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A Diffusion Approximation in the Ruin Problem for a Controlled Markov Chain

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The reward from a controlled Markov chain is approximated by a diffusion process. From a control policy maximizing its expected discounted trajectory under a penalty for reaching zero a control of the original Markov chain is derived.

The ruin problem in controlled Markov process was considered by Z. Koutský in [4]. In the present paper a diffusion appproximation is used to calculate controls taking the ruin probability into account. In Part 1 the problem is defined and the proposed solution is explained. In Part 2 a limit theorem is given which confirms the legitimacy of the approximations employed.

1. THE STATEMENT OF THE PROBLEM

Let $\{X_n, n = 0,1,\ldots\}$ denote the trajectory of a controlled Markov chain with transition probabilities

$$p(i, j; z), \quad z \in \mathscr{Z}(i) \quad i, j \in I . \tag{1}$$

Here I is the finite state space of the chain, $\mathscr{Z}(i)$ the set of control parameter values in state I, $i \in I$. $\mathscr{Z}(i)$, $i \in I$, are assumed to be closed and bounded in R^s. $p(i, j; z)$ is the transition probability from state i into state j under control parameter value z. Further, let $c(i, j; z)$ denote the reward the controller gets from such transition. The functions

$$c(i, j; z), \quad z \in \mathscr{Z}(i), \quad i, j \in I ,$$

as well as the probabilities (1), are assumed to be continuous in z.

Let Z_n be the control parameter the controller selects after n steps. $\{Z_n, n = 0, 1, \ldots\}$ is thus a sequence of random variables depending on the past trajectory. Suppose that the controller posseses an initial capital C_0. His capital after M steps includes the reward from the chain, and equals therefore

$$C_M = C_0 + \sum_{m=0}^{M-1} c(X_m, X_{m+1}; Z_m), \quad M = 1, 2, \ldots$$

Introduce $R = \inf\{M : C_M \leqq 0\}$. If $R < \infty$, we say that the controller was ruined after R steps. To balance the change of being ruined and his aim to maximize the reward when selecting the control policy, the controller employs the criterion

$$E\{C_0 + \sum_{m=0}^{R-1} d^{m+1} c(X_m, X_{m+1}; Z_m) - N d^R\}, \tag{2}$$

where d is a discount factor, $0 \leqq d < 1$, and $N > 0$ is a penalty for the ruin

From the Markovian property it follows that after n steps, (X_n, C_n) contains sufficient information for controlling the chain in an optimal way according to criterion (2). The controller thus looks for a function

$$z(i, C), \quad i \in I, \quad C \in (0, \infty), \tag{3}$$

such that the expectation (2) is maximal for $Z_n = z(X_n, C_n)$, $n = 0, 1, \ldots, R - 1$.

Let Ω be the set of all functions $\omega \sim z(i)$ mapping $i \in I$ into $\mathscr{Z}(i)$. Ω is the set of stationary controls. (3) can be written as

$$\omega(C), \quad C \in (0, \infty). \tag{4}$$

To obtain a diffusion approximation for C_n, $n = 0, 1, \ldots,$ introduce the duration τ of one step in the chain. Thus, the controller's capital at time t equals

$$\mathscr{C}_t = C_{[t/\tau]} + \{t/\tau\} (C_{[t/\tau]+1} - C_{[t/\tau]}). \tag{5}$$

In (5), $[a]$ $\{a\}$ denote the integral part and the fractional part of a, respectively. Linear interpolation is used to make $\mathscr{C}_t$ continuous. Assume first that (4) defines a stationary control, i.e.

$$\omega(C) \equiv \omega \sim z(i), \quad C \in (0, \infty).$$

Then $\{X_n, n = 0, 1, \ldots\}$ is a homogeneous Markov chain with transition probabilities

$$\|p(i, j; z(i))\|_{i,j \in I}. \tag{6}$$

Thorought the paper we shall make the following hypothesis.

Assumption. For arbitrary $\omega \in \Omega$ the states which are recurrent with respect to the transition probability matrix (6) form only on irreducible set.

From the central limit theorem for Markov chains follows that C_n is asymptotically normally distributed $N(\Theta(\omega)\, n, \sigma^2(\omega) n)$ as $n \to \infty$. Denote $1/\sqrt{\tau} = k$. Let

$$(5') \qquad C_0 \approx k\,, \quad \Theta(\omega) \approx 1/k\,, \quad \sigma^2(\omega) \approx 1\,,$$

where k is fairly large. $\mathscr{C}_{t+\Delta} - \mathscr{C}_t$ will be approximately normal $N(\Theta(\omega)\, k^2 \Delta$, $\sigma^2(\omega)\, k^2 \Delta)$ for $k^2 \Delta$ large. Thus we expect that the evolution of $\mathscr{C}_t/k$ will be sufficiently closely described by the stochastic differential equation

$$(6') \qquad \mathrm{d}\gamma_t = \Theta(\omega)\, \mathrm{k}\, \mathrm{d}t + \sigma(\omega)\, \mathrm{d}W_t\,, \quad t \geqq 0\,,$$

where $\{W_t, t \geqq 0\}$, is a standartized Wiener process.

In Part 2 of the paper we give a limit theorem establishing the convergence of $\mathscr{C}_t/k$ to the solution of (6′) in the non-stationary case provided that $\omega(C)$ is continuous. ω in (6) then depends on $k\gamma_t$. To approximate the criterion, we set $d = \exp(-\lambda/k^2)$ and consider, instead of (2),

$$(7) \qquad E\left(\gamma_0 + \int_0^\zeta \mathrm{e}^{-\lambda t}\, \mathrm{d}\gamma_t - \nu\, \mathrm{e}^{-\lambda\zeta}\right) = E\left(\lambda \int_0^\zeta \mathrm{e}^{-\lambda t}\, (\gamma_t + \nu)\, \mathrm{d}t\right) - \nu\,.$$

where

$$\zeta = \inf\{t : \gamma_t \leqq 0\}\,, \quad \nu = N/k\,.$$

The original problem is thus converted into the problem of controlling the diffusion (6′) in such way that (7) is maximal. The following recipe can be found in the literature ([5], [7]). Solve

$$\max_{\omega \in \Omega}\left\{\tfrac{1}{2}\sigma^2(\omega)\, \frac{\mathrm{d}^2 v}{\mathrm{d}\gamma^2} + \Theta(\omega)\, k\, \frac{\mathrm{d}v}{\mathrm{d}\gamma}\right\} - \lambda v + \lambda(\gamma + \nu) = 0\,,$$

$$v(0) = 0\,, \quad v(\gamma) = O(\gamma) \quad \text{as} \quad \gamma \to \infty\,.$$

Let a control $\hat{\omega}(\gamma)$, $\gamma \in [0, \infty)$, be such that

$$\tfrac{1}{2}\sigma^2(\hat{\omega}(\gamma))\, \frac{\mathrm{d}^2 v(\gamma)}{\mathrm{d}\gamma^2} + \Theta(\hat{\omega}(\gamma))\, k\, \frac{\mathrm{d}v(\gamma)}{\mathrm{d}\nu} - \lambda v(\gamma) + \lambda(\gamma + \nu) = 0\,.$$

Then $\hat{\omega}(\gamma)$ is optimal.

If the conditions for the validity of the diffusion approximation (i.e. essentially the order relations (5′) and the continuity of $\hat{\omega}(\gamma)$) are fulfilled, then a choice of (4) which is nearly optimal with respect to the criterion (2) is given by

$$\omega(C) = \hat{\omega}(C/k)\,, \quad C \in [0, \infty)\,,$$

or

$$Z_n = \hat{z}(X_n, C_n/k)\,, \quad n = 0, 1 \ldots$$

Further, the maximal value of (2) is approximately $kv(C_0/k) - N$.

Finally let us mention that to determine $\Theta(\omega)$, $\sigma^2(\omega)$ for given $\omega \sim z(i)$ one has to solve

$$\sum_j p(i, j; z(i)) [c(i, j; z(i)) + w_j] - w_i - \Theta = 0, \quad i \in I, \tag{8}$$

and

$$\sum_j p(i, j; z(i)) [(c(i, j; z(i)) - \Theta)^2 + 2(c(i, j; z(i)) - \Theta) w_j + w_{2j}] - \\ - w_{2i} \sigma^2 - = 0, \quad i \in I, \tag{9}$$

for the unknowns Θ, w_i, $i \in I$, and σ^2, w_{2i}, $i \in I$, respectively [1], [6].

2. THE LIMIT THEOREM

Let the reward functions c depend on an auxiliary parameter $k = 1, 2, \ldots$, and denote them by

$$c(i, j; z, k), \quad z \in \mathscr{Z}(i), \quad i, j \in I, \quad k = 1, 2, \ldots$$

The functions c are assumed to be uniformly bounded. To each k there corresponds a controlled Markov chain with transition probabilities (1), as described in Section 1. To mark the dependence on the parameter, we shall add the index k to the symbols like X_n^k, C_n^k, Z_n^k etc.

Introduce

$$\sum_j p(i, j; z)\, c(i, j; z, k) = r_1(i, z; k), \quad z \in \mathscr{Z}(i), \quad i \in I, k = 1, \ldots,$$

$$\sum_j p(i, j; z)\, c(i, j; z, k)^2 = r_2(i, z; k), \quad z \in \mathscr{Z}(i), \quad i \in I, \quad k = 1, 2, \ldots.$$

Assume

$$\left.\begin{aligned} \lim_{k \to \infty} k r_1(i, z; k) &= \varrho_1(i, z) \\ \lim_{k \to \infty} k r_2(i, z; k) &= \varrho_2(i, z) \end{aligned}\right\} \text{uniformly in } z \in \mathscr{Z}(i), \quad i \in I. \tag{10}$$

Theorem. *Let, for $i \in I$, $z(i, \gamma)$ be a continuous mapping of $\gamma \in [0, \infty)$ into $\mathscr{Z}(i)$. Assume that $\{X_n^k, n = 0, 1, \ldots\}$, $k = 1, 2, \ldots$, is controlled by $Z_n^k = z(X_n^k, C_n^k/k)$, $n = 0, 1 \ldots$. Let $T > O$. Denote by $\mathscr{P}_T^k$ the probability distribution of*

$$\{\gamma_t^k = k^{-1}[C_{[tk^2]}^k + \{tk^2\} (C_{[tk^2]+1}^k - C_{[tk^2]}^k)], \quad t \in [0, T]\}$$

in the space γ of continuous functions on $[0, T]$.

If (10) holds, and $\lim_{k \to \infty} C_0^k/k = \bar{\gamma}$, then $\mathscr{P}_T^k$ as $k \to \infty$ converges weakly to the *probability distribution $\mathscr{P}_T$ of the Markov process $\{\gamma_t, t \in [0, T]\}$, satisfying the stochastic differential equation*

(11) $$d\gamma_t = \Theta(\gamma_t)\,dt + \sigma(\gamma_t)\,dW_t\,, \quad t \geqq 0\,; \quad \gamma_0 = \bar{\gamma}\,.$$

$\{W_t, t \geqq 0\}$ is a standartized Wiener process. $\Theta(\gamma)$ and $\sigma(\gamma)$ are obtained from the equations

$$\varrho_1(i, z(i, \gamma)) + \sum_j p(i, j; z(i, \gamma))\, w_j - w_i - \Theta = 0\,, \quad i \in I\,,$$

$$\varrho_2(i, z(i, \gamma)) + \sum_j p(i, j; z(i, \gamma))\, w_{2j} - w_{2i} - \sigma^2 = 0\,, \quad i \in I\,,$$

for the unknowns Θ, w_i, $i \in I$, σ^2, w_{2i}, $i \in I$.

The proof of the theorem uses the methods developed in [6], the tightness of probability measures ([2]), and Doob's Theorem 3.3 ([3]). The course of the proof will be outlined in the subsequent four paragraphs.

a) Solve

$$r_1(i, z(i, \gamma); k) + \sum_j p(i, j; z(i, \gamma))\, w_j^k(\gamma) - w_i^k(\gamma) - \Theta^k(\gamma) = 0\,, \quad i \in I\,,$$

$$\sum_j p(i, j; z(i, \gamma))\,[(c(i. j; z(i, \gamma), k) - \Theta^k(\gamma))^2 + 2w_j^k(\gamma)\,(c(i, j; z(i, \gamma), k) - \Theta^k(\gamma)) + $$
$$+ w_{2j}^k(\gamma)] - w_{2i}^k(\gamma) - \sigma_k^2(\gamma) = 0\,, \quad i \in I\,.$$

Introduce

(12) $$M_n^k = C_n^k - \sum_{m=0}^{n-1} \Theta^k(C_m^k/k) + \sum_{m=0}^{n-1} [w_{X_{m+1}}^k(C_m^k/k) - w_{X_m}^k(C_m^k/k)]$$

or

$$M_n^k = C_n^k - \sum_{m=0}^{n-1} \Theta(C_m^k/k) + \sum_{m=1}^{n-1} [w_{X_m}^k(C_{m-1}^k/k) - w_{X_m}^k(C_m^k/k)] +$$
$$+ w_{X_n}^k(C_{n-1}^k/k) - w_{X_0}^k(C_0^k/k)\,, \quad n = 1, 2, \ldots$$

Then $\{M_n^k, n = 1, 2, \ldots\}$ is a martingale with respect to $\{\mathscr{F}_n^k, n = 1, 2, \ldots\}$, where $\mathscr{F}_n^k$ denotes the Borel field of random events defined on $\{X_0^k, X_1^k, \ldots, X_n^k\}$.

Furthermore,

(13) $$E^k\{(M_{n+l}^k - M_n^k)^2\,|\mathscr{F}_n^k\} = E^k\{w_{2X_0}^k(C_n^k/k) - w_{2X_{n+l}}^k(C_{n+l-1}^k/k) +$$
$$+ \sum_{m=n+1}^{n+l-1} [w_{2X_m}^k(C_m^k/k) - w_{2X_m}^k(C_{m-1}^k/k)] + \sum_{m=n}^{n+l-1} \sigma_k^2(C_m^k/k)\,|\mathscr{F}_n^k\}\,,$$
$$n = 0, 1 \ldots\,, \quad l = 1, 2, \ldots$$

b) Set

$$\mu_t^k = k^{-1}[M_{[tk^2]}^k + \{tk^2\}\,(M_{[tk^2]+1}^k - M_{[tk^2]}^k)]\,, \quad t \in [0, T]\,.$$

Denote by $\mathcal{Q}_T^k$ the probability distribution of $\{\mu_t^k,\ t \in [0, T]\}$ on γ. The sequence $\{\mathcal{Q}_T^k,\ k = 1, 2, \ldots\}$ is tight. In fact, consider, for given $\varepsilon > 0$, the following limit

$$\lim_{\delta\to 0} \lim_{k\to\infty} P^k \{\sup_{|s-t|<\delta} |\mu_s^k - \mu_t^k| > \varepsilon\} .$$

It holds

$$P^k \left\{ \sup_{|s-t|<\delta} |\mu_s^k - \mu_t^k| > \varepsilon \right\} \leqq \sum_{l<T/\delta} P^k \left\{ \sup_{l\delta \leqq s \leqq (l+1)\delta} |\mu_s^k - \mu_{l\delta}^k| > \frac{\varepsilon}{4} \right\},$$

$$P^k \left\{ \sup_{l\delta \leqq s \leqq (l+1)\delta} |\mu_s^k - \mu_{l\delta}^k| > \frac{\varepsilon}{4} \right\} \leqq P^k \left\{ \max_{a_l \leqq r \leqq a_{l+1}} \left| \sum_{j=a_l+1}^{r} Y_j^k \right| > \frac{\varepsilon}{4} \right\} \leqq$$

$$\leqq \left(\frac{4}{k\varepsilon}\right)^4 E\left(\max_{a \leqq r \leqq a_{l+1}} \left| \sum_{j=a_l+1}^{r} Y_j^k \right| \right)^4 ,$$

where $a_l = [l\delta k^2]$.

To estimate the last term calculate

$$E\left(\sum_{j=a_l+1}^{a_{l+1}} Y_j^k\right)^4 = \sum_{a_l \leqq i,j,m,n \leqq a_{l+1}} E(Y_i^k Y_j^k Y_m^k Y_n^k) .$$

If the largest index is not matched by any other, then, by $E(Y_n^k | \mathcal{F}_{n-1}^k) = 0$, the term vanishes; hence

$$E\left(\sum_{j=a_l+1}^{a_{l+1}} Y_j^k\right)^4 = \sum_{m=a_l+1}^{a_{l+1}} E(Y_m^k)^4 + 4 \sum_{a_l \leqq i < m \leqq a_{l+1}} E\{Y_i^k (Y_m^k)^3\} +$$

$$+ 6 \sum_{m=2}^{[\delta k_2]} E\left\{\left(\sum_{j=a_l+1}^{a_l+m-1} Y_j^k\right)^2 (Y_{a_l+m}^k)^2\right\} \leqq \delta^2 k^4 \text{ const} .$$

From the martingale inequality (Doob's Theorem 3.4, p. 317).

$$E\{ \max_{a_l \leqq r \leqq a_{l+1}} |M_r^k - M_{a_l}^k|^\nu \} \leqq \left(\frac{\nu}{\nu - 1}\right)^4 E\{|M_{a_{l+1}}^k - M_{a_l}^k|^\nu\} ,$$

we get

$$E\{ \max_{a_l \leqq r \leqq a_{l+1}} \left(\sum_{j=a_l+1}^{r} Y_j^k \right)^4 \} \leqq (4/3)^4 k^4 \delta^2 \,.\, \text{const} .$$

Consequently,

$$P^k\{ \sup_{|s-t \leqq \delta} |\mu_s^k - \mu_t^k| > \varepsilon \} \leqq \left(\frac{4}{k\varepsilon}\right)^4 \left(\frac{4}{3}\right)^4 k^4 \delta^2 \,.\, \text{const} \frac{T}{\delta} = \text{const.}\ \delta .$$

We conclude that

$$\lim_{\delta\to 0} \lim_{k\to\infty} P^k\{ \sup_{|s-t| \leqq \delta} |\mu_s^k - \mu_t^k| > \varepsilon \} = 0 .$$

Furthermore, from (12), (10) follows

$$\mu_t^k = \gamma_t^k - \int_0^t \Theta^k(\gamma_u^k)\,\mathrm{d}u + \eta_t^k\,, \quad t \geqq 0\,, \tag{14}$$

where

$$\lim_{k\to\infty} P^k\{\sup_{0\leqq t\leqq T} |\eta_t^k| > \varepsilon\} = 0 \quad \text{for} \quad \varepsilon > 0\,. \tag{15}$$

Let $\overline{\mathscr{Q}}_T^k$ be the probability distribution of

$$\mu_s^k - \eta_t^k = \gamma_t^k - \int_0^t \Theta^k(\gamma_u^k)\,\mathrm{d}u\,.$$

We have

$$P^k\left\{\sup_{|s-t|<\delta} |\gamma_s^k - \gamma_t^k - \int_t^s |\Theta^k(\gamma_u^k)\,\mathrm{d}u| < \varepsilon\right\} \leqq$$

$$\leqq P^k\left\{\sup_{|s-t|<\delta} |\mu_s^k - \mu_t^k| > \frac{\varepsilon}{2}\right\} + P^k\left\{\sup_{|s-t|<\delta} |\eta_s^k - \eta_t^k| > \frac{\varepsilon}{2}\right\}.$$

By the above result and by (15) the right hand side converges to zero as $k \to \infty$, $\delta \to 0$. Thus, $\{\overline{\mathscr{Q}}_T^k, k = 1, 2, \ldots\}$ is tight. Similarly, from $P^k\{\sup_{|s-t|\leqq\delta} |\int_t^s \Theta(\gamma_u^k)\,\mathrm{d}u| > \varepsilon/_2\} \to 0$ as $\delta \to 0$, it follows that $\{\mathscr{P}_T^k, k = 1, 2, \ldots\}$ is tight.

c) From this we imply that there exist a subsequence $\{\mathscr{P}_T^{k_j}, j = 1, 2, \ldots\}$ of $\{\mathscr{P}_T^k, k = 1, 2, \ldots\}$, $\lim_{j\to\infty} k_j = \infty$, possesing the weak limit $\mathscr{P}_T$. Define

$$\mu_t = \gamma_t - \int_0^t \Theta(\gamma_u)\,\mathrm{d}u\,, \quad t \in [0, T]\,.$$

Then $\{\mu_t, t \in [0, T]\}$ is a martingale on $(\gamma, \mathscr{P}_T)$ with respect to $\{\Phi_t, t \in [0, T]\}$, where Φ_t denotes the Borel field of random events defined on $\{\gamma_s, s \in [0, t]\}$. From (13) trough a passage to the limit follows

$$\mathscr{E}_T\{(\mu_{t+h} - \mu_t)^2 \,|\Phi_t\} = \mathscr{E}_T\left\{\int_t^{t+h} \sigma^2(\gamma_s)\,\mathrm{d}s\,|\Phi_t\right\}, \quad 0 \leqq t < t + h \leqq T. \tag{17}$$

d) Using (17) and

$$\mathscr{E}_T\{(\gamma_{t+h} - \gamma_t)\,|\Phi_t\} = \mathscr{E}_T\left\{\int_t^{t+h} \Theta(\gamma_s)\,\mathrm{d}s\,|\Phi_t\right\}, \quad 0 \leqq t < t + h \leqq T,$$

the assumptions of Doob's Theorem 3.3 ([3] p. 287) are verified for $\{\gamma_t, t \in [0, T]\}$ on $(\gamma, \mathscr{P}_T)$. This shows that $\mathscr{P}_T$ is the probability distribution of a Markov process, satisfying (11). Such probability distribution is unique. Consequently, $\{\mathscr{P}_T^k, k = 1, 2, \ldots\}$ has only one accumulation point. This together with its tightness implies the assertion of the theorem.

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