Scenario Analysis Approach for Operational Risk in Insurance Companies
Analýza scénářů operačního rizika v pojišťovnách

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Abstract
The article deals with the possibility of calculating the required capital in insurance companies allocated to operational risk under Solvency II regulation and the aim of this article is to come up with model that can be use in insurance companies for calculating operational risk required capital. In the article were discussed and compared the frequency and severity distributions where was chosen Poisson for frequency and Lognormal for severity. For the calculation, was used only the real scenario and data from small CEE insurance company to see the effect of the three main parameters (typical impact, Worst case impact and frequency) needed for building the model for calculation 99,5% VaR by using Monte Carlo simulation. Article comes up with parameter sensitivity and/or ratio sensitivity on calculating capital. From the database arose two conclusions related to sensitivity where the first is that the impact of frequency is much higher in the interval (0;1) than above the interval to calculated capital and second conclusion is Worst case and Typical Case ratio, where we saw that if the ratio is around 150 or higher the calculated capital is increasing faster that the ration increase demonstrated on the scenario calculation.

Keywords
operational risk, insurance, scenario analysis, distribution, sensitivity

JEL Classification
C150, G320, C100

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Abstrakt
Článek se zabývá možností výpočtu požadovaného regulatorního kapitálu v pojišťovnách pro operační riziko podle nařízení Solventnost II. Cílem tohoto článku je přijít s modelem, který lze v pojišťovnách použít pro výpočet kapitálu alokovaného pro operační riziko. V článku byla diskutována a porovnána rozdělení četnosti a dopadu, kde bylo zvoleno Poissonovo rozdělení pro frekvenci a Lognormální rozdělení pro dopad. Výpočet se zakládá na reálném scénáři a datech z malé pojišťovny ze střední a východní Evropy, aby bylo možné pozorovat vliv tří hlavních parametrů (typického dopadu, nejhoršího možného dopadu a frekvence), které jsou potřebné pro sestavení modelu pro výpočet na hladině 99,5 % VaR pomocí simulace Monte Carlo. Článek přichází s analýzou citlivosti parametrů a / nebo poměrovou citlivostí při výpočtu kapitálu. Z databáze vznikly dva závěry týkající

se citlivosti. Dle prvního závěru je dopad frekvence v intervalu (0; 1) mnohem vyšší než nad intervalem pro vypočtený kapitál. Jako druhý závěr lze vypozorovat, že pokud je poměr mezi nejhorším možným případem a typickým případem okolo 150 nebo vyšší, vypočtený kapitál roste rychleji než poměrový ukazatel při výpočtu scénáře.

Klíčová slova
operační riziko, pojištění, analýza scénářů, rozdělení, citlivost

Introduction

Scenario analysis the recurring process of obtaining expert opinion with own operational event recorded in company/group to identify and evaluate major potential Operational risk events and assess their potential impacts, ensuring a forward-looking risk point of view (Rippel and Teplý, 2008). From a measurement perspective Scenario Analysis provides a forward-looking cross-functional assessment of the potential size and likelihood of acceptable operational losses or events and delivers the proper inputs for Operational Risk capital requirement calculation by using the Internal Model. On the other hand from a management perspective Scenario Analysis, may start or drive the process of identification Operational risks which are existing currently or may potentially appear with impact to company and control weaknesses, with the purpose of defining and addressing the risk prevention and their mitigation techniques or strategies. Scenario analysis in banking industry as a calculating method was mentioned or used in Arai (2006), Mulvey and Erkan (2003), Rosengren (2006) or Dutta (2014) where scenarios had two important elements: Evaluation of future possibilities and Present knowledge and Dutta (2014) did not put such emphasis on historical data. Aim of this paper is come up with model based on three parameters which can be derive from historical data or collected from experts from insurance companies (expert judgement) during meetings and come with issues that can arise during parameters collection.

1 Data and Methodology

As opposed to banks, insurance companies do not have such a large database of operational risk events because they started to deal with the risks later on. For this reason, there is a problem with the data used for both scenario creation and scenario parameters to calculate the capital required. For this reason, it is clear that only data from our own experience can not be used and it is necessary to resort more to market data and expert judgments.

Figure 1: Data Sources

		Type of Sources	
		External	**Internal**
Time View	**Forward–Looking**	– use consultance	– use previous operational risk assessments (if they are foreward–looking) – use strategic planning from senior management or parent company
	Historical	– use operational risk database from the world – buy database from another company or broker	– use international loss data database – work with key risk indicators – use audit findings – use parent company database

Source: Author

The problem may arise, in particular, in the use of external resources, because the business and overall set-up or risk appetite of one insurer is not always the same as others, therefore it may threaten other risks, even in the group may be different risk perception between mother and subsidiary company. This raises another problem with using external databases. Different states face different risks with different impacts, which need to be further considered and treated with caution. Last but not least, it is necessary to correctly adjust the weights between the above four quadrants for appropriate setting.

2 Parameter selection

It is needed to define two parameters for severity calibration. First is typical impact and second is Worst case. To obtain Typical case as a severity distribution parameter the parameter has to be matched with a central tendency measure. Common statistics tendencies are mode (most frequent loss), median (loss amount which separates losses to two halves and expected value (mean, the probability-weighted average of all losses). The main problem with using mode as parameter is in the skewed distribution because the mode is matched with small negligible losses and the difference between mode and expected value can be really significant and this difference becomes larger when the frequency is increasing. Median has to deal with significant issue when the distribution is not symmetric and when number of losses is quite low the explanatory value is poor. On the other hand expected value is commonly use in statistics and can deal with problem right skewed distribution. All three parameters have problem with Worst Case represents the worst possible economic impact arises from an operational risk occurrence. The event should be considered as an extreme but still realistic scenario on the basis of internal controls system, environmental factors (because of lack of big operational risk losses).

Frequency is defined as annual expected number of loss and is the only one parameter for calculation.

3 Severity distribution

The sub-exponential distributions have tails that are descending slower than the exponential distribution (meaning a fatter tail). A fat tailed distribution guarantees a relevant (higher) level of conservatism and captures the tail behavior of the operational losses (low frequency but high impact).

3.1 Lognormal distribution

Lognormal is a continuous distribution, defined on R^+, and identified by two parameters, a scale parameter μ and a shape parameter σ.

3.2 Weilbull distribution

Weibull is a continuous distribution, defined on R^+, and identified by two parameters, a shape parameter k and a scale parameter λ, that are non-negative. This distribution is sub-exponential only if the shape parameter is lower than 1.

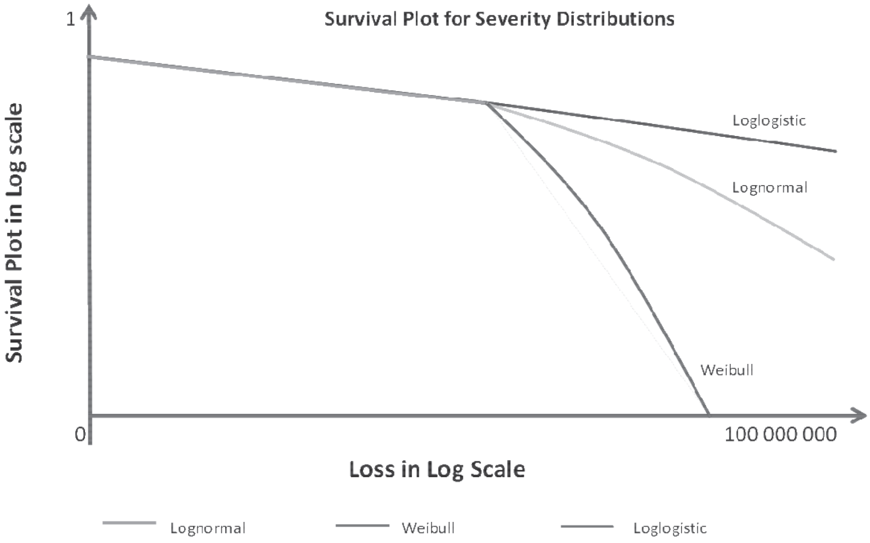
3.3 Log logistic distribution

Log-logistic is a continuous distribution, defined on R^+, identified by two parameters, α is the scale parameter and β is the shape parameter. Distribution is always sub-exponential.

3.4 Severity distribution quantitative analysis

The main difference between the distributions described above is the (long) tail behavior. Pretty useful graphical tool for analyzing the (long) tail behavior is the survival plot (1-F(x)). The survival plot you can see below shows the tail behavior of the three mentioned distributions calibrated with the same set of inputs. Weibull distribution presents the fastest tail decay, while the Log-logistic presents the slowest tail decay: given the same Worst Case the extreme values drawn by the Loglogistic are higher than the extreme value drawn from Lognormal, and the extreme values drawn from Lognormal are higher than the extreme value drawn from Weibull.

Figure 2: Survival Plot for Severity Distributions



Source: Author

Because of lack of data in database especially in the long tail the selected distribution we can not use a goodness of fit test approach. According to the lack of data will be impossible to select certain distribution that will provide us a conservative figure for each scenario.

3.5 Distribution comparison

Related to lack of enough big dataset we do not truncate the distribution because it is impossible to detect the certain breaking point. So we decided to apply the one only distribution same as authors in the banking industry Shevchenko & Peter (2013), Gatzert & Kobl (2014), Frachot, Georges and Roncalli (2001) or Chernobai (2007) because there is a lack of literature related to insurance industry.

The lognormal distribution seems to be the most appropriate distribution to model the severity from the following points:

- The Lognormal distribution allows to apply a prudential approach in line with industry standards
- It has only two parameters (mu and sigma) as compare to other distributions where there are three variables
- Several studies show that the lognormal is a good choice to model the operational risk losses. The literature shows how the Log-Normal is a common distribution used to analyze the Operational risk. In their analysis, Dutta and Perry (2006) came up with conclusion that Log-Normal distribution produces reasonable capital estimates for many business lines. In additional the Log-Normal performance

is less complicated with similar results compared with distributions that have 3 or 4 parameters as mentioned above. Even Basel Committee used the Log-Normal Distribution to fit the results from 2008 Loss Data Collection Exercise for Operational Risk purposes. Basel Committee also confirms that the Log-Normal distribution is used by banks frequently for various purposes, and that it tends to fit actual loss data well. Cruz (2015), stated that the Log-Normal often give a good fit for Operational risk losses. Log-Normal distribution is the common distribution used to model the severity in Chernobai et al. (2007).

- Survival plot shows that it is not possible to select a priori distribution that is conservative for each scenario due to their diversity. However, since the Log-normal tail behavior is intermediate (between high and low tail heaviness). Log-Normal distribution is more optimal compared with other sub-exponential distribution because the probability of high VaR deviation from probably real distribution is minimized.

4 Frequency Distribution Selection

Frequency represents the average number of operational risk losses events whose occurrence is expected within a on-year time horizon and taking into account experience of internal resources, skills, business complexity and exposure to environmental factors.

Frequency distribution provides information about number of operational losses occurrence in certain time period. The distribution is modelled by using a discrete distribution therefore the number of occurrence has to be integer. The frequency of random events can be likened to a discrete random variable where the number of possible observations finite or countable. The most common statistical distributions used in operational risk models are Binomial, Poisson and Negative Binomial distribution.

4.1 Binomial distribution

Binominal distribution is represented by Bi(n,p) and id a discrete distribution which can be applied to the frequency's model part for operational losses in a given interval with n events that has only two outcomes: failure and success with probabilities 1-p and p, respectively (Dyer, G., 2003).

The binomial distribution can better fit for modeling count data where the variance is less than the mean (Cruz, M, 2002). One major reversal in using the binomial distribution to model frequency of operational losses is the assumption of the number of trials (n) in the calculation (Ross, 2002). This may be the reason why this distribution is not widely used (Klugman, 2004) because the n is unknown. More so, when n is large and p is small, the binomial distribution can be approximated by a Poisson distribution.

4.2 Poisson distribution

Poisson distribution can be used to model for number of such arrivals that occur in a defined fixed period of time. In operational risk, Poisson process can help in modeling the frequency of operational losses that is a pre-requisite in estimating the regulatory operational VaR. The Poisson distribution is one of the most popular and common used frequency estimation because of its simplicity of use (Cruz, 2002). Poisson distribution was used also for operational risk modelling for LDA (Gatzert, 2014).

The most simplistic and attractive property of the Poisson distribution is that only the only one parameter lambda is needed to identify both the scale and shape of the distribution. To fit a Poisson distribution the only one step needed is to estimate the mean number of events in a defined time interval. This distribution is particularly used when the mean number of operational losses is sort of constant over time.

Another property is that the sum of n Poisson distribution with parameters λ1, λ2,…λn follows a Poisson distribution with parameters λ1+λ2+…+ λn.

4.3 Negative binomial distribution

The negative binomial distribution is a discrete probability distribution of the number of successes in a sequence of independent and identically distributed Bernoulli trials before a specified (non-random) number of failures (denoted r) occur. In operational risk terminology, the number of failures (n) until a fixed number of successes (r) can comprise the number of days (n) that elapsed before a fixed number of operational losses (r) was observed.

The negative binomial distribution is probably the most popular distribution in operational risk after the Poisson (Cruz, G, 2002) because of it's two parameters and the additional parameter offers greater flexibility in the shape of its distribution. This two-parameter property releases the assumption of a constant rate of loss occurrence in over time assumed by the Poisson. Variance is greater than the mean is another assumption of the negative binomial distribution.

From information above can be seen that the negative binomial distribution is a special generalized case of the Poisson distribution where the intensity rate λ is no longer constant but can follow a Gamma distribution with a transformed λ = m, k (where m = mean, while k is a measure of dispersion of such distribution). This implies that λ has now been split into two parameters to consider the inherent dispersion in the data set which is a place to refine.

4.4 Frequency conclusion

Parameter sigma (shape) has impact calculating VaR in comparison to parameter mu. When the sigma is increasing the difference between Negative Binominal and Poisson has decrease behaviour because if sigma increases the severity distribution tail becomes more flat. The Negative Binominal distribution is more conservative in comparison to Poisson distribution but only when the frequency is very low and the severity tail is light, than the difference is only material. Low sigma and low frequency are connected to scenarios with the smallest VaR value and their impact is relatively negligible, so the choice of the distribution has a minimum impact on the overall results.

The other main advantages for choosing Poisson distribution compared to other distributions are:

- Easy to calibrate: Poisson is identified by only one parameter (λ)
- Easy to interpret: the λ parameter is interpretable as the average annual frequency
- Endorsed by literature: use of Poisson for modeling the frequency is often reported in literature (Bening & Korolev, 2002; Grandell, 1997; Ross, 2002 and Dutta & Babbel, 2014)

5 Aggregated Loss Distribution

We have decided to use frequency calculated for one year and the probability distribution function of the single event severity impact for each risk scenario as under the Loss Distribution Approach (LDA). LDA is commonly use in banks compared to insurance companies not just because of not enough large databases. Usage of LDA deals with issue that random observation from the severity distribution can be calculated by either Fourier or Laplace transforms as suggested in Klugman et al. (2004) and used in Dutta & Babbel (2014) by Monte Carlo simulation as they used for banks. We assume implicitly that the random variables and number of events are both independently distributed same as in Dutta & Babbel (2014) as they used for banks. We can find LDA approach in Frachot, Antoine and Georges and Roncalli (2001), Schevchenko & Peters (2013) or Wang et al. (2017). Operationally a single random value of the aggregated loss distribution can be obtained using extract a random observation (n) from the Poisson distribution defined by λ for frequency and extract (n) random and independent observations from Lognormal distribution defined by the μ and δ parameters for severity purposes and we assume that Worst case happens one time every 100 events. Then we obtain the random observation (i) from aggregated loss distribution as a sum of the (n) random values extracted in frequency and severity step. For computing the aggregated loss distribution we decided to use Monte Carlo calculated on a 99.5% quantile according to Solvency II purposes. Lognormal distribution and Poisson are chosen because of possible usage in insurance sector where as mentioned above is a lack of historical data and scenario analysis has to be build up more on expert judgements. That could be serious issue to obtain more detailed parameters than typical case represented by expected value and Worst case so it is necessary to use simpler approach.

6 Scenario analysis – Internal fraud

In the tables below you can find stress tests of frequency, typical case (represented by expected value) and worst case. Scenario analysis represented Internal fraud where the Typical case is 27 000 EUR, WC was estimated by expert judgement to value 359 000 and the annual frequency is 16.

Table 1: Sensitivity Results (Frequency)

Frequency	Typical Impact (Severity)	Worst Case (Severity)	VaR 99.5%
0.01	27,000	359,000	15,515
0.05	27,000	359,000	87,763
0.10	27,000	359,000	144,890
0.25	27,000	359,000	259,963
0.50	27,000	359,000	372,527
0.75	27,000	359,000	464,011
1	27,000	359,000	565,189
5	27,000	359,000	1,253,474
10	27,000	359,000	1,264,194
16	27,000	359,000	1,442,142
25	27,000	359,000	1,773,186
50	27,000	359,000	2,659,061
75	27,000	359,000	3,555,068
100	27,000	359,000	4,410,375
200	27,000	359,000	7,741,911

Source: Insurance company database + authorial computation

Table 2: Sensitivity Results (Typical Impact)

Frequency	Typical Impact (Severity)	Worst Case (Severity)	VaR 99.5%
16	1,000	359,000	2,816,705
16	1,500	359,000	2,247,802
16	1,750	359,000	2,116,856
16	2,000	359,000	2,024,425
16	2,500	359,000	1,872,702
16	3,000	359,000	1,799,234
16	5,000	359,000	1,539,391
16	7,500	359,000	1,394,534
16	10,000	359,000	1,364,785

16	20,000	359,000	1,356,525
16	27,000	359,000	1,444,485
16	50,000	359,000	1,879,699
16	100,000	359,000	3,060,741

Source: Insurance company database + authorial computation

Table 3: Sensitivity Results (Worst Case)

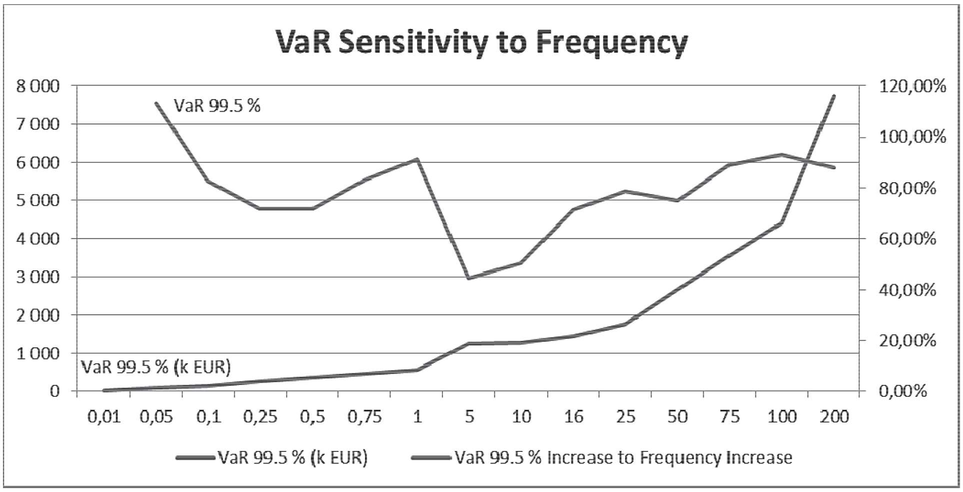
Frequency	Typical Impact (Severity)	Worst Case (Severity)	VaR 99.5%
16	27,000	50,000	754,116
16	27,000	75,000	789,536
16	27,000	100,000	828,504
16	27,000	150,000	926,774
16	27,000	250,000	1,148,618
16	27,000	359,000	1,450,015
16	27,000	500,000	1,896,440
16	27,000	1,000,000	3,787,161
16	27,000	1,500,000	6,058,194
16	27,000	2,000,000	8,504,698
16	27,000	3,500,000	18,479,688
16	27,000	5,000,000	28,464,726
16	27,000	6,500,000	41,588,647

Source: Insurance company database + authorial computation

7 Conclusion

In this paper we develop model for calculating operational risk on VaR 99.5% as required from Solvency II directive. This model is based on the selection of Poisson distribution for frequency with the only one parameter lambda, which is representing the annual loss occurrence and the selection of Lognormal distribution for severity purposes where we use two parameters (typical case and Worst case). The biggest advantage of this developed model is that every scenario can be calculated by using just three parameters and the parameters cannot be based just on historical losses from database but can reflect the forward-looking scenario nature. On the other hand could be challenge or issue to keep the expert judgment in proper way and avoid possible biases.

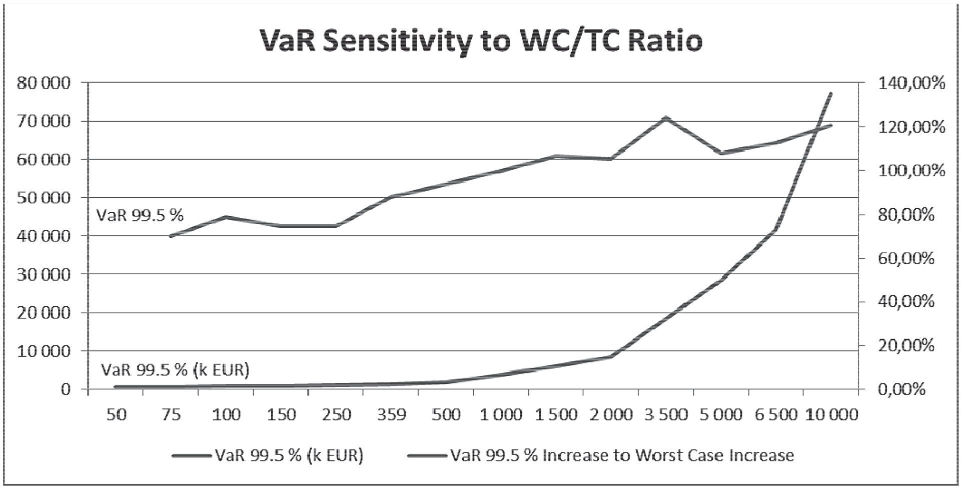
Figure 3: VaR Sensitivity to Frequency



Source: Author

The Figure 1 shows that the frequency parameter λ has a higher sensitivity and/or impact on the calculated capital at VaR 99.5% in interval (0;1) and then above 25 loss events per year. We have proved that this method fits to operational risk because of the typical losses, which the company worried about, are happening less than one per year and choosing Poisson distribution for this scenario example is correlating to Bening & Korolev (2002), Grandell (1997), Ross (2002) and Dutta & Babbel (2014).

Figure 4: VaR Sensitivity to Worst Case and Typical Case Ratio



Source: Author

As a further interest in the calculations, the ratio between the Worst case scenario and the typical case scenario arose with focus on VaR sensitivity. From the chart above is obvious that if the typical case is stable (27 k EUR) and Worst case is increasing, the VaR sensitivity is ascending related to Worst case to Typical ratio. Except few point the curve VaR sensitivity is slightly increasing the whole time.

Although the typical case is, for example, lower than another typical case, the final amount of capital required may be higher due to the large ratio between the Worst case and the typical case. As we can see from the calculated results above, the typical case is the capital driver when the difference between typical case and Worst case in not that high and the values are close to each other.

After computing all operational risk scenarios we will come across a series of correlations between them. Most of the correlation between the categories of operational risk or operational risk scenarios, which may not always accurately replicate the structure, will be based on expert estimates due to a lack of data. The correlation between categories or scenarios cannot be measured every day, as is the case with market risk, and it is therefore very important to set up correct correlations, which will probably have a major impact on the final amount of capital required to meet the operational risk requirements.

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