

[4] A. Kolmogorov, *Über die analytischen Methoden in der Wahrscheinlichkeitsrechnung*, *Mathematische Annalen* 104 (1931), p. 415-458.

[5] I. Koźniewska, *Ergodicity of non-homogeneous Markov chains with two states*, *Colloquium Mathematicum* 5 (1958), p. 208-215.

[6] А. Марков, *Исследование общего случая испытаний, связанных в цепь*, *Избранные Труды*, Москва 1951.

[7] J. L. Mott, *Conditions for the ergodicity of non-homogeneous finite Markov chains*, *Proceedings of the Royal Edinburgh Society, Section A*, 64 (1957), p. 369-380.

[8] J. L. Mott and H. Schneider, *Matrix norms applied to weakly ergodic Markov chains*, *Archiv of Mathematics* 8 (1957), p. 331-333.

[9] Т. А. Саримсаков, *Об эргодическом принципе для неоднородных цепей Маркова*, *Доклады Академии Наук СССР* 90 (1952), p. 25-28.

[10] Т. А. Саримсаков и Х. А. Мустафик, *К эргодической теореме для неоднородных цепей Маркова*, *Труды Средне-Азиатского Университета* 74 (1957), *Физ.-мат. науки* 15, p. 1-38.

[11] С. Х. Сираждинов, *Эргодический принцип для неоднородных цепей Маркова*, *Доклады Академии Наук СССР* 71 (1950), p. 821-834.

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ON THE JOINT LIMITING DISTRIBUTION
OF TIMES SPENT IN PARTICULAR STATES
BY A MARKOV PROCESS

BY

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We consider a homogeneous separable Markov process $\xi(t)$ with a finite number of possible states a_0, a_1, \dots, a_k . Let $p_{ij}(t)$ be the probabilities of transition from the state a_i to the state a_j in time t ($i, j = 0, 1, \dots, k$). We suppose that

$$1^\circ \lim_{t \rightarrow 0^+} p_{ii}(t) = 1 \quad (i = 0, 1, \dots, k),$$

2° for each pair i, j ($i, j = 0, 1, \dots, k$) there exists t_0 such that $p_{ij}(t_0) > 0$.

It follows from these assumptions that almost all sample functions are step functions and $p_{ij}(t) > 0$ if $t > 0$ (cf. [2], chapter VI).

Denote by $X_i(t)$ the total time spent in the state a_i during the time interval $[0, t]$. Thus

$$(1) \quad X_i(t) = \int_0^t \chi_i(u) du \quad (i = 0, 1, \dots, k),$$

where $\chi_i(t)$ is the characteristic function of the set $\{t: \xi(t) = a_i\}$ ($i = 0, 1, \dots, k$). It is quite clear that $\sum_{i=0}^k X_i(t) = t$.

The aim of this paper is to find the limiting k -dimensional cumulative distribution function of the random variable $\{X_1(t), \dots, X_k(t)\}$ when $t \rightarrow \infty$.

The one-dimensional variable $X_i(t)$ has been investigated by Takács [7]–[9] and Rényi [5] (in [8] and [9] the assumptions are more general). In the case of Markov chains the above-mentioned problem was treated by Romanowski [6], p. 233, and Kolmogorov [4].

Since almost all sample functions are step functions, we may define a sequence of random variables $x_1^i, \bar{x}_1^i, x_2^i, \bar{x}_2^i, \dots$, as follows:

1° if $\xi(0) = a_i$, then

$$\begin{aligned} x_i^1 &= \sup\{t: \xi(u) = a_i \text{ for } 0 \leq u \leq t\}, \\ \bar{x}_i^1 &= \sup\{t: \xi(u + x_i^1) \neq a_i^1 \text{ for } 0 \leq u \leq t\}, \\ x_i^2 &= \sup\{t: \xi(u + x_i^1 + \bar{x}_i^1) = a_i \text{ for } 0 \leq u \leq t\}, \\ \bar{x}_i^2 &= \sup\{t: \xi(u + x_i^1 + \bar{x}_i^1 + x_i^2) \neq a_i \text{ for } 0 \leq u \leq t\}, \\ &\dots \end{aligned}$$

2° If $\xi(0) \neq a_i$, then

$$\begin{aligned} \bar{x}_i^1 &= \sup\{t: \xi(u) \neq a_i \text{ for } 0 \leq u \leq t\}, \\ x_i^1 &= \sup\{t: \xi(\bar{x}_i^1 + u) = a_i \text{ for } 0 \leq u \leq t\}, \\ &\dots \end{aligned}$$

Thus $x_i^1, \bar{x}_i^1, x_i^2, \bar{x}_i^2, \dots$ denote the lengths of intervals on the time axis, in which successively $\xi(t) = a_i, \neq a_i, a_i$, and so on.

Let us write

$$m_i = \mathbb{E}(x_i^j), \quad \bar{m}_i = \mathbb{E}(\bar{x}_i^j), \quad s_i^2 = \text{Var}(x_i^j), \quad \bar{s}_i^2 = \text{Var}(\bar{x}_i^j) \\ (i = 0, 1, \dots, k; j = 1, 2, \dots).$$

The main result of this paper is the following theorem:

THEOREM 1. Let $X_i(t)$ ($i = 0, 1, \dots, k$) be defined by (1). Then

$$(2) \quad \lim_{t \rightarrow \infty} \mathbb{P} \left\{ \frac{X_i(t) - \frac{m_i t}{m_i + \bar{m}_i}}{\sqrt{t}} \leq c_i; i = 1, 2, \dots, k \right\} \\ = \frac{1}{(2\pi)^{k/2} \sqrt{|L|}} \int_{-\infty}^{c_1} \dots \int_{-\infty}^{c_k} \exp \left\{ -\frac{1}{2|L|} \sum_{i,j=1}^k |L_{ij}| u_i u_j \right\} du_1, \dots, du_k,$$

where L_{ij} are cofactors of the elements of the determinant $|l_{ij}|$ and l_{ij} are given by the formulae

$$(3) \quad l_{ij} = \begin{cases} \frac{\bar{m}_i^2 \bar{s}_i^2 + m_i^2 s_i^2}{(m_i + \bar{m}_i)^3} & \text{for } i = j, \\ \frac{1}{(m_i + \bar{m}_i)(m_j + \bar{m}_j)} \left[\frac{m_i(m_j^2 \bar{s}_j^2 + \bar{m}_j^2 s_j^2)}{m_j^2 - \bar{m}_j^2} + \frac{m_j(m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2)}{m_i^2 - \bar{m}_i^2} + \right. \\ \left. + \frac{m_i m_j (\bar{m}_i \bar{m}_j - m_i m_j)(s_0^2 + \bar{s}_0^2)}{(\bar{m}_i - m_i)(\bar{m}_j - m_j)(\bar{m}_0 + m_0)} \right] & \text{for } i \neq j. \end{cases}$$

An analogous formula for the one-dimensional variable has been shown in papers [7] and [5]. We may write it in the following form:

$$(4) \quad \lim_{t \rightarrow \infty} \mathbb{P} \left\{ \frac{X_i(t) - \frac{m_i t}{m_i + \bar{m}_i}}{\sqrt{t}} \leq c \right\} = \frac{1}{\sqrt{2\pi D_i}} \int_{-\infty}^c e^{-x^2/2D_i} dx,$$

where

$$D_i = \frac{m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2}{(m_i + \bar{m}_i)^3}.$$

This formula has been proved under the condition that the following assumptions are satisfied:

Z₁. The random variables x_i^j ($j = 1, 2, \dots$) are non-negative and have the same distribution with finite variance. The random variables \bar{x}_i^j ($j = 1, 2, \dots$) are non-negative and have the same distribution with finite variance.

Z₂. All random variables x_i^j, \bar{x}_i^r ($j = 1, 2, \dots; r = 1, 2, \dots$) are independent.

An inspection of the proof of the theorem given in paper [5] shows that it remains valid if we replace the assumption **Z₂** by the assumption

Z₃. The two-dimensional random variables (x_i^j, \bar{x}_i^j) ($j = 1, 2, \dots$) are all independent and identically distributed and random variables x_i^j and \bar{x}_i^j are uncorrelated.

In this paper we shall use this fact.

Theorem 1 is a consequence of the following theorem:

THEOREM 2. If

(i) $\{u_i^1, \dots, u_i^k\}$, $i = 1, 2, \dots$, is a sequence of k -dimensional independent and identically distributed random variables,

(ii) $\mathbb{E}(u_i^j) = 0, \mathbb{E}(u_i^j u_i^q) = l_{jq}$,

(iii) $N(t)$ is a positive integer-valued random variable such that $N(t)/t$ is stochastically convergent to a number $c > 0$ as $t \rightarrow \infty$,

(iv) $z_i^{N(t)} = \sum_{j=1}^{N(t)} u_i^j$,

then

$$\lim_{t \rightarrow \infty} \mathbb{P} \left\{ \frac{z_i^{N(t)}}{\sqrt{N(t)}} \leq c_i; i = 1, 2, \dots, k \right\} \\ = \frac{1}{(2\pi)^{k/2} |L|} \int_{-\infty}^{c_1} \dots \int_{-\infty}^{c_k} \exp \left\{ -\frac{1}{2|L|} \sum L_{ij} u_i u_j \right\} du_1, \dots, du_k,$$

where L_{ij} are cofactors of the elements of the determinant $|l_{ij}|$.

Proof of theorem 2. For any positive number $\varepsilon > 0$ we can find a t_0 such that for $t > t_0$ we have

$$P\left(\left|\frac{N(t)}{t} - c\right| > \varepsilon c\right) < \varepsilon,$$

whence

$$\begin{aligned} P\left(\left|\frac{N(t)}{t} - c\right| > \varepsilon c\right) &= P\left(\frac{N(t)}{t} - c < -\varepsilon c\right) + P\left(\frac{N(t)}{t} - c > \varepsilon c\right) \\ &= P(N(t) < ct - \varepsilon ct) + P(N(t) > ct + \varepsilon ct) \\ &= P(N(t) \leq N_1) + P(N(t) > N_2) < \varepsilon, \end{aligned}$$

where $N_1 = [ct - \varepsilon ct]$, $N_2 = [ct + \varepsilon ct]$.

In virtue of the total probability theorem we may write

$$\begin{aligned} P\left(\frac{z_i^{N(t)}}{\sqrt{N(t)}} \leq c_i; i = 1, 2, \dots, k\right) &= \sum_{n=1}^{\infty} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\ &= \sum_{n=1}^{N_1} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) + \\ &+ \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) + \\ &+ \sum_{n=N_2+1}^{\infty} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right). \end{aligned}$$

Now we are going to prove that for sufficiently large t the first and the third sums can be as small as we like. We have

$$\begin{aligned} \sum_{n=1}^{N_1} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) + \\ + \sum_{n=N_2+1}^{\infty} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\ \leq \sum_{n=1}^{N_1} P(N(t) = n) + \sum_{n=N_2+1}^{\infty} P(N(t) = n) = P(N(t) \leq N_1) + P(N(t) > N_2) < \varepsilon. \end{aligned}$$

Then

$$\begin{aligned} P\left(\frac{z_i^{N(t)}}{\sqrt{N(t)}} \leq c_i, i = 1, 2, \dots, k\right) - \\ - \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i; N(t) = n; i = 1, 2, \dots, k\right) < \varepsilon. \end{aligned}$$

Write

$$\varrho_i = \max_{N_1 < n \leq N_2} \left| \sum_{N_1 < i \leq n} u_i^k \right|.$$

According to Kolmogorov inequality (cf. [8], p. 202) we have

$$P(\varrho_i \geq \sqrt[3]{\varepsilon} \sqrt{N_1}) \leq \frac{N_2 - N_1}{N_1 \varepsilon^{2/3}} l_{ii}.$$

It is easy to verify that

$$\frac{N_2 - N_1}{N_1 \varepsilon^{2/3}} \leq \frac{ct(1+\varepsilon)}{ct(1-\varepsilon)-1} \varepsilon^{2/3} - \varepsilon^{2/3} < 4\sqrt[3]{\varepsilon}$$

for $t > 1/\varepsilon c$ and $\varepsilon < \frac{1}{8}$. Then

$$P(\varrho_i \geq \sqrt[3]{\varepsilon} \sqrt{N_1}) < 4\sqrt[3]{\varepsilon} l_{ii} < \varepsilon_1.$$

Now let us remark that for $N_1 < n \leq N_2$ the following inequalities are true:

$$z_i^n \leq z_i^{N_1} + \varrho_i, \quad z_i^{N_1} \leq z_i^n + \varrho_i.$$

This last inequality follows from the relations:

$$z_i^n + \varrho_i = z_i^{N_1} + u_i^{N_1+1} + \dots + u_i^n + \varrho_i \text{ and } u_i^{N_1+1} + \dots + u_i^n + \varrho_i \geq 0.$$

Let A_i denote the event $\varrho_i \leq \sqrt[3]{\varepsilon} \sqrt{N_1}$, B the event $N_1 < N(t) \leq N_2$, C the event $z_i^{N_1}/\sqrt{N_1} \leq c_i \sqrt{(1+\varepsilon)/(1-2\varepsilon)} + \varrho_i/\sqrt{N_1}$ ($i = 1, 2, \dots, k$), D the event $z_i^{N_1}/\sqrt{N_1} \leq c_i - \sqrt[3]{\varepsilon}$ ($i = 1, 2, \dots, k$) and E the event $z_i^{N_1}/\sqrt{N_1} \leq c_i - \varrho_i/\sqrt{N_1}$ ($i = 1, 2, \dots, k$). Then

$$\begin{aligned} \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\ \leq \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^{N_1} - \varrho_i}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\ \leq \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^{N_1} - \varrho_i}{\sqrt{N_2}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \end{aligned}$$

$$\begin{aligned}
&= P(z_i^{N_1} \leq c_i \sqrt{N_2} + \varrho_i, N_1 < N(t) \leq N_2; i = 1, 2, \dots, k) \\
&\leq P(z_i^{N_1} \leq c_i \sqrt{N_2} + \varrho_i; i = 1, 2, \dots, k) \\
&\leq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i \sqrt{\frac{N_2}{N_1}} + \frac{\varrho_i}{\sqrt{N_1}}; i = 1, 2, \dots, k\right) \\
&\leq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i \sqrt{\frac{1+\varepsilon}{1-2\varepsilon}} + \frac{\varrho_i}{\sqrt{N_1}}; i = 1, 2, \dots, k\right) = P(C) \\
&= P(CA_1 A_2 \dots A_k) + P(C\bar{A}_1 A_2 \dots A_k) + P(C\bar{A}_2 A_3 \dots A_k) + \\
&\quad + P(C\bar{A}_3 A_4 \dots A_k) + \dots + P(C\bar{A}_{k-1} A_k) + P(C\bar{A}_k) \\
&\leq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i \sqrt{\frac{1+\varepsilon}{1-2\varepsilon}} + \sqrt[3]{\varepsilon}; i = 1, 2, \dots, k\right) + \\
&\quad + P(\bar{A}_1) + P(\bar{A}_2) + \dots + P(\bar{A}_k) \\
&\leq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i \sqrt{\frac{1+\varepsilon}{1-2\varepsilon}} + \sqrt[3]{\varepsilon}; i = 1, 2, \dots, k\right) + k\varepsilon_1.
\end{aligned}$$

Thus we have found the upper estimate; now we shall find the lower estimate. Let us remark that

$$\begin{aligned}
&\sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^n}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\
&\geq \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^{N_1} + \varrho_i}{\sqrt{n}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\
&\geq \sum_{n=N_1+1}^{N_2} P\left(\frac{z_i^{N_1} + \varrho_i}{\sqrt{N_1}} \leq c_i, N(t) = n; i = 1, 2, \dots, k\right) \\
&= P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i - \frac{\varrho_i}{\sqrt{N_1}}, N_1 < N(t) \leq N_2; i = 1, 2, \dots, k\right) \\
&= P(\mathcal{E}) - P(\mathcal{E}, N(t) \leq N_1) - P(\mathcal{E}, N(t) > N_2) \\
&\geq P(\mathcal{E}) - P(N(t) \leq N_1) - P(N(t) > N_2) > P(\mathcal{E}) + \varepsilon \\
&\geq P(\mathcal{E}A_1 \dots A_k) + \varepsilon \\
&\geq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i - \sqrt[3]{\varepsilon}, A_1 \dots A_k; i = 1, 2, \dots, k\right) \\
&= P(D) - P(D\bar{A}_1 \dots \bar{A}_k) \geq P(D) - P(\bar{A}_1 \dots \bar{A}_k)
\end{aligned}$$

$$\begin{aligned}
&= P(D) - P(\bar{A}_1 A_2 \dots A_k) - P(\bar{A}_2 A_3 \dots A_k) - \dots - P(\bar{A}_k) \\
&\geq P(D) - P(\bar{A}_1) - P(\bar{A}_2) - \dots - P(\bar{A}_k) \\
&\geq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i - \sqrt[3]{\varepsilon}; i = 1, 2, \dots, k\right) - k\varepsilon_1.
\end{aligned}$$

Finally we have

$$\begin{aligned}
&P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i - \sqrt[3]{\varepsilon}; i = 1, 2, \dots, k\right) - k\varepsilon_1 \\
&\leq P\left(\frac{z_i^{N(t)}}{\sqrt{N(t)}} \leq c_i; i = 1, 2, \dots, k\right) \\
&\leq P\left(\frac{z_i^{N_1}}{\sqrt{N_1}} \leq c_i \sqrt{\frac{1+\varepsilon}{1-2\varepsilon}} + \sqrt[3]{\varepsilon}; i = 1, 2, \dots, k\right) + k\varepsilon_1.
\end{aligned}$$

If $t \rightarrow \infty$, then N_1 also tends to infinity.

Now the assertion of theorem 2 immediately follows from the last relation and the central limit theorem.

To prove theorem 1 we need the following lemma:

LEMMA 1. Suppose that η_1, η_2, \dots are independent and identically distributed random variables with mean values m and finite variances σ^2 . Further, let $N(t)$ denote a positive integer-valued random variable defined for any $t > 0$ such that $N(t)/t$ converges for $t \rightarrow \infty$ in probability to a constant $c > 0$. Then we have for an arbitrary $\varepsilon > 0$

$$\lim_{t \rightarrow \infty} P\left(\left|\frac{\eta_1 + \eta_2 + \dots + \eta_{N(t)}}{N(t)} - m\right| < \varepsilon\right) = 1.$$

In [5] the following formula has been proved:

$$\lim_{t \rightarrow \infty} P\left(\frac{(\eta_1 - m) + \dots + (\eta_{N(t)} - m)}{\sqrt{N(t)}} \leq \varepsilon\right) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\varepsilon} e^{-u^2/2\sigma^2} du.$$

The proof of lemma 1 is analogous to the proof of the above relation and we may omit it.

Now suppose that $\xi(0) = a_0$. (In the case $\xi(0) \neq a_0$ some modifications ought to be introduced to the proof of theorem 1 and lemma 2. These modifications are not essential and we shall not consider each of the cases $\xi(0) = a_0$ and $\xi(0) \neq a_0$ separately.)

Now we introduce the following notation:

Let $\tau_0 < \tau_1 < \tau_2 < \dots$ be points on the real axis such that

$$\tau_0 = 0, \quad \tau_i = \sum_{j=1}^i x_0^j + \bar{x}_0^j.$$

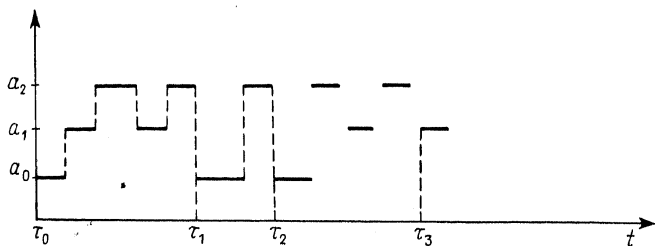
Let y_i^j be random variables such that

$$(5) \quad y_i^j = \int_{\tau_{j-1}}^{\tau_j} \chi_i(u) du \quad (i = 1, 2, \dots, k; j = 1, 2, \dots)$$

and

$$(6) \quad \bar{y}_i^j = \bar{x}_0^j + \bar{x}_0^j - y_i^j \quad (i = 1, 2, \dots, k; j = 1, 2, \dots).$$

The random variable y_i^j is the time spent in the state a_i between the $(j-1)$ -th and j -th appearance of the state a_0 .



The case $k = 2$.

From the properties of the process considered it follows that the random variables y_i^j ($j = 1, 2, \dots$) are independent and identically distributed.

LEMMA 2. The moments of the random variables \bar{x}_i^j , y_i^j , \bar{y}_i^j are given by the formulae

$$(7) \quad \mathbb{E}(\bar{x}_i^j) = \bar{m}_i = - \left. \frac{dL_i(z)}{dz} \right|_{z=0},$$

$$(8) \quad \text{Var}(\bar{x}_i^j) = \bar{s}_i^2 = \frac{d^2 L_i(z)}{dz^2} - \left[\left. \frac{dL_i(z)}{dz} \right]^2 \right|_{z=0},$$

$$(9) \quad \mathbb{E}(y_i^j) = \mu_i = \frac{m_i}{m_i + \bar{m}_i} (m_0 + \bar{m}_0) < \infty,$$

$$(10) \quad \text{Var}(y_i^j) = \sigma_i^2 = \frac{(m_0 + \bar{m}_0)(m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2) - m_i^2 (m_i + \bar{m}_i)(s_0^2 + \bar{s}_0^2)}{(m_i + \bar{m}_i)^2 (\bar{m}_i - m_i)},$$

$$(11) \quad \mathbb{E}[(y_i^j - \mu_i)(y_l^j - \mu_l)] = 0 \quad \text{for } i \neq l,$$

$$(12) \quad \mathbb{E}(\bar{y}_i^j) = \bar{\mu}_i^j = m_0 + \bar{m}_0 - \mu_i,$$

$$(13) \quad \text{Var}(\bar{y}_i^j) = \bar{\sigma}_i^2 = s_0^2 + \bar{s}_0^2 - \sigma_i^2,$$

where

$$L_i(z) = 1 + \frac{z}{\lambda_i} - \frac{1}{\lambda_i \int_0^\infty e^{-zt} p_{ii}(t) dt}, \quad \lambda_i = \lim_{t \rightarrow 0} \frac{1 - p_{ii}(t)}{t}.$$

Proof. The random variable \bar{x}_i^j is the time of return to the state a_i . The mean value and the variance of this variable has been found in [7, § 3.3].

Since

$$\lim_{t \rightarrow \infty} p_{ij}(t) = \frac{m_i}{m_i + \bar{m}_i} > 0 \quad \text{and} \quad m_i < \infty,$$

we have $\bar{m}_i < \infty$.

Now we shall prove formula (9). We define positive integer-valued random variables $N_i(t)$ by the inequalities:

$$(14) \quad \sum_{j=1}^{N_i(t)} (x_i^j + \bar{x}_i^j) \leq t < \sum_{j=1}^{N_i(t)+1} (x_i^j + \bar{x}_i^j) \quad (i = 0, 1, \dots, k).$$

It follows from (6) that the following inequalities are also true:

$$(15) \quad \sum_{j=1}^{N_0(t)} (y_i^j + \bar{y}_i^j) \leq t < \sum_{j=1}^{N_0(t)+1} (y_i^j + \bar{y}_i^j) \quad (i = 0, 1, \dots, k).$$

Representing $X_i(t)$ as the sum of the segments y_i^j , we have the inequalities

$$\frac{\sum_{j=1}^{N_0(t)} y_i^j}{N_0(t)} \cdot \frac{N_0(t)}{t} = \frac{\sum_{j=1}^{N_0(t)} y_i^j}{t} \leq \frac{X_i(t)}{t} < \frac{\sum_{j=1}^{N_0(t)+1} y_i^j}{t} = \frac{\sum_{j=1}^{N_0(t)+1} y_i^j}{N_0(t)+1} \cdot \frac{N_0(t)+1}{t}.$$

Taking into account

$$\frac{N_0(t)}{t} \xrightarrow{\text{stochast.}} \frac{1}{\mu_0 + \bar{\mu}_0}$$

and lemma 1, we have

$$(16) \quad \frac{X_i(t)}{t} \xrightarrow{\text{stochast.}} \frac{\mu_i}{\mu_0 + \bar{\mu}_0}.$$

On the other hand, we may represent $X_i(t)$ as the sum of the segments \bar{x}_i^j . Then we may write

$$\frac{\sum_{j=1}^{N_i(t)} \bar{x}_i^j}{N_i(t)} \cdot \frac{N_i(t)}{t} \leq \frac{X_i(t)}{t} < \frac{\sum_{j=1}^{N_i(t)+1} \bar{x}_i^j}{N_i(t)+1} \cdot \frac{N_i(t)+1}{t}.$$

It follows from lemma 1 and the relation

$$\frac{N_i(t)}{t} \xrightarrow{\text{stochast.}} \frac{1}{m_i + \bar{m}_i}$$

that

$$(17) \quad \frac{X_i(t)}{t} \xrightarrow{\text{stochast.}} \frac{m_i}{m_i + \bar{m}_i}.$$

Now, comparing (16) and (17), we have

$$\frac{m_i}{m_i + \bar{m}_i} = \frac{\mu_i}{\mu_i + \bar{\mu}_i}.$$

Using the relation $\mu_i + \bar{\mu}_i = m_0 + \bar{m}_0$, we obtain

$$\mu_i = \frac{m_i}{m_i + \bar{m}_i} (m_0 + \bar{m}_0).$$

Thus formula (9) is proved.

Representing $X_i(t)$ as the sum of the segments y_i^j and using formula (4) (the assumptions Z_1 and Z_3 being satisfied for y_i^j, \bar{y}_i^j) we get

$$(18) \quad \lim_{t \rightarrow \infty} \mathbb{P} \left(\frac{X_i(t) - \frac{\mu_i t}{\mu_i + \bar{\mu}_i}}{\sqrt{t}} \leq c \right) = \frac{1}{\sqrt{2\pi B_i}} \int_{-\infty}^c e^{-x^2/2B_i} dx,$$

where

$$B_i = \frac{\mu_i^2 \bar{\sigma}_i^2 + \bar{\mu}_i^2 \sigma_i^2}{(\mu_i + \bar{\mu}_i)^3}.$$

Now, representing $X_i(t)$ as the sum of the segments x_i^j and using again formula (4) (the assumptions Z_1 and Z_2 being satisfied), we get

$$(19) \quad \lim_{t \rightarrow \infty} \mathbb{P} \left(\frac{X_i(t) - \frac{m_i t}{m_i + \bar{m}_i}}{\sqrt{t}} \leq c \right) = \frac{1}{\sqrt{2\pi D_i}} \int_{-\infty}^c e^{-x^2/2D_i} dx,$$

where

$$D_i = \frac{m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2}{(m_i + \bar{m}_i)^3}.$$

The left sides of the formulae (18), (19) being equal, the right sides must also be equal, that is

$$(20) \quad \frac{\mu_i^2 \bar{\sigma}_i^2 + \bar{\mu}_i^2 \sigma_i^2}{(\mu_i + \bar{\mu}_i)^3} = \frac{m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2}{(m_i + \bar{m}_i)^3}.$$

Now taking into account that $\mu_i + \bar{\mu}_i = m_0 + \bar{m}_0$ and finding σ_i^2 from formula (20), we get

$$\sigma_i^2 = \frac{(m_0 + \bar{m}_0)(m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2) - m_i^2 (m_i + \bar{m}_i)(s_0^2 + \bar{s}_0^2)}{(m_i + \bar{m}_i)^2 (\bar{m} - m_i)}.$$

We have thus proved formula (10).

Now we are going to show that the random variables y_i^j and y_l^j are uncorrelated for $i \neq l$.

Let us denote by $h_{il}(u, v)$ the frequency function of the two-dimensional random variable (y_i^j, y_l^j) and by $q_0(r, s)$ — the probability of the appearance of the state a_i r times and of the state a_l s times between two successive appearances of the state a_0 . Then

$$(21) \quad h_{il}(u, v) = \sum_{r,s} q_0(r, s) q_i(u) q_l(v),$$

where

$$g_i(u) = \frac{d}{du} P(y_i^j \leq u), \quad g_l(v) = \frac{d}{dv} P(y_l^j \leq v).$$

From formula (21) it follows that

$$\begin{aligned} & E[(y_i^j - \mu_i)(y_l^j - \mu_l)] \\ &= \int_0^\infty \int_0^\infty \sum_{r,s} q_0(r, s) [(u - \mu_i) g_i(u)] [(v - \mu_l) g_l(v)] du dv \\ &= \sum_{r,s} q_0(r, s) \int_0^\infty (u - \mu_i) g_i(u) du \int_0^\infty (v - \mu_l) g_l(v) dv = 0. \end{aligned}$$

We have thus proved formula (11).

Formulae (12) and (13) immediately follow from (6) and (11).

Proof of the theorem 1. It follows from the previous considerations that

$$(22) \quad \begin{aligned} & \lim_{t \rightarrow \infty} \mathbb{P} \left(\frac{(X_i(t) - \frac{m_i}{m_i + \bar{m}_i} t)}{\sqrt{t}} \leq c_i; i = 1, 2, \dots, k \right) \\ &= \lim_{t \rightarrow \infty} \mathbb{P} \left(\frac{X_i(t) - \frac{\mu_i}{\mu_i + \bar{\mu}_i} t}{\sqrt{t}} \leq c_i; i = 1, 2, \dots, k \right). \end{aligned}$$

Let us remark that we may estimate $X_i(t)$ in the following way:

$$(23) \quad \sum_{j=1}^{N_0(t)} y_i^j \leq X_i(t) < \sum_{j=1}^{N_0(t)+1} y_i^j,$$

where $N_0(t)$ is defined by (15).

In view of (15) and (23)

$$(24) \quad \sum_{j=1}^{N_0(t)} y_i^j - \frac{\mu_i}{\mu_i + \bar{\mu}_i} \sum_{j=1}^{N_0(t)+1} (y_i^j + \bar{y}_i^j) \leq X_i(t) - \frac{\mu_i}{\mu_i + \bar{\mu}_i} t$$

$$\leq \sum_{j=1}^{N_0(t)+1} y_i^j - \frac{\mu_i}{\mu_i + \bar{\mu}_i} \sum_{j=1}^{N_0(t)} (y_i^j + \bar{y}_i^j).$$

Write

$$\mu_i + \bar{\mu}_i = m_0 + \bar{m}_0 = M$$

and

$$\alpha_i^j = \frac{1}{M^{3/2}} [M y_i^j - \mu_i (y_i^j + \bar{y}_i^j)] = \frac{1}{M^{3/2}} [\mu_i y_i^j - \mu_i \bar{y}_i^j].$$

Then inequality (24) can be expressed as follows:

$$(25) \quad \sum_{j=1}^{N_0(t)} \alpha_i^j \sqrt{m} - \frac{\mu_i}{M} (y_i^{N_0(t)+1} + \bar{y}_i^{N_0(t)+1}) \leq X_i(t) - \frac{\mu_i t}{M} \leq \sum_{j=1}^{N_0(t)} \alpha_i^j \sqrt{m} + y_i^{N_0(t)+1}.$$

Now we are going to find the moments of the random variables α_i^j . The mean value is equal to

$$\mathbb{E}(\alpha_i^j) = \frac{1}{M^{3/2}} [\bar{\mu}_i \mathbb{E}(y_i^j) - \mu_i \mathbb{E}(\bar{y}_i^j)] = 0.$$

In the same way as we have proved formula (11), we may show that

$$\mathbb{E}[(y_i^j - \mu_i)(\bar{y}_i^j - \bar{\mu}_i)] = \mathbb{E}[(y_i^j - \mu_i)(y_i^j - \mu_1 + \dots + y_i^{j-1} - \mu_{i-1} + y_{j+1}^j - \mu_{i+1} + \dots + y_k^j - \mu_k + \alpha_0^j - m_0)] = 0.$$

From the last relation and the definition of the random variable α_i^j it follows that

$$\text{Var}(\alpha_i^j) = \frac{\bar{\mu}_i^2 \sigma_i^2 + \mu_i^2 \bar{\sigma}_i^2}{M^3}.$$

In view of (20) the last relation can be written in the following form:

$$\text{Var} \alpha_i^j = \frac{\bar{m}_i^2 s_i^2 + m_i^2 \bar{s}_i^2}{(m_i + \bar{m}_i)^3}.$$

Now, taking into consideration that

$$y_i^j + \bar{y}_i^j = \bar{y}_i + \bar{y}_i^j = \alpha_0^j + \bar{\alpha}_0^j,$$

we have

$$\begin{aligned} \mathbb{E}(\alpha_i^j \alpha_i^j) &= \frac{1}{M^3} \mathbb{E}[M y_i^j - \mu_i (y_i^j + \bar{y}_i^j)] \cdot [M y_i^j - \mu_i (y_i^j + \bar{y}_i^j)] \\ &= \frac{1}{M^3} \{M^2 \mu_i \mu_i - M \mu_i \mathbb{E}[y_i^j (y_i^j + \bar{y}_i^j)] - M \mu_i \mathbb{E}[y_i^j (y_i^j + \bar{y}_i^j)] + \mu_i \mu_i \mathbb{E}(\alpha_0^j + \bar{\alpha}_0^j)^2\} + \\ &\quad + \frac{2}{M^3} \mu_i \mu_i M \mathbb{E}(\alpha_0^j + \bar{\alpha}_0^j) + \frac{2}{M^3} \mu_i \mu_i M \mathbb{E}(\alpha_0^j + \bar{\alpha}_0^j) \\ &= \frac{1}{M^3} \mu_i \mu_i \mathbb{E}(\alpha_0^j + \bar{\alpha}_0^j - M)^2 + \frac{1}{M^2} [\mu_i^2 \mu_i + \mu_i \mu_i^2 - \mu_i \mathbb{E}(y_i^{j2}) - \mu_i \mathbb{E}(y_i^{j2})] \\ &= \frac{1}{M^3} [\mu_i \mu_i (s_0^2 + \bar{s}_0^2) - M(\mu_i \sigma_i^2 + \mu_i \bar{\sigma}_i^2)]. \end{aligned}$$

In view of (9), (10) $\mathbb{E}[\alpha_i^j \alpha_i^j]$ can be written in the following form:

$$\mathbb{E}(\alpha_i^j \alpha_i^j) = \frac{1}{(m_i + \bar{m}_i)(m_i + \bar{m}_i)} \left[\frac{m_i(m_i s_i^2 + \bar{m}_i^2 \bar{s}_i^2)}{m_i^2 - \bar{m}_i^2} + \frac{m_i(m_i^2 \bar{s}_i^2 + \bar{m}_i^2 s_i^2)}{m_i^2 - \bar{m}_i^2} + \frac{(\bar{m}_i \bar{m}_i - m_i m_i)(s_0^2 + \bar{s}_0^2)}{(\bar{m}_i - m_i)(\bar{m}_i - m_i)(\bar{m}_0 + m_0)} \right].$$

From (25) it follows that

$$\begin{aligned} &P\left(\frac{\sum_{j=1}^{N_0(t)} \alpha_i^j}{\sqrt{N_0(t)}} \cdot \sqrt{\frac{N_0(t)}{t}} M + \frac{y_i^{N_0(t)+1}}{\sqrt{t}} \leq c_i; i = 1, 2, \dots, k\right) \\ &\leq P\left(\frac{X_i(t) - \frac{\mu_i t}{M}}{\sqrt{t}} \leq c_i; i = 1, 2, \dots, k\right) \\ &\leq P\left(\frac{\sum_{j=1}^{N_0(t)} \alpha_i^j}{\sqrt{N_0(t)}} \cdot \sqrt{\frac{N_0(t)}{t}} M - \frac{\mu_i}{M} \frac{y_i^{N_0(t)+1} + \bar{y}_i^{N_0(t)+1}}{\sqrt{t}} \leq c_i; i = 1, 2, \dots, k\right). \end{aligned}$$

The random variable

$$\frac{N_0(t)}{t} M \xrightarrow{\text{stochast.}} 1.$$

The mean values and the variances of y_i^j and \bar{y}_i^j are finite, and so y_i^j/\sqrt{t} and \bar{y}_i^j/\sqrt{t} are stochastically convergent to 0. The random variable α_i^j satisfies the assumptions of theorem 2. The assertion of theorem 1 follows immediately from lemma 2, theorem 2 and the last inequality.

REFERENCES

- [1] M. S. Bartlett, *An introduction to the theory of stochastic processes with special references to methods and applications*, Cambridge 1955.
- [2] J. L. Doob, *Stochastic processes*, New York 1953.
- [3] M. Fisz, *Rachunek prawdopodobieństwa i statystyka matematyczna*, 2nd edition, Warszawa 1958.
- [4] А. Н. Колмогоров, *Локальная предельная теорема для классических цепей Маркова*, Известия Академии Наук СССР 13 (4) (1949), p. 281-300.
- [5] A. Rényi, *On the asymptotic distribution of the sum of a random number of independent random variables*, Acta Mathematica Academiae Scientiarum Hungaricae 8 (1957), p. 193-199.
- [6] В. И. Романовский, *Дискретные цепи Маркова*, Москва-Ленинград 1949.
- [7] L. Takács, *On certain sojourn time problems in the theory of stochastic processes*, Acta Mathematica Academiae Scientiarum Hungaricae 8 (1957), p. 169-191.
- [8] — *On a sojourn time problem*, Теория вероятностей и ее применения 3 (1958), p. 61-69.
- [9] — *On a sojourn time problem in the theory of stochastic processes*, Transactions of the American Mathematical Society 93 (1959), p. 531-540.

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MIECZYŚLAW BIERNACKI

(30. III. 1891—21. XI. 1959)

Né le 30 mars 1891 à Lublin, fils d'un médecin, Mieczysław Biernacki y passa en 1909 son baccalauréat et, après deux ans d'études de la chimie à l'Université de Cracovie, prit l'inscription à la Sorbonne comme étudiant des mathématiques. Depuis 1914 jusqu'à 1919 il participa comme volontaire aux luttes de l'armée française et puis de la formation polonaise du général J. Haller contre les Allemands au front occidental. Intoxiqué par gaz asphyxiant et grièvement blessé, il retourna, aussitôt rétabli, sur le front français et, démobilisé en 1919, rentra dans son pays avec l'armée Haller.

Dès 1921 Biernacki poursuivit à la Sorbonne ses études mathématiques, y passa sa licence et y soutint le 11 mai 1928 sa thèse du doctorat auprès de la Commission d'examen présidée par le professeur Paul Montel.

Retourné en Pologne, il fut nommé en 1928 assistant à l'Université de Wilno, en 1929 professeur extraordinaire des mathématiques à l'Université de Poznań et en 1937 professeur ordinaire à la même université. Il n'arrêta pas ses recherches scientifiques pendant les terribles années 1939-1944 de l'occupation allemande en Pologne. Il les passa à Lublin, où quelques leçons privées qu'il y donnait lui ont permis de survivre.

En 1944 il devint professeur ordinaire des mathématiques à l'Université Marie Skłodowska-Curie à Lublin et prit une part particulièrement active à l'organisation de cette université. Il y enseignait jusqu'à la fin de ses jours.

Ses mérites publics et scientifiques lui ont valu des distinctions et des prix. En 1936 la France lui attribua la Croix d'Officier de la Légion d'Honneur; en 1950 il a été décoré par la République Polonaise de la Croix d'or de l'Ordre du Mérite, en 1954 de celle du Chevalier et en 1959 du Commandeur de l'Ordre *Polonia Restituta*. En 1950 il a reçu le Prix scientifique de l'Etat (II^{me} degré). Deux fois la Société Polonaise