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## SOME APPROXIMATIONS USED IN THE RISK PROCESS OF INSURANCE COMPANY


#### Abstract

In an insurance company, the risk process estimation and the estimation of the ruin probability are important concerns for an actuary: for researchers, at the theoretical level, and for the management of the company, as these influence the insurer strategy. We consider the evolution on an extended period of time of an insurer surplus process. In this paper, we present some processes of estimating of the ruin probability. We discuss the approximations of ruin probability with respect to the parameters of the individual claim distribution, with the load factor of premiums and with the intensity parameter of the number of claims process. We analyze the model where the premiums are computed on the basis of the mean value principle. We give numerical illustration.


Keywords: ruin probability, risk process, adjustment coefficient.
JEL Classification: C020, G220, G320

## 1. INTRODUCTION

The mathematical model of an insurance risk business is composed of the following objects:
a) A sequence $\left\{X_{i}\right\}_{i=1,2,3 \ldots}$ of independent and identically distributed random variables (i.i.d.r.v.), having the common distribution function $F . X_{i}$ is the cost of the $i^{\text {th }}$ individual claim.
b) A stochastic process $N=\{N(t) ; t \geq 0\} . N$ is the number of claims paid by the company in the time interval $[0, t]$. The counting process $N$ and the sequence $\left\{X_{i}\right\}$ are independent objects.

The total amount of claims paid by the company in the time interval $[0, t]$ is $D(t)=\sum_{i=1}^{N(t)} X_{i} \quad(\{D(t) ; t \geq 0\} \quad$ being the claim process $)$. The risk process $Y=\{Y(t) ; t \geq 0\}$ is defined by $Y(t)=c \cdot t-D(t)$, where $c$ is a positive real constant number corresponding to the average premium income per unit of time. We shall consider that the process $N$ is a homogeneous Poisson process with intensity $\lambda$ and that we will use the mean value principle in order to compute the net premiums, thus $c=(1+\theta) \cdot \lambda \cdot m_{1}$, where $\theta$ is the relative safety loading and $m_{1}$ is the expected value of the individual claim or the expected cost of a claim. We denote $m_{k}=E\left[X_{i}^{k}\right], k=1,2,3, \ldots$ We shall denote by $r$-initial capital, $C(t)$ - the capital of the company at moment $t$, hence $r=C(0)$ and $C(t)=r+Y(t)$. We define the ruin as being the situation when the capital of the company takes a negative value. The ruin moment $\tau$ is defined as $\tau=\inf \{t \geq 0 \mid C(t)<0\}$.
Let $h(r)=\int_{0}^{\infty}\left(e^{r \cdot x}-1\right) d F(x)$ and $g(\theta)=(1+\theta) \cdot \lambda \cdot m_{1}$.
We denote by $\Psi_{n}(r, \theta)$ the ruin probability up to moment $n$ and by $\Psi(r, \theta)$ the ruin probability on an infinite time horizon, so
$\Psi_{n}(r, \theta)=P(\tau<n \mid C(0)=r, g(\theta)=c)$,
$\Psi(r, \theta)=P(\tau<\infty \mid C(0)=r, g(\theta)=c)$ and $\Psi(r, \theta)=\lim _{n \rightarrow \infty} \Psi_{n}(r, \theta)$.
The adjustment coefficient (or Lundberg exponent) $R$ is the positive solution of the equation $\lambda \cdot h(r)-c \cdot r=0$.
A well-known result is that: if the adjustment coefficient $R$ exists, the ruin probability
is $\quad \Psi(r, \theta)=e^{-R \cdot r} \cdot\left(E\left[e^{R \cdot S(\tau)}\right]\right)^{-1}$,
where $S(\tau)=(-C(\tau) \mid \tau<\infty))$ represents the severity of the loss at the moment of ruin.
In case the individual claim follows an exponential distribution, $X_{i} \in \operatorname{Exp}(\alpha), \alpha>0$ then

$$
\begin{equation*}
\Psi(r, \theta)=\frac{\lambda}{\alpha \cdot g(\theta)} \cdot e^{-\left(\alpha-\frac{\lambda}{g(\theta)}\right) \cdot r} \tag{2}
\end{equation*}
$$

The integrated tail distribution is $F_{I}(z)=\frac{1}{m_{1}} \cdot \int_{0}^{2}(1-F(x)) d x$. It is known the Beekman's convolution (or Pollaczek-Khinchine) formula:

$$
\begin{equation*}
\Psi(r, \theta)=\frac{\theta}{1+\theta} \cdot \sum_{n=0}^{\infty}\left(\frac{1}{1+\theta}\right)^{n} \cdot \tilde{F}_{I}^{n^{*}}(r) \tag{3}
\end{equation*}
$$

where $\tilde{F}_{I}(r)=1-F_{I}(r)$. If $F$ is the cumulative distribution function for a exponential distributed loss, then $F_{I}=F$.

## 2. SOME APPROXIMATIONS OF RUIN PROBABILITY

De Vylder (1978) proposed the following approximation, which is based on the idea to replace the risk process $Y$ by a risk process $\tilde{Y}$ with exponential distributed claims such that $E\left[\tilde{Y}^{k}(t)\right]=E\left[Y^{k}(t)\right], k=1,2,3$. The risk process $\tilde{Y}$ is determined by the parameters $(\tilde{\lambda}, \tilde{\theta}, \tilde{\alpha})$. Since $\ln z=\ln r+i \cdot \theta$, where $z=r \cdot e^{i \cdot \theta}$, we have
$\ln E\left[e^{i \cdot \cdot \cdot Y(t)}\right]=t \cdot\left(i \cdot v \cdot \theta \cdot \lambda \cdot m_{1}-\frac{v^{2}}{2} \cdot \lambda \cdot m_{2}+i \cdot \frac{v^{3}}{3!} \cdot \lambda \cdot m_{3}+0\left(v^{3}\right)\right)$ and we get $\tilde{m}_{1}=\frac{1}{\tilde{\alpha}}=\frac{m_{3}}{3 \cdot m_{2}}, \tilde{\theta}=\frac{2}{3} \cdot \frac{m_{1} \cdot m_{3}}{m_{2}^{2}} \cdot \theta \quad$ and $\quad \tilde{\lambda}=\frac{9}{2} \cdot \frac{m_{2}^{3}}{m_{3}^{2}} \cdot \lambda$. Thus, we obtain the approximation

$$
\begin{equation*}
\Psi(r, \theta) \approx \Psi_{D V}(r, \tilde{\theta})=\frac{1}{1+\tilde{\theta}} \cdot e^{-\frac{\tilde{\theta} \cdot \tilde{\alpha}}{1+\tilde{\theta}} \cdot r} \tag{4}
\end{equation*}
$$

$$
\begin{equation*}
\Psi_{D V}(r, \theta)=\frac{3 \cdot m_{2}^{2}}{3 \cdot m_{2}^{2}+2 \cdot m_{1} \cdot m_{3} \cdot \theta} \cdot e^{-\frac{6 \cdot m_{1} \cdot m_{2} \cdot \theta \cdot r}{3 \cdot m_{2}^{2}+2 \cdot m_{1} m_{3} \cdot \theta}} \tag{5}
\end{equation*}
$$

If $X:\binom{n_{i}}{p_{i}}_{i \in I \subset \mathbf{N}}, p_{i}>0, \sum_{i \in I} p_{i}=1, \quad$ we introduce $\quad b_{i}=\frac{n_{i} \cdot p_{i}}{m_{1}}, a_{i}=\frac{n_{i}^{2} \cdot p_{i}}{m_{2}}$, $X^{\prime}:\binom{n_{i}}{a_{i}}_{i \in I}, \quad X^{\prime \prime}:\binom{n_{i}}{b_{i}}_{i \in I}$ and we obtain $\tilde{m}_{1}=\frac{1}{3} \cdot E\left(X^{\prime}\right), \tilde{\theta}=\frac{2}{3} \cdot \frac{E\left(X^{\prime}\right)}{E\left(X^{\prime \prime}\right)} \cdot \theta$, $\tilde{\lambda}=\frac{9}{2} \cdot \frac{E(X) \cdot E\left(X^{\prime \prime}\right)}{E\left(X^{\prime}\right)} \cdot \lambda$ and

$$
\begin{equation*}
\Psi_{D V}(r, \theta)=\frac{3 \cdot E\left(X^{\prime \prime}\right)}{3 \cdot E\left(X^{\prime \prime}\right)+2 \cdot E\left(X^{\prime}\right) \cdot \theta} \cdot e^{-\frac{6 \cdot \theta \cdot r}{3 \cdot E\left(X^{\prime \prime}\right)+2 \cdot E\left(X^{\prime}\right) \cdot \theta}} \tag{6}
\end{equation*}
$$

The most famous approximation is the Cramer-Lundberg approximation:

$$
\begin{equation*}
\Psi(r, \theta) \approx \Psi_{C L}(r, \theta)=\frac{\theta \cdot \lambda \cdot m_{1}}{\lambda \cdot h^{\prime}(R)-c} \cdot e^{-R \cdot r} \tag{7}
\end{equation*}
$$

Let $S E$ be the class of subexponential distribution, i.e. $F \in S E$ if $\lim _{x \rightarrow \infty} \frac{\tilde{F}^{2 *}(x)}{\tilde{F}(x)}=2$. It
is shown by Embrechts and Veroverbeke (1982), that, if $F_{I} \in S E$, then

$$
\begin{equation*}
\Psi(r, \theta)=\frac{1}{1+\theta} \cdot \tilde{F}_{I}(r) \tag{8}
\end{equation*}
$$

We showed that if $F_{I} \in S E$ then

$$
\begin{equation*}
\lim _{r \rightarrow \infty} \frac{\Psi(r, \theta)}{1-F_{I}(r)}=\frac{\lambda \cdot m_{1}}{g(\theta)-\lambda \cdot m_{1}} \tag{9}
\end{equation*}
$$

Another well known result is $\lim _{r \rightarrow \infty} \Psi(r, \theta) \cdot e^{R \cdot r}=C$, where
$C=\frac{\theta \cdot m_{1}}{R \cdot \int_{0}^{\infty} x \cdot e^{R \cdot x} \cdot \tilde{F}(x) d x}$ is Cramer constant and $R$ is Lundberg exponent.
For small $\theta$ we have $\frac{m_{1}}{m_{2}} \cdot \theta<R<2 \frac{m_{1}}{m_{2}} \cdot \theta$, so that we may have $R \approx \frac{3 m_{1}}{2 m_{2}} \cdot \theta$.
Let $H(r)=P\left(-\inf _{t \geq 0} Y(t) \leq r \mid-\inf _{t \geq 0} Y(t)>0\right)$.
We have $\Psi(r, \theta)=\frac{1}{1+\theta} \cdot(1-H(r)), \mu_{H}=\frac{(1+\theta) \cdot m_{2}}{2 \cdot \theta \cdot m_{1}}$ and $\sigma_{H}^{2}=\frac{(1+\theta) \cdot m_{2}}{2 \cdot \theta \cdot m_{1}}\left(\frac{2 m_{3}}{3 m_{2}}+\frac{(1-\theta) m_{2}}{2 \cdot \theta \cdot m_{1}}\right)$, where $\mu_{H}$ and $\sigma_{H}^{2}$ are the mean and the variance corresponding to $H$. The idea of Beekman-Bowers approximation is to replace $H(r)$ with a $\Gamma$-distribution function $G(r)$, such that the two first moments of $H$ and $G$ should match. It this way, it is obtained the approximation formula

$$
\begin{equation*}
\Psi(r, \theta) \approx \Psi_{\mathrm{BB}}(r, \theta)=\frac{1}{(1+\theta) \cdot \Gamma(a)} \int_{b r}^{\infty} x^{a-1} \cdot e^{-x} d x \tag{10}
\end{equation*}
$$

where $a=\frac{3(1+\theta) \cdot m_{2}^{2}}{3 m_{2}^{2}+\theta\left(4 m_{1} m_{3}-3 m_{2}^{2}\right)}$ and $b=\frac{6 m_{1} m_{2} \theta}{3 m_{2}^{2}+\theta\left(4 m_{1} m_{3}-3 m_{2}^{2}\right)}$.
In the case of exponentially distributed claims we have $a=1, b=\frac{\alpha \theta}{1+\theta}$ and $\Psi_{\mathrm{BB}}(r, \theta)=\frac{1}{1+\theta} \cdot e^{-\frac{\alpha \theta r}{1+\theta}}=\Psi(r, \theta)$.
The simplest approximation, which only depends on some moments of $F$, seems to be the diffusion approximation:

$$
\begin{equation*}
\Psi(r, \theta) \approx \Psi_{\mathrm{D}}(r, \theta)=e^{-2 \cdot \frac{m_{1}}{m_{2}} \cdot \theta \cdot r} \tag{11}
\end{equation*}
$$

As the Lundberg exponent $R$ is small for small values of $\theta$ we have $h(R)=m_{1} \cdot R+\frac{m_{2}}{2} \cdot R^{2}+o\left(R^{3}\right) \quad$ which leads to $R=2 \frac{m_{1}}{m_{2}} \cdot \theta+o\left(\theta^{2}\right) \quad$ and
$\Psi_{\mathrm{CL}}(r, \theta)=\frac{\theta \cdot \lambda \cdot m_{1}}{\lambda \cdot h^{\prime}(R)-c} \cdot e^{-R \cdot r}=\frac{1}{1+o\left(\theta^{2}\right)} \cdot e^{-2 \frac{m_{1}}{m_{2}} \cdot \theta \cdot r+o\left(\theta^{2}\right)}$.
Thus the diffusion approximation may be regarded as a simplified Cramer-Lundberg approximation. Since the diffusion approximation is not very accurate, Grandell (2000) proposed to use for $h(r)$ three moments. Thus $R=2 \frac{m_{1}}{m_{2}} \cdot \theta-\frac{4 m_{1}^{2} m_{3} \theta^{2}}{3 m_{2}^{3}}+o\left(\theta^{3}\right)$,

$$
\begin{align*}
& \frac{\theta \cdot \lambda \cdot m_{1}}{\lambda \cdot h^{\prime}(R)-c}=\frac{3 m_{2}^{2}}{3 m_{2}^{2}+2 m_{1} m_{3} \theta}+o\left(\theta^{2}\right) \quad \text { and } \\
& \Psi_{\mathrm{G}}(r, \theta)=\frac{3 m_{2}^{2}}{3 m_{2}^{2}+2 m_{1} m_{3} \theta} \cdot e^{-\left(2 \frac{m_{1}}{m_{2}} \cdot \theta-\frac{4 m_{1}^{2} m_{3} \theta^{2}}{3 m_{2}^{3}}\right) \cdot r} \tag{12}
\end{align*}
$$

Since $2 \frac{m_{1}}{m_{2}} \cdot \theta-\frac{4 m_{1}^{2} m_{3} \theta^{2}}{3 m_{2}^{3}}=\frac{6 m_{1} m_{2} \theta}{3 m_{2}^{2}+2 m_{1} m_{3} \theta}+o\left(\theta^{2}\right)$ the De Vylder approximation may be regarded as a simplified Grandell approximation.
Another approximation is obtained using Renyi's theorem about the $p$-thinning of the point process. Thus

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$$
\begin{equation*}
\Psi_{\mathrm{R}}(r, \theta)=\frac{1}{1+\theta} \cdot e^{-\frac{2 m_{1} \theta r}{m_{2} \cdot(1+\theta)}} \tag{13}
\end{equation*}
$$

Kalashnikov (1997) showed that $\sup _{r}\left|\Psi_{\mathrm{R}}(r, \theta)-\Psi(r, \theta)\right| \leq \frac{4 m_{1} m_{3} \theta}{3 m_{2}^{2}(1+\theta)}$ for all $\theta>0$.

## 3. NUMERICAL RESULTS AND CONCLUSIONS

In this section, our purpose is to compare the different approximations listed above, through a numerical example. We have to deal with the absolute error $(\delta)$ and the relative error $(\varepsilon)$. Thus, for approximation $\Psi_{\mathrm{A}}$ of $\Psi$ we have $\delta_{\mathrm{A}}(r, \theta)=\left|\Psi_{\mathrm{A}}(r, \theta)-\Psi(r, \theta)\right| \quad$ and $\quad \varepsilon_{\mathrm{A}}(r, \theta)=\frac{\delta_{\mathrm{A}}(r, \theta)}{\Psi(r, \theta)}$. In order to compare an approximation $\Psi_{\mathrm{A}}$ with another approximation $\Psi_{\mathrm{B}}$, we will use $\delta_{\mathrm{AB}}(r, \theta)=\left|\Psi_{\mathrm{A}}(r, \theta)-\Psi_{\mathrm{B}}(r, \theta)\right|$ and $\varepsilon_{\mathrm{AB}}(r, \theta)=\frac{\delta_{\mathrm{AB}}(r, \theta)}{\Psi_{\mathrm{A}}(r, \theta)}$.
Let $X:\left(\begin{array}{cc}1 & 5 \\ 0.875 & 0.125\end{array}\right)$ be a discrete random variable describing a claim (a loss) which takes the value of 1 monetary unit a high probability, and a relatively large value of 5 monetary units (in the case of a natural disaster, for example) with a relatively low probability. In the following, we list the approximations of ruin probability, ARP (see table 1-4). For graphic illustration (see figure 1-4) we compute $\operatorname{MARP}=10^{6} \cdot \mathrm{ARP}$, which is shown in figures.

ARP for $\theta=0.2$

| $r$ | $\Psi_{\text {DV }}$ | $\Psi_{\text {BB }}$ | $\Psi_{\mathrm{R}}$ | $\Psi_{\text {D }}$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.732078 | 0.733542 | 0.735414 | 0.860708 |
| 5 | 0.445179 | 0.444494 | 0.446051 | 0.472367 |
| 10 | 0.239060 | 0.238377 | 0.238754 | 0.223130 |
| 20 | 0.068937 | 0.068845 | 0.068480 | 0.049787 |
| 30 | 0.019879 | 0.019917 | 0.019598 | 0.011109 |
| 40 | 0.005732 | 0.005767 | 0.005615 | 0.002479 |
| 50 | 0.001653 | 0.001670 | 0.001609 | 0.000553 |



Figure 1

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Table 2
ARP for $\theta=0.3$

| $r$ | $\Psi_{\text {DV }}$ | $\Psi_{\text {BB }}$ | $\Psi_{\mathrm{R}}$ | $\Psi_{\mathrm{D}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.643143 | 0.644393 | 0.646979 | 0.798516 |
| 5 | 0.323441 | 0.322402 | 0.323761 | 0.324652 |
| 10 | 0.136979 | 0.136533 | 0.136268 | 0.105399 |
| 20 | 0.024568 | 0.024610 | 0.024140 | 0.011109 |
| 30 | 0.004406 | 0.004447 | 0.004276 | 0.001171 |
| 40 | 0.000790 | 0.000805 | 0.000758 | 0.000123 |
| 50 | 0.000142 | 0.000146 | 0.000134 | 0.000013 |



Figure 2

ARP for $\theta=0.5$

| $r$ | $\Psi_{\mathrm{DV}}$ | $\Psi_{\mathrm{BB}}$ | $\Psi_{\mathrm{R}}$ | $\Psi_{\mathrm{D}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.515174 | 0.516071 | 0.519201 | 0.687289 |
| 5 | 0.191486 | 0.190638 | 0.191003 | 0.153355 |
| 10 | 0.055573 | 0.055507 | 0.054723 | 0.023518 |
| 20 | 0.004681 | 0.004740 | 0.004492 | 0.000553 |
| 30 | 0.000394 | 0.000407 | 0.000369 | 0.000013 |
| 40 | 0.000033 | 0.000035 | 0.000030 | $0.3 \cdot 10^{-6}$ |
| 50 | 0.000003 | 0.000003 | 0.000002 | $0.7 \cdot 10^{-8}$ |



Figure 3

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Table 4
ARP for $\theta=0.8$

| $r$ | $\Psi_{\mathrm{DV}}$ | $\Psi_{\mathrm{BB}}$ | $\Psi_{\mathrm{R}}$ | $\Psi_{\mathrm{D}}$ |
| :--- | :--- | :--- | :--- | :--- |
| 1 | 0.394417 | 0.394444 | 0.398073 | 0.548812 |
| 5 | 0.105883 | 0.105335 | 0.104931 | 0.049787 |
| 10 | 0.020461 | 0.020516 | 0.019819 | 0.002479 |
| 20 | 0.000764 | 0.000789 | 0.000707 | 0.000006 |
| 30 | 0.000029 | 0.000030 | 0.000025 | $0.15 \cdot 10^{-7}$ |
| 40 | 0.000001 | 0.000001 | $0.9 \cdot 10^{-6}$ | $0.38 \cdot 10^{-10}$ |
| 50 | $0.4 \cdot 10^{-7}$ | $0.5 \cdot 10^{-7}$ | $0.3 \cdot 10^{-7}$ | $0.9 \cdot 10^{-13}$ |

MARP for $\theta=0.8$


Figure 4
As we illustrate relative error (see tables 5-6) we compute $\operatorname{MERR} 1=10^{5} \cdot \varepsilon_{D V, B B}$, $\operatorname{MERR} 2=10^{5} \cdot \varepsilon_{D V, R}$ and MERR3 $=10^{5} \cdot \varepsilon_{D V, D}$ which are shown in figures 5-6.

Table 5
$\varepsilon_{\mathrm{DV},}$, for $\theta=0.3$

| $r$ | $\varepsilon_{\mathrm{DV}, \mathrm{BB}}$ | $\varepsilon_{\mathrm{DV}, \mathrm{R}}$ | $\varepsilon_{\mathrm{DV}, \mathrm{D}}$ |
| :---: | :---: | :---: | :---: |
| 1 | 0.00194 | 0.00596 | 0.24158 |
| 5 | 0.00321 | 0.00099 | 0.00374 |
| 10 | 0.00326 | 0.00519 | 0.23055 |
| 20 | 0.00171 | 0.01742 | 0.54783 |
| 30 | 0.00931 | 0.02951 | 0.73423 |
| 40 | 0.01899 | 0.04051 | 0.84430 |
| 50 | 0.02817 | 0.05634 | 0.90845 |



Figure 5

Table 6

| $\varepsilon_{\mathrm{DV},}$, for $\theta=0.5$ |  |  |  |
| :--- | :--- | :---: | :---: |
| $r$ | $\varepsilon_{\mathrm{DV}, \mathrm{BB}}$ | $\varepsilon_{\mathrm{DV}, \mathrm{R}}$ | $\varepsilon_{\mathrm{DV}, \mathrm{D}}$ |
| 1 | 0.00174 | 0.00782 | 0.33409 |
| 5 | 0.00443 | 0.00252 | 0.19913 |
| 10 | 0.00119 | 0.01529 | 0.57681 |
| 20 | 0.01260 | 0.04038 | 0.88186 |
| 30 | 0.03299 | 0.06345 | 0.96700 |
| 40 | 0.06061 | 0.09090 | 0.99091 |
| 50 | 0.03682 | 0.17200 | 0.99767 |



Figure 6

We consider that the approximations $\Psi_{\mathrm{DV}}, \Psi_{\mathrm{BB}}$ and $\Psi_{\mathrm{R}}$ are better. They are maxim absolute errors up to 0.0015 for $\theta=0.2$, up to 0.0013 for $\theta=0.3$, up to 0.0009 for $\theta=0.5$ and maxim relative errors up to $2.7 \%$ for $\theta=0.2$, up to $5.5 \%$ for $\theta=0.3$ etc. We observe that the relative errors increase when initial capital increases while the
ruin probability decreases. The diffusion approximation is not very accurate because its relative errors are very high, up to $99 \%$ if $\theta=0.5$. For the repartition of claim, which we used there are no exact ruin probabilities available.

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