta\overline{w}_{\max}$. As we shall see in the next proposition, the distribution of $\overline{V}_\infty$ is a convex combination of a Dirac mass at $\delta\overline{w}_{\max}$ and a density function on $[0, \delta\overline{w}_{\max}]$.

Proposition 18. *The distribution of $\overline{V}_\infty$ has a mass η at $\delta\overline{w}_{max}$, with*

$$(30)\quad 1/\eta = 1 + \prod_{n=1}^{+\infty}(1-\delta^{2n})\left(\sum_{n=0}^{+\infty}\frac{1}{\prod_{k=1}^{n}(1-\delta^{2k})}\left(e^{\delta^{2n}\overline{w}_{max}^2/2} - e^{\delta^{2(n+1)}\overline{w}_{max}^2/2}\right)\right)$$

and a density function $\tilde{h}_\delta$ on $[0,\delta\overline{w}_{max}]$ given by

$$(31)\quad \tilde{h}_\delta(x) = h_\delta(x) + x\eta\sum_{n=1}^{+\infty}\left(k_n\left(x^2-\delta^{2(n+1)}\overline{w}_{max}^2\right) - k_n\left(x^2-\delta^{2n}\overline{w}_{max}^2\right)\right),$$

where h_δ is the density function given by (22) *and for, $n \geq 1$, $k_n(2x)$ is the density of $\delta^2 E_1 + \cdots + \delta^{2n}E_n$ when the random variables (E_i) are i.i.d. exponentially distributed with parameter* 1.

The function k_n can be expressed explicitly as a linear combination of the functions $\exp(-\delta^{-2k}x)$, $x \geq 0$, $k = 1, \ldots, n$. (Notice that k_n vanishes on $\mathbb{R}_-$).

With the expressions (30) and (31), it is easily seen that the distribution of $\overline{V}_\infty$ converges to the distribution with density h_δ when $\overline{w}_{\max}$ tends to infinity.

Proof. If we set $Z = \overline{V}_\infty^2/2$, $\beta = \delta^2$ and $w = \beta\,\overline{w}_{\max}^2/2$, the relation (29) shows that the variable Z satisfies the following relation

$$Z \stackrel{\text{dist.}}{=} \min(\beta(Z+E), w),$$

where E is an exponential variable with parameter 1 independent of Z. If ϕ denotes the Laplace transform of Z, the above equation can be written as, for $\xi \geq 0$,

$$\phi(\xi) = \mathbb{E}\left(e^{-\xi Z}\right) = \mathbb{E}\left(e^{-\xi\beta(Z+E)}1_{\{\beta(Z+E)<w\}}\right) + e^{-\xi w}P(\beta(Z+E)\geq w).$$

By using the fact that E and Z are independent, we get

$$(32)\qquad \phi(\xi) = \mathbb{E}\left(e^{-\xi\beta Z}\frac{\left(1-e^{-(\xi\beta+1)(w/\beta - Z)}\right)}{1+\xi\beta}\right) + e^{-\xi w}\mathbb{E}\left(e^{-(w/\beta - Z)}\right),$$

therefore,

$$(33)\qquad \phi(\xi) = \frac{1}{1+\beta\xi}\phi(\xi\beta) + \frac{\xi\beta}{1+\xi\beta}e^{-(\xi+1/\beta)w}\phi(-1),$$

if the above relation is used recursively, we obtain for $n \geq 1$,

$$\phi(\xi) = \frac{1}{\prod_{k=1}^{n}(1+\xi\beta^k)}\phi(\xi\beta^n) + \phi(-1)e^{-w/\beta}\sum_{k=0}^{n-1}\frac{\xi\beta^{k+1}}{\prod_{i=1}^{k+1}(1+\xi\beta^i)}e^{-\xi\beta^k w},$$

since $\phi(\xi\beta^n) \to 1$ as n goes to infinity (recall that $\beta < 1$), the Laplace transform ϕ can be expressed as

$$\phi(\xi) = \frac{1}{\prod_{k=1}^{+\infty}(1+\xi\beta^k)} + \phi(-1)e^{-w/\beta}\sum_{k=0}^{+\infty}\frac{\xi\beta^{k+1}}{\prod_{i=1}^{k+1}(1+\xi\beta^i)}e^{-\xi\beta^k w}.$$

If we take $\xi = -1$ in this identity we get that

$$1/\phi(-1) = \left(1 + e^{-w/\beta}\sum_{n\geq 0}\frac{\beta^{n+1}}{\prod_{k=1}^{n+1}(1-\beta^k)}e^{\beta^n w}\right)\prod_{n=1}^{+\infty}(1-\beta^n).$$

If we set $\eta = \phi(-1)e^{-w/\beta}$, then clearly

$$\eta = \mathbb{P}(\beta(Z+E) > w) = \mathbb{P}(\overline{V}_\infty + \overline{G}_{\overline{V}_\infty} > \overline{w}_{\max}) = \mathbb{P}(\overline{V}_\infty = \delta\overline{w}_{\max}),$$

according to relation (29). It is then easily seen that ϕ can be written as

$$\phi(\xi) = \frac{1}{\prod_{k=1}^{+\infty}(1+\xi\beta^k)} + \eta\left(e^{-\xi w} + \sum_{n=1}^{+\infty}\frac{1}{\prod_{i=1}^{n}(1+\xi\beta^i)}\left(e^{-\xi\beta^n w} - e^{-\xi\beta^{n-1}w}\right)\right).$$

The above Laplace transform is then easy to invert and yields the identity (31). $\square$

The throughput. With the same argument leading to the relation (23) for the infinite maximum window size, the throughput $\rho^\alpha(\delta)$ (Definition 14) can be expressed as

$$\rho^\alpha(\delta)\mathbb{E}(\tau^\alpha) = \mathbb{E}\left(\sum_{k=0}^{\tau^\alpha-1} W_k^\alpha\right),$$

where τ^α is the first time there is a loss when the initial window size is V_∞^α. Notice that τ^α is $G_{V_\infty^\alpha}^\alpha$ only if a loss occurs before (W_n^α) hits the level $w_{\max}^\alpha$. When the maximum window size is reached, the window size remains constant for a geometrically distributed period H^α with parameter $\exp(-\alpha w_{\max}^\alpha)$. This gives the following identities

$$\tau^\alpha = G_{V_\infty^\alpha}^\alpha 1_{\left\{V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha < w_{\max}^\alpha\right\}} + (w_{\max}^\alpha - V_\infty^\alpha + H^\alpha)\, 1_{\left\{V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha \geq w_{\max}^\alpha\right\}}, \tag{34}$$

$$\sum_{k=0}^{\tau^\alpha-1} W_k^\alpha = \sum_{k=V_\infty^\alpha}^{V_\infty^\alpha+G_{V_\infty^\alpha}^\alpha} k + \left(w_{\max}^\alpha H^\alpha - \sum_{k=w_{\max}^\alpha}^{V_\infty^\alpha+G_{V_\infty^\alpha}^\alpha} k\right) 1_{\left\{V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha \geq w_{\max}^\alpha\right\}}. \tag{35}$$

If η^α is the probability of this event (by invariance $\eta^\alpha = \mathbb{P}(V_\infty^\alpha = \delta w_{\max}^\alpha)$), we get

$$\begin{aligned}\alpha\mathbb{E}\left(\sum_{k=0}^{\tau^\alpha-1} W_k^\alpha\right) &= \frac{1}{2}\mathbb{E}\left(\left(\sqrt{\alpha}V_\infty^\alpha + \sqrt{\alpha}G_{V_\infty^\alpha}^\alpha\right)^2\right) - \frac{1}{2}\mathbb{E}\left((\sqrt{\alpha}V_\infty^\alpha)^2\right) + o(\sqrt{\alpha}) \\ &+ \eta^\alpha\sqrt{\alpha}w_{\max}^\alpha\mathbb{E}\left(\sqrt{\alpha}H^\alpha\right) - \frac{\eta^\alpha}{2}\left(\mathbb{E}\left(\sqrt{\alpha}w_{\max}^\alpha + \sqrt{\alpha}G_{w_{\max}^\alpha}^\alpha\right)^2 - \left(\sqrt{\alpha}w_{\max}^\alpha\right)^2\right),\end{aligned}$$

this identity is a consequence of the Markov property of (W_n^α). The variable $V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha$ conditionally on the event

$$\left\{V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha \geq w_{\max}^\alpha\right\}$$

has the same distribution as $w_{\max}^\alpha + G_{w_{\max}^\alpha}^\alpha$. The scaling relation (4) for $w_{\max}^\alpha$ implies that $\sqrt{\alpha}H^\alpha$ converges in distribution to an exponentially distributed random variable with mean $1/\overline{w}_{\max}$, using Theorem 9, we obtain

$$\begin{aligned}\lim_{\alpha\to 0}\alpha\mathbb{E}\left(\sum_{k=0}^{\tau^\alpha-1} W_k^\alpha\right) &= \frac{1}{2}\left(\mathbb{E}\left(\overline{V}_\infty + \overline{G}_{\overline{V}_\infty}\right)^2 - \mathbb{E}\left(\overline{V}_\infty\right)^2\right) \\ &\qquad + \eta - \frac{\eta}{2}\left(\mathbb{E}\left(\overline{w}_{\max} + \overline{G}_{\overline{w}_{\max}}\right)^2 - \overline{w}_{\max}^2\right) = 1,\end{aligned} \tag{36}$$

by Proposition 11. Similarly for τ^α,

$$\tau^\alpha = (w_{\max}^\alpha - V_\infty^\alpha)\wedge G_{V_\infty^\alpha}^\alpha + H^\alpha 1_{\left\{V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha \geq w_{\max}^\alpha\right\}}$$

therefore

$$\begin{aligned}\mathbb{E}(\tau^\alpha) &= \mathbb{E}\left(w_{\max}^\alpha \wedge \left(V_\infty^\alpha + G_{V_\infty^\alpha}^\alpha\right) - V_\infty^\alpha\right) + \eta^\alpha \mathbb{E}(H^\alpha) \\ &= \frac{1-\delta}{\delta}\mathbb{E}(V_\infty^\alpha) + \eta^\alpha \mathbb{E}(H^\alpha)\end{aligned}$$

by the invariance relation (15) for V_∞^α.

The following proposition is therefore a consequence of the last identity and relation (36).

Proposition 19. *If $\rho^\alpha(\delta)$ is the throughput of an AIMD algorithm with multiplicative decrease factor δ and maximum window size w_{max}^α, then*

$$\lim_{\alpha\to 0}\sqrt{\alpha}\rho^\alpha(\delta) = \frac{\delta}{(1-\delta)\mathbb{E}(\overline{V}_\infty) + \delta\eta/\overline{w}_{max}}, \tag{37}$$

the constant η and the distribution of $\overline{V}_\infty$ are given by Proposition 18.

The above formulas have been used in Figure 3 and 4 to represent the dependence of the throughput and η with respect to the maximum congestion window size.

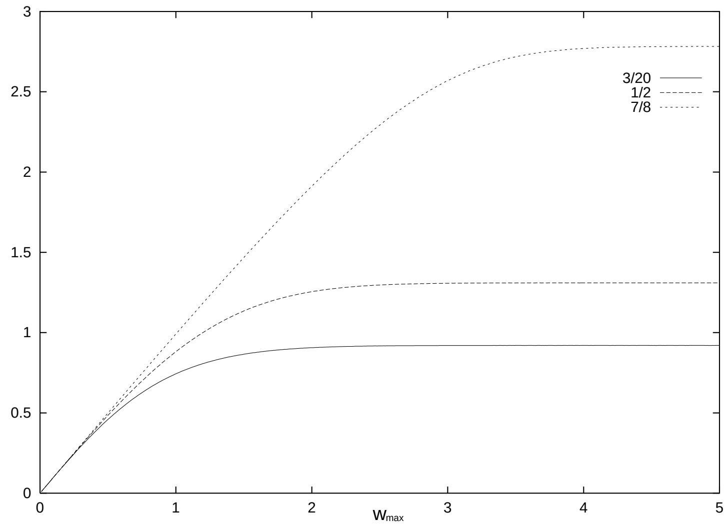

FIGURE 3. The throughput for $\delta = 3/20$, $1/2$ and $7/8$

5. The distribution of the hitting times

In this section we study the hitting time of some level by the size of the congestion window. Its practical importance is fairly clear since the performance of the transmission is optimal when the maximal congestion window is reached.

Definition 20. *If $x > 0$, S_x^α is the first time (W_n^α) reaches the level $x/\sqrt{\alpha}$,*

$$S_x^\alpha = \inf\left\{n \geq 1 : W_n^\alpha \geq x/\sqrt{\alpha}\right\} \text{ and } \overline{S}_x = \inf\left\{t > 0 : \overline{W}(t) \geq x\right\}$$

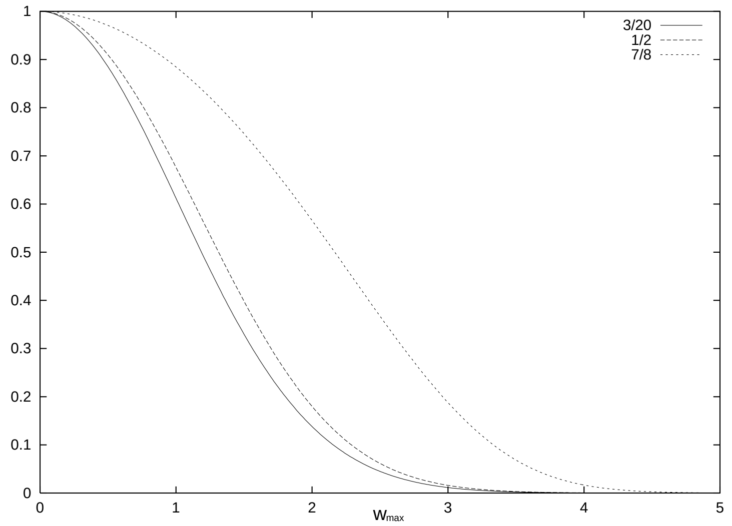

FIGURE 4. The stationary probability of hitting the maximum window size before a loss

The convergence result of Proposition 5 gives the key to the limiting behavior of S_x^α, it suggests that S_x^α is of order $1/\sqrt{\alpha}$. The next result show that this is indeed the case. Moreover, the limiting distribution is expressed with the help of an eigenvector of the infinitesimal generator Ω defined by (11). These results are an illustration of the interest of the functional limit theorems proved in Section 2.

Theorem 21. *If $\lim_{\alpha\to 0}\sqrt{\alpha}W_0^\alpha = x_0 < \overline{W}(0) = x$, the variable $\sqrt{\alpha}S_x^\alpha$ converges in distribution to $\overline{S}_x$ as α tends to 0. Its Laplace transform given by, for $\xi \geq 0$,*

$$\mathbb{E}\left(e^{-\xi\overline{S}_x}\right) = \frac{f_\xi(x_0)}{f_\xi(x)},$$

where f_ξ is the unique solution of the equation

$$f'(y) + yf(\delta y) = (\xi + y)f(y), \tag{38}$$

with $f(0) = 1$.

Proof. For $a \geq 0$, by definition

$$\left\{\sqrt{\alpha}S_x^\alpha > a\right\} = \left\{\sup_{0\leq t\leq a}\sqrt{\alpha}W^\alpha_{\lfloor t/\sqrt{\alpha}\rfloor} < x\right\},$$

since the function $g \to \sup\{g(u);\, 0 \leq u \leq a\}$ is continuous on the Skorohod space of functions on $\mathbb{R}_+$ (see Ethier and Kurtz [11]), Proposition 5 shows that

$$\lim_{\alpha\to 0}\mathbb{P}\left(\sqrt{\alpha}S_x^\alpha > a\right) = \mathbb{P}\left(\sup_{0\leq t\leq a}\overline{W}(t) < x\right) = \mathbb{P}\left(\overline{S}_x > a\right)$$

the variable $\sqrt{\alpha}S_x^\alpha$ converges in distribution to $\overline{S}_x$ as α tends to 0.

We now prove that equation (38) has a unique solution. If f is such a solution, taking $g(y) = \exp(-(\xi+y)^2/2)f(y)$, we get the differential equation,

$$g'(y) = -ye^{-(1-\delta)y(\xi+(1+\delta)y)/2}g(\delta y),$$

hence

$$g(y) = e^{-\xi^2/2} - \int_0^y u e^{-(1-\delta)u(\xi+(1+\delta)u)/2} g(\delta u)\, du. \tag{39}$$

Since $\delta < 1$, the above equation can be seen as a fixed point equation on the space $C([0,1/2])$ of the continuous function on $[0,1/2]$. If $\psi(g)$ denotes the right hand side of (39), it is clear that ψ is a contracting functional on $C([0,1/2])$ endowed with the uniform norm. The operator ψ has therefore a unique fixed point on $C([0,1/2])$. If g is this fixed point, then g can be continued on the real line. For $y \in \mathbb{R}_+$, according to (39), the value of $g(y)$ is expressed with the values of g on the interval $[0,\delta y]$. The existence and uniqueness of equation (38) are proved.

Using expression (19) of the infinitesimal generator Ω, equation (38) can also be written as $\Omega(f)(x) = \xi f(x)$ for $x \geq 0$. (Here $\overline{w}_{\max}$ does not play a role, it is assumed to be infinite). Using a classical result on the martingales of Markov processes (see Rogers and Williams [19] for example), we get that

$$\left(e^{-\xi\, t\wedge \overline{S}_x} f\left(\overline{W}(t\wedge \overline{S}_x)\right)\right)$$

is a local martingale. Since f is continuous on $[0,x]$, this local martingale is bounded hence a regular martingale, therefore

$$f(x_0) = \mathbb{E}\left(e^{-\xi\,\overline{S}_x} f\left(\overline{W}(\overline{S}_x)\right)\right) = f(x)\mathbb{E}\left(e^{-\xi\,\overline{S}_x}\right).$$

The theorem is proved. □

We have not been able to find a closed form expression for the solution of equation (38). Nevertheless it is possible to get some explicit results on the distribution of the hitting times $(\overline{S}_x)$. If f is the solution of the following equation, for $x > 0$,

$$\Omega(f)(x) = 1,$$

with $f(0) = 0$, when $\overline{W}(0) = x_0 < x$ the same arguments as in the proof of the previous theorem show that $\mathbb{E}(\overline{S}_x) = f(x) - f(x_0)$. The functional equation to solve is

$$f'(x) + x(f(\delta x) - f(x)) = 1,$$

for $x \geq 0$, with $f(0) = 0$. If $g(x) = \exp(-x^2/2)f(x)$, then this equation becomes

$$g(x) - \int_0^x e^{-u^2/2}\, du = \psi(g)(x) \stackrel{\text{def}}{=} - \int_0^x u e^{-(1-\delta^2)u^2/2} g(\delta u)\, du, \tag{40}$$

for $x \geq 0$. As before this fixed point equation has a unique solution which can be obtained by iteration. If this equation has some similarity with identity (39), its solution can be represented explicitly with the following trick. For a, $b \in \mathbb{R}_+$, we denote by $H[a,b]$ the function

$$H[a,b](x) = e^{-ax^2/2} \int_0^x e^{-bu^2/2}\, du,$$

for $x \geq 0$; the operator ψ applied to $H[a,b]$ gives the relation

$$\psi\left(H[a,b]\right) = \frac{\delta}{a+1-\delta^2}\Big(H\left[a+\delta^2 b + 1 - \delta^2, \delta^2 b\right] - H\left[0, a + \delta^2 b + 1 - \delta^2\right]\Big). \tag{41}$$

Definition 22. *The countable subset $\mathcal{T}$ of $\mathbb{R}_+^2$ and the function $L : \mathcal{T} \to \mathbb{R}_+$ are defined as follows:*

- $(0,1) \in \mathcal{T}$ *and* $L((0,1)) = (1-\delta^2)/(1+\delta-\delta^2)$;
- *if* $z = (a,b) \in \mathcal{T}$ *then the elements* $e_0(z) = (a+\delta^2 b + 1 - \delta^2, \delta^2 b)$ *and* $e_1(z) = (0, a+\delta^2 b+1-\delta^2)$ *are also in* $\mathcal{T}$ *with*

$$L(e_i(z)) = \frac{(-1)^i \delta}{a+1-\delta^2} L(z),$$

for $i=0$ *and for* $i=1$ *if* $z \neq (0,1)$.

In this manner $\mathcal{T}$ has a binary natural tree structure with $(0,1)$ as the ancestor, the children of $z \in \mathcal{T}$ are $e_0(z)$ and $e_1(z)$. Notice that the function $z \to e_0(z)$ has no fixed point and $(0,1)$ is the only one for $z \to e_1(z)$ If we combine the representation of the solution of the equation (40) by iteration together with the identity (41), we obtain the following proposition.

Proposition 23. *If* $\overline{W}(0) = x_0 < x$ *then* $\mathbb{E}(\overline{S}_x) = f(x) - f(x_0)$ *with*

$$f(x) = e^{x^2/2} \sum_{z \in \mathcal{T}} L(z) h[z](x), \tag{42}$$

where

$$h[z](x) = e^{-ax^2} \int_0^x e^{-bu^2}\, du,$$

if $z = (a,b)$ *and the set* $\mathcal{T}$ *and the function* $L(\cdot)$ *are given by definition 22.*

We finish by an estimation of the mean value of $\overline{S}_x$, it can be refined with an arbitrary precision by using the above proposition.

Corollary 24. *With the notation of the above proposition, if* $\overline{W}(0) = 0$, *the inequality* $m(x) \leq \mathbb{E}\left(\overline{S}_x\right) \leq M(x)$ *holds, with*

$$m(x) = \frac{e^{x^2/2}}{1-\delta^2} \left((1-\delta-\delta^2) \int_0^x e^{-u^2/2}\, du + \delta \int_0^x e^{-\delta^2 u^2/2}\, du \right),$$
$$M(x) = e^{x^2/2} \int_0^x e^{-u^2/2}\, du.$$

Proof. Since the solution of the fixed point equation (40) is clearly non negative, the relation

$$g(x) \leq \int_0^x e^{-u^2/2}\, du,$$

holds, therefore the upper bound is true. This inequality applied in the right hand side of (40) gives the lower bound. □

The set $\mathcal{T}$ is apparently not easy to describe explicitly (if we forget the tree structure).

We conclude with a convergence result on the hitting times of the embedded Markov chain $(\overline{V}_n)$,

$$\tau_x^\alpha = \inf\left\{n \geq 1 : V_n^\alpha \geq x/\sqrt{\alpha}\right\} \text{ and } \overline{\tau}_x = \inf\left\{n \geq 1 : \overline{V}_n \geq x\right\}.$$

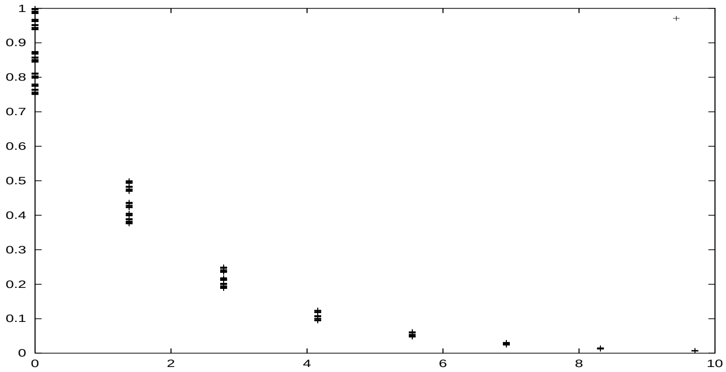

FIGURE 5. The set $\mathcal{T}$ for $\delta = 1/2$

Theorem 25. *If* $\lim_{\alpha\to 0}\sqrt{\alpha}V_0^\alpha = x_0 < x$, *the variables* τ_x^α, $\alpha > 0$ *converges in distribution to* $\overline{\tau}_x$ *when* $\alpha \to 0$. *The generating function of* $\overline{\tau}_x$ *is given by, for* $0 < u < 1$,

$$\mathbb{E}\left(u^{\overline{\tau}_x}\right) = \frac{f_u(x_0)}{f_u(x)}, \text{ with } f_u(x) = \sum_{n\geq 0} \frac{u^{n+1}}{\prod_{k=1}^n (1-\delta^{2k})} e^{x^2\delta^{2n}/2}, \tag{43}$$

Proof. The convergence is fairly clear from Corollary 4. The equation

$$u\,\mathbb{E}\left(f\left(\overline{V}_1\right) \middle| \overline{V}_0 = x\right) = f(x) \tag{44}$$

is equivalent to

$$f'(x) = xf(x) - uxf(\delta x).$$

The function defined by (43) clearly satisfies such an equation, therefore the identity (44) implies that the sequence

$$\left(u^{n\wedge\overline{\tau}_x} f_u\left(\overline{V}_{n\wedge\overline{\tau}_x}\right)\right)$$

is a bounded martingale, we conclude by taking its expected value at infinity. □

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