EXTRA-LARGE CLAIMS ESTIMATE SENSITIVITY BASED ON THE LOSS TABLE ASSUMPTIONS

Michal Kuban

Abstract

Reinsurance is very important product for insurance companies. It allows to transfer the risky part of the portfolio, which the insurance company does not like to have. To be able to set the reinsurance cover parameters, it is necessary to estimate the volume of future losses. The so-called loss-tables are generally used for this purpose. We will show different methods to calculate the loss-tables and its impact to estimate the reinsurance premium in this article.

Keywords: *Insurance, Reinsurance, Loss Table, Stochastic model, Extra-large claims*

1 INTRODUCION

Insurance companies tries to avoid big financial risks, which are natural in their business. One of these threats are the extra-large claims. In is in fact difficult to have the explicit definition of extra-large claims. Interesting article about this topic is in [2]. Basic explanation is that the extra-large claim overreaches the company managements risk appetite (which is usually the part of the internal regulation). Its severity can differ for each portfolio.

The very effective way, how to protect against these treats, is reinsurance. The reinsurance is the product, which allows overstocking the portfolios risky part for the fixed price. On the other hand, it is also very expensive. Because of that, insurance companies are trying to estimate the future potential losses. Based on that, it is possible to compare the reinsurance premium with the expectations.

There are several ways, how to estimate the future potential losses. We are focusing to the loss-table problematic in this article.

2 LOSS TABLE

We will describe, what the loss table actually is, in this chapter. The methodology, how to use the loss table, is also mentioned here.

2.1 Description

We can imagine the matrix of future potential losses under the term loss-table. Each row in the matrix represents one loss scenario (in our case it means claims over one years). Each column represents the claim. It should be noted, that the number of claims varies over simulations. Hence, some values are equal to zero. The column dimension of the matrix is every time equal to maximal number of expected claims over all simulations.

The row dimension of the matrix is optional and represents the number of simulations used. We should consider the computation time and the memory utilization, while choosing this number. The higher number of simulations means results, which are more precious and less sensitive to random numbers. On the other hand, computation time and memory usage is higher.

In this article we decided to use 100 000 stochastic scenarios. This number provides stable enough results balanced by satisfactory computing time.

2.2 Historical losses

To be able to create the loss table, the insurance company needs to have its historical losses, or be able to simulate the history using equalities in portfolio or similar company. It is also desirable to adjust the historical losses. For example, the very old claim have to be increased due to inflation. The frequency of claims has to be adjusted in case the portfolio size significantly changes. Any factor can also change during the time because of changing regulation or social environment.

There are many possibilities, how to improve historical claims to better fit the future. These methods are out of scope of this article. We will assume, that our base data are adjusted as good as possible.

3 MODEL

There are several possibilities, how to construct the loss table. In this chapter are shortly described the most common approaches.

3.1 Frequency

The claims frequency is usually estimated based on adjusted data using any of bellow noted discreet probability distribution. The most common are:

- Poisson distribution,
- Binomial distribution,
- Negative binomial distribution.

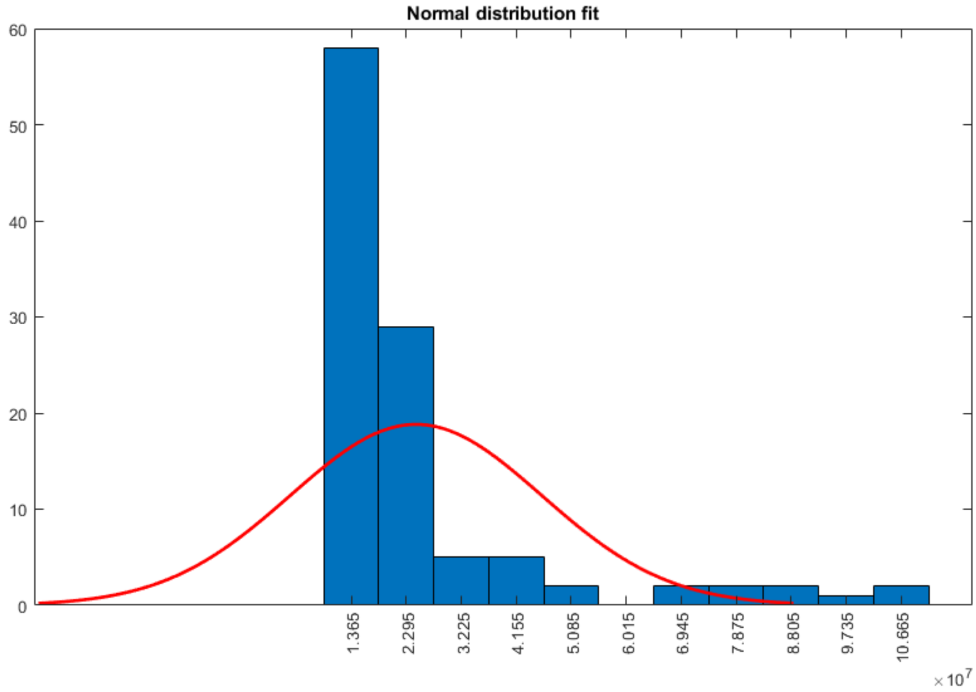
In this paper, the Poisson distribution is used for estimate the frequency.

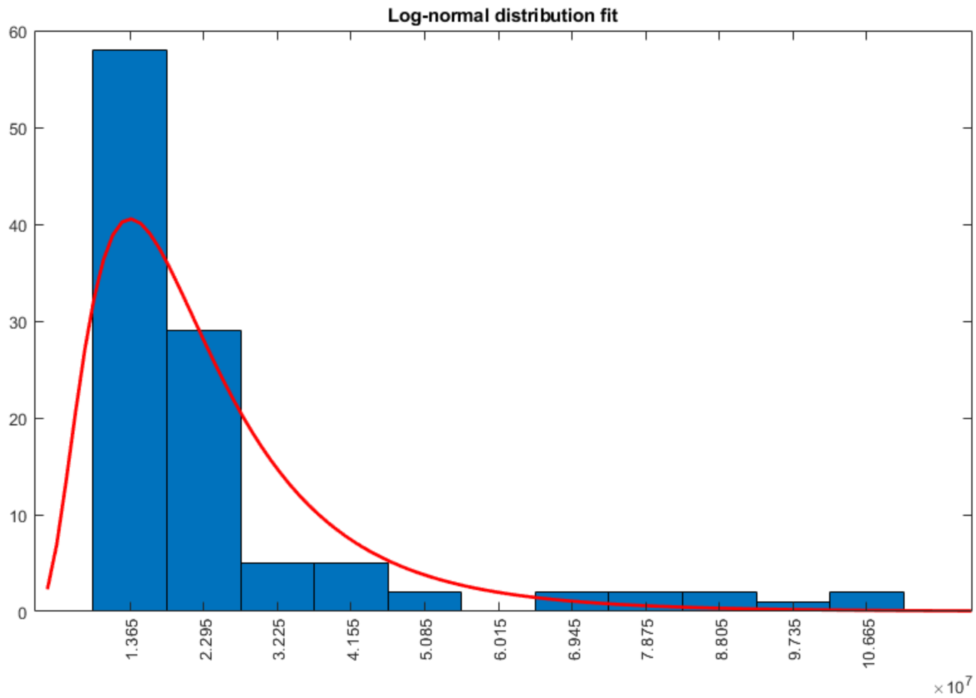
3.2 Severity

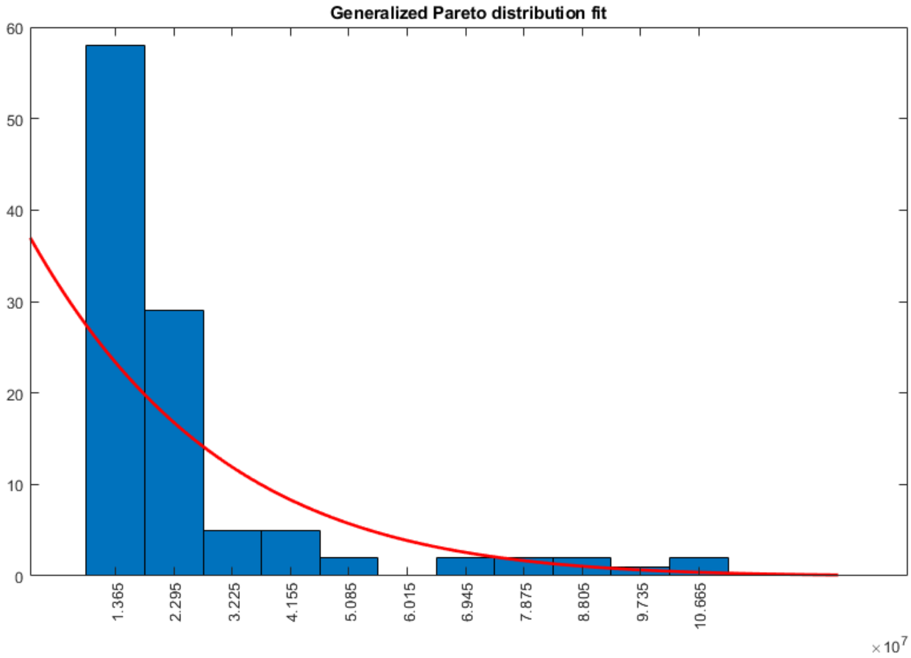
Comparing to frequency, there are much more possibilities, how to estimate the claims severity. In this paper, we decided to compare four different approaches. The adjusted historical claims are estimated using:

- Normal distribution,
- Log-normal distribution,
- Generalized Pareto distribution,
- Random select from adjusted historical claims (following named as Monte Carlo).

The graphical representation of the distribution fitting is bellow:


Normal distribution fit
60
50
40
30
20
10
0
1.365
2.295
3.225
4.155
5.085
6.015
6.945
7.875
8.805
9.735
10.665
×10^7


Log-normal distribution fit
60
50
40
30
20
10
0
1.365
2.295
3.225
4.155
5.085
6.015
6.945
7.875
8.805
9.735
10.665
×10^7



It can be seen, from the graphs, that the normal distribution is not appropriate to estimate the extra-large claims. On the other hand, Log-normal and Generalized Pareto distribution fits the adjusted historical claims effectively.

3.3 Reinsurance treaty

In this exercise, non-proportional excess of loss treaty is assumed (more about reinsurance treaties in [1], chapter 1.2.3). In this case the treaty has following parameters:

	Deductible	**Limit**	**Number of reinstatements**	**ROL**	**Reinstatement share**
Layer 1	15 000 000	5 000 000	3	20%	3@100%
Layer 2	20 000 000	30 000 000	2	8%	2@100%
Layer 3	50 000 000	50 000 000	1	1%	1@100%

4 CUMULATIVE CLAIMS ON PERCENTILES

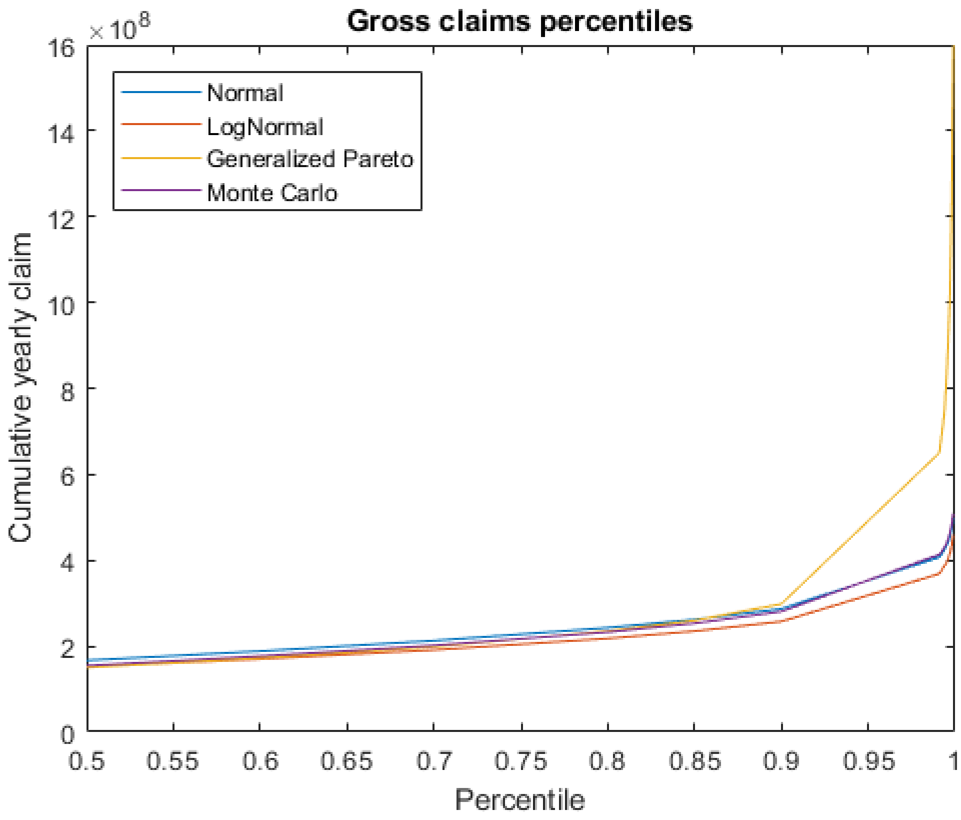
In this chapter, the total cumulative loss on the probability level is searched. All claims over 10 000 000 from the database were assumed as extra-large. Based on this value, all distribution parameters were calibrated. There was 108 claims over the threshold. Based on that, the Poisson distribution lambda is 6.75.

After fit the above mentioned distribution, the parameters are following:

- Normal distribution
  - μ=24 590 575.59
  - σ=21 284 306.83
- Log-normal distribution
  - μ= 16.79
  - σ= 0.60
- Generalized Pareto distribution
  - k= 0.503
  - σ= 7988277.09
  - θ= 9 999 999

4.1 Gross claims

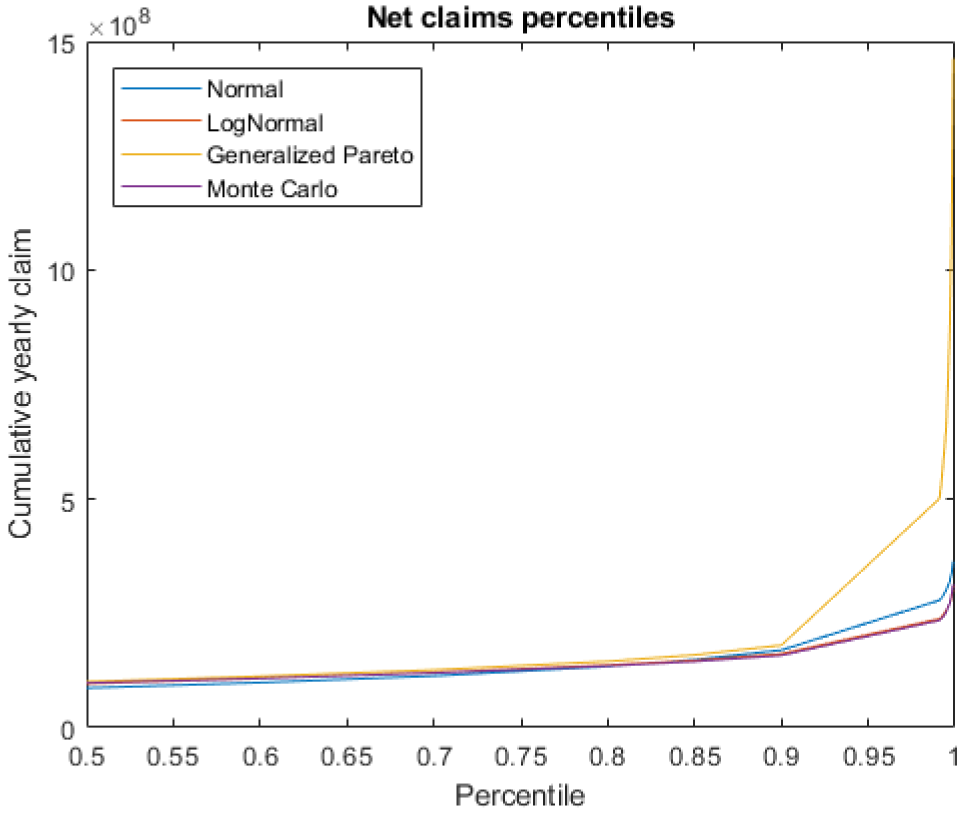
Under the term Gross claim is understood the cumulative yearly claim before reinsurance treaty activation. In the following graph, the cumulative gross annual loss on the percentile is shown. There is also the fourth approach, randomly selected historical claims, mentioned as Monte Carlo method.



It can be seen, from the graph, that until the 0.9 percentile the annual cumulative losses are very close to each other. The conclusion from these graph is, that if you are interested in the return period bellow 1 in 100, all the approaches are similar. This result is not valid for higher return periods. There can be seen, that the heavy tail of Generalized Pareto distribution estimates higher cumulative losses, than the other three approaches.

4.2 Net claims

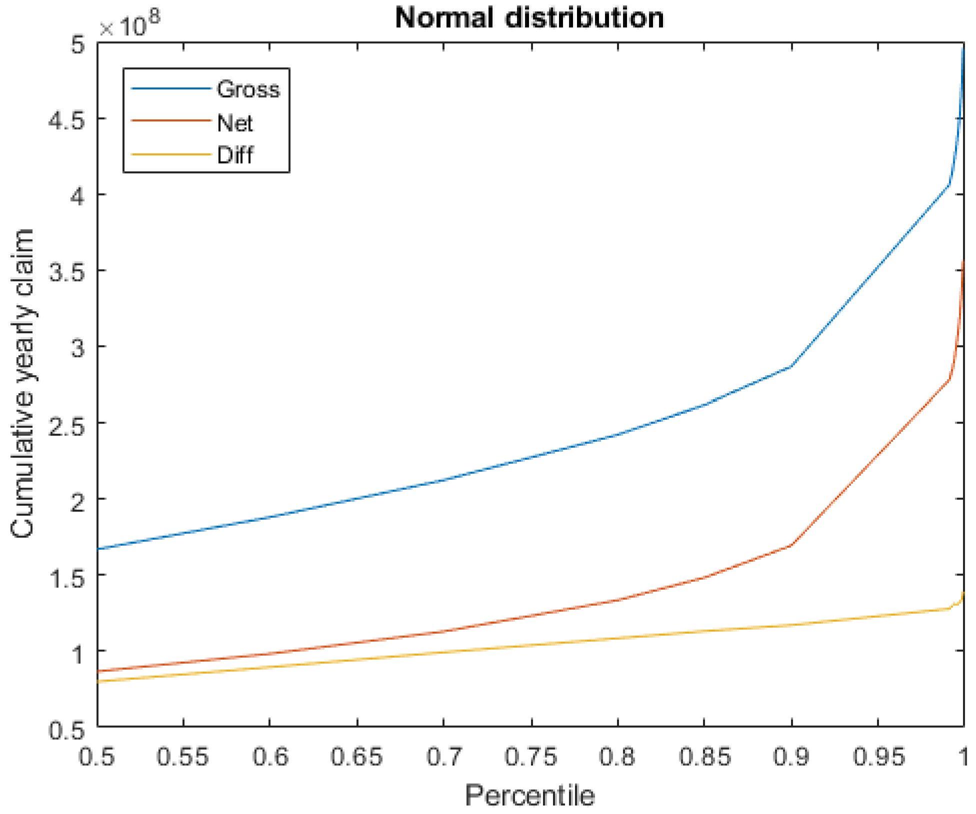
Net claims in this case means the cumulative annual loss after the reinsurance treaty activation. In the graph bellow, the cumulative annual net loss on the percentile is shown.

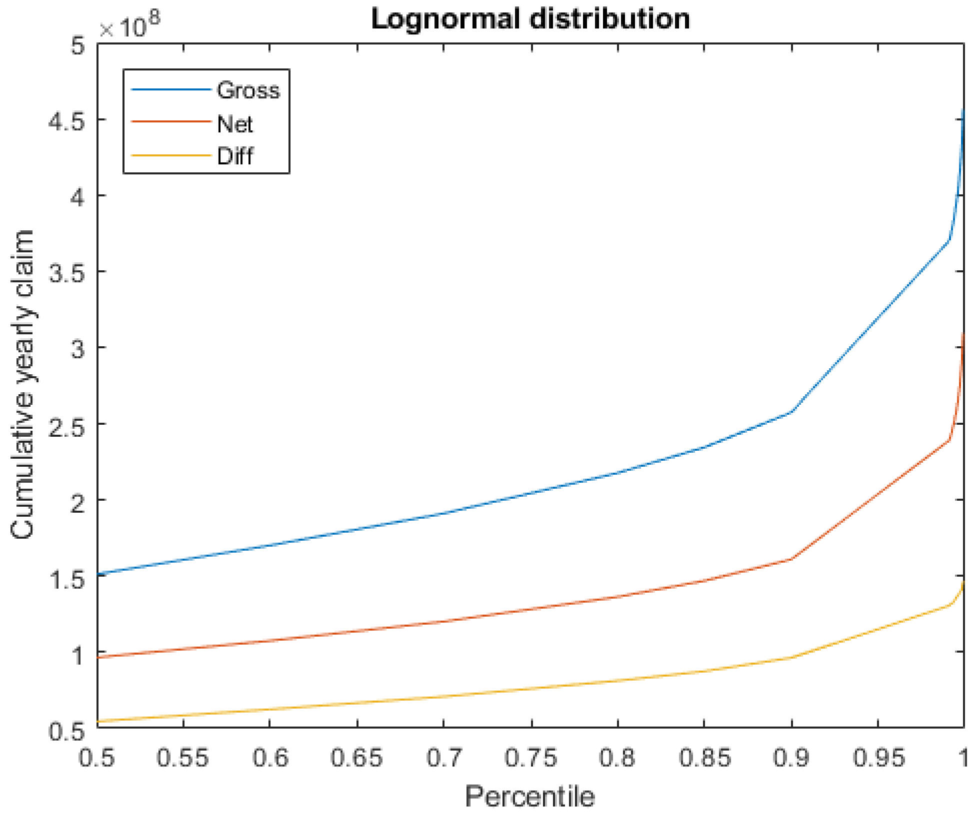


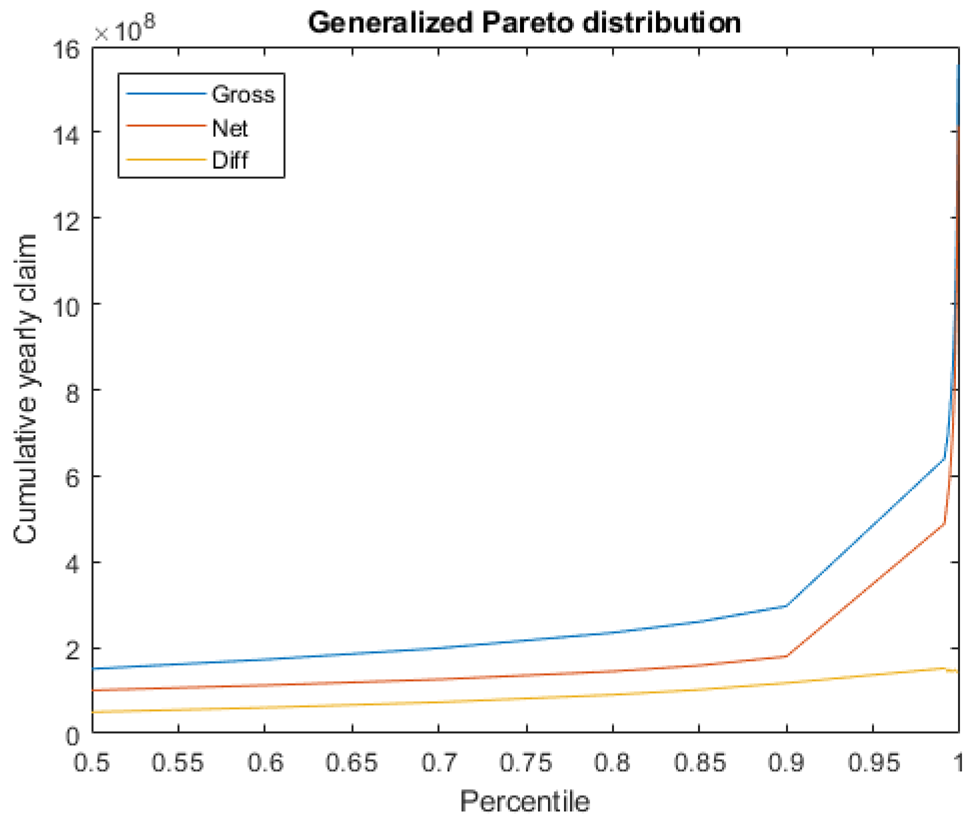
The same conclusion, as for the gross claims, is also valid for the net annual loss. The Generalized Pareto distribution estimates higher claims on return period above 1 in 100.

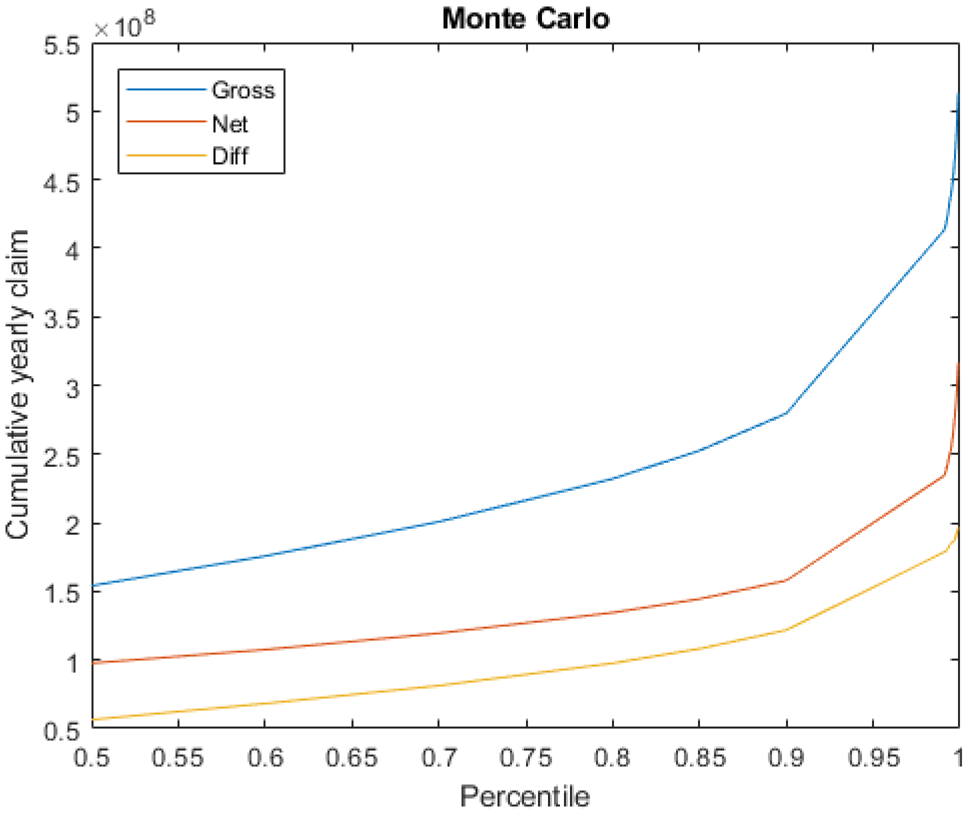
4.3 Gross vs. net claims

In the following graphs, the difference between gross and net cumulative annual claim is shown. The curve Diff means the difference between these two curves. In fact, it shows the reinsurance indemnity. It also can be used to estimate the reinsurance premium.


Normal distribution
×10^8
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
Cumulative yearly claim
Gross
Net
Diff
0.5
0.55
0.6
0.65
0.7
0.75
0.8
0.85
0.9
0.95
1
Percentile


Lognormal distribution
×10^8
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
Cumulative yearly claim
Gross
Net
Diff
0.5
0.55
0.6
0.65
0.7
0.75
0.8
0.85
0.9
0.95
1
Percentile





It should be noted, that there is absolutely different shape of the Diff curve in Generalized Pareto and Monte Carlo case. While, there is not any significant change of direction at Generalized Pareto graph, there is huge one in Monte Carlo graph.

The explanation is that the Generalized Pareto distribution estimates bigger cumulative annual loss than the Monte Carlo approach. This loss exceeds the capacity of the assumed reinsurance treaty (which is 200 000 000). Hence, there is no reinsurance cover anymore and the difference between gross and net result remains stable.

5 CONCLUSION

Four different approaches for creating loss tables was shown in this paper. While the Normal distribution was selected mainly for the reason, that it is the most commonly used, its results were similar to the distributions, which fits the exercise theoretically better.
In addition, the similarity of two different approaches – Log-normal distribution and the Monte Carlo method is not expectable on the first sight.
The Generalized Pareto distribution is mentioned in a lot of articles, which deals with the extra-large claims prediction. Despite the fact, that its results are different against all three other approaches, it can be recommended to use this one. Using the Generalized Pareto distribution makes the estimate more conservative on the higher return periods. This will cause better protection against adverse effects.

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Sources

1. Antal Peter Dr., Mathematical Methods in Reinsurance, Swiss Re, May 2009, https://www.actuaries.ch/fr/downloads/aid!b4ae4834-66cd-464b-bd27-1497194efc96/id!96/Reinsurance_Script2009_v2.pdf
2. Teugels Jef L., Large claims in insurance mathematics, Katholieke Universiteut Leuven, Belgium, https://www.casact.org/library/astin/vol13no2/81.pdf
3. Verlaak Robert, Hürlimann Werner, Beirlant Jan, Benchmark Rates for Excess of Loss Reinsurance Programs, http://www.actuaries.org/ASTIN/Colloquia/Zurich/Verlaak_Huerlimann_Bierlant.pdf

Contact

Ing. Michal Kuban
Univerzita Pardubice
Studentská 96, Pardubice, Czech Republic
Tel: +420 605 825 449
email: michal.kuban@upce.cz