On some tractable growth collapse processes with renewal collapse epochs
Boxma, O.J.; Kella, O.; Perry, D.

Published: 01/01/2010

Document Version
Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

• A submitted manuscript is the author's version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

Citation for published version (APA):

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Download date: 02. Feb. 2018
EURANDOM PREPRINT SERIES
2010-012

On some tractable growth collapse processes with renewal collapse epochs

O. Boxma, O. Kella, D. Perry
ISSN 1389-2355
ON SOME TRACTABLE GROWTH COLLAPSE PROCESSES WITH RENEWAL COLLAPSE EPOCHS

ONNO BOXMA,* EURANDOM and Eindhoven University of Technology

OFFER KELLA,** The Hebrew University of Jerusalem

DAVID PERRY,*** Haifa University

Abstract

In this paper we generalize existing results for the steady state distribution of growth collapse processes with independent exponential inter-collapse times to the case where they have a general distribution on the positive real line having a finite mean. In order to compute the moments of the stationary distribution, no further assumptions are needed. However, in order to compute the stationary distribution, the price that we are required to pay is the restriction of the collapse ratio distribution from a general one concentrated on the unit interval to minus-log-phase-type distributions. A random variable has such a distribution if the negative of its natural logarithm has a phase type distribution. Thus, this family of distributions is dense in the family of all distributions concentrated on the unit interval. The approach is to first study a certain Markov modulated shot-noise process from which the steady state distribution for the related growth collapse model can be inferred via level crossing arguments.

Keywords: Growth collapse; shot noise process; minus-log-phase-type distribution; Markov modulated.

* Postal address: EURANDOM and Department of Mathematics and Computer Science; Eindhoven University of Technology; P.O. Box 513; 5600 MB Eindhoven; The Netherlands (boxma@win.tue.nl).
** Postal address: Department of Statistics; The Hebrew University of Jerusalem; Mount Scopus, Jerusalem 91905; Israel (Offer.Kella@huji.ac.il).
*** Postal address: Department of Statistics; Haifa University; Haifa 31905; Israel (dperry@stat.haifa.ac.il).
1. Introduction

Consider a growth collapse process that grows linearly at some given rate c. The collapses occur at renewal instants with inter-renewal time distribution function \( F \) with mean \( \mu \) and Laplace-Stieltjes transform (LST) \( G \). The remaining level (e.g., funds) after a given collapse form a random fraction of the level just before the collapse occurred. It is assumed that the sequence of random proportions \( X_1, X_2, \ldots \) are i.i.d. and independent of the underlying renewal process. Of course, since these are proportions it is naturally assumed that \( P[0 \leq X_1 \leq 1] = 1 \) and, to avoid trivialities, that \( 0 < EX_1 < 1 \). From, e.g., [14] it is known that this process is stable without any further conditions. We aim at identifying a relatively broad family of distributions of \( X_1 \), which is dense in the family of all distributions on \([0, 1]\), for which the stationary distribution of this process can be calculated.

The idea is to first consider an on/off process, where during on times the process increases linearly at rate \( c \) and during off times, whenever the process is at level \( x \) it decreases at the rate \( rx \) for some \( r > 0 \). As assumed, on times have some general distribution \( F \) while off times, denoted by \( P_1, P_2, \ldots \), will be assumed to have a phase type distribution. If we restrict the process to off times, then what we obtain is a shot-noise type process with upward jumps having the distribution \( F(\cdot/c) \) with mean \( c\mu \), LST \( G(c\alpha) \), and inter-arrival times which have a phase type distribution.

Given that at the beginning of an off time the level is given by some \( x \), as long as the period does not end, the dynamics of the process is given via

\[
W(t) = x - r \int_0^t W(s)ds
\]  

(1)

where \( t \) is the time that has elapsed since the beginning of this period. Hence, as is well known, it follows that \( W(t) = xe^{-rt} \) for \( 0 \leq t \leq P_i \) for some index \( i \). Thus at the end of this period the level will be \( xe^{-rP_i} \). Setting \( X_i = e^{-rP_i} \) we see that when we restrict our process to on times, then it becomes the type of process that is described in the first paragraph. For example, when \( P_i \) are exponential with rate \( r \) then \( X_i \) are Uniform(0, 1). If \( P_i \) have an Erlang distribution, then \( X_i \) are products of uniform random variables.
For a general phase-type distribution, $X_i$ are (possibly infinite) mixtures of products of uniformly (on $(0,1)$) distributed random variables. Since phase-type distributions are dense in the family of all distributions on $[0,\infty)$, then the family of distributions of the collapse ratio is dense in the family of all distributions on $[0,1]$.

For the process at hand, it follows from [12] that if $f_0$ is the stationary density for the process restricted to on times and $f_1$ is the stationary density for the process restricted to off times, provided that they exist (note that starting from a positive state, the process as described never hits zero), then $cpf_0(x) = rx(1-p)f_1(x)$ where $p = \frac{\mu}{\mu + EP_1}$ is the fraction of on times. Thus, studying the workload in the shot-noise-type model is in some sense equivalent with studying the workload in the growth collapse model. Also we note that the growth collapse model with growth rate 1 and inter-collapse times with LST $G(\alpha)$ has the same stationary distribution as for the model initially proposed (with growth rate $c$) and thus we will, without loss of generality, assume from now on in order to simplify notations, that $c = 1$.

The paper is organized as follows. Regarding shot noise, in Section 2 we actually study a more general model and then restrict to the special case of the model proposed in this introduction. Section 3 relates the moments of the shot noise process to the moments of the original growth collapse process. Section 4 studies the steady-state behavior of the growth collapse process right after a collapse. Several distributions for the inter-collapse times and the collapse proportions are being considered.

2. Shot noise type processes with phase type interarrival times

In [3] a shot-noise type process with Markov modulated release rate was considered. [16] studied a more general model where the input is a Markov additive process (MAP) and the release rate is Markov modulated as well. In the latter paper, the MAP is not the most general possible. In particular it did not include the additional jumps that can occur at state changes of the underlying Markov chain. This additional aspect, which we very much need here, can be included applying a technique from [4]. We will first write some general results regarding the most general setup, that is, the one dimensional version of [16] but with the possibility of additional jumps at state change epochs. We will then specialize to the case which we need to solve the
problem of this paper. Thus, let \((X, J) = \{(X(t), J(t)) | t \geq 0\}\) be a nondecreasing MAP (see [4]) with exponent matrix \(F(\alpha) = Q \circ G(\alpha) + \text{diag}((\phi_1(\alpha) \ldots \phi_K(\alpha)))\), where \(Q \circ G(\alpha) \equiv (q_{ij}G_{ij}(\alpha))\), \(J\) is an irreducible finite state space continuous time Markov chain with states \(1, \ldots, K\) and rate transition matrix \(Q = (q_{ij})\) and stationary probability vector \(\pi = \pi_i\) and \(G_{ij}(\alpha)\) is the LST of the distribution of the (nonnegative) jump occurring when the Markov chain \(J\) changes states from \(i\) to \(j\) and \(G_{ii}(\alpha) \equiv 1\) for all \(\alpha \geq 0\) (LST of the constant 0). \(\phi_i\) is the Laplace exponent of a nondecreasing Lévy process which is of the form

\[
\phi_i(\alpha) = -c_i\alpha - \int_{(0,\infty)} (1 - e^{-\alpha x})d\nu_i(x)
\]

where \(\nu_i\) is a Lévy measure satisfying \(\int_{(0,\infty)} \min(x, 1)d\nu_i(x) < \infty\). Moreover, we assume that \(\mu(i,j) \equiv -G'_{ij}(0) < \infty\) and \(\rho(i) \equiv -\phi'_i(0) = c_i + \int_{(0,\infty)} xd\nu_i(x) < \infty\) for all \(i\) and \(j\).

As in [4], we recall that the process \(X\) behaves like a nondecreasing Lévy process (subordinator) with exponent \(\phi_i(\cdot)\) when \(J\) is in state \(i\) and when \(J\) switches from state \(i\) to a different state \(j\), then in addition \(X\) jumps up by an independent amount which has a distribution having the LST \(G_{ij}(\cdot)\).

Now consider the following Markov modulated linear dam process:

\[
W(t) = W(0) + X(t) - \int_0^t r(J(s))W(s)ds
\]

where the input is the process \(X\) and the output rate is proportional to the content of the dam where the proportion \(r(J(s))\), where \(r(i) \geq 0\) for all \(i\), is modulated by the Markov process \(J\). Then we have the following:

**Theorem 2.1.** If, in addition to the irreducibility of \(J\) and the assumption that \(\rho_i < \infty\) and \(\mu(i,j) < \infty\ \forall i, j\) (see above), there is at least one \(i\) for which \(r(i) > 0\), then a unique stationary distribution for the joint (Markov) process \((W, J)\) exists; and it is also the limiting distribution, which is independent of initial conditions.

Before we prove this result let us first show the following result concerning an alternating renewal process.

**Lemma 2.1.** Let \(\{(X_n, Y_n) | n \geq 1\}\) be independent pairs of nonnegative random variables which are identically distributed for \(n \geq 2\), \(P[Y_2 > 0] > 0\) and \(E X_1, E X_2 <\)
On some tractable growth collapse processes with renewal collapse epochs

Set $S_0 = 0$, $S_n = \sum_{i=1}^{n} (X_i + Y_i)$ for $n \geq 1$ and

$$I(t) = \begin{cases} 
0 & \text{if } t \in \bigcup_{n=0}^{\infty} [S_n, S_n + X_{n+1}), \\
1 & \text{if } t \in \bigcup_{n=0}^{\infty} [S_n + X_{n+1}, S_{n+1}) 
\end{cases} \quad (4)$$

Then, for any positive constant $r$, $E \int_{0}^{\infty} e^{-rtZ(t)} dt < \infty$.

Proof. For simplicity, we prove this for the case where $(X_1, Y_1)$ has the same distribution as for the rest of the sequence. The generalization to the case where the first pair has a different distribution is trivial. Since

$$Z(t) = \int_{0}^{t} I(s) ds \quad (5)$$

and $Z(S_n) = S'_n$ where $S'_0 = 0$ and $S'_n = \sum_{i=1}^{n} Y_i$ for $n \geq 1$, it follows that

$$E \int_{0}^{\infty} e^{-rZ(t)} dt = \sum_{n=0}^{\infty} e^{-rS'_n} (X_{n+1} + r^{-1} (1 - e^{-rY_{n+1}})) = r^{-1} + \sum_{n=0}^{\infty} e^{-rS'_n} X_{n+1} \quad (6)$$

Thus, as $E e^{-rY_1} < 1$ (since $P[Y_1 > 0] > 0$), it follows that

$$E \int_{0}^{\infty} e^{-rZ(t)} dt = r^{-1} + \frac{EX_1}{1 - E e^{-rY_1}} < \infty \quad (8)$$

as required. $
$

We note that in Lemma 2.1, the off-times ($Z(t) = 0$) must have a finite mean while, for $n \geq 2$, the on-times ($Z(t) = 1$) cannot be almost surely zero. These are the minimal assumptions in the sense that if one of them fails to hold then $E \int_{0}^{\infty} e^{-rZ(t)} dt = \infty$.

We note that it is possible that $X_1$, $X_2$ or $Y_1$ are a.s. zero.

Proof. (of Theorem 2.1) From (3) and Theorem 1 of [17] it follows that

$$W(t) = W(0) e^{-\int_{0}^{t} r(J(s)) ds} + \int_{[0,t]} e^{-\int_{u}^{t} r(J(s)) ds} dX(u) \quad (9)$$

and thus if we start the system with two different initial conditions $W^1(0)$ and $W^2(0)$ then

$$W^1(t) - W^2(t) = (W^1(0) - W^2(0)) e^{-\int_{0}^{t} r(J(s)) ds} \quad (10)$$
Since there is at least one $i$ for which $r(i) > 0$ and $J$ is irreducible, it follows that a.s. $\int_0^\infty r(J(s))ds = \infty$ so that the right side of (10) converges a.s. to zero as $t \to \infty$. Thus, if there is a limiting distribution for $(W(t), J(t))$, it does not depend on $W(0)$. It is standard that $J$ can be coupled with its stationary version after an a.s. finite time. Since the value of $W$ at this coupling time has no effect on the limiting distribution if it exists (for the same reasons as just explained for the initial conditions), we may assume without loss of generality that $J$ is stationary. For this case the two dimensional process $\left\{ (\int_0^t r(J(s))ds, X_t) \mid t \geq 0 \right\}$ has stationary increments in the strong sense that the distribution of $\left\{ (\int_0^{t+u} r(J(s))ds, X_{t+u} - X_u) \mid t \geq 0 \right\}$ is independent of $u$. Thus, we can extend this process together with $J$ to be a double sided process having these properties. From Theorem 2 of [17] it follows that to complete the proof it remains to show that a.s.

$$\int_{(-\infty,0]} e^{-\int_u^0 r(J(s))ds} dX(u) < \infty. \quad (11)$$

We will in fact show that

$$E \int_{(-\infty,0]} e^{-\int_u^0 r(J(s))ds} dX(u) < \infty. \quad (12)$$

Denoting $\bar{J}(t) = J(-t)$ and $\bar{X}(t) = -X(-t)$ for $t \geq 0$ we have that $\{(\bar{X}(t), \bar{J}(t)) \mid t \geq 0\}$ is also a Markov additive process where $\bar{J}$ is stationary with transition rates $\bar{q}_{ij} = \pi_j q_{ji}/\pi_i$, $\bar{G}_{ij} = G_{ji}$ and $\bar{\phi}_i = \phi_i$. By the method of uniformization, let $\{\bar{N}(t) \mid t \geq 0\}$ be a Poisson process with some (finite) rate $\lambda \geq \max_i (-\bar{q}_{ii}) = \max_i (-q_{ii})$, in which arrival epochs we embed a (stationary) discrete time Markov chain $\{\bar{J}_n \mid n \geq 0\}$ with transition probabilities

$$\bar{p}_{ij} = \begin{cases} \frac{\bar{q}_{ij}}{\lambda}, & i \neq j, \\ 1 + \frac{\bar{q}_{ii}}{\lambda}, & i = j. \end{cases} \quad (13)$$

Now, by conditioning on $\bar{J}$ we have that

$$E \int_{(-\infty,0]} e^{-\int_u^0 r(J(s))ds} dX(u) = E \int_{[0,\infty)} e^{-\int_0^u r(J(s))ds} d\bar{X}(u)$$

$$= E \int_{[0,\infty)} e^{-\int_0^u r(J(s))ds} \rho(J(t))dt + E \int_{[0,\infty)} e^{-\int_0^u r(J(s))ds} d \sum_{n=1}^{N(t)} \mu(\bar{J}_{n-1}, \bar{J}_n),$$
On some tractable growth collapse processes with renewal collapse epochs

where we recall that \( \rho(i) = -\phi_i'(0) < \infty \) and \( \mu(i, j) = -G_{ij}'(0) < \infty \). Denoting \( \bar{\rho} = \max_i \rho(i) \) and \( \bar{\mu} = \max_{i,j} \mu(i,j) \) we have that the right hand side of (14) is bounded above by

\[
\bar{\rho} E \int_{[0,\infty)} e^{-\int_0^t r(J(s))ds} dt + \bar{\mu} E \int_{[0,\infty)} e^{-\int_0^t r(J(s))ds} d\bar{N}(t).
\]

(14)

Since \( \{\bar{N}(t) - \lambda t, t \geq 0\} \) is a zero mean right continuous Martingale and \( e^{-\int_0^t r(J(s))ds} \) is adapted, continuous and bounded, it follows that (14) is equal to

\[
(\bar{\rho} + \lambda \bar{\mu}) E \int_{[0,\infty)} e^{-\int_0^t r(J(s))ds} dt .
\]

(15)

For any \( i \) such that \( r(i) > 0 \),

\[
E \int_{[0,\infty)} e^{-\int_0^t r(J(s))ds} dt \leq E \int_{[0,\infty)} e^{-\int_0^t r(J(s))ds} dt
\]

(16)

and the right side is finite by the irreducibility, hence positive recurrence, of \( J \) (due to that of \( J \)) and Lemma 2.1.

From [4], we have that the following is a zero mean martingale:

\[
\int_0^t e^{-\alpha W(s)} 1_{J(s)} ds F(\alpha) + e^{-\alpha W(0)} 1_{J(0)} - e^{-\alpha W(t)} 1_{J(t)}
\]

(17)

\[+ \alpha \int_0^t e^{-\alpha W(s)} 1_{J(s)} r(J(s)) W(s) ds .\]

Thus, if \( (W^*, J^*) \) has the stationary distribution associated with the process \( (W, J) \), then from (17) it follows that

\[
E e^{-\alpha W^*} 1_{J^*} F(\alpha) = \alpha \frac{d}{d\alpha} E e^{-\alpha W^*} 1_{J^*} r(J^*)
\]

(18)

and thus, with \( w(\alpha) = E e^{-\alpha W^*} 1_{J^*=i} \), \( w(\alpha) = (w_i(\alpha)) \) and with \( D_r = \text{diag}(r(1), \ldots, r(K)) \), we have that

\[
w(\alpha)^T F(\alpha) = \alpha w'(\alpha)^T D_r
\]

(19)

where \( \pi_i = w_i(0) \) is the stationary distribution for the Markov chain \( J \), summing to one and satisfying \( \pi^T Q = 0 \). We do not expect to be able to solve it analytically. Nevertheless, it can immediately be deduced from this equation by differentiation that

\[
\sum_{k=0}^n \binom{n}{k} w^{(k)}(0)^T F^{(n-k)}(0) = nw^{(n)}(0)^T D_r
\]

(20)
and since $F^{(0)}(0) = F(0) = Q$ we have that
\[
\sum_{k=0}^{n-1} \binom{n}{k} w^{(k)}(0)^T F^{(n-k)}(0) = w^{(n)}(0)^T (nD_r - Q) \tag{21}
\]
Thus, when $nD_r - Q$ is invertible, then we have a recursion formula that computes the moments $E(W^*1_{\{J^* = i\}})$.

Specializing to the problem we set out to solve, assume that instead of $K$ states for the modulating Markov chain there are $K+1$ indexed by $0, \ldots, K$. We will first consider the modulated process with $r(0) = 0, r(1) = \ldots = r(K) = 1$, with $G_{i0}(\alpha) = G(\alpha)$ and for all other $i, j$, $G_{ij}(\alpha) = 1$. Finally, we assume that other than the jump that occurs when entering state 0 and the specified rates, nothing happens. That is, $\phi_0(\alpha) = \ldots = \phi_K(\alpha) = 0$. Thus we see that if we restrict the process to the intervals where the modulating Markov chain spends in the states $1, \ldots, K$ then we have a shot-noise process with phase-type inter-arrival times and general i.i.d. jumps.

It is easy to check that (19) becomes
\[
\sum_{i=1}^{K} w_i(\alpha) q_{ij} = \alpha w'_j(\alpha) \tag{22}
\]
for $j \neq 0$ and for $j = 0$ we have that
\[
-q_0 w_0(\alpha) + G(\alpha) \sum_{i=1}^{K} w_i(\alpha) q_{i0} = 0 \tag{23}
\]
where $q_0 = -q_{00}$ and by substitution we thus have that for $j \neq 0$
\[
\sum_{i=1}^{K} w_i(\alpha) \left( q_{ij} + \frac{q_{0i}q_{0j}}{q_0} G(\alpha) \right) = \alpha w'_j(\alpha) \tag{24}
\]
with the initial conditions $w_i(0) = \pi_i$ where $\pi$ is the stationary distribution for the modulating Markov chain. Thus the stationary LST for the shot-noise process with phase-type inter-arrival times and jumps with distribution having LST $G$ is given by
\[
w(\alpha) = \frac{\sum_{i=1}^{K} w_i(\alpha)}{1 - \pi_0}. \tag{25}
\]
It is easy to check that
\[
\sum_{j=1}^{K} \left( q_{ij} + \frac{q_{0i}q_{0j}}{q_0} \right) = 0 \tag{26}
\]
and that
\[ \sum_{j=1}^{K} \pi_j \left( q_{ij} + \frac{q_{0j}q_j}{q_0} \right) = 0 \]  
and thus (24) can be written as follows
\[ \mu \frac{q_{ij}}{q_0} \sum_{i=1}^{K} w_i(\alpha)q_{i0} = - \sum_{i=1}^{K} \frac{w_i(0) - w_i(\alpha)}{\alpha} \left( q_{ij} + \frac{q_{0j}q_j}{q_0} \right) - w_j'(\alpha) \]  
where \( G_\alpha(\alpha) = \frac{1-G(\alpha)}{\alpha} \) is the stationary residual lifetime LST associated with \( G \). If we similarly denote
\[ w_{i,j}(\alpha) = \frac{w_i(0) - w_i(\alpha)}{-w_j'(0)\alpha} = \frac{1 - E[e^{-\alpha W^*} | J^* = i]}{E[W^* | J^* = i] / \alpha} \]  
and we let \( \mu_{i,j}^w = E[(W^*)^n | J^* = i] \) then
\[ \mu \frac{q_{ij}}{q_0} G_\alpha(\alpha) \sum_{i=1}^{K} w_i(\alpha)q_{i0} = - \sum_{i=1}^{K} \pi_i \mu_{i,j}^w w_{i,j}(\alpha) \left( q_{ij} + \frac{q_{0j}q_j}{q_0} \right) - w_j'(\alpha). \]  
In particular, letting \( \alpha \downarrow 0 \),
\[ \mu \pi_0 q_{0j} = \mu \frac{q_{ij}}{q_0} \sum_{i=1}^{K} \pi_i q_{i0} = - \sum_{i=1}^{K} \pi_i \mu_{i,j}^w \left( q_{ij} + \frac{q_{0j}q_j}{q_0} \right) + \pi_j \mu_{j,j}^w \]
\[ = \sum_{i=1}^{K} \pi_i \mu_{i,j}^w \left( \delta_{ij} - \bar{q}_{ij} \right), \]
where \( \bar{q}_{ij} = q_{ij} + q_{0j}q_j/q_0 \). It follows from (26) and (27) that \( \bar{Q} = (\bar{q}_{ij})_{1 \leq i,j \leq K} \) is a rate transition matrix with stationary distribution \( \pi_i/(1 - \pi_0) \) for \( i = 1, \ldots, K \).

The following is a straightforward exercise, but we include it for ease of reference.

**Lemma 2.2.** If \( P \) is a stochastic matrix, \( D_1 \) and \( D_2 \) are nonnegative diagonal matrices and \( D_1 + D_2 \) has a strictly positive diagonal, then \( D_1 - (D_2(P - I)) \) is nonsingular.

**Proof.** Note that \( D_1 - (D_2(P - I)) = (D_1 + D_2)(I - (D_1 + D_2)^{-1}D_2P) \) and thus it suffices to show that with \( A = ((D_1 + D_2)^{-1}D_2P) \), \( A^n \to 0 \) as \( n \to \infty \), since then \( (I - A)^{-1} = \sum_{n=0}^{\infty} A^n \). To show this, we note that \( (D_1 + D_2)^{-1}D_2 \) is a nonnegative diagonal matrix where the diagonal entries are all strictly less than one. Thus if we let \( d \) denote the maximum of these entries then \( A^n \leq d^n P^n \) and since the entries of \( P^n \) are bounded the result immediately follows.
Since a rate transition matrix of a finite state space continuous time Markov chain is of the form $D(P-I)$ for some nonnegative diagonal matrix $D$ and some stochastic matrix $P$, it follows from Lemma 2.2 that $I-\tilde{Q}$ is nonsingular and thus (31) has a unique solution for the unknowns $\mu^w_{n,i}$. Denoting by $\mu_n$ the $n$th moment with respect to the jump distribution $F$ (with LST $G$) then, since $\mu G^{(n-1)}(0) = (-1)^{n-1} \frac{\mu_n}{n}$ and similarly

$$\mu^w_{1,i,w}^{(n-1)}(0) = (-1)^{n-1} \frac{\mu^w_{n,i}}{n}$$ (32)

then it is easy to check that after differentiating $n-1$ times and letting $\alpha \downarrow 0$, the following recursion holds:

$$q_0 \sum_{k=0}^{n-1} \binom{n-1}{k} \mu_k \sum_{i=1}^{K} \pi_i \mu^w_{n-1-k,i} q_0 = \sum_{i=1}^{K} \pi_i \mu^w_{n,i} \left( \delta_{ij} - \tilde{q}_{ij} \right)$$ (33)

which upon multiplying by $n$, observing that $\binom{n-1}{k} \frac{n!}{k!(n-k)!} = \binom{n}{k+1}$ and making an obvious change of variables in the first sum gives

$$q_0 \sum_{k=0}^{n} \binom{n}{k} \mu_k \sum_{i=1}^{K} \pi_i \mu^w_{n-k,i} q_0 = \sum_{i=1}^{K} \pi_i \mu^w_{n,i} \left( n \delta_{ij} - \tilde{q}_{ij} \right)$$ (34)

Finally, denoting by $\tilde{p}_0$ a vector with coordinates $p_{0j} = q_{0j}/q_0$, then with $\tilde{a}^T = \tilde{p}_0^T (I - \tilde{Q})^{-1}$ we have that

$$\pi_j \mu^w_{n,j} = \tilde{a}_j \sum_{k=0}^{n} \binom{n}{k} \mu_k \sum_{i=1}^{K} \pi_i \mu^w_{n-k,i} q_0.$$ (35)

Thus, setting $m^w_n = \sum_{i=1}^{K} \pi_i \mu^w_{n,i} q_0$ and

$$\tilde{a} = \sum_{i=1}^{K} \tilde{a}_i q_0 = 1 - \frac{1}{q_0} \sum_{i=1}^{K} \sum_{j=1}^{K} q_{0i}(I - \tilde{Q})^{-1}_{ij} q_{0j},$$ (36)

we have that for $n \geq 1$

$$m^w_n = \tilde{a} \sum_{k=1}^{n} \binom{n}{k} \mu_k m^w_{n-k}$$ (37)

so that

$$\mu^w_{n,j} = \frac{\tilde{a}_j}{\tilde{a}} m^w_n$$ (38)

and the unconditional moment is

$$\frac{1}{1 - \pi_0} \sum_{j=1}^{K} \pi_j \mu^w_{n,j} = \frac{m^w_n}{(1 - \pi_0)\tilde{a}} \sum_{j=1}^{K} \tilde{a}_j.$$ (39)
On some tractable growth collapse processes with renewal collapse epochs

11

Markov transition rates: uniquely defined by its moments then $G$ and upon multiplying by $(-\alpha)^n$, dividing by $n!$ and summing and noting that if $G$ is uniquely defined by its moments then $G(\alpha) = \sum_{k=0}^{\infty} \frac{(-1)^{x_k} \alpha^{k}}{k!}$, one obtains that

$$m_w(\alpha) = \sum_{n=0}^{\infty} \frac{(-1)^{n}m_{w}^{n}}{n!} \alpha^{n} = \frac{1}{1 - \frac{\alpha}{1 + a} G(\alpha)} = \sum_{k=0}^{\infty} \frac{1}{1 + \tilde{a}} \left(\frac{\tilde{a}}{1 + \tilde{a}}\right)^{k} G^{k}(\alpha).$$

This implies that if we let

$$H(x) = \sum_{k=0}^{\infty} \frac{1}{1 + \tilde{a}} \left(\frac{\tilde{a}}{1 + \tilde{a}}\right)^{k} F^{*k}(x),$$

then $m_w$ is the $n$th moment with respect to $H$. If $S_n$ is a sum of $n$ i.i.d. random variables distributed $F$ ($S_0 = 0$) and $N$ is an independent geometric random variable with probability of success $(1 + \tilde{a})^{-1}$, counting only the number of failures, then $H$ is the distribution of $S_N$. Although this seems nice, we should point out that the analysis is not complete as we have not shown that these moments define a unique distribution.

2.1. The case $K = 2$

With $a_{ij} = \frac{q_{ij} q_{i0} q_{j0}}{q_{00}}$, (24) reduces to

$$\alpha w'_1(\alpha) = w_1(\alpha)(q_{11} + a_{11}G(\alpha)) + w_2(\alpha)(q_{21} + a_{21}G(\alpha)), \quad (43)$$

$$\alpha w'_2(\alpha) = w_1(\alpha)(q_{12} + a_{12}G(\alpha)) + w_2(\alpha)(q_{22} + a_{22}G(\alpha)). \quad (44)$$

Differentiating the second of these equations, using (43) for $w'_1(\alpha)$ and finally (44) to eliminate $w_1(\alpha)$, we obtain the following second order differential equation in $w_2(\alpha)$:

$$\alpha w'_2(\alpha) = w_2(\alpha) \left[ -1 + q_{22} + a_{22}G(\alpha) + q_{11} + a_{11}G(\alpha) + \frac{\alpha a_{12}G'(\alpha)}{q_{12} + a_{12}G(\alpha)} \right]$$

$$+ w_2(\alpha) \left[ \frac{1}{\alpha}(q_{21} + a_{21}G(\alpha))(q_{12} + a_{12}G(\alpha)) + a_{22}G'(\alpha) \right]$$

$$- \frac{1}{\alpha}(q_{22} + a_{22}G(\alpha))(q_{11} + a_{11}G(\alpha)) + \frac{q_{22} + a_{22}G(\alpha)}{q_{12} + a_{12}G(\alpha)} G'_2(\alpha).$$

Now consider the special case of $\exp(\mu)$ jumps, i.e., $G(\alpha) = \frac{\alpha}{\mu + \alpha}$, and the following Markov transition rates: $q_{12} = -q_{11} = \nu_1$, $q_{20} = -q_{22} = \nu_2$, and $q_{01} = -q_{00} = \nu_0$, i.e.,
the times in state $i$ are $\exp(\nu_i)$ distributed, for $i = 0, 1, 2$. Then (45) reduces to

$$
\alpha(\mu + \alpha)w''_2(\alpha) + (\nu_1 + \nu_2 + 1)(\mu + \alpha)w'_2(\alpha) + \nu_1\nu_2w(\alpha) = 0. \tag{46}
$$

Taking $z = \mu + \alpha$, $a = \nu_1$, $b = \nu_2$ and $c = 0$ in the differential equation (15.5.1) on p. 562 of [1] reduces that differential equation to (46). Its solution is given by the hypergeometric functions 15.5.20 and 15.5.21 on p. 564 of [1].

3. Back to the growth collapse model

In this section we relate the $n$th moment of the stationary distribution of the growth collapse model to the $n + 1$st moment of the stationary distribution of the shot noise model. Consider the growth collapse model with collapse ratio distribution being minus-log-phase-type. Let $P$ denote a generic interarrival time of the corresponding shot-noise process; $P$ is phase-type (cf. Section 1). An expression for $EP$ is given via the system of equations for the $t_i$, which are mean interarrival times when the first phase is $i$:

$$
t_i = \frac{1}{q_i} + \sum_{j \neq 0,i} \frac{q_{ij}}{q_i} t_j \tag{47}
$$
or equivalently

$$
\sum_{j \neq 0} q_{ij} t_j = -1 \tag{48}
$$

which has a unique solution. $EP$ is then a weighted average of $t_1, \ldots, t_K$ where the weights are the initial distribution of the phase-type distribution which is in our case chosen to be $q_0/q_0$.

From [12] we recall that, for the on/off model of Section 1, the relationship between the stationary density during on times ($f_0(\cdot)$) and that during off times ($f_1(\cdot)$) is given by $p f_0(x) = (1-p) x f_1(x)$, where $p = \mu/(\mu + EP)$. Hence

$$
\int_0^\infty e^{-\alpha x} f_0(x)dx = \frac{EP}{\mu} \int_0^\infty e^{-\alpha x} f_1(x)dx = -\frac{EP}{\mu} \frac{d}{d\alpha} \int_0^\infty e^{-\alpha x} f_1(x)dx \tag{49}
$$

so that the $n$th moment of the stationary distribution for the growth collapse model is given by $EP/\mu$ times the $n + 1$st moment (see (39)) for the shot noise model with phase type inter-arrival times.
4. The discrete time process embedded after collapse epochs

In this section we study the steady-state behavior of the growth collapse process right after the \( n \)th collapse, \( V_n \), defined by

\[
V_n = (V_{n-1} + Y_n)X_n, \tag{50}
\]

where \( V_0 \) is the initial state.

As observed, for example in (2) of [14],

\[
V_n = V_0 \prod_{j=1}^{n} X_j + \sum_{i=1}^{n} Y_i \prod_{j=1}^{n} X_j. \tag{51}
\]

We assume in the sequel that \( \{X_i | i \geq 1\} \) and \( \{Y_i | i \geq 1\} \) are independent sequences of i.i.d. random variables distributed like \( X \) and \( Y \), where \( X \) and \( Y \) are independent and nonnegative. We shall initially assume that \( X \) has support \([0, 1]\). From [14] it follows that when \( EX < 1 \) and \( EY < \infty \), a limiting distribution for the process \( \{V_n | n \geq 0\} \) exists, which is independent of the initial condition \( V_0 \); and it has a unique stationary version. It is easy to check that this continues to hold when \( X \) is nonnegative but is not necessarily restricted to \([0, 1]\), as when \( EX_1 < 1 \), \( \prod_{j=1}^{n} X_j \to 0 \) a.s. as \( n \to \infty \) and \( \sum_{i=1}^{n} Y_i \prod_{j=1}^{n} X_j \) is stochastically increasing (as it is distributed like \( \sum_{i=1}^{n} Y_i \prod_{j=1}^{i} X_j \)) and its mean is bounded above by \( \frac{EYEX}{1-EX} < \infty \). Thus, throughout this section it is assumed that \( EX < 1 \) and \( EY < \infty \).

The fact that when starting from \( V_0 = 0 \), \( V_n \) is stochastically increasing can also be used to justify the fact that the limiting distribution of \( V_n \) has a finite \( m \)th moment if and only if \( EY^m < \infty \) and \( EX^m < 1 \), as in this case

\[
(1 - EX^m)EV_n^m \leq EV_n^m - EX^m EV_{n-1}^m = EX^m \sum_{k=0}^{m-1} \binom{m}{k} EV_{n-1}^k EY^{m-k}, \tag{52}
\]

where by induction, \( EV_n^k < \infty \) and converges to the \( k \)th moment of the limiting distribution by monotone convergence (finite or infinite). Thus if the first \( m - 1 \) moments of the limiting distribution of \( V_n \) are finite, \( EY^m < \infty \) and \( EX^m < 1 \) then the \( m \)th moment is finite as well. If either \( EY^m = \infty \) or \( EX^m \geq 1 \) then (52) also implies that the \( m \)th moment of the limiting distribution of \( V_n \) is necessarily infinite.

Let \( V \) denote a random variable having this distribution, such that \( X, Y \) and \( V \) are independent. Then

\[
V \overset{d}{=} (V + Y)X. \tag{53}
\]
We might also focus on $Z := V + Y$, which has the limiting distribution of the state of the system right before collapses. This leads to

$$Z \overset{d}{=} ZX + Y.$$  \hfill (54)

Much of the literature on Equation (50) has concentrated on the existence of a limiting distribution, and on the tail behavior of that limiting distribution. In the present section we know that this limiting distribution exists provided that $EX < 1$. Our goal is to determine it, for a number of choices for the distributions of $X$ and $Y$.

We start with the following formula for the LST $\psi(\alpha)$ of $V$, with $\eta(\alpha)$ denoting the LST of $Y$,

$$\psi(\alpha) = E\psi(\alpha X)\eta(\alpha X) = \int_{[0,1]} \psi(\alpha x)\eta(\alpha x)dF_X(x),$$  \hfill (55)

where $F_X(x) = P[X \leq x]$. We shall also study $EV^n$ in a number of cases, comparing it with the expression

$$EV^n = \frac{EX^n}{1 - EX^n} \sum_{j=0}^{n-1} \binom{n}{j} EV^j EY^{n-j},$$  \hfill (56)

as in (34) of [14]. In the sequel we assume that all required moments of $Y$ are finite, with the exception of an example of regular variation at the end of the section, and note that since $X$ has support $[0,1]$ and $EX < 1$ then also $EX^n < 1$ for all $n \geq 1$.

We start with a case that has already been treated by Vervaat [21]. We review it here, as it is the basis for extensions later in this section.

4.1. Case 1: $X \sim \text{Beta}(D, 1)$

In this case, $X$ has distribution $F(x) = P(X \leq x) = x^D$, $0 \leq x \leq 1$. When $D$ is a positive integer, $X$ is distributed like the maximum of $D$ independent random variables distributed $U[0,1]$. From (55) we have

$$\psi(\alpha) = \int_0^\alpha \psi(u)\eta(u)D\left(\frac{u}{\alpha}\right)^{D-1} \frac{du}{\alpha},$$  \hfill (57)

or

$$\alpha^D\psi(\alpha) = D \int_0^\alpha \psi(u)\eta(u)u^{D-1}du.$$  \hfill (58)

Differentiation yields, after some rearrangement, that

$$\psi'(\alpha) = -D\psi(\alpha) \frac{1 - \eta(\alpha)}{\alpha},$$  \hfill (59)
so, since \( \psi(0) = 1 \),

\[
\psi(\alpha) = e^{-D \int_{v=0}^{\alpha} \frac{1-\eta(v)}{v} dv} = e^{-DEY \int_{0}^{\alpha} \eta_e(v) dv}
\]  

where \( \eta_e(v) = \frac{1-\eta(v)}{vEY} \) is the LST of the stationary residual lifetime distribution of \( Y \).

**Remark 4.1.** For \( D = 1 \), \( \psi(\alpha) \) is the LST of the classical shot-noise process, see [13]. For integer \( D > 1 \), \( V \) apparently is the sum of \( D \) independent shot-noise processes each having \( D = 1 \). This is not a coincidence. It follows from the fact that if

\[
W_i(t) = X_i(t) - r \int_{0}^{t} W_i(s) ds
\]  

for \( i = 1, \ldots, D \), then

\[
\sum_{i=1}^{D} W_i(t) = \sum_{i=1}^{D} X_i(t) - r \int_{0}^{t} \sum_{i=1}^{D} W_i(s) ds
\]  

so that if \( X_i(\cdot) \) are independent processes then also \( W_i(\cdot) \) are independent shot-noise processes and \( \sum_{i=1}^{D} W_i(\cdot) \) is itself a shot-noise process with driving process \( \sum_{i=1}^{D} X_i(\cdot) \). In this particular case one may observe from the relationship discussed earlier between the shot-noise and growth collapse processes, that a uniformly distributed jump ratio for the growth collapse process corresponds to exponentially distributed inter-jump times for the shot noise process. Thus in this case for \( D = 1 \), \( X_i(\cdot) \) are independent compound Poisson processes with arrival rate \( \lambda = 1 \) and jumps distributed like \( Y \), so that \( \sum_{i=1}^{D} X_i(\cdot) \) is also a compound Poisson process with arrival rate \( D \) and jumps distributed like \( Y \).

**4.1.1. Moments** It follows from (59) after \( k-1 \) differentiations and denoting by \( Y_e \) a random variable with the stationary residual lifetime distribution associated with \( Y \), that

\[
EV^n = DEY \sum_{k=0}^{n-1} \binom{n-1}{k} EV^k EY_e^{n-1-k},
\]  

from which recursion all moments of \( V \) can be obtained (starting with \( EV = DEY \)). The equivalence with (56) follows by observing that \( EX^n = \frac{D}{D+n} \) and that \( EY_e^n = \frac{EY_e^{n+1}}{(n+1)EY} \).
4.2. Case 2: \( X \sim \text{Beta}(\zeta_1, \zeta_2) \) and \( Y \sim \text{Gamma}(\zeta_2, \beta) \)

In this case there is the following short-cut. It is well known (usually given as a standard exercise in a first year probability course when discussing multi-dimensional transformations and Jacobians) that if \( V \) is \( \text{Gamma}(\zeta_1, \beta) \) distributed and \( Y \) is \( \text{Gamma}(\zeta_2, \beta) \) distributed, \( V \) and \( Y \) are independent, then \( \frac{V}{V+Y} \) is distributed \( \text{Beta}(\zeta_1, \zeta_2) \) and is independent of \( V + Y \), which is distributed \( \text{Gamma}(\zeta_1 + \zeta_2, \beta) \). Thus, the joint distribution of \((X, V + Y)\) is the same as that of \( \left( \frac{V}{V+Y}, V + Y \right) \) which implies that \( X(V + Y) \) is distributed like \( V \), so that (53) is satisfied. As there is a unique limiting distribution for the recursion (50), it must be \( \text{Gamma}(\zeta_1, \beta) \).

**Remark 4.2.** It is easily verified that, in the case of \( Y \) being exponentially distributed, i.e., \( \text{Gamma}(1, \beta) \), and \( X \) being \( \text{Beta}(D, 1) \) distributed as in Case 1, Formula (60) yields that \( \psi(\alpha) = \left( \frac{1}{1 + \beta \alpha} \right)^D \); so indeed \( V \) has a \( \text{Gamma}(D, \beta) \) distribution. This particular case is mentioned on p. 765 of Vervaat [21].

4.2.1. Moments

Since \( V \) has a \( \text{Gamma}(\zeta_1, \beta) \) distribution, it immediately follows that

\[
EV^n = \beta^n \frac{\Gamma(\zeta_1 + n)}{\Gamma(\zeta_1)},
\]

(64)

4.3. Case 3: \( X \) has an atom at zero

Suppose that \( P(X = 0) = p > 0 \), and that \( X \) assumes with probability \( 1 - p \) values on \((0, \infty)\) (so we do not necessarily restrict \( X \) to \([0, 1]\)). It is easy to see that the limiting distribution of \( \{V_n| n \geq 0\} \) always exists as zero is a regenerative state with geometrically distributed (hence, aperiodic finite mean) regeneration epochs. We shall study several subcases.

4.4. Case 3a: \( X \) has atoms at 0 and \( c \)

Assume that \( P(X = 0) = 1 - P(X = c) = p \), with \( p > 0 \) and \( c > 0 \) (allowing also \( c > 1 \)). From (50),

\[
\psi(\alpha) = p + (1 - p)\psi(c\alpha)\eta(c\alpha),
\]

(65)

of which repeated iterations yield

\[
\psi(\alpha) = \sum_{j=0}^{\infty} p(1 - p)^j \prod_{i=1}^{j} \eta(c^i \alpha).
\]

(66)
The sum obviously converges for all \(0 < p \leq 1\). Inversion of the LST reveals that

\[
V \triangleq \sum_{i=1}^{N} c^i Y_i, \tag{67}
\]

where \(N\) is geometrically distributed (counting only failures) with probability of success \(p\) and is independent of \(\{Y_i\} \ni i \geq 1\). Indeed, this also follows directly by applying (50), in the form \(V_n = c(V_{n-1} + Y_n)\), \(N\) times, with \(V_0 = 0\). See also p. 762 of Vervaat [21] (where \(c = 1\)).

4.4.1. Moments

From (67),

\[
EV^n = \sum_{j=0}^{\infty} p(1-p)^j \sum_{\sum_{i=1}^{n} n_i=n} \frac{n!}{\prod_{i=1}^{n_i} n_i!} c^{\sum_{i=1}^{n} n_i} \prod_{i=1}^{n_i} EY_i^n. \tag{68}
\]

4.5. Case 3b: \(X \sim\) mixture of an atom at 0 and Beta\((D, 1)\)

Assume that \(P(X \leq x) = p + (1-p)x^D, 0 \leq x \leq 1, p > 0\). In this case, (55) reduces to

\[
\psi(\alpha) = p + (1-p) \int_0^1 \psi(\alpha x) \eta(\alpha x) dx, \tag{69}
\]

yielding after similar manipulations as in Case 1:

\[
\psi'(\alpha) = \frac{pD}{\alpha} + \psi(\alpha) \frac{(1-p)D\eta(\alpha) - D}{\alpha}. \tag{70}
\]

The solution of this first-order inhomogeneous differential equation is:

\[
\psi(\alpha) = C \exp \left[ D \int_0^\alpha \frac{(1-p)D\eta(v) - D}{v} dv \right] + \int_0^\alpha \frac{pD}{z} \exp \left[ \int_z^\alpha \frac{(1-p)D\eta(v) - D}{v} dv \right] dz. \tag{71}
\]

It is easily seen that the first integral on the right hand side of (71) diverges, so we have to take \(C = 0\). By observing that \(\frac{(1-p)D\eta(v) - D}{v}\) is bounded between \(-D/v\) and \(-pD/v\), and that hence the expression in the last line of (71) is bounded between \(\int_0^\alpha \frac{pD}{z} (z/\alpha)^{pD} dz\) and \(\int_0^\alpha \frac{pD}{z} (z/\alpha)^{pD} dz\), it follows that the expression in the last line of (71) has a value between \(p\) and 1. When \(\alpha \downarrow 0\), then the above bound \(-pD/v\) becomes tight and the expression in the last line of (71) approaches 1.
4.5.1. Moments The most suitable approach to obtain $EV^n$ via the LST here seems to be to multiply both sides of Formula (70) with $\alpha$ and differentiate $k - 1$ times. However, the resulting calculation is not really easier then when starting from (56), and hence we omit it.

4.5.2. Tail behavior Suppose that the distribution of $Y$ is regularly varying at infinity with index $-\nu$. Then application of Lemma 8.1.6 of [5] to (71) readily shows that $V$ is also regularly varying, with the same index. We don’t provide details, because considerably more general tail results can be obtained for (50); see Volkovitch and Litvak [20] for regularly varying $Y$, and Denisov and Zwart [8] for light-tailed $Y$.

4.6. Case 3c: $X \sim$ mixture of an atom at 0 and a product of two i.i.d. $U[0,1]$

The density of the product of two i.i.d. random variables which are uniformly distributed on $[0,1]$ is $-\ln x$, $0 < x < 1$. Formula (55) now reduces to:

$$\psi(\alpha) = p - (1 - p) \int_0^1 \psi(\alpha x) \eta(\alpha x) \ln x \, dx,$$

so

$$\alpha \psi(\alpha) = p \alpha - (1 - p) \int_0^\infty \psi(u) \eta(u) \ln(u/\alpha) \, du,$$

which after two differentiations leads to

$$\alpha^2 \psi''(\alpha) + 3 \alpha \psi'(\alpha) + (1 - (1 - p) \eta(\alpha)) \psi(\alpha) = p. \tag{74}$$

In the special case that $Y \sim \exp(\mu)$, hence $\eta(\alpha) = \frac{\mu}{\mu + \alpha}$, this equation simplifies into

$$\alpha^2 (\mu + \alpha) \psi''(\alpha) + 3 \alpha (\mu + \alpha) \psi'(\alpha) + (\mu + \alpha - (1 - p) \mu) \psi(\alpha) = p. \tag{75}$$

$p = 0$ gives a known case:

$$\alpha (\mu + \alpha) \psi''(\alpha) + 3 (\mu + \alpha) \psi'(\alpha) + \psi(\alpha) = 0. \tag{76}$$

Note that this is the differential equation (46) for the case of $\nu_1 = \nu_2 = 1$, which makes sense: $Y$ being exponential and $X$ being a product of two independent $U[0,1]$ random variables corresponds to having an exponential on-time distribution and an Erlang-2 off-time distribution in the on-off model of Section 1 (that was directly related
to the growth collapse model and the shot noise model). Slightly more generally, if \(X = U_1^{1/\nu_1} U_2^{1/\nu_2}\), with \(U_1\) and \(U_2\) independent and \(U[0,1]\) distributed, then one gets (46) with \(\nu_1\) and \(\nu_2\).

**Remark 4.3.** We note that the density of the product of \(k \geq 2\) i.i.d. random variables which are uniformly distributed on \([0, 1]\) is \((\ln(x))^{k-1}, 0 < x < 1\), thus in a similar manner one may derive a \(k\)th order differential equation for \(\psi(\alpha)\).

**Remark 4.4.** When \(p = 0\) and \(\eta(\alpha) = (\mu_1, \mu_2)^2\), i.e., \(Y\) is Erlang-2, then (74) becomes:

\[
\psi''(\alpha) + \frac{3}{\alpha} \psi'(\alpha) + \frac{\alpha + 2\mu}{\alpha(\mu + \alpha)^2} \psi(\alpha) = 0.
\]

When \(p = 0\) and \(\eta(\alpha) = b \mu_1 (1 - b) \mu_2\) with \(0 < b < 1\), i.e., \(Y\) is hyperexponentially distributed, then (74) becomes:

\[
\psi''(\alpha) + \frac{3}{\alpha} \psi'(\alpha) + \frac{b(\mu_2 + \alpha) + (1 - b)(\mu_1 + \alpha)}{\alpha(\mu_1 + \alpha)(\mu_2 + \alpha)} \psi(\alpha) = 0.
\]

Both (77) and (78) are special cases of Heun’s differential equation, cf. [10].

### 4.7. Case 4: \(X \sim U[0, a]\)

We are interested in studying a case in which \(X\) is not restricted to \([0, 1]\). We assume that \(X\) is \(U[0, a]\) distributed, with \(EX = a/2 < 1\). As noted in the first paragraph of this section, together with \(EY < \infty\) this implies stability. Formula (55) now becomes

\[
\psi(\alpha) = \frac{1}{a} \int_0^a \psi(\alpha x) \eta(\alpha x) dx = \frac{1}{a \alpha} \int_0^a \psi(u) \eta(u) du,
\]

and differentiation gives (see (59))

\[
\psi'(\alpha) = \psi(a \alpha) \frac{\eta(a \alpha)}{\alpha} - \frac{\psi(\alpha)}{\alpha}.
\]

By introducing \(\zeta(\alpha) \equiv \psi(e^\alpha)\) one can rewrite (80) as the differential-difference equation

\[
\zeta'(\alpha) = \zeta(\alpha + c) \xi(\alpha + c) - \zeta(\alpha),
\]

with \(c = \ln a < 0\) and \(\xi(\alpha) := \eta(e^\alpha)\). There is an extensive literature on differential-difference equations, see for example [11]. However, solutions of such equations are
only known in special cases such as when \( \xi(\alpha) \) is a constant. Below we consider (80) in the special case that \( Y \sim \exp(\mu) \). Equation (80) then reduces to

\[
(\mu + a\alpha)\alpha \psi'(\alpha) = \mu \psi(a\alpha) - (\mu + a\alpha)\psi(\alpha).
\]  

One might solve it by introducing the Taylor series expansion \( \psi(\alpha) \equiv \sum_{n=0}^{\infty} f_n \alpha^n \), with \( f_0 = \psi(0) = 1 \), and solving the resulting recursion for \( f_n \) (which is \( (-1)^n \mu^n EV^n \)).

We prefer an alternative approach, starting from (56):

\[
EV^n = \frac{EX^n}{1-EX^n} \sum_{k=0}^{n-1} \binom{n}{k} EV^k (EV^{n-k})
\]

If we denote \( B_n = \sum_{k=0}^{n} \frac{EV^k}{k!} \) then \( B_n - B_{n-1} = \frac{a^n}{(n+1)(n+1-a^2)} B_{n-1} \) so that \( B_n = \frac{n+1}{n+1-a^2} B_{n-1} \) which implies that \( B_n = \prod_{i=1}^{(n+1)/2} \left( i + 1 - a^2 \right) \). Hence

\[
\frac{\mu^n EV^n}{n!} = B_n - B_{n-1} = \frac{a^n n!}{\prod_{i=1}^{(n+1)/2} (i + 1 - a^2)}
\]

and thus when \( a < (1+n)^{1/n} \):

\[
EV^n = \frac{(a/\mu)^n (n!)^2}{\prod_{i=1}^{n} (i + 1 - a^2)}.
\]

**Remark 4.5.** \( a = 1 \) yields \( EV^n = \frac{n!}{(n!)^2 \mu^n} \), corresponding to \( V \) being exponentially distributed; see already Remark 2. We further recall \( EV^n < \infty \) if and only if \( EX^n = \frac{a^n}{n+1-a^2} < 1 \) (see (52) and discussion there). Note that \( (1+n)^{1/n} \) equals 2 for \( n = 1 \) and decreases to 1 as \( n \to \infty \), so that for \( 0 < a \leq 1 \) all the moments exist but not for \( 1 < a < 2 \).

**Acknowledgements.** The research of O.J. Boxma was done within the framework of the BRICKS project and the European Network of Excellence Euro-NF. D. Perry gratefully acknowledges a visitor grant from the Netherlands Organisation for Scientific Research NWO.

**References**

On some tractable growth collapse processes with renewal collapse epochs


