SOJOURN TIME PROBLEMS

By Lajos Takács

Case Western Reserve University

It is supposed that in the time interval $(0, \infty)$ a stochastic process is alternately in states A and B. Denote by $\alpha_1, \beta_1, \alpha_2, \beta_2, \cdots$ the lengths of the successive intervals spent in states A and B respectively. In this paper the distribution and the asymptotic distribution of the total time spent in state A (B) in the interval (0, t) are determined in the case where (α_1, β_1) , (α_2, β_2) , \cdots are mutually independent and identically distributed vector variables.

1. Introduction. Let $\{\eta(u), 0 \le u < \infty\}$ be a stochastic process with state space $A \cup B$ where A and B are disjoint sets. If $\eta(u) \in A$, then we say that the process is in state A at time u, and if $\eta(u) \in B$, then we say that the process is in state B at time u. Let us assume that in any finite interval (0, t) the process changes states only a finite number of times with probability one. Let $\mathbf{P}\{\eta(0) \in A\} = 1$ and denote by $\alpha_1, \beta_1, \alpha_2, \beta_2, \cdots$ the lengths of the successive intervals spent in states A and B respectively in the interval $(0, \infty)$. Denote by $\alpha(t)$ the total time spent in state A in the interval (0, t) and by A in the interval A i

In this paper we determine the distributions of $\alpha(t)$ and $\beta(t)$ in the general case, and the asymptotic distributions of $\alpha(t)$ and $\beta(t)$ in the case where (α_1, β_1) , $(\alpha_2, \beta_2), \dots, (\alpha_n, \beta_n), \dots$ are mutually independent and identically distributed vector random variables which belong to the domain of normal attraction of a two-dimensional distribution function. The case where $\{\alpha_n\}$ and $\{\beta_n\}$ are independent sequences has been considered earlier by the author [3].

2. The distributions of $\alpha(t)$ and $\beta(t)$. Let us introduce the notation $\gamma_n = \alpha_1 + \alpha_2 + \cdots + \alpha_n$ for $n = 1, 2, \cdots$ and $\gamma_0 = 0$, furthermore, $\delta_n = \beta_1 + \beta_2 + \cdots + \beta_n$ for $n = 1, 2, \cdots$ and $\delta_0 = 0$.

THEOREM 1. If $0 < x \le t$, then

(1) $\mathbf{P}\{\alpha(t) < x\} = \sum_{n=1}^{\infty} [\mathbf{P}\{\gamma_n < x, \delta_{n-1} \le t - x\} - \mathbf{P}\{\gamma_n < x, \delta_n \le t - x\}]$ and if $0 \le x < t$, then

(2)
$$P{\beta(t) \le x} = \sum_{n=0}^{\infty} [P{\delta_n \le x, \gamma_n < t - x} - P{\delta_n \le x, \gamma_{n+1} < t - x}].$$

PROOF. Since $P\{\alpha(t) < x\} = 1 - P\{\beta(t) \le t - x\}$ for $0 \le x \le t$, it is sufficient to prove (2). For $0 \le x < t$ denote by $\tau = \tau(t - x)$ the smallest $u \in [0, \infty)$ for

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which $\alpha(u) = t - x$, provided that such a u exists. Then $\eta(\tau) \in A$ and we have

(3)
$$\{\beta(t) \le x\} \equiv \{\beta(\tau) \le x\}.$$

This follows from the following identities

$$\{\beta(t) \le x\} \equiv \{\alpha(\tau) \le \alpha(t)\} \equiv \{\tau \le t\} \equiv \{\alpha(\tau) + \beta(\tau) \le t\} \equiv \{\beta(\tau) \le x\}.$$

Here we used that $\alpha(t) + \beta(t) = t$ for all $t \ge 0$, and that $\alpha(t)$ and $\beta(t)$ are non-decreasing functions of t for $0 \le t < \infty$.

Since $\beta(\tau) = \delta_n$ $(n = 0, 1, \dots)$ if $\gamma_n < t - x \le \gamma_{n+1}$, it follows from (3) that

(5)
$$\mathbf{P}\{\beta(t) \le x\} = \sum_{n=0}^{\infty} \mathbf{P}\{\delta_n \le x \text{ and } \gamma_n < t - x \le \gamma_{n+1}\}$$

for $0 \le x < t$ which proves (2).

If for each $t \ge 0$ we define $\omega(t)$ as a discrete random variable taking on positive integers only and satisfying the relation

$$\{\omega(t) \le n\} \equiv \{\delta_n > t\}$$

for all $t \ge 0$ and $n = 0, 1, 2, \dots$, then we can write that

(7)
$$\mathbf{P}\{\alpha(t) < x\} = \mathbf{P}\{\gamma_{\omega(t-x)} < x\}$$

for $0 \le x \le t$. We note that $P\{\omega(0) = 1\} = 1$.

If for each $t \ge 0$ we define $\rho(t)$ as a discrete random variable taking on non-negative integers only and satisfying the relation

(8)
$$\{\rho(t) < n\} \equiv \{\gamma_n \ge t\}$$

for all $t \ge 0$ and $n = 1, 2, \dots$, then we can write that

(9)
$$\mathbf{P}\{\beta(t) \le x\} = \mathbf{P}\{\delta_{\rho(t-x)} \le x\}$$

for $0 \le x \le t$. We note that $P{\rho(0) = 0} = 1$.

3. The asymptotic distributions of $\alpha(t)$ and $\beta(t)$. Formulas (7) and (9) make it possible to determine the asymptotic distributions of $\alpha(t)$ and $\beta(t)$ as $t \to \infty$ if we know the asymptotic distribution of $\gamma_{\omega(t)}$ as $t \to \infty$ or the asymptotic distribution of $\delta_{\rho(t)}$ as $t \to \infty$. In our case the asymptotic distributions of $\alpha(t)$ and $\beta(t)$ can be determined by Theorem 2. In Theorem 2 and in the rest of the paper if we say that a family of distribution functions converges to a limiting distribution function then by this we mean that the distribution functions converge in every continuity point of the limiting distribution function.

THEOREM 2. Let us suppose that either 0 < d < 1, $D_1 > 0$, $D_2 > 0$ or $d \ge 1$, $D_1 = 0$, $D_2 > 0$. If

(10)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\gamma_{\omega(t)} - D_1 t}{D_2 t^d} \le x\right\} = \mathbf{P}\{\theta \le x\},\,$$

then

(11)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\alpha(t)-M_1t}{M_2t^m} \leq x\right\} = R(x),$$

and if

(12)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\delta_{\rho(t)} - D_1 t}{D_2 t^d} \le x\right\} = \mathbf{P}\{\theta \le x\},\,$$

then

(13)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\beta(t)-M_1t}{M_2t^m} \le x\right\} = R(x),$$

where the constants M_1 , M_2 , m and the distribution function R(x) are given in the following table.

TABLE 1

d	M_1	M_2	m	R(x)
<i>d</i> > 1	1	$D_2^{-1/d}$	$\frac{1}{d}$	$\mathbf{P}\{-\theta^{-1/d} \le x\}$
d = 1	0	1	1	$\mathbf{P}\left\{\frac{D_2\theta}{1+D_2\theta}\leq x\right\}$
<i>d</i> < 1	$\frac{D_1}{1+D_1}$	$\frac{D_2}{(1+D_1)^{1+d}}$	d	$\mathbf{P}\{\theta \leq x\}$

PROOF. Both (11) and (13) can be proved in a similar way. Let us prove (13). Let us define

$$(14) u = t + D_1 t + x D_2 t^d$$

for $t \ge 0$. If x is such that $u \ge t$, then by (9) we have

(15)
$$\mathbf{P}\{\beta(u) \leq u - t\} = \mathbf{P}\{\delta_{\delta(t)} \leq D_1 t + x D_2 t^d\}.$$

If $d \ge 1$ and $x \ge 0$ or d < 1, $-\infty < x < \infty$, and t is sufficiently large, then $u \ge t$ is satisfied and $t \to \infty$ as $u \to \infty$. Thus we have

(16)
$$\lim_{u\to\infty} \mathbf{P}\{\beta(u)\leq u-t\} = \mathbf{P}\{\theta\leq x\}$$

where t = t(u), which satisfies $0 \le t \le u$ for sufficiently large u, can be obtained by (14).

If d > 1, then $D_1 = 0$ and for x > 0 we obtain that

(17)
$$t = \left(\frac{u}{x D_2}\right)^{1/d} + o(u^{1/d})$$

as $u \to \infty$. Thus by (16)

(18)
$$\lim_{u\to\infty} \mathbf{P}\left\{\beta(u) \le u - \left(\frac{u}{xD_0}\right)^{1/d}\right\} = \mathbf{P}\{\theta \le x\}$$

for x > 0.

If d = 1, then $D_1 = 0$ and for $x \ge 0$ we obtain that

$$(19) t = \frac{u}{1 + xD_2}$$

for $u \ge 0$. Thus by (16)

(20)
$$\lim_{u\to\infty} \mathbf{P}\left\{\beta(u) \le \frac{uxD_2}{1+xD_2}\right\} = \mathbf{P}\{\theta \le x\}$$

for $x \ge 0$.

If d < 1, then $D_1 > 0$ and we obtain that

(21)
$$t = \frac{u}{1+D_1} - \frac{xD_2}{1+D_1} \left(\frac{u}{1+D_1}\right)^d + o(u^d)$$

as $u \to \infty$. Thus by (16)

(22)
$$\lim_{u\to\infty} \mathbf{P}\left\{\beta(u) \le \frac{D_1 u}{1+D_1} + \frac{xD_2}{1+D_1} \left(\frac{u}{1+D_1}\right)^d\right\} = \mathbf{P}\{\theta \le x\}.$$

The limit relations (18), (20), (22) prove (13).

Our next aim is to find the asymptotic distributions of $\gamma_{\omega(t)}$ and $\delta_{\rho(t)}$ as $t \to \infty$ in the case where $(\alpha_1, \beta_1), (\alpha_2, \beta_2), \dots, (\alpha_n, \beta_n), \dots$ are mutually independent and identically distributed vector random variables which belong to the domain of normal attraction of a two-dimensional distribution function F(x, y). In this case we have

(23)
$$\lim_{n\to\infty} \mathbf{P}\left\{\frac{\gamma_n - A_1 n}{A_2 n^a} \le x, \frac{\delta_n - B_1 n}{B_2 n^b} \le y\right\} = F(x, y)$$

where the normalizing constants satisfy the conditions $\frac{1}{2} \le a < 1$, $A_1 > 0$, $A_2 > 0$ or $a \ge 1$, $A_1 = 0$, $A_2 > 0$ and $\frac{1}{2} \le b < 1$, $B_1 > 0$, $B_2 > 0$ or $b \ge 1$, $B_1 = 0$, $B_2 > 0$.

We shall use the following auxiliary theorem due to F. J. Anscombe [1].

Lemma 1. Let us suppose that $\nu(t)$ $(0 \le t < \infty)$ are discrete random variables taking on nonnegative integers only and that

$$\lim_{t \to \infty} \frac{\nu(t)}{t} = c$$

in probability where c is a positive constant. Let $\zeta(n)$ $(n=0,1,2,\cdots)$ be a sequence of real random variables for which

(25)
$$\lim_{n\to\infty} \mathbf{P}\left\{\frac{\zeta(n)}{b(n)} \le x\right\} = Q(x)$$

and

(26)
$$\lim_{\varepsilon \to 0} \lim \inf_{m \to \infty} \mathbf{P}\{\max_{|n-m| < m\delta(\varepsilon)} |\zeta(n) - \zeta(m)| < \varepsilon b(m)\} = 1$$

for some $\delta(\varepsilon) > 0$ such that $\delta(\varepsilon) \to 0$ as $\varepsilon \to 0$. Then

(27)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\zeta(\nu(t))}{b([ct])} \le x\right\} = Q(x)$$

regardless of whether $\{\nu(t)\}\$ depends on $\{\zeta(n)\}\$ or not.

F. J. Anscombe [1] demonstrated that if $\zeta(n)$ is the *n*th partial sum of a sequence of mutually independent and identically distributed random variables and if 0 < Q(0) < 1, then (26) is satisfied and thus Lemma 1 is applicable. We can easily show that Lemma 1 is still applicable if Q(0) = 0 or Q(0) = 1.

THEOREM 3. Let us suppose that (α_n, β_n) $(n = 1, 2, \cdots)$ are mutually independent, and identically distributed vector variables for which (23) holds with $a \ge 1$ and $b \ge 1$. Let

(28)
$$\Phi(s,q) = \int_0^\infty \int_0^\infty e^{-sx-qy} d_x d_y F(x,y)$$

for $Re(s) \ge 0$ and $Re(q) \ge 0$. Then

(29)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\gamma_{\omega(t)}}{A_{\sigma}B_{\sigma}^{-a/b}t^{a/b}} \le x\right\} = Q(x)$$

exists and

(30)
$$\int_0^\infty x^s dQ(x) = \frac{1}{\Gamma(1-s)\Gamma(1+as/b)} \int_0^\infty x^s dV(x)$$

for sufficiently small |Re(s)| where

(31)
$$V(s) = 1 - \frac{\log \Phi\left(\frac{1}{s}, 0\right)}{\log \Phi\left(\frac{1}{s}, 1\right)}$$

for $\operatorname{Re}(s) > 0$.

PROOF. In proving this theorem we may assume without loss of generality that $A_2 = B_2 = 1$. Let

(32)
$$\Psi(s, q) = \mathbb{E}\left\{e^{-s\alpha_n - q\beta_n}\right\}$$

for Re $(s) \ge 0$ and Re $(q) \ge 0$. By (23) it follows that

(33)
$$\lim_{n\to\infty} \left[\Psi\left(\frac{s}{n^a}, \frac{q}{n^b}\right) \right]^n = \Phi(s, q)$$

and

(34)
$$\lim_{n\to\infty} n \left[\Psi\left(\frac{s}{n^a}, \frac{q}{n^b}\right) - 1 \right] = \log \Phi(s, q)$$

for Re $(s) \ge 0$ and Re $(q) \ge 0$. We note that necessarily $\log \Phi(s, 0) = -As^{1/a}$ and $\log \Phi(0, q) = -Bq^{1/b}$ where A and B are positive constants.

For simplicity let us write $\xi(t) = \gamma_{\omega(t)}$ for $t \ge 0$ and denote by I(A) the indicator variable of the event A, that is, I(A) = 1 if A occurs and I(A) = 0 if A does not occur. By (6) we have

(35)
$$\mathbf{E}\{e^{-s\xi(t)}\} = 1 - [1 - \Psi(s, 0)]M(t, s)$$

for Re $(s) \ge 0$ where

(36)
$$M(t, s) = \sum_{n=0}^{\infty} \mathbb{E}\left\{e^{-s\gamma_n}I(\delta_n \leq t)\right\}.$$

If we express the sum in (36) in the form of an integral, then we can write that

(37)
$$M(t^{b}, st^{-a}) = t \int_{0}^{\infty} \mathbb{E}\{\exp\left[-st^{-a}\gamma_{[ut]}\right] I(\delta_{[ut]} \leq t^{b})\} du$$

for Re $(s) \ge 0$ and t > 0.

We shall prove that if $Re(s) \ge 0$, then

(38)
$$\lim_{t \to \infty} \frac{M(t, st^{-a/b})}{t^{1/b}} = \lim_{t \to \infty} \frac{M(t^b, st^{-a})}{t} = \mu(s)$$

exists and

(39)
$$\mu(s) = \int_0^\infty \mathbf{E} \{e^{-su^a \gamma} I(\delta \le u^{-b})\} du$$

where $P{\gamma \le x, \delta \le y} = F(x, y)$.

For $Re(s) \ge 0$ we have

(40)
$$|\mu(s)| \leq \mu(0) = \int_0^\infty \mathbf{P}\{\delta \leq u^{-b}\} du = \mathbf{E}\{\delta^{-1/b}\} = \frac{1}{B\Gamma(1+1/b)}$$

where the last equality follows from $E\{e^{-s\delta}\}=e^{-Bs^{1/b}}$ for $Re(s)\geq 0$.

Since by (34) $\lim_{s\to+0} [1-\Psi(s,0)]s^{-1/a} = A$, it follows from (35) and (38) that

(41)
$$\lim_{t\to\infty} \mathbb{E}\{\exp[-s\xi(t)t^{-a/b}]\} = 1 - As^{1/a}\mu(s)$$

for $Re(s) \geq 0$.

It remains to prove (38). First, let s = 0. Since

(42)
$$\int_0^\infty e^{-qt} dM(t,0) = \frac{1}{1 - \Psi(0,q)}$$

for Re(q) > 0 and since $\lim_{q \to +0} [1 - \Psi(0, q)] q^{-1/b} = B$, it follows from a Tauberian theorem of O. Szász [2] that

(43)
$$\lim_{t\to\infty} \frac{M(t,0)}{t^{1/b}} = \frac{1}{B\Gamma(1+1/b)}.$$

This proves (38) for s = 0.

By (23) it follows that if $t \to \infty$, then the integrand in (37) tends to the integrand in (39) for u > 0 and $\text{Re}(s) \ge 0$. Since (38) holds for s = 0, we can conclude that for any K > 0 and $\text{Re}(s) \ge 0$ we have

$$(44) \quad |\int_{K}^{\infty} \mathbf{E}\{\exp\left[-st^{-a}\gamma_{[ut]}\right]I(\delta_{[ut]} \leq t^{b})\} du| \leq \int_{K}^{\infty} \mathbf{P}\{\delta_{[ut]} \leq t^{b}\} du \\ \rightarrow \int_{K}^{\infty} \mathbf{P}\{\delta \leq u^{-b}\} du \quad \text{as } t \to \infty,$$

and the extreme right member is arbitrarily close to 0 if K is sufficiently large. Thus by the dominated convergence theorem it follows that in (37) the integral tends to $\mu(s)$ for $\text{Re}(s) \ge 0$ as $t \to \infty$. This proves (38).

By (40) it follows that the right-hand side of (41) tends to 1 as $s \to +0$. Thus by the continuity theorem of Laplace-Stieltjes transforms we can conclude that the limiting distribution

(45)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\xi(t)}{r^{a/b}} \le x\right\} = Q(x)$$

exists, and

(46)
$$\int_0^\infty e^{-sx} dQ(x) = 1 - As^{1/a} \mu(s)$$

for $Re(s) \ge 0$. However, we can also obtain Q(x) in another way. By (35) we have

(47)
$$q \int_0^\infty e^{-qt} \mathbf{E}\{e^{-s\xi(t)}\} dt = 1 - \frac{1 - \Psi(s, 0)}{1 - \Psi(s, q)}$$

for $\text{Re}(s) \ge 0$ and Re(q) > 0. Now let ν be a positive real random variable which is independent of the process $\{\xi(t), 0 \le t < \infty\}$ and for which $\mathbf{P}\{\nu \le x\} = 1 - e^{-x}$ if $x \ge 0$. Then by (47) we have

(48)
$$\mathbb{E}\{e^{-s\xi(\nu/q)}\} = 1 - \frac{1 - \Psi(s, 0)}{1 - \Psi(s, q)}$$

for $Re(s) \ge 0$ and q > 0. By (34) and (48) we get

(49)
$$\lim_{q\to 0} \mathbf{E}\{\exp\left[-sq^{a/b}\xi(\nu/q)\right]\} = 1 - \lim_{q\to 0} \frac{\left[1 - \Psi(sq^{a/b}, 0)\right]q^{-1/b}}{\left[1 - \Psi(sq^{a/b}, q)\right]q^{-1/b}}$$
$$= 1 - \frac{\log \Phi(s, 0)}{\log \Phi(s, 1)} = V\left(\frac{1}{s}\right)$$

for $Re(s) \ge 0$ where we used the definition (31).

If ξ , ν_1 , ν_2 are mutually independent random variables for which $\mathbf{P}\{\xi \le x\} = Q(x)$ and $\mathbf{P}\{\nu_1 \le x\} = \mathbf{P}\{\nu_2 \le x\} = 1 - e^{-x}$ for $x \ge 0$, then by (49) we have

(50)
$$\mathbf{P}\{\xi \nu_1^{-1} \nu_2^{a/b} \le x\} = V(x)$$

for x > 0. Hence it follows that

(51)
$$E\{\xi^{s}\}E\{\nu_{1}^{-s}\}E\{\nu_{2}^{as/b}\} = \int_{0}^{\infty} x^{s} dV(x)$$

for sufficiently small |Re(s)|. This proves (30). From (30) we can obtain Q(x) by Mellin's inversion formula.

In the particular case when a = b we have

(52)
$$\int_0^\infty x^s dQ(x) = \frac{\sin \pi s}{\pi s} \int_0^\infty x^s dV(x)$$

for sufficiently small |Re(s)|, and hence it follows by inversion that

(53)
$$\frac{dQ(x)}{dx} = \frac{V(xe^{\pi i}) - V(xe^{-\pi i})}{2\pi ix}$$

for x > 0 where the definition of V(x) is extended by analytical continuation to the complex plane cut along the negative real axis from 0 to ∞ .

In the particular case when γ and δ are independent random variables, that is, $F(x, y) = \mathbf{P}\{\gamma \le x\}\mathbf{P}\{\delta \le y\}$ we have

(54)
$$Q(x) = \mathbf{P}\{\gamma \delta^{-a/b} \le x\}.$$

This follows easily from (46). Conversely, we can prove that if (54) is true, then γ and δ are necessarily independent random variables.

To prove this last statement let us suppose that the vector variable (γ, δ) and ν_1 and ν_2 are mutually independent. Let $\mathbf{P}\{\gamma \leq x, \delta \leq y\} = F(x, y)$ with Laplace–Stieltjes transform $\Phi(s, q)$ defined by (28), and $\mathbf{P}\{\nu_1 \leq x\} = \mathbf{P}\{\nu_2 \leq x\} = 1 - e^{-x}$ for $x \geq 0$. Then we have

(55)
$$\mathbf{P}\{\gamma \nu_{1}^{-1} \leq x, \, \delta \nu_{2}^{-1} \leq y\} = \Phi\left(\frac{1}{x}, \frac{1}{y}\right)$$

for x > 0 and y > 0. Hence we can deduce that

(56)
$$\mathbf{P}\{\gamma \delta^{-a/b} \nu_1^{-1} \nu_2^{a/b} \le x\} = \frac{axV'(x)}{[1 - V(x)]}$$

for x > 0 where V(x) is given by (31). If we compare (50) and (56), then we can conclude that

$$\frac{axV'(x)}{1-V(x)} = V(x)$$

is a necessary and sufficient condition for the validity of (54). The general solution of (57) is

$$V(x) = \frac{Cx^{1/a}}{1 + Cx^{1/a}}$$

for x > 0 where C is a positive constant. This implies that

(59)
$$\Phi(s, q) = \exp\left[-A(s^{1/a} + Cq^{1/b})\right]$$

for $\text{Re}(s) \ge 0$ and $\text{Re}(q) \ge 0$. Hence it follows that C = B/A and that γ and δ are independent.

Finally, the asymptotic distribution of $\alpha(t)$ is given by (11) where now d = a/b, $D_1 = 0$, $D_2 = A_2 B_2^{-a/b}$, and $P\{\theta \le x\} = Q(x)$.

We note that in a similar way we can prove that

(60)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\delta_{\rho(t)}}{B_2 A_2^{-b/a} t^{b/a}} \le x\right\} = Q^*(x)$$

exists and

(61)
$$\int_0^\infty x^s \, dQ^*(x) = \frac{1}{\Gamma(1-s)\Gamma(1+bs/a)} \int_0^\infty x^s \, dV^*(x)$$

for sufficiently small |Re(s)| where

(62)
$$V^*(s) = \frac{\log \Phi(1, 0)}{\log \Phi(1, 1/s)}$$

for Re(s) > 0. The asymptotic distribution of $\beta(t)$ is given by (13) where now d = b/a, $D_1 = 0$, $D_2 = B_2 A_2^{-b/a}$, and $P\{\theta \le x\} = Q^*(x)$.

We observe that

(63)
$$V^*(x) = 1 - V(x^{-a/b})$$

for x > 0.

The following theorem contains the case $a \ge 1$, $\frac{1}{2} \le b < 1$ as a particular case.

THEOREM 4. If $\alpha_1, \alpha_2, \dots, \alpha_n, \dots$ are mutually independent and identically distributed random variables for which

(64)
$$\lim_{n\to\infty} \mathbf{P}\left\{\frac{\gamma_n}{A_n n^a} \le x\right\} = \mathbf{P}\{\gamma \le x\}$$

where $a \ge 1$ and $A_2 > 0$, and if

$$\lim_{n\to\infty}\frac{\delta_n}{n}=B_1$$

in probability where $B_1 > 0$, then we have

(66)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\gamma_{\omega(t)}B_1^a}{A_2t^a} \leq x\right\} = \mathbf{P}\{\gamma \leq x\}.$$

PROOF. By (6) and (65) it follows that

$$\lim_{t\to\infty} \frac{\omega(t)}{t} = \frac{1}{B_1}$$

in probability. Thus (66) immediately follows from Lemma 1.

In this case the asymptotic distribution of $\alpha(t)$ is given by (11) where now d = a, $D_1 = 0$, $D_2 = A_2 B_1^{-a}$ and $P\{\theta \le x\} = P\{\gamma \le x\}$.

The following theorem contains the case $b \ge 1$, $\frac{1}{2} \le a < 1$ as a particular case.

THEOREM 5. If $\beta_1, \beta_2, \dots, \beta_n, \dots$ are mutually independent and identically distributed random variables for which

(68)
$$\lim_{n\to\infty} \mathbf{P}\left\{\frac{\delta_n}{B_n n^b} \le x\right\} = \mathbf{P}\{\delta \le x\}$$

where $b \ge 1$ and $B_2 > 0$, and if

$$\lim_{n\to\infty}\frac{\gamma_n}{n}=A_1$$

in probability where $A_1 > 0$, then we have

(70)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\delta_{\rho(t)}A_1^b}{B_2t^b} \leq x\right\} = \mathbf{P}\{\delta \leq x\}.$$

PROOF. By (8) and (69) it follows that

(71)
$$\lim_{t \to \infty} \frac{\rho(t)}{t} = \frac{1}{A_t}$$

in probability. Thus (70) immediately follows from Lemma 1.

In this case the asymptotic distribution of $\beta(t)$ is given by (13) where now d = b, $D_1 = 0$, $D_2 = B_2 A_1^{-b}$ and $P\{\theta \le x\} = P\{\delta \le x\}$.

THEOREM 6. If (α_n, β_n) $(n = 1, 2, \dots)$ are mutually independent and identically distributed vector variables for which (23) holds with $\frac{1}{2} \le a < 1$ and $\frac{1}{2} \le b < 1$, then

(72)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{A_1\delta_{\rho(t)}-B_1t}{A_1^{-d}t^d}\leq x\right\}=Q(x)$$

exists where $d = \max(a, b)$,

(73)
$$Q(x) = \mathbf{P}\{A_1 B_2 \delta \leq x\} \qquad \text{for } b > a,$$

$$= \mathbf{P}\{A_1 B_2 \delta - B_1 A_2 \gamma \leq x\} \qquad \text{for } b = a,$$

$$= \mathbf{P}\{-B_1 A_2 \gamma \leq x\} \qquad \text{for } b < a,$$

and $P{\gamma \le x, \delta \le y} = F(x, y)$.

PROOF. By (23) it follows that

(74)
$$\lim_{n\to\infty} \mathbf{P}\left\{\frac{A_1\delta_n - B_1\gamma_n}{n^d} \le x\right\} = Q(x)$$

where $d = \max(a, b)$ and Q(x) is given by (73).

By (8) and (23) it follows that

(75)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\rho(t) - t/A_1}{A_2A_1^{-(1+a)}t^a} \le x\right\} = \mathbf{P}\{-\gamma \le x\},\,$$

and

$$\lim_{t\to\infty}\frac{\rho(t)}{t}=\frac{1}{A_1}$$

in probability. If we spply Lemma 1 to the random variables $\zeta(n) = A_1 \delta_n - B_1 \gamma_n$ $(n = 0, 1, 2, \dots)$, and $\{\rho(t), 0 \le t < \infty\}$, then we obtain that

(77)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{A_1\delta_{\rho(t)}-B_1\gamma_{\rho(t)}}{(t/A_1)^d}\leq x\right\}=Q(x).$$

It remains to show that (77) implies (72). This follows from the inequalities

(78)
$$A_1 \delta_{\rho(t)} - B_1 \gamma_{\rho(t)+1} \le A_1 \delta_{\rho(t)} - B_1 t \le A_1 \delta_{\rho(t)} - B_1 \gamma_{\rho(t)}$$

for $t \ge 0$ and from the fact that

(79)
$$\lim_{t\to\infty} \frac{\alpha_{\rho(t)+1}}{t^a} = 0$$

in probability. The relation (79) follows from the inequality

(80)
$$\mathbf{P}\left\{\frac{\alpha_{\rho(t)+1}}{t^a} > \varepsilon\right\} \leq \mathbf{P}\left\{\left|\rho(t) - \frac{t}{A}\right| > Kt^a\right\} + 2Kt^a\mathbf{P}\left\{\alpha_1 > t^a\varepsilon\right\}$$

which holds for $\varepsilon > 0$ and K > 0. Since $P\{\alpha_1 \le x\}$ belongs to the domain of normal attraction of a stable distribution function with characteristic exponent 1/a, it follows that

(81)
$$\lim_{t\to\infty} \mathbf{P}\{\alpha_1 > t^a \varepsilon\} (t^a \varepsilon)^{1/a} = c$$

where c is a nonnegative constant. $(c = 0 \text{ if } a = \frac{1}{2}.)$ This implies that the second term on the right-hand side of (80) tends to 0 as $t \to \infty$. If $t \to \infty$ and $K \to \infty$, then by (75) the first term on the right-hand side of (80) tends to 0. Since $\varepsilon > 0$ is arbitrary, this implies (79). This completes the proof of the theorem.

Now the asymptotic distribution of $\beta(t)$ is given by (13) where $d = \max(a, b)$, $D_1 = B_1$, $D_2 = 1/A_1^d$ and $P\{\theta \le x\} = Q(x)$ is given by (73).

4. Examples. First, let us suppose that (23) holds with $a = b = 1/\alpha$ where $0 < \alpha < 1$, $A_1 = B_1 = 0$, $A_2 > 0$, $B_2 > 0$ and that

(82)
$$\Phi(s,q) = e^{-s^{\alpha} - q^{\alpha}}$$

for $Re(s) \ge 0$ and $Re(q) \ge 0$ where $\Phi(s, q)$ is defined by (28). Then by (31) we have

$$(83) V(x) = \frac{x^{\alpha}}{1 + x^{\alpha}}$$

for $x \ge 0$ and (29) holds with

(84)
$$\frac{dQ(x)}{dx} = \frac{x^{\alpha} \sin \alpha \pi}{\pi x (1 + 2x^{\alpha} \cos \alpha \pi + x^{2\alpha})}$$

for x > 0. This follows from (53). Thus by Theorem 2 we obtain that

(85)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\alpha(t)}{t} \le x\right\} = Q\left(\frac{B_2 x}{A_2(1-x)}\right)$$

for $0 \le x \le 1$.

Second, let us suppose that (23) holds with $a=b=1/\alpha$ where $0<\alpha<1$, $A_1=B_1=0,\ A_2>0,\ B_2>0$ and that

(86)
$$\Phi(s,q) = e^{-(s+q)^{\alpha}}$$

for $Re(s + q) \ge 0$ where $\Phi(s, q)$ is defined by (28). Then by (31) we have

(87)
$$V(x) = 1 - \frac{1}{(1+x)^{\alpha}}$$

for $x \ge 0$ and (29) holds with

(88)
$$\frac{dQ(x)}{dx} = \frac{\sin \alpha \pi}{\pi x (x-1)^{\alpha}} \quad \text{for } x > 1,$$

$$= 0 \quad \text{for } x \le 1.$$

This follows from (53). Thus by Theorem 2 we obtain that

(89)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\alpha(t)}{t} \le x\right\} = Q\left(\frac{B_2 x}{A_2(1-x)}\right)$$

for $0 \le x \le 1$.

We note that in the second example by (62) we obtain that

$$(90) V^*(x) = \frac{x^{\alpha}}{(1+x)^{\alpha}}$$

for $x \ge 0$ and thus (60) holds with

(91)
$$\frac{dQ^*(x)}{dx} = \frac{\sin \alpha \pi}{\pi x^{1-\alpha} (1-x)^{\alpha}} \quad \text{for} \quad 0 < x < 1,$$
$$= 0 \quad \text{for} \quad x \ge 1.$$

Now by Theorem 2 we obtain that

(92)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\beta(t)}{t} \le x\right\} = Q^*\left(\frac{A_2x}{B_0(1-x)}\right)$$

for $0 \le x \le 1$. Of course (89) and (92) are merely different versions of the same limit theorem.

Third, let us suppose that (23) holds with $a = b = \frac{1}{2}$, $A_1 > 0$, $B_1 > 0$, $A_2 > 0$, $B_2 > 0$ and that F(x, y) is a two-dimensional normal distribution function of type

(93)
$$N(||0||, ||\frac{1}{r}, \frac{r}{1}||)$$
.

Then by (72) and (13) we obtain that

(94)
$$\lim_{t\to\infty} \mathbf{P} \left\{ \frac{\beta(t) - \frac{B_1 t}{A_1 + B_1}}{\left(\frac{A_1}{A_1 + B_1}\right)^{\frac{3}{2}} t^{\frac{1}{2}}} \le x \right\} = \mathbf{P} \left\{ \frac{A_1 B_2 \delta - B_1 A_2 \gamma}{A_1^{\frac{3}{2}}} \le x \right\}$$

where the random variables γ and δ have a two-dimensional normal distribution of type (93). By (94) we can write also that

(95)
$$\lim_{t\to\infty} \mathbf{P}\left\{\frac{\beta(t) - M_1 t}{M_0 t^{\frac{1}{2}}} \le x\right\} = \Phi(x)$$

where $M_1 = B_1/(A_1 + B_1)$,

(96)
$$M_2 = \frac{(A_1^2 B_2^2 + B_1^2 A_2^2 - 2r A_1 B_1 A_2 B_2)^{\frac{1}{2}}}{(A_1 + B_1)^{\frac{3}{2}}},$$

and $\Phi(x)$ is the normal distribution function of type N(0, 1).

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DEPARTMENT OF MATHEMATICS AND STATISTICS CASE WESTERN RESERVE UNIVERSITY CLEVELAND, OHIO 44106